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Intelligent Sensors for Condition Monitoring, Diagnosis, and Prognostics

Edited by
Tianyu Gao, Yinsheng Chen, Jianyu Wang and Xiaoli Zhao

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Intelligent Sensors for Condition Monitoring, Diagnosis, and Prognostics

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Article

Rehabilitation Driven Optimized YOLOv11 Model for Medical X-Ray Fracture Detection

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Highlights:

Main Findings

- A medical X-ray fracture detection model with precise localization based on YOLOv11n is proposed to solve the problems of false localization and poor accuracy in existing models.
- The improved model, trained with an expanded dataset using data augmentation and enhanced with a Bone-MSCA module and Focal-SIoU loss function, outperforms other mainstream single-object detection models, with significant improvements in detection accuracy, recall rate, F1-Score and mean Average Precision 50.

Implication of the Main Findings

- The proposed model can provide more accurate and reliable fracture detection from X-ray images, which is beneficial for timely and appropriate medical treatment.
- The techniques used in this research, such as data augmentation, the Bone-MSCA module and Focal-SIoU loss function, can be a reference for other medical image detection research, potentially improving the performance of related models.

Abstract: Accurately identifying fractures from X-ray images is crucial for timely and appropriate medical treatment. However, existing models suffer from problems of false localization and poor accuracy. Therefore, this research proposes a medical X-ray fracture detection model with precise localization based on the You Only Look Once version 11 nano (YOLOv11n) model. Firstly, a data augmentation technique combining random rotation, translation, flipping and content recognition padding is designed to expand the public dataset, alleviating the overfitting risk due to scarce medical imaging data. Secondly, a Bone-Multi-Scale Convolutional Attention (Bone-MSCA) module, designed by combining multi-directional convolution, deformable convolution, edge enhancement and channel attention, is introduced into the backbone network. It can capture fracture area features, explore multi-scale features and enhance attention to spatial details. Finally, the Focal mechanism is combined with Smoothed Intersection over Union (Focal-SIoU) as the loss function to enhance sensitivity to small fracture areas by adjusting sample weights and optimizing direction perception. Experimental results show that the improved model trained with the expanded dataset outperforms other mainstream single-object detection models. Compared with YOLOv11n, its detection accuracy, recall rate, F1-Score and mean Average Precision 50 increase by 4.33%, 0.92%, 2.52% and 1.24%, respectively, reaching 93.56%, 86.29%, 89.78% and 92.88%. Visualization of the results verifies its high accuracy and positioning ability in medical X-ray fracture detection.

Keywords: fracture; X-ray; data augmentation; YOLOv11 model; object detection

1. Introduction

Fracture is a type of bone structure damage caused by trauma or bone diseases, characterized by sudden onset and a high likelihood of triggering complications [1]. As a result of the intensification of global population aging and the increasing frequency of sports-related injuries, the incidence of fractures continues to rise, and consequently, it severely affects the quality of life of patients. The clinical hazards of fractures are not limited to acute injuries; the prevention and treatment of their complications, such as nonunion, infection, and deep vein thrombosis, have become key challenges during the rehabilitation period [2]. Statistics show that approximately 8–10% of fracture patients develop chronic nonunion due to delayed diagnosis or missed diagnosis, requiring secondary surgical treatment, which increases medical costs by 3–5 times. Therefore, early and accurate diagnosis is a core prerequisite for reducing the disability rate of fractures and improving prognosis [3].

Although X-ray imaging remains the first-line method for fracture diagnosis due to its convenience and low cost [4], its clinical application has significant limitations. Firstly, after three-dimensional skeletal structures are projected into two-dimensional images, overlapping anatomical sites (such as ribs and spine), limitations in projection angles, and low contrast of subtle fracture lines (such as crack fractures) result in a missed diagnosis rate of approximately 18–35% [5]. Secondly, in the early stage of callus formation, the small density difference between newly formed bone tissue and soft tissue makes it difficult to distinguish normal healing from delayed healing, and the inability to quantify callus biological activity easily leads to deviations in treatment decisions [6]. Furthermore, variations in operational standards (such as body position and exposure parameters) and physician experience further amplify errors; the misdiagnosis rate of complex fractures in primary hospitals is twice as high as that in tertiary hospitals, and imaging interference from special populations such as children with epiphyses and elderly patients with osteoporosis also increases the difficulty of interpretation. These technical bottlenecks collectively lead to significant challenges in distinguishing fracture areas from normal bone tissue in medical X-ray films, and may even cause over-medical treatment or delayed treatment due to missed diagnoses and misjudgments [7].

Against the backdrop of continuous advancements in medical imaging, the traditional diagnostic model for fractures is undergoing technological innovations towards intelligence and automation. Consequently, currently, deep-learning-based technologies are gradually being applied in the field of bone injury identification, and they exhibit significant advantages in clinical diagnosis compared with conventional detection methods [8]. In the architecture of deep-learning detection models, there are currently two major categories. Specifically, traditional detection models adopt two-stage models, such as Region with Convolutional Neural Network features (R-CNN) [9] and Faster R-CNN [10]. These models first extract candidate regions and then classify the candidate regions and perform bounding-box regression. Unfortunately, these models generally take a long time, occupy a large amount of disk space, and have a lot of model redundancy. To address such issues, single-stage models have been proposed, such as Single Shot MultiBox Detector (SSD) [11] and the You Only Look Once (YOLO) series [12]. Remarkably, with basically the same detection accuracy, these models treat the object-detection task as a regression problem. By omitting the redundant calculations in steps such as candidate-region extraction, they significantly improve the detection speed.

In recent years, deep learning has emerged as a transformative force in medical imaging fracture detection, offering innovative solutions to enhance diagnostic efficiency and accuracy. Within this rapidly evolving field, the YOLO series of models has garnered significant attention, with multiple studies demonstrating their clinical potential: Son et al. [13] developed a radiologist-independent deep-learning system for mandibular fracture detection in panoramic X-rays, directly validating YOLO's feasibility for fracture identification tasks. Building on this foundation, Hržić et al. [14] applied the YOLOv4 architecture to wrist fracture diagnosis, introducing the YOLO 512 Anchor model-AI. Critically, their work mitigated fracture missed diagnosis rates while highlighting synergies between AI and clinicians, thereby establishing a pragmatic, child-specific solution for pediatric wrist fracture detection. Concurrently, Ahmed et al. [15] addressed dual challenges in pediatric wrist imaging radiology resource scarcity and inefficiencies of traditional two-stage detection models by exploring single-stage YOLO-based alternatives. Their findings, notably a mean average precision (mAP) of 77% for YOLOv8x, underscored single-stage models' capacity to advance pediatric wrist fracture diagnostics. Expanding the scope further, Zou et al. [16] proposed a whole-body fracture detection framework using an improved YOLOv7 variant, achieving an mAP of 80.2%. This outcome specifically validated the clinical utility of enhanced loss functions and attention mechanisms in fracture detection workflows. Finally, Zheng et al. [17] leveraged 4493 X-rays from two institutional datasets, employing Demo-YOLO for data processing and augmentation. Their results conclusively demonstrated that dataset augmentation yielded substantial improvements in model detection accuracy.

Overall, in the studies mentioned above, researchers used public datasets or datasets processed via data augmentation, directly applied YOLO-series models or their improved variants, and successfully detected fracture areas in various parts of the body. However, three critical limitations remain: suboptimal mean average precision, unresolved missed detections and localization errors in small fractures, and poor data generalization. To address these issues, this study selected YOLOv11n as the baseline, optimized its localization and precision, and proposed the Bone Fracture-YOLOv11n (BF-YOLOv11n) model for whole-body, multi-site fracture detection. The main contributions are as follows:

(1) First of all, multiple public datasets were collected. Subsequently, a data augmentation technique combining random rotation, translation, flipping, and content recognition filling was proposed. This was performed to effectively alleviate the problem of data scarcity and thereby enhance the generalization ability of the model.

(2) Building on the foundation of Multi-Scale Convolutional Attention (MSCA) [18], a Bone-MSCA attention mechanism module was designed. Specifically, this module combines multi-directional convolution, deformable convolution, edge enhancement, and channel attention mechanism. Then, the Bone-MSCA was integrated into the backbone network of the YOLOv11n model. The purpose of this integration was to accurately extract the features of the fracture area. By enhancing the edges of the fracture lines through edge enhancement and adaptively adjusting the feature channels via channel attention, global information was effectively aggregated. As a result, the perception of spatial details in X-ray fracture images was significantly improved.

(3) Finally, the Focal mechanism [19] was combined with Smoothed Intersection over Union (SIoU) [20] as the loss function. This combination aimed to enhance the sensitivity to small fracture areas and optimize the accuracy of bounding-box regression. Consequently, the accuracy of medical X-ray fracture area detection was further improved.

The rest of this paper is organized as follows. Section 2 introduces the acquisition of medical X-ray fracture images and data augmentation methods, elaborates on the model structure and principle of YOLOv11n, and provides a detailed description of the

BF-YOLOv11n model; Section 3 contains detailed information about all the experiments; Section 4 presents the research conclusions and future prospects.

2. Materials and Methods

2.1. Acquisition of Medical X-Ray Fracture Images

In this research, multiple public datasets of medical X-ray images of bone fractures in various parts of the whole body across all age groups were integrated [21–23]. Specifically, a total of 34,990 original images covering all age ranges and various parts of the whole body including limbs and trunk were included. Subsequently, through a multi-level screening process initially postgraduate students majoring in orthopedics eliminated three types of images based on clinical imaging diagnostic standards normal images without fractures blurred images caused by equipment noise motion artifacts or improper exposure and non-standard position images where the proportion of bones outside the field of view exceeds 30% such as excessively tilted limb X-rays. Next, orthopedic and radiology physicians double-blindly excluded cases according to the imaging features of fracture diagnosis in the guidelines of the American Academy of Orthopaedic Surgeons (AAOS) including old fractures with healing period over 6 weeks non-traumatic bone lesions such as bone tumors infections and suspicious cases that cannot be clearly judged due to artifact interference such as areas obscured by metal implants. Eventually, 10,153 valid fracture images were retained. Some image samples are presented in Figure 1.

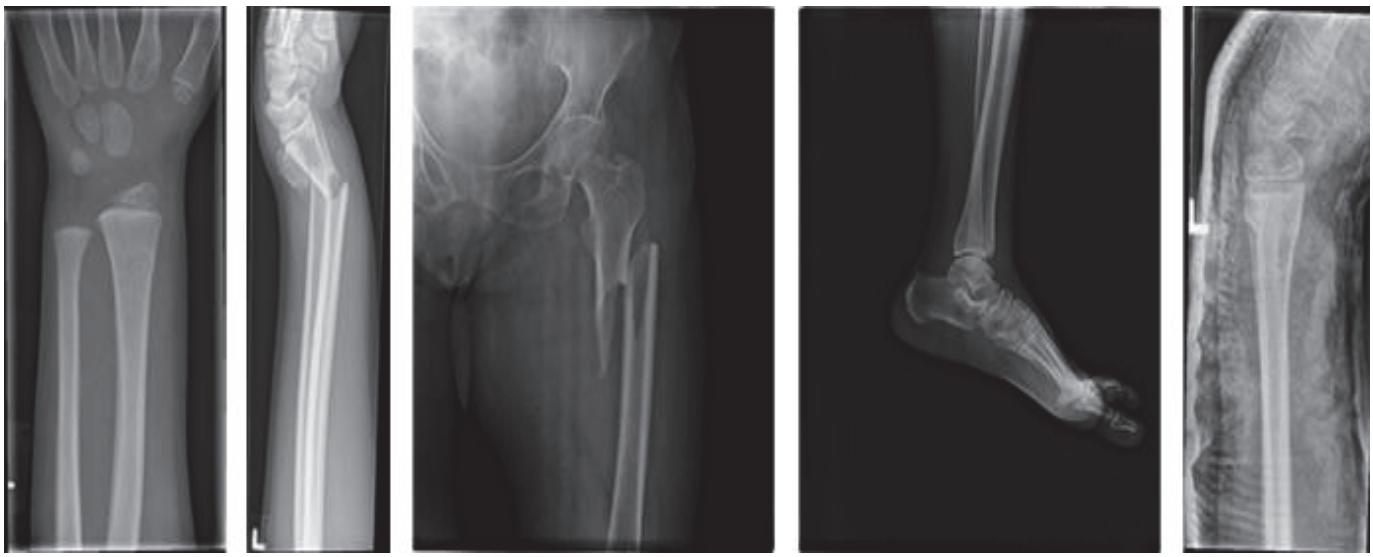


Figure 1. Sample Images from the X-ray Fracture Dataset.

This study employed a data augmentation method encompassing random rotation, translation, flipping, and core content-aware filling [24] to enhance medical X-ray fracture images. Among these techniques, content-aware filling serves as a crucial technical pillar, playing an irreplaceable role in simulating image diversity caused by variations in shooting angles, equipment, and patient positions. It not only works in conjunction with other transformation methods to improve dataset coverage and model generalization but also ensures the natural integration of fracture regions with surrounding tissues by accurately inferring and filling blank areas generated after image transformations. This maximizes the preservation of image authenticity and effectively avoids artificial noise interference that might be introduced by traditional filling methods. This technical feature enables the YOLOv11 model to more accurately capture the subtle variability of fracture features while learning rotation invariance and positional robustness. Consequently, under limited

data conditions, the model's accuracy in locating complex fractures has been improved. Techniques such as random selection, translation, and flipping can be easily implemented using OpenCV and NumPy libraries. The research also introduces a novel content-aware filling approach, which infers and fills blank areas after image transformations to ensure natural integration with the image content.

2.1.1. Blank Area Detection

Let the image be represented as a three-dimensional tensor $I \in \mathrm{R}^{H \times W \times C}$. Typically, blank areas result from invalid pixels that emerge after affine transformations, including rotation and translation. Specifically, when the transformed pixels fail to map to the valid region of the original image, their values are set to the background color [0, 0, 0]. Subsequently, for every pixel point (*i*,*j*), a binary mask $\mathrm{M} \in \{0,1\}^{H \times W}$ is created, as described below:

$$M_{i,j} = \begin{cases} 1 & \text{if } I_{i,j} = [0,0,0] \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

2.1.2. Edge Color Sampling and Statistical Inference

Achieving a more natural filling effect demands inferring colors from the edge pixels within the valid region of the image. In fact, since the edge colors of the image are adjacent to the blank areas, it is reasonable to use them as the basis for the filling operation. Then, for each RGB channel, the subsequent formula is employed to calculate the mean value of the edge pixels:

$$Top = \frac{1}{W} \sum_{j=0}^{W-1} I_{0,j,c} \tag{2}$$

$$Bottom = \frac{1}{W} \sum_{j=0}^{W-1} I_{H-1,j,c} \tag{3}$$

$$Left = \frac{1}{H} \sum_{j=0}^{H-1} I_{i,0,c} \tag{4}$$

$$Right = \frac{1}{H} \sum_{j=0}^{H-1} I_{i,W-1,c} \tag{5}$$

where the notations *Top*, *Bottom*, *Left*, and *Right*, respectively, denote the upper, lower, left, and right edges of the edge-sampling region.

Subsequently, a global average color operation is carried out:

$$color_{\text{avg}} = \frac{Top + Bottom + Left + Right}{4} \tag{6}$$

By leveraging the continuity of the image gradient, the filled area can be seamlessly integrated with the surrounding pixels through the minimization of an energy function. The Poisson blending formula is as follows:

$$color_{\text{Seamless}} = \min_{I_{\text{fill}}} \iint_{\Omega} | \nabla I_{\text{fill}} - \nabla I_{\text{src}} |^2 dxdy \tag{7}$$

where Ω denotes the filling region, and ∇ stands for the gradient operator. Specifically, $| \nabla I_{\text{fill}} - \nabla I_{\text{src}} |$ quantifies the difference between the gradient of the source image and the gradient of the filled image.

2.1.3. Final Filling Operation

During the initial stage, a simple mean-filling approach is adopted to rapidly cover the blank regions. This is performed to circumvent the high computational expenses that would result from directly applying Poisson blending to large-scale blank areas. Specifically, the corresponding formula is as follows:

$$I^1_{\text{fill}}[M] = color_{\text{avg}} \tag{8}$$

During the subsequent stage, I^1_{fill} is regarded as the source image I_{src}. Building upon the mean-filling process, the gradient continuity between the filled region and the neighboring pixels is further enhanced to eradicate color discontinuities. Specifically, the relevant formula is as follows:

$$I^2_{\text{fill}} = \min_I \iint_\Omega |\nabla I - \nabla I^1_{\text{fill}}|^2 dxdy \tag{9}$$

Through coarse filling to offer reasonable initial values and Poisson blending to fine-tune the edges, an equilibrium between efficiency and quality is established. Notably, several of the augmented samples are depicted in Figure 2.

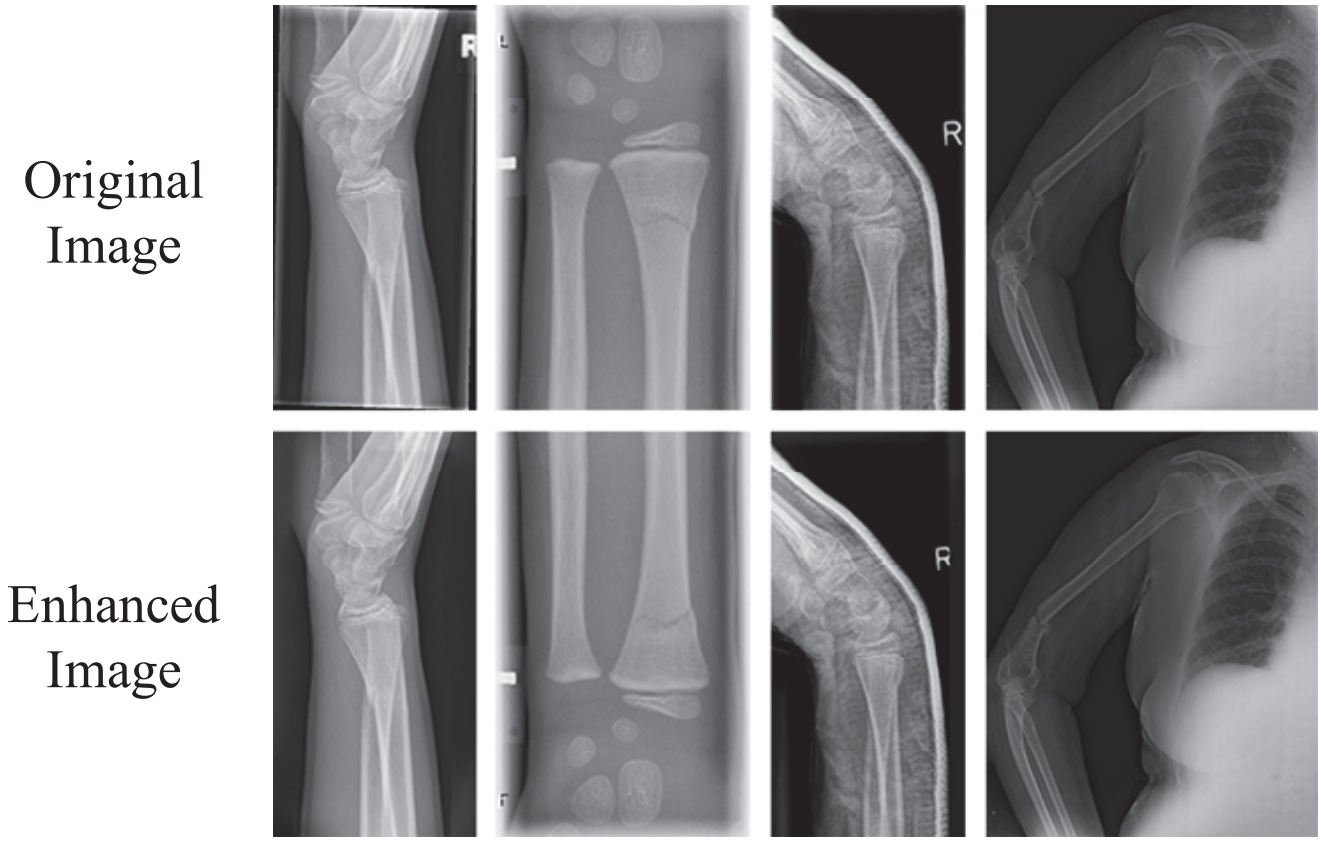


Figure 2. Sample Display of Augmented X-ray Fracture Dataset.

Following data augmentation, the images underwent rigorous screening by orthopedic postgraduate students, orthopedic physicians, and radiologists. Ultimately, 4114 augmented images were selected. These images conformed to the criteria regarding realism and defect features and were then incorporated into the dataset of this research. As a result, the comprehensively constructed medical X-ray fracture dataset encompasses a total of 14,267 images.

By utilizing the dataset annotation tool LabelImg, the bounding-box annotation of 14,267 image samples is manually carried out. Specifically, the category and location information of fracture targets within these images are annotated. The label is designated as "Fracture". The annotation results are then saved as txt files, thus finalizing the construction of the medical X-ray fracture dataset in the YOLO format. Thereafter, the images in the dataset are randomly partitioned into a training set (9987 images), a validation set (2854 images), and a test set (1426 images) at a ratio of 7:2:1.

2.2. Medical X-Ray Fracture Target Detection Model and Its Optimization

2.2.1. YOLOv11n

YOLOv11, introduced by Ultralytics in 2024 [25], is a member of the YOLO series. Its network architecture, built upon YOLOv8, adopts a lightweight object-detection framework. The core elements of this architecture consist of three main parts: the Backbone, the Neck, and the Head.

In the backbone network, a total of 13 convolutional layers are configured, and three key module upgrades have been implemented compared to previous models such as YOLOv8n: The C3k2 module replaces the C3 module in YOLOv8n, adopting a hybrid convolution kernel of 3×3 and 1×1, which optimizes information flow through a smaller receptive field, effectively reducing computational overhead while preserving local feature details such as subtle fracture lines; The C2PSA module integrates partial spatial attention mechanism into the C2f structure, replacing the basic C2f module of YOLOv8n, which enhances the model's attention to key fracture boundaries through adaptive weighted spatial regions and improves the feature extraction accuracy of low-contrast bone fissures. The neck network includes 6 convolutional layers and adopts the PANet structure instead of the traditional FPN, significantly improving small target detection capability through a top-down path aggregation strategy; The head network integrates dynamic head mechanism and depthwise separable convolution technology to achieve adaptive weight adjustment, reducing redundant computation while improving detection accuracy and efficiency; The Concat module in the neck fuses multi-scale features by concatenating feature maps in the channel dimension, enriching feature representation and improving detection accuracy. Overall, these technical improvements enable YOLOv11 to significantly reduce model parameters and computational requirements while maintaining high-performance detection.

The reason for selecting YOLOv11n as the baseline model is based on its comprehensive advantages in lightweight design, real-time performance, and network structure adaptability. Additionally, the C3k2, SPPF, and C2PSA modules in its backbone network can effectively capture subtle features of fracture regions in X-ray images, laying a foundation for the subsequent integration of the Bone-MSCA module and optimization of the Focal-SIoU loss function.

2.2.2. Optimized Model for Medical X-Ray Fracture Target Detection

YOLOv11n, a lightweight object detection model, exhibits certain limitations when applied to medical X-ray fracture detection. Specifically, on one hand, the lightweight nature of the model might result in the oversight of minute fractures or low-contrast bone fissures because of its inadequate feature extraction capabilities. Moreover, it struggles to discern the texture disparities among complex fracture types, such as comminuted fractures. On the other hand, YOLOv11n is highly sensitive to image noise and artifacts. In low-quality medical X-ray images, it is likely to make incorrect judgments. Additionally, the pursuit of real-time performance optimization may come at the cost of positioning accuracy, thereby impeding the accurate delineation of fracture boundaries. In response

to the above issues, this research presents an enhanced model. Specifically, it conducts a targeted improvement on the MSCA. In the network architecture, multi-directional convolution, deformable convolution, an edge enhancement module, and channel attention (Squeeze-and-Excitation Networks, SE) [26] are incorporated, giving rise to the design of Bone-MSCA.

Bone-MSCA is then integrated into the terminal part of the YOLOv11n backbone network. By means of multi-directional convolution and deformable convolution, the irregular shapes of fracture lines can be dynamically captured. In combination with Sobel edge enhancement, the high-contrast features of bone cortex interruptions are accentuated. The SE attention mechanism serves to suppress soft-tissue artifact noise, thereby minimizing false detections and missed detections. Simultaneously, lightweight grouped convolution guarantees computational efficiency. To enhance the sensitivity of detecting tiny fractures, the weights of challenging samples are increased. To refine the positioning accuracy of complex fractures, the interference from bone overlap and noise is mitigated. Through category imbalance adjustment, background interference is curbed, and the model's ability to learn fracture regions is bolstered. Focal-SIoU jointly optimizes bounding-box regression and classification confidence, accelerating the model's convergence rate and ensuring high robustness in low-quality images. The network structure of the Bone Fracture-YOLOv11n (BF-YOLOv11n) model is illustrated in Figure 3.

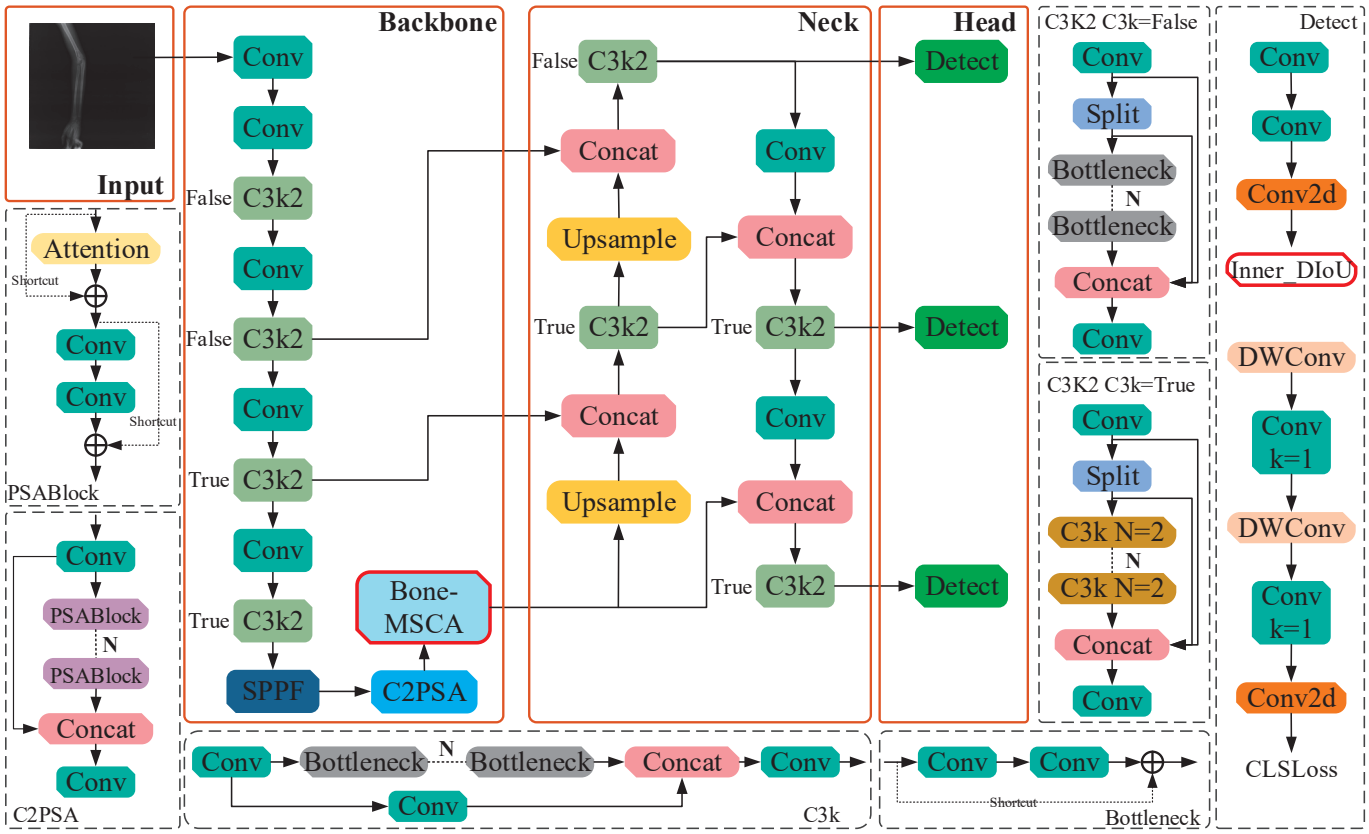


Figure 3. The network structure of BF-YOLOv11n.

2.2.3. BF-MSCA Module

Bone-MSCA harnesses multi-directional convolution to comprehensively capture the characteristics of fracture lines oriented in various directions. Simultaneously, deformable convolution adapts to the irregular geometries of fracture lines, enabling precise localization. The edge enhancement module, leveraging the Sobel kernel, accentuates the edges of fracture lines, thereby enhancing detection accuracy. The channel attention

mechanism emphasizes the features of fracture-relevant channels, boosting the model's performance. Moreover, the residual connection preserves the original information, facilitating the model's convergence. Furthermore, grouped convolution is employed to curtail parameters and computational intricacy, achieving both computational efficiency and a lightweight architecture. The parameter-sharing strategy inherent in grouped convolution helps prevent overfitting and bolsters the model's generalization ability. By utilizing convolution kernels of varying sizes and dilation rates, multi-scale feature fusion is realized, which effectively detects target regions of different dimensions. Notably, each module within Bone-MSCA has a well-defined function. This clarity enhances the model's interpretability, enabling researchers to more easily comprehend the decision-making process and optimize the model accordingly.

In this research, Bone-MSCA is integrated into the terminal part of the YOLOV11 backbone network. Specifically, by capitalizing on modules within Bone-MSCA, including multi-directional convolution, deformable convolution, edge enhancement, and channel attention, the multi-directional and irregular shape features of fracture lines can be precisely captured. Concurrently, edge and key channel features are accentuated. Through this approach, Bone-MSCA can effectively mirror the details and crucial features present in medical X-ray fracture images. It optimizes the amalgamation of multi-dimensional features, endowing the network with greater flexibility and accuracy when localizing fracture regions. Moreover, it enhances the robustness of detection in the face of complex fracture scenarios and low-quality images. As a result, the capacity of YOLOV11 to represent fracture-related features is significantly boosted. The structural design of Bone-MSCA is meticulously crafted to suit the characteristics of fracture images. Its implementation in YOLOV11 leads to superior performance in the fracture detection task. The architecture of the Bone-MSCA attention mechanism is depicted in Figure 4.

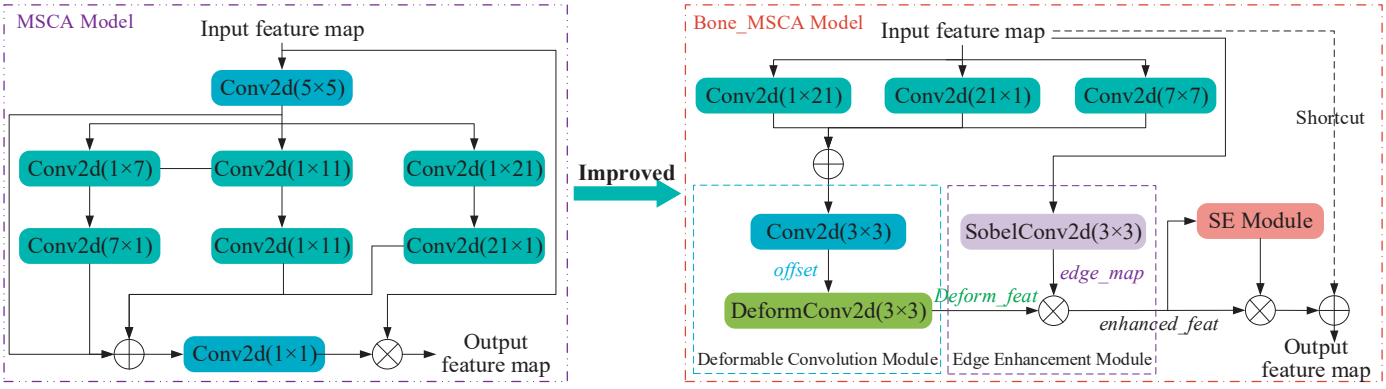


Figure 4. Bone-MSCA Attention Mechanism Structure Diagram.

As is evident from Figure 4, Bone-MSCA initiates with performing vertical convolution, horizontal convolution, oblique dilated convolution, and feature fusion operations on the input feature map $X \in R^{B \times H \times W \times C}$. Specifically, the corresponding mathematical expression is as follows:

$$Vert = X * Conv(1 \times 21) \tag{10}$$

$$Hori = X * Conv(21 \times 1) \tag{11}$$

$$Diag = X * d_1 Conv(7 \times 7) + X * d_2 Conv(7 \times 7) \tag{12}$$

$$Fuse = Vert + Hori + Diag \tag{13}$$

where *Vert*, *Hori*, and *Diag*, respectively, denote vertical, horizontal, and oblique dilated convolutions. Meanwhile, Fuse stands for feature fusion, and di indicates the dilation rate.

The mathematical formulation for the deformable convolution module is presented as follows:

$$offset = Conv_{3\times3}(Fuse) \tag{14}$$

$$deform_feat = DeformConv(Fuse, offset) \tag{15}$$

where *offest* represents the offset amount, and *offest* $\in \mathrm{R}^{B \times H \times W \times (2 \times 3 \times 3 \times C)}$; DeformConv represents the deformable convolution operation.

The mathematical representation of the edge enhancement module is given as follows:

$$edge_map = \sigma(X * W_{\text{sobel}}) \tag{16}$$

$$enhanced_feat = deform_feat \otimes (1 + edge_map) \tag{17}$$

where σ denotes the Sigmoid function. Meanwhile, W_{sobel} represents the fixed Sobel kernel, with $W_{\text{sobel}} \in \mathrm{R}^{3 \times 3 \times C}$.

The mathematical expression of the channel attention enhancement module is:

$$\begin{cases} z = GlobalAvgPool(enhanced_feat) & \\ s_1 = W_1 \times z & W_1 \in R^{C/(4\times C)} \\ s_2 = ReLU(s_1) & \\ s = \sigma(W_2 \times s_2) & W_2 \in R^{(C\times C)/4} \end{cases} \tag{18}$$

$$refined_feat = enhanced_feat \otimes s \tag{19}$$

where *GlobalAvgPool* and *ReLU* represent the global average pooling operation and the ReLU activation function, respectively; W_i is the weight of the fully connected layer of the SE module; the final channel weight $s \in \mathrm{R}^{B \times 1 \times 1 \times C}$; after channel recalibration, the *refined-feat* is obtained.

Ultimately, the output feature map is derived via the residual connection. The corresponding formula is as follows:

$$output = X + refined_feat \tag{20}$$

The Bone-MSCA attention mechanism integrates multi-directional convolution, deformable convolution, edge enhancement, and channel attention modules to comprehensively extract features across diverse directions and scales. Specifically, it discerns the orientation of fracture lines via multi-directional convolution, adapts to irregular shapes through deformable convolution, accentuates edges using edge enhancement, and modulates feature channels with channel attention. Collectively, these components effectively enhance the spatial detail perception of medical X-ray fracture images. When combined with the YOLOv11n backbone network, this mechanism further mitigates background interference, thereby bolstering detection capability across a broad spectrum of fracture scenarios including subtle fracture lines and intricate fracture morphologies. Ultimately, it provides a robust and precise feature representation for medical X-ray fracture detection.

2.2.4. Focal-SIoU Loss Function

By default, YOLO v11n adopts the Complete Intersection over Union (CIoU) loss function as the reference approach for bounding-box positioning. In the calculation process, this loss function incorporates a regression term related to the aspect ratio of the bounding box. However, it suffers from two primary drawbacks. Specifically, it does not efficiently handle the imbalance issue between positive and negative samples. Moreover, it imposes insufficient constraints on the spatial orientation features of the detection boxes, a phe-

nomenon that becomes especially prominent when the length-width characteristics of the target objects are not distinct.

In response to the aforementioned issues, a two-pronged improvement strategy is proposed in this research. Specifically, on one hand, the original loss calculation approach is substituted by the SIoU function with integrated angular constraints, which enhances the directional sensitivity of the detection boxes. On the other hand, the introduction of the Focal weight adjustment mechanism aims to mitigate the impact of category distribution imbalance during the training phase, particularly in the common scenario within medical imaging where the quantity of healthy area samples far exceeds that of lesion areas. In the domain of object detection, the IOU, a crucial quantitative metric for detection accuracy, is defined as the ratio of the overlapping area between the predicted region and the ground-truth annotated region to the area of their union, as presented in Equation (21):

$$IoU = \frac{|\boldsymbol{B} \cap \boldsymbol{B}_{\mathrm{T}}|}{|\boldsymbol{B} \cup \boldsymbol{B}_{\mathrm{T}}|} \tag{21}$$

where $\boldsymbol{B}$ and $\boldsymbol{B}_{\mathrm{T}}$ respectively denote the predicted bounding-box region and the actual bounding-box region.

The SIoU loss function innovatively incorporates four crucial cost functions, namely the angle, distance, shape, and intersection-over-union functions, via a multi-dimensional geometric constraint mechanism. Specifically, a schematic illustration depicting the calculation of the angle cost is presented in Figure 5.

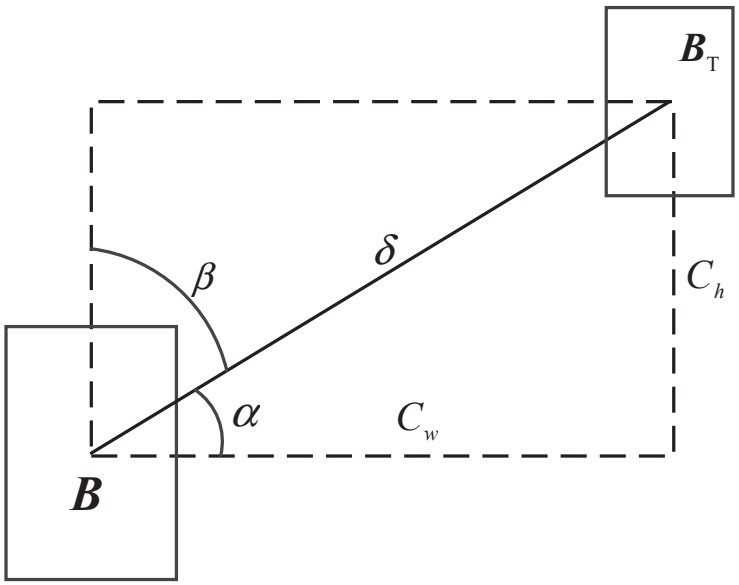


Figure 5. Schematic diagram of angle cost calculation in SIoU.

The angle cost function serves to capture angle information. The corresponding formula is presented as follows:

$$\Lambda = 1 - 2\sin^2(\arcsin(x) - \frac{\pi}{4}) \tag{22}$$

where

$$x = c_h/\delta = \sin(\alpha) \tag{23}$$

$$\sigma = \sqrt{(b_{\mathrm{cx}}^{\mathrm{gt}} - b_{\mathrm{cx}})^2 - (b_{\mathrm{cy}}^{\mathrm{gt}} - b_{\mathrm{cy}})} \tag{24}$$

$$c_h = \max(b_{\mathrm{cy}}^{\mathrm{gt}}, b_{\mathrm{cy}}) - \min(b_{\mathrm{cy}}^{\mathrm{gt}}, b_{\mathrm{cy}}) \tag{25}$$

The position cost changes with the angle cost, as shown in Equation (26):

$$\Delta = \sum_{t=x,y} (1 - e^{-\gamma \rho_t}) \tag{26}$$

where

$$\rho_x = (\frac{b_{cx}^{gt} - b_{cx}}{c_w}),\ \rho_y = (\frac{b_{cy}^{gt} - b_{cy}}{c_h}),\ \gamma = 2 - \Lambda \tag{27}$$

where $(b_{cx}^{gt}, b_{cy}^{gt})$ and (b_{cx}, b_{cy}) respectively denote the center point of the actual bounding box and the center point of the predicted bounding box.

The shape cost is calculated based on the distance cost, as depicted in Equation (28):

$$\Omega = \sum_{t=w,h} (1 - e^{-\omega_t})^{\theta} \tag{28}$$

where

$$\omega_w = \frac{|w - w^{gt}|}{\max(w, w^{gt})}, \omega_h = \frac{|h - h^{gt}|}{\max(h, h^{gt})} \tag{29}$$

where the notations w^{gt} and h^{gt} respectively denote the width and height of the actual bounding box, and θ is set to 1.

In summary, the formula for calculating the overall SIoU loss function is presented as follows:

$$L_{SIoU} = 1 - IoU + \frac{\Delta + \Omega}{2} \tag{30}$$

By balancing the evaluation of the importance of high-and low-confidence samples, this research integrates the Focal mechanism with SIoU. Specifically, through the introduction of a balancing factor τ, the Focal mechanism adjusts the sample weights, allowing the model to focus more intently on hard-to-distinguish samples. The value of τ can be adjusted flexibly according to the real-world situation to achieve optimal results. The relevant formula is presented as follows:

$$L_{Focal\text{-}SIoU} = -(1 - IoU)^{\tau} \log(IoU) L_{SIoU} \tag{31}$$

The Focal-SIoU Loss function, shaped by the two mechanisms, dynamically regulates the weight equilibrium between healthy tissues and fracture lesions via the gradient-focusing mechanism. This effectively mitigates the sample-imbalance issue in cases where the proportion of the fracture area is minuscule. When integrated with the direction-morphology dual-constraint model, the function boosts the positioning precision of minute or inclined fractures, thereby ultimately enhancing the overall detection performance of the model.

2.2.5. Training Environment and Methods

The training environment for this research is built upon the Pytorch framework. It serves in the establishment, training, and analysis of the medical X-ray fracture detection model. Specifically, the detailed configurations of the software and hardware platforms are presented in Table 1.

Table 1. Hardware and Software Platform Configuration.

Name	Version Information
System	Ubuntu 22.04.3 LTS
Operating System Kernel	GNU/Linux 5.15.0-124-generic
Central Processing Unit	Intel® Xeon® Platinum 8365A CPU
Graphics Processing Unit	NVIDIA GeForce RTX 3090 24 GB
Python	3.11.10
Deep-learning Frameworks and Libraries	Pytorch 2.4.0, Cuda 12.1.1, cuDNN 9.1.0

During the training stage, the hyperparameters are configured as follows. First, the images are uniformly resized to 640 × 640 pixels. Subsequently, the batch size is set to 8, and the number of threads is configured to 4. The Stochastic Gradient Descent (SGD) model is chosen as the optimizer. Then, a full 200-iteration training process is implemented. Regarding the learning rate, it is adjusted according to the cosine annealing decay strategy [27]. Meanwhile, other hyperparameters maintain the default values provided in the YOLOv11 source code.

In order to assess the performance of the medical X-ray fracture target detection model, this research utilizes the following metrics to analyze the experimental results: Precision (p), Recall (R), Average Precision (AP), F1-Score (F_1), mean Average Precision (mAP), Parameters, GFLOPs, as well as Inference metrics including preprocessing, inference, and post-processing stages [28]. Specifically, the mathematical expressions are as follows:

$$P = \frac{T_p}{T_p + F_p} \times 100\% \tag{32}$$

$$R = \frac{T_p}{T_p + F_n} \times 100\% \tag{33}$$

$$F_1 = 2 \times \frac{P \times R}{P + R} \tag{34}$$

$$mAP = \frac{\sum_{i=1}^{N} P_i(R)dR}{N} \times 100\% \tag{35}$$

where T_p denotes the number of samples with correctly detected defects. Similarly, F_p denotes the number of samples mis-identified as having defects, and F_n represents the number of samples where defects are not accurately detected. The symbol n represents the number of defect categories. In the context of this research, since the focus is uniformly on detecting the fracture area, n = 1.

3. Results

3.1. Impact of Dataset Expansion on Model Performance

In order to objectively assess the influence of the augmented dataset presented in this research on the model, the precision boxplot and the mAP50 (IoU = 0.5) variation graph are utilized to contrast the detection performance of YOLOv11n for the medical X-ray fracture dataset before and after augmentation. Specifically, the relevant data is presented in

As is manifest from Figure 6, the comparative analysis of data before and after augmentation reveals that the utilization of the augmented dataset leads to a significant enhancement of the model's performance during YOLOv11 training. Box-plot analysis demonstrates that the median of the augmented dataset exceeds that of the original dataset. Although the distribution ranges of the 25–75% quantiles are comparable, the overall performance center experiences an upward shift. This indicates that the augmentation

strategy effectively boosts the average detection accuracy of the model. Throughout the training process, the mAP50 value of the augmented dataset consistently remains higher than that of the original dataset. Specifically, at the final training endpoint, the mAP50 value increases from 90.19% to 91.64%, and during long-term training, the mAP50 value shows a tendency towards stability. Consequently, a rational data augmentation strategy can improve the model's training outcomes and performance. Figure 6.

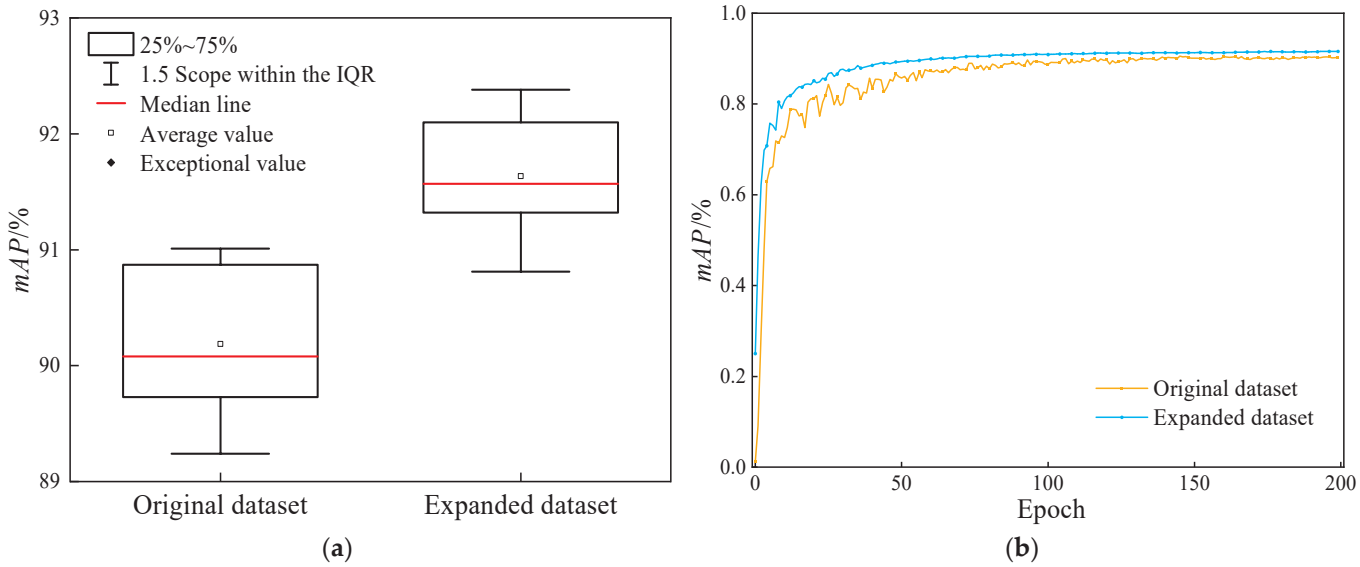
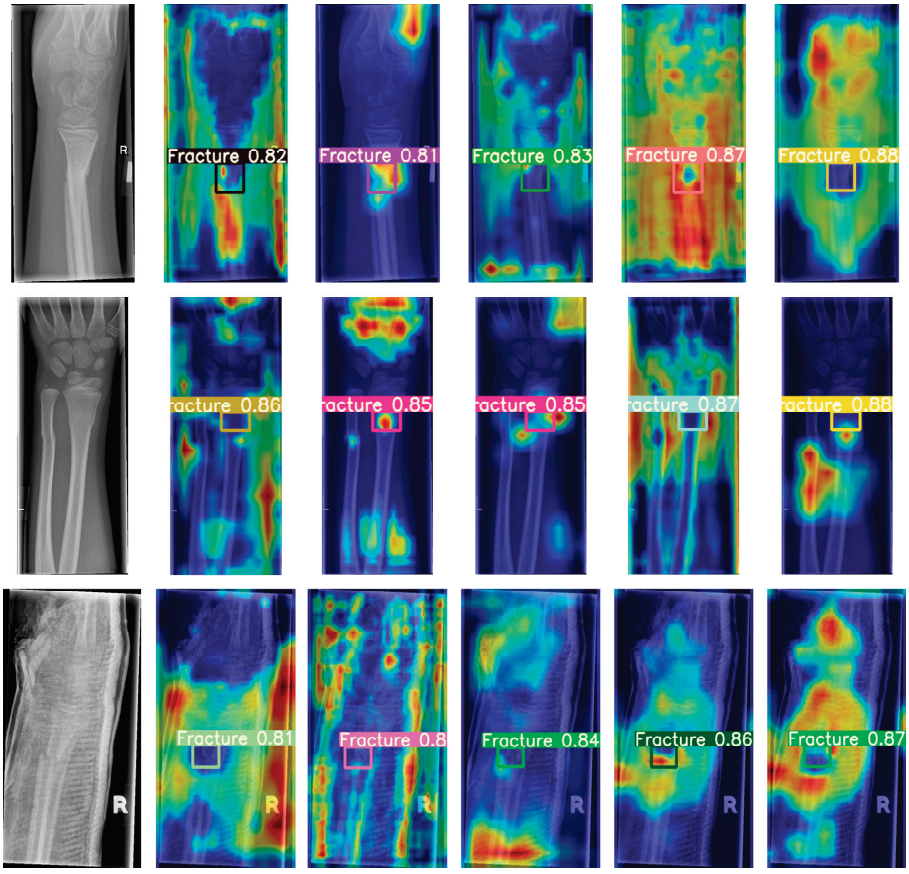


Figure 6. Comparison of the detection performance of the YOLOv11n model before and after dataset augmentation. (**a**) Comparison chart of box plots for the mAP50 of models; (**b**) Comparison chart of mAP50 changes.

3.2. Performance Comparison of Different Attention Mechanisms

By accurately assessing the function of the attention mechanism in boosting the detection performance of medical X-ray fracture areas, this research undertakes comparative experiments with multiple attention mechanisms, namely Efficient Channel Attention (ECA) [29], Convolutional Block Attention Module (CBAM) [30], Global Attention Mechanism (GAM) [31], MSCA, and Bone-MSCA. During training, Gradient-weighted Class Activation Mapping (Grad-CAM) [32] is employed to generate a heatmap for a particular fracture in each instance. This serves to visually illustrate how the model learns feature information when handling different defect targets. By analyzing the brightness variations in specific regions of the heatmap, the areas within the image that significantly influence the model's output can be uncovered. Figure 7 presents a comparison of heatmaps obtained using different attention mechanisms.

As can be clearly observed from Figure 7, upon the completion of training, the Bone-MSCA attention mechanism put forward in this research can detect medical X-ray fracture regions with higher confidence levels and more vivid regional colors. Moreover, it devotes more attention to defects. The Bone-MSCA realizes cross-scale defect representation via multi-branch parallel convolution. Additionally, it introduces an adaptive weight-fusion mechanism. This mechanism adaptively adjusts the contribution ratio of multi-scale features, enhances the separation between defects and the background, and improves the fine-grained detection capability for multi-morphological surface defects under complex lighting conditions.



(a) Original (b) ECA (c) CBAM (d) GAM (e) MSCA (f) Bone_MSCA

Figure 7. Visualization Analysis of Heatmaps for Model Detection Results under Different Attention Mechanisms. (**a**) Original image; (**b**) Using ECA attention mechanism; (**c**) Using CBAM attention mechanism; (**d**) Using GAM attention mechanism; (**e**) Using MSCA attention mechanism; (**f**) Using Bone_MSCA attention mechanism. In the figure, blue indicates low intensity, yellow indicates medium intensity, and red indicates high intensity. This color coding is used to visually distinguish the fracture detection sensitivity of different algorithms.

3.3. Comparative Experiment of Loss Functions

In order to validate the influence of various loss functions on the model's performance, comparative experiments are conducted. These experiments utilize the CIoU, Focal-IoU, SIoU, Focal-CIoU, and Focal-SIoU loss functions, building upon the original improved model. Specifically, the experimental results are presented in Table 2.

Table 2. Comparative Experiments on Loss Functions.

Loss Functions	*p*/%	*R*/%	F_1	mAP50/%
CIoU	89.23	85.37	87.26	91.64
Focal-IoU	90.10	86.29	88.15	92.08
SIoU	80.33	92.26	85.88	91.83
Focal-CIoU	90.75	86.44	88.54	92.22
Focal-SIoU	92.08	85.86	88.86	92.38

As is evident from Table 2, when compared to other loss functions, the Focal-SIoU loss function employed in this research exhibits the best F1 and mAP50 values, reaching 88.86% and 92.38%, respectively. This is because SIoU enhances the model's positioning precision for irregular fracture areas through the introduction of an angle-penalty mechanism. Meanwhile, Focal Loss boosts the model's sensitivity to small-target and low-contrast fractures

by suppressing the weight of the background area, thus significantly improving the precision. The combined effect of these two functions not only mitigates the issue of highly unbalanced positive and negative samples in medical images but also strikes a balance between precision and recall, thereby achieving a more robust detection performance.

3.4. Performance Comparison of BF-YOLOv11n Ablation Experiments

In this research, ablation experiments are employed to validate the viability of the strategy that incorporates the Bone-MSCA attention mechanism and the Focal-SIoU loss function into the YOLOv11n model. Specifically, the experimental results are presented in Table 3.

Table 3. Comparison of Ablation Experimental Performance.

Bone-MSCA	Focal-SIoU	p/%	R/%	F_1	mAP50/%
/	/	89.23	85.37	87.26	91.64
√	/	93.19	85.26	89.05	92.51
/	√	92.08	85.86	88.86	92.38
√	√	93.56	86.29	89.78	92.88

It is clear from Table 3 that within the medical X-ray fracture detection task, incorporating Bone-MSCA and Focal-SIoU significantly enhances the model's performance. Bone-MSCA integrates multi-scale fracture features via oblique dilated convolution to capture directional fracture line disparities and, in conjunction with the SE module to suppress bone-overlap noise, intensifies the response of key regions. This leads to an increase in precision from 89.23% to 93.56% and a 1.24% elevation in mAP50 a core metric for detection accuracy. Conversely, Focal-SIoU mitigates the sparsity issue of fracture regions in X-ray images by dynamically adjusting the weights of easy- and hard-to-detect samples via the Focal mechanism to enhance blurred fracture detection and optimizing the direction-aware bounding box. While preserving the model's lightweight characteristic, it boosts the recall by 0.92% a metric reflecting the model's ability to capture all true fractures.

When these two components collaborate, the feature-extraction capacity of Bone-MSCA and the loss-guiding function of Focal-SIoU create a closed-loop. As a result, the comprehensive metric F_1 balancing precision and recall experiences a 2.52% increase, indicating robust optimization of overall detection performance.

3.5. Comparative Experiments of Mainstream Object Detection Models

In order to validate the efficacy of the BF-YOLOv11n model put forward in this research, comparative experiments are carried out. These experiments involve the mainstream single-stage object detection model SSD and the recent nano-level versions of the YOLO series, namely YOLOv8n, YOLOv9t [33], YOLOv10n, YOLOv11n [34], YOLOv11n + ResNet_GAM [35], and YOLOv12n [36]. The experimental results are presented in Table 4.

Based on the analysis of the results in Table 4, regarding detection performance, the F1 value of the BF-YOLOv11n model is 50.18%, 16.8%, 22.76%, 2.68%, 2.52%, 0.25%, and 12.99% higher than those of the other six models, respectively. Similarly, its mAP50 value is 33.07%, 1.33%, 0.99%, 1.83%, 1.24%, 0.35%, and 1.46% higher, respectively. Evidently, the BF-YOLOv11n model demonstrates top-tier performance among these models. The recall rate of the SSD model stands at 26.35%, suggesting significant missed detections, thus restricting its practical utility. Additionally, YOLOv11n + ResNet_GAM has a large number of parameters, which is unfavorable for model lightweighting. For YOLOv8n, YOLOv9t, and YOLOv12n, although their recall rates surpass 90%, their precision rates are subpar. Consequently, their F1-Scores are all below 80%, indicating a high false-positive

issue. All YOLO-series models exhibit an mAP50 exceeding 91%, signifying their robust positioning capabilities. However, the precision rate fluctuates by 40.67%, underscoring the importance of enhancing feature discrimination and small-target positioning judgment in model optimization. The Parameters and GFLOPs of BF-YOLOv11n are 2.7×10^6 and 6.4×10^9, respectively, which are slightly higher than those of YOLOv11n and YOLOv12n overall. However, the inference time for processing an image is 2.2 ms, which also meets the real-time requirements. Overall, when compared to other models, the BF-YOLOv11n model offers the advantages of precise detection and high robustness in the medical X-ray fracture detection task.

Table 4. Comparative Experimental Evaluation of Mainstream Detection Models.

Detection Models	*p*/%	*R*/%	F_1	*mAP50*/%	*Parameters*/10^6	*GFLOPs*/10^9	*Inference*/*ms*
SSD	79.68	26.35	39.60	59.81	26.28	62.7	28.40
YOLOv8n	60.75	91.37	72.98	91.55	3.01	8.1	3.5
YOLOv9t	52.66	92.15	67.02	91.89	1.97	7.6	3.3
YOLOv10n	90.33	84.09	87.10	91.05	2.71	8.2	2.4
YOLOv11n	89.23	85.37	87.26	91.64	2.58	6.3	1.8
YOLOv11n + ResNet_GAM	93.47	85.90	89.53	92.53	5.39	15.2	4.3
YOLOv12n	74.95	90.02	81.80	91.42	2.56	6.3	2.1
BF-YOLOv11n	93.56	86.29	89.78	92.88	2.70	6.4	2.2

Given that the mAP50 value of the SSD model is below 60% and does not meet the criteria for precise medical X-ray fracture detection, subsequent reasoning and detection for this model will not be conducted. To evaluate the performance of the BF-YOLOv11n model in detecting medical X-ray fractures, this research performs comparative experimental analyses on YOLOv8n, YOLOv9t, YOLOv10n, YOLOv11n, YOLOv12n, and BF-YOLOv11n, using four groups of images from the test set. Specifically, the related results are presented in Figure 8.

As is evident from Figure 8, owing to the high false-positive issue in YOLOv8n and YOLOv9t, these two models failed to detect any fracture regions. Although YOLOv12n is capable of detecting fracture regions, its positioning capability is inadequate, resulting in generally low detection confidence levels. For YOLOv10n, when it comes to detecting the first image, obvious false detections occur. Both YOLOv11n and BF-YOLOv11n demonstrate good performance in the medical X-ray fracture detection task. Specifically, BF-YOLOv11n exhibits higher detection confidence, more precise target positioning, and greater model robustness, with no instances of missed or false detections.

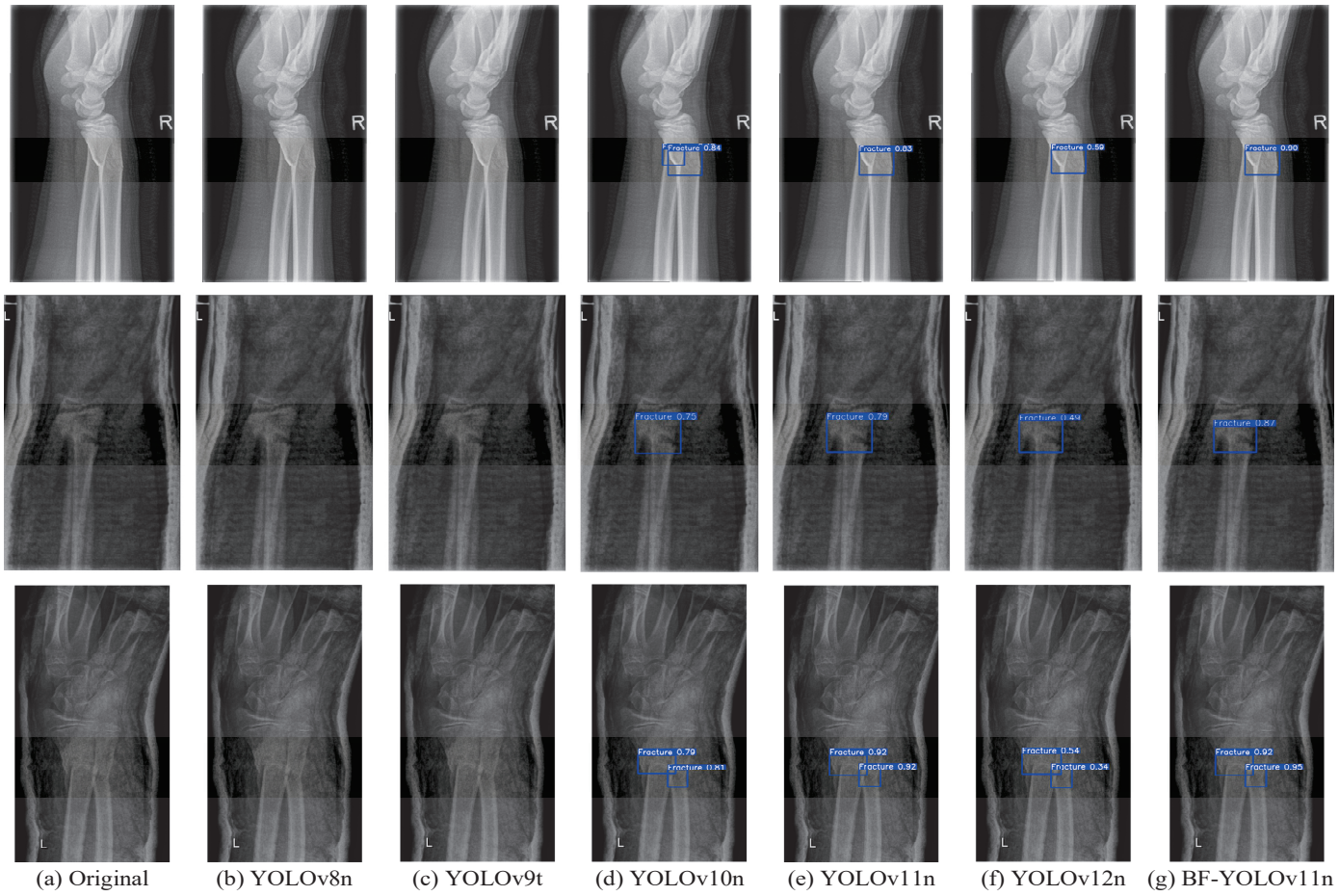


Figure 8. Comparative Effectiveness of Mainstream X-ray Fracture Detection Models. (**a**) Untreated original image; (**b**) Image detection using YOLOv8n; (**c**) Image detection using YOLOv9t; (**d**) Image detection using YOLOv10n; (**e**) Image detection using YOLOv11n; (**f**) Image detection using YOLOv12n; (**g**) Image detection using BF-YOLOv11n.

4. Conclusions

This research aims to tackle problems like the occlusion of fine fracture lines, the challenge of identifying early-stage callus, and the susceptibility of traditional models to noise in medical X-ray fracture detection. It does so by putting forward an enhanced BF-YOLOv11n model. First, a dataset expansion strategy is introduced. This strategy encompasses random rotation, translation, flipping, along with an innovative content recognition filling technique. In doing so, it mimics the image diversity in actual clinical scenarios, effectively broadening the dataset's coverage and bolstering the model's generalization capabilities. Second, the Bone-MSCA attention mechanism is incorporated. When combined with multi-directional convolution, deformable convolution, an edge enhancement module, and a channel attention mechanism, it enables the effective capture of the irregular morphology and edge features of fracture lines. Simultaneously, it suppresses image noise and artifact interference. Finally, the Focal-SIoU loss function is employed. Through the dynamic adjustment of the weights for easy-to-detect and hard-to-detect samples, along with direction-aware optimization, the imbalance issue of positive and negative samples in medical images is significantly mitigated.

Experimental results indicate that the augmented dataset boosts the model's mAP50 from 90.19% to 91.64%, validating the positive impact of data augmentation on the detection of complex fracture regions. The precision, recall, F1-Score, and mAP50 of the improved model on the test set, respectively, reach 93.56%, 86.29%, 89.78%, and 92.88%. Evidently, its

comprehensive performance outperforms that of other mainstream single-stage detection models. BF-YOLOv11n integrates high precision and strong robustness, offering reliable technical support for clinical fracture-assisted diagnosis.

In future research, efforts will focus on validating the model's generalizability across broader public datasets and multi-institutional clinical data to enhance rehabilitation outcome prediction capabilities. We will further explore the classification of specific fracture types such as transverse, oblique and comminuted fractures by incorporating anatomical location and morphological features, aiming to develop a subtype-specific detection framework that supports precise clinical decision-making. The application of transfer learning to non-traumatic fractures such as osteoporotic fractures will be explored to develop personalized rehabilitation pathway models. To address clinical needs for real-time rehabilitation monitoring and adaptive treatment planning, we will further reduce model parameters and optimize computational efficiency, enabling deployment on mobile/edge devices for continuous point-of-care rehabilitation assessment.

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Data-Driven Fouling Detection in Refinery Preheat Train Heat Exchangers Using Neural Networks and Gradient Boosting

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Abstract: Fouling detection in refinery crude distillation unit (CDU) preheat trains is essential for maintaining energy efficiency and operational reliability. This study presents a virtual sensing approach for fouling monitoring using data-driven and semi-empirical models. Specifically, Long Short-Term Memory (LSTM) neural networks, Extreme Gradient Boosting (XGB), and the ε-NTU method (effectiveness—Number of Transfer Units) were compared for predicting heat exchanger outlet temperatures, which serve as indicators of fouling. Models were trained on clean operational data to estimate baseline performance. A growing discrepancy between predicted and actual outlet temperatures over time indicated heat transfer degradation. Fouling resistance was calculated from the difference between predicted and actual heat transfer coefficients, enabling effectiveness loss assessment. The LSTM model showed high accuracy in capturing dynamic operational trends, while XGB provided a lightweight alternative with limited extrapolation capability under unfamiliar conditions. Both models outperformed the ε-NTU approach in fouling detection sensitivity. Inefficiencies from a single fouled exchanger were estimated to result in an additional 175 tons of CO_2 emissions and an economic loss of approximately EUR 12,000 over two months. This study highlights the potential of AI-enabled virtual sensors for real-time fouling monitoring in industrial heat exchangers. Such tools can significantly enhance predictive maintenance strategies, improve energy efficiency, and reduce emissions.

Keywords: fouling detection; machine learning; preventive maintenance; preheat train; heat efficiency CDU; heat exchanger

1. Introduction

It has been a long-lasting challenge for the process industry to reduce energy consumption and emissions in crude oil refineries as one of the biggest energy consumers in the process industry [1]. The Crude distillation unit (CDU) is the central process unit of a refinery and is also one of its most energy intensive operations inside the refinery. In the process of crude distillation, the crude oil enters the distillation column at temperatures between 330 °C and 380 °C which is being reached with the heat exchanger network (HEN) and the furnace [2]. HENs, as key operations for efficiently energy utilization, have been subject to many studies on the optimization and design of networks [3], as well as the processes inside the heat exchangers such as heat transfer efficiency and the formation of fouling depositions [4]. Depositions on the heat transfer surface degrade heat transfer efficiency, which usually brings more primary fuel consumption [5]; therefore, the operators need timely and purposeful information about the behavior in order to react and optimize fuel consumption and carbon emissions. Timely information also gives the operator the ability

to schedule cleanings of heat exchangers to minimize operational disruptions [6], thus extending equipment lifetime, avoiding unnecessary shutdowns and expensive repairs. There is a significant amount of research concerning the detection and prediction of fouling, which can be attributed to its serious environmental and financial implications. In the US refining sector alone, heat exchanger fouling in CDUs was projected to cost approximately 1 to 1.2 billion USD in 2019 [7]. Furthermore, a loss of efficiency in heat exchangers leads to negative environmental effects with excessive carbon emissions [8].

In the extensive research on semi-empirical fouling models, Ur Rehman et al. [9] highlighted the differences and advancements between deterministic, threshold, and modern computational fluid dynamics (CFD) simulation models. The authors reviewed methods for determining mechanisms involved in the formation of deposition and mechanism incorporation in semi-empirical models, concluding that great effort has been made by researchers in the field. However, the complexity related to crude oil composition remains a considerable challenge. Additionally, while some of the reviewed CFD simulations made a strong breakthrough, they were primarily based on laboratory-scale experimental and simulated data, lacking validation with field data from heat exchangers in CDUs. Fouling inside HENs is a complex phenomenon due to a lack of understanding of the physical and chemical mechanisms involved [10]. Developing a widely accepted fundamental model has been challenging due to the dynamics of change in operating parameters, system geometry, as well as variations in crude oil used inside real-world refinery plants [11,12]. Another approach was reviewed in the summary by Wilson et al. [13], which provides an overview of various studies on fouling prediction. The authors included an additional group of models—artificial neural network (NN) models for fouling determination. These data-driven models identify correlations between the defined process features and provide sufficient insights into process behavior without entering the underlying mechanism complexity [11]. Although these models have demonstrated notable success in various studies, they often rely on simulated conditions, laboratory-scale experiments, or predefined predict fouling resistance (R_f) values—parameters that are frequently unavailable or impractical to determine in real industrial settings. The methodology presented in this study, on the other hand, is based solely on real operational data collected from refinery heat exchangers under actual process conditions. This avoids the issue of idealized models that cannot capture the operational dynamics and frequent feedstock changes typical of industrial settings. Furthermore, the proposed approach eliminates the need to include R_f as an output variable in the model, significantly simplifying its implementation in real-time monitoring applications. Instead, the predicted outlet temperature serves as an indicator of exchanger cleanliness, with the gradual deviation from measured values directly reflecting the extent of fouling. This framework allows for the continuous tracking of the heat exchanger performance using only plant-available data and minimal computational effort. These advantages are visible while comparing the proposed method with conventional methods. Conventional methods for monitoring fouling in heat exchangers include tracking changes in heat transfer coefficients, pressure drops, and temperature differences across the unit, as well as using ultrasonic, electrical, or gravimetric techniques. While these approaches are widely used in industry, they have several important limitations. Methods based on heat transfer and temperature require stable operating conditions and provide limited information about the location or nature of fouling. Pressure drop measurements are influenced by the design of the exchanger and process conditions and do not reliably indicate the extent of deposition. Ultrasonic and electrical sensors allow for localized detection but are often expensive, sensitive to temperature changes, and ineffective if fouling occurs outside the monitored area. Gravimetric analysis, although accurate, requires shutdown and disassembly, making it unsuitable for continuous use. These limitations underline the need for more flexible and

continuous monitoring strategies, particularly those based on data analysis and machine learning techniques that can account for changing operating conditions [11].

Fouling is defined as the physical and/or chemical deposition of unwanted materials on the heat exchanger surfaces over time [8]. This indicates that the dynamics of deposition is time-dependent, suggesting that valuable information about current fouling can be extracted from the historical data preceding the current state. This research leverages the advantages of LSTM neural networks in terms of capturing time-dependent correlations between input and output data by introducing historical data to the input layer of the model. This methodology is used to develop an effective tool for technologists for the detection of fouling in a highly dynamic environment, using continuously collected field data.

Due to these advantages—including the use of real process data, the exclusion of R_f from the model outputs, and the retention of operational dynamics—this study represents a meaningful advancement in the development of practical diagnostic tools for industrial heat exchanger monitoring.

Research specifically focused on using LSTM models for fouling detection and prediction in CDU heat exchangers is limited. However, there are some examples of LSTM networks being applied in this context. Madhu et al. [14] used LSTM networks to predict R_f in heat exchangers in thermal power plants and refineries. The thickness of the deposition on the heat transfer surface of an aircraft heat exchanger was predicted using LSTMs by Wang et al. [15]. Because of its advantages of remembering the importance of certain historical data, LSTM finds its use in several challenges within chemical process engineering. LSTM's fault detection capabilities were tested by Kang [16], where LSTMs were utilized to early detect fault operations in complex chemical processes such as the Tennessee Eastman process. Han et al. [17] utilized LSTM in order to analyze the production and energy consumption of two highly complex chemical processes of purified terephthalic acid and ethylene production processes.

In real process operations, the processing time is a variable of great importance. Therefore, a newly developed XGB machine learning model is inspected for this challenge. Introduced by Chen and Guestrin [18] in 2016, XGB is a technique that enhances prediction accuracy and computational efficiency, lowers the risk of overfitting, and requires less training time [19,20]. Its effectiveness has been proven in predicting porosity and permeability in crude oil fields, leading to the better exploration and development of oil and gas resources [21]. Additionally, its superior accuracy has been demonstrated in predicting the adsorption and separation performance of noble gases in metal–organic frameworks [22] and the absorption capabilities of substances harmful to the environment and public health [20]. The application of XGB models in oil and gas chemical process engineering is still an emerging research area, with not many published papers. However, there are several studies showing high accuracy in predicting crude oil prices [23] and its strong performance in forecasting oil and gas production [24].

2. Fouling Detection Methodology and Theory

2.1. Fouling Detection Methodology

This research proposes a method for fouling detection by predicting clean heat exchanger outlet temperatures for both hot and cold flows using plant data and laboratory tests conducted with different crude oils over the examined period. By relying on real operational data, this calculation inherently accounts for potential imperfections in operating parameters, geometry, and other specific parameters of a real process unit, rather than using values calculated by design equations and heat balances, which typically give idealized results. Models for predicting the temperatures ought to be trained and validated on the data of the process called the initiation phase. The initiation phase is the first of

several phases of fouling deposition on the heat transfer surface in which its considered depositions do not affect the heat transfer. It typically lasts for about the first 400 h until the first signs of fouling [25]. The time needed for fouling resistance to return to the zero value before the fouling rate starts to rise in time is called the roughness delay time. The initiation phase is a segment of the full roughness delay time [26]. Figure 1 shows the timespan of four characteristic fouling curves after the roughness delay time: linear (A), falling (B), asymptotic (C), and saw-tooth (D) fouling curves.

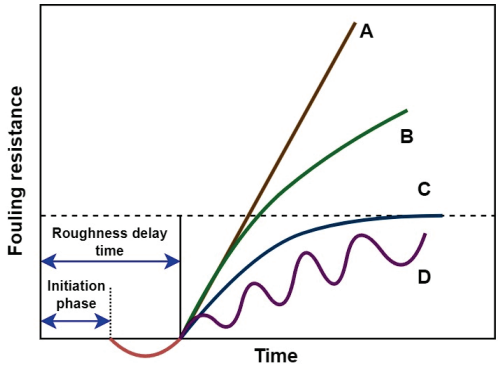


Figure 1. Typical fouling curves [26].

As mentioned, data from the initiation phase was used to develop the LSTM, XGB model, and ε-NTU method, serving as the training set to predict what the clean heat exchanger outlet temperatures would look like. The models are trained with high accuracy on the dataset, with outlet temperatures of the initiation phase being the targets, and the rest of the selected operational and laboratory data acquired as features. When the new data after the initiation phase was introduced to the model, it would give the predictions of what the model presumes are the clean state outlet temperatures, when in reality, the heat exchanger is already under fouling. Real outlet temperatures are then used for the calculation of the real, dirty overall heat transfer coefficient, and model output clean temperatures are used for the calculation of the clean overall heat transfer coefficient. Reciprocal values of differences between clean and dirty overall heat transfer coefficients are the value of fouling resistance in the examined heat exchanger. Model clean outlet temperatures and real dirty outlet temperatures are also used for the calculations of fouled heat exchanger effectiveness drop. The procedure of the LSTM and XGB model-based fouling and effectiveness calculation method is shown in Figure 2.

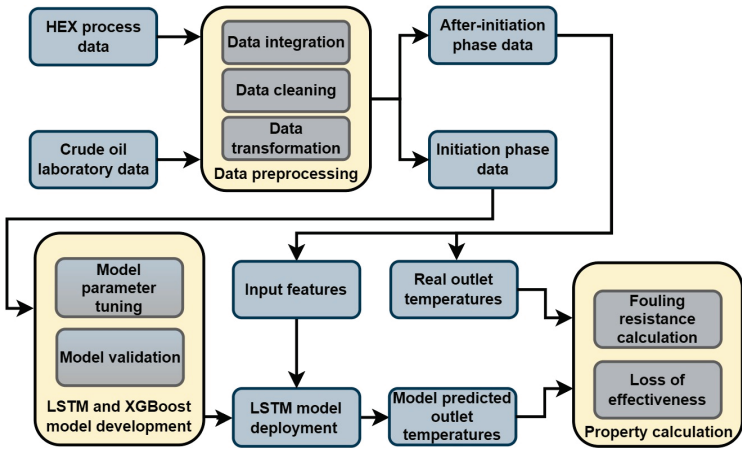


Figure 2. The procedure of LSTM and XGB-based fouling and effectiveness calculation method.

The Number of Transfer Units method provides a quick approach for estimating the fouling resistance rate based on the NTU values of a clean operating state of heat exchangers. In this research, the clean state is represented by the above-mentioned initiation phase. The average NTU value ($\overline{\mathrm{NTU}}_{IP}$), calculated from process data during the initiation phase, represents the geometric and hydrodynamic characteristics of that clean phase. However, this approach does not offer validated accuracy based on the input–output patterns of trained data-driven methods; therefore, it is used as an informative comparison tool. This approach is derived from the widely known effectiveness-NTU (ε-NTU) method, used and explained in detail by Ujević Andrijić et al. [11].

2.2. Heat Exchanger Heat Balances

Typical hot and cold side heat balances are represented by Equations (1) and (2):

$$Q_H = \dot{m}_H \cdot c_{p,H} \Delta T_H \tag{1}$$

$$Q_C = \dot{m}_C \cdot c_{p,C} \Delta T_C \tag{2}$$

Q represents heat transfer rate, $\dot{m}$ is mass flow rate, c_p is fluid specific heat capacity, and ΔT is a temperature difference in fluids. H and C subscripts denote hot and cold sides, respectively.

If the heat exchanger is affected by the formation of deposits, the heat transfer decreases, i.e., the efficiency of the heat exchanger decreases, which is given by Equation (3):

$$\varepsilon = \frac{Q_a}{Q_{max}} \tag{3}$$

Q_a is the actual delivered amount of heat, and Q_{max} is the maximum possible amount of heat transferred. They are defined by expressions:

$$Q_a = C_H(\Delta T_H) = C_C(\Delta T_C) \tag{4}$$

$$Q_a = \dot{m}_H \cdot c_{p,H} \Delta T_H = \dot{m}_C \cdot c_{p,C} \Delta T_C \tag{5}$$

$$Q_{max} = C_{min} \cdot \Delta T_{max} \tag{6}$$

Q_a is defined as the product of the mass flow of the fluid, the specific heat capacity, and the temperature difference at the inlet and outlet of the exchanger and is valid for both sides, as seen in Equations (4) and (5). Q_{max} is defined as the product of the minimum value, C_{min}, and the maximum temperature difference at a given moment. C_{min} is the product of the mass flow rate and the specific heat capacity of the fluid that achieves a greater temperature difference. From the collected thermodynamic data from the heat exchanger, C_{min} takes the following form:

$$C_{min} = \dot{m}_H \cdot c_{p,H} \tag{7}$$

$\Delta T_{\max}$ is the largest temperature difference between the inlet temperatures of both fluids, $\Delta T_{\max} = (T_{\mathrm{H,\,i}} - T_{\mathrm{C,\,i}})$, based on relations of inlet and outlet temperatures along the length of the countercurrent heat exchanger.

The obtained relations can further be used to develop an expression for efficiency:

$$\varepsilon = \frac{Q_a}{Q_{max}} = \frac{\dot{m}_H \cdot c_{p,H} \Delta T_H}{C_{min} \cdot \Delta T_{max}} = \frac{\dot{m}_H \cdot c_{p,H}(T_{H,i} - T_{H,o})}{\dot{m}_H \cdot c_{p,H}(T_{H,i} - T_{C,i})} \tag{8}$$

which can then be arranged as

$$\varepsilon = \frac{(T_{H,i} - T_{H,o})}{(T_{H,i} - T_{C,i})} \tag{9}$$

The heat transfer can be calculated using

$$Q = U \cdot A \cdot \Delta T_{\mathrm{LM}} \tag{10}$$

U is the overall heat transfer coefficient, A is the heat transfer area, ΔT_{LM} is the logarithmic temperature difference between hot and cold streams given as

$$\Delta T_{\mathrm{LM}} = \frac{(T_{H,i} - T_{C,o}) - (T_{H,o} - T_{C,i})}{\ln((T_{H,i} - T_{C,o}) / T_{H,o} - T_{C,i}))} \tag{11}$$

The overall heat transfer coefficient is calculated as follows:

$$U = \frac{\dot{m} \cdot c_p \cdot \Delta T}{A \cdot F \cdot \Delta T_{LM}} \tag{12}$$

where F is the correction factor. The fouling resistance is calculated by

$$R_f = \frac{1}{U_{fouling}} - \frac{1}{U_{clean}} \tag{13}$$

where U_{fouling} represents the heat transfer coefficient in the presence of fouling, while U_{clean} corresponds to the heat transfer coefficient when the heat exchanger is in a clean state. The Number of Transfer Units or NTU is a dimensionless parameter that represents the relationship between the overall heat transfer coefficient, heat transfer area, fluid flow rate, and heat capacity:

$$\mathrm{NTU} = \frac{U \cdot A}{m \cdot c_p} \tag{14}$$

NTU serves as a valuable efficiency indicator of a heat exchanger, as it integrates geometric and hydrodynamic characteristics [11].

2.3. LSTM Architecture

The first LSTM model was presented by Hochreiter and Schmidhuber [27] in 1997 as an upgrade to recurrent neural networks (RNNs) to overcome challenges while learning long-term dependencies. One LSTM unit is structured with a memory cell and input, output, and forget gates defined to selectively regulate irrelevant from relevant information. A typical LSTM unit is shown in Figure 3.

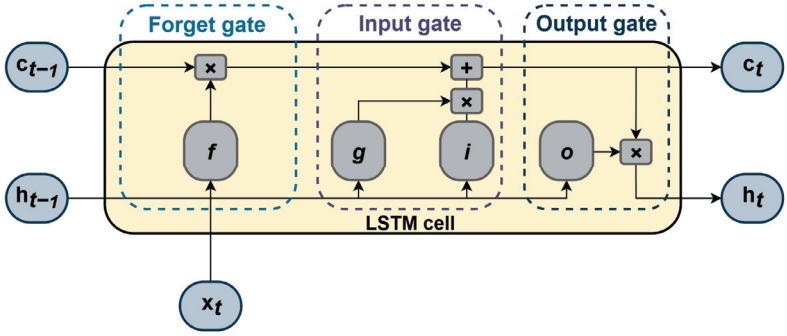


Figure 3. Typical LSTM unit structure [28].

The structure of the LSTM unit is described in the following section [28]: At time t, the unit stage consists of the output stage, h(t), which represents the output at that moment, and the cell stage, c(t), which retains information from previous time steps h($t-1$) and c($t-1$). At each time step, c(t) is updated by adding or removing information through gates, while the latest input is x(t).

An LSTM unit consists of several key components: the input gate, i, which processes incoming data by integrating the current input with the previous output and cell state; the forget gate, f, which regulates the retention or removal of information from the previous cell state; the output gate, o, responsible for determining the final output; and the cell input, g, which updates the inputs by incorporating both the current input and the previous output stage. The cell state c(t) and the initial state h(t), are then computed as follows:

$$c(t) = f(t) \odot c(t-1) + i(t) \odot g(t) \tag{15}$$

$$h(t) = o(t) \odot \sigma_c(c(t)) \tag{16}$$

where $\odot$ denotes the Hadamard product, representing element-wise multiplication between two vectors. At time t, the states of the LSTM unit components are described by the following equations:

$$i(t) = \sigma_g[W_i x(t) + RW_i h(t-1) + b_i] \tag{17}$$

$$f(t) = \sigma_g\left[W_f x(t) + RW_f h(t-1) + b_f\right] \tag{18}$$

$$g(t) = \sigma_c\left[W_g x(t) + RW_g h(t-1) + b_g\right] \tag{19}$$

$$o(t) = \sigma_g[W_o x(t) + RW_o h(t-1) + b_o] \tag{20}$$

where σ_g and σ_c represent the sigmoid and hyperbolic tangent activation functions, respectively. The trainable parameters of the LSTM unit include biases b, input weights W, and recurrent weights RW, indexed according to its corresponding gate.

2.4. XGB Architecture

The Extreme Gradient Boosting (XGB) algorithm was presented by Chen and Guestrin in 2016. It is distinguished by its ability to scale beyond a vast number of examples while using far less resource power on a single machine, and as much as a ten times faster computational time compared with other popular solutions [18]. XGB utilizes gradient boosting to improve a weak model by combining it with many other weak models to create a strong model. For small to medium-sized structured data, decision tree-based algorithms such as XGB are currently considered the most effective [29]. This scalability is utilized by gradient boosting in a decision tree ensemble algorithm. The structure of XGB is shown in Figure 4.

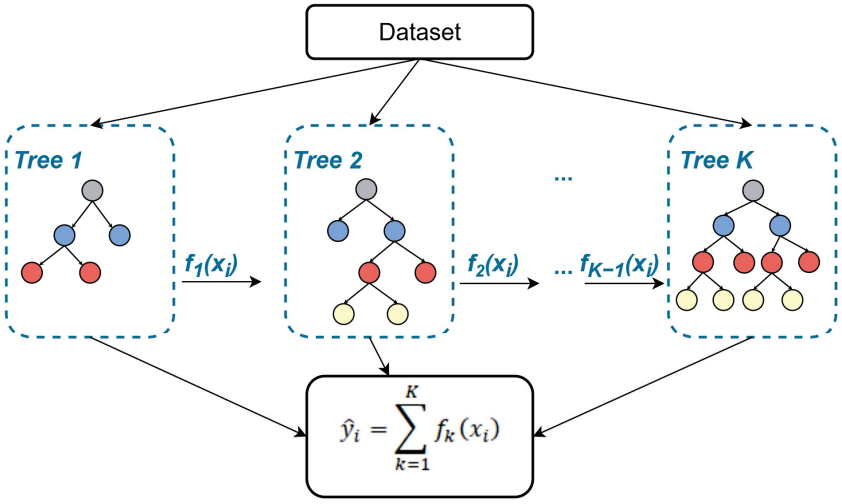


Figure 4. A general architecture of XGB [30].

XGB calculates predicted value $\hat{y}_i$ using a tree ensemble model consisting of K number of trees for the x_i input feature, which could contain n samples within the i observation, and f_k as the specific tree structure [20]:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{21}$$

The objective function L is then calculated as a sum of loss function l on the total number of observations between predicted $\hat{y}_i$ and true y_i value, and a regularization term Ω, which penalizes model complexity, thus avoids overfitting:

$$L = \sum_{i=1}^{I} l(\hat{y}_i, y_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{22}$$

3. Model Development

The investigated heat exchanger is a conventional industrial shell-and-tube type. According to the standards of the Tubular Exchanger Manufacturers Association (TEMA), the heat exchanger is of AES type, class R. The AES code identifies the design configuration of specific components of the heat exchanger:

- A—Indicates a front head design: channel with removable cover;
- E—Indicates a shell design: one-pass shell;
- S—Indicates a rear head design: floating head with backing device.

Class R refers to rugged service applications typically found in the oil and gas industry. The exchanger contains 556 tubes arranged in a square pitch at 45°, with a length of 4877 mm and an outside diameter of 25.4 mm. The design includes one shell-side pass for the hot fluid and two tube-side passes for the cold fluid. Turbulent flow conditions on the shell side are ensured by 13 baffles spaced at 250 mm intervals. Additional heat exchanger characteristics are shown in Table 1.

Table 1. Geometric characteristics of investigated heat exchanger.

Parameter	Value	Unit
Type	AES	-
Orientation	Horizontal	-
Medium (hot)	Atmospheric residue	-
Medium (cold)	Reduced crude	-
Area	207	m^2
Tube length	4877	mm
Number of tubes	556	-
Tube diameter	25.4	mm
Shell diameter	940	mm
Shell passes	1	-
Tube passes	2	-
Shell material	Carbon steel	-
Tube material	Carbon steel	-
Number of baffles	13	-
Baffle spacing	250	mm

Table 1 shows a horizontal orientation of the examined heat exchanger, as well as the mediums flowing inside. The cold medium is the crude oil, reduced after the flash column, and the hot medium is the atmospheric residue. Table 1 also shows that the heat exchanger corresponds to a TEMA AES-type exchanger with one shell pass and two tube passes, indicating the need to apply a correction factor, F, to the logarithmic mean temperature

difference, in order to account for the deviation from the ideal countercurrent flow. F is a correlation of two dimensionless temperature ratios [31]:

$$R = \frac{T_{H,i} - T_{\mathrm{H,o}}}{T_{C,o} - T_{C,i}} \tag{23}$$

and

$$S = \frac{T_{C,o} - T_{C,i}}{T_{H,i} - T_{C,i}} \tag{24}$$

From ratios for one shell and two tube passes, the F is calculated as

$$F = \frac{\sqrt{(R^2-1)}\, ln[(1-S)/(1-RS)]}{(R-1)ln\left[\frac{2-S\left[R+1-\sqrt{(R^2+1)}\right]}{2-S\left[R+1+\sqrt{(R^2+1)}\right]}\right]} \tag{25}$$

The temperature correction factor, F, for the examined process period is close to 1, with a mean of 0.985. This is expected, since the terminal temperature differences are large.

Process data was obtained from the plant's history database, covering one year of refinery production. The collected data contained two periods of regular plant production divided by an overhaul period. To ensure data quality and relevance, it is important to analyze and select data representing the complete operating regime of the heat exchanger. Consequently, data from the period immediately following the overhaul (after heat exchanger cleaning) was used for model development. This period captured the full working cycle of the process heat exchanger, from start-up after the overhaul to the next process shutdown. Heat exchangers' input and output process data were collected with a sample time of 5 min, with a count of 61170 data points. This totals slightly above the 7 full months of heat exchanger work. The dataset included hot flow inlet temperature ($T_{\mathrm{H,i}}$), hot flow outlet temperature ($T_{\mathrm{H,o}}$), cold flow inlet temperature ($T_{\mathrm{C,i}}$), cold flow outlet temperature ($T_{\mathrm{C,o}}$), as well as cold flow mass flow ($\dot{m}_{\mathrm{C}}$), and hot flow mass flow ($\dot{m}_{\mathrm{H}}$). A statistical analysis of the collected process data over the examined period is shown in Table 2:

Table 2. Statistical analysis of the process data over the examined period.

Data	Count	Mean	STD	Min	Max
$\dot{m}_{\mathrm{H}}$/kg/s	61,170	68.788	24.313	19.223	204.43
$\dot{m}_{\mathrm{C}}$/kg/s	61,170	434.399	13.394	356.943	477.784
$T_{\mathrm{H,I}}$/K	61,170	550.762	16.218	496.635	618.826
$T_{\mathrm{H,o}}$/K	61,170	501.811	17.106	463.210	563.588
$T_{\mathrm{C,I}}$/K	61,170	459.367	4.124	446.420	468.213
$T_{\mathrm{C,o}}$/K	61,170	465.084	4.575	452.168	477.513

From the descriptive statistics for the process variables, it can be seen that the cold stream, flowing through the tubes, exhibits high and stable mass flow with narrow inlet and outlet temperatures, which indicates thermal consistency throughout operation. This could also suggest that the fouling is far more likely to initiate on the hot side where the description shows higher variability in both mass flow and temperature.

Data collection from real plants is challenging because it relies on various measurement devices that are often prone to malfunction and inaccurate readings due to the process nature and deviations from designed process conditions. Therefore, the data were preprocessed to remove and replace the missing values and outliers. Fortunately, the occurrence of missing values was limited and appeared only locally in short segments. Therefore, due to the short duration of these gaps, missing values were imputed using the mean value within

a local data window. As the data were sampled every 5 min, the temporal resolution was adequate to ensure that local averaging did not obscure relevant time-dependent variations. To ensure data integrity, trends were visually and statistically examined. Although vertical lines in the trends are visible in Figure 5, these do not represent outliers but are rather real dynamic events within the process lasting over 10 data sample points, equaling more than 50 min of process time. Process conditions are visible via trends of process variables in Figure 5.

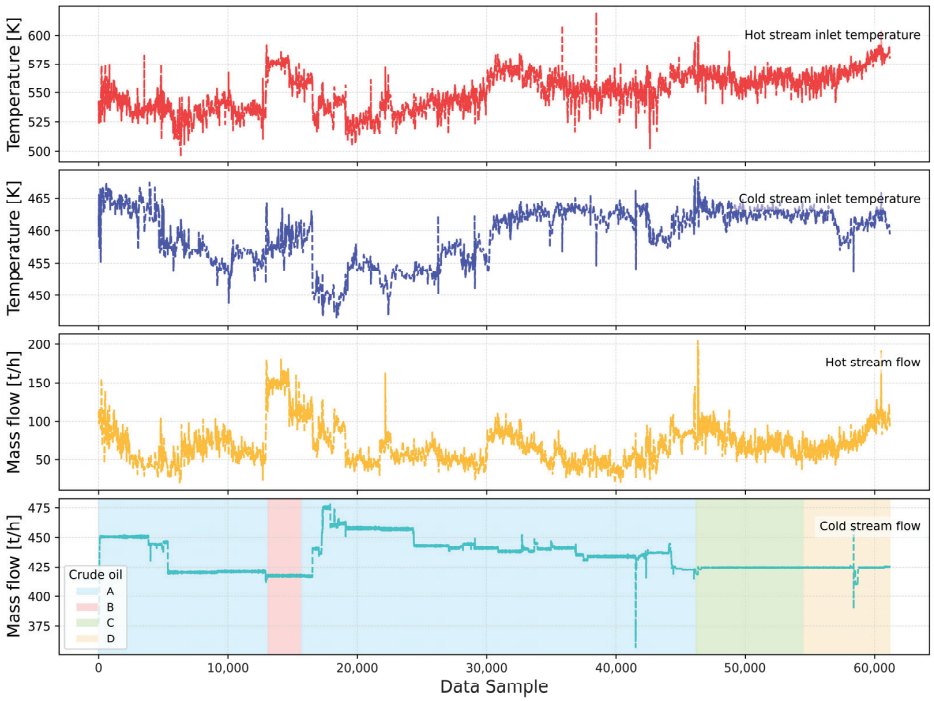


Figure 5. Trends of the inlet process variables.

The potentially misleading outlier appearance arises from the high density of data points in the plots, which visually masks the natural gradual transitions toward local extrema. This interpretation is further supported by the relatively low standard deviation values reported in Table 2. Figure 5 also shows periods of different crude oil batches, as indicated by the shaded regions in the fourth subplot. These segments reflect discrete operational phases corresponding to changes in crude oil type, labeled A through D, and are particularly visible in the cold-stream flow signal. Each transition results in a subtle shift in the baseline mass flow rate, which may arise from differing fluid properties such as density and viscosity. Importantly, these changes occur without abrupt disturbances, indicating controlled adjustments rather than transient instabilities. This level of process stability further justifies treating the early operational phase—particularly within the first crude type A—as a valid baseline for clean-state modeling, given its consistency across both thermal and flow variables.

Through the examined period, there were four different crude oils over the examined period, which, for confidentiality reasons, were labeled as A, B, C, and D. Crudes A and B were used in their pure form, while C and D were prepared as blends incorporating crude A. All available crude oil properties data associated with fouling and measured in the laboratory were collected during the study period. The crude oil properties measured in the laboratory included density (ρ), basic sediments and water (BSW), asphaltene content (Asp), nitrogen content (NC), salt content (SC), and water content (WC). A statistical analysis of the collected laboratory data is shown in Table 3:

Table 3. Statistical analysis of the crude oil laboratory data over the examined period.

Crude Oil	A (Mean ± STD)	B (Mean ± STD)	C (Mean ± STD)	D (Mean ± STD)
ρ/kgm^{-3}	839.2 ± 4.7	845.0 ± 3.8	852.2 ± 1.8	852.1 ± 2.1
$Asp/\%\ (m/m)$	14.9 ± 16.4	49.3 ± 23.8	5.8 ± 2.2	5.0 ± 0.0
$BSW/\%\ (v/v)$	4.7 ± 10.4	5.3 ± 2.3	2.5 ± 1.6	4.6 ± 6.0
$WC/\%\ (v/v)$	3.7 ± 4.4	7.6 ± 11.2	3.6 ± 4.3	3.9 ± 2.6
NC/mgkg^{-1}	1.24 ± 0.13	1.06 ± 0.05	1.31 ± 0.06	1.20 ± 0.04
SC/mgkg^{-1}	1.73 ± 1.79	5.06 ± 7.02	0.90 ± 1.25	1.28 ± 0.89

Table 3 provides a statistical overview of laboratory-measured fouling-related properties for each crude oil used during the examined period. Crude B stands out with the highest asphaltene content (49.3% m/m) and salt content (5.06 mg/kg), both known contributors to fouling formation through precipitation and corrosion mechanisms. It also exhibits the highest water content (7.6% v/v) and variability (STD 11.2), which may further promote fouling under unstable emulsified conditions. In contrast, Crudes C and D, although denser than A and B, show relatively low and consistent asphaltene and salt values, suggesting better thermal stability in the exchanger. These differences align with the flow trends in Figure 5, where the periods corresponding to Crudes C and D (highlighted in green and orange) exhibit more stable cold-stream behavior, while the segment corresponding to Crude B shows increased variability and a distinct rise in hot-stream flow and inlet temperature. This operational adjustment may have been an intentional response to the high fouling potential of Crude B, as inferred from its extreme asphaltene, salt, and water content values reported in Table 3. Increasing the hot side temperature and flow rate could have been aimed at maintaining heat transfer efficiency by enhancing turbulence and reducing deposition rates on heat transfer surfaces. Such mitigation strategies are consistent with plant-level responses to processing problematic crudes, especially those prone to asphaltene precipitation and salt crystallization. The timing of these changes—occurring just after the Crude B period—further suggests a process adaptation on specific crude properties.

After data preprocessing, the development of the LSTM and XGB models was conducted. The models were developed for the estimation of the outlet temperatures of the cold and hot flows, using data when the heat exchanger operated in a clean state throughout the observed process period. The heat transfer coefficient for the clean and dirty heat exchangers is calculated using Equations (26) and (27):

$$U_{fouling} = \dot{m} \cdot c_p (T_{H,i} - T_{H,o}) / A \cdot F \frac{(T_{H,i} - T_{C,o}) - (T_{H,o} - T_{C,i})}{ln((T_{H,i} - T_{C,o}) / T_{H,o} - T_{C,i}))} \tag{26}$$

$$U_{clean} = \dot{m} \cdot c_p (T_{H,i} - T_{H,o,model}) / A \cdot F \frac{(T_{H,i} - T_{C,o,model}) - (T_{H,o,model} - T_{C,i})}{ln((T_{H,i} - T_{C,o,model}) / T_{H,o,model} - T_{C,i}))} \tag{27}$$

$U_{fouling}$ is calculated based on the measured outlet temperatures, while U_{clean} is calculated based on the model prediction outlet temperatures. The fouling resistance is then calculated using Equation (13) using the clean overall heat transfer coefficient calculated from both LSTM and XGB models' predicted temperatures as well as the ε-NTU method. The decrease in heat exchanger efficiency over the examined period can be measured by the difference between the actual efficiency calculated using Equation (9) and the clean heat exchanger efficiency calculated using the temperatures predicted by the model using Equation (26):

$$\varepsilon_{clean} = \frac{\left(T_{H,i} - T_{H,o,model}\right)}{(T_{H,i} - T_{C,i})} \tag{28}$$

The gradually increasing trend of the fouling resistance and the decreasing trend of the efficiency difference should indicate that the performance of the heat exchangers is decreasing due to the formation of deposits over the studied time.

As previously mentioned, the outputs of the model are predicted using the input data from the initiation phase. The initiation phase is the period when fouling has little or no effect on heat transfer in the heat exchanger, and it begins after the process is overhauled and the heat exchanger is commissioned, while the equipment is still in a clean state. Based on discussions with experienced refinery operators, it is assumed that the period of the first 5000 data points, equivalent to approximately two and a half weeks after cleaning, represents the initiation phase.

The first 5000 data points from the initiation phase were used to develop models for the prediction of outlet temperatures. The subsequent 1000 data points were used in the blind test phase. In this phase, the discrepancy between the model calculated and actual temperatures needed to become apparent to proceed with the method. For the development of the LSTM model, the dataset was divided into training 80% and validation 20%. The search for optimal LSTM model hyperparameters is both time-consuming and labor-intensive; therefore, the KerasTuner [32] was employed. KerasTuner is a scalable and easy-to-use hyperparameter optimization framework that simplifies the hyperparameter search designed for researchers. It allows the easy configuration of search spaces with a define-by-run syntax and includes built-in optimization algorithms. The preliminary results suggested using a single hidden layer of LSTM units, with several parameters selected for detailed examination. The number of historical data in the input layer varied from 2 to 24, representing a historical span of approximately 10 to 120 min. The number of units in the hidden layer was examined from 5 to 250 units with a step of 5. Hidden layer activation function was examined between three commonly used tanh, sigmoid, and relu functions.

The inclusion of a Dropout layer was evaluated to determine its necessity in preventing overfitting, thereby improving the generalization of the model, resulting in a better performance on the validation and test sets. Lastly, two different optimizers, Stochastic Gradient Descent (SGD) and Adam were examined to assess their impact on model performance.

GridSearchCV, a function within the scikit-learn library, was employed to find an optimal set of hyperparameters for the XGB model. GridSearchCV performs a search over a user-defined parameter grid to find the optimal combination of parameters, using cross-validation as the evaluation method. The parameter grid consisted of nine parameters with different values. The n_estimator parameter is used to define the number of trees in the ensemble. Increasing the value means higher performance but increased training time and overfitting potential. The contribution of each tree is scaled by the learning_rate parameter, which with a smaller number requires more trees but makes model more robust. The ratio between overfitting and underfitting is defined by the maximum depth of each tree or the max_dep parameter. To control overfitting by restricting the model from learning specific patterns to individual observations, the value of min_child_weight needs to be increased. Parameters subsample and colsample_bytree serve as reductions in overfitting by introducing randomness into the tree by defining the fraction of samples per each tree and the number of features per each tree, respectively. Lower values increase the randomness, while higher values make the model more deterministic. To manage the splitting of a model and thus its complexity, the gamma parameter is introduced. This parameter defines the minimum loss reduction required for further partitioning of a leaf node. A higher gamma value leads to fewer splits, reducing model complexity. Lastly, two parameters, reg_alpha and reg_lambda, serve as regularization terms to prevent the

complexity of the model and overfitting by regulating weights within the model. The LSTM and XGB models' hyperparameters were systematically examined, and the value grid used in the optimization process is shown in Table 4.

Table 4. Examined hyperparameters and the value grid.

Model	Parameter	Value
LSTM	History data	2 to 25 (step = 1)
	Units in hidden layer	5 to 250 (step = 5)
	Activation function	tanh, sigmoid, relu
	Dropout	True, False
	Optimizer	adam, SGD
XGB	n_estimators	100; 200; 300
	learning_rate	0.01; 0.05; 0.1
	max_depth	3; 5; 7
	min_child_weight	1; 3; 5
	Subsample	0.6; 0.8; 1.0
	colsample_bytree	0.6; 0.8; 1.0
	Gamma	0; 0.1; 0.2
	reg_alpha	0; 0.01; 0.1
	reg_lambda	1; 1.5; 2

All models were developed in Python 3.12.3 using the following libraries: numpy (1.26.4), pandas (2.3.0), scikit-learn (1.5.0), XGBoost (2.0.3), Keras (3.3.3), and matplotlib (3.9.0). Development and training were performed on a Windows 10 system with an Intel(R) Core(TM) i5-9400F CPU @ 2.90 GHz and 8 GB of RAM, without GPU acceleration. Inference time was measured for both models on the full deployment dataset, which begins immediately after the initiation phase used for development. The LSTM model required approximately 4.81 s (cold stream) and 4.35 s (hot stream), whereas the XGBoost model completed inference in 0.047 s (cold) and 0.031 s (hot). These results confirm that both models, particularly XGBoost, are suitable for near-real-time prediction scenarios in process monitoring, considering the sample time of process variables is every 5 min.

To assess model performance, standard statistical metrics were applied. The mean squared error (MSE) and root mean squared error (RMSE) were used to describe the average size of the prediction errors, with RMSE expressing those errors in the same units as the predicted variable. The mean absolute error (MAE) provided a highly intuitive measure of prediction accuracy, focusing on the average of absolute differences without being overly influenced by extreme values. The coefficient of determination (R^2) was used to evaluate how well the model captures the overall variability of the target variable. In addition, Pearson's correlation coefficient was calculated to examine the strength and direction of the linear relationship between the predicted and actual values. In addition to the numerical evaluation, model performance was also examined through visual inspection, including error histograms, scatter plots, and comparisons of predicted and actual values over time. This type of graphical analysis allows for a clearer understanding of local discrepancies, sudden shifts, or patterns that may not be evident from numerical metrics alone. It serves as a useful supplement to quantify how the model responds across different parts of the dataset.

4. Results and Discussion

This section presents the results of the developed LSTM and XGB machine learning models, as well as the traditional ε-NTU method, applied to predict the outlet temperatures of both hot and cold flows in a refinery heat exchanger. This section includes graphical

and numerical comparisons of model performance, an analysis of fouling resistance trends, an evaluation of exchanger effectiveness, and an assessment of the impact of thermal inefficiency on furnace operation.

The search for the optimal combination of hyperparameters for the LSTM models was conducted using KerasTuner, configured to evaluate 50 different trials for each historical time step chosen by the algorithm. This approach resulted in testing more than a thousand different combinations of hyperparameters. The tuner's objective was to minimize the validation mean squared error (MSE), and the parameter combinations presented in Table 5 yield the best overall score. Similarly, out of several thousand potential combinations, the XGB optimal combination of hyperparameters was found using GridSearchCV from the scikit-learn library. The search was designed to find the lowest mean squared error on the training set. The best hyperparameter configuration is also shown in Table 5.

Table 5. Best hyperparameters for LSTM and XGB models.

Model	Parameter	Cold Flow Model	Hot Flow Model
		Value	**Value**
LSTM	History data	12	12
	Units in hidden layer	135	105
	Activation function	tanh	sigmoid
	Dropout	False	False
	Optimizer	adam	adam
XGB	n_estimators	300	300
	learning_rate	0.1	0.1
	max_depth	3	3
	min_child_weight	1	5
	Subsample	1.0	0.6
	colsample_bytree	1.0	0.6
	Gamma	0	0
	reg_alpha	0	0
	reg_lambda	1	1

4.1. LSTM Outlet Temperatures Model Results

As previously stated, the development of the hot and cold outlet temperature prediction models was conducted using the first 5000 data points, belonging to the initiation phase.

Achieving the highest possible accuracy in the development dataset was crucial to ensure a robust representation of the relationship between the input and output variables. This approach was taken to guarantee that any systematic deviations observed during deployment over extended periods could be confidently attributed to real process changes rather than errors stemming from model development. Figures 6 and 7 represent the cold and hot flow outlet temperature model development performance based on visual error comparison (a), a histogram of errors (b), and a scatter plot (c). The visual comparison of the cold model (Figure 6) demonstrates that the predicted temperatures closely follow the real temperatures, indicating high predictive accuracy. Slight deviations are noticeable in an isolated segment of the validation set.

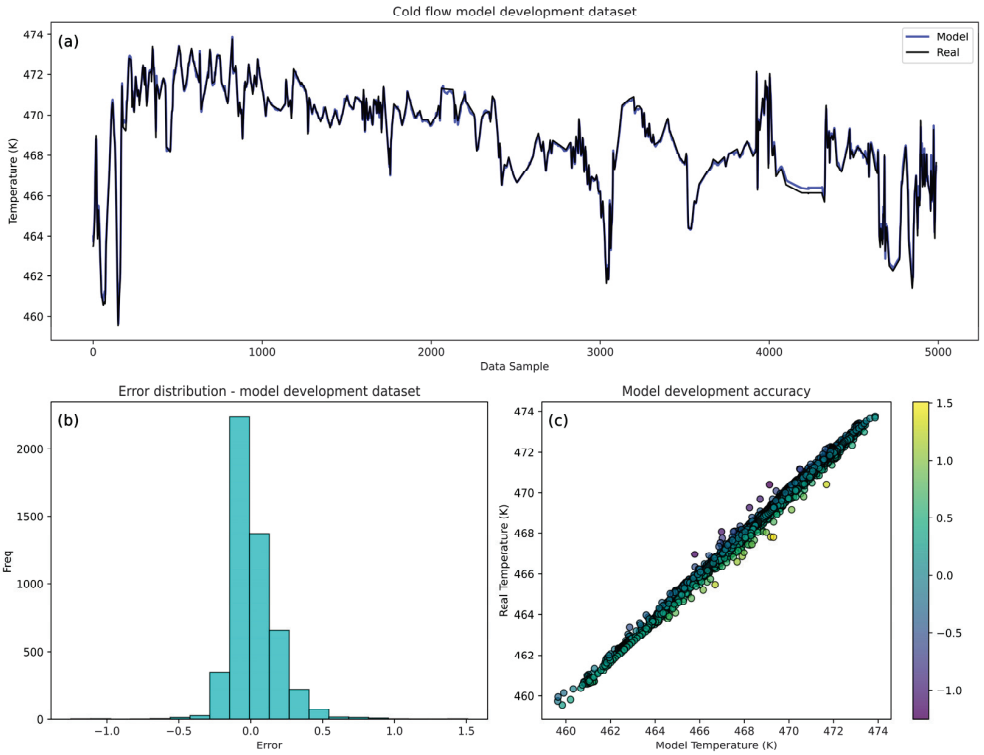


Figure 6. LSTM model training dataset accuracy analysis for cold flow. (**a**) Comparison between real and model-predicted temperatures. (**b**) Cold flow model histogram of errors. (**c**) Scatter plot of real vs. model-developed temperatures.

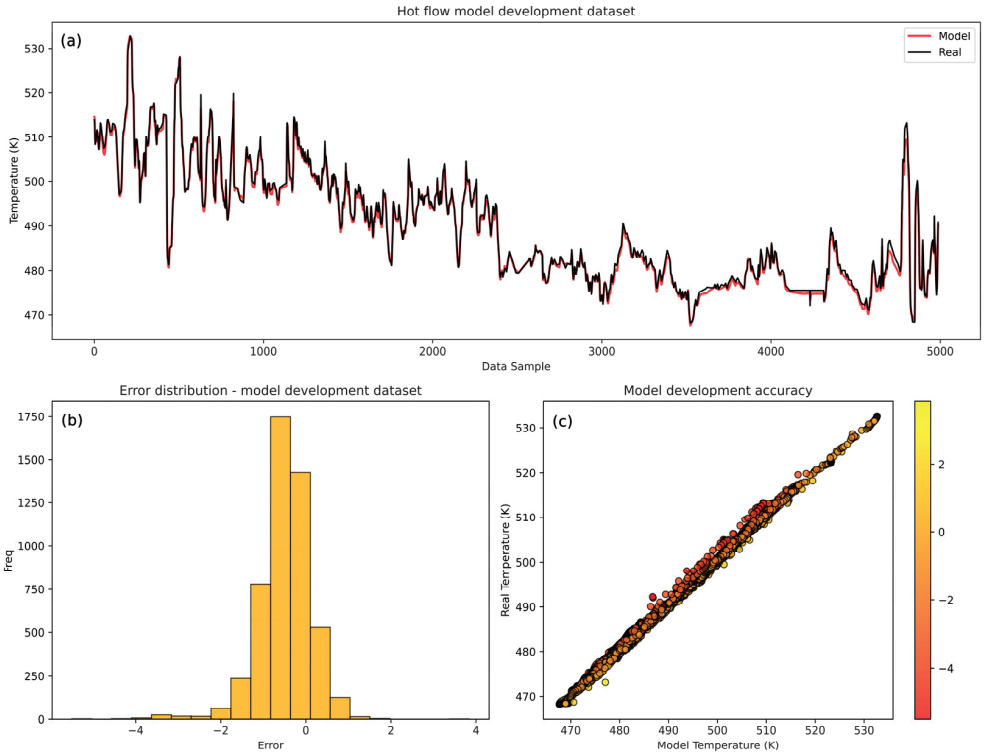


Figure 7. LSTM model training dataset accuracy analysis for hot flow. (**a**) Visual comparison between real and model-predicted temperatures. (**b**) Hot flow model histogram of errors. (**c**) Scatter plot of real vs. model-developed temperatures.

This portion of the data exhibits more abrupt changes in the real values, where the model struggles to maintain the same level of accuracy observed in other parts of the

dataset. This is also confirmed by a slightly higher mean squared error on the validation set shown in Table 6. The histogram of error shows high levels of accuracy with the errors centered around zero. The narrow distribution of errors shows no significant systematic error or bias, with higher errors confirming the deviations shown in the above visual comparison. The model shows a high correlation between the real and model-predicted temperatures, confirmed by the strong clustering around the diagonal line in the scatter plot. Higher errors are observed farther from the diagonal line, indicating the span of temperatures where the model encounters difficulties, typically corresponding to sudden changes in the real value. Overall, the cold flow model shows great performance, with errors reaching up to ± 1.5 K, although the majority of errors (90%) are within ± 0.3 K. When compared to the mean temperature range, it is an acceptable error of approximately 0.32% yet confirms the high accuracy and reliability of the model.

Table 6. Frequency table of LSTM model results (cold flow).

Error Range (K)	Frequency	Percentage (%)
−1.3 to −1.0	4	0.08
−1.0 to −0.7	4	0.08
−0.7 to −0.3	44	0.88
−0.3 to +0.0	2456	49.23
0.0 to +0.3	2303	46.16
+0.3 to +0.7	151	3.03
+0.7 to +1.0	20	0.40
+1.0 to +1.3	6	0.12
+1.3 to +1.7	1	0.02

The numerical results of the residuals presented in Table 6 clearly show that more than 95% of the prediction errors lie within the ± 0.3 K interval, demonstrating the high accuracy and robustness of the LSTM model in predicting cold flow temperature.

Hot flow model performance (Figure 7) shows a highly accurate model with the model prediction trend capturing the trend dynamics of the real temperature values. However, the model encounters minor challenges with certain abrupt changes happening near the end of the development dataset in the validation set. Similarly to the cold flow model, this is reflected in the higher mean squared errors on the validation set (Table 6).

The histogram of errors shows a wider distribution of the errors compared to the cold flow model, indicating less consistency in the predictions of the hot flow model. The broader range of errors suggests that the hot model is less accurate than the cold model, which is confirmed by the comparison of the MSE values of the LSTM cold and hot models (Table 7). However, the values r and R^2 are slightly higher than the cold model's values, suggesting that the hot model has a better ability to follow data trends despite individual errors. The cold model has a lower MSE because its actual values fall within a narrower range, leading to more precise predictions. However, the R^2, which measures how well the model explains the variability of the target variable relative to the mean, is lower compared to the hot model because the variance of the cold data is smaller (2.398) compared to the hot side data (12.818). This greater variance allows the hot model to maintain a higher R^2 as it captures more of the data's variability. Similarly, the Pearson correlation coefficient is higher, as its predictions align more closely with the overall data trend. Despite the lower accuracy, strong diagonal clustering in the scatter plot confirms the overall model's high performance. The hot model errors range up to ± 4.39 K at their highest, giving an error of 0.89% of the mean temperature range. Nevertheless, the majority of errors (over 90%) are within ± 1 K, indicating that while the hot model performs well, its accuracy is slightly

lower than that of the cold flow model. These results confirm the acceptability of the hot model's performance but also highlight its slightly lesser accuracy.

Table 7. Model accuracy metrics comparison.

Model	LSTM		XGB	
Metric	Cold	Hot	Cold	Hot
Training MSE	0.045	0.443	0.010	0.480
Validation MSE	0.154	0.787	0.009	0.603
Training RMSE	0.212	0.666	0.100	0.693
Validation RMSE	0.392	0.887	0.095	0.777
Training MAE	0.206	0.441	0.081	0.452
Validation MAE	0.408	0.554	0.071	0.418
Training R^2	0.992	0.998	0.998	0.997
Validation R^2	0.952	0.985	0.998	0.989
Training r	0.998	0.998	0.999	0.999
Validation r	0.994	0.997	0.999	0.995

According to Table 8, 90.9% of the prediction errors of the LSTM model for the hot flow lie within ± 1 K, indicating slightly reduced accuracy compared to the cold flow case but still reflecting reliable model behavior under more variable operating conditions.

Table 8. Frequency table of LSTM model results (hot flow).

Error Range (K)	Frequency	Percentage (%)
−1.3 do −1.0	66	1.32
−1.0 do −0.7	171	3.43
−0.7 do −0.3	390	7.82
−0.3 do +0.0	946	18.96
+0.0 do +0.3	1360	27.26
+0.3 do +0.7	1076	21.57
+0.7 do +1.0	590	11.83
+1.0 do +1.3	200	4.01
+1.3 do +1.7	76	1.52

The observed deviations in performance between the training and validation sets are minor, suggesting that the models generalize well and are not overfitted. This conclusion is further supported by the use of early stopping, a widely accepted regularization technique that monitors validation performance during training and halts the process once performance begins to deteriorate [33]. This approach reduces the risk of overfitting by preventing the model from continuing to learn noise from the training data. Additionally, care was taken to ensure that both the training and validation sets were sufficiently large and representative, as unbalanced data splits may lead to misleading conclusions about model generalization. In this study, 20% of the development dataset was allocated for validation, which aligns with standard practices in machine learning and provides a reliable basis for model evaluation and early stopping. With high and similar r and R^2 values for both the training and validation sets, it is evident that the models interpreted the data very well, further reinforcing that overfitting is not a concern. The LSTM and XGB models' accuracy metrics for both hot and cold flows are presented in Table 7.

The first 5000 data points, corresponding to the initiation phase, were used for model development, with 4000 for training and 1000 for validation. The test dataset consists of another 1000 data points immediately following this phase. The objective of this test set was to identify the slow ascending difference between the model-predicted and real data, representing the physical meaning of resistance to heat transfer occurring in the heat

exchanger. This subset represents approximately 16.7% of the dataset intended for model development. It was purposefully selected to reflect the earliest signs of fouling development, allowing the model's predictive behavior to be assessed under changing physical conditions. The focus was on capturing the gradual deviation between the model output and real measurements rather than achieving general statistical representativeness. It is worth noting that the entire development set was used for model training and validation, without setting aside a separate test split from this period. The model maintains high predictive accuracy even at the very beginning of the test set, before gradual deviations start to appear. This further supports the fact that the model is well-fitted to the clean phase of operation. The test set is not used to assess model accuracy in the usual way, but to track when the model starts to diverge, which indicates the beginning of fouling.

Figures 8 and 9 show a comparison of the real and model-predicted outlet temperatures for the cold and hot flows after the initiation phase.

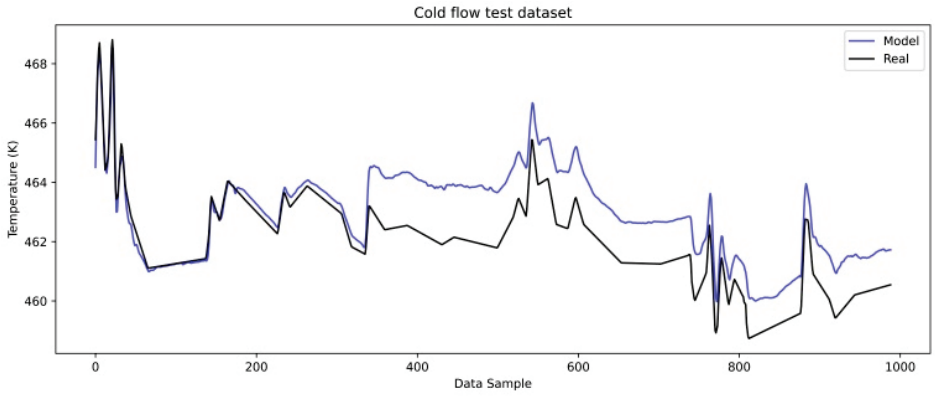


Figure 8. LSTM model test dataset cold flow.

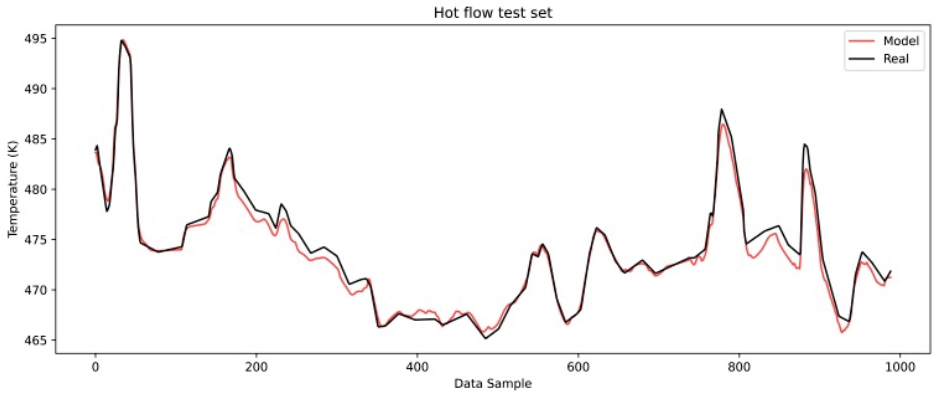


Figure 9. LSTM model test dataset hot flow.

The cold flow model shows a gradual increase in the difference between the predicted and real temperatures, indicating that heat transfer resistance is occurring between the hot and cold mediums. Figure 9 shows the hot flow outlet temperature comparison and a slightly different behavior of the cold flow.

Here, the model predicted values follow the real ones with certain accuracy yet are slightly lower than those on the development set. This should indicate that the heat transfer resistance on the hot side of the heat exchanger is less pronounced during the observed period. It indicates that fouling on the hot side either has not yet started or has minimal influence on heat transfer.

The models are then deployed on the complete cold and hot deployment datasets of roughly seven months of heat exchanger operation. The cold side results are shown in

Figure 10 with the corresponding error analysis in Figure 11, while the hot side results are shown in Figure 12 with the corresponding error analysis in Figure 13. The complete dataset spans the development, test, and remaining dataset, covering the period from start-up to the overhaul of the heat exchangers within one operating cycle. The gradual divergence between real and model-predicted outlet temperature values was observed and confirmed for both cold and hot models.

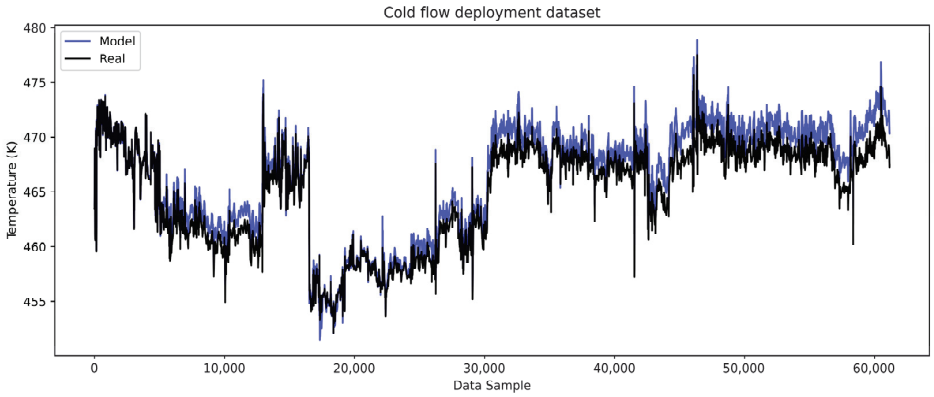


Figure 10. LSTM model complete dataset cold flow.

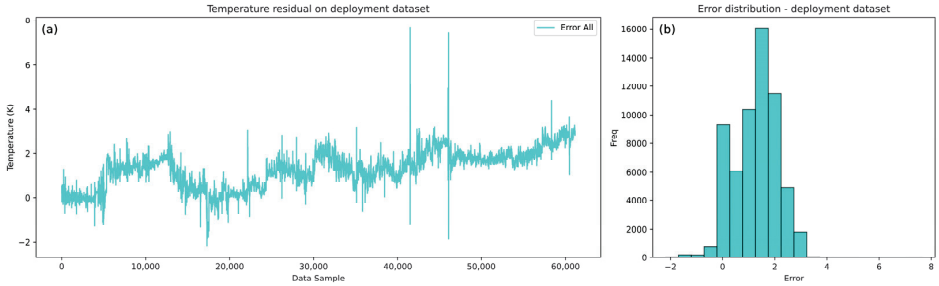


Figure 11. LSTM model complete dataset cold flow outlet temperature error analysis. (**a**) Residual of errors on the deployment dataset. (**b**) Histogram of errors for the deployment dataset.

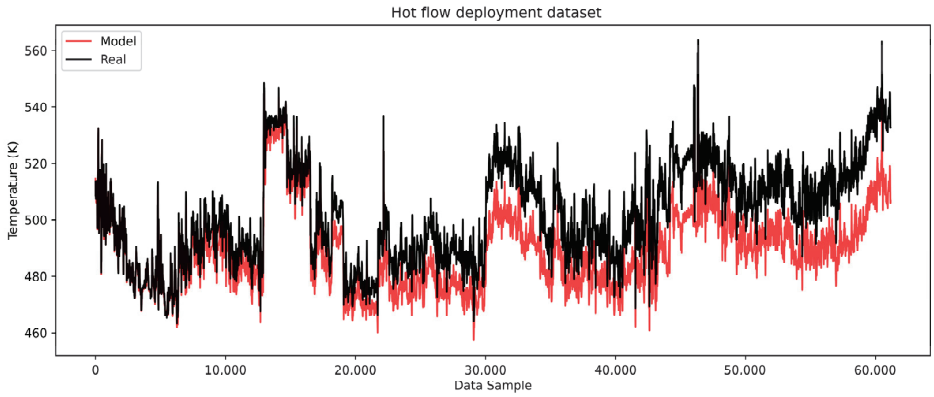


Figure 12. LSTM model complete dataset hot flow.

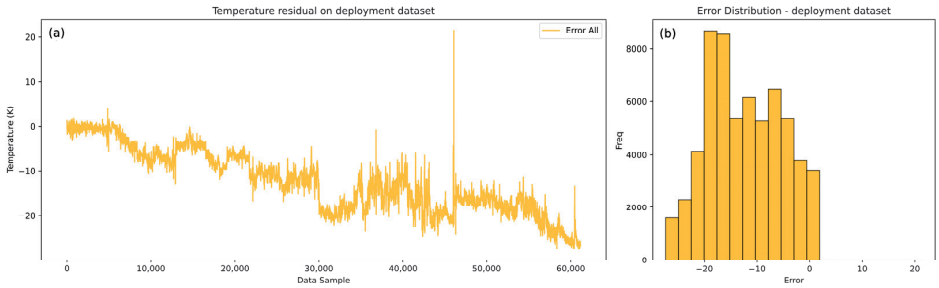


Figure 13. LSTM model complete dataset hot flow outlet temperature error distribution. (**a**) Residual of errors on the deployment dataset. (**b**) Histogram of errors for the deployment dataset.

In Figure 10, the cold flow model captures the overall trend and dynamics of the real temperature data but with a positive bias. The model's predictions show gradually higher temperature values than the real values, suggesting that the cold flow temperature would be higher if the heat transfer was conducted under clean conditions. This behavior implies that there is a growing resistance to heat transfer from the hot to the cold medium. This error trend is more evident in Figure 11a, where the gradual rise in the error is notable, reaching the highest errors of about 2.5 K, when excluding outliers.

The histogram of errors (Figure 11b) further confirms a systematic positive bias with errors generally spread on the positive side. This consistent bias supports the conclusion that resistance to heat transfer is present and gradually increasing. The hot flow model, as illustrated in Figure 12, similarly captures the trend and dynamics of the real process but with a negative systematic bias.

The model-predicted temperatures are progressively lower than the real values, indicating that the hot flow temperatures would be reduced if heat transfer occurred under clean conditions. This suggests a growing resistance to heat exchange between the hot and cold flows. This indication could be used to calculate the overall heat spent to hold the cold medium at the optimal conditions, which directly impacts the financial picture of the refinery. The error analysis of the hot flow outlet temperature shown in Figure 13 highlights the negative bias, with a gradually increasing error trend in the negative direction.

The maximum error reaches approximately -27 K. This significant deviation indicates that the hot side of the heat exchanger is more severely impacted by deposition or heat transfer resistance. The pronounced impact on the hot side can be attributed to chemical fouling, likely driven by higher temperatures. In the case of the examined heat exchanger, the medium (atmospheric residue) contains components such as heavy hydrocarbons, asphaltenes, and resins, which are prone to fouling. These components deposit more readily at elevated temperatures, exacerbating the resistance to heat transfer. This behavior is well-aligned with the known mechanisms of chemical fouling in high-temperature systems. Elevated temperatures promote the thermal destabilization of heavy hydrocarbon fractions, particularly asphaltenes and resins, leading to their aggregation and subsequent deposition on heat transfer surfaces. These mechanisms are well-documented in the crude oil fouling literature and are considered a primary cause of increased thermal resistance in the hot-stream section of heat exchangers [9]. The lower predicted hot outlet temperatures also provide insights into the energy requirements to maintain optimal conditions for the cold medium. This highlights the financial implications for refinery operations, as additional heat input is required to compensate for the reduced heat transfer efficiency caused by fouling. Overall, the results demonstrate the models' capability to capture the dynamics of the process and provide valuable insights into the progression of fouling, which directly impacts the operational and economic aspects of heat exchanger performance.

The model-predicted outlet temperatures are further used to calculate the overall heat transfer coefficient as it would be if the heat exchanger remained clean throughout the entire period, using Equation (27), while the real outlet temperature values were used to calculate the real heat transfer coefficient based on Equation (26). The R_f was then calculated from the overall heat transfer coefficients, Equation (13), and is shown in Figure 14. It can be seen that the R_f follows a slowly ascending trend through the observed period, ending with a value of approximately 0.004 W^{-1} m^2 K.

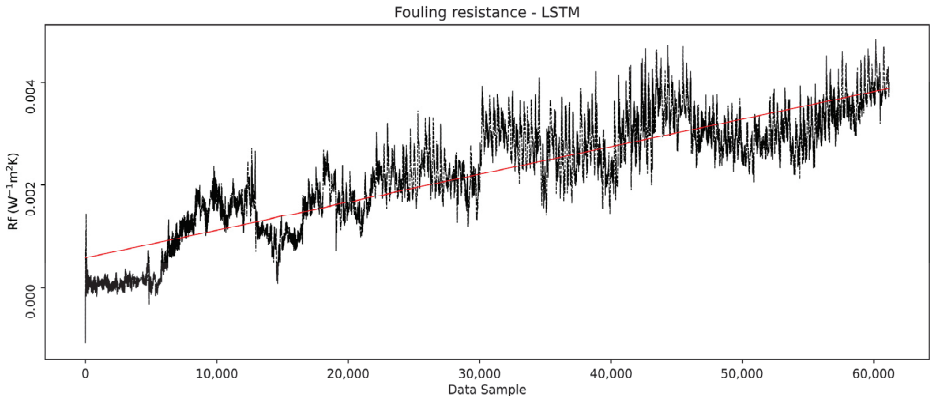


Figure 14. LSTM model calculated the fouling resistance.

The overall trendline in Figure 14 represents the growth of R_f, capturing the dynamics of the deposition growth and detachment from the surface, resembling the so-called "saw-tooth" fouling type, which is frequent in industrial heat exchangers. This type of fouling dynamics occurs when parts of already accumulated deposits reach a critical deposit thickness, thus breaking off again, with the contributing factor of periodic variations in process conditions [26].

An analysis of the heat exchanger efficiency trend, as shown in Figure 15, reveals the values significantly impacted by high fluctuations in process dynamics, whether operational conditions, disturbances, or changes in fluid properties.

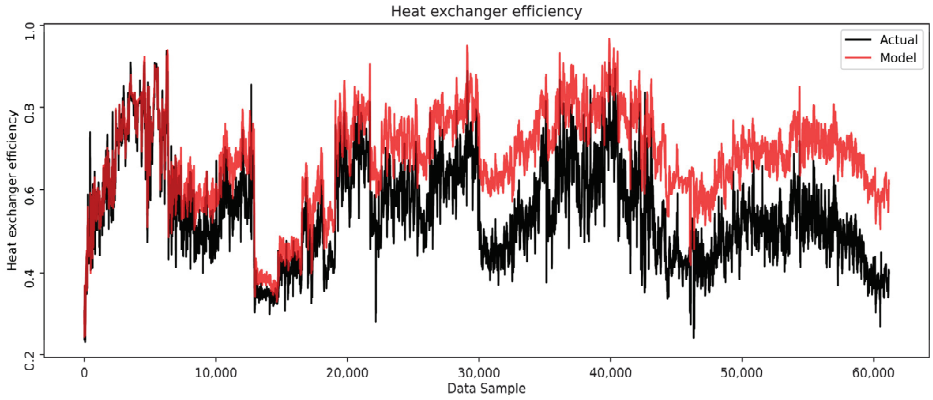


Figure 15. Heat exchanger effectiveness.

The efficiency ranges from about 0.8 to 0.3, depending on the process dynamics. Despite these fluctuations, it shows a gradual degradation in real efficiency over time, contrasting with the overall efficiency trend derived from the model-predicted outlet temperatures. This suggests that real efficiency is influenced not only by process dynamics but also by additional factors such as fouling and its potential mechanical implications on the heat exchangers. A slow decrease in the actual efficiency can be noticed as a negative error trend. Over time, a clear efficiency drop of about 20% is observed, confirming the

influence of the fouling on the heat exchanger's performance during the examined period (Figure 16).

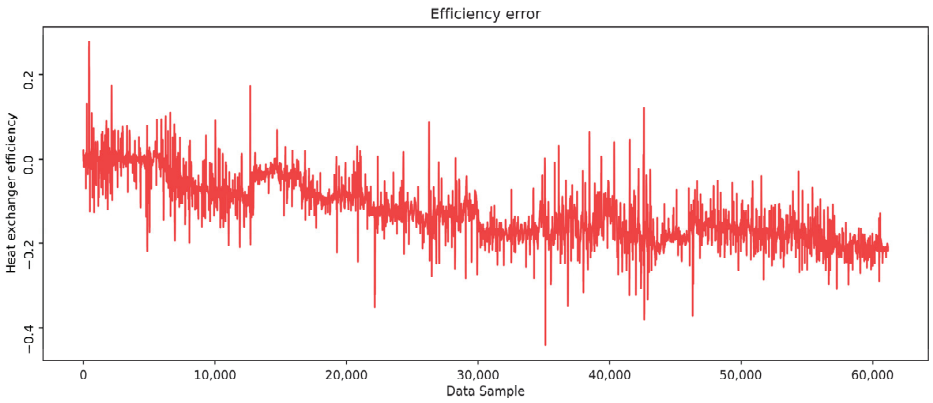


Figure 16. Effectiveness loss.

4.2. XGB Outlet Temperature Model Results

The XGB development model procedure followed the same steps in procedure as the LSTM model development. The accuracy of the cold and hot flow XGB models is shown in Figures 17 and 18, respectively.

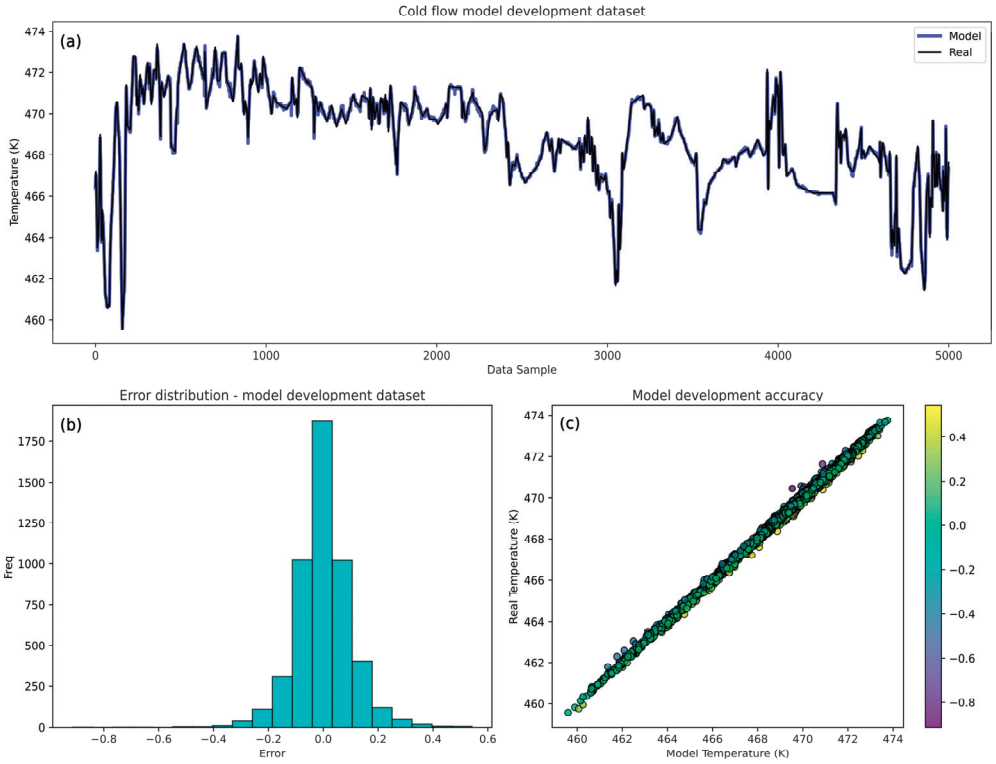


Figure 17. XGB model training dataset accuracy analysis for cold flow. (**a**) Visual comparison between real and model-predicted temperatures. (**b**) Cold flow model histogram of errors. (**c**) Scatter plot of real vs. model-developed temperatures.

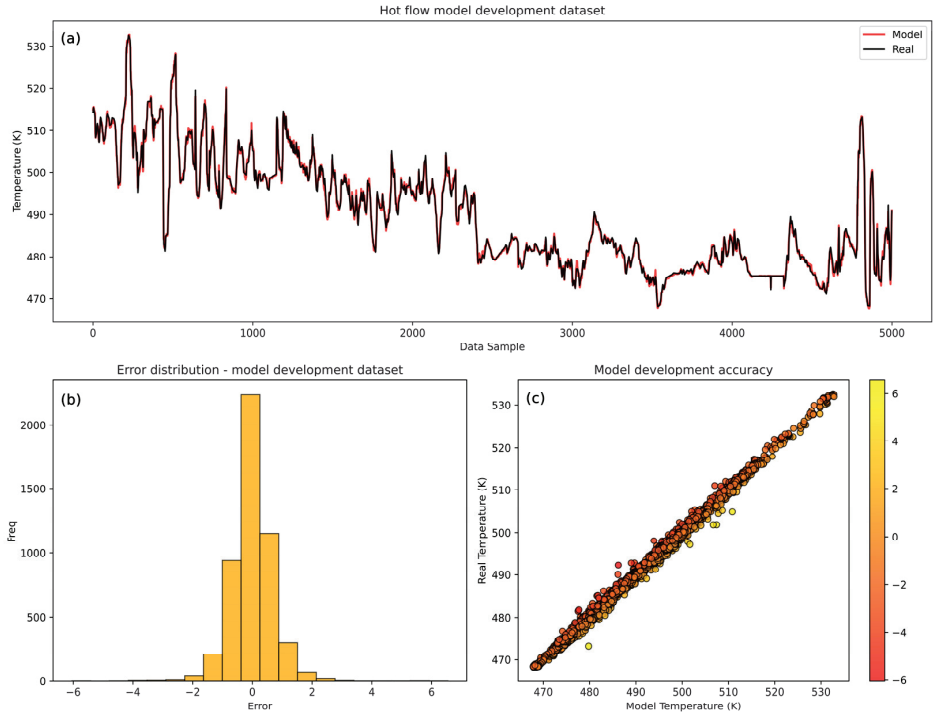


Figure 18. XGB model training dataset accuracy analysis for hot flow. (**a**) Visual comparison between real and model-predicted temperatures. (**b**) Cold flow model histogram of errors. (**c**) Scatter plot of real vs. model-developed temperatures.

The residual distribution presented in Table 9 shows that 95.1% of the prediction errors produced by the XGB model lie within the ±0.3 K range, confirming its high accuracy and suitability for cold flow temperature prediction.

Table 9. Frequency table of XGB model results (cold flow).

Error Range (K)	Frequency	Percentage (%)
−1.3 to −1.0	1	0.02
−1.0 to −0.7	2	0.04
−0.7 to −0.3	32	0.64
−0.3 to +0.0	2471	49.42
+0.0 to +0.3	2453	49.06
+0.3 to +0.7	39	0.78
+0.7 to +1.0	2	0.04
+1.0 to +1.3	0	0.00
+1.3 to +1.7	0	0.00

The differences between the XGB and LSTM models are noticeable, with the XGB models being more accurate on both the training and validation sets for cold and hot flow models. This observation is confirmed by the model performance metrics seen in Table 8.

As presented in Table 10, 83.6% of the prediction errors of the XGB model for hot flow lie within the ±1 K interval, indicating slightly lower accuracy compared to the cold flow case, but still acceptable performance for practical applications.

Table 10. Frequency table of XGB model results (hot flow).

Error Range (K)	Frequency	Percentage (%)
−1.3 to −1.0	146	2.92
−1.0 to −0.7	340	6.80
−0.7 to −0.3	671	13.42
−0.3 to +0.0	1241	24.82
+0.0 to +0.3	1240	24.80
+0.3 to +0.7	688	13.76
+0.7 to +1.0	315	6.30
+1.0 to +1.3	138	2.76
+1.3 to +1.7	55	1.10

Additionally, the XGB models were developed in less time than the more complex LSTM models. Despite the XGB advantages, limitations began to emerge when the models were deployed across the complete dataset. The downside of the highly accurate XGB models lies in their sensitivity to the training data distribution.

By examining Figures 19 and 20, a divergence in the ability of XGB models to capture the process dynamics can be noticed, particularly in regions with sudden changes.

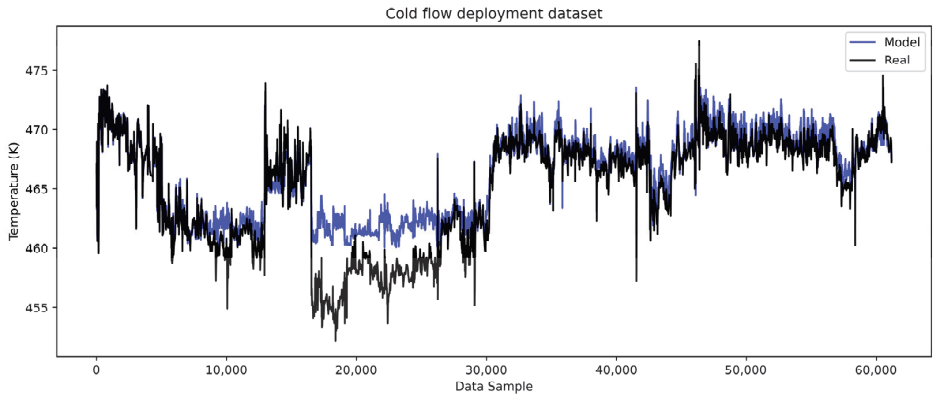


Figure 19. XGB model complete dataset cold flow.

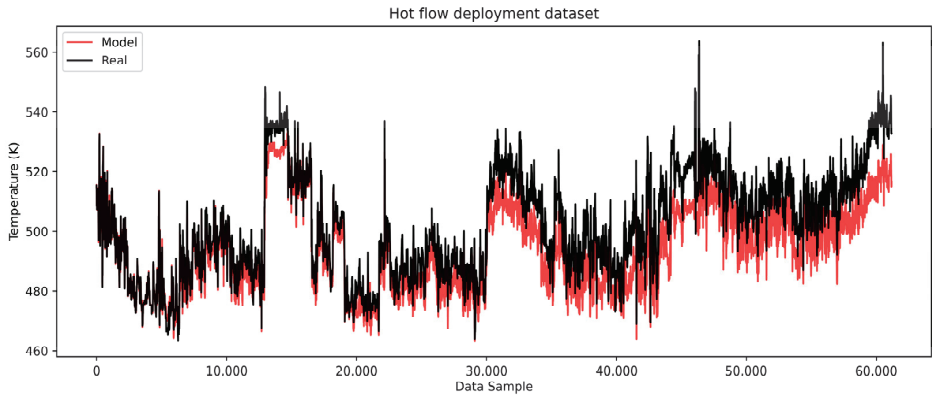


Figure 20. XGB model complete dataset hot flow.

These issues were not observed during the training and validation phases, as the LSTM models showed better adaptability to such dynamics. Consequently, errors arising from sudden changes in the output variables should not be attributed to model development flaws or overtraining.

The overall accuracy of the XGB models remains satisfactory across the entire dataset, and their performance in capturing general trends is reliable. However, challenges arise in

segments where the output variable exhibits ranges not encountered in the development datasets. This highlights the inadequate extrapolation capabilities of XGB models. While XGB models excel in the interpolation of data inside the regions defined by the training set, the decision trees struggle to extrapolate outside the boundaries set by the training, as the thresholds on the tree nodes are defined by the minimum and maximum values of specific features encountered during training [34].

Figure 21 shows the R_f calculated based on the XGB model outlet temperatures. The results are largely consistent with those derived from what the LSTM models indicate as similar overall trends.

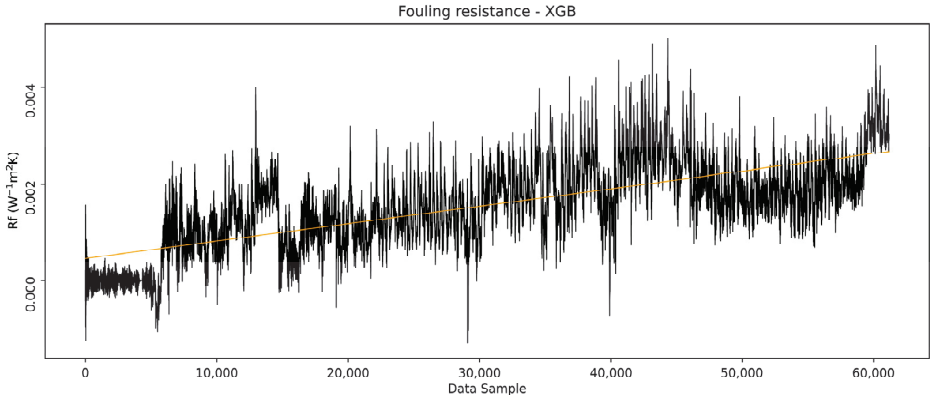


Figure 21. XGB model calculated the fouling resistance.

However, local peaks are observed on the parts of the data where the XGB model poorly represented due to its inability to extrapolate. These results show that XGB models are capable of capturing the dynamics of fouling resistance in the examined heat exchanger for a defined period. However, their success in this case is attributed to the fact that local, smaller segments of the data fell outside the training range. This alignment does not guarantee that the model will perform equally well for other heat exchangers, as operational conditions and temperature ranges may vary significantly. If monitoring relies on the real-time evaluation of values outside the initiation phase training range, this method becomes unreliable.

Therefore, while the XGB model can effectively handle interpolation within the training data range, its limited extrapolation capability can make it unsuitable for the presented fouling detection method in cases where significant deviations from the training data are expected.

4.3. ε-NTU Method Fouling Resistance Results

The ε-NTU method was conducted to compare the results derived from the developed models. The average $\overline{\mathrm{NTU}}_{IP}$, calculated as the average NTU value in the initiation phase, assumed to represent the geometric and hydrodynamic characteristics of the clean phase, was used to calculate the clean overall heat transfer coefficient using the relations in Equation (14). Similarly, the real NTU values were used for the calculation of the real overall heat transfer coefficient. The R_f was then calculated using Equation (13), similarly to the calculations of model-based approaches. Figure 22 shows the R_f calculated by the ε-NTU method.

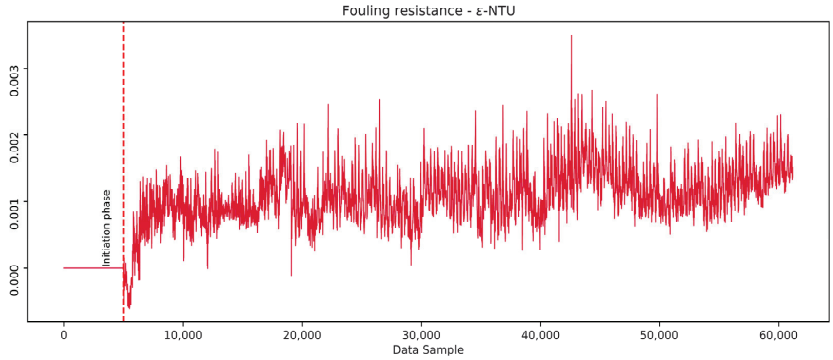


Figure 22. ε-NTU model calculated the fouling resistance.

The vertical line separates the initiation phase from the rest of the examined period data. The comparison between the model-based approaches and the ε-NTU method reveals similarities in the increasing trend of fouling. However, the trend shows a higher level of noise, suggesting that either the method is too sensitive or lacks the ability to account for all relevant information from the data. This random variability undermines the method's reliability. Based on the nature of the trend, it shows less dynamics compared to the model-based approaches. This could indicate that the method is less capable of capturing the real-time process dynamics as well as more complex model-based approaches, particularly in scenarios involving sudden changes or fluctuations. Since the ε-NTU method is relatively straightforward to implement and provides some trend information, it can serve as a useful baseline for identifying general trends in fouling resistance and is advantageous due to its simplicity. However, its inability to capture the complexity and dynamics of fouling deposition, as well as its susceptibility to noise, makes it less reliable than more advanced model-based approaches. For applications requiring detailed insights into fouling dynamics, the model-based methods provide superior performance and accuracy.

Although conducted on different or not entirely comparable processes, the obtained results were compared with similar studies based on machine learning models from the literature. Madhu et al. [14] applied an RF-LSTM architecture for fouling prediction in industrial heat exchangers and reported accuracies of 97–99%, supporting the applicability of time-series neural networks in this field. Similarly, Kang [16] demonstrated that RNNs significantly outperform traditional models in fault detection for the refinery process. Biyanto et al. [35] used a NARX neural network to estimate fouling resistance in a refinery heat exchanger, achieving RMSE values of 1.454 °C and 1.067 °C for the hot and cold sides, respectively. In comparison, the LSTM model developed in this study demonstrated similar performance, achieving an RMSE of approximately 0.8 °C and an R^2 of 0.99 for the hot flow outlet, while the cold flow prediction exhibited an even lower error with an RMSE of about 0.3 °C and the same R^2 value. These findings confirm the relevance of LSTM-based models for tracking fouling progression in complex industrial environments.

A comparative evaluation of the LSTM, XGB, and ε-NTU methods highlights distinct modeling behaviors. The LSTM model captured gradual increases in fouling resistance along with characteristic short-term oscillations, aligning with expected industrial fouling dynamics involving deposit growth and detachment. The XGB model demonstrated a similar overall trend but exhibited local deviations, particularly in regions with operating conditions not fully represented during training, suggesting reduced robustness in extrapolation scenarios. The ε-NTU method also indicated an increasing fouling trend but with higher signal variability and lower responsiveness to process fluctuations. While this method remains computationally simple and useful for general trend observation, its sensitivity to noise and lack of integration of full process context limit its interpretive depth when compared to data-driven approaches.

4.4. Impact of Thermal Inefficiency on Furnace Operation

For a clearer interpretation of the calculated fouling resistance, the excess CO_2 emissions resulting from furnace operation were estimated based on the arbitrarily set 95% furnace efficiency. In the lack of actual values, the fuel gas composition used to calculate excess CO_2 emissions was assumed to contain 20% hydrogen and an equal mix of methane and ethane, typical for the industrial furnace [36]. The calorific value of the fuel gas was taken as 44.22 MJ/m^3, with an average emission factor of 1.96 kg of CO_2/m^3 [37]. The additional heat required for reheating was calculated based on the difference between the model-predicted outlet temperatures representing an ideal (clean) heat exchanger and the actual outlet temperatures of the cold flow. This excess CO_2 emission estimation provides an approximation of CO_2 required solely to compensate for the inefficiency of this specific heat exchanger. However, the total CO_2 consumption of the furnace is also influenced by other heat exchangers in the preheat train, as well as CO_2 capture efficiency and overall process variability. Figure 23 demonstrates the thermal inefficiency of the analyzed heat exchanger and its cascading impact on furnace operation.

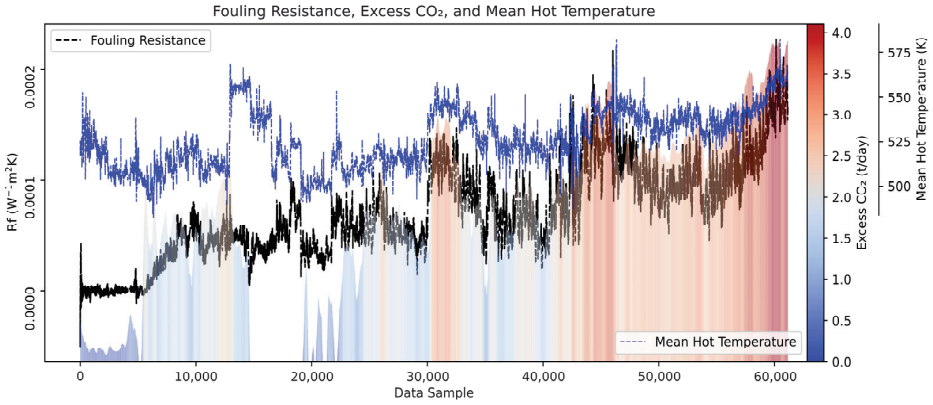


Figure 23. Analysis of thermal inefficiency and its impact on furnace operation due to a fouled heat exchanger.

The mean hot side temperature of the heat exchanger, shown as a blue dotted trend, is primarily influenced by the inlet temperature, but it also reflects heat accumulation due to reduced heat transfer to the cold side. In the early stages, temperature elevation enhances heat transfer performance. However, toward the end of the analyzed period, it is indicative that further temperature increases no longer provide any significant benefit in restoring heat exchanger efficiency, as it cannot overcome fouling resistance. Daily excess CO_2 consumption, represented by the height of the bars and a color gradient from blue (low consumption) to red (high consumption), follows both trends while providing additional critical insight into when the performance of the heat exchanger becomes unsatisfactory. It can be seen that toward the end of the analyzed period, excess CO_2 values remain persistently high, suggesting that even with an increase in temperature, the system can no longer compensate for the losses, and the additional CO_2 consumption remains consistently elevated. This trend signifies a critical stage of heat exchanger degradation, marking a threshold beyond which operational intervention becomes necessary.

The analyzed heat exchanger is a part of a preheat train; therefore, its degradation does not only affect its efficiency but also the performance on subsequent heat exchangers in the network. As this exchanger loses effectiveness, downstream units must compensate for its thermal inefficiencies, leading to a cascading increase in overall energy consumption. Consequently, excess CO_2, although presented here as a direct result of this specific heat exchanger's inefficiency, also serves as an indicator of the broader impact on the overall preheating system.

Once the heat exchanger reaches a phase where further temperature increases no longer improve efficiency, the resulting increase in CO_2 emissions can serve as a crucial metric for evaluating the overall system load. These insights aid decision-making on optimization and preventive maintenance strategies, provided that fuel gas composition and furnace performance are known. In this case study, persistently high excess CO_2 values start at about 2.5 months before shutdown. The total excess CO_2 emissions for this period were estimated at roughly 175 tons. Based on the average price of EU Carbon Permits per ton of CO_2 in 2024, the economic impact was approximately EUR 12,000. Had timely intervention been performed, these environmental and economic costs could have been significantly reduced or prevented.

5. Conclusions

In this study, LSTM and XGB models for predicting the outlet temperatures of a heat exchanger in the CDU preheat train were compared to the traditional ε-NTU method. Both machine learning models show strong predictive capabilities.

The LSTM models exhibited robust performance in capturing the overall trends and dynamics of the heat exchanger processes. Despite their complexity and longer training times, these models were able to predict outlet temperatures with high accuracy, effectively reflecting the real process dynamics. However, the XGB models encountered limitations with sudden process variations in the validation set. Conversely, the XGB models were easier to train, less computationally intensive, and performed well when interpolating within the bounds of the training data. However, they performed poorly when extrapolating to data ranges not represented during training in more dynamic or variable operational conditions.

This study also highlighted the implications of fouling on heat exchanger efficiency. The gradual increases in error trends and systematic biases observed in the predictions of both the LSTM and XGB models indicate a continuous accumulation of deposits on the heat exchanger surfaces. This fouling is likely attributed to the chemical composition of the fluids, which promotes deposition formation. The resulting decrease in heat transfer efficiency, demonstrated by the discrepancies between predicted and actual effectiveness and the effectiveness errors, highlights the effect of fouling on operational performance.

Additionally, this study examined the impact of fouling on excess CO_2 emissions, estimating that roughly 175 tons of excess CO_2 were emitted over the last two months due to the degraded performance of the heat exchanger. Based on the average 2024 EU Carbon Permit price per ton of CO_2, the economic impact of these emissions is estimated to be approximately EUR 12,000. Had corrective action been taken earlier, these environmental and financial costs could have been avoided. The trend of excess CO_2 consumption serves as a valuable indicator for assessing system load and decision-making in process optimization and preventive maintenance, provided that fuel gas composition and furnace performance are well-understood.

The comparison of model-based approaches with the ε-NTU method revealed significant differences in their ability to capture fouling dynamics. While the ε-NTU method provided a simpler and more stable trend of fouling resistance, it lacked the sensitivity and complexity required to accurately reflect the dynamic process behavior captured by the LSTM and XGB models. This suggests that although traditional methods like ε-NTU are valuable for their ease of implementation, they may not be as effective as more advanced methods in monitoring fouling in industrial heat exchangers.

This paper suggests that the LSTM and XGB models offer valuable insights into heat exchanger performance and fouling prediction. However, the choice between these models should be guided by the specific needs of the application. LSTM models may be more suitable for scenarios requiring detailed trend analysis and the ability to capture complex dynamic processes. On the other hand, XGB models may be preferred for quicker, less resource-intensive applications within well-defined and stable data ranges.

Despite the promising results, this study has certain limitations related to the nature of real industrial data. Sensor readings, as is often the case in empirical settings, can occasionally be affected by hardware issues, leading to potential noise or bias that is difficult to eliminate entirely. In addition, the operational conditions of the unit vary depending on the type of crude oil processed, which significantly influences fouling behavior. This means that although the developed models performed well on the current dataset, retraining may be necessary when applied to different feedstocks or operating regimes. Still, the applied methodology from data preparation through model evaluation remains robust and transferable across similar cases. Future research should place greater emphasis on model interpretability. While the current study demonstrates strong predictive performance, understanding why the model makes certain predictions remains equally important for practical deployment in industrial environments. Deeper post hoc analyses could help identify which variables most influence the predictions and how these effects change over time. This would not only support model validation but also offer valuable process insights that are often hidden behind purely numerical performance metrics.

Author Contributions: Conceptualization, Ž.U.A. and N.R.; methodology, Ž.U.A.; software, N.R.; validation, Ž.U.A. and N.R.; formal analysis, N.R.; investigation, N.R.; resources, Ž.U.A.; data curation, N.R.; writing—original draft preparation, N.R.; writing—review and editing, Ž.U.A.; visualization, N.R.; supervision, Ž.U.A.; All authors have read and agreed to the published version of the manuscript.

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Abbreviations

The following abbreviations are used in this manuscript:

CDU	Crude Distillation Unit
LSTM	Long Short-Term Memory neural network
XGB	Extreme Gradient Boosting
NTU	Number of Transfer Units
ε-NTU	Effectiveness—Number of Transfer Units method
HEN	Heat Exchanger Network
CFD	Computational Fluid Dynamics

NN	Neural Network
RNN	Recurrent Neural Network
TEMA	Tubular Exchanger Manufacturers Association
STD	Standard Deviation
MSE	Mean Squared Error

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Dual-Branch Deep Learning with Dynamic Stage Detection for CT Tube Life Prediction

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Abstract: CT scanners are essential tools in modern medical imaging. Sudden failures of their X-ray tubes can lead to equipment downtime, affecting healthcare services and patient diagnosis. However, existing prediction methods based on a single model struggle to adapt to the multi-stage variation characteristics of tube lifespan and have limited modeling capabilities for temporal features. To address these issues, this paper proposes an intelligent prediction architecture for CT tubes' remaining useful life based on a dual-branch neural network. This architecture consists of two specialized branches: a residual self-attention BiLSTM (RSA-BiLSTM) and a multi-layer dilation temporal convolutional network (D-TCN). The RSA-BiLSTM branch extracts multi-scale features and also enhances the long-term dependency modeling capability for temporal data. The D-TCN branch captures multi-scale temporal features through multi-layer dilated convolutions, effectively handling non-linear changes in the degradation phase. Furthermore, a dynamic phase detector is applied to integrate the prediction results from both branches. In terms of optimization strategy, a dynamically weighted triplet mixed loss function is designed to adjust the weight ratios of different prediction tasks, effectively solving the problems of sample imbalance and uneven prediction accuracy. Experimental results using leave-one-out cross-validation (LOOCV) on six different CT tube datasets show that the proposed method achieved significant advantages over five comparison models, with an average MSE of 2.92, MAE of 0.46, and R^2 of 0.77. The LOOCV strategy ensures robust evaluation by testing each tube dataset independently while training on the remaining five, providing reliable generalization assessment across different CT equipment. Ablation experiments further confirmed that the collaborative design of multiple components is significant for improving the accuracy of X-ray tubes remaining life prediction.

Keywords: CT equipment; X-ray tube; remaining useful life; deep learning; residual self-attention; temporal convolutional network

1. Introduction

CT scanners are important medical imaging devices that provide three-dimensional images of internal body tissues through X-ray tomography, which play a key role in disease screening, localization, and diagnosis [1]. However, these critical and expensive medical assets face significant operational challenges, with X-ray tube failures representing the most costly and disruptive maintenance issue. Unexpected tube failures can result

in equipment downtime lasting days to weeks, directly impacting patient care delivery and hospital operations. Traditional reactive and preventive maintenance approaches are inadequate for managing such critical equipment, motivating the development of intelligent predictive maintenance solutions specifically designed for medical environments. Currently, healthcare institutions are increasingly focusing on the application of predictive maintenance (PdM) strategies for medical equipment. CT scanners frequently experience downtime due to sudden failures of components such as X-ray tubes, which not only affect the normal healthcare operations of hospitals but also delay timely diagnosis for patients [2]. Traditional preventive maintenance (PvM) strategies have limited ability to handle random sudden failures [3]. Therefore, accurately predicting the remaining useful life of CT tubes helps hospitals develop reasonable tube replacement plans and further reduce the risk of unexpected CT equipment downtime [4].

Predictive maintenance (PdM) has been widely applied in modern industrial production [5], especially in predicting equipment's remaining useful life (RUL) in engineering, mechanical, and automation applications [6,7]. Equipment maintenance spans the entire lifecycle of the equipment, and a good maintenance strategy can significantly extend equipment lifespan and reduce failure rates [8,9]. PdM, based on historical data collected during equipment operation, utilizes advanced data analysis and machine learning technologies to achieve the precise prediction of equipment RUL, providing a scientific basis for equipment maintenance decisions [10,11].

Compared to traditional physics-based methods, data-driven degradation prediction methods can automatically learn equipment degradation patterns and rules from large-scale heterogeneous data without an in-depth understanding of complex failure mechanisms, thus possessing stronger universality and adaptability [12,13]. With the rapid development of sensor technology, IoT, and big data processing capabilities, the acquisition and storage of large amounts of operational data have become easier, providing a solid foundation for data-driven degradation prediction methods [14,15].

Currently, data-driven degradation prediction methods can be categorized into three main types: statistical learning methods, machine learning methods, and deep learning methods [16–18]. Statistical learning methods model the degradation process through probability and statistics theory [19], such as hidden Markov models, Weibull distribution models, Gamma processes [20], Wiener processes [21], and random filtering [22,23]. However, these methods rely on prior assumptions about the degradation process and have limitations in handling complex non-linear relationships, making them difficult to adapt to the multi-stage variation characteristics in CT tube life prediction. Machine learning methods such as support vector machines and random forests extract features from historical data and learn degradation patterns [24]. Wei et al. [25] proposed a method combining support vector regression (SVR) with particle filters to predict the RUL of lithium-ion batteries. This method could improve prediction accuracy to some extent but still struggles to capture complex temporal dependencies when processing long sequence data, making it difficult to learn features directly from raw data. Deep learning methods such as long short-term memory (LSTM) networks and convolutional neural networks can automatically learn complex temporal features from raw data, achieving end-to-end degradation prediction [26]. For example, Ciani et al. [27] used LSTM and a single exponential degradation model to accurately estimate the RUL of lithium batteries in wireless sensor networks based on a limited number of data records. Ma et al. [28] combined the CNN with feature extraction capability and LSTM with recurrent memory capability to carry out bearing degradation trend prediction. Deep learning methods, such as LSTM networks and convolutional neural networks, can automatically learn complex temporal features from raw data, achieving end-to-end degradation prediction. However, single deep learning

models have limitations in CT tube life prediction. For example, LSTM may encounter gradient vanishing or explosion problems with long sequences, while CNN lacks the ability to model temporal dependencies when processing time series data.

Despite significant progress in data-driven degradation prediction methods, the development of a prediction method suitable for X-ray tubes of CT equipment still faces enormous challenges [29]. On the one hand, there are evident issues of data non-linearity and multi-phase characteristics for the collected CT tube data. The tube lifespan data exhibits complex non-linear degradation patterns and shows different degradation features at different usage stages. There are significant differences in data distribution between early stages, mid-use periods, and near-failure phases, making it difficult for a traditional model to capture the variation patterns throughout the entire lifecycle. Additionally, factors such as the uncertainty of the various working environments, parameter fluctuations, and load changes further increase the complexity of data modeling, leading to insufficient prediction accuracy of traditional or single-stage models in practical applications. On the other hand, from the perspective of prediction model construction, traditional static model structures cannot dynamically adjust prediction strategies based on different data characteristics, lacking adaptive mechanisms to handle different types of temporal patterns [30]. The architecture of a single model is also unable to process different types of temporal patterns simultaneously. For example, a pure LSTM model encounters gradient vanishing or exploding problems with long sequences, making it difficult to capture long-term dependencies. A pure temporal convolutional network (TCN) model, although capable of handling long sequences, lacks the ability to process sequential and state information. In addition, simple loss functions result in the model being insensitive to state transitions at turning points in the data, and the use of standard MSE or MAE loss functions fails to distinguish the importance of different types of samples. Fixed-weight loss functions also cannot adapt to the requirements of different training stages [31,32].

To address the above issues, this paper proposes a CT tube life intelligent prediction architecture based on a dual-branch neural network (DDLNet). Firstly, an adaptive phase-aware framework is applied to identify the different phases of tube, enabling the model to adaptively adjust prediction strategies according to the current phase, which can address the problem of insufficient model adaptability. Secondly, a dual-branch collaborative architecture is applied to enhance the modeling capability of long-term dependencies from temporal data, effectively capturing non-linear changes in the degradation phase and overcoming the limitations of a single model. Finally, a dynamically weighted triplet mixed loss function is designed to adaptively adjust the weight ratios of different prediction tasks, solving the problems of sample imbalance and uneven prediction accuracy.

Moreover, the evaluation methodology presents another critical challenge in CT tube RUL prediction research. Due to the limited availability of complete lifecycle data from medical equipment and the substantial costs associated with CT tube replacement, most studies rely on small datasets. This necessitates robust evaluation strategies that can provide reliable performance assessment despite limited sample sizes. Traditional train–test splits may lead to optimistic performance estimates when dealing with such constrained datasets, making it essential to employ rigorous cross-validation methodologies that ensure model generalization across different equipment and operating conditions.

Despite these advances, several critical research gaps remain in CT tube RUL prediction. First, existing single-model approaches cannot effectively capture the multi-phase degradation characteristics of CT tubes, as they lack adaptive mechanisms to handle the distinct patterns between stable and degradation phases. Second, current methods fail to synergistically combine long-term dependency modeling with multi-scale temporal feature extraction, limiting their effectiveness in complex industrial environments. Third, tradi-

tional loss functions do not adequately address the sample imbalance issues inherent in CT tube datasets, where stable phase data significantly outnumber degradation phase samples.

To better clarify our contributions, the key innovations of this work include the following.

(1) A dual-branch neural network architecture that integrates RSA-BiLSTM with D-TCN for CT tube RUL prediction. The RSA-BiLSTM branch uses a CNN-QKV generator to transform input sequences into query, key, and value representations and employs a forward-looking attention mechanism where query vectors at time step $t + 1$ interact with key vectors at time step t to capture state transitions. The D-TCN branch uses dilated convolutions with dilation rates of 1, 2, 4, and 8 to extract multi-scale temporal features. This dual-branch design addresses gradient vanishing problems in single LSTM models and temporal dependency limitations of pure CNN models.

(2) An adaptive phase-aware framework with dynamic stage detection for binary CT tube degradation states. The framework identifies the stable phase ($\geq$30 days) and the degradation phase (<30 days) to enable adaptive prediction strategies across different operational states.

(3) A dynamically weighted triplet mixed loss function combining base value loss, phase classification loss, and smoothness loss. The dynamic weighting mechanism adjusts each component's contribution based on real-time metrics, including prediction error, change point density, and prediction smoothness. This automatically adapts the loss function emphasis during training to handle sample imbalance and improve prediction accuracy across different RUL ranges.

The remainder of this paper is organized as follows: Section 2 introduces the proposed method and related knowledge, Section 3 introduces the experimental dataset sources and data processing. Section 4 demonstrates the superiority and effectiveness of the proposed method through comparison with existing methods and ablation experiments. Section 5 concludes the paper.

2. Experiment Dataset and Preprocessing Step

2.1. Data Description

The Internet of Medical Things (IoMT) system achieves the collection, processing, and analysis of medical data through a multi-layer architecture, including sensor layer, transmission layer, and application layer [33,34]. The sensor layer consists of various sensors monitoring patient physiological data and medical device status. The transmission layer utilizes wireless communication protocols to transmit data to central servers. The application layer is responsible for data storage, analysis, and ensuring secure access.

All data used in this research comes from the IoMT system of West China Hospital. The research team selected 6 X-ray tubes with complete lifecycles from 6 CT devices for RUL prediction research. Table 1 shows the specific information of 6 X-ray tubes, including CT number, tube number, start time, end time, and data volume.

Table 1. X-ray tube information.

CT Number	Tube Number	Start Time	End Time	Data Volume
CT-1	Tube-1	5 August 2021	8 April 2023	223,346
CT-2	Tube-2	26 July 2019	27 June 2023	368,026
CT-3	Tube-3	10 March 2021	23 September 2023	342,590
CT-4	Tube-4	19 July 2019	19 July 2022	401,173
CT-5	Tube-5	1 November 2022	21 July 2023	101,592
CT-6	Tube-6	16 March 2017	2 July 2018	315,587

The collected data includes a total of 45 parameters, categorized into device identification, time information, device control parameters, interruption information, and

lifespan-related parameters. These parameters reflect various aspects of CT tube operation and degradation, including scan counts that indicate cumulative usage, voltage fluctuations that affect tube stress, temperature measurements that reflect thermal conditions, and arc events that signal electrical anomalies. Data sampling frequency is not fixed, with sampling intervals ranging from 20 to 60 s. Among these, the device control parameters include 5 variables: "focus", "kind", "mode", "region", and "dom_type".

The experiment primarily uses the control parameters of 6 tubes. "Focus" refers to the position where the electron beam hits the target material, with the values "3" and "1" representing large focus and small focus, respectively. The data shows that small focus is used more frequently, indicating a greater demand for high-resolution imaging in clinical applications. Scan types ("kind") mainly include the SEQ, SPI, TOP, and ROT modes. Exposure modes ("mode") primarily include "A", "AB", and "B", with this research mainly using the "A" mode. Scanning regions ("region") are divided into "head" and "body", with the data showing that body scans are predominant, which aligns with clinical practice as body scans encompass chest, abdomen, and pelvic examinations. "Dom_type" represents the tube current dynamic adjustment mode, including "AEC" (360° rotation tube current mode), "ZEC" (Z-direction automatic tube current adjustment mode), and "No" (standard tube current mode without adjustment). These detailed parameter data provide a solid foundation for studying the performance degradation characteristics of CT X-ray tubes and predicting their remaining useful life.

The CT tube lifespan data in the dataset is divided into two phases: the stable phase and the degradation phase. The stable phase is characterized by a lifespan value of 30 days or more, indicating that the equipment is operating normally. The degradation phase is marked by a lifespan value of less than 30 days, indicating that the performance of the equipment is declining and approaching failure. This binary phase division reflects the characteristic changes of CT tubes at different usage stages and provides a basis for the model to distinguish between different working states, thereby enhancing prediction accuracy and adaptability.

2.2. Preprocessing Step

The initial phase requires collecting CT operation log data through the medical IoMT system. Our dataset contains complete lifecycle data for 6 CT X-ray tubes, with each tube generating approximately 45 parameters. These parameters can be divided into three main categories: 8 parameters related to device identification and time information, 7 parameters related to device control and operational interruptions, and 30 parameters directly related to tube lifespan characteristics.

For effective analysis, we first apply min–max normalization to 30 lifespan-related parameters to address the issue of varying measurement units and scales between different parameters, which can not only improve the prediction performance of the model but also accelerate convergence during the training process. The *min–max* normalization is calculated as follows:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

After normalization, feature engineering is performed to derive new features from the normalized parameters. This process includes creating interaction terms between existing features through basic arithmetic operations (such as differences, sums, products, and ratios). These derived features capture complex relationships that might not be evident in the original parameters, effectively revealing hidden patterns in the data and enhancing the ability of the model to recognize non-linear relationships.

To determine the most relevant parameters for predicting RUL, this research employs Pearson correlation analysis. This technique evaluates the linear relationship between each

feature and the target variable. The Pearson correlation coefficient ranges from −1 to 1, with values closer to either extreme indicating stronger relationships. The Pearson correlation coefficient is defined as

$$r_{xy} = \frac{\Sigma_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\Sigma_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\Sigma_{i=1}^{n}(y_i - \overline{y})^2}} \quad (2)$$

This research sets a correlation threshold of 0.75, selecting only those features with absolute correlation coefficients exceeding this value. The Pearson correlation method provides computational efficiency and direct interpretability, allowing the research to quickly identify the most important predictors without involving the complexity or potential instability of other techniques. The correlation analysis reveals several highly correlated features, including parameters related to scan counts, voltage fluctuations, temperature measurements, and arc events.

Finally, we apply sliding window processing to the screened features and data, but original window data often contains significant fluctuations that may mask potential degradation trends. To address this issue, two key processing techniques are applied.

Downsampling: By selecting points at regular intervals (sampling interval T = 20), data density is reduced, which helps smooth short-term fluctuations.

Exponential Moving Average (EMA): Applying EMA smoothing operations further reduces noise and highlights gradual degradation patterns.

3. The Proposed Method

3.1. Method Overview

This paper develops a DDLNet model to address the problem of predicting the RUL of CT X-ray tubes with multiple working conditions. This architecture integrates the strengths of RSA-BiLSTM and D-TCN and further introduces a dynamic phase detector and dynamically weighted triplet mixed loss function to achieve high-precision prediction. The core of this architecture lies in identifying the binary nature of tube lifespan states: the stable phase (lifespan value of 30 days or more) and the degradation phase (lifespan value less than 30 days). The structure of DDLNet is shown in Figure 1.

Firstly, the processed feature sequences are simultaneously fed into the RSA-BiLSTM and D-TCN branches for parallel feature extraction. The former captures long-term temporal dependencies from stable-phase features through a CNN-QKV generator and BiLSTM, while the latter utilizes multi-layer dilated convolutions to build multi-scale receptive fields and address non-linear changes in degradation phase. Secondly, based on the feature representation from the RSA-BiLSTM branch, the dynamic phase detector generates a state confidence score indicating the current working phase of the tube. Finally, the system adaptively integrates the prediction results from both branches based on the output. When the detection value is greater than 0, it is determined to be in the stable phase and directly outputs 30. Otherwise, it adopts the prediction value from the D-TCN branch as the final output. During the training process, this paper designs a dynamically weighted triplet mixed loss function including base value loss, phase loss, and smoothness loss. The model optimizes prediction accuracy, phase classification accuracy, and prediction curve smoothness simultaneously through the dynamically weighted triplet mixed loss function, combined with a phased pre-training strategy to improve the convergence efficiency and prediction performance of the model. To ensure robust model evaluation and validate generalization capability across different CT equipment, this research employs a LOOCV strategy throughout the experimental validation process.

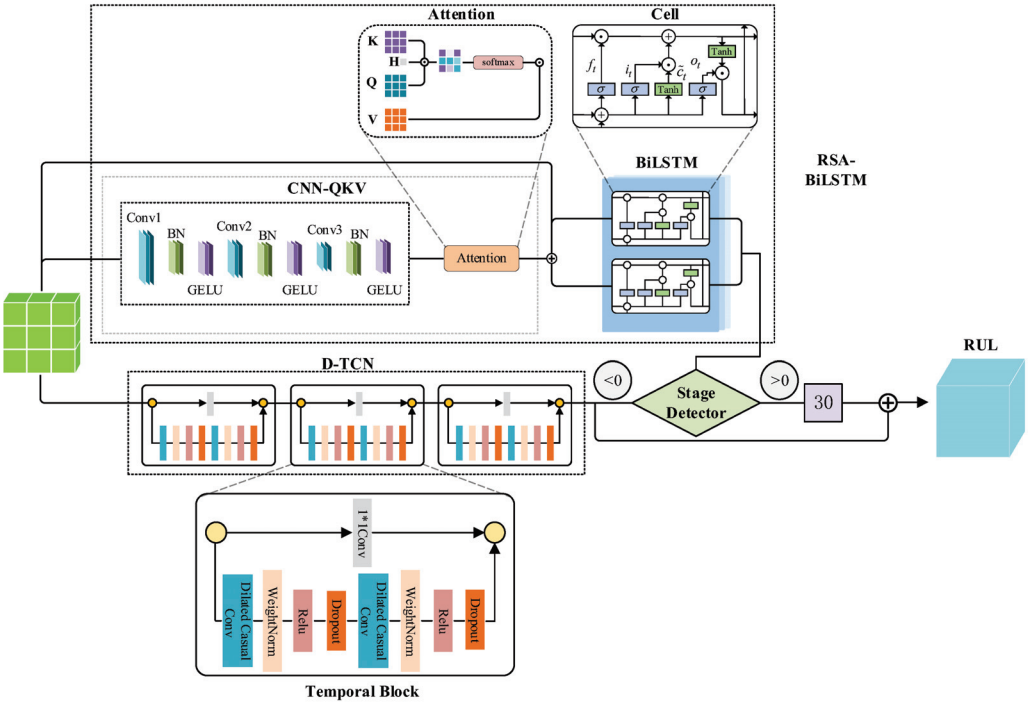


Figure 1. Structure of DDLNet.

3.2. RSA-LSTM Branch

In the hybrid model, the RSA-BiLSTM branch is specifically used to capture long-term dependencies and key state transition points in CT tube time series data. RSA-LSTM combines the advantages of convolutional neural networks, self-attention mechanisms, and bidirectional LSTM, forming a new architecture capable of precisely identifying specific patterns.

In the RSA-BiLSTM branch, the first key component is the CNN-QKV generator, which extracts features from the input sequence and generates query (Q), key (K), and value (V) representations through convolutional neural networks. This component is designed as follows.

Given an input sequence $X_t \in \mathbb{R}^{B\times L\times D}$, where B is the batch size, L is the sequence length, and D is the feature dimension, the CNN-QKV generator first performs dimension conversion on the input:

$$X_{trans} = X_t.transpose(0,2,1) \in \mathbb{R}^{B\times D\times L} \tag{3}$$

Then features are extracted through a three-layer one-dimensional convolution $Conv1D$, as shown in Equations (2)–(4).

$$F_1 = \sigma(BN(Conv1D(X_{trans}))) \tag{4}$$

$$F_2 = \sigma(BN(Conv1D(F_1))) \tag{5}$$

$$F = \sigma(BN(Conv1D(F_2))) \in \mathbb{R}^{B\times H\times L} \tag{6}$$

where σ is the Gaussian error linear unit (GELU) activation function. BN is batch normalization. H is the hidden-layer dimension. Finally, QKV representations are generated through three independent 1×1 convolution projections.

$$Q = W_q(F)^T \in \mathbb{R}^{B\times L\times H} \tag{7}$$

$$K = W_k(F)^T \in \mathbb{R}^{B\times L\times H} \tag{8}$$

$$V = W_v(F)^T \in \mathbb{R}^{B\times L\times H} \tag{9}$$

Next, we designed a special recursive self-attention mechanism that enhances the perception of temporal patterns by the model through information interaction across the time dimension, which is beneficial to adapt to the characteristics of temporal prediction tasks. The self-attention module processes Q, K, and V by time step. For each time step t, we employ a "forward-looking" mechanism, where the query vector of time step $t+1$ interacts with the key vector of the current time step t.

$$a_t = \frac{Q_{t+1}K_t^T}{\sqrt{H}} \tag{10}$$

$$\alpha_t = softmax(a_t) \tag{11}$$

$$c_t = \alpha_t V_t \tag{12}$$

where $\sqrt{H}$ is a scaling factor used to prevent gradient vanishing problems and α_t is the attention weight. c_t is the context vector obtained through the attention mechanism. This forward-looking attention mechanism enables the model to better capture state transition information in the sequence.

After obtaining the attention context vector, we perform feature fusion of the original input features X_t with the context vector c.

$$f_t = LayerNorm\Big(W_f[X_t; c_t] + b_f\Big) \tag{13}$$

$$X'_t = X_t + \lambda \cdot f_t \tag{14}$$

where W_f and b_f are learnable parameters. λ is the attention scaling factor (learned through parameters). $[X_t, c_t]$ represents vector concatenation. Through residual connections, we enhance the feature expression capability of the model while preserving the original information.

After feature enhancement, X'_t is input into a bidirectional *LSTM* network.

$$\overrightarrow{h}_t, \overrightarrow{c}_t = LSTM_{forward}\Big(X'_t, \overrightarrow{h}_{t-1}, \overrightarrow{c}_{t-1}\Big) \tag{15}$$

$$\overleftarrow{h}_t, \overleftarrow{c}_t = LSTM_{forward}\Big(X'_t, \overleftarrow{h}_{t-1}, \overleftarrow{c}_{t-1}\Big) \tag{16}$$

where the forward *LSTM* captures historical information from the start position to the end position of the sequence. The backward *LSTM* processes from the sequence end position to the start position, capturing future information. $\overrightarrow{h}_t$ and $\overleftarrow{h}_t$ represent the hidden states of the forward and backward *LSTM* at time step t, respectively. $\overrightarrow{c}_t$ and $\overleftarrow{c}_t$ represent the corresponding cell states.

After obtaining the hidden states of the bidirectional LSTM, we merge the forward and backward hidden states through linear mapping:

$$h_t = W_o[\overrightarrow{h}_t; \overleftarrow{h}_t] + b_o \tag{17}$$

Here, $[\overrightarrow{h}_t; \overleftarrow{h}_t]$ represents vector concatenation. W_o and b_o are learnable parameters. By combining information from both directions, the model can utilize both past and future contexts to obtain a more comprehensive sequence representation.

At the same time, to improve the robustness and generalization capability of the model, we employ a two-layer stacked bidirectional LSTM structure to enhance representation capability, and further apply dropout between LSTM layers to prevent overfitting [35,36].

$$h_t^{(1)} = BiLSTM^{(1)}(X_t') \tag{18}$$

$$\widetilde{h}_t^{(1)} = Dropout\left(h_t^{(1)}, p\right) \tag{19}$$

$$h_t^{(2)} = BiLSTM^{(2)}(\widetilde{h}_t^{(1)}) \tag{20}$$

3.3. TCN Branch

The other branch is TCN structure, which adopts a dilated convolutional architecture that effectively expands the receptive field and preserves local features, capable of capturing multi-scale temporal dependencies. Given an input sequence $X_t \in \mathbb{R}^{B\times L\times D}$, where B is the batch size, L is the sequence length, and D is the feature dimension. The *TCN* branch first performs dimension conversion.

$$X_{trans} = X_t.transpose(0,2,1) \in \mathbb{R}^{B\times D\times L} \tag{21}$$

This conversion facilitates subsequent convolutional operations. The *TCN* branch consists of multiple stacked temporal blocks, with the overall structure being in Equation (20).

$$Y = TCN(X) = W_o \cdot TCN_{net}(X_{trans})^T + b_o \tag{22}$$

where W_o and b_o are output layer parameters. TCN_{net} represents the main body of the TCN network. To enhance the representation capability and training stability of TCN, this research improves the traditional temporal convolutional block by introducing more efficient residual connection structures and regularization techniques. Each temporal convolutional block contains of two layers of dilated convolution, structured as follows:

$$Z_1 = Conv1D(X_i, k, d_i, p_i) \tag{23}$$

$$Z_2 = BatchNorm(Z_1) \tag{24}$$

$$Z_3 = ReLU(Z_2) \tag{25}$$

$$Z_4 = Dropout(Z_3, p = 0.2) \tag{26}$$

$$Z_5 = Conv1D(Z_4, k, d_i, p_i) \tag{27}$$

$$Z_6 = BatchNorm(Z_5) \tag{28}$$

$$Z_7 = Dropout(Z_6, p = 0.2) \tag{29}$$

$$X_{i+1} = ReLU(Z_7 + Residual(X_i)) \tag{30}$$

Here, the residual connection is a key design element that allows information to flow directly from input to output, solving the gradient vanishing problem in deep network training. The basic idea of residual connection is to create a "shortcut" that adds the input directly to the output of the convolutional layer. This residual function is defined by Equations (29) and (30), respectively.

If the number of channels in X_i and Z_7 are the same,

$$Residual(X_i) = X_i \tag{31}$$

If the number of channels in X_i and Z_7 are different,

$$Residual(X_i) = Conv1D(X_i, kernel_{size} = 1, stride = 1) \tag{32}$$

Here, 1×1 convolution is used to adjust the number of channels without changing the sequence length. This residual connection allows the network to learn new features or preserve original features. As network depth increases, if adding more layers no longer improves performance, residual connection allows additional layers to approximate identity mappings.

To enable the model to simultaneously attend to local details and global trends, we introduce a multi-scale feature fusion mechanism to establish skip connections between different dilation layers, which can integrate features from different receptive field levels.

$$F_{multi} = \sigma\left(\sum_{i=0}^{2} W_i \cdot F_i\right) \tag{33}$$

where F_i represents the output features of the i-th dilated convolutional layer. W_i is the corresponding weight parameter. σ is the activation function. These features are then transformed into prediction values through a specially designed output mapping layer.

$$Y = W_o \cdot F_{multi}[:, -1, :] + b_o \tag{34}$$

3.4. Model Loss Function

To address the issue of prediction accuracy differences across different ranges in CT tube RUL prediction, this paper proposes a mixed loss function:

$$L_{total} = \alpha \cdot L_{value} + \beta \cdot L_{stage} + \gamma \cdot L_{smooth} \tag{35}$$

where α, β and γ are dynamically adjusted weight coefficients that control the contribution of each component loss. Unlike traditional fixed-weight methods, we introduced an adaptive dynamic weight adjustment mechanism based on data characteristics:

$$\alpha = \alpha_{base} \cdot (1 + sigmoid(diff_{mean} - 1)) \tag{36}$$

$$\beta = \beta_{base} \cdot (1 + sigmoid(density_{change} \cdot 10 - 5)) \tag{37}$$

$$\gamma = \gamma_{base} \cdot (1 + sigmoid(smoothness - 0.5)) \tag{38}$$

where $diff_{mean}$ is the average difference between predicted and actual values. When prediction error increases, $diff_{mean}$ will rise. And through the *sigmoid* function, α will also increase, thereby enhancing the weight of basic prediction loss. $density_{change}$ is the change point density (defined as the ratio of the number of change points to the total number of samples). We multiply it by 10 and subtract 5 to map typical distributions of $density_{change}$ values to the sensitive region of the *sigmoid* function, making the adjustment more effective. *smoothness* is the average value of differences between consecutive prediction samples. When the prediction results fluctuate significantly, *smoothness* increases, and γ correspondingly increases, causing the model to focus on the smoothness of the prediction curve.

The base value loss uses weighted mean squared error, assigning different importance to different target values:

$$L_{value} = \frac{1}{n}\sum_{i=1}^{n} w_i(pred_i - target_i)^2 \tag{39}$$

The phase loss is designed for the classification task, aimed at optimizing the ability of the model to recognize the characteristic value of 30:

$$L_{stage} = \frac{1}{n}\sum_{i=1}^{n}\left(stage^{i}_{prob} - true^{i}_{stage}\right)^{2} \tag{40}$$

The smoothness loss is specifically designed for the stability in the 30 value region, ensuring smooth changes in prediction results between adjacent time steps:

$$L_{smooth} = \frac{1}{m}\sum_{i=1}^{n}\left(pred_{i+1} - pred_{i}\right)^{2} \cdot I \tag{41}$$

3.5. Phase Detector Design and Phased Training Strategy

Since the labeled data has been divided, it exhibits a clear binary phase characteristic: a stable period (value equal to 30.0) and a degradation period (value less than 30.0). To distinguish between these two phases and improve prediction accuracy, we design a dedicated phase detector.

$$Stage(x) = \tanh(W_2 \cdot LeakyReLU(W_1 \cdot x + b_1) + b_2) \tag{42}$$

where $x \in \mathbb{R}^D$ is the feature vector output from the RSA-LSTM branch and W_1 and W_2 are weight matrices. b_1 and b_2 are bias terms. When $Stage(x) > 0$, it is determined to be in the stable period, whose prediction value is 30.0, When $Stage(x) \leq 0$, it is determined to be in the degradation period, and the prediction value adopts the prediction result from TCN branch. The choice of tanh as the activation function considers its zero-centered nature. The introduction of LeakyReLU is to avoid the gradient vanishing problem in the negative value region.

Next, this paper adopts a phased pre-training strategy. For the RSA-LSTM branch, we use stable period data samples for targeted pre-training, while the TCN branch uses degradation period data samples for targeted pre-training. Based on the standard MSE loss function, both branches' pre-training processes use the AdamW optimizer and OneCycleLR learning rate scheduler with a cosine annealing strategy.

4. Case Study

4.1. Evaluation Metrics

To evaluate the performance of the RUL model, this research selects three key evaluation metrics, i.e., Mean Squared Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). These metrics reflect the prediction accuracy of the model from different perspectives, as follows:

1. Mean Squared Error (MSE): MSE is particularly suitable for RUL prediction as it heavily penalizes large prediction errors, which are critical in maintenance planning. In CT tube maintenance, a significant prediction error (e.g., predicting 20 days when actual RUL is 5 days) could lead to equipment failure and patient care disruption. *MSE* is calculated as Equation (45):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^{2} \tag{43}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the sample size. *MSE* evaluates the performance of prediction models through squared errors, which is sensitive to large errors.

2. Mean Absolute Error (MAE): MAE provides an intuitive understanding of average prediction accuracy in the same units as the target variable (days). This is directly interpretable by maintenance personnel who need to understand the typical prediction uncertainty when planning maintenance schedules. Unlike MSE, MAE is less sensitive to outliers, providing a robust measure of typical model performance. MAE calculated as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{44}$$

3. Coefficient of Determination (R^2): R^2 indicates how well the model explains the variance in RUL values, which is crucial for assessing model reliability across different CT tubes and operating conditions. In medical equipment maintenance, understanding the proportion of RUL variance that can be explained by the model helps in risk assessment and decision-making confidence. R^2 is calculated as

$$R^2 = 1 - \frac{\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2}{\Sigma_{i=1}^{n}(y_i - \overline{y})^2} \tag{45}$$

where $\overline{y}$ is the mean of the actual values. The R^2 value typically ranges between 0 and 1, with values closer to 1 indicating better model fit, meaning the model can explain more variance in the dependent variable. These three metrics provide complementary perspectives: MSE emphasizes accuracy in critical situations, MAE provides practical interpretability, and R^2 assesses overall model reliability.

To ensure robust evaluation and avoid overfitting, this study employs a LOOCV strategy. Given the limited number of CT tubes (six tubes), LOOCV provides the most comprehensive evaluation by using each tube as a test set while training on the remaining five tubes. This approach ensures that the model's performance is evaluated on completely unseen data from different CT scanners, providing a more realistic assessment of the model's generalization capability across different equipment and operating conditions. While LOOCV provides rigorous evaluation within our dataset, it cannot address the fundamental limitation of domain diversity. The claims of generalizability across different healthcare institutions and CT equipment types remain insufficiently substantiated.

4.2. Comparative Experiments

The experiments are conducted on a system with the following configuration: a Windows 10 (22H2) operating system, equipped with an Intel(R) i7-9750H processor and an Nvidia RTX2060 graphics card. The software environment included Python 3.12.1 and PyTorch 2.3.1 for implementing and training the neural network models. All experimental results reported in this study are obtained using LOOCV. For each iteration, one tube dataset is held out as the test set, while the remaining five tube datasets are used for training and validation. This process is repeated six times, ensuring each tube serves as the test set exactly once. The reported metrics (MSE, MAE, and R^2) represent the average performance across all six cross-validation folds. To evaluate the performance of DDLNet in the CT tube RUL task, this research compared it with five network models, i.e., LSTM, Transformer, CNN-BiLSTM-Attention, CNN-LSTM, and CNN-LSTM-Attention.

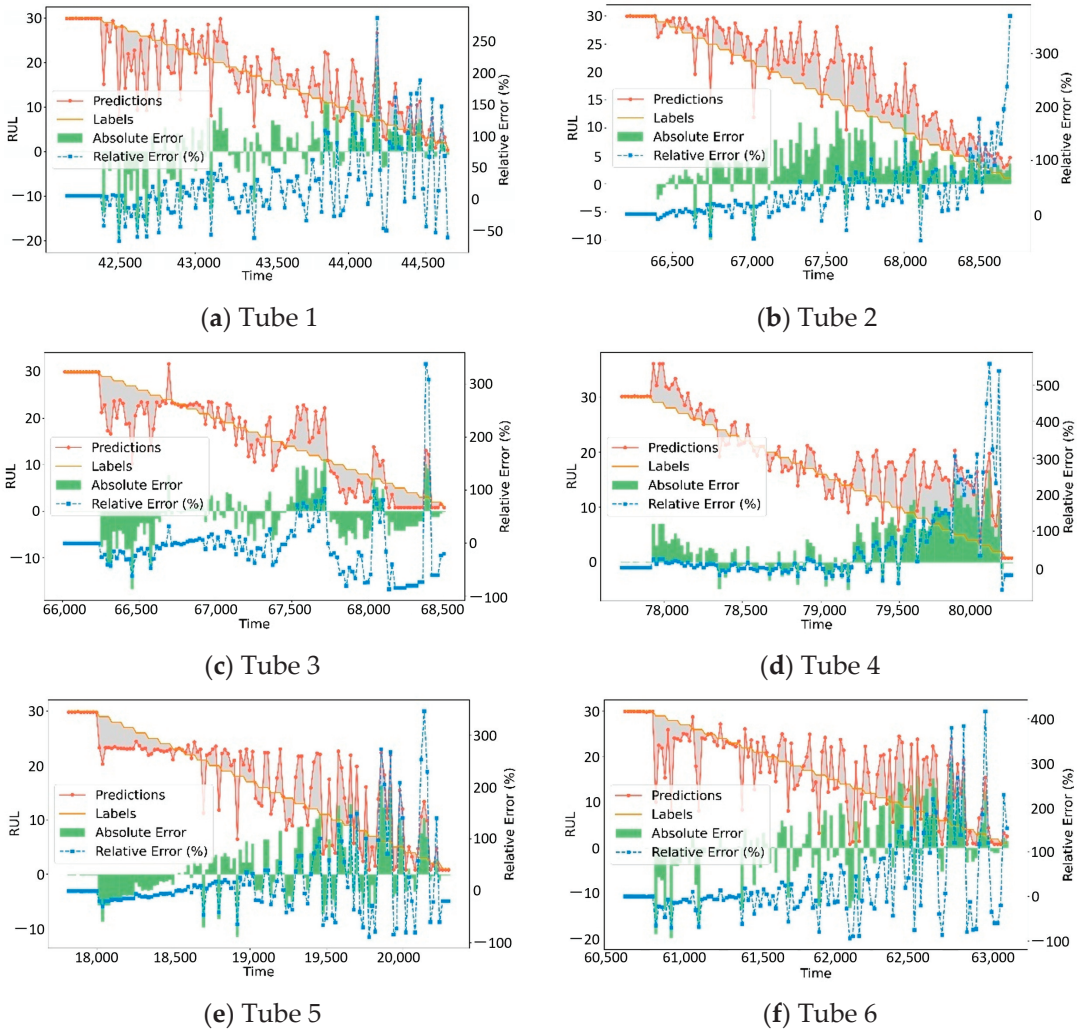
Table 2 shows the MSE, MAE, and R^2 metric values of each model on six different CT tube datasets (Tube 1–6). From the experimental data, DDLNet obtains the best performance on the MSE, MAE, and R^2 metrics. Notably, on Tube 5, other models generally have low R^2 values (such as LSTM at 0.0018, CNN-BiLSTM-Attention at 0.0643), while DDLNet reaches a 0.8576 R^2 value. On all datasets, the R^2 of DDLNet remained above 0.62, while other models had multiple instances below 0.25. The inclusion of standard deviations

reveals that DDLNet demonstrates not only superior mean performance but also the lowest variability across different CT tubes (std: 1.39 for MSE, 0.18 for MAE, 0.10 for R^2), indicating more consistent and reliable predictions compared to baseline methods. Through comparative analysis, DDLNet showed good performance on all three evaluation metrics, especially when handling complex datasets such as Tube 4 and Tube 5, maintaining relatively stable prediction performance with lower MSE and MAE and higher R^2.

Table 2. Comparative Experimental Results (LOOCV).

		Tube 1	**Tube 2**	**Tube 3**	**Tube 4**	**Tube 5**	**Tube 6**	**Average**	**Mean ± Std**
LSTM	MSE	7.0079	5.5311	7.2104	6.9019	30.6251	7.9749	10.8752	10.88 ± 9.42
	MAE	1.0671	0.9354	0.8343	1.0600	2.0037	1.5975	1.2497	1.25 ± 0.42
	R^2	0.4904	0.4202	0.2181	0.1665	0.0018	0.2406	0.2563	0.26 ± 0.18
Transformer	MSE	9.8224	6.7637	8.0440	7.9642	25.6668	8.8649	11.1877	11.19 ± 6.89
	MAE	1.3350	1.0859	1.2381	1.0490	1.8629	1.6177	1.3648	1.36 ± 0.31
	R^2	0.2858	0.2910	0.1277	0.0383	0.2286	0.1558	0.1879	0.19 ± 0.09
CNN-BiLSTM-Attention	MSE	7.9168	6.9328	7.2402	6.5597	28.7354	8.3603	10.9575	10.96 ± 8.44
	MAE	1.3342	0.8737	1.0731	0.5802	2.1097	1.3533	1.2207	1.22 ± 0.51
	R^2	0.4243	0.2732	0.2148	0.2079	0.0643	0.2039	0.2314	0.23 ± 0.11
CNN-LSTM	MSE	11.0675	7.1686	8.3275	6.5126	27.3177	7.5794	11.3289	11.33 ± 7.75
	MAE	0.7506	0.7373	0.8901	0.5626	1.8493	1.1650	0.9925	0.99 ± 0.43
	R^2	0.1952	0.2485	0.0969	0.2132	0.1096	0.2782	0.1903	0.19 ± 0.07
CNN-LSTM-Attention	MSE	10.1311	4.8093	8.1599	6.9712	28.0831	8.9272	11.1803	11.18 ± 8.35
	MAE	0.8454	1.1660	1.4669	0.9929	1.8041	1.0507	1.221	1.22 ± 0.36
	R^2	0.2633	0.4958	0.1151	0.1582	0.0846	0.1499	0.2112	0.21 ± 0.14
DDLNet	MSE	4.3101	1.4099	2.2568	1.2323	4.3685	3.9320	2.9183	2.92 ± 1.39
	MAE	0.5401	0.2618	0.4395	0.2396	0.6989	0.6072	0.4645	0.46 ± 0.18
	R^2	0.6866	0.8522	0.7553	0.8512	0.8576	0.6256	0.7714	0.77 ± 0.10

To visually demonstrate the performance of the DDLNet model in the CT tube RUL prediction, Figure 2 shows the prediction results, actual label values, absolute errors, and relative errors on six test datasets. The red line represents the predicted values, the orange line represents the actual label values, the green bars represent absolute errors, and the blue dashed line represents relative errors. From the visualization results, it can be observed that the prediction values can generally track the changes in the actual RUL values. At most time points, the differences between predicted and actual values are small, with absolute errors generally kept at low levels. The model shows high prediction accuracy in the mid-life stage of CT tubes (RUL values between 10–25). It is worth noting that in all six datasets, when the RUL value is low (i.e., when the tube is approaching the end of its life), the relative error increases. This is mainly because the RUL value itself is small, so even small absolute errors can lead to large relative error percentages. When the RUL approaches 5 or below, increased fluctuations in relative error can be observed, occasionally exceeding 200% relative error peaks. Additionally, in the initial phase of the time series (RUL around 30), the fit between the predicted values of the model and actual values is generally good, with consistently small absolute errors. As time progresses, the prediction curve can capture the downward trend of actual RUL values. Overall, the DDLNet model demonstrates good prediction capability across all six test datasets, effectively tracking the changing trends in CT tubes' remaining life.



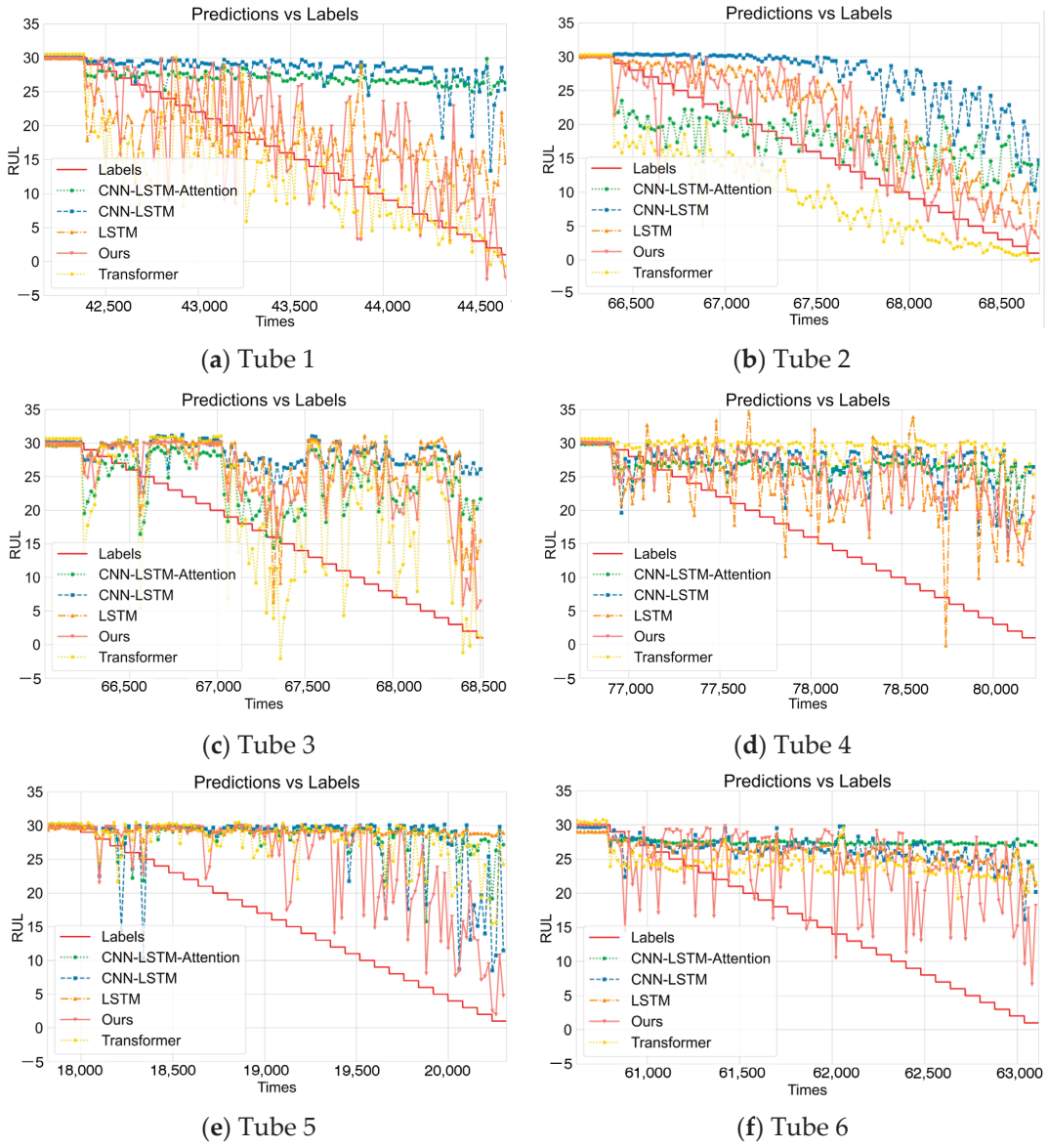
(**a**) Tube 1 (**b**) Tube 2

(**c**) Tube 3 (**d**) Tube 4

(**e**) Tube 5 (**f**) Tube 6

Figure 2. Prediction results.

To further visually compare the differences in prediction capabilities between DDLNet and comparison methods, Figure 3 shows the comparison of prediction results and actual label values for various models on six test datasets. Overall, the DDLNet model achieved significant advantages in MSE, MAE, and R^2 evaluation metrics, particularly showing higher prediction accuracy and stability when handling complex datasets. Tube 4 presents a special case where all comparative models show obvious prediction stability issues in the high RUL region (20–30), with predicted values exhibiting large fluctuations around the actual values. While the DDLNet model also shows some fluctuations, it can better reflect the downward trend of RUL; especially in the region where RUL is below 15, its prediction accuracy is significantly better than those of other models. This indicates that the DDLNet model can effectively address the challenges posed by the multi-phase variation characteristics of CT tubes, providing reliable CT tube remaining life predictions for medical institutions and helping to formulate scientific maintenance plans.



(**a**) Tube 1 (**b**) Tube 2

(**c**) Tube 3 (**d**) Tube 4

(**e**) Tube 5 (**f**) Tube 6

Figure 3. Comparison of different models.

4.3. Ablation Study

To further verify the contribution of each component of DDLNet, this research designed a series of ablation experiments using the same LOOCV strategy. Figure 4 shows the comparison of prediction performance between the complete DDLNet model (marked as "Ours") and variant models with specific components removed or modified on six test datasets. This experiment mainly examined the following variants:

1. No pre-training model (No_Pretraining): Removed the pre-training phase, directly training with randomly initialized model parameters to verify the impact of the pre-training strategy on model performance.
2. Residual self-attention model (RSA): Only retained the RSA-BiLSTM branch of DDLNet to evaluate the effectiveness of the RSA-BiLSTM branch acting alone.
3. Simplified loss function model (Simplified_Loss): Used standard mean squared error (MSE) to replace the composite loss function proposed in this paper, removing the relative error term to verify the impact of loss function design on prediction accuracy.
4. Temporal convolutional network model (TCN): Only retained the TCN branch to evaluate the effectiveness of the TCN branch acting alone.

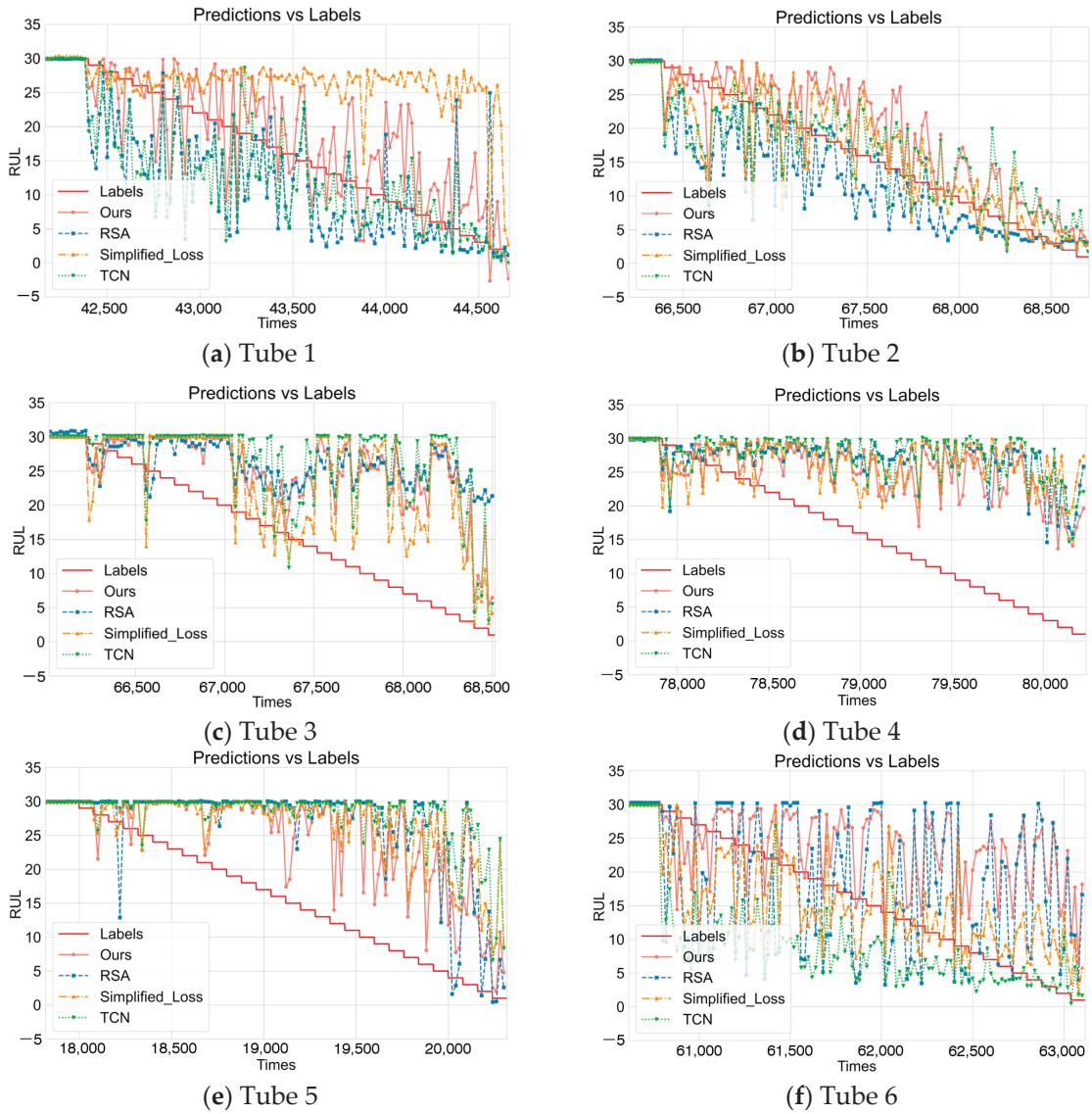


Figure 4. Ablation experiments.

According to the data in Table 3, there are significant performance differences between the variant models and the complete DDLNet. Regarding the pre-training strategy, the No_Pretraining variant has an average MSE of 4.5034, higher than DDLNet's 2.8016, and its average R^2 is 0.6479, lower than DDLNet's 0.7714. Specifically for each dataset, on Tube 3, the MSE of the No_Pretraining model is 3.8784, 71.9% higher than DDLNet (2.2568), and on Tube 4, the MSE of the No_Pretraining model is 3.6361, 195.1% higher than DDLNet (1.2323). However, on Tube 5, the No_Pretraining model's R^2 reached 0.7980, close to DDLNet's 0.8576, indicating that the impact of the pre-training strategy varies across different datasets.

Regarding the contribution of the RSA-BiLSTM branch, the variant model that only retained this branch showed inconsistent performance across different datasets. The RSA variant has an average MSE of 6.5116 and an average MAE of 0.7711, higher than the complete DDLNet. On Tube 2, the RSA variant's R^2 value reaches 0.6857, close to DDLNet, but on Tube 1, the R^2 value is only 0.4081, 40.6% lower than DDLNet's 0.6866. On Tube 5, the RSA variant's MAE is 1.5266, 118.4% higher than DDLNet's 0.6989, indicating that using the RSA-BiLSTM branch alone has limited adaptability to different feature patterns.

Table 3. Ablation experimental results.

		Tube 1	Tube 2	Tube 3	Tube 4	Tube 5	Tube 6	Average
No_ Pretraining	MSE	5.6894	3.0773	3.8784	3.6361	6.1974	4.2178	4.4494
	MAE	0.7138	0.4869	0.5031	0.3441	0.7910	0.6226	0.5769
	R^2	0.5863	0.6774	0.5794	0.5609	0.7980	0.5983	0.6334
RSA	MSE	8.1404	2.9982	5.0797	1.9206	14.9232	6.2074	6.5449
	MAE	0.8099	0.4659	1.0019	0.3161	1.5266	0.9060	0.8377
	R^2	0.4081	0.6857	0.4491	0.7681	0.5136	0.4089	0.5389
Simplified_Loss	MSE	8.0198	2.6110	5.6173	2.6930	7.2068	6.8265	5.4957
	MAE	1.0629	0.4379	0.5650	0.4537	0.7515	0.8406	0.6853
	R^2	0.4168	0.7263	0.3908	0.6748	0.7651	0.3154	0.5482
TCN	MSE	7.7832	2.6779	4.8627	2.3752	6.7110	6.2493	5.1099
	MAE	1.0474	0.5253	0.6724	0.2997	0.7228	0.7227	0.6651
	R^2	0.4341	0.7193	0.4727	0.7132	0.7813	0.4049	0.5876
Ours	MSE	4.3101	1.4099	2.2568	1.2323	4.3685	3.9320	2.9183
	MAE	0.5401	0.2618	0.4395	0.2396	0.6989	0.6072	0.4645
	R^2	0.6866	0.8522	0.7553	0.8512	0.8576	0.6256	0.7714

The loss function design also has a significant impact on prediction performance. The Simplified_Loss variant has an average MSE of 5.3374 and an average MAE of 0.6119, 90.5% and 53.8% higher than DDLNet, respectively. On Tube 1 and Tube 6, the Simplified_Loss model's MSE is 8.0198 and 6.8265, 86.3% and 73.8% higher than DDLNet, respectively. Notably, on Tube 5, the Simplified_Loss model's R^2 reaches 0.7651, indicating that standard MSE loss can also achieve good results on certain datasets.

Regarding the contribution of the TCN branch, the variant model that only retained the TCN branch has an average MSE of 5.0932 and an average MAE of 0.5983. Its performance is also inconsistent across datasets. For instance, on Tube 5, the TCN variant's R^2 is 0.7813, close to DDLNet, while on Tube 1, R^2 is only 0.4341, significantly lower than DDLNet's 0.6866. The MSE of the TCN variant on Tube 1 is 7.7832, 80.6% higher than DDLNet, indicating that the capability of the TCN structure varies when processing different temporal features.

Figure 4 shows the comparison of prediction results between the complete DDLNet model and various variant models on the six test datasets. Through visual analysis, it can be seen that the pre-training strategy, RSA-BiLSTM branch, TCN branch, and composite loss function each play different roles in enhancing model performance. The pre-training strategy (as shown in tubes 1 and 4) provides better parameter initialization, significantly reducing prediction fluctuations, with an average MSE reduction of 60.7%. The RSA-BiLSTM branch (Tube 2) excels at capturing global dependencies in temporal data with its residual self-attention mechanism, achieving an R^2 of 0.6857 on Tube 2. The TCN branch (Tubes 5 and 6) provides multi-scale feature extraction capability through multi-layer dilated convolutions, performing well in handling smooth change regions, with an R^2 of 0.7813 on Tube 5. The composite loss function (tubes 3 and 5) improves the sensitivity of the model to low RUL value regions by combining absolute and relative errors, reducing MSE by 86.3% and 73.8% on Tube 1 and Tube 6, respectively.

To further validate the rationality of our loss function design, we conducted a comprehensive sensitivity analysis on the dynamic weighting mechanism of the triplet mixed loss function. Using leave-one-out cross-validation across all six CT tube datasets, we systematically evaluated the impact of weight variations on model performance. Our experimental design included the following.

(1) Individual parameter sensitivity testing by varying each weight parameter while keeping others constant;

(2) Parameter interaction analysis through simultaneous variations;

(3) Extreme boundary testing to assess model robustness limits.

As demonstrated in Table 4, our empirically selected configuration (α_base = 0.8, β_base = 0.15, γ_base = 0.05) achieves optimal performance across all evaluation metrics. The individual parameter sensitivity analysis reveals distinct characteristics: α_base exhibits the highest sensitivity, with performance degrading significantly when deviating from 0.8 (MSE increases from 2.92 to 3.45 when α_base = 0.6, representing an 18.2% deterioration). β_base shows moderate sensitivity, with MSE increasing to 3.28 and 3.19 when changed to 0.10 and 0.20, respectively. γ_base demonstrates the least individual impact, though still meaningful, with MSE rising to 3.12 and 3.25 for values of 0.03 and 0.07. The parameter interaction analysis (rows 10–11) shows that simultaneous moderate changes can maintain reasonable performance, while extreme combinations (rows 12–13) result in substantial performance degradation, with MSE increasing by up to 33.2%. This systematic analysis validates that our weight selection represents a well-optimized configuration that effectively balances the contributions of base value loss, phase classification loss, and smoothness regularization.

Table 4. Sensitivity analysis results on loss function weights (average LOOCV performance).

α_Base	β_Base	γ_Base	Average MSE	Average MAE	Average R^2
0.8	0.15	0.05	2.92 ± 1.39	0.46 ± 0.18	0.77 ± 0.10
0.6	0.15	0.05	3.45 ± 1.52	0.53 ± 0.19	0.70 ± 0.13
0.7	0.15	0.05	3.08 ± 1.42	0.48 ± 0.17	0.75 ± 0.11
0.9	0.15	0.05	3.15 ± 1.44	0.49 ± 0.17	0.74 ± 0.12
1.0	0.15	0.05	3.38 ± 1.50	0.52 ± 0.19	0.71 ± 0.12
0.8	0.10	0.05	3.28 ± 1.47	0.50 ± 0.18	0.73 ± 0.12
0.8	0.20	0.05	3.19 ± 1.45	0.49 ± 0.17	0.74 ± 0.11
0.8	0.15	0.03	3.12 ± 1.43	0.48 ± 0.17	0.75 ± 0.11
0.8	0.15	0.07	3.25 ± 1.48	0.51 ± 0.19	0.72 ± 0.12
0.7	0.10	0.05	3.42 ± 1.51	0.52 ± 0.19	0.71 ± 0.13
0.9	0.20	0.05	3.56 ± 1.54	0.54 ± 0.20	0.68 ± 0.14
0.6	0.20	0.07	3.89 ± 1.63	0.58 ± 0.22	0.64 ± 0.15
1.0	0.10	0.03	3.71 ± 1.59	0.56 ± 0.21	0.66 ± 0.14

The collaborative effect of these components enables DDLNet to demonstrate excellent prediction accuracy and stability across datasets with different characteristics, confirming the effectiveness and necessity of the multi-component collaborative design.

4.4. Discussion

While our experimental results demonstrate the effectiveness of DDLNet on real CT tube data, several important directions warrant further investigation for practical deployment:

(1) Domain Adaptation and Transferability

Future work should focus on enhancing the model's adaptability across different CT scanner manufacturers, tube types, and operational environments. The development of domain adaptation techniques could enable our approach to generalize effectively to new hospital settings with minimal retraining, addressing the inherent variability in medical equipment configurations and usage patterns.

(2) Practical System Integration and Deployment

Translating our research findings into operational clinical systems requires comprehensive engineering efforts. This includes developing robust data pipelines for continuous parameter collection, implementing real-time prediction algorithms with appropriate failover mechanisms, establishing integration protocols with existing hospital information systems, and conducting extensive validation studies across multiple institutions to ensure reliability and safety standards.

(3) Model Interpretability and Clinical Trust

A critical aspect for medical equipment applications is enhancing model interpretability to build clinical trust and support regulatory approval. Future research should explore explainable AI techniques that can provide clear reasoning for RUL predictions, develop uncertainty quantification methods to communicate prediction confidence, and establish clinical decision support frameworks that integrate predictions with existing maintenance protocols while maintaining human oversight and accountability.

5. Conclusions

This paper addresses the challenge of RUL prediction of CT X-ray tubes by an improved DDLNet model. The architecture employs an adaptive phase-aware framework that combines RSA-BiLSTM and D-TCN and further introduces a dynamic phase detector and triplet mixed loss function to guide the training process. This approach effectively overcomes the limitations of traditional single models in handling the multi-phase variation characteristics of CT tubes.

Through rigorous LOOCV evaluation, experimental results show that DDLNet significantly outperforms models such as LSTM and Transformer across six different CT tube datasets, with an average 2.92 MSE, 0.46 MAE, and 0.77 R^2 values. This enables healthcare institutions to obtain reliable predictions of CT tube remaining life, helping them formulate scientific maintenance plans.

While our approach demonstrates excellent prediction accuracy and stability, several limitations must be acknowledged, including the purely data-driven nature limiting interpretability and single-institution evaluation constraining generalizability claims. As detailed in Section 4.4, future work should focus on hybrid modeling approaches, multi-institutional validation, and enhanced model interpretability to advance practical clinical deployment. Despite these limitations, the collaborative design of multiple components confirms the effectiveness of the multi-component approach for improving X-ray tube remaining life prediction accuracy.

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Abbreviations

The following abbreviations are used in this manuscript:

RUL	Remaining Useful Life
CT	Computed Tomography
PdM	Predictive Maintenance
PvM	Preventive Maintenance
IoMT	Internet of Medical Things
DDLNet	Dual-branch Deep Learning Network
RSA-BiLSTM	Residual self-attention Bidirectional Long Short-Term Memory
D-TCN	Dilation-Temporal Convolutional Network
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
QKV	Query-Key-Value
MSE	Mean Squared Error
MAE	Mean Absolute Error
R^2	Coefficient of Determination
EMA	Exponential Moving Average
SVR	Support Vector Regression
CLSTM	Convolutional Long Short-Term Memory
AEC	Automatic Exposure Control
ZEC	Z-direction Exposure Control
LOOCV	Leave-One-Out Cross-Validation

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A New Method of Remaining Useful Lifetime Estimation for a Degradation Process with Random Jumps

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Abstract: With the deepening of degradation, the stability and reliability of the degrading system usually becomes poor, which may lead to random jumps occurring in the degradation path. A non-homogeneous jump diffusion process model is introduced to more accurately capture this type of degradation. In this paper, the proposed degradation model is translated into a state–space model, and then the Monte Carlo simulation of the state dynamic model based on particle filtering is employed for predicting the degradation evolution and estimating the remaining useful life (RUL). In addition, a general model identification approach is presented based on maximization likelihood estimation (MLE), and an iterative model identification approach is provided based on the expectation maximization (EM) algorithm. Finally, the practical value and effectiveness of the proposed method are validated using real-world degradation data from temperature sensors on a blast furnace wall. The results demonstrate that our approach provides a more accurate and robust RUL estimation compared to CNN and LSTM methods, offering a significant contribution to enhancing predictive maintenance strategies and operational safety for systems with complex, non-monotonic degradation patterns.

Keywords: remaining useful life estimation; particle filtering; expectation maximization algorithm; state–space model; jump diffusion process

1. Introduction

Lifetime or remaining useful life (RUL) prognostics, as an essential part of prognostics and health management (PHM), have attracted increasing attention and play an important role in many engineering systems [1–3]. In general, the common way of lifetime or RUL prognostics includes degradation process modeling and failure probability predicting [4–6]. Due to the difference in the degradation model, data-driven approaches can be classified into machine learning and statistics-based approaches [7]. Nowadays, statistical data-driven approaches that only rely on the available observed data and statistical models, one of the most popular degrading model methods, have been gaining in momentum and are applied in a variety of industrial assets [4,5]. In addition, based on the type of monitoring degradation data, the statistical data-driven approaches can be classified into the methods based on directly observed data and the methods based on indirectly observed data [4]. In this paper, we mainly focus on the statistical data-driven approaches for degrading systems.

In fact, owing to the complexity and uncertainty of the systems and their operating environment, the data directly observed from many industrial systems often cannot be obtained. A common way is to measure some given intermediate performance indicators,

just like the temperature sensors for the thickness of the furnace wall [3–11]. As such, some outstanding random jumps exist in the degradation process. In addition, with the deepening of the systems' deterioration, the stability of the systems becomes gradually worse, which makes the systems more vulnerable to random shock. It should be noted that if we ignore these random jumps, the degradation model is not suitable, which must affect the accuracy of the lifetime or RUL estimation [12]. In this paper, we mainly concentrate on degrading systems with random jumps.

To describe the character of these jumps, a direct way is to adopt the jump diffusion processes to describe such a degradation process. That is to say, the traditional diffusion process is used to describe the continuous degradation and the compound jump process to depict random jumps [13–16]. For example, the normal jump diffusion process is presented by Merton for a financial model in 1976 [17]. On this basis, Abundo provided an approximate FPT expression for the homogeneous jump diffusion process. Platen and Bruti-Liberati systematically discussed and reviewed the differential equation, numerical simulation method, and parameter identification [18]. However, as discussed in [19], if the jumps are described as a Gaussian variable, the analytical solution of the first passage time (FPT) cannot be obtained. Recently, Zhang et al. provided an approximate approach to derive the FPT, and the solution with the single integral form was attained [14]. Thus, it could be concluded that the lifetime or RUL estimation problem for the jump diffusion degradation process has not been well studied, and it is still challenging.

In this paper, we propose a non-homogeneous compound Poisson degradation process model to describe this kind of degradation trajectory. Unlike the traditional method, such as [20–22], we first translate the degradation model into the state–space model. Considering the nonlinear form of the degradation model, particle filtering (PF) is adopted to approximate the future degradation path and predict the lifetime and RUL. Compared with other classical Monte Carlo methods, it can reduce the size of the samples and the computational complexity. In addition, we propose a general identification method for such a degradation model and an iterative for linear degradation model based on an expectation maximization (EM) algorithm. To illustrate the applicability and rationality of our method, a practical case is provided.

The remaining sections are organized as follows. In Section 2, the motivating examples and problem formulation are given. In Section 3, a new stochastic model is proposed to describe the degradation path and the framework of the EM method for unknown model parameters is presented. Section 4 includes the main result of the RUL estimation. An illustrated example is presented to clarify the feasibility and applicability of the proposed model in Section 5. This paper is concluded in Section 6.

2. Motivating Examples and Formulation

2.1. Motivating Examples of Blast Furnace

Blast furnaces are large-scale degrading complex systems, and their degradation is caused by the erosion of molten iron. Due to the high cost of blast furnace downtime and the difficulty of directly measuring the furnace wall thickness, temperature sensors are commonly used in industrial practice to monitor the degree of wall degradation. In engineering practice, sensors are strategically placed at a suitable depth within the furnace wall to ensure safety [10,11]. A temperature reading that approaches that of molten iron (approx. 1400 °C) is a clear indicator that erosion has progressed to at least the sensor's depth. Figure 1 illustrates the degradation process of the furnace wall. Consequently, once the temperature surpasses a predetermined threshold, the furnace must be taken offline for a major overhaul. Since this overhaul requires the complete reconstruction of the wall, it defines the end of the blast furnace's lifespan.

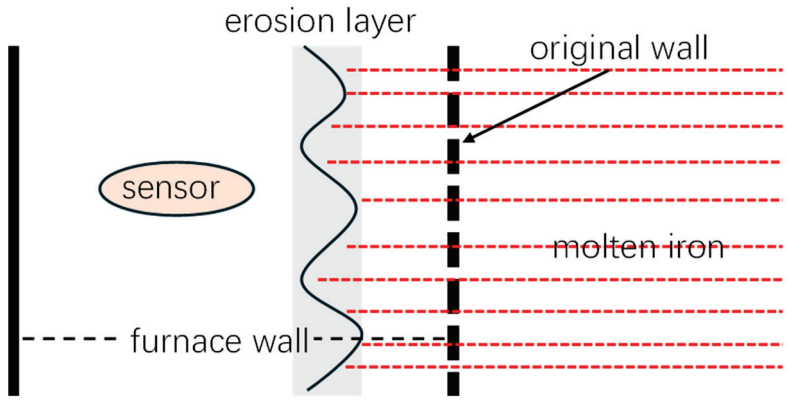


Figure 1. A chart of the furnace wall degradation.

Figure 2 presents the degradation signals acquired from two sensors over a span of approximately one year, with a sampling rate of once every 5 min. It is noted that the blast furnace is just put into operation for a short time and the furnace wall is healthy. Because the erosion level of the furnace wall is low (the failure threshold is over 800 °C at least in engineering practice), no maintenance has been adopted for the furnace wall so far [12–14].

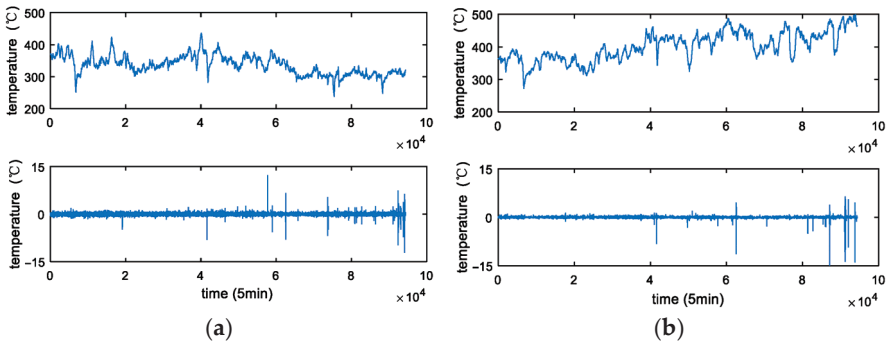


Figure 2. The actual degradation data from temperature sensors. (**a**) The actual degradation data from temperature sensor 1. (**b**) The actual degradation data from temperature sensor 2.

It is important to understand that the wall thickness degradation is a non-monotonic process. This occurs because two things happen at once: first, the molten iron erodes the wall, reducing its thickness. Second, it reacts to create unstable chemical compounds. These compounds are constantly being created and then breaking away from the wall. Because their ability to conduct heat is different from the wall's, they cause the temperature sensor data to fluctuate randomly. This is precisely what we refer to as "random jumps" in our work [13,14].

Thus, from Figure 1, it can be found that the frequency of random jumps becomes higher over time. This is because as the furnace wall erodes and these complex compounds accumulate, the sensor becomes more sensitive to temperature variations. Neglecting these random jumps in favor of modeling only the continuous degradation component for RUL prognosis will inevitably introduce prediction bias. Such bias can lead to catastrophic failures and significant losses, thereby making it imperative to incorporate these stochastic events into the modeling framework.

2.2. Problem Formulation

Following the clarification in Section 1, we focus on the degradation model based on stochastic process. Define $X(t)$ as the performance variable of degrading systems as time t,

and as usual, $X(t)$ is a stochastic process to depicting the degradation path. As per the definition in [23], the nonlinear degradation model could be described as follows:

$$X(t) = X(0) + \int_0^t \mu(\tau; \boldsymbol{\theta}) d\tau + \sigma_B B(t) \tag{1}$$

where $X(t)$ represses as a nonlinear Brownian motion with drift function $\mu(\tau; \boldsymbol{\theta})$ and diffusion coefficient σ_B and $B(t)$ denotes the standard Brownian motion. Moreover, its stochastic differential equation (SDE) can be presented as follows:

$$dx(t) = \mu(\tau; \boldsymbol{\theta}) d\tau + \sigma_B dB(t) \tag{2}$$

In fact, the monitored data of degradation processes are not continuous, so let $\boldsymbol{X}_{0:n} = \{x_0, x_1, \ldots, x_n\}$ denote the degradation data at time t_i. Based on the Euler approximation [24], when Δt is small enough, the increment of Equation (2) has the following form:

$$\Delta x_i = \mu(t_i; \boldsymbol{\theta}) \Delta t_i + \sigma_B B(\Delta t_i) \tag{3}$$

where $\Delta x_i = x_{i+1} - x_i$ and $\Delta t_i = t_{i+1} - t_i$.

In order to model the degradation system with time-varying jumps, we defined two stochastic processes for description: one is used to describe the normal degradation process as Equations (1) and (2) shown, the other is used to depict the random jump process. Inspired by Merton's model in [17], the jump diffusion degradation process model is defined as follows:

$$X(t) = X(0) + \int_0^t \mu(\tau; \boldsymbol{\theta}) d\tau + \sigma_B B(t) + \sum_{i=1}^{N(t)} g_i \tag{4}$$

where $\{N(t), t \geq 0\}$ is the non-homogeneous Poisson process with locally integrable positive intensity function $\lambda(t)$ and g_i is an independent and identically Gaussian distributed random variable with mean μ_g and variance σ_g^2. Then the SDE of the jump diffusion process is given as follows:

$$dX(t) = \mu(t; \boldsymbol{\theta}_\mu) dt + \sigma_B dB(t) + dY(t) \tag{5}$$

where $Y(t) = \sum_{j=0}^{N(t)} g_i$ is the non-homogeneous compound Poisson process. It is noted that if the intensity function $\lambda(t)$ is constant, the probability of the jump occurrence will not be changed during the same time interval, i.e., the homogeneous compound Poisson process. If $\lambda(t)$ is integrable, positive, and time-varying, the probability of the jump occurrence will increase over time. It should be noted that we assume the g_i follows a Gaussian distribution. This choice is primarily motivated by the distribution's mathematical simplicity and tractability, as well as its widespread use in mathematical modeling and machine learning. Furthermore, the effectiveness of the Gaussian assumption is validated in our subsequent case studies. Of course, since the increments of the random jumps can be both positive and negative, other distributions could also be used to model g_i. The derivation process in such cases would be analogous to the one presented in this paper.

In this paper, we focus on the lifetime under the concept of the FPT. That is to say, if the degradation process crosses the failure threshold, the systems fail at once. As defined in [16], the lifetime has the following form:

$$T := \inf\{t : X(t) \geq \xi | X(0) \leq \xi\} \tag{6}$$

where T is the FPT, and is often defined as the lifetime and ξ denotes the failure threshold that is the constant value determined by engineering practical requirement. Let $f_T(t)$ and $F_T(t)$ express the probability density function (PDF) and cumulative distribution function (CDF) of T. Define $\boldsymbol{X}_{0:k} = \{x_0, x_1, \ldots, x_k\}$ as the degradation data at time $t_0, t_1, \ldots, t_k$, then the RUL under concept of FPT is often defined as follows:

$$L_k := \inf\{l_k : X(t_k + l_k) \geq \xi | X(t_k) \leq \xi\} \tag{7}$$

where L_k denotes the RUL with PDF $f_{l_k}(t)$ and CDF $F_{l_k}(t)$.

Then, the remaining parts of this paper include two main goals: how to estimate the parameters in Equation (6) or Equation (7) through the conditional monitored data $\boldsymbol{X}_{0:k} = \{x_0, x_1, \ldots, x_k\}$ and how to derive the RUL via the degradation model and the estimated parameters.

3. Parameter Estimation for Degradation Model

In this section, we will introduce how to identify the proposed degradation model in a statistical way.

3.1. General Approach Based on MLE

Above all, for better illustration, the following Lemma 1 is given as follows:

Lemma 1 [25]. *Based on the definition of non-homogeneous Poisson process, we can define*

$$\Lambda(t, t + \Delta t) = \int_t^{t+\Delta t} \lambda(\tau) d\tau \tag{8}$$

Then the probability of jumps occurrence in $(t, t + \Delta t)$ *is shown as follows:*

$$\Pr(N(t, t + \Delta t) = n) = \frac{[\Lambda(t, t + \Delta t)]^n}{n!} \exp(-\Lambda(t, t + \Delta t)) \tag{9}$$

Let $\boldsymbol{\theta}_\lambda$ denote the parameter vector of $\Lambda(t, t + \Delta t)$, then $\Lambda(t, t + \Delta t)$ is rewritten as $\Lambda(t, t + \Delta t; \boldsymbol{\theta}_\lambda)$. In this way, it should be noticed that $\boldsymbol{\Theta} = [\boldsymbol{\theta}_\lambda, \boldsymbol{\theta}_\mu, \sigma_B, \mu_g, \sigma_g]$ denotes all unknown parameters.

Then, as the definition in the above section, $\boldsymbol{X}_{0:k} = \{x_0, x_1, \ldots, x_k\}$ denotes all observed degradation data. Then we further define $\Delta \boldsymbol{X}_{1:k} = \{\Delta x_1, \Delta x_2, \ldots, \Delta x_k\}$ as the increment data, where $\Delta x_i = x_i - x_{i-1}$. According to the proposed degradation model, it is noted that the increment is independent and has Markov properties. Then we can formulate the likelihood as follows:

$$\begin{aligned} L(\boldsymbol{\Theta} | \Delta \boldsymbol{X}_{1:k}) &= \ln \prod_{i=1}^{k} p(\Delta x_i; \boldsymbol{\Theta}) \\ &= \sum_{i=1}^{k} \ln \sum_{n=0}^{+\infty} p(\Delta x_i | N(t_{i-1}, t_i) = n; \boldsymbol{\Theta}) \times \Pr(N(t_{i-1}, t_i) = n; \boldsymbol{\Theta}) \\ &= \sum_{i=1}^{k} \ln \sum_{n=0}^{+\infty} \frac{\exp(-\Lambda(t_{i-1}, t_i)) \Lambda^n(t_{i-1}, t_i)}{\sqrt{2\pi(n\sigma_g^2 + \Delta t_i \sigma_B^2)} n!} \exp\left(- \frac{(\Delta x_i - \int_{t_{i-1}}^{t_i} \mu(\tau; \boldsymbol{\theta}_\mu) d\tau - n\mu_g)^2}{2n\sigma_g^2 + 2\Delta t_i \sigma_B^2} \right) \end{aligned} \tag{10}$$

In this case, MLE is the direct method for estimating parameters, which has the following equation [26,27]:

$$\begin{aligned}\hat{\boldsymbol{\Theta}}_k &= \underset{\boldsymbol{\Theta}}{\operatorname{argmax}}\, L(\boldsymbol{\Theta}|\boldsymbol{X}_{1:k}) \\ &= \underset{\boldsymbol{\Theta}}{\operatorname{argmax}}\, L(\boldsymbol{\Theta}|\Delta\boldsymbol{X}_{1:k})\end{aligned} \tag{11}$$

However, it is hard to derive the analytical solution of Equation (26) based on a traditional optimization algorithm. As such, the common way is choosing some heuristic optimization methods such as ant colony algorithm, the genetic algorithm, Tabu search algorithm, and so on. In addition, the existence and convergence of the optimization function is difficult to analyze.

3.2. Parameters Estimation Based on EM Algorithm

From Figure 2, it can be found that the degradation increments except the random jumps seem to be stationary, so the linear model is appropriate for practical data. In this subsection, we will introduce an iterative parameter estimation method based on the EM algorithm.

When the degradation model is linear, the likelihood can be translated into the following:

$$\begin{aligned}L(\boldsymbol{\Theta}|\Delta\boldsymbol{X}_{1:k}) &= \ln \prod_{i=0}^{k} p(\Delta x_i;\boldsymbol{\Theta}) \\ &= \sum_{i=0}^{k} \ln \sum_{n=0}^{+\infty} p(\Delta x_i|N(t_{i-1},t_i)=n;\boldsymbol{\Theta}) \times \Pr(N(t_{i-1},t_i)=n;\boldsymbol{\Theta}) \\ &= \sum_{i=0}^{k} \ln \sum_{n=0}^{+\infty} \frac{\exp(-\Lambda(t_{i-1},t_i))\Lambda^n(t_{i-1},t_i)}{\sqrt{2\pi(n\sigma_Y^2+\Delta t_i\sigma_B^2)}n!} \exp\left(-\frac{(\Delta x_i-\mu\Delta t_i-n\mu_Y)^2}{2n\sigma_Y^2+2\Delta t_i\sigma_B^2}\right)\end{aligned} \tag{12}$$

Based on the character of the non-homogeneous Poisson process, the following results can be known:

$$\begin{aligned}P\{N(t+\Delta t)-N(t)=1\} &= \lambda(t)\Delta t+o(\Delta t) \\ P\{N(t+\Delta t)-N(t)\geq 2\} &= o(\Delta t)\end{aligned} \tag{13}$$

where $o(h)$ is asymptotic or little-o notation for $o(h)/h \to 0$ as $h \to 0$. That is to say, when the interval time Δt is small, the probability of $P\{N(t+\Delta t)-N(t)\geq 2\}$ is very little. Thus, the following Assumption 1 is provided for simplifying the problem.

Assumption 1. *If the sampling interval is small enough ($\Delta t$is small), it is assumed that the random jump only occurs once or not during sampling interval time Δt and these random jumps have the same expression. That is to say, we define $P\{N(t+\Delta t)-N(t)=1\}=\lambda(t)\Delta t$ and $P\{N(t+\Delta t)-N(t)=0\}=1-\lambda(t)\Delta t$.*

In this way, we can find that the degradation increments have the following property,

$$\Delta x_i = \alpha_{1,t_i}[\mu\Delta t_i+\sigma_B B(\Delta t_i)]+\alpha_{2,t_i}[\mu\Delta t_i+\sigma_B B(\Delta t_i)+\Delta g_i] \tag{14}$$

where $\alpha_{1,t_i}+\alpha_{2,t_i}=1$, $\alpha_{1,t_i},\alpha_{2,t_i}\in(0,1)$, $P\{\alpha_{1,t_i}=0,\alpha_{2,t_i}=1\}=\lambda(t)\Delta t$, $P\{\alpha_{1,t_i}=1,\alpha_{2,t_i}=0\}=1-\lambda(t)\Delta t$. Thus, Δx_i follows a two-dimension Gaussian mixture distribution with mean $\mu\Delta t_i+\mu_g$ and variance $\Delta t_i\sigma^2+\sigma_g^2$. For better illustration, we define the following:

$$\begin{aligned}&\mu_0=\mu\Delta t_i, \mu_1=\mu\Delta t_i+\mu_g, \cdots \mu_j=\mu\Delta t_i+j\mu_g \\ &\sigma_0^2=\Delta t_i\sigma_B^2, \sigma_1^2=\Delta t_i\sigma_B^2+\sigma_g^2, \cdots \sigma_j^2=\Delta t_i\sigma_B^2+j\sigma_g^2\end{aligned} \tag{15}$$

Clearly, the probability of a jump occurring, as governed by $\frac{1}{i}[\Lambda(t, t+\Delta t)]$, decreases as i increases. For $i \geq 2$, we consider this probability to be negligible. Furthermore, our statistical analysis of the blast furnace degradation case shows that even when the sampling interval is doubled to 10 min, the probability of two or more jumps occurring within an interval is merely 0.000159, which further validates the effectiveness of Assumption 1.

It is noted that if the interval time is fixed, i.e., $\Delta t_i = \Delta t$, $\{\Delta x_1, \Delta x_2, \ldots, \Delta x_k\}$ can be regarded as the observation samples of a two-dimension Gaussian mixture distribution with mean μ_1 and μ_2 and variance σ_1^2 and σ_2^2. In addition, the two weights (i.e., $w_{1,k}$ and $w_{2,k}$) of such a two-dimension Gaussian mixture distribution at time t_k can be written as follows [27]:

$$\begin{aligned} w_{1,k} &= 1 - \sum_{i=1}^{k} \lambda(t_i)\Delta t_i \\ w_{2,k} &= \sum_{i=1}^{k} \lambda(t_i)\Delta t_i \end{aligned} \tag{16}$$

In this case, it is natural for the algorithm to estimate the parameters of such a two-dimensional mixture of Gaussian distribution.

Firstly, let $\boldsymbol{Y}_{1:k} = \{y_1, y_2, \ldots, y_k\}$, $y_i \in \{0, 1\}$ denote the latent variables which determine the degradation data from which the model originates, e.g., if $y_i = 1$, it means $\Delta x_i \sim N(\mu_1, \sigma_1^2)$ and if $y_i = 0$, it means $\Delta x_i \sim N(\mu_2, \sigma_2^2)$. Then the complete-data likelihood function holds the following form:

$$\ln L(\Xi|\Delta \boldsymbol{X}, \boldsymbol{Y}) = \ln \prod_{i=1}^{k} p(\Delta x_i, y_i \,|\Xi\,) = \sum_{i=1}^{k} \ln\Big(w_{y,k} p_{y,i}(x_i|\boldsymbol{\theta}_y\,)\Big) \tag{17}$$

where $\hat{\Xi}_k^{(i)} = [\hat{w}_k^{(i)}, \hat{\mu}_{1,k}^{(i)}, \hat{\sigma}_{1,k}^{(i)}, \hat{\mu}_{2,k}^{(i)}, \hat{\sigma}_{2,k}^{(i)}]$, $\boldsymbol{\theta}_y = [\mu_y, \sigma_y]$, $y_i \in \{0, 1\}$. Generally, the EM method mainly includes E-step and M-step [28].

E-step:

$$\begin{aligned} \ln L(\Xi_k\Big|\hat{\Xi}_k^{(i)}.) &= E_{Y|\Delta X_{1:k}, \hat{\Xi}_k^{(i)}}\Big\{\ln p(\Delta \boldsymbol{X}_{1:k}, \boldsymbol{Y}_{1:k}\Big|\hat{\Xi}_k^{(i)}\,)\Big\} \\ &= \sum_{y} \ln L(\hat{\Xi}_k^{(i)}|\Delta \boldsymbol{X}_{1:k}, y\,) p(y\Big|\Delta \boldsymbol{X}_{1:k}, \hat{\Xi}_k^{(i)}\,) \\ &= \sum_{y} \sum_{i=1}^{k} \ln\big(w_{y,i} p_y(\Delta x_i|\boldsymbol{\theta}_y\,)\big) p(y\Big|\Delta x_i, \hat{\Xi}_k^{(i)}\,) \\ &= \sum_{y=1}^{2} \sum_{i=1}^{k} \ln\big(w_{y,i} p_y(\Delta x_i|\boldsymbol{\theta}_y\,)\big) p(y\Big|\Delta x_i, \hat{\Xi}_k^{(i)}\,) \end{aligned} \tag{18}$$

where

$$\begin{aligned} p(y\Big|\Delta x_j, \hat{\Xi}^{(i)}\,) &= \frac{p(y, \Delta x_j\Big|\hat{\Xi}^{(i)}\,)}{\sum_{y'=1}^{2} p(y', \Delta x_j\Big|\hat{\Xi}^{(i)}\,)} = \frac{\hat{w}_{y,k}^{(i)} p_y(\Delta x_j\Big|\hat{\Xi}^{(i)}\,)}{\sum_{m'=1}^{2} \hat{w}_{y',k}^{(i)} p_{y'}(\Delta x_j\Big|\hat{\Xi}^{(i)}\,)} \\ p_y(\Delta x_j\Big|\hat{\Xi}^{(i)}\,) &= \frac{1}{\sqrt{2\pi\Delta t \hat{\sigma}_{y,k}^{2(i)}}} \exp\left(-\frac{(\Delta x_j - \hat{\mu}_{y,k}^{(i)})^2}{2\Delta t \hat{\sigma}_{y,k}^{2(i)}}\right) \end{aligned} \tag{19}$$

M-step:

Then let $\frac{\partial \ln L(\Xi_k | \hat{\Xi}_k^{(i)})}{\partial \Xi_k} = 0$, the closed-form solutions of $\hat{\Xi}_k^{(i+1)}$ can be obtained.

$$\begin{aligned}
\hat{\mu}_{y,k}^{(i)} &= \frac{\sum_{j=1}^{k} \Delta x_j p(y | \Delta x_j, \hat{\Xi}^{(i-1)})}{\Delta t \sum_{j=1}^{k} p(y | \Delta x_j, \hat{\Xi}^{(i-1)})}, \\
\hat{\sigma}_{y,k}^{2(i)} &= \frac{\sum_{j=1}^{k} (\Delta x_j - \hat{\mu}_{m,k}^{(i)}) p(y | \Delta x_j, \hat{\Xi}^{(i-1)})}{\Delta t \sum_{j=1}^{k} p(y | \Delta x_j, \hat{\Xi}^{(i-1)})}, (y = 1 \; or \; 2) \\
\hat{w}_{y,k}^{(i)} &= \frac{1}{k} \sum_{j=1}^{k} p(y | \Delta x_j, \hat{\Xi}^{(i-1)}),
\end{aligned} \tag{20}$$

where

$$\begin{aligned}
p(y | \Delta x_j, \hat{\Xi}^{(i-1)}) &= \frac{\hat{c}_{y,k}^{(i-1)} p_y(\Delta x_j | \hat{\Xi}^{(i-1)})}{\sum_{y'=1}^{2} \hat{c}_{y',k}^{(i-1)} p_{y'}(\Delta x_j | \hat{\Xi}^{(i-1)})} \\
p_y(\Delta x_j | \hat{\Xi}^{(i-1)}) &= \frac{1}{\sqrt{2\pi \Delta t \hat{\sigma}_{y,k}^{2(i-1)}}} \exp\left(- \frac{(\Delta x_j - \hat{\mu}_{y,k}^{(i-1)})^2}{2\Delta t \hat{\sigma}_{y,k}^{2(i-1)}} \right)
\end{aligned} \tag{21}$$

In this way, we can obtain the estimates of $\hat{\Xi}_k = [\hat{w}_k, \hat{\mu}_{1,k}, \hat{\sigma}_{1,k}, \hat{\mu}_{2,k}, \hat{\sigma}_{2,k}]$ and then the estimates of $\mu, \sigma_B, \mu_g, \sigma_g$ can be derived based on the relationship in Equation (15). As discussed before, let $\boldsymbol{\theta}_\lambda$ denote the known parameters of $\lambda(t)$, then we can derive the $\hat{\boldsymbol{\theta}}_A$ incorporating the estimates of $\left\{ \hat{w}_{y,1}, \hat{w}_{y,2}, \ldots, \hat{w}_{y,k} \right\}$, which can be concluded as solving the over-determined equations.

$$\begin{cases}
\sum_{i=1}^{1} \lambda(t_i) \Delta t = \hat{w}_{y,1} \\
\sum_{i=1}^{2} \lambda(t_i) \Delta t = \hat{w}_{y,2} \\
\quad \vdots \\
\sum_{i=1}^{k} \lambda(t_i) \Delta t = \hat{w}_{y,k}
\end{cases} \tag{22}$$

where the over-determined equations can be solved via least squares method and heuristic optimization methods [29].

Remark 1. *Unlike utilizing the traditional EM method directly, the heuristic optimization methods are only used once at each sampling time, which can reduce the running time and improve the online capacity.*

4. RUL Estimation Based on State-Space Model

In this section, we further introduce how to obtain the RUL of the proposed degradation model. As discussed in many research studies, it is hard to derive the analytical solution of the lifetime subject to the proposed jump diffusion degradation process model. Therefore, we provide a Monte Carlo approach to derive the RUL under the concept of the FPT. Figure 3 illustrates the flowchart of the particle filter estimation method proposed in this Section.

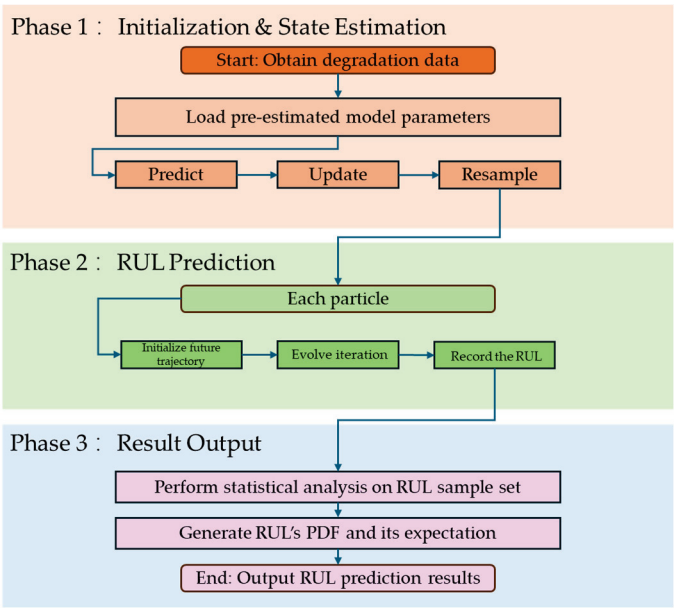


Figure 3. A flowchart of the particle filter estimation method.

According to the proposed degradation model and its stochastic differential equation, we can utilize the Euler approximation method to translate the continuous degradation process into a state–space model, as shown in the following equation.

$$\begin{aligned} x_{1,k} &= x_{1,k-1} + \int_{t_{k-1}}^{t_k} u(\tau;\boldsymbol{\theta})d\tau + \sigma_B B(\Delta t_k) \\ N(t_k) &= N(t_{k-1}) + Po(\Delta t_k;\boldsymbol{\theta}_\lambda) \\ x_k &= x_{1,k} + N(t_k) \times g_k \end{aligned} \tag{23}$$

where $Po(\Delta t_k;\boldsymbol{\theta}_\lambda)$ is a random variable and follows a Poisson distribution with interval time Δt_k and parameters $\boldsymbol{\theta}_\lambda$. It is worth mentioning that $x_{1,k}$ and $N(t_k)$ can be regarded as the system state, which reflects the continuous degradation and the number of random jumps accordingly. In addition, x_k is the observed degradation data, which can be treated as the measurement output. In this case, we can build a nonlinear and non-Gaussian state-space model as follows:

$$\begin{aligned} \boldsymbol{z}_k &= f_k(\boldsymbol{z}_{k-1}, \boldsymbol{\nu}_{k-1}) \\ x_k &= h_k(\boldsymbol{z}_k, g_k) \end{aligned} \tag{24}$$

where $\boldsymbol{z}_k = \begin{bmatrix} x_{1,k} \\ N(t_k) \end{bmatrix}$ denotes the system state; $\boldsymbol{\nu}_k = \begin{bmatrix} \sigma_B B(\Delta t_k) \\ Po(\Delta t_k;\boldsymbol{\theta}_\lambda) \end{bmatrix}$ represents the independent and identically distributed process noise sequence; and g_k denotes the measurement noise sequence.

It is noted that if we want to simulate the RUL at time t_k based on the Monte Carlo approach, it is essential to estimate the system state, i.e., $x_{1,k}$ and $N(t_k)$. However, since the state–space model is nonlinear and non-Gaussian, the traditional Kalman filtering is not available for this state–space model. As such, it is natural to adopt particle filtering to estimate the system state and predict the future system state and measurement output owing to its good feature for nonlinear and non-Gaussian system.

It is well-known that the key of the particle filtering is to approach the posterior PDF through a given set of particles $\left\{z_k^{(j)}\right\}_{j=1}^{n}$, where n denotes the number of the particles. Generally, the standard particle filtering includes the following steps:

(1) Let $k = 0$ and then generate the initial particles $\boldsymbol{z}_0^{(j)} \sim p(\boldsymbol{z}_0), i = 1, 2, \ldots, n$

(2) Define and assign the weight of each particle,

$$\omega_k^{(j)} = \omega_{k-1}^{(j)} p(x_k|z_{k-1}^{(j)}) = \omega_{k-1}^{(j)} \frac{p(x_k|z_{k-1}^{(j)}) p(z_k^{(j)}|z_{k-1}^{(j)})}{q(z_k^{(j)}|z_{0:k-1}^{(j)}, x_{1:k})} \tag{25}$$

and then normalize the weights we can obtain,

$$\omega_k^{(j)} = \frac{\omega_k^{(j)}}{\sum_{j=1}^{n} \omega_k^{(j)}} \tag{26}$$

(3) If $n_{eff} = \frac{n}{\sum_{j=1}^{n} \left[\omega_k^{(j)}\right]^2}$ is less than n, do the re-sampling precedence based on the $\omega_k^{(j)}$ and obtain the new sample $\widetilde{z}_k^{(j)} \sim p(z_{0:k}^{(j)}|x_{1:k})$ with new weights $\widetilde{\omega}_k^{(j)} = \frac{1}{n}$ to replace the previous one; else $\widetilde{z}_k^{(j)} \sim \widetilde{z}_k^{(j)}$, and $\widetilde{\omega}_k^{(j)} = \omega_k^{(j)}$.

(4) Then the estimate of the state of the system can be calculated as follows:

$$\hat{z}_k = \sum_{j=1}^{n} \widetilde{\omega}_k^{(j)} \widetilde{z}_k^{(j)} \tag{27}$$

In this way, we can obtain the estimate of the system state in this degradation state–space model. Then, based on the state–space model, we can predict the RUL based on the following equation:

$$L_k = \sum_{j=1}^{n} \widetilde{\omega}_k^{(j)} L_k^{(j)} \tag{28}$$

where $L_k^{(j)}$ denotes the FPT of the j-th particle reaching the failure threshold. It is worth mentioning that in the FPT of each particle exists some predicted bias due to the Euler approximation method.

5. Case Study

In this section, two examples are provided for illustration: (1) the numerical simulation is adopted to verify the accuracy of the parameter estimation and estimate of the state–space model; (2) the actual degradation data of the furnace wall is used to illustrate the feasibility of the proposed model.

5.1. Numerical Example

In this subsection, we mainly introduce a numerical simulation to illustrate the proposed model identification method based on the EM algorithm and state–space estimation approach based on particle filtering. As discussed before, the frequency of the jump occurrence becomes larger, so the form of $\lambda(t)$ in compound Poisson process should not be a fixed value. In addition, what should be noticed is that the frequency of the jump occurrence in practical cases will not increase with the deepening of the degradation all the time. As such, in this paper, we define the expression of $\lambda(t)$ as shown in the following equation:

$$\lambda(t) = \boldsymbol{\theta}_{\lambda 3} \Phi(\boldsymbol{\theta}_{\lambda 2} + \boldsymbol{\theta}_{\lambda 1} t) \tag{29}$$

where $\Phi(\cdot)$ denotes the CDF of the norm Gaussian distribution. In addition, we assume the continuous degradation process is linear, the degradation process model can be written as follows:

$$X(t) = X(0) + \mu t + \sigma_B B(t) + \sum_{i=1}^{N(t)} g_i \tag{30}$$

The initial parameters are shown in Table 1.

Table 1. The setting value of parameters for simulation.

Parameter	μ	μ_g	σ_B	σ_g	$\theta_{\lambda 1}$	$\theta_{\lambda 2}$	$\theta_{\lambda 3}$
value	0.01	20	1	1	5/100,000	−5	0.02

Then based on the given parameters, we define the interval time as 1 and then can obtain the degradation path and the increment process are shown in Figures 4 and 5.

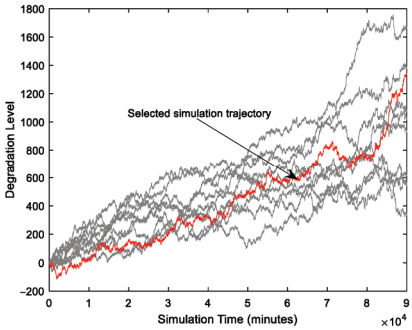


Figure 4. Degradation data from simulation.

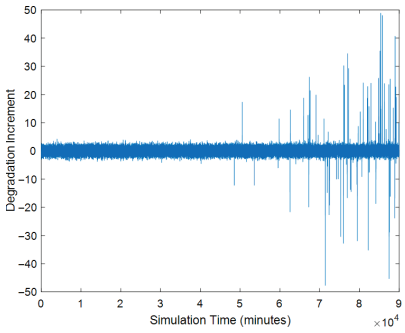


Figure 5. The degradation increments.

As shown in Figure 4, the simulated degradation trajectory does not monotonically increase or decrease over time. This is due to the inherent stochastic effects of the model. From Figure 5, it is noted that the frequency of the random jump occurrence is higher over time. Then, based on the proposed parameter estimation approach, we can obtain the parameter estimates.

From Table 2, it can be found that the estimation error decreases gradually. However, unlike μ_1, μ_2, σ_1, and σ_2, $\theta_{\lambda 1}$, $\theta_{\lambda 2}$, and $\theta_{\lambda 3}$ are estimated via solving the over-determined equation.

Table 2. Parameter estimates at different time.

Sampling Interval	μ_1	μ_g	σ_B	σ_g	$\theta_{\lambda 1}$	$\theta_{\lambda 2}$	$\theta_{\lambda 3}$
t = 55,000	0.016	26.5	1.262	22.4	0.000079	−6.05	0.023
t = 60,000	0.014	22.7	0.988	19.6	0.000065	−5.23	0.021
t = 65,000	0.011	21.4	1.134	20.5	0.000069	−5.74	0.024
t = 70,000	0.011	19.3	0.996	20.1	0.000061	−5.68	0.022

Moreover, we further estimate the number of the jumps, i.e., $N(t)$ in Equation (23) based on particle filtering. Figure 6 shows the comparison between the actual value and its estimates.

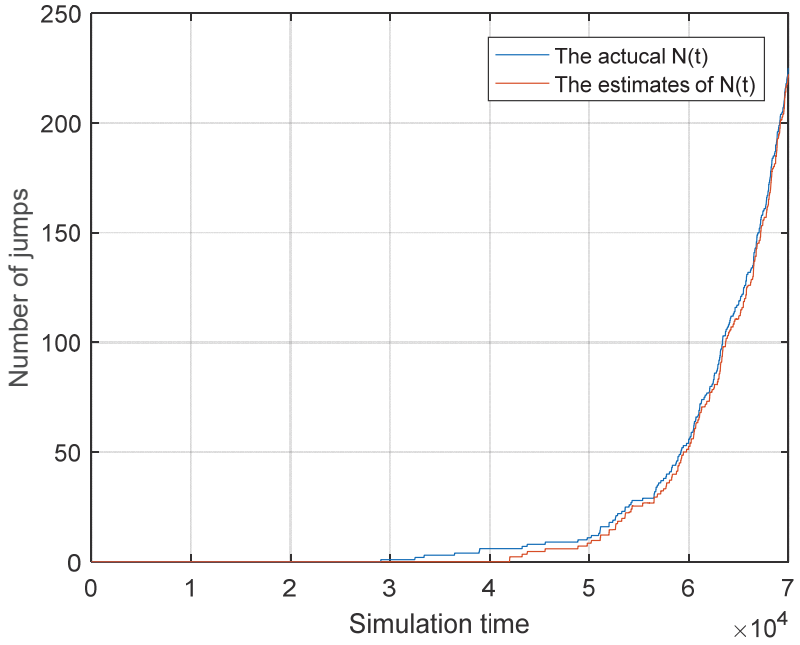


Figure 6. The estimates, actual value, and theoretical value of $N(t)$.

From Figure 6, we can see that the error between the estimates and the actual value is small, but the error between the actual value and the theoretical value always existed, which is inevitable in the numerical simulations.

5.2. Practical Example for Furnace Wall

As introduced in Section 2, it is noted that the furnace wall is a typical degradation process. In this subsection, we choose the data whose degradation feature is obvious, as shown in Figure 2. In practice, the failure threshold is usually set as 800 °C. Unfortunately, the degradation data of this furnace wall is below the soft failure threshold. For better illustration, we choose the upper limit of alert, i.e., 500 °C as the soft failure threshold in this paper.

From Figure 2, it can be found that the degradation increments except the random jumps seem to be stationary, so the linear model is appropriate for the practical data. That is to say, we choose the degradation model as Equation (27) to describe the degradation process of furnace wall.

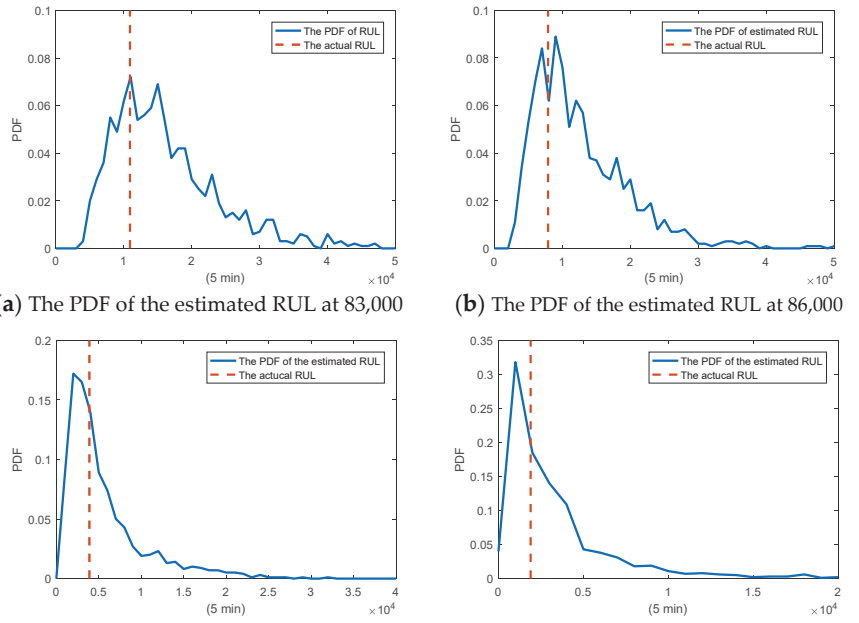
Based on the proposed model identification method, we can obtain the estimates of all parameters as shown in the following table.

From Table 3, it is noteworthy that σ_g is much larger than σ_B, which can illustrate the existence of the random jumps. Then, combing the estimates of the parameters, we can

predict the RUL based on the particle filtering method. Figure 7 shows the estimate of RUL at different testing times. Empirical tests on an Intel Core i9-13900H processor produced by Intel Corporation, Santa Clara, CA, USA. show that with 200 particles, the prediction time is 168 s, which is well below the 5-min sampling interval. This demonstrates the method's feasibility for real-time industrial applications. It is important to note, however, that this prediction is performed on a large-scale dataset within a two-dimensional state–space. Therefore, while the prediction time is acceptable, it is still relatively slow. Future work could focus on reducing the number of particles to further decrease the computation time.

Table 3. The estimates of all parameters in practical case.

μ	μ_g	σ_B	σ_g	θ_1	θ_2	θ_3
9.023×10^{-4}	0.0212	0.238	1.23	5.631×10^{-6}	-1.4634	0.0222



(**a**) The PDF of the estimated RUL at 83,000 (**b**) The PDF of the estimated RUL at 86,000

(**c**) The PDF of the estimated RUL at 90,000 (**d**) The PDF of the estimated RUL at 92,000

Figure 7. The PDF of the estimated RUL at different testing times.

Figure 8 compares the results of our proposed method with those of the CNN and LSTM methods. Table 4 presents the quantitative metrics of our proposed method for RUL prediction, in comparison with the CNN and LSTM methods.

Table 4. Comparison of RUL prediction metrics for the proposed method vs. CNN and LSTM.

	Our Method	**LSTM**	**CNN**
MAE (10^3)	2.7826	3.5505	3.2198
RMSE (10^3)	1.8541	6.9281	6.3769

From the above figures and table, it is interesting to see that our results could predict the RUL better than the traditional methods. As shown in Table 4, our proposed method significantly outperforms both the CNN and LSTM baselines in RUL prediction. After correcting for an apparent swap in our method's metric values, our model achieves an MAE of 1.8541×10^3 and an RMSE of 2.7826×10^3. These results represent a performance improvement of over 42% in MAE and 56% in RMSE compared to the next-best model (CNN). This demonstrates the enhanced accuracy and robustness of our approach. Thus,

it can be summarized that it is essential to consider such random jumps in degradation modeling and RUL prediction.

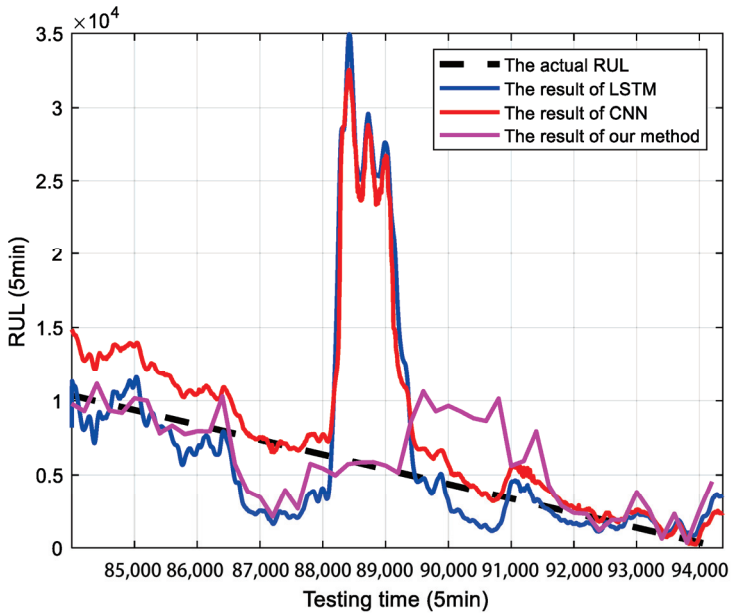


Figure 8. Comparison of RUL prediction results between the proposed method, CNN, and LSTM.

6. Discussion

This paper proposes a non-homogeneous jump diffusion model to describe complex degradation processes involving time-varying random jumps. By reformulating it into a state–space form and integrating particle filtering (PF) and the expectation maximization (EM) algorithm, the model demonstrates superior accuracy and robustness in RUL prediction compared to traditional methods.

However, the proposed method has its limitations. Its key assumptions—a single jump per interval and a Gaussian jump magnitude—may not be suitable for all applications. Furthermore, the high computational cost associated with the particle filter and EM algorithm restricts the model's use in high-dimensional or demanding real-time scenarios.

Future research directions include: (1) relaxing the model assumptions, such as considering multiple jumps and non-Gaussian distributions; (2) employing more efficient filtering algorithms to reduce the computational burden; and (3) extending the framework to multivariate degradation systems and other engineering domains.

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Abbreviations

The following abbreviations are used in this manuscript:

RUL	remaining useful life
MLE	maximization likelihood estimation
EM	expectation maximization
PF	particle filtering
FPT	first passage time
PDF	probability density function
CDF	cumulative density function

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Anomaly Detection Method for Hydropower Units Based on KSQDC-ADEAD Under Complex Operating Conditions

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Abstract: The safe and stable operation of hydropower units, as core equipment in clean energy systems, is crucial for power system security. However, anomaly detection under complex operating conditions remains a technical challenge in this field. This paper proposes a hydropower unit anomaly detection method based on K-means seeded quadratic discriminant clustering and an adaptive density-aware ensemble anomaly detection algorithm (KSQDC-ADEAD). The method first employs the KSQDC algorithm to identify different operating conditions of hydropower units. By combining K-means clustering's initial partitioning capability with quadratic discriminant analysis's nonlinear decision boundary construction ability, it achieves the high-precision identification of complex nonlinear condition boundaries. Then, an ADEAD algorithm is designed, which incorporates local density information and improves anomaly detection accuracy and stability through multi-model ensemble and density-adaptive strategies. Validation experiments using 14-month actual operational data from a 550 MW unit at a hydropower station in Southwest China show that the KSQDC algorithm achieves a silhouette coefficient of 0.64 in condition recognition, significantly outperforming traditional methods, and the KSQDC-ADEAD algorithm achieves comprehensive scores of 0.30, 0.34, and 0.23 for anomaly detection at three key monitoring points, effectively improving the accuracy and reliability of anomaly detection. This method provides a systematic technical solution for hydropower unit condition monitoring and predictive maintenance.

Keywords: hydropower units; anomaly detection; operating condition recognition; ensemble learning; density adaptation

1. Introduction

With the advancement of global energy transformation and carbon neutrality goals, hydropower units, as core equipment in clean energy systems, require safe and stable operation that holds strategic significance for power system security. However, these units feature complex structures and are influenced by multiple factors including hydraulic, mechanical, and electrical elements, making the rapid and accurate identification of operational anomalies under complex operating conditions a major technical challenge for the power industry. Traditional vibration diagnostic techniques exhibit limitations in hydroelectric turbine anomaly detection, including slow processing speeds and narrow frequency

measurement ranges [1]. More critically, the substantial variations in normal operational characteristics across different operating conditions further complicate anomaly detection. While advancements in data acquisition technologies have established a foundation for condition assessment through extensive monitoring data, effectively identifying anomalies within these data presents new challenges.

The primary objective of anomaly detection is to identify outlier samples typically resulting from errors, noise, or abnormal behavior [2]. In the field of hydropower unit monitoring, traditional approaches primarily rely on statistical methods, employing techniques such as mean-variance analysis, the 3σ rule, and box plots for anomaly determination [3]. Wu et al. conducted a comprehensive analysis of anomaly identification and data cleaning methods for wind farm power data, highlighting the significant limitations of statistical methods when processing time-series data [4]. Despite their simplicity and intuitive nature, statistical methods face increasingly evident performance bottlenecks as industrial data complexity increases, with their primary constraint being insufficient consideration of internal data structures and temporal correlations. Shen et al. investigated wind–speed–power data distribution characteristics in wind turbines, employing change-point grouping to identify accumulation-type anomalies and quartile methods to eliminate dispersion-type anomalies [5]. Song et al. designed an anomaly detection model combining K-means and random forest for big data, effectively reducing computation time and false positive rates [6]. Both Wang et al.'s Copula function-based wind power anomaly identification model [7] and Hu et al.'s confidence equivalent boundary model [8] demonstrate that when processing complex operational condition data, statistical methods struggle to balance detection sensitivity and accuracy, particularly when temporal correlations exist, where fixed-threshold cleaning strategies often lead to under-deletion or over-deletion, diminishing anomaly detection effectiveness.

With their powerful feature learning and pattern recognition capabilities, machine learning methods demonstrate significant advantages in hydroelectric unit anomaly detection. Mo et al. proposed an isolation forest-based anomaly noise detection method that achieved 97.45% accuracy in hydroelectric unit detection by extracting high-dimensional time-frequency features and determining optimal partition paths [9]. Wang et al. innovatively integrated sliding windows with interval coverage rates to construct a dynamic interval anomaly detection framework, effectively addressing the limitations of point prediction methods [10]. Compared to traditional statistical approaches, machine learning methods adaptively learn complex patterns from data and capture subtle features of anomalies, performing exceptionally well in scenarios with high-dimensional and complex distributions. Guha et al. proposed a robust random partition method based on isolation forests, termed robust random cut forest (RRCF), which improved algorithm robustness against noise by enhancing the isolation forest's random partition strategy [11]. Chen et al. applied a density and grid-based clustering method to anomaly detection in power monitoring data, achieving favorable identification effects with low false alarm rates [12]. These studies collectively demonstrate that machine learning methods possess unparalleled advantages over traditional approaches in handling complex data distributions and capturing nonlinear anomaly patterns. Zhang et al. employed RRCF for anomaly detection in transformer loss data, demon-strating the method's computational efficiency and accuracy [13]. Yassin et al. proposed a hybrid detection method combining K-means and Bayesian classifiers, achieving a 95.4% detection rate on the ISCX2012 dataset through a process of clustering followed by identi-fication [14].

However, in actual hydroelectric unit operating environments, anomaly detection methods still face challenges such as variable operating conditions and poor data quality. Hydroelectric unit monitoring data is highly correlated with operating conditions, with

significant differences in normal state characteristics under different conditions [15]. Duan et al. addressed issues of highly condition-dependent monitoring data with anomalies and missing values by proposing a condition indicator construction method for hydroelectric units under variable operating conditions based on low-quality data, effectively cleaning low-quality data using the DBSCAN algorithm [16]. Condition-aware anomaly detection strategies are becoming crucial for resolving anomaly identification in multi-condition environments; by first identifying operating conditions and then designing specific detection strategies for different conditions, detection accuracy can be significantly improved while reducing false alarm rates. Tan et al. innovatively combined KD-Tree and DBSCAN technologies to achieve efficient cleaning of hydroelectric unit monitoring data with a correct identification rate of 97.78% [17]. Du et al. proposed a least squares support vector machine-based anomaly monitoring and alarm method for hydroelectric unit equipment to address high false alarm rates in traditional methods, effectively improving monitoring and alarm effectiveness by extracting vibration signal features [18]. These studies collectively indicate that considering condition information is key to improving hydroelectric unit anomaly detection accuracy, and that single anomaly detection models struggle to address the complexity of multi-condition operation.

Based on the above analysis, this paper proposes a hydropower unit anomaly detection method based on KSQDC-ADEAD under complex operating conditions. The method first employs the KSQDC clustering algorithm to identify different operating conditions of hydroelectric units, then designs an improved isolation forest algorithm for anomaly detection according to the characteristics of each condition. The main innovations of this method include the following:

(1) KSQDC Condition Identification Algorithm: A novel two-stage learning paradigm that synergistically combines K-means clustering's initialization capability with quadratic discriminant analysis's nonlinear boundary construction. This integration enables precise identification of complex nonlinear condition boundaries and accurate classification of hydroelectric unit operational states.
(2) ADEAD Ensemble Anomaly Detection Algorithm: An adaptive density-aware ensemble framework comprising five complementary sub-models: base isolation forest, extended isolation forest, local density estimation, local outlier factor, and cluster-based scoring. The algorithm enhances detection accuracy and robustness through dynamic inter-model collaboration and adaptive weight fusion strategies.
(3) Integrated Condition-Adaptive Framework: A comprehensive end-to-end system that automates the entire pipeline from data preprocessing and condition identification to anomaly detection. The framework achieves performance optimization through feedback mechanisms and provides a systematic solution for hydroelectric unit health monitoring and predictive maintenance.

This research offers a novel technical approach for hydroelectric unit condition monitoring, effectively improving the accuracy and reliability of anomaly detection and providing robust support for the safe and stable operation of hydropower units, which holds significant importance for advancing clean energy technology development.

The paper is structured as follows: Section 2 reviews related works, including K-means, quadratic discriminant clustering, and isolation forest; Section 3 presents the proposed KSQDC-ADEAD integrated method; Section 4 conducts experimental studies, including data description, experimental design, and result analysis; and Section 5 concludes the research and discusses future work.

2. Related Works

2.1. K-Means

K-means clustering is one of the most fundamental and widely used unsupervised learning algorithms in data mining and pattern recognition. The algorithm partitions n observations into k clusters, where each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. The standard algorithm was first proposed by Stuart Lloyd in 1957 as a technique for pulse-code modulation, though it was not published until 1982, and recent improvements have focused on initialization and scalability [19]. The algorithm operates by iteratively assigning data points to the nearest centroid and then updating the centroids based on the new cluster assignments [20]. Mathematically, K-means aims to minimize the within-cluster sum of squares (WCSS), also known as the inertia, which is defined as follows:

$$J = \sum_{j=1}^{k} \sum_{i \in S_j} \|x_i - \boldsymbol{\mu}_j\|^2 \tag{1}$$

where x_i is the i-th data point, $\boldsymbol{\mu}_j$ is the centroid of cluster S_j, and $\|x_i - \boldsymbol{\mu}_j\|^2$ represents the squared Euclidean distance between the data point and the centroid.

However, the K-means algorithm has obvious limitations in practical applications, as its linear decision boundaries based on Euclidean distance struggle to handle complex non-convex data distributions, and it is sensitive to initial centroid selection, easily falling into local optima.

2.2. Quadratic Discriminant Clustering (QDC)

QDC looks beyond linear boundaries by leveraging principles from quadratic discriminant analysis (QDA) for clustering tasks. QDC accommodates clusters with different shapes, orientations, and volumes by modeling each cluster using a multivariate Gaussian distribution with its covariance matrix. This provides significantly more flexibility in capturing complex data structures. The mathematical foundation of QDC lies in the probability density function of a multivariate Gaussian distribution:

$$p(x \mid \boldsymbol{\mu}_k, \Sigma_k) = \frac{1}{(2\pi)^{d/2} \mid \Sigma_k \mid^{1/2}} \exp\left(-\frac{1}{2}(x - \boldsymbol{\mu}_k)^T \Sigma_k^{-1} (x - \boldsymbol{\mu}_k)\right) \tag{2}$$

where $\boldsymbol{\mu}_k$ is the mean vector, Σ_k is the covariance matrix for cluster k, d is the dimensionality of the data, and $|\Sigma_k|$ is the determinant of the covariance matrix. The clustering assignment is determined by the quadratic discriminant function:

$$\delta_k(x) = -\frac{1}{2}\log|\Sigma_k| - \frac{1}{2}(x - \boldsymbol{\mu}_k)^T \Sigma_k^{-1} (x - \boldsymbol{\mu}_k) + \log \pi_k \tag{3}$$

where π_k represents the prior probability of cluster k. QDC is implemented through an expectation-maximization (EM) algorithm, which alternates between assigning points to clusters based on the current parameters (E-step) and updating the parameters to maximize the likelihood of the observed data given the assignments (M-step) [21].

Although QDC can construct nonlinear decision boundaries, this method requires the assumption that data follows multivariate Gaussian distributions, and covariance matrix estimation tends to be numerically unstable in high-dimensional data and small sample scenarios. Additionally, QDC lacks an effective mechanism for automatic cluster number determination.

2.3. Isolation Forest

Isolation forest stands as a revolutionary anomaly detection algorithm that fundamentally differs from traditional density or distance-based approaches. Developed by Liu, Ting, and Zhou in 2008 [22], this method is based on the key insight that anomalies are few and different, making them more susceptible to isolation through random partitioning. Unlike clustering methods that focus on finding similarities among normal data points, isolation forest explicitly isolates anomalies by leveraging the structural characteristics of outliers [23]. The core principle operates through an ensemble of isolation trees, where each tree randomly partitions the data space using a binary tree structure. The algorithm randomly selects a feature and a split value between the maximum and minimum values of that feature, recursively partitioning the data until instances are isolated. Mathematically, the anomaly score for an instance x is defined as

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{4}$$

where $E(h(x))$ is the average path length for instance x across all trees in the forest, and $c(n)$ is the average path length of unsuccessful search in a binary search tree, approximated as

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n} \tag{5}$$

with $H(i)$ being the harmonic number estimated as $H(i) \approx \ln(i) + 0.5772156649$ (Euler's constant). As illustrated in Figure 1, anomalies (represented by red points) require fewer partitions to be isolated compared to normal points (shown in blue), resulting in shorter path lengths in the isolation trees. The figure demonstrates how the algorithm constructs multiple trees that randomly split the data space, with anomalies consistently appearing in the shallower branches across the ensemble. This visualization highlights the intuitive nature of the method—anomalies are easier to separate from the rest of the data. The three-dimensional plot in Figure 1b further shows how the anomaly scores form a landscape where outliers create distinct peaks, making them easily identifiable through simple thresholding techniques.

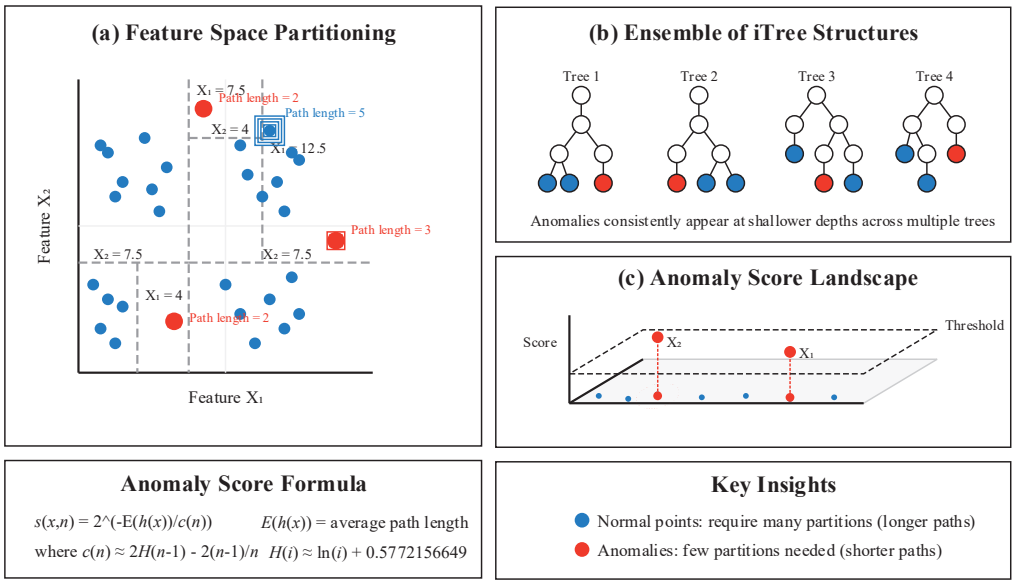


Figure 1. Isolation forest algorithm for anomaly detection.

While isolation forest performs excellently in anomaly detection, this method has limitations when processing data with significant density variations, and single models

struggle to adapt to complex and variable operating conditions. In practical engineering applications, isolation forest is susceptible to changes in data distribution characteristics, leading to unstable detection performance.

3. The Proposed Method

3.1. KSQDC-ADEAD Integrated Anomaly Detection Method

The proposed KSQDC-ADEAD method addresses anomaly detection challenges in hydropower units under complex operating conditions through a condition-adaptive strategy. As shown in Figure 2, the method constructs a four-layer progressive architecture, consisting of a data preprocessing layer, a condition recognition layer, a condition-adaptive anomaly detection layer, and a result output layer, achieving end-to-end automated processing from raw multi-dimensional monitoring data to precise anomaly identification.

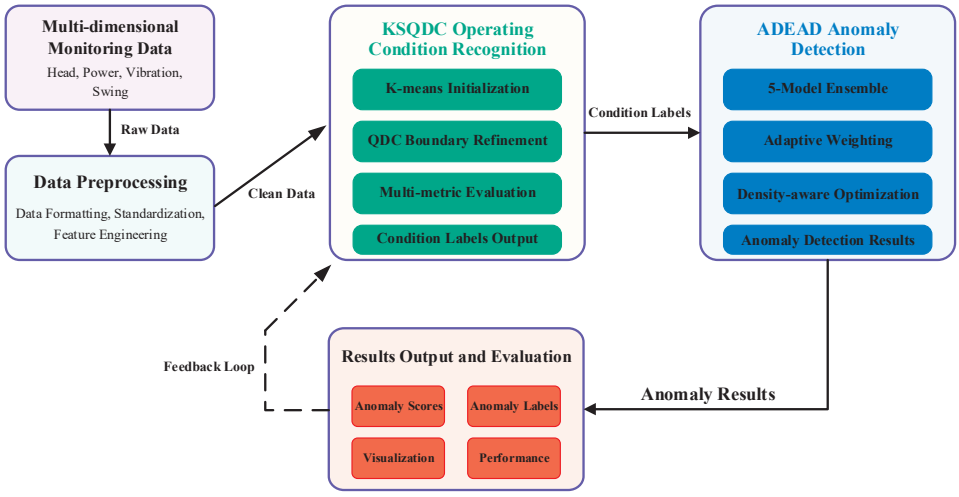


Figure 2. KSQDC-ADEAD overall framework.

The core philosophy decomposes the hydropower unit anomaly detection problem into two interconnected sub-problems: operating condition recognition and conditioned anomaly detection. The KSQDC algorithm employs the multi-metric ensemble evaluation mechanism (Section 3.2.2) to automatically determine the optimal number of operating conditions, then identifies unit operating conditions based on head and power features and, subsequently, constructing ADEAD anomaly detection models for each condition, ultimately achieving overall performance optimization through feedback mechanisms.

The methodological implementation follows a systematic five-step execution framework, where each phase builds upon the previous one to ensure comprehensive anomaly detection capabilities:

Step 1: multi-dimensional monitoring data input, encompassing time-series data including water head, active power, vibration, and shaft swing measurements from comprehensive monitoring systems.

Step 2: The data preprocessing module performs basic data formatting, standardization, and feature engineering operations to ensure data consistency and compatibility. This phase implements timestamp synchronization, data format unification, and feature scaling techniques to prepare the dataset for subsequent analysis while preserving all original data patterns.

Step 3: The KSQDC condition recognition phase first applies the four-metric ensemble evaluation (silhouette coefficient, Calinski–Harabasz index, Davies–Bouldin index, and elbow method) to determine the optimal number of conditions, then establishes basic

condition partitioning through K-means initial clustering and, subsequently, constructs nonlinear decision boundaries using QDC to achieve precise condition identification.

Step 4: The ADEAD anomaly detection phase constructs five-sub-model ensemble detectors within each identified condition, incorporating base isolation forest, extended isolation forest, local density estimation, local outlier factor, and cluster-based scoring mechanisms. The phase enhances detection precision through adaptive weight fusion and density-aware optimization strategies that dynamically adjust model contributions based on local data characteristics.

Step 5: results output and evaluation, generating anomaly scores, anomaly labels, visualization results, and performance evaluation metrics.

Based on the theoretical analysis above, this section presents the specific implementation procedure of the KSQDC-ADEAD integrated algorithm as detailed in Algorithm 1. The algorithm organically combines operating condition recognition and anomaly detection to achieve end-to-end automated processing. The KSQDC-ADEAD method addresses the growing need for explainable AI in industrial applications by providing inherent interpretability through physically meaningful operating condition recognition and transparent ensemble decision-making. The KSQDC algorithm identifies conditions based on interpretable hydraulic parameters (water head and active power), enabling operators to understand the physical basis of condition assignments. The ADEAD ensemble structure allows tracing anomaly decisions back to individual model contributions, providing transparency about which detection principles (isolation, density deviation, or clustering) drive the final anomaly classification. This interpretability feature is crucial for gaining operator trust and meeting regulatory requirements in critical infrastructure monitoring.

Algorithm 1: KSQDC-ADEAD integrated framework

Input: Multi-dimensional monitoring data $\mathbf{x} \in R^d$, maximum clusters $K_{\max}$

Output: Operating condition labels z_i, anomaly scores $s_{\text{final}}(\mathbf{x})$, anomaly labels A

Data preprocessing: $\mathbf{x}_{\text{norm}}$ = StandardScaler(x)

For $K = 2$ to $K_{\max}$ do

  Compute multi-metric evaluation: SC_K, CH_K, DB_K, SSE_K

End for

Optimal cluster determination:

$K^* = \arg\max_K \text{Voting}(SC_K, CH_K, DB_K, SSE_K)$

K-means initialization: $U_{KM} = \sum_{k=1}^{K} \sum_{i:z_i=k} |\mathbf{x}_i - \boldsymbol{\mu}_k|^2$

For $k = 1$ to K^* do

  $\boldsymbol{\mu}_k = \frac{1}{n_k} \sum_{i:z_i-k} \mathbf{x}_i$

  $\boldsymbol{\Sigma}_k = \frac{1}{n_k-1} \sum_{i:z_i-k} (\mathbf{x}_i - \boldsymbol{\mu}_k)(\mathbf{x}_i - \boldsymbol{\mu}_k)^T$

  $\pi_k = \frac{n_k}{n}$

End for

QDA boundary refinement: For $i = 1$ to n do

  $\delta_k(\mathbf{x}_i) = -\frac{1}{2} \log \boldsymbol{\Sigma}_k - \frac{1}{2} (\mathbf{x}_i - \boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{x}_i - \boldsymbol{\mu}_k) + \log \pi_k$

  $z_i = \arg\max_k \delta_k(\mathbf{x}_i)$

End for

For $k \in \{1, 2, \ldots, K^*\}$ do

  $\mathbf{X}_k = \{\mathbf{x}_i : z_i = k\}$

  ADEAD sub-model initialization:

  M_1 = BaseIsolationForest ($\mathbf{X}_k$)

  M_2 = ExtendedIsolationForest ($\mathbf{X}_k$)

Algorithm 1: *Cont.*

$M_3 = \text{LocalDensityEstimation}\ (\mathbf{X}_k)$
$M_4 = \text{LocalOutlierFactor}\ (\mathbf{X}_k)$
$M_5 = \text{ClusterBasedScoring}\ (\mathbf{X}_k)$
For $i = 1$ to 5 do
  $s_i(\mathbf{x}) = M_i.\ \text{decision function}(\mathbf{X}_k)$
  $\widehat{s}_i(\mathrm{x}) = \frac{s_i(\mathrm{x}) - \min(s_i)}{\max(s_i) - \min(s_i)}$
End for
Adaptive weight calculation:
$\rho_i = \frac{1}{4}\sum_{j \neq i} \text{corr}\left(\widehat{s}_i, \widehat{s}_j\right)$
$w_i = \frac{\rho_i}{\sum_{j-1}^{5} \rho_j} \cdot \lambda_i + (1 - \lambda_i) \cdot w_i^{\text{default}}$
Score fusion: $s_{\text{final}}\ (\mathbf{x}) = \sum_{i-1}^{5} w_i \cdot \widehat{s}_i(\mathbf{x})$
Boundary optimization using silhouette coefficient:
$\text{SC}_{\text{boundary}}\ (\mathbf{x}) = \frac{d_{\text{inter}}\ (\mathbf{x}) - d_{\text{intra}}\ (\mathbf{x})}{\max\{d_{\text{intra}}\ (\mathbf{x}), d_{\text{inter}}\ (\mathbf{x})\}}$
If $s(i) < \tau_a$ for anomaly or $s(i) > \tau_n$ for normal then exchange labels
Update $\mathcal{A}_{\text{new}} = (\mathcal{A} \setminus \mathcal{A}_{\text{bad}}) \cup \mathcal{N}_{\text{good}}$
End for
Return Operating condition labels z_i, anomaly scores $s_{\text{final}}\ (\mathbf{x})$, anomaly labels A

3.2. K-Means Seeded Quadratic Discriminant Clustering (KSQDC)

KSQDC is a clustering algorithm designed for non-convex shapes and variable density distributions. The algorithm organically combines K-means' initial partitioning capability with QDA's non-linear decision boundary construction through a two-stage learning paradigm, improving clustering accuracy and interpretability. The KSQDC algorithm first generates initial clustering with linear decision boundaries, then constructs non-linear decision boundaries through QDA, significantly improving clustering results.

3.2.1. Non-Linear Decision Boundary Construction

The core of the KSQDC algorithm is to transform unsupervised clustering results into prior information for supervised learning, enabling the evolution of decision boundaries from linear to non-linear. Assuming data can be represented by feature vector $\mathbf{x} \in \mathrm{R}^d$, its conditional probability density function under class k is

$$p(\mathbf{x} \mid k) = \frac{1}{(2\pi)^{d/2} \mid \boldsymbol{\Sigma}_k \mid^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{x} - \boldsymbol{\mu}_k)\right) \tag{6}$$

where $\boldsymbol{\mu}_k \in \mathrm{R}^d$ and $\boldsymbol{\Sigma}_k \in \mathrm{R}^{d \times d}$ are the mean vector and covariance matrix of class k, respectively. KSQDC endows the model with the ability to capture the unique geometric characteristics of each class by introducing regime-specific covariance matrices.

The first stage of the algorithm uses K-means to generate initial class labels by minimizing the objective function:

$$J_{KM} = \sum_{k=1}^{K} \sum_{i:z_i=k} \|x_i - \mu_k\|^2 \tag{7}$$

where z_i represents the regime label of sample x_i, and μ_k is the center of the k-th class. Although the initial labels provided by K-means are based on simple Euclidean distance metrics, they provide necessary prior information for the subsequent refined discrimination

phase. In Figure 3, the K-means algorithm begins with randomly initialized centroids (represented by stars) and iteratively refines the cluster assignments (shown in different colors) until convergence. The figure illustrates how data points are partitioned into distinct regions based on their proximity to the nearest centroid, forming Voronoi cells in the feature space.

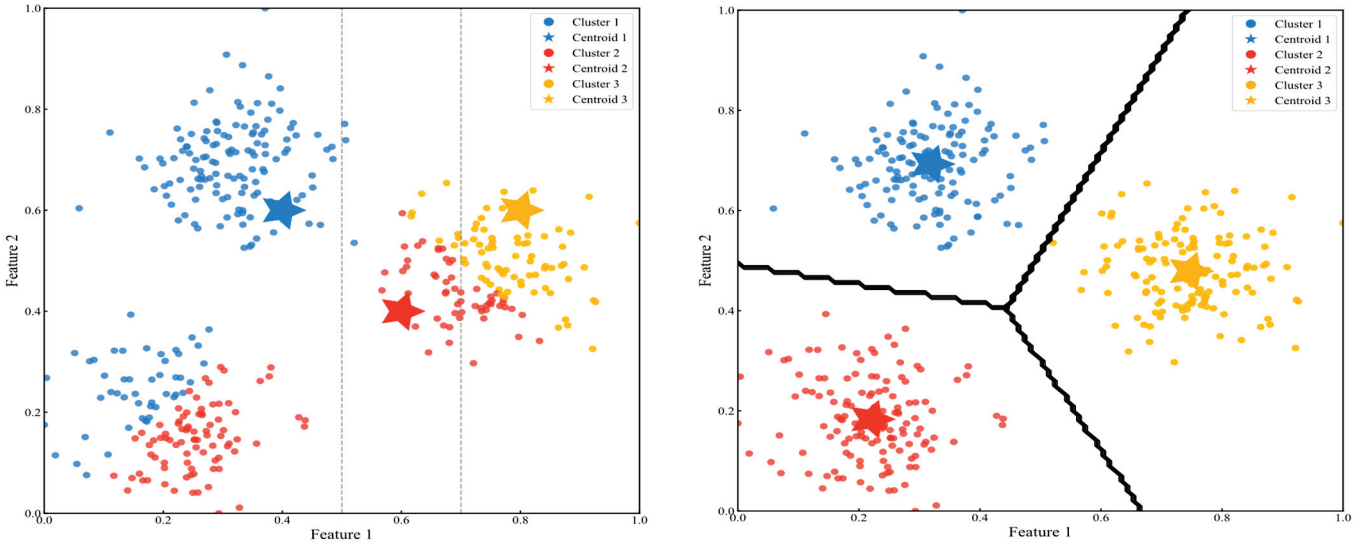


Figure 3. K-means clustering algorithm. ((**a**). Initial state with randomly placed centroids (**b**). Final converged state with optimal centroids and decision boundaries).

In the refined discrimination phase, QDA constructs non-linear decision boundaries based on Bayesian discrimination theory. For a given sample $\mathbf{x}$, its posterior probability of belonging to class k is

$$P(k \mid \mathbf{x}) = \frac{\pi_k p(\mathbf{x} \mid k)}{\sum_{j=1}^{K} \pi_j p(\mathbf{x} \mid j)} \tag{8}$$

The discriminant function of QDA is

$$\delta_k(\mathbf{x}) = -\frac{1}{2}\log|\mathbf{\Sigma}_k| - \frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_k)^T\mathbf{\Sigma}_k^{-1}(\mathbf{x}-\boldsymbol{\mu}_k) + \log \pi_k \tag{9}$$

where π_k is the prior probability of regime k. The isosurfaces of the discriminant function form quadratic surface decision boundaries, effectively capturing non-linear boundaries between regimes. For any sample $\mathbf{x}$, its assigned regime label is the class number that maximizes $\delta_k(\mathbf{x})$.

3.2.2. Adaptive Determination of Optimal Number of Classes

A key challenge for the KSQDC method is determining the optimal number of clusters K. This research designs a multi-metric ensemble evaluation mechanism that automatically determines the number of clusters by synthesizing multiple validity indicators. This mechanism balances internal cohesion and external separation and introduces method-specific adjustment factors.

Core evaluation metrics include the silhouette coefficient [24], Calinski–Harabasz Index [25], Davies–Bouldin Index [26], and elbow method [27]. The silhouette coefficient measures the cohesion and separation degree of samples to their assigned classes, calculated as

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{10}$$

where $a(i)$ is the average distance of sample i to other samples in the same class, and $b(i)$ is the average distance of sample i to samples in the nearest different class.

The Calinski–Harabasz Index is based on the ratio of between-class to within-class dispersion, calculated as

$$CH = \frac{\mathrm{tr}(\mathbf{B}_K)}{\mathrm{tr}(\mathbf{W}_K)} \times \frac{n-K}{K-1} \tag{11}$$

where $\mathbf{B}_K$ and $\mathbf{W}_K$ are between-class and within-class dispersion matrices, respectively. The Davies–Bouldin Index measures class compactness and separation, calculated as

$$DB = \frac{1}{K}\sum_{i=1}^{K}\max_{j\neq i}\left\{\frac{\sigma_i+\sigma_j}{d(\boldsymbol{\mu}_i,\boldsymbol{\mu}_j)}\right\} \tag{12}$$

where σ_i is the average distance of samples in class i to the class center.

The elbow method determines the optimal number of clusters by calculating the within-cluster sum of squared errors (SSE):

$$SSE = \sum_{k=1}^{K}\sum_{i\in C_k}\|\mathbf{x_i}-\boldsymbol{\mu}_k\|^2 \tag{13}$$

where C_k represents the k-th cluster and μ_k is the cluster center.

Considering the characteristics of the KSQDC method, a method-specific adjustment factor λ_{KSQDC} is introduced:

$$I_{\mathrm{adjusted}} = I_{\mathrm{original}} + \lambda_{\mathrm{KSQDC}} \times \frac{K}{K_{\max}} \tag{14}$$

The optimal number of clusters is ultimately determined through a voting mechanism across metrics, where each metric's optimal K value receives one vote, and the K value with the most votes is selected. In case of tied votes, a weighted average determines the final number of clusters.

3.3. Adaptive Density-Aware Ensemble Anomaly Detection Algorithm (ADEAD)

The ADEAD effectively addresses the adaptability limitations of traditional methods to variable density data by integrating multiple complementary anomaly detection sub-models and incorporating local density-sensitive scoring mechanisms. As shown in Figure 4, the ADEAD algorithm consists of five sub-models, uses correlation calculation and adaptive weights for fusion, and then generates final anomaly detection results through boundary optimization.

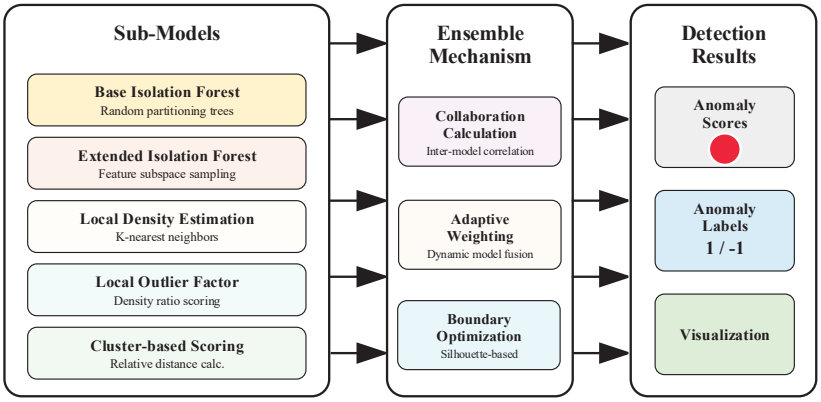


Figure 4. Adaptive density-aware ensemble anomaly detection architecture.

3.3.1. Multi-Model Ensemble Architecture for Anomaly Detection

The theoretical foundation of the ADEAD method is the combination of ensemble learning and density-aware theory, introducing local density information into anomaly scoring and model fusion processes for the first time. The algorithm constructs five complementary anomaly detection sub-models, each capturing different characteristics of data distribution. The base isolation forest builds isolation trees through random partitioning, evaluating the anomaly degree based on the average path length from samples to leaf nodes; the extended isolation forest adopts an improved random subset sampling strategy for feature space, enhancing sensitivity to anomalies in feature subspaces; the local density estimation provides adaptive local density evaluation based on K-nearest neighbors, enhancing sensitivity to density variations through exponentially weighted distance calculation; the local outlier factor performs anomaly scoring based on the sample local reachability density ratio, effectively identifying anomalies in variable density regions; and the cluster-based scoring combines K-means clustering with relative clustering distance calculation, evaluating the sample dispersion degree relative to its assigned cluster.

For the base isolation forest, the anomaly score s_1 is calculated as

$$s_1(\mathbf{x}) = 2^{\frac{E(h(\mathbf{x}))}{c(n)}} \tag{15}$$

where $E(h(\mathbf{x}))$ is the average path length of sample $\mathbf{x}$ in the random tree ensemble, and $c(n)$ is a data scale adjustment factor.

For local density estimation, the anomaly score s_3 is defined as

$$s_3(\mathbf{x}) = \frac{1}{k}\sum_{i=1}^{k} d\left(\mathbf{x}, \mathbf{x}_i^{NN}\right) \cdot (1 + \sigma_d(\mathbf{x})) \tag{16}$$

where $d\left(\mathbf{x}, \mathbf{x}_i^{NN}\right)$ is the distance from sample $\mathbf{x}$ to its i-th nearest neighbor, and $\sigma_d(\mathbf{x})$ is the standard deviation of these distances, introducing variability weighting.

The innovation of the ADEAD method lies in fusing anomaly scores from multiple submodels through an adaptive weighting mechanism:

$$s_{\text{final}}(\mathbf{x}) = \sum_{i=1}^{5} w_i \cdot \widehat{s}_i(\mathbf{x}) \tag{17}$$

where $\widehat{s}_i$ is the normalized anomaly score, and weights w_i are dynamically determined through inter-model collaboration:

$$w_i = \frac{\rho_i}{\sum_{j=1}^{5} \rho_j} \cdot \lambda_i + (1 - \lambda_i) \cdot w_i^{\text{default}} \tag{18}$$

where ρ_i represents the average collaboration degree of the i-th sub-model with other models, λ_i is a balancing factor, and w_i^{default} is the preset base weight.

3.3.2. Density-Adaptive Anomaly Optimization Strategy

Another key innovation of the ADEAD method is the introduction of a density-adaptive anomaly boundary optimization strategy. As shown in Figure 5, this strategy enables the precise adjustment of anomaly boundaries through silhouette coefficient analysis of boundary samples. For the preliminarily labeled anomaly sample set $\mathcal{A}$ and normal sample set $\mathcal{N}$, the boundary optimization silhouette coefficient is calculated as

$$\text{SC}_{\text{boundary}}(\mathbf{x}) = \frac{d_{\text{inter}}(\mathbf{x}) - d_{\text{intra}}(\mathbf{x})}{\max\{d_{\text{intra}}(\mathbf{x}), d_{\text{inter}}(\mathbf{x})\}} \tag{19}$$

where $d_{\text{intra}}(\mathbf{x})$ is the average distance from sample $\mathbf{x}$ to other samples of the same class, and $d_{\text{inter}}(\mathbf{x})$ is the average distance from sample $\mathbf{x}$ to the nearest samples of different classes. The silhouette coefficient provides a score within the range $[-1, 1]$ for samples, where a value close to 1 indicates high compatibility with the assigned class, and a value close to -1 suggests possible misclassification.

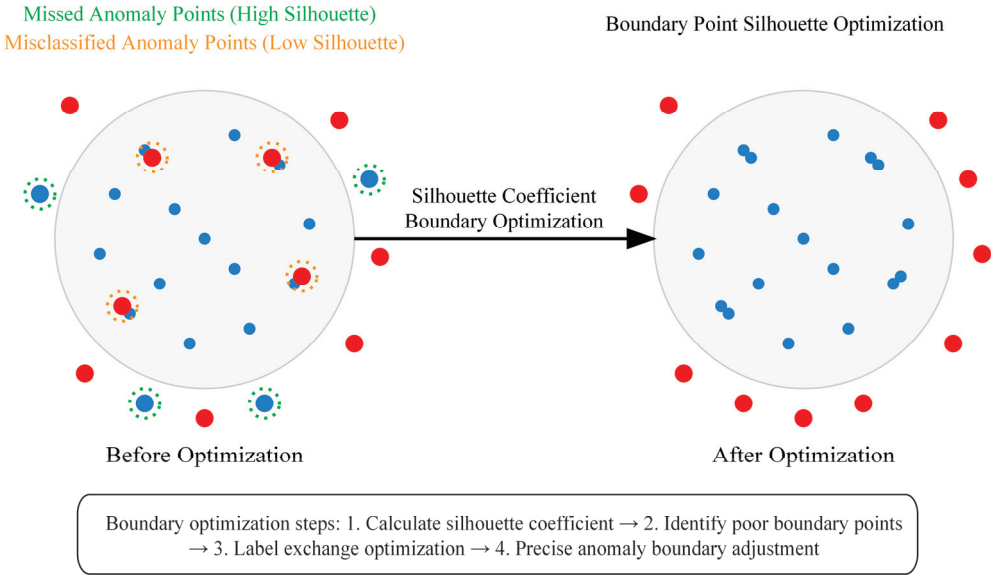


Figure 5. Density adaptive anomaly optimization strategy.

For anomaly samples $\mathbf{x}_a \in \mathcal{A}$ with lower silhouette coefficients and normal samples $\mathbf{x}_n \in \mathcal{N}$ with higher silhouette coefficients, label exchange is implemented:

$$\begin{aligned} \mathcal{A}_{\text{new}} &= (\mathcal{A} \setminus \mathcal{A}_{\text{bad}}) \cup \mathcal{N}_{\text{good}} \\ \mathcal{N}_{\text{new}} &= \left(\mathcal{N} \setminus \mathcal{N}_{\text{good}}\right) \cup \mathcal{A}_{\text{bad}} \end{aligned} \tag{20}$$

where $\mathcal{A}_{\text{bad}}$ represents the subset of anomaly samples with silhouette coefficients below threshold τ_a, and $\mathcal{N}_{\text{good}}$ represents the subset of normal samples with silhouette coefficients above threshold τ_n. The exchange quantity is constrained by maintaining the set anomaly proportion.

4. Experimental Study

4.1. Data Description

This study utilizes operational data from Unit 4 of a hydropower station in Southwest China for validation, as summarized in Table 1. The unit is a 550 MW mixed-flow turbine with a design head of 165 m and an operating head range of 135–190 m. As illustrated in Figure 6, the hydropower monitoring and analysis platform implements a comprehensive data acquisition and processing architecture. The system is modularly designed and comprises three main stages: signal monitoring, signal acquisition, and signal processing. It encompasses multiple monitoring dimensions—including vibration, shaft displacement, key position, and pressure—to provide real-time, full-scope surveillance of unit operating status. Data were collected at 10-minute intervals over 14 months from July 2023 to September 2024, resulting in a multi-dimensional dataset covering head, power output, vibration, shaft displacement, and other key parameters.

Table 1. Principal technical specifications of the hydropower unit.

Parameter	Value
Turbine type	Mixed-flow
Rated capacity	550 MW
Design water head	165 m
Operating head range	135–190 m
Rated speed	125 r/min
Commissioning date	Late 1990s

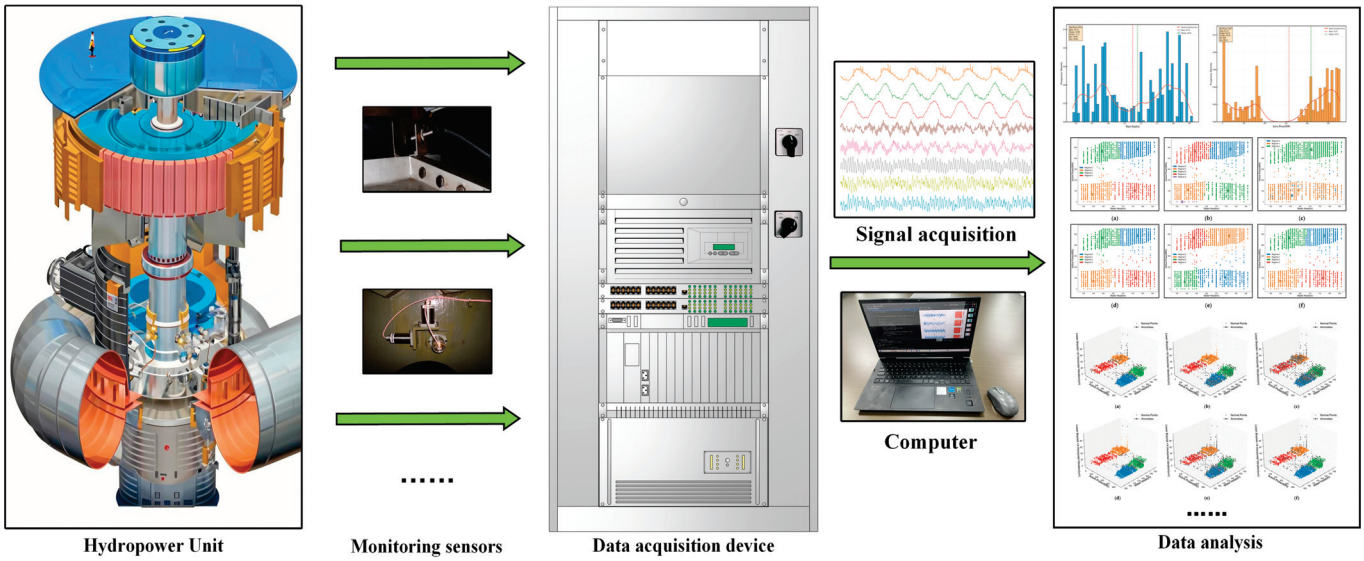


Figure 6. Monitoring and analysis platform for the hydropower unit.

In Table 2, the monitoring system for Unit 4 comprises a comprehensive multi-dimensional network of 31 measurement points across four parameter categories. Water head monitoring is performed at a single sensor, while active power output is recorded in real time by one dedicated power measurement point. Vibration monitoring covers 22 critical locations on the unit—including the lower bracket, stator frame, stator core, upper cover, and upper bracket—with multi-directional accelerometers at each site. Shaft displacement (whirling) is measured bilaterally at the upper guide, water guide bearing, and thrust bearings.

Table 2. Monitoring parameter categories and statistics.

Parameter Category	Key Metrics	Measurement Points	Value Range	Sampling Interval
Water pressure	Gross and net head	2	150–185 m	10 min
Power output	Active power	1	0–500 MW	10 min
Vibration	Multi-directional at 22 sites	22	Highly variable	10 min
Shaft displacement	Whirling at guide and thrust bearings (upper guide, lower guide, thrust)	6	0–175 μm	10 min
Total	—	31	—	10 min

Figure 7a–e illustrates the temporal evolution of key parameters for Unit 4 during the monitoring period. The head data exhibit pronounced seasonal cycles, with values predominantly ranging from 150 m to 185 m. The overlaid red moving-average line clearly delineates the long-term trend, peaking in May–June 2024—the highest head observed over the entire monitoring window—reflecting both the seasonal inflow patterns of the

watershed and upstream reservoir regulation. The active power output demonstrates intermittent operation: It fluctuates between 0 and 500 MW, with frequent zero-power intervals corresponding to unit shutdowns that align with grid-dispatch requirements and underscore the station's role in peak-load regulation. The Upper Guide + X-Axis Swing remains relatively stable, varying mostly within 0–75 μm; occasional spikes likely correspond to transient conditions during unit startup and shutdown. In contrast, the Water Guide + X-Axis Swing shows greater volatility, concentrating around 50–150 μm under normal operation but occasionally exceeding 175 μm—anomalies that may indicate vortex-rope phenomena or shaft-system instability. Finally, the Lower Bracket + X-Axis Vibration signal displays complex fluctuation patterns: its amplitude correlates with power output and increases markedly during unit startups, shutdowns, and load transitions.

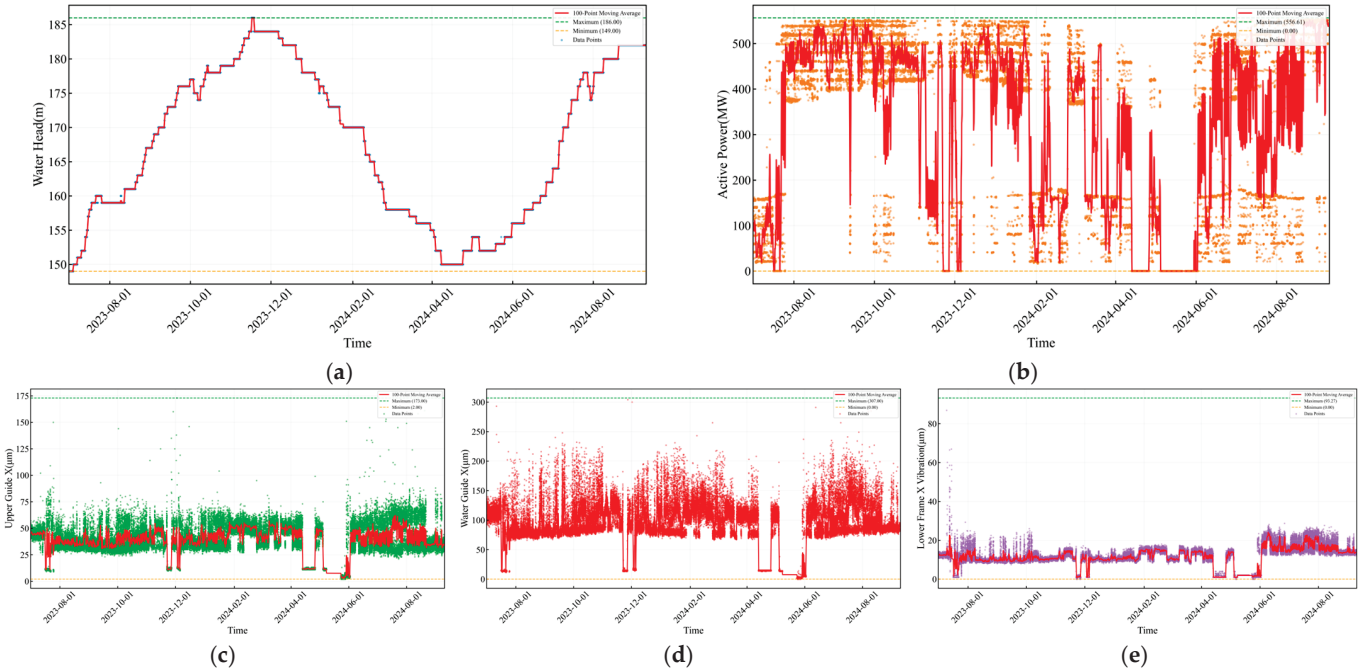


Figure 7. Actual monitoring data of the hydropower unit. (**a**) Water head. (**b**) Active power. (**c**) Upper Guide +X-Axis Swing. (**d**) Water Guide +X-Axis Swing. (**e**) Lower Bracket +X-Axis Vibration.

Figure 8 presents a detailed statistical analysis of each monitored parameter. The head distribution exhibits a bimodal pattern, with a primary mode between 165 m and 175 m and a secondary mode between 155 m and 165 m, reflecting two dominant operating regimes under varying hydrological conditions. The active power output distribution shows three distinct peaks: zero power corresponding to shutdown periods, a mid-range peak at 300–350 MW during normal operation, and a high-power peak at 450–500 MW under full-load conditions. These modes align closely with the operational zones defined in Table 2. The Upper Guide + X-Axis Swing distribution is tightly clustered around 40–60 μm, with a small standard deviation, indicating stable bearing performance. The Water Guide + X-Axis Swing distribution is markedly right-skewed, with a mean of approximately 65 μm and a long upper tail, suggesting intermittent or cyclical displacement anomalies. Finally, the Lower Bracket + X-Axis Vibration distribution is compact and symmetric around 6–12 μm, demonstrating the overall mechanical stability of the unit.

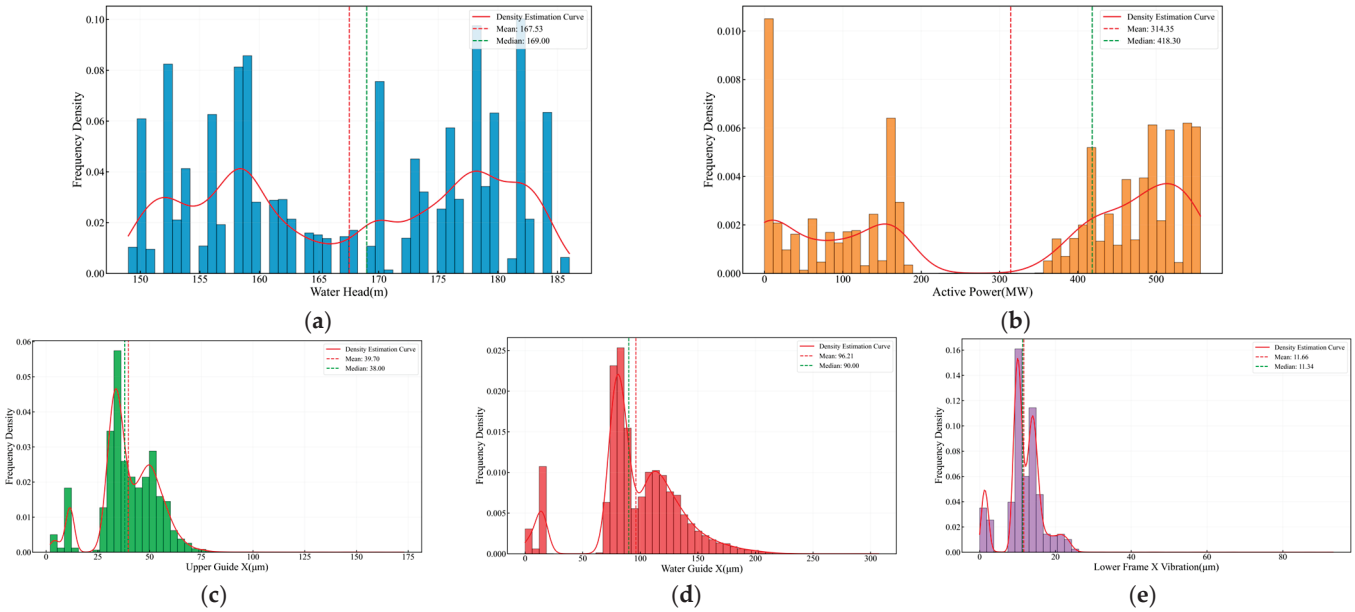


Figure 8. Distribution characteristics of key parameters. (**a**) Water head. (**b**) Active power. (**c**) Upper Guide +X-Axis Swing. (**d**) Water Guide +X-Axis Swing. (**e**) Lower Bracket +X-Axis Vibration.

4.2. Experimental Design

4.2.1. Experimental Methods

This research adopts a two-stage analytical framework comprising operating condition recognition and anomaly detection. As shown in Table 3, 12 methods were selected for the experiment. In the operating condition recognition stage, six methods (GNB [28], GMM [29], HMM [30], KM [14], HC [31], and KSQDC) were applied to identify the operating conditions of the hydropower unit based on water head (m) and active power (MW). In the anomaly detection stage, six methods (iForest [22], LOF [32], DBSCAN [33], EE [3], OCSVM [34], and ADEAD) were applied to three key monitoring points (Lower Bracket +X Horizontal Vibration, Upper Guide +X Swing, and Water Guide +X Swing) within each identified operating condition. All methods were implemented in Python3.8 using the standard implementations from the scikit-learn library, ensuring fair comparison between methods.

Table 3. Operating condition recognition and anomaly detection methods.

Stage	Full Method Name	Abbreviation	Fundamental Principle
Operating condition recognition	Gaussian Naive Bayes	GNB	Classification method based on conditional probability and feature independence assumptions
	Gaussian Mixture Model	GMM	Data distribution modeling using weighted combinations of multiple Gaussian distributions
	Hidden Markov Model	HMM	Time-series data analysis through hidden state transition probability modeling
	K-means Clustering	KM	Clustering method minimizing the sum of squared distances from samples to cluster centers
	Hierarchical Clustering	HC	Clustering method that builds a hierarchy of clusters using linkage criteria
	K-means Seeded Quadratic Discriminant Analysis	KSQDC	Hybrid method combining K-means clustering and quadratic discriminant analysis

Table 3. *Cont.*

Stage	Full Method Name	Abbreviation	Fundamental Principle
Anomaly detection	Isolation Forest	iForest	Isolation of sample points through random decision tree construction
	Local Outlier Factor	LOF	Anomaly identification based on local density deviation
	Density-Based Spatial Clustering	DBSCAN	Anomaly detection through identification of high- and low-density regions
	Elliptic Envelope	EE	Identification of distribution edge anomalies by fitting minimum volume ellipsoids
	One-Class Support Vector Machine	OCSVM	Separation of normal samples from anomalies using hyperspheres
	Adaptive Density Ensemble	ADEAD	Integration of multiple basic anomaly detectors with adaptive weight adjustment

4.2.2. Parameter Configuration

This study optimized algorithm parameters to ensure result reliability. To eliminate randomness effects, all algorithms used a unified random seed (GLOBAL_RANDOM_SEED = 42). Key parameters for condition recognition methods included: the GMM with full covariance matrix and five different initializations, the HMM with 200 maximum iterations, KM with 10 different initial values, original HC using the Ward linkage method for agglomerative clustering, and an improved version using sample size-adapted distance thresholds. The optimal number of conditions was automatically determined through multiple indicators including the silhouette coefficient, CH index, and DB index. Key parameters for anomaly detection methods included the contamination ratio adaptively set based on data size, iForest with 100 trees, the LOF with adaptively adjusted neighbor counts, DBSCAN density threshold calculated through k-distance distribution, the OCSVM boundary parameter set to twice the anomaly ratio, and the ADEAD method with dynamically calculated ensemble weights [0.26, 0.22, 0.20, 0.14, 0.18]. These parameter settings comprehensively considered algorithm stability, computational efficiency, and detection accuracy.

4.3. Experimental Results

4.3.1. Analysis of Operating Condition Recognition Results

Hydropower units exhibit varying vibration and displacement characteristics under different operating states, making accurate condition recognition a prerequisite for anomaly detection. This section comprehensively evaluates the performance of the proposed method in operating condition identification. As shown in Figure 9, the Upper Guide +X-Axis Swing, Water Guide +X-Axis Swing, and Lower Bracket +X-Axis Vibration exhibit distinct clustering in the head-power-measurement three-dimensional space, with different head and power combinations producing significantly different operating states. The Lower Bracket +X-Axis Vibration (Figure 9c) shows more compact clustering across conditions, indicating higher discrimination capability, while the guide bearing swing measurements demonstrate greater state variability, possibly related to hydraulic disturbances and shaft dynamic characteristics. This discovery provides important clues for subsequent anomaly detection, suggesting different monitoring points have varying diagnostic value.

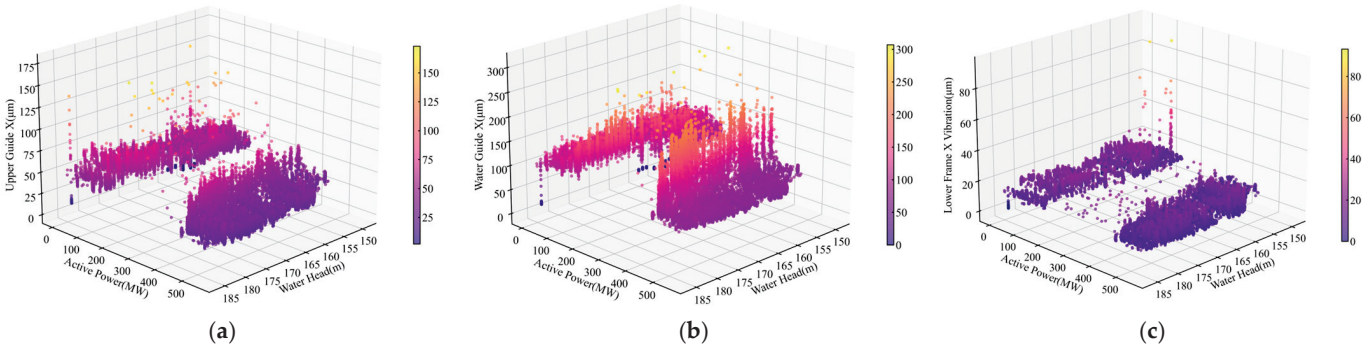


Figure 9. Scatter plots of monitoring signals across all operating conditions. (**a**) Upper Guide +X-Axis Swing. (**b**) Water-Guide +X-Axis Swing. (**c**) Lower Bracket +X-Axis Vibration.

Determining the optimal number of operating conditions is a key challenge in clustering analysis. This study employs a multi-metric ensemble evaluation mechanism to address this issue. As shown in Figure 10, we calculated multiple validity indicators including the silhouette coefficient, CH index, DB index, and SSE curve trends as functions of condition count. Results indicate that when the number of conditions is four, the silhouette coefficient (a comprehensive metric measuring cluster compactness and separation) reaches a local maximum, the CH index maintains a relatively high level, the DB index remains relatively low, and the SSE curve shows a clear "elbow point". This multi-indicator consistency strongly suggests that four is the optimal number of operating conditions. Compared to traditional empirical division or single-indicator assessment, this multi-metric ensemble method significantly improves the scientific validity and reliability of condition recognition.

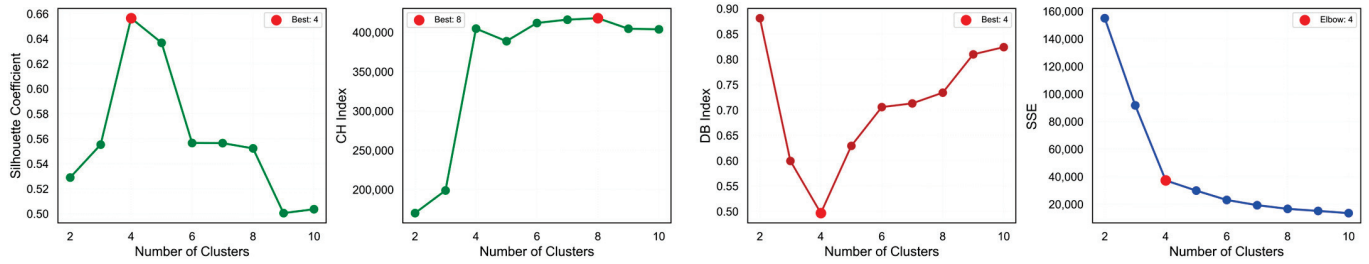


Figure 10. KSQDC operating condition count evaluation results.

Further analyzing the distribution characteristics of each condition, Figure 11 shows the probability density distributions of four conditions in the water head and active power dimensions. The water head distribution exhibits a clear bimodal characteristic, concentrated in the 155–165 m and 165–175 m intervals, reflecting two primary states of reservoir regulation. Active power presents a more complex multimodal distribution, with shutdown condition (near 0 MW), low load (around 100 MW), medium load (approximately 300 MW), and full load (about 500 MW) as four typical operating ranges, closely related to grid peak-shaving demands. The distribution of conditions in feature space is not simply ellipsoidal but exhibits complex non-convex shapes, which is precisely what traditional linear partitioning methods struggle to effectively handle, and is the primary motivation for the KSQDC method proposed in this paper.

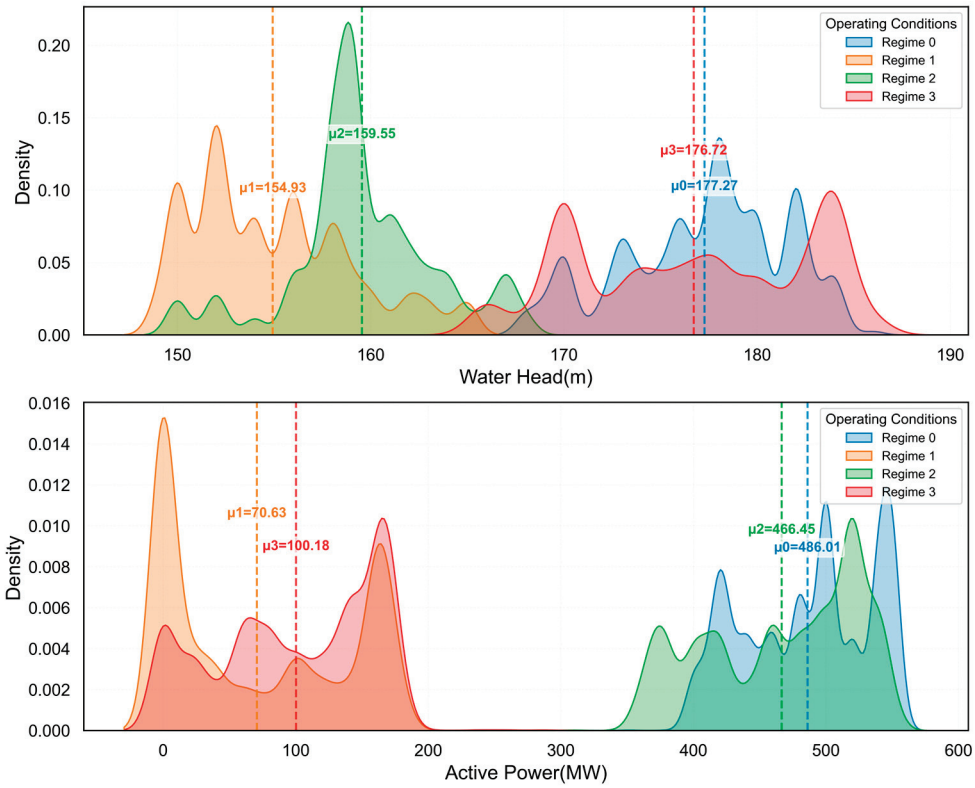


Figure 11. Distribution of operating condition features.

Table 4 further presents the statistical characteristics of each condition quantitatively. Comparing the features of the four conditions reveals that Condition 0 (high water head–high power) accounts for the largest proportion (36.36%), representing the unit's optimized operation zone; Condition 1 (low water head–low power) follows (26.88%), corresponding to low-load or peak-regulating states; Condition 2 (medium-low water head–high power) represents 20.98%, reflecting power generation dispatch under special hydrological conditions; and Condition 3 (high water head–medium-low power) has the smallest proportion (15.78%), possibly related to ecological flow release under high reservoir levels. From the compactness indicator, Condition 0 shows the highest internal compactness (465.12), indicating the most stable operation, while Condition 3 has the lowest compactness (233.39), displaying greater state fluctuation, possibly related to complex hydraulic conditions during regulation operation under high water head.

Table 4. Statistical characteristics and distribution features of four operating conditions.

Operating Condition	Sample Count	Proportion (%)	Water Head Mean (m)	Head Standard Deviation (m)	Active Power Mean (MW)	Active Power Standard Deviation (MW)	Compactness
0	22,191	36.36%	177.29	4.15	486.90	47.55	465.12
1	16,404	26.88%	154.61	3.76	67.84	68.21	426.48
2	12,805	20.98%	159.58	3.81	465.04	57.10	287.53
3	9631	15.78%	176.08	6.31	103.42	59.39	233.39

4.3.2. Comparison of Different Operating Condition Recognition Methods

To validate the effectiveness of the proposed KSQDC method, we compared several mainstream condition recognition approaches. Figure 12 visually demonstrates the condition recognition results of various methods. From the spatial partitioning results, the methods show different clustering patterns and boundary characteristics. The HMM method (Figure 12c) exhibits considerable overlap between different regions with less

distinct boundaries. The GMM method (Figure 12b) identifies five distinct clusters, while most other methods identify four clusters. Traditional clustering methods like K-means (Figure 12d) and HC (Figure 12e) show clear separation between different colored regions. The proposed KSQDC method (Figure 12f) demonstrates well-separated clusters with relatively uniform data point distributions within each cluster.

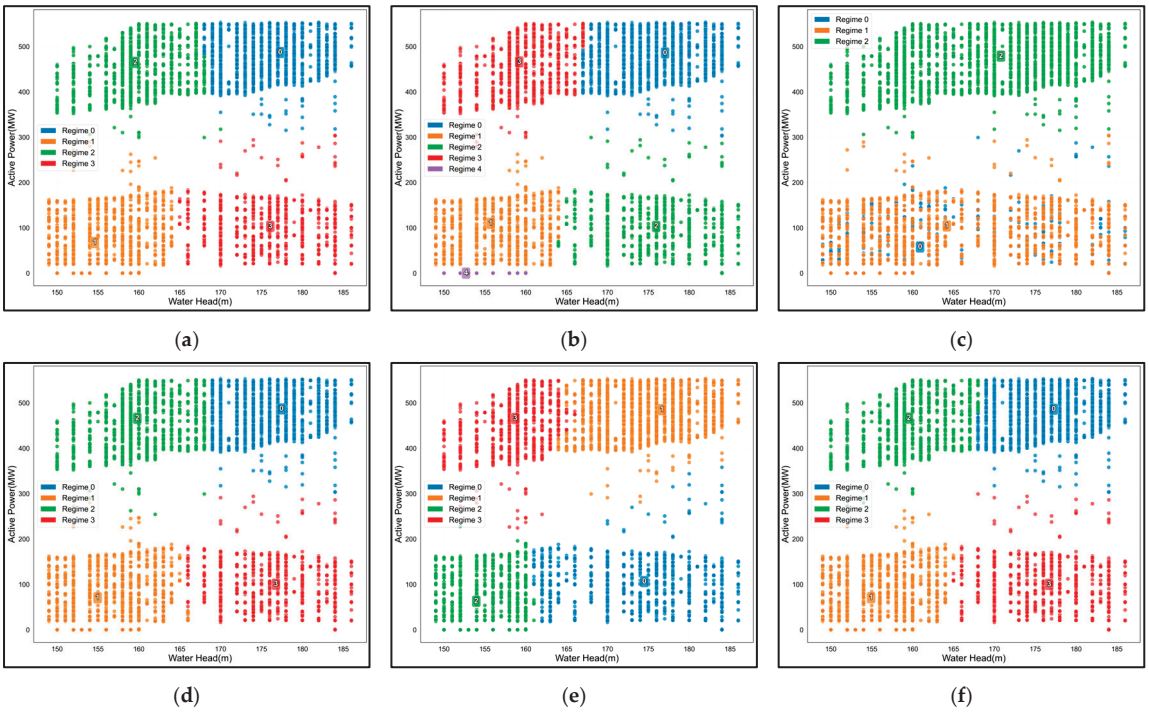


Figure 12. Spatial partitioning effects of six operating condition recognition methods. (**a**) GNB. (**b**) GMM. (**c**) HMM. (**d**) KM. (**e**) HC. (**f**) KSQDC.

Table 5 systematically evaluates each method across multiple quantitative indicators. Results show that the KSQDC method delivers the best overall performance on key performance metrics: It achieves the highest silhouette coefficient (SC, 0.64) and condition distribution balance (CDB, 0.98), indicating an optimal balance between internal cohesion and external separation. In terms of computational efficiency, KSQDC's total execution time is 36.29 s, second only to the HMM's 36.15 s, ranking second among all methods and demonstrating excellent time efficiency. While the HC method shows slightly higher internal compactness (IC, 384.15 vs. 354.45), its silhouette coefficient (0.60) is lower than that of KSQDC, suggesting that extremely high internal compactness may lead to overfitting; the GMM's abnormally high internal compactness (71,512.02) further confirms this point, with its overfitting resulting in a notably reduced silhouette coefficient (0.53). It is noteworthy that although the GMM performs relatively well in execution time (37.88 s), its severe performance degradation indicates that computational speed advantages alone cannot compensate for algorithmic limitations. The HMM method performs poorly across all indicators, particularly with a silhouette coefficient of only 0.32, and despite having the shortest execution time (36.15 s), its extremely low recognition accuracy makes it unsuitable for practical engineering applications. These results fully validate the advanced nature and effectiveness of the KSQDC method in addressing nonlinear operating condition recognition problems in hydropower units, achieving the optimal balance between recognition accuracy and computational efficiency.

Table 5. Performance metric comparison of various operating condition recognition methods.

Method	IC	CDB	SC	Total Time/s
GNB	353.13	0.96	0.62	38.48
GMM	71,512.02	0.94	0.53	37.88
HMM	239.90	0.89	0.32	36.15
KM	351.48	0.96	0.63	36.58
HC	384.15	0.96	0.60	37.90
KSQDC	354.45	0.98	0.64	36.29

4.3.3. Analysis of Anomaly Detection Results

From the 3D visualization results shown in Figures 13–15, distinct differences in anomaly detection performance across various methods become apparent for the three key monitoring points. The traditional iForest method demonstrates reasonable anomaly identification capabilities but exhibits limitations in boundary precision, particularly in high-density normal sample regions where false positives frequently occur. The LOF method shows advantages in local anomaly detection due to its density-based nature, yet it tends to identify excessive anomaly samples, resulting in higher false alarm rates. DBSCAN's density clustering characteristics make it effective in low-density regions, but its performance becomes unstable in complex boundary areas where normal and abnormal samples intermingle. In contrast, the proposed ADEAD method demonstrates superior anomaly identification accuracy and stability across all three monitoring points through its multi-model ensemble and density-adaptive strategies, with anomaly sample distributions more closely aligned with the physical principles of actual hydropower unit operations.

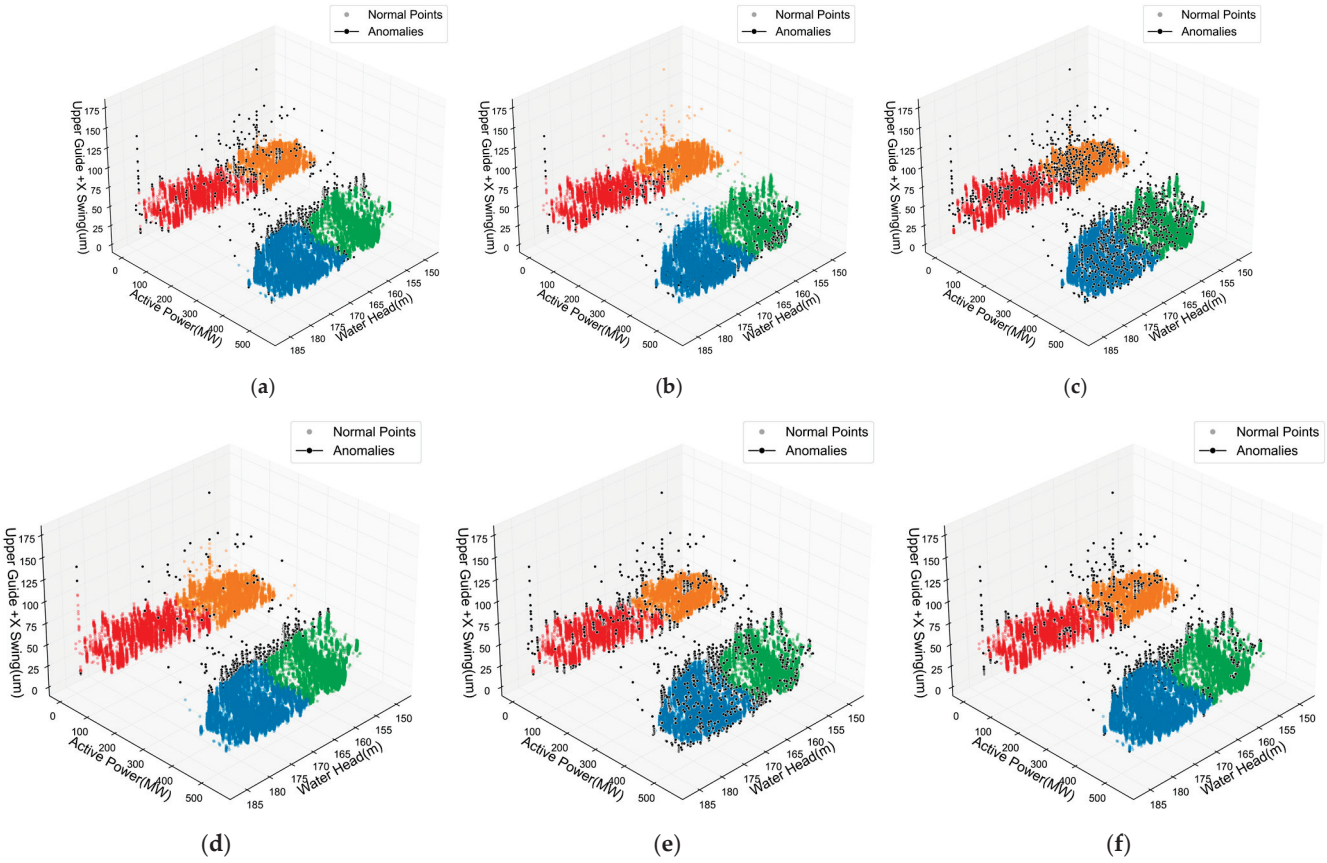


Figure 13. 3D scatter plot of anomaly detection results for Upper Guide +X-Axis Swing. (**a**) iForest. (**b**) LOF. (**c**) DBSCAN. (**d**) EE. (**e**) OCSVM. (**f**) ADEAD.

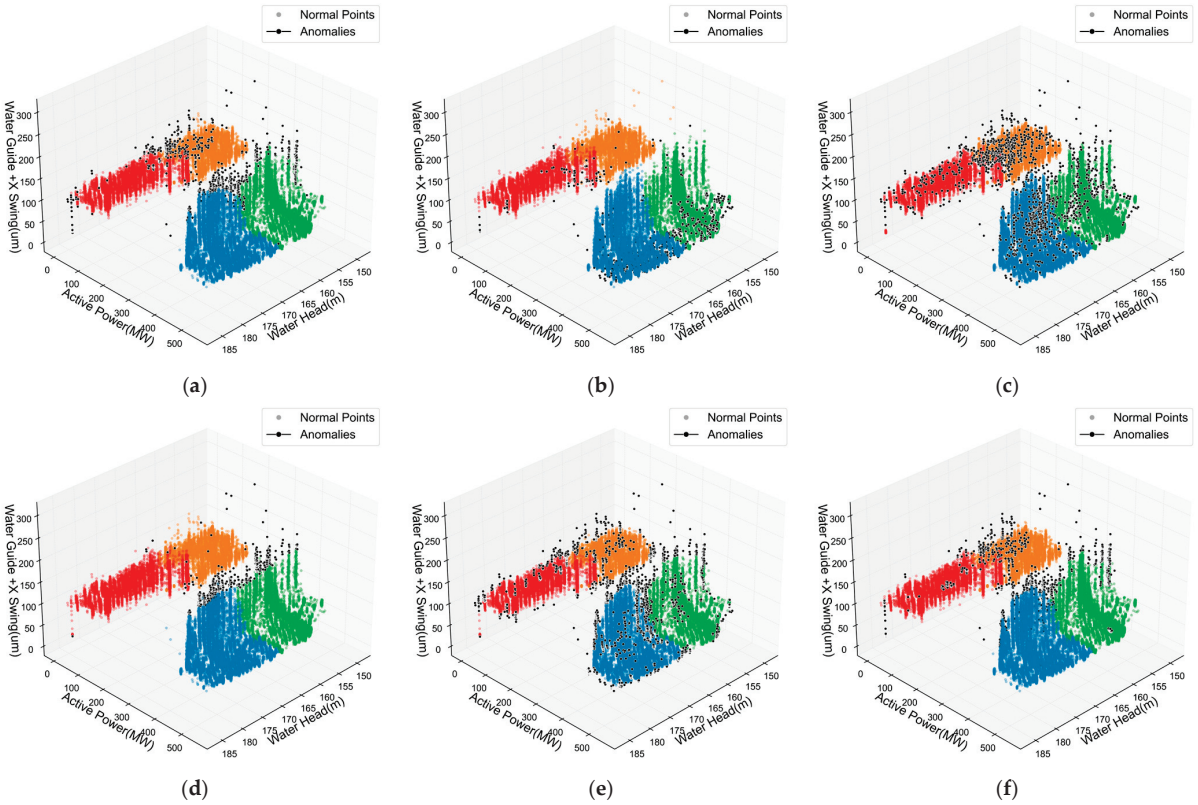


Figure 14. 3D scatter plot of anomaly detection results for Water Guide +X-Axis Swing. (**a**) iForest. (**b**) LOF. (**c**) DBSCAN. (**d**) EE. (**e**) OCSVM. (**f**) ADEAD.

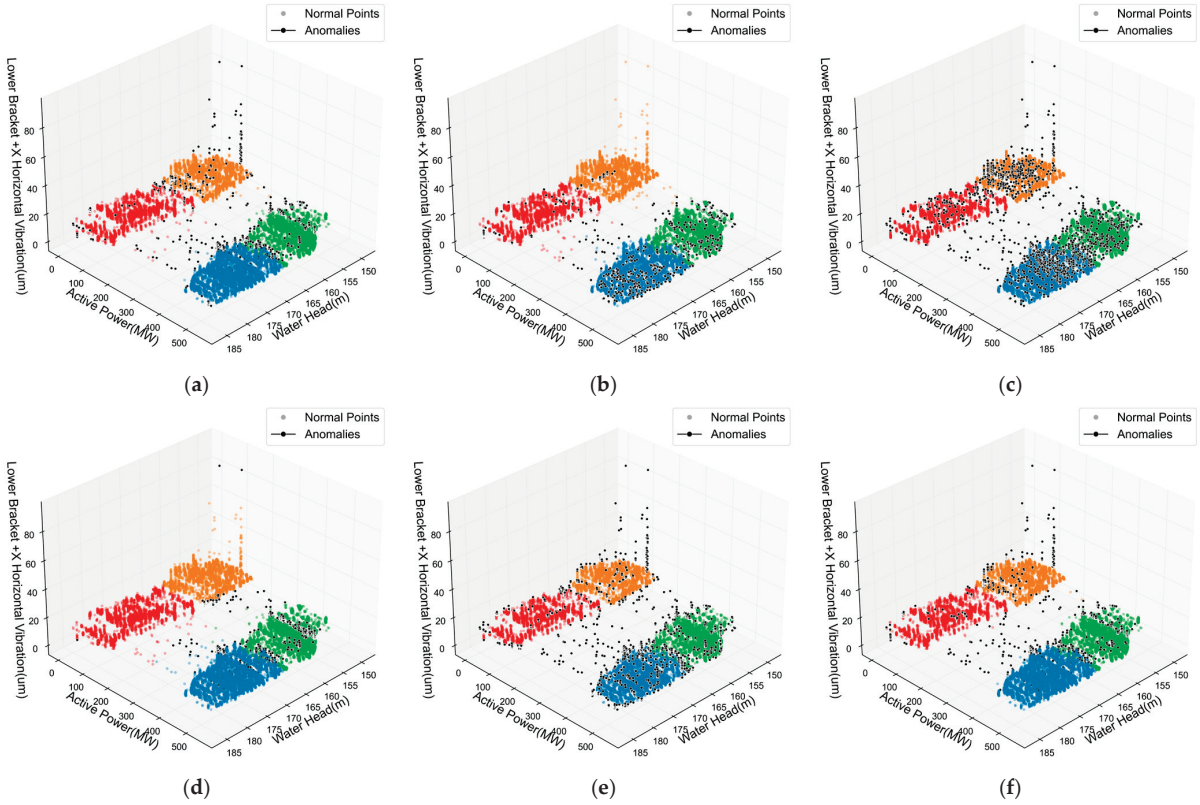


Figure 15. 3D scatter plot of anomaly detection results for Lower Bracket +X-Axis Vibration. (**a**) iForest. (**b**) LOF. (**c**) DBSCAN. (**d**) EE. (**e**) OCSVM. (**f**) ADEAD.

The quantitative performance evaluation results presented in Tables 6–8 provide comprehensive validation of ADEAD's superiority. For the Upper Guide +X-Axis Swing monitoring point, ADEAD achieves the highest silhouette coefficient of 0.28 and a comprehensive score of 0.30, significantly outperforming competing methods such as iForest (0.25), the LOF (0.21), and DBSCAN (0.18). In terms of execution time, ADEAD requires a total time of 6.29 s, making it slower than lightweight methods like iForest (0.43 s), the LOF (1.22 s), and DBSCAN (1.37 s), but this time overhead is entirely acceptable considering its superior detection accuracy. The results for Water Guide +X-Axis Swing are even more impressive, with ADEAD reaching a silhouette coefficient of 0.34 and a comprehensive score of 0.34, with a total execution time of 5.60 s, demonstrating enhanced adaptability when processing complex hydraulic disturbance signals. The density ratio metric reveals ADEAD's balanced approach, achieving 28.33%, 40.22%, and 16.93% for the three monitoring points, respectively, indicating effective adaptation to varying local density characteristics while maintaining consistent anomaly detection accuracy.

Table 6. Performance comparison of anomaly detection methods for Upper Guide +X-Axis Swing.

Method	SC	Anomaly Count	Anomaly Ratio	Density Ratio	Efficiency Score	Separation	Comprehensive_Score	Total Time/s
iForest	0.19	1182	2.00%	17.23%	8.37	2.72	0.25	0.43
LOF	0.11	1171	1.98%	69.37%	21.01	2.48	0.21	1.22
DBSCAN	0.08	1367	2.31%	16.20%	8.87	2.44	0.18	1.37
EE	0.19	1184	2.00%	17.04%	0.44	2.74	0.25	10.95
OCSVM	0.16	2681	4.54%	26.99%	3.44	2.57	0.23	7.39
ADEAD	0.28	1184	2.00%	28.33%	0.88	3.02	0.30	6.29

Table 7. Performance comparison of anomaly detection methods for Water Guide +X-Axis Swing.

Method	SC	Anomaly Count	Anomaly Ratio	Density Ratio	Efficiency Score	Separation	Comprehensive_Score	Total Time/s
iForest	0.20	1174	2.00%	23.33%	8.49	2.78	0.26	0.35
LOF	0.12	1155	1.97%	60.49%	20.46	2.47	0.21	1.09
DBSCAN	0.06	1291	2.20%	19.75%	7.37	2.36	0.17	1.27
EE	0.20	1176	2.00%	24.08%	0.45	2.76	0.25	5.87
OCSVM	0.18	2939	5.00%	40.02%	3.88	2.65	0.24	6.02
ADEAD	0.34	1176	2.00%	40.22%	1.09	3.30	0.34	5.60

Table 8. Performance comparison of anomaly detection methods for Lower Bracket +X-Axis Vibration.

Method	SC	Anomaly Count	Anomaly Ratio	Density Ratio	Efficiency Score	Separation	Comprehensive_Score	Total Time/s
iForest	0.15	1210	2.00%	17.22%	8.69	2.56	0.22	0.42
LOF	0.10	1208	2.00%	57.77%	18.72	2.40	0.20	1.07
DBSCAN	0.07	1594	2.64%	15.86%	9.82	2.42	0.18	1.34
EE	0.11	1210	2.00%	31.49%	1.13	2.46	0.20	6.42
OCSVM	0.09	2331	3.86%	23.97%	2.79	2.40	0.19	7.32
ADEAD	0.16	1210	2.00%	16.93%	0.43	2.63	0.23	6.75

The unique anomaly patterns associated with different sensor locations become evident through comparative analysis of detection characteristics across the three monitoring points. Water Guide +X-Axis Swing, as a direct indicator of hydraulic characteristics, presents the highest detection complexity due to vortex rope effects, cavitation, and flow regime transitions. Upper Guide +X-Axis Swing maintains relative stability during normal operation but exhibits transient anomaly features during unit startup and shutdown

processes. Lower Bracket +X-Axis Vibration is a comprehensive indicator of overall mechanical condition, with anomaly signals typically related to shaft imbalance, foundation resonance, and other mechanical factors. ADEAD's incorporation of local density information and adaptive weighting mechanisms enables effective adaptation to these varied anomaly characteristics across different monitoring points, achieving more precise anomaly boundary optimization while completing detection tasks within acceptable time frames, and providing reliable technical support for hydropower unit condition monitoring and predictive maintenance strategies.

This study adopts an unsupervised anomaly detection approach, a choice based on the practical characteristics of hydropower unit operation: Normal operation states occupy the vast majority of time (typically over 95%), while real anomaly events are relatively rare and difficult to pre-label. Unsupervised methods can automatically learn normal operation patterns without relying on extensive labeled data, which better aligns with actual industrial site conditions. To verify the reliability of detection results, we employed multiple validation strategies: First, statistical analysis confirmed that detected anomaly points indeed deviate from normal distribution ranges across monitoring parameters; second, cross-validation with maintenance records and operation logs from the hydropower station revealed a high temporal correlation between detected anomalies and actual equipment faults and maintenance events; and finally, experienced hydropower operation experts were invited to evaluate typical anomaly cases, confirming their engineering reasonableness.

From a physical mechanism perspective, detected anomalies mainly correspond to the following fault modes: Upper guide bearing anomalies primarily manifest as increased axial and radial vibrations, typically caused by bearing wear, poor lubrication, or installation misalignment; water guide bearing anomalies often present as excessive swing, mainly due to hydraulic instabilities causing vortex rope phenomena, cavitation, and abnormal shaft system dynamic responses; and lower bracket vibration anomalies are often related to rotor imbalance, foundation loosening, or transmission system faults. These physical explanations highly align with common fault modes in hydropower units, validating the engineering significance of detection results.

Regarding anomaly processing procedures, detected anomaly points are processed according to severity levels: Minor anomalies are included in trend monitoring with continuous tracking of their development; moderate anomalies trigger warning signals, alerting operators to pay attention and arrange further inspections; and severe anomalies immediately generate alarms, requiring appropriate safety measures. All anomaly information is recorded in the condition monitoring database, providing valuable historical data for subsequent fault diagnosis, maintenance decisions, and model optimization. Meanwhile, anomaly cases confirmed by experts are used to continuously improve the parameter settings and threshold standards of the detection algorithm.

5. Conclusions

The proposed hydropower unit anomaly detection method based on KSQDC-ADEAD effectively addresses the challenge of anomaly identification under complex operating conditions. The KSQDC algorithm successfully constructs nonlinear condition decision boundaries by organically combining unsupervised clustering with statistical discriminant analysis, outperforming traditional methods in terms of the silhouette coefficient, internal compactness, and the condition distribution balance, particularly demonstrating superior discrimination capability in condition overlap regions. The ADEAD algorithm significantly improves the accuracy and stability of anomaly detection through multi-model ensemble and density-adaptive optimization strategies, achieving optimal comprehensive scores at all three key monitoring points. The experimental results fully validate the effectiveness

and practicality of the proposed method in actual hydropower unit condition monitoring, providing reliable technical support for the safe operation and predictive maintenance of hydropower units.

However, this study also has certain limitations. Compared to recent deep learning methods, this approach has deficiencies in handling large-scale datasets and temporal modeling, as deep learning methods can automatically learn more complex data representations and long-term temporal dependencies. Compared to online learning methods, this approach has limited adaptability to concept drift and requires periodic retraining to cope with long-term changes such as equipment aging. Although this study has made preliminary explorations in interpretability, it has not fully considered deep-level model explanation and causal reasoning mechanisms, which will be an important direction for future research. In ultra-large-scale multi-unit deployments, computational complexity may become a limiting factor. Nevertheless, this method still has obvious advantages in engineering applicability and small-to-medium-scale application scenarios, being particularly suitable for industrial environments with high system transparency requirements.

Future research can be further developed in the following directions: first, combining deep learning technology to construct more complex feature extraction networks to improve the recognition capability of weak anomaly signals; second, introducing temporal information and multi-sensor fusion technology to build a more comprehensive unit health assessment system; third, developing online real-time anomaly detection systems to achieve continuous monitoring and early warning of hydropower unit operating status; and finally, expanding the applicability of the method to apply it to the anomaly detection of other types of rotating machinery equipment, promoting the industrial application and standardized development of related technologies.

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An Interpretability Method for Broken Wire Detection

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Abstract: As an indispensable piece of production equipment in the industrial field, wire rope is directly related to personnel safety and the normal operation of equipment. Therefore, it is necessary to perform broken wire detection. Deep learning has powerful feature-learning capabilities and is characterized by high accuracy and efficiency, and the YOLOv8 object detection model has been adopted to detect wire breaks in electromagnetic signal images of wire rope, achieving better results. Nevertheless, the black box problem of the model brings a new trust challenge, and it is difficult to determine the correctness of the model's decision and whether it has any potential problems, so an interpretability study needed to be carried out. In this work, a perturbation-based interpretability method—ESTC (Eliminating Splicing and Truncation Compensation)—is proposed, which distinguishes itself from other methods of the same type by targeting the signaling object instead of the ordinary object. ESTC is compared with other model-agnostic interpretable methods, LIME, RISE, and D-RISE, using the same model on the same test set. The results indicate that our proposed method is objectively superior to the others, and the interpretability analysis shows that the model predicts in a way that is consistent with the priori knowledge of the manual rope inspection. This not only increases the credibility of using the object detection model for broken wire detection but also has important implications for the practical application of using object detection model to detect wire breaks.

Keywords: object detection; interpretability AI; broken wire detection; electromagnetic signal; LIME; RISE; D-RISE

1. Introduction

Wire rope is extensively used in the industrial field due to its high strength, excellent toughness, and wear resistance, and it has become an indispensable and important material in the industrial field. Affected by factors such as high strength, long-time load, and environment, steel wire rope is susceptible to problems such as broken wire, wear, corrosion, and deformation. To ensure the safety of personnel and the stable operation of equipment, it needs to replace steel wire rope, the breaking force of which does not meet the requirements of the current regulations, to avoid unnecessary losses caused by fracture accidents. Consequently, it is increasingly important to detect the wire rope. An important index to determine whether the wire rope needs to be replaced is whether there is a broken wire. When the number of broken wires in a lay pitch exceeds a certain number, it should be replaced. The manual rope inspection process is presented in Figure 1. The principle of the detection device is the electromagnetic magnetic flux leakage detection method [1,2], which

has the characteristics of non-contact, strong anti-interference, high accuracy, and superior efficiency. The original signal is obtained by putting the wire rope under sensor detection of the detection equipment; after signal processing, the signal is converted into a signal image, and then the broken wire is marked by manual observation.

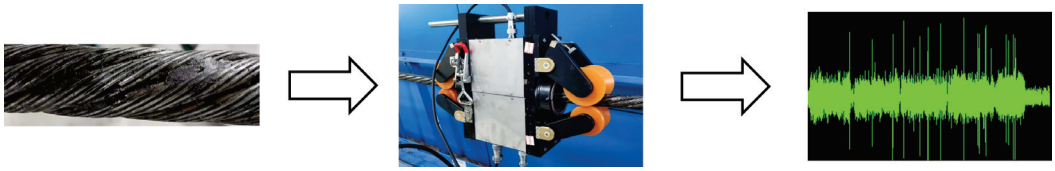


Figure 1. The process of manual rope inspection.

With the rapid advancement of deep learning, the IoT field is becoming more closely integrated with deep learning technologies [3], and manual rope inspection has become inefficient and difficult to integrate into automation. Compared with deep learning, machine learning methods cannot efficiently deal with the complex and diverse conditions of wire rope breakage and are not as accurate as manual rope inspection. Considering this, it is proposed to transform wire rope breakage signals into image data non-destructively through visualization and then adopt object detection to learn the wire rope breakage signals in a data-driven way. In this approach, the process of manual rope inspection can be simulated while reflecting the powerful feature extraction capability of deep learning and its strong adaptability to complex scenes, leading to accurate and efficient wire rope breakage detection. The hardware adaptability and portability of the target detection algorithm make it easier to integrate this approach into automation systems.

Existing object detection methods can be divided into one-stage and two-stage detectors according to whether the candidate region is produced or not. Two-stage detectors, such as the RCNN series [4–7], RFCN [8], SPPNET [9], etc., have two stages of explicitly generating the candidate region and performing object classification and localization. They have higher accuracy but slower speed and are suitable for scenes requiring higher detection accuracy. One-stage detectors, such as the YOLO series [10], SSD [11], etc., combine candidate region generation and object classification and localization in one stage, directly predicting the target location and accumulating chants from input images. They have faster speed and slightly lower accuracy and are suitable for real-time detection and embedded devices and other scenes requiring higher speed. In the semantic segmentation task, the DeepLab series [12,13] developed by the Google team is good at dealing with complex scenes with multi-scale context information. Song et al. [14] used a DeepLab v3 convolutional neural network architecture and ResNet-50 [15] as the backbone network for binary image segmentation to achieve pixel-level cancer detection. EfficientNet [16] is a general deep learning model architecture. Its design concept focuses on efficient feature extraction, breaking the bottleneck dictating that the accuracy and efficiency of traditional models cannot be combined, and it can be widely adapted to a variety of computer vision tasks. Kabir et al. [17] realized the triple optimization of accuracy, efficiency, and cost through EfficientNet, providing a universal automation solution for durability evaluation of building materials.

Though object detection achieves good performance, the complex structure of the model, the large number of parameters, the abstract feature representation, etc., not only bring the black box problem of deep learning [18–21], leading to poor interpretability and difficulty in performing fault detection and optimization, but also bring a crisis of confidence. Particularly, the condition of the wire rope directly affects the smooth production and the safety of personnel's lives and properties; thus, it is necessary to understand the

basis of the model for decision-making. To overcome the challenges posed by the black box problem of deep learning, deep learning interpretability plays a crucial role.

Deep learning interpretability is the key to improving model understanding and trust, discovering model flaws, and guiding model adjustments. According to the principle of explaining the basis of model decision-making, interpretability methods can be divided into two types—gradient-based methods and perturbation-based methods—both of which mainly visualize the regions that are important for model decision-making using a saliency map. The principle of the gradient-based interpretability method is to quantify the importance of input features for model prediction by calculating and analyzing the gradient of the model output on the input features. Zhou et al. [22] developed a visualization technique called CAM, which generates class activation maps for interpretable analysis using the output feature maps of the global average pooling layer. Selvaraju et al. [23] extended CAM and devised Grad-CAM to use it with a broader range of modeling architectures. Chattopadhay et al. [24] presented Grad-CAM++, which generates more accurate class activation maps by further optimizing Grad-CAM. Wang et al. [25] designed Score-CAM, which generates class activation maps by recalculating the feature scores after masking. Layer-CAM [26] generates more comprehensive and high-resolution class activation maps by combining feature maps from several convolutional layers. Perturbation-based interpretability methods are model-agnostic, as they generate saliency maps by perturbing input features or regions and then observing changes in the model outputs, finally evaluating the features or regions that have a large impact on the model. Zeiler and Fergus [27] aimed to understand the behavior of a model through occlusion analysis. Ribeiro et al. [28] developed LIME, a black box interpretation method for locally interpretable models. This method approximates the predictive behavior of a complex model with a simple and interpretable model as a local neighbor of the samples to be interpreted. The core idea of RISE [29] is to generate a random mask obscuring the image region and generate a saliency map with a weighted average of the masks, making it mainly applicable to image classification models. Compared with RISE, D-RISE [30] has improved object detection, and its application scope is more expansive. Certainly, there are some problems in the gradient-based and perturbation-based methods. To resolve these problems, Chen et al. [31] put forward a visually accurate search method, which generates accurate attribution maps with fewer regions.

The existing classical perturbation-based interpretability methods are aimed at ordinary targets rather than signal targets. Signal targets often have physical constraints, have stronger integrity and continuity compared to ordinary targets, and are closely related to each feature. RISE and D-RISE interfere with the disturbance mode of input data by generating random occlusion modes. This method cannot guarantee the continuity and integrity of the signal context in the process of disturbing the electromagnetic signal of the wire rope. At the same time, the disturbance-based method does not consider the distortion problem caused by signal truncation during the disturbance process, which leads to inaccurate feature attribution. In order to solve the above problems, this paper considers electromagnetic signals of wire ropes and proposes a model-agnostic perturbation-based post hoc localizable interpretability method called ESTC (Eliminating Splicing and Truncation Compensation). This method uses compensation and splicing to avoid the problem of signal distortion and destruction of signal continuity after truncation. At the same time, interpretability analysis is performed for the characteristics of different regions of the signal. The main contributions of this work are as follows:

- The electromagnetic signal of the wire rope is transformed into image data and made into a dataset through manual labeling. Then, the dataset is divided into a training

set, a validation set, and a test set to train the YOLOv8 [32] object detection model for broken wire prediction.

- A new post hoc locally interpretable perturbation-based method called ETSC is proposed. ETSC distinguishes itself from other perturbation-based methods in the perturbation mode as it adopts corresponding perturbation modes according to the characteristics of different regions of the broken wire electromagnetic signals, specifically using the elimination of splicing for the middle region of the broken wire signals and using the truncation of the compensation for the two-end region. The perturbation method does not cause damage to the signal and avoids a significant reduction in the confidence score of the model due to the failure to recognize the signal characteristics.
- By using the ETSC method of perturbation, the impact of the weight on the model in different regions of the broken wire signals can be derived. The saliency map produced using the weight can intuitively show the influence of the model decision-making degree in different regions of the broken wire signals. Then, the model decision-making is understood based on the broken wire signals of the main characteristics of the method, which is important to promote the practical application of the method of deep learning.
- The proposed interpretable method ETSC is compared with three model-agnostic perturbation-based interpretable methods, LIME, RISE, and D-RISE. The results indicate that the saliency map obtained by ETSC can obtain accurate and reliable results, demonstrating that the decision-making behaviors of the model are consistent with existing methods of artificial rope inspection.

2. Materials and Methods

2.1. Wire Rope Dataset Production and Processing

Some of the wire ropes used in different mines were selected, and broken wire detection devices were employed to collect electromagnetic signals from each wire rope, where the sensors detected electromagnetic signals containing location information and defect information. This information was transmitted to different information sites through shielded cables. Then, these signals were further processed (e.g., signal denoising) at these sites, and the numerical data of each wire rope was finally obtained. Some software was used to plot the data of each wire rope into a certain number of images, and then LabelImg was utilized to label broken wires on the images produced for these different wire ropes. Only three target categories were set: single broken wire, two broken wires, and three broken wires. The three signal categories are not the same, and the larger the category, the smaller the number. Even though there may be more types of broken wire, the data is too sparse to be set, and the different types of broken wire are illustrated in Figure 2. After filtering out some invalid images caused by the vibration of the wire rope during the acquisition process, despite the limited number of broken wire ropes, more than 3500 broken wire images were collected for the broken wire dataset. The collected images were used for training and validation at a ratio of 8:2, and then the 600 signal images were used for the test set alone; these images are independent of the training and validation sets, preventing evaluation bias due to data leakage. The test set comprehensively covers all broken wire types and various wire rope types encountered during training, ensuring dataset diversity.

The dataset includes three categories of broken wire conditions for different types of steel wire ropes, where “different types” denote ropes from distinct mining regions. These rope types differ in electromagnetic signal characteristics. Moreover, the dataset shows substantial class imbalance among the three classes: single broken wires, double broken wires, and triple broken wires. The number of single broken wires significantly

exceeds that of double and triple ones at a ratio of approximately 8.5:1:0.5. In practice, the number of double and triple broken wires is likely even lower, a phenomenon common in operational steel wire ropes. A higher number of multi-broken wires typically indicates the rope has approached or met the scrap standard. This imbalance causes the YOLOv8 model to demonstrate poorer fitting performance for multi-broken wires than single ones. To mitigate this, data augmentation was applied to multi-broken wire samples to improve the model's generalization capability.

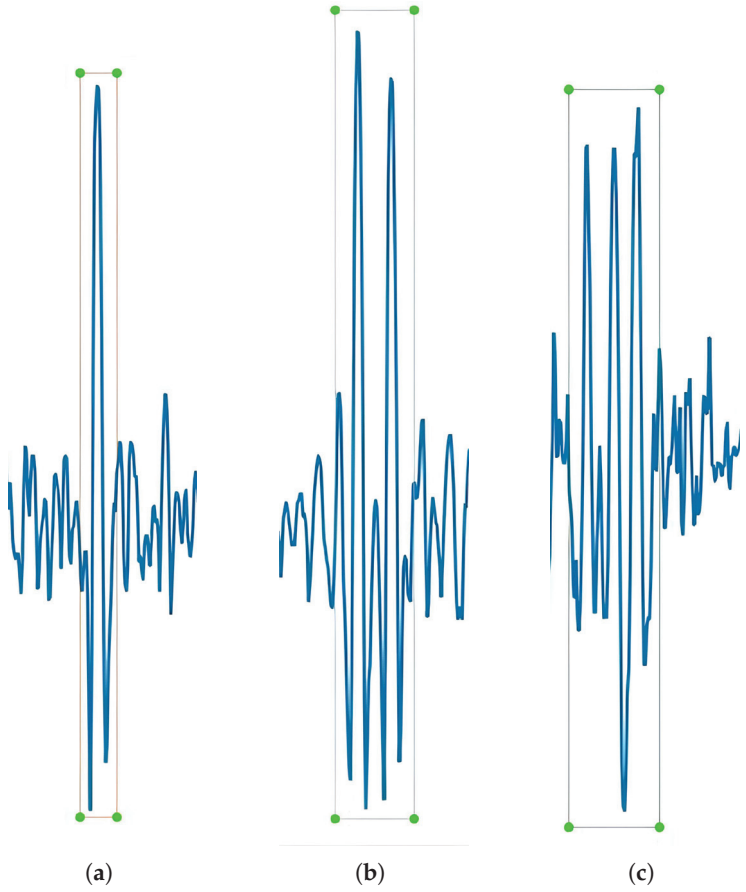


Figure 2. Three categories of broken wire signals in most cases, and the number of troughs is twice the number of peaks: (**a**) single broken wire, (**b**) double broken wire, and (**c**) triple broken wire.

2.2. YOLOv8 Model Experimental Process and Environment

Considering the possibility of deploying the model in edge devices to integrate it into automation systems, the size of the selected model parameters and the required computational resources should not be too large so as not to exceed the storage and processing capacity of the edge device. Meanwhile, the detection speed cannot be too slow; otherwise, it will affect the real-time response performance of the whole automation system, thereby reducing the operational efficiency and reliability.

To determine the performance gap between two-stage and one-stage object detection algorithms, a representative two-stage algorithm, Faster R-CNN, and a representative one-stage algorithm, YOLOv8, were selected. We compared Faster R-CNN and YOLOv8 on the same dataset and in the same hardware conditions(Nvidia RTX4060); the results are shown in Table 1. It was found that Faster R-CNN has much larger model parameters and higher inference memory than YOLOv8. Moreover, its FPS is lower than YOLOv8, and it fails to reach the real-time detection standard, while its mAP also lags behind YOLOv8. Therefore, we ceased selecting two-stage detection algorithms. Notably, the YOLO series describes a group of end-to-end one-stage object detection algorithms, which have the

advantages of fast detection speed, good real-time performance, strong generalization ability, easy deployment, and iterative updating. So, we chose one of the most stable and reliable versions, YOLOv8, for experiments and interpretability analysis.

Table 1. Comparison of Faster R-CNN and YOLOv8n.

Model	Parameters (M)	FPS	Inference Memory (MB)	@mAP0.5
Faster R-CNN (Resnet50)	43.1 M	14.6	105.5	0.787
YOLOv8n	3.1 M	57.7	43.57	0.846

The model was trained on eight Nvidia RTX3090 GPUs. The model structure of YOLOv8 was not modified, and only the training parameters were modified to obtain the best weight file—specifically, the number of epochs was set to 500, batch size was set to 64, and the number of warmup epochs was set to 10. These parameters were determined through an exhaustive search conducted using a fixed dataset, fixed hardware configurations, and fixed hyperparameters. The optimal combination was validated using mAP, and we performed a loss comparison between the training and validation sets and considered test set metrics including accuracy and false detection rate. The reason for why we did not modify the structure of YOLOv8 is because interpretability analysis needed to be conducted on the model afterward; interpretability analysis can be easily used to discover potential problems in the model or dataset. The final PR curve was obtained and is shown in Figure 3.

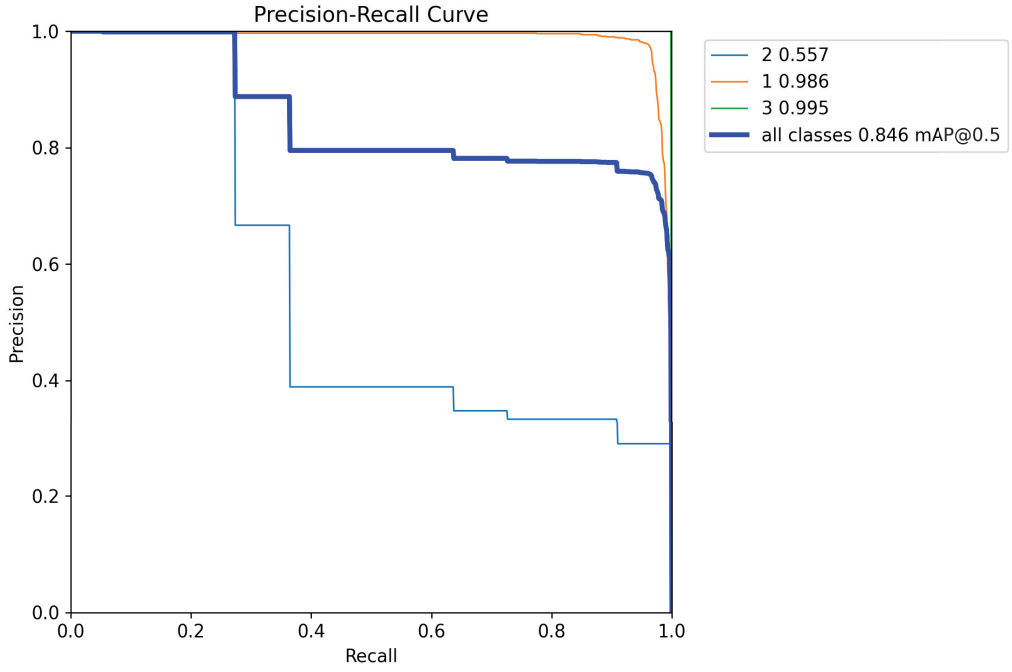


Figure 3. The PR curves for YOLOv8 model.

2.3. Defects of the Traditional Perturbation Method

2.3.1. RISE Methodology Modification

Since the RISE method is mainly used to model image classification and YOLOv8 belongs to the object detection model, it is impossible to directly apply the RISE method to YOLOv8. To this end, this paper has made the following two modifications to RISE to make it applicable to YOLOv8 for interpretability analysis:

- The image preprocessing method in RISE differs from that in the YOLOv8 model. To use the YOLOv8 model for inference, the image preprocessing method in RISE needs to be modified to align with that in YOLOv8;
- In the RISE interpretable method, before multiplying the processing masks and weight scores, the weight scores are acquired by the image classification model after softmax processing, while the results acquired by the YOLOv8 model after inference are different. In this paper, the confidence scores of the target categories in the image were obtained from the YOLOv8 model after inference with non-maximum suppression, which was multiplied with the produced random mask to acquire the saliency map.

2.3.2. Inappropriate Perturbation Method

After applying the RISE method to the YOLOv8 model, it was found that the highlighted red area in the saliency map is always concentrated in the middle of the broken wire signal, as illustrated in Figure 4. Though manual rope testing is performed based on the change in the amplitude of the broken wire signal and the characteristics of the signal peaks and troughs, the results obtained by the RISE interpretability method are opposite to manual rope testing.

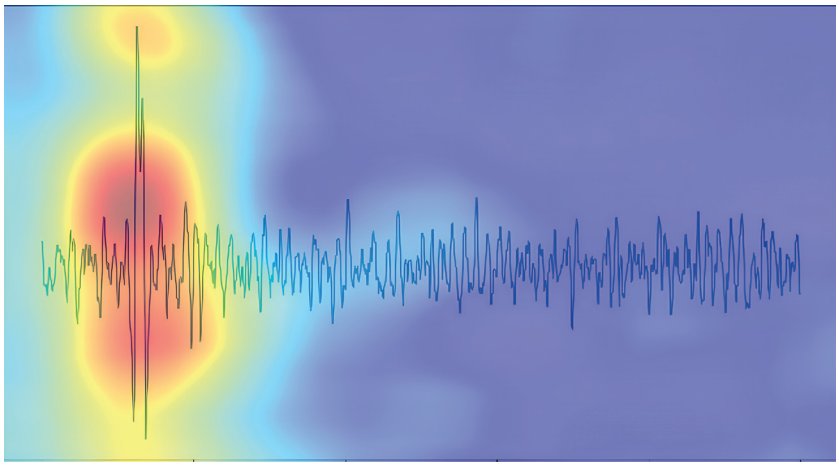


Figure 4. Results of the RISE method applied on the YOLOv8 model.

To determine whether the reason for this result is that the model mainly focuses on the middle region of the broken wire signal for discrimination or whether there is a problem with this perturbation method, experiments were designed.

Note that the RISE interpretability method utilizes random masks for perturbation in a similar way to region masking, both of which work by eliminating pixels from the image. Then, two perturbation approaches were designed in the broken wire signal, i.e., masking the pixel blocks and eliminating the masked areas and splicing the signal, to determine the efficacy of this masking approach by comparing the confidence scores derived from the YOLOv8 model predictions, and the results are presented in Figure 5.

Both methods illustrate the impact of the same perturbed region on the model prediction, but the masking approach destroys the signal's continuity and integrity, characteristics of the signal, and it introduces new features of the pixel block, causing the model prediction confidence score to decrease significantly.

In contrast, the use of splicing removal not only eliminates the influence of regions on the model but also ensures the continuity and integrity of the broken wire signal without introducing new features. This shows the inappropriateness of using perturbations such as region masking on the broken wire signal and also suggests that the model has a focus on the middle region of the broken wire signal, but this is not significant.

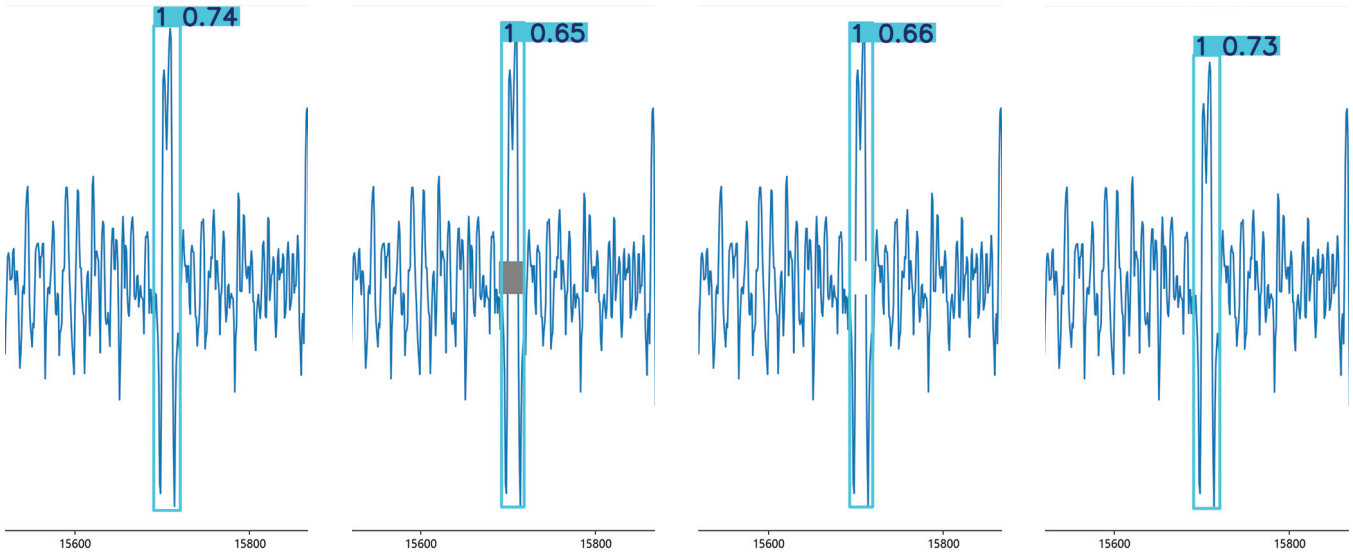


Figure 5. Comparison of two different perturbation approaches. (**a**) The results after the YOLOv8 model predictions have a confidence score of 0.74. (**b**) After masking the middle region of this signal using a gray pixel block, the confidence score is reduced to 0.65, as predicted by the YOLOv8 model. (**c**) Adjusting the pixel value of the gray pixel block to a white pixel block consistent with the background leads to a confidence score of 0.66, as predicted by the model. (**d**) Splicing the upper and lower regions of the interrupted (**c**) broken wire signal leads to a confidence score of 0.73, as predicted by the YOLOv8 model.

2.4. A New Way of Perturbing

Two different perturbation methods are used for the broken wire signal in the middle region and the two ends of the region with different characteristics, respectively. Elimination splicing in the middle region and truncation compensation at the two ends of the region are both perturbation methods used to ensure the continuity and integrity of the signal, as shown in Figure 6.

Initially, the position of the bounding box and the confidence score of the image broken wire signal are acquired through model inference. The diagonal coordinates of the detection box are specified as $(x_1, y_1), (x_2, y_2)$, respectively. The corresponding confidence score is represented as P. The ratio of the range of the center region of the bounding box in the vertical direction to the regions at the two ends is 6:4. This ratio is derived from experiments and is optimal. The methods of calculating the height, width, and height of the central area of the fault signal are given by

$$H_{\text{signal}} = |y_2 - y_1| \tag{1}$$

$$W_{\text{signal}} = |x_2 - x_1| \tag{2}$$

$$H_{\text{center}} = \frac{3 \times H_{\text{signal}}}{5} \tag{3}$$

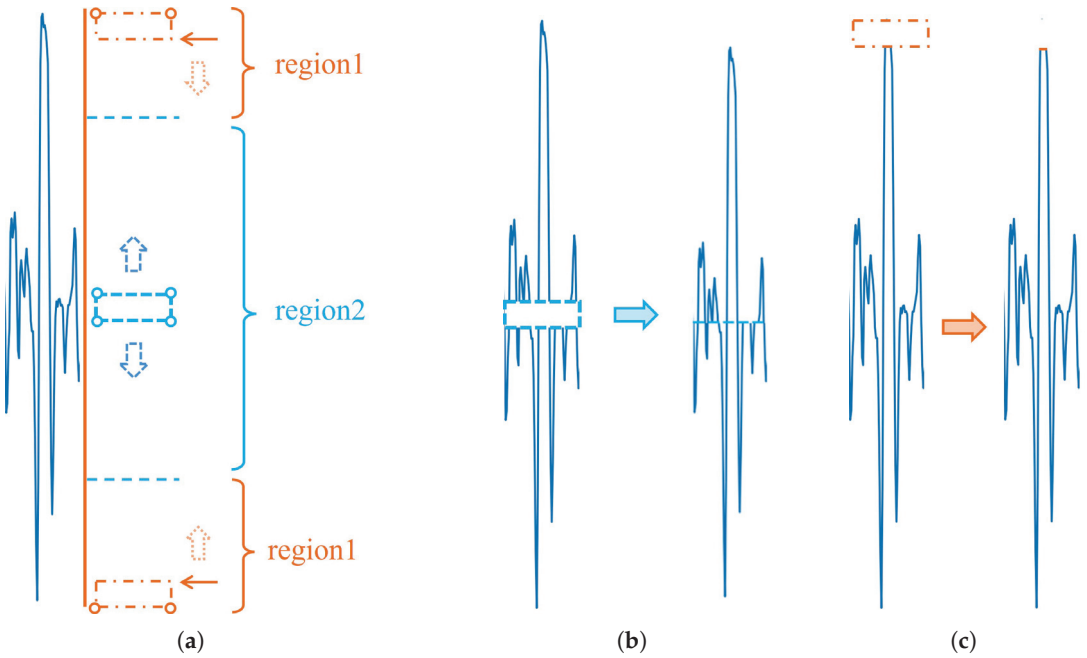


Figure 6. Different perturbation methods are used for different regions of the broken wire signal. (**a**) In region 1, one end of the truncation box is fixed, and its height varies with the number of perturbations until it covers the boundary region. In region 2, the elimination box has a fixed size, and it will move in region 2 until it covers the entire intermediate region. (**b**) The eliminating and splicing process. (**c**) The truncation compensation process.

In the eliminating and splicing perturbation method, the elimination box is set to have the same width as the bounding box. The central region of the broken wire signal exhibits stable and smooth characteristics, whereas the terminal regions display sharp fluctuations and pronounced variability, necessitating separate processing for these two segments. The central region constitutes the majority of the broken wire signal, while the terminal regions comprise a smaller proportion. After testing ratios of 7:3 and 8:2, it was observed that these proportions inadequately encompass the terminal regions. Conversely, a 6:4 ratio effectively covers both terminal regions without excessively encroaching upon the central segment.

During the experiment, it was observed that when the height of an elimination box exceeds 1/24th the height of the central region, discontinuities occur at the splice points, causing signal misalignment across the junction. Therefore, the height of the elimination box must be constrained, and it is necessary to ensure that the height of the central region is an integer multiple of the elimination box height. This ensures the elimination box moves in integer steps, allowing its coverage to precisely span the entire central region. Thus, the elimination box height should be set to, at most, 1/24th that of the central region. The width, height, and movement range of the elimination box are given by

$$W_{\text{elimination box}} = W_{\text{signal}} \tag{4}$$

$$H_{\text{elimination box}} = \frac{H_{\text{center}}}{n} \quad (n \geq 24, n \in \mathbb{N}^*) \tag{5}$$

$$y_1 + \frac{H_{\text{signal}}}{5} \leq y \leq y_2 - \frac{H_{\text{signal}}}{5} \tag{6}$$

Let the diagonal coordinates of the bounding box of the fault signal after each eliminating and splicing perturbation be $(x_3, y_3), (x_4, y_4)$. Then, after this perturbation, the coordinates of the bounding box of the fault signal are calculated as follows:

$$x_3 = x_1, x_4 = x_2 \tag{7}$$

$$\begin{cases} y_3 = y_1 + H_{\text{elimination box}}, y_4 = y_2, & y_1 + \frac{H_{\text{signal}}}{5} \le y \le y_1 + \frac{H_{\text{signal}}}{2} \\ y_3 = y_1, y_4 = y_2 - H_{\text{elimination box}}, & y_1 + \frac{H_{\text{signal}}}{2} \le y \le y_2 - \frac{H_{\text{signal}}}{5} \end{cases} \tag{8}$$

Considering that the height of the center region of the original bounding box is n times that of the elimination box, this eliminating and splicing perturbation is executed n times. Let the confidence score of the model prediction after each eliminating and splicing perturbation be $P^i_{\text{eliminate}} (i \le n)$, and the difference is normalized; then, the weight of this perturbed region after executing each elimination perturbation is as follows:

$$w_i = \frac{|P - P^i_{\text{eliminate}}|}{P} \quad (i \le n) \tag{9}$$

For the perturbation method of truncation compensation, the truncation box is fixed at one end in the vertical direction, and after each perturbation, the height of the truncation box is doubled up to the boundary of the center region. The compensation is used to keep the truncated signal continuous. Specifically, pairs of truncation points are observed at the truncation location and then connected using straight lines of the same pixel as the signal. The calculation of the width and height of the truncation box are given by

$$W_{\text{truncation box}} = W_{\text{signal}} \tag{10}$$

$$H_{\text{truncation box}} = \frac{H_{\text{signal}}}{k} \quad (k \ge 30, k \in \mathbb{N}^*) \tag{11}$$

Let variable i be the number of perturbations; after each truncation compensation perturbation, the height of the truncation box varies as follows:

$$H^i_{\text{truncation box}} = H_{\text{truncation box}} \times i \left(\frac{i}{k} < \frac{1}{5}, i \in 1, 2, 3 \dots \right) \tag{12}$$

Let the diagonal coordinates of the bounding box after the truncation and compensation of the fault signal be $(x_5, y_5), (x_6, y_6)$; then, its coordinates are calculated as follows:

$$x_5 = x_1, x_6 = x_2 \tag{13}$$

$$\begin{cases} y_5 = y_1 + H^i_{\text{truncation box}}, y_6 = y_2, & y_1 \le y_i \le y_1 + \frac{H_{\text{signal}}}{5} \\ y_5 = y_1, y_6 = y_2 - H^i_{\text{truncation box}}, & y_2 - \frac{H_{\text{signal}}}{5} \le y_i \le y_2 \end{cases} \tag{14}$$

Denote the confidence score of the output predicted by the model after each truncation–compensation perturbation as $P^j_{\text{truncation box}}$ and the total number of perturbations at both ends of this fault signal as j. Then, the corresponding weights after each perturbation are calculated as follows:

$$w_j = \frac{|P - P^j_{\text{truncation box}}|}{P} \tag{15}$$

The perturbation weights consisting of w_i and w_j are the weights of the impact of each region of the fault signal in an image on the model. Even if the image contains many fault

signals, it is possible to use this method to calculate the weights of different regions of all the fault signals affecting the model.

Based on the weights obtained for each perturbed region in the detection box, the weight value can be mapped to a pixel range of 0–255 using different pixel values rather than weights for visualization. Then, a separate saliency map of the pixel values produced by the weights in each detection box in the image is drawn, and Gaussian blurring is utilized to remove sharp edge regions. Since a saliency map of the original image size is generated for each detection box in the figure, multiple detection boxes yield multiple individual saliency maps. Overlaying these on the original image may compromise clarity. To address this, all non-zero pixels from the generated saliency maps are integrated into a single-composite saliency map based on their spatial positions, which is then overlaid onto the original image. This approach avoids multiple overlays that could diminish image clarity.

2.5. General Overview of ESTC Application on YOLOv8

Finally, the ESTC method was applied to the YOLOv8 model, and its processing is illustrated in Figure 7. First, a broken wire signal dataset was constructed by manual labeling after signal processing (wavelet transform, etc.) of the signals acquired from the sensor acquisition, where the training set and validation set were used for model training to obtain the best model. Then, the best model was utilized for test set prediction to obtain the confidence score and location information of each broken wire signal on the test set. Taking an image on the test set as an example, if there is a broken wire signal in the image, a batch of perturbed images will be produced after the perturbation, with each image representing a perturbed region of the broken wire signal, and the batch of images will cover the entire broken wire region. Then, through the inference of the YOLOv8 model, the confidence score of each region of the broken wire signal after perturbation will be obtained. The difference between the unperturbed confidence score and the perturbed confidence score is normalized. The weights of the different regions of the image that affect the model are finally obtained, and a saliency map is acquired by overlaying them on the original image.

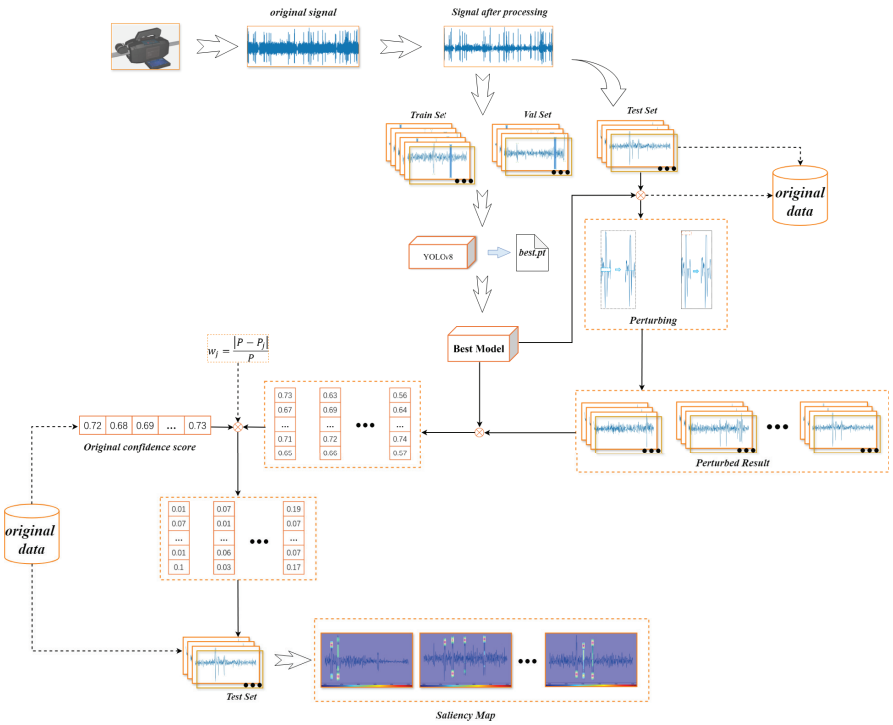


Figure 7. Overview of ESTC application on YOLOv8.

3. Results and Discussion

This paper focuses only on the interpretability analysis of visualizations. To ensure the scientific validity and accuracy of the comparisons, D-RISE, RISE, LIME, and our proposed ESTC method were selected for comparison on the same test set using the same YOLOv8 model weight file. According to the priori knowledge accumulated from manual rope testing, broken wires are mainly judged based on the amplitude of the signal, as well as the shape of the peaks and troughs at the two ends and other features. It is noteworthy that all the interpretable methods are model-agnostic, fully demonstrating that they are sufficiently objective.

Firstly, the highlighted red areas in the saliency map are represented as heat values and are considered as the basis for modeling decisions. Then, the model decision basis produced by each interpretability method is compared with the manual decision basis. If the model decision basis produced by a certain interpretability method better fits with the manual decision basis, it suggests that the interpretability method is superior, indicating that it is more suitable for interpretable analysis of model detection of broken wire signals. The following will show the performance of these four methods on different wire rope categories and multi-target images.

Figure 8 illustrates the results of applying four different interpretable methods to the YOLOv8 model in an image with only one target, and the category is the single-broken-wire category. Regarding the accuracy of the location of the produced heat values, ESTC and RISE all produced heat values at the location of the broken wire signal, except for D-RISE, while LIME also produced a block of pixels in dark red at that location. While D-RISE's heat distribution is around the image and fails to determine how the model generates a decision basis, LIME cannot locate the exact area of the broken wire signal due to the large pixel block. The heat distribution produced by RISE is concentrated in the middle region of the broken wire signal and covers nearly the entire broken wire signal, which only demonstrates that the model pays attention to the entire broken wire signal, especially the middle region, due to the large range of heat values. By contrast, for the ESTC method proposed in this paper, its heat distribution is mainly concentrated in peaks and troughs of the broken wire signal, fitting the best with the manual decision-making basis, indicating that the ESTC method performs better than the other methods in the single-target category of the broken wire image.

Figure 9 shows the interpretability analysis of the four interpretability methods against the YOLOv8 model in the double-broken-wire category of the wire rope break image. The saliency map presented by the ESTC method indicates that the heat values are concentrated at the trough position of the broken wire signal. The D-RISE method employs a detection box to label the target, but the heat distribution is not only around the target but also in the blank area. The LIME method exhibits dark pixel blocks in the target region to differentiate them from the other light-colored pixel blocks, suggesting that it has identified the target region. The RISE method nearly covers the whole target area.

To summarize the comparison, it can be observed that the heat map presented by the D-RISE method does not provide effective assistance for the model to perform interpretable analysis, and the LIME method can locate the more important pixel block areas in the target region, but due to its large pixel block region, it can only conduct a coarse-grained analysis. Though the RISE method provides almost full heat coverage of the entire target region, it is not conducive to analyzing the impact of different regions of the broken wire signal on the model. The method presented by ESTC can reveal the influence of different regions of the target on the model, indicating that the trough location is among the more important regions relative to the other locations of the broken wire signal of the type, while providing a finer granularity of of interpretation.

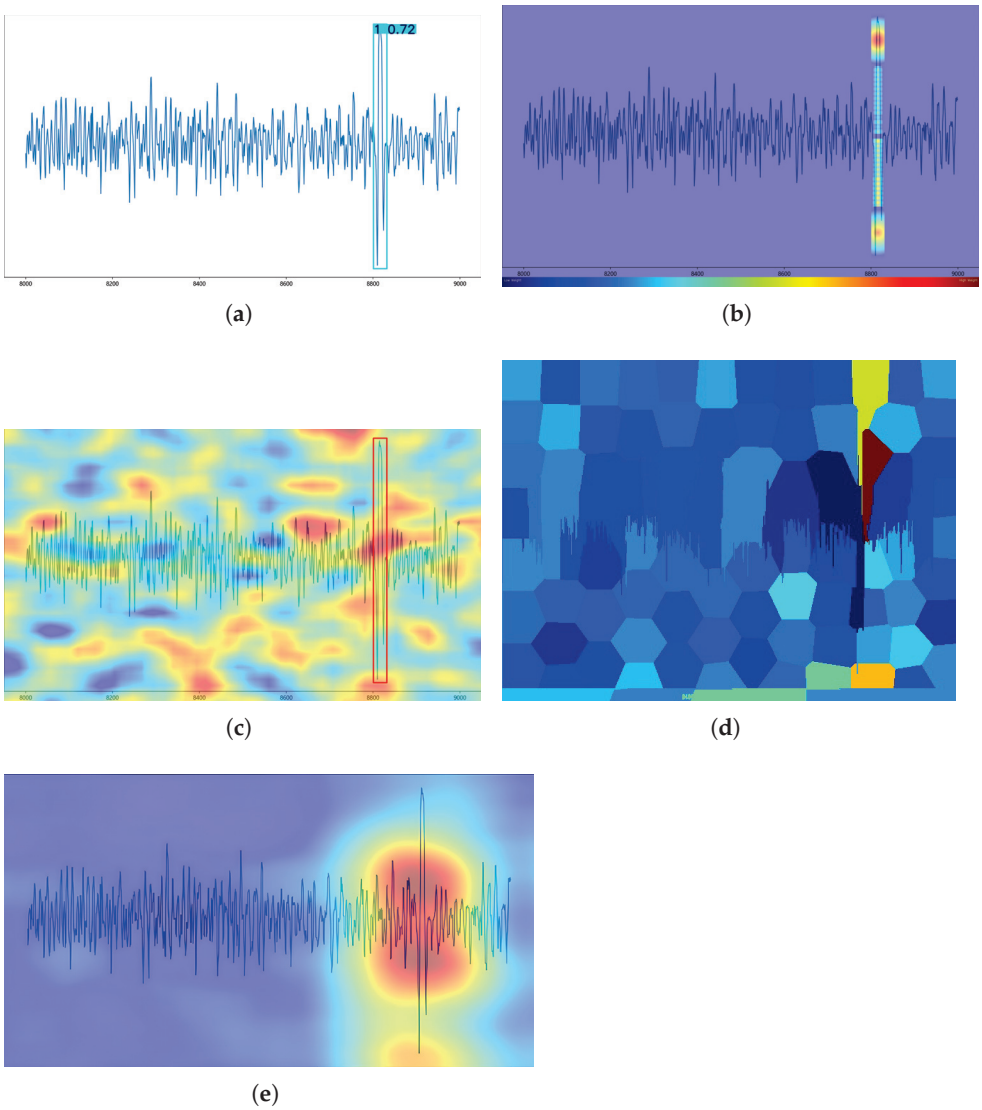


Figure 8. Four interpretability methods were employed to analyze the images with broken wire signals classified into the single-broken-wire category. (**a**) The original image predicted by the YOLOv8 model to belong to the category of single broken wires with a confidence score of 0.72. (**b**) Interpretability analysis results for ESTC with n-ratio set to 1/30 (elimination box size ratio) and k-ratio set to 1/50 (truncation box size ratio). (**c**) Interpretability analysis results for D-RISE. (**d**) Interpretability analysis results for LIME, where the number *num-samples* of samples produced by LIME is 3000. (**e**) Interpretability analysis results for RISE, where the number N of masks in RISE is 6000, the grid size s is 8, and the sparsity ratio $p1$ of masks is 0.2.

Figure 10 shows the interpretability analysis results of the model when there are multiple targets in the broken wire signal image. In the saliency map presented by ESTC, there is heat distribution on each target, concentrated at the two ends of the target, and it should be noted that the heat in the left target is mainly concentrated at the lower end. The detection box in D-RISE only labels a single object, while the heat is distributed in all regions of the image, so it is impossible to determine which regions have a large impact on the model. The LIME method generates blocks of red pixels distributed across many target regions, with each pixel block covering a wider area. The heat produced by RISE does not cover all the targets but is concentrated in the upper-middle region of the two targets on the left side, while the heat distribution of the targets on the right side is not evident.

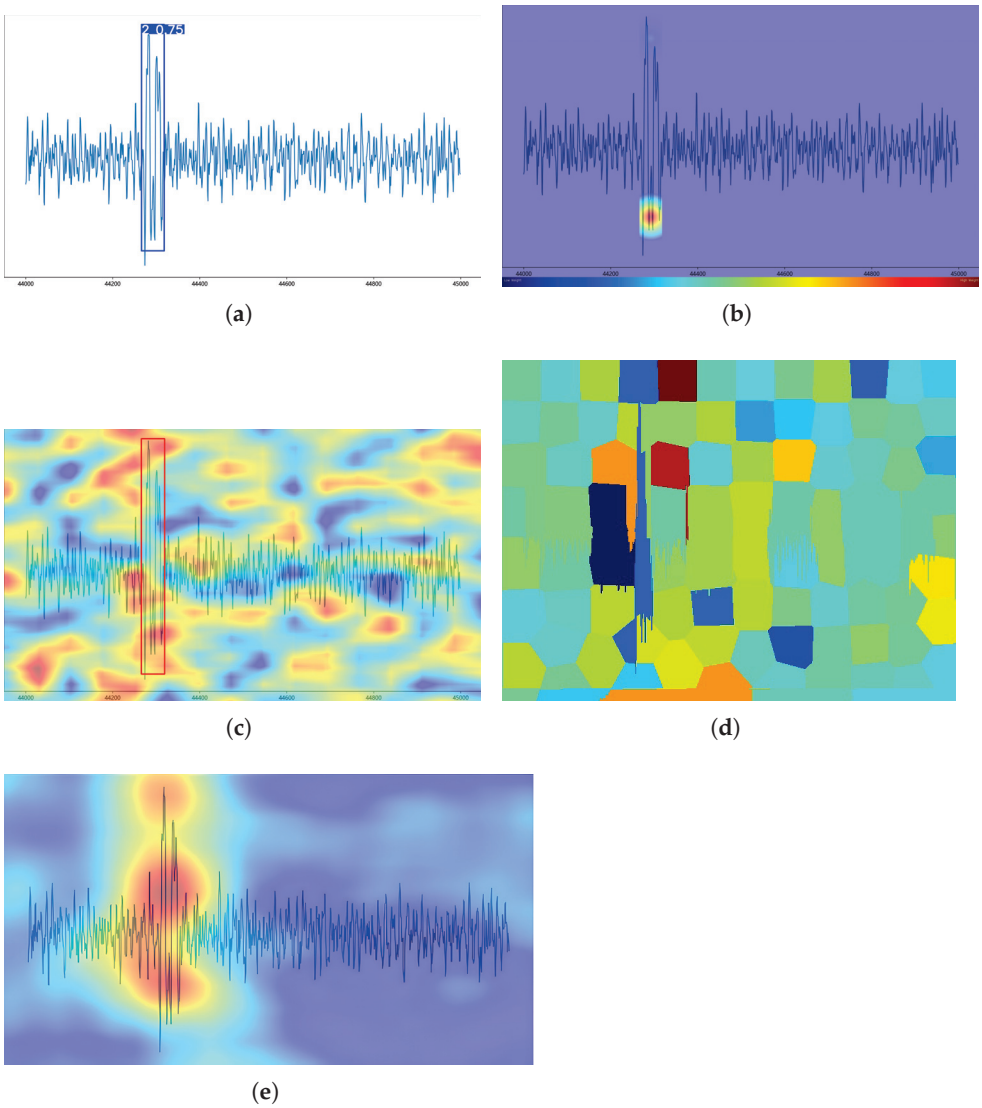


Figure 9. Four interpretability methods were used to analyze the images that were classified as double-broken-wire signals. The parameters of all methods are the same as those in Figure 8. (**a**) The original image predicted by the YOLOv8 model to belong to the category of single broken wires with a confidence score of 0.75. (**b**) Interpretability analysis results for ESTC (**c**) Interpretability analysis results for D-RISE. (**d**) Interpretability analysis results for LIME. (**e**) Interpretability analysis results for RISE.

The comparison results indicate that ESTC outperforms the other three methods, attributed to its more fine-grained explanatory strength, heat distribution for all targets, and the generation of a model decision basis most compatible with manual decision-making.

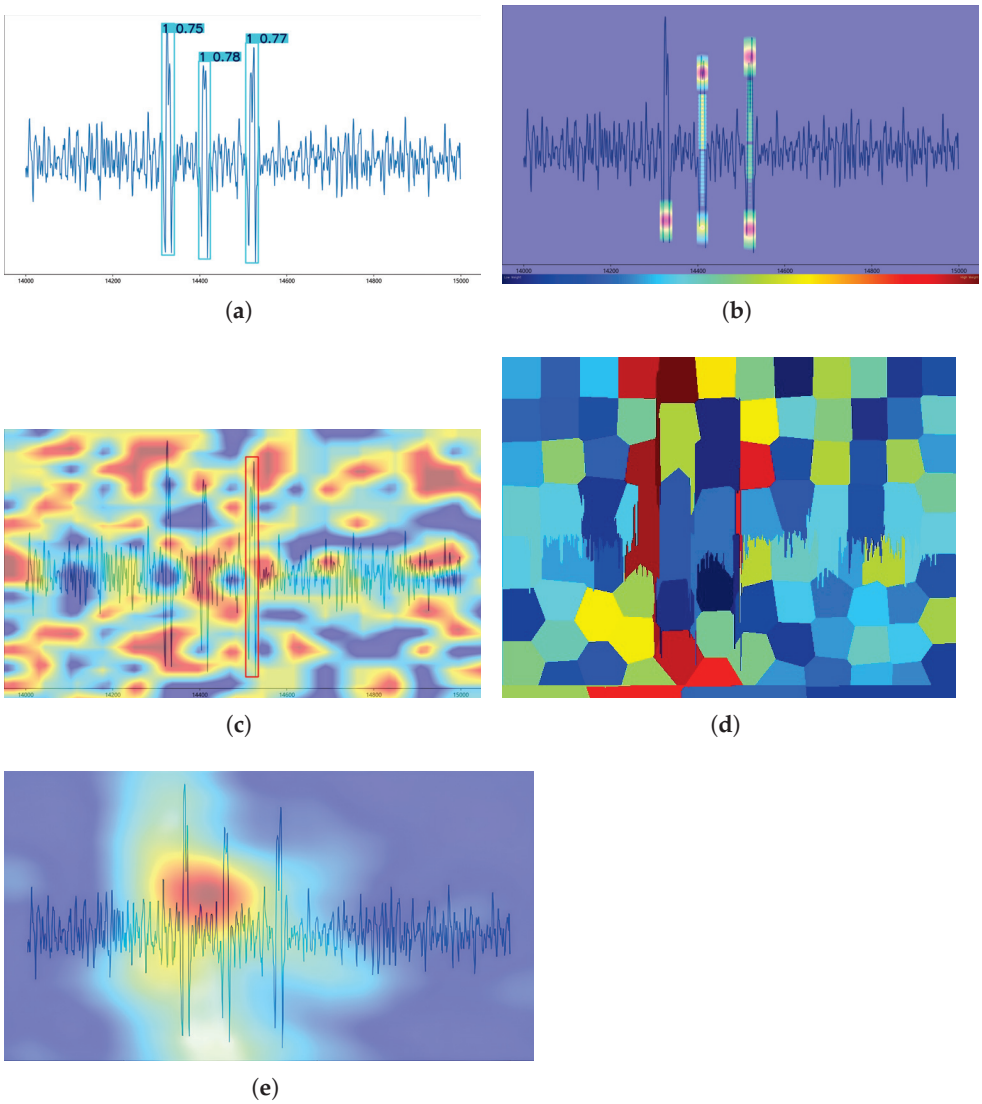


Figure 10. Four interpretability techniques were used to conduct a comprehensive analysis of the images categorized as multi-broken wire signals. The parameters of all methods are the same as those in Figure 8. (**a**) The original image predicted by the YOLOv8 model to belong to the category of single broken wires with a confidence score of 0.75. (**b**) Interpretability analysis results for ESTC. (**c**) Interpretability analysis results for D-RISE. (**d**) Interpretability analysis results for LIME. (**e**) Interpretability analysis results for RISE.

The above four interpretability methods were applied to the entire test set, extensive comparative analyses were carried out, and the performance results were all identical to those of the three experiments described above, where the images in the three comparative experiments were randomly selected from each category in the test set.

When YOLOv8 detects wire rope defects, false positives may occur (—for example, misclassifying normal signals as broken wire signals). Statistical analysis of the test set shows that when background noise increases signal amplitude globally, false detection rates rise because broken wire signals have amplitudes similar to normal ones. This phenomenon is likely caused by wire rope vibrations during sensor data collection. As an interpretable perturbation-based method, ESTC is model-agnostic, meaning its saliency maps can only reflect the contribution weights of signal components during correct or incorrect model detections.

Currently, the ESTC methodology has been validated only for wire rope electromagnetic signal detection. The employed perturbation strategy relies on significant feature differences between target and noise signals, for example, in ECG, where target signals are easily distinguishable from noise signals, which indicates potential applicability. However, for other signal types, if their time-frequency distributions and statistical characteristics differ markedly from those of wire rope signals, direct application of the ESTC approach may be ineffective. Thus, extending ESTC to new signal domains requires adapting the perturbation strategy to specific signal features, involving parameter recalibration and algorithmic optimization, requiring significant implementation costs.

In practical deployment scenarios, the ESTC faces multiple constraints: Firstly, the limited computational capability of edge devices leads to excessive inference latency. Secondly, processing large-scale, long-sequence data significantly elevates memory consumption due to perturbation calculations, often requiring custom hardware acceleration or multi-GPU parallelization. Thirdly, the complex operational conditions of wire ropes—including oil contamination and vibrational exposure—significantly hinder the model's capability to accurately identify wire breakage signals, thereby deteriorating the interpretability and reliability of the ESTC.

4. Conclusions

In this study, the YOLOv8 object detection model was adopted for broken wire detection of wire rope electromagnetic signals, and the best weight files produced by the model were used for interpretability analysis. A new perturbation-based model-agnostic interpretability method called ESTC was proposed, and this method provides a novel signal perturbation approach without destroying signal continuity and integrity compared to traditional perturbation approaches used for common targets. Also, it can determine the weights of the impact of each region where the perturbation is performed on the model decision.

Compared with other model-agnostic perturbation-based interpretability methods, our method shows a finer-grained interpretation, and its interpreted model decision behavior is the most consistent with the decision behavior of the manual rope inspection, validating its superiority for signal detection. The explanation it provides is important for improving human trust in the model for broken wire detection and for integrating the model into industrial automation systems.

With the advancement of deep learning technology, the ESTC algorithm can be integrated with more advanced deep learning models in the future. Interpretability analysis of new detection models will guide the optimization of model architectures and parameters, enabling simultaneous improvements in detection accuracy and decision interpretability. Furthermore, ESTC can be embedded into industrial IoT and intelligent diagnostic platforms, collaborating with monitoring data and diagnostic models of other industrial equipment. By interpreting the wire rope broken detection model and integrating it with operational data across the industrial system, comprehensive equipment health management and fault prediction can be achieved, providing deeper support for the intelligentization of industrial development.

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Time-Series Forecasting Method Based on Hierarchical Spatio-Temporal Attention Mechanism

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Abstract: In the field of intelligent decision-making, time-series data collected by sensors serves as the core carrier for interaction between the physical and digital worlds. Accurate analysis is the cornerstone of decision-making in critical scenarios, such as industrial monitoring and intelligent transportation. However, the inherent spatio-temporal coupling characteristics and cross-period long-range dependency of sensor data cause traditional time-series prediction methods to face performance bottlenecks in feature decoupling and multi-scale modeling. This study innovatively proposes a Spatio-Temporal Attention-Enhanced Network (TSEBG). Breaking through traditional structural designs, the model employs a Squeeze-and-Excitation Network (SENet) to reconstruct the convolutional layers of the Temporal Convolutional Network (TCN), strengthening the feature expression of key time steps through dynamic channel weight allocation to address the redundancy issue of traditional causal convolutions in local pattern capture. A Bidirectional Gated Recurrent Unit (BiGRU) variant based on a global attention mechanism is designed, leveraging the collaboration between gating units and attention weights to mine cross-period long-distance dependencies and effectively alleviate the gradient disappearance problem of Recurrent Neural Network (RNN-like) models in multi-scale time-series analysis. A hierarchical feature fusion architecture is constructed to achieve multi-dimensional alignment of local spatial and global temporal features. Through residual connections and the dynamic adjustment of attention weights, hierarchical semantic representations are output. Experiments show that TSEBG outperforms current dominant models in time-series single-step prediction tasks in terms of accuracy and performance, with a cross-dataset R^2 standard deviation of only 3.7%, demonstrating excellent generalization stability. It provides a novel theoretical framework for feature decoupling and multi-scale modeling of complex time-series data.

Keywords: time-series forecasting; BiGRU; SENet; GlobalAttention

1. Introduction

Driven by the Internet of Things (IoT) and big data technologies, massive amounts of data have been accumulated in fields such as industry, finance, and the natural sciences. Advances in sensor, computing, and communication technologies continuously generate data for time series. These technological innovations have profoundly changed the way complex systems are monitored and controlled. Time-series data, which consists of data

points arranged in chronological order, has become a critical element in the operations of many fields. Its continuous accumulation over time and ability to accurately predict future trends play a vital role in practical applications. For example, in the financial sector, the prediction of stock price trends [1] and cash flows directly affects the success or failure of investment decisions. In retail, traffic flow forecasting [2] is used to optimize supply chains and inventory management effectively. Scenarios such as meteorological change analysis and tourism traffic estimation [3] also rely on time-series data to provide solid data support for decision-makers and facilitate scientific decision-making.

The core task of time-series forecasting is to reasonably predict the observed value at time T + 1 based on the data at time T (the current moment). Given the wide applications of time-series forecasting in real life, numerous scholars have conducted in-depth research in this field. Currently, mainstream forecasting methods are mainly divided into traditional forecasting methods and machine learning-based forecasting methods. Traditional methods include the autoregressive (AR) [4], Moving Average (MA) [5], Autoregressive Moving Average (ARMA) [6], and Autoregressive Integrated Moving Average (ARIMA) [7] models, among others. However, these methods still have certain limitations when faced with complex and changeable real-world data. This study aims to overcome the existing challenges in time-series forecasting, further improve the effectiveness and accuracy of forecasting, and provide more reliable technical support for the development of related fields.

In recent years, deep learning has emerged as a new approach in which each module transforms one level of abstraction into another, enabling deep learning to learn features from data. In the field of time-series forecasting, the deep learning model RNN [8] has been widely used; however, it is prone to gradient disappearance and explosion during training. To address this, a Long Short-Term Memory Network (LSTM) [9] and GRU [10] were developed. Although they effectively solved the gradient problem, the prediction accuracy remained unsatisfactory. Compared with traditional recurrent networks, such as LSTM and GRU, TCN [11] has higher accuracy and a simpler structure. However, it does not consider the weight relationship between channels, leading to low-importance information participating in the calculations and weakening the weight of key information. While GRU can handle long-range dependencies and avoid gradient disappearance to a certain extent, its reset gate mechanism tends to ignore most of the current information during processing. Although BiGRU [12] can bidirectionally extract local features, it lacks the ability to integrate global information, making it difficult to achieve dimensionality elevation from local time-domain features to global vision feature representations. Although TCN and BiGRU variant models combined with attention mechanisms have shown certain advantages in time-series forecasting, such models only optimize network performance from a single dimension, lacking multi-scale and multi-level information interaction and fusion, and thus struggle to fully exploit complex features and dependency relationships in the data, which limits further improvements in model performance. To address the long-range dependency problem, models combined with attention mechanisms have become a research hotspot. For example, Attention-LSTM enhances the focus on key time steps through a self-attention mechanism; however, the computational complexity increases quadratically with the sequence length. The Informer uses a sparse attention mechanism to reduce the complexity to linearity, achieving a 2.3-fold improvement in the inference speed for meteorological data prediction. However, such models are mostly optimized from a single dimension (e.g., only enhancing attention in the time dimension) and lack weight screening in the feature dimension. In the field of time-series forecasting, traditional and deep learning models have long been constrained by the dual challenges of single-dimensional feature extraction and insufficient long-range dependency modeling capabilities. This study proposes the TSEBG hybrid network model, which deeply integrates SENet [13] and the Global Attention

mechanism [14] into the TCN and BiGRU models. It primarily reconstructs the time-series forecasting paradigm through three core innovations:

(1) This study proposes a TSEBG hybrid network model that innovatively fuses channel and global attention mechanisms. Specifically, the SENet is embedded in the TCN to construct a dynamic weight-allocation system that enhances the cross-dimensional features. Global attention is introduced into BiGRU to build a long-range dependency framework that accurately captures sequential features. The collaboration of these two mechanisms breaks through traditional bottlenecks and significantly improves the prediction accuracy of multivariate time series.

(2) To address the challenge of fragmented processing of local and global information in traditional models, a hierarchical collaborative feature fusion network is constructed. Based on a dual-channel structure, it realizes complementary learning of multi-time-scale features and designs a cross-layer fusion strategy to achieve multi-level alignment of spatial-temporal information. Synergistically optimizing local details and the global context-time series significantly enhances the representation capability of complex time-series data.

(3) The TSEBG model was applied to time-series forecasting and compared with mainstream deep learning models on the Electricity Transformer Temperature (ETT) dataset. The results of the experiments show that the model reduces the root mean square error (RMSE) by an average of 18.4%, decreases the mean absolute error (MAE) by 21.9%, and significantly optimizes R^2. With its dual-channel collaboration and cross-layer fusion architecture, the TSEBG can capture time-series features more accurately and demonstrate excellent error control capabilities in single-step prediction tasks.

This study focuses on the shortcomings of traditional and deep learning methods in feature extraction and long-range dependency modeling for time-series forecasting and proposes the TSEBG model enhanced by dual attention mechanisms. By innovatively integrating attention mechanisms and constructing a hierarchical feature collaboration network, it breaks through existing technical bottlenecks. Experiments confirmed that the proposed model exhibited strong performance and prediction capabilities. This study provides new ideas and methods for constructing time-series forecasting models and enriches the theoretical system of time-series forecasting.

2. Related Work

The development of time-series forecasting models began with the autoregressive (AR) model proposed by the British statistician Yule. The core of this model lies in the fact that the output variable largely depends on its own previous values and random conditions. To enhance predictive capabilities, the academic community has improved the AR model by deriving the Moving Average (MA) and Autoregressive Moving Average (ARMA) models. However, the ARMA model has limitations in handling non-stationary time-series data. To address this issue, the Autoregressive Integrated Moving Average (ARIMA) model was developed, which stabilizes data through one or more differencing steps. However, differencing operations often amplify data noise and affect the prediction accuracy. Based on this, Peter and Slivia [15] proposed the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model, which introduces external variables to enhance the explanatory power of time-series data.

Traditional time-series forecasting methods have obvious shortcomings. On the one hand, they have large prediction errors, struggle to uncover dynamic relationships between multiple variables, and fail to effectively capture complex dependency structures. On the other hand, they exhibit low efficiency and high computational complexity when processing large-scale datasets. To overcome these drawbacks, machine learning techniques have

been widely applied to non-stationary time-series forecasting, such as support vector machines (SVM) and neural networks [16]. Thissen et al. [17] and Gui et al. [18] proposed a prediction model based on support vector machines (SVM) called support vector regression (SVR), which yields better results than ARIMA. Least squares support vector machines (LS-SVM) modify the constraints of the objective function. Wang and Hu [19] compared SVM and LS-SVM in solving regression prediction problems and found that LS-SVM is more suitable for large-scale problems. These methods can automatically learn features from data and have stronger modeling capabilities for complex, nonlinear relationships. Sun and Zhao [20] compared the short- and long-term performance differences between artificial neural networks (ANN) and LS-SVM in exchange rate forecasting, verifying the advantages of LS-SVM in handling large-scale data and complex nonlinear relationships. Zhao and Xia [21] applied neural networks to short-term time-series forecasting of nonlinear data.

In recent years, deep learning has been applied to time-series forecasting. Wu and Xu et al. [22] proposed the Autoformer model, which combines sequence decomposition and autocorrelation mechanisms to significantly improve long-term time-series forecasting performance; Liu et al. [23] proposed innovative solutions for the non-stationarity of time series. Kaleem and Muhammad [24] proposed a hybrid model combining CNN and LSTM to predict load values at the next time point under STLF (Short-Term Load Forecasting), demonstrating significantly improved performance compared to the traditional ARIMA model. Dasgupta and Osogami [25] proposed a Gaussian Dynamic Boltzmann Machine (Gaussian DyBM) by integrating an RNN. The parameter update method of the Gaussian DyBM does not rely on backpropagation algorithms; therefore, parameter updates are independent of data dimensions or maximum lags. These features render the Gaussian DyBM more robust and scalable. In 2023, WEN et al. [26] proposed an LSTM-Attention-LSTM parallel prediction model and compared it with some CNN and LSTM variant models. In the same year, Cai et al. [27] proposed a method based on the parallel fusion of CNN and GRU to improve the accuracy and efficiency of power-quality disturbance classification. However, LSTM has black-box properties, making its internal operating mechanisms difficult to intuitively interpret and leading to insufficient interpretability. RNN [28] can set output data based on current and past input sequences, but they use the Backpropagation Through Time (BPTT) algorithm for network training, which causes gradient disappearance when processing long time intervals sequentially. GRU also has limitations in interpretability, making it difficult to clearly demonstrate decision-making processes and logically understand data features. To address these issues, this paper designs a model that combines a Temporal Convolutional Network (TCN) with a Bidirectional Gated Recurrent Unit (BiGRU), endowing it with strong capabilities to effectively capture sequence patterns and dependency relationships between elements. Therefore, channel and global attention mechanisms were introduced to further enhance the model's precise time-series modeling capabilities, especially in handling complex seasonal and periodic patterns. This allows the model to focus more accurately on key information and achieve accurate analysis and processing of time series.

In summary, during the iterative development of time-series forecasting models from traditional to machine learning and deep learning models, while there have been certain improvements in prediction accuracy, prediction errors have not been significantly reduced. This paper innovatively proposes a TSEBG time-series forecasting model. To address issues such as the non-stationarity of time series, we propose starting with strengthening sequence feature capture and key information, designing a multimodal feature fusion network to model sequences from different perspectives, and achieving high-precision time series forecasting.

3. Methodology

To address the challenges of feature extraction and dependency modeling in time-series forecasting, the TSEBG model proposes a dual-channel collaborative feature extraction and spatio-temporal feature fusion network architecture. This architecture fully integrates the advantages of the TCN and BiGRU. The dual-domain attention collaborative network achieves adaptive weight allocation for the Temporal Convolutional Network (TCN) and integrates the global time-domain features extracted by the Bidirectional Gated Recurrent Unit (BiGRU), enabling the efficient decomposition of multi-scale features and cross-layer fusion. This allows the model to accurately capture long- and short-term dependencies, strengthen key feature representation, and overcome the single-dimensional processing limitations of traditional models. The detailed architecture is illustrated in Figure 1.

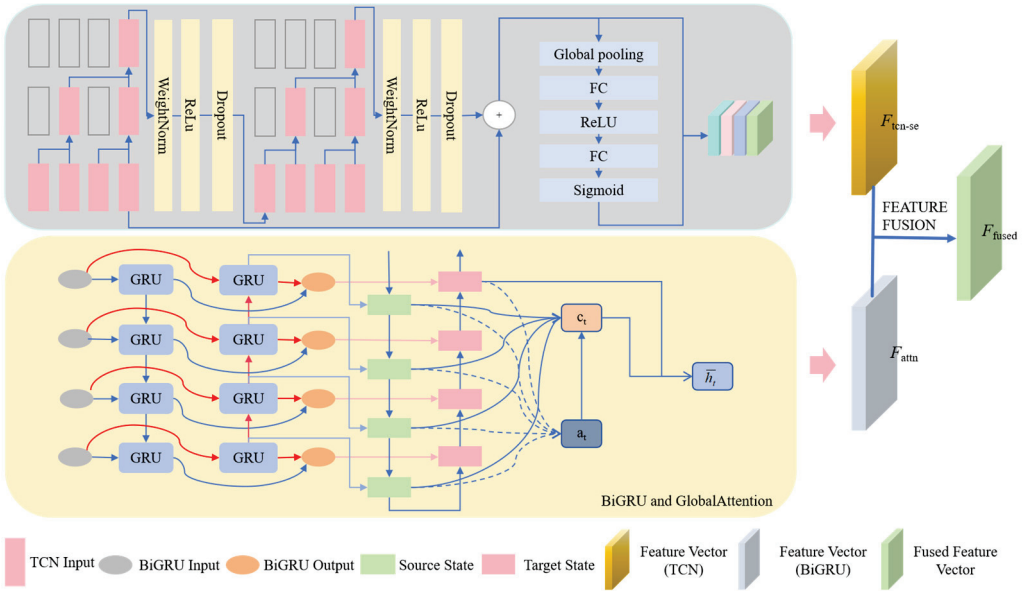


Figure 1. TSEBG model structure diagram.

3.1. Spatio-Temporal Convolutional Feature Adaptive Extraction Network Based on SENet

To overcome the limitations of traditional Temporal Convolutional Networks (TCN) in single-dimensional feature processing, the TSEBG model proposed in this paper constructs a first-of-its-kind feature extraction channel. By innovatively integrating the channel attention mechanism (SENet) with the Temporal Convolutional Network (TCN), it achieves adaptive adjustment of the channel weights in the TCN network. This enables cross-dimensional dynamic enhancement and selective extraction of time series features, effectively addressing the single-dimensional feature processing limitations of traditional TCN. Its multi-scale information mining capability lays the foundation for subsequent multimodal feature fusion and long-range dependency modeling. The detailed network architecture is illustrated in Figure 2.

In this channel, the input data $X \in \mathbb{R}^{B\times T\times D}$ is received, where B represents the batch size, T is the number of time steps, and D is the feature dimension. The output Y_{conv1} of the dilated causal convolution of the first residual block in TCN is:

$$Y_{conv1} = \sum_{k=0}^{K-1} w_k \times X_{t-d\cdot k} \tag{1}$$

where w_k represents the weight of the convolution kernel, d is the dilation factor, whose value grows exponentially with the increase of network depth; K represents the number of

convolution filter windows (kernels), and k refers to a specific convolution filter window. This operation can effectively expand the receptive field without increasing the computational load and only considers data from the current and past time steps without involving future data [29]. Subsequently, it passes through normalization, the activation function $(ReLU(Y_{conv1}))$ and the Dropout layer in sequence. Since the residual block of TCN contains this process twice, the output of the second—layer dilated causal convolution is Y_{conv2}, which then passes through normalization, the activation function, and the Dropout layer again, and the final output is Y'_{conv2}. Finally, a residual connection operation is performed within the residual [30] block as follows:

$$Y_{res} = \mathrm{Re}LU\left(Y'_{conv2} + Conv1D_{1\times1}(Y)\right) \tag{2}$$

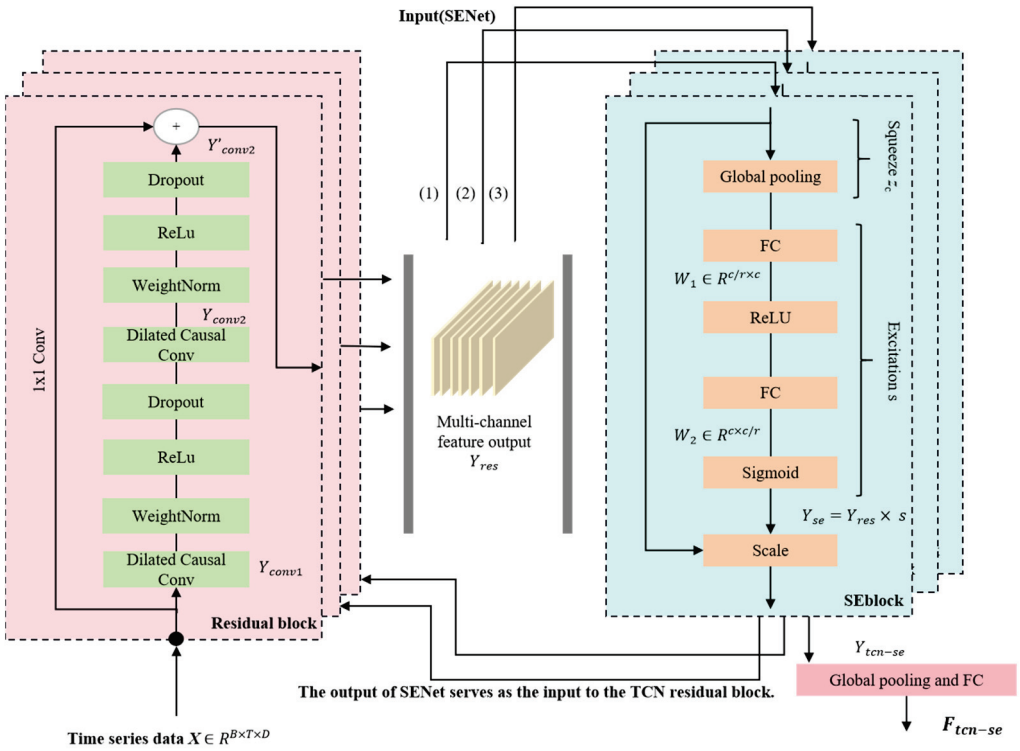


Figure 2. TCN Network structure diagram integrated with SENet.

In this process, there is a 1D convolution operation to ensure that X and Y'_{conv2} can have aligned dimensions for element—wise addition. This connection method not only helps stabilize the training process but also enables the capture of richer information (Yang et al. [31]). The output Y_{res} of the TCN residual block is a multi—information channel. To adaptively select the most discriminative subset of information, we introduce the SENet channel attention mechanism here. Taking Y_{res} as the input of SENet, the global average pooling (Squeeze) operation is performed:

$$z_c = \frac{1}{T}\sum_{t=1}^{T} Y_{res,t} \tag{3}$$

z_c is the compressed value of the c-th channel. This operation aggregates the global information of the feature maps. By compressing the feature map in the spatial dimension, the two-dimensional spatial information of each feature map channel is transformed into a real number, thus obtaining a channel descriptor. This descriptor can capture the global statistical information of the entire feature map across all the channels. Subsequently, an

excitation operation is performed. The channel weights are learned through two fully—connected layers:

$$s = \sigma(\mathrm{W}_2 \cdot \mathrm{Re}LU(\mathrm{W}_1 \cdot z)) \tag{4}$$

where $W_1 \in \mathbb{R}^{C/r \times C}$ and $W_2 \in \mathbb{R}^{C \times C/r}$ are the weights of the fully connected layers, and the reduction factor is 16. First, this operation is processed by a fully—connected layer, and the output size is $(C/reduction)$; subsequently, it passes through a ReLU activation layer, and then through another fully—connected layer, the dimension is restored to the original C. Finally, sigmoid normalization is performed to obtain a value between 0 and 1, which is the weight of each channel. In the last step of SENet, the weight s is multiplied $(scale)$ with the corresponding channel of the original input Y_{res} to obtain the final output Y_{se}:

$$Y_{se} = Y_{res} \cdot s \tag{5}$$

The TCN network of the TSEBG model contains multiple residual blocks. We introduce the SENet attention mechanism after each residual block. The output of the SENet in the first layer is then used as the input for the residual block in the second layer. Through this alternating stacking of TCN and SENet, a hierarchical feature extraction structure is formed:

$$Y_{tcn-se} = SEBlock(TCN(SEBlock(TCN(X)))) \tag{6}$$

Finally, through global average pooling and a fully—connected layer, the prediction result F_{tcn-se} is generated. In the model architecture, the SENet and TCN modules form a cascaded processing unit of "temporal convolutional feature extraction—channel attention optimization". This not only provides a more focused feature input for the subsequent temporal dynamic modeling of BiGRU but also significantly enhances the model's ability to represent complex time—series patterns through the re-distribution of information in the channel dimension.

3.2. Bidirectional Gated Global Temporal Feature Extraction Network Based on Global Attention Mechanism

To achieve in-depth modeling of complex dynamic features in time-series data, this paper innovatively constructs a Bidirectional Gated Recurrent Unit (BiGRU) based on a global attention mechanism as the second feature extraction channel. This module breaks the traditional unidirectional information processing model and deeply couples the bidirectional information flow structure with the global attention mechanism to build a novel architecture with spatio-temporal feature perception. This module can simultaneously capture long-range dependencies in time-series data from both forward and reverse dimensions, accurately screen, and effectively integrate temporal context information in the sequence. The detailed network architecture is illustrated in Figure 3.

In the TSEBG model, BiGRU and TCN jointly receive the input sequence $X \in \mathbb{R}^{B \times T \times D}$, where B represents the batch size, T is the number of time steps, and D is the feature dimension. BiGRU ingeniously concatenates two GRU modules. Its mechanism is rooted in splitting standard GRU neurons into two different states: forward and backward (representing positive and negative time directions, respectively) [32]. X is first output through forward and backward GRUs. The GRU is composed of two key gate structures, the update gate z_t and the reset gate r_t, and the calculation formulas are as follows:

$$z_t = \sigma(W^z \cdot x_t + U^z \cdot h_{t-1}) \tag{7}$$

$$r_t = \sigma(W^r \cdot x_t + U^r h_{t-1} + b^r) \tag{8}$$

$$h'_t = \tanh\left(W^{h'} \cdot x_t + U^{h'} \cdot (r_t \odot h_{t-1}) + b^{h'}\right) \tag{9}$$

$$h_t = (1 - z_t) \times h_{t-1} + z_t \times h'_t \tag{10}$$

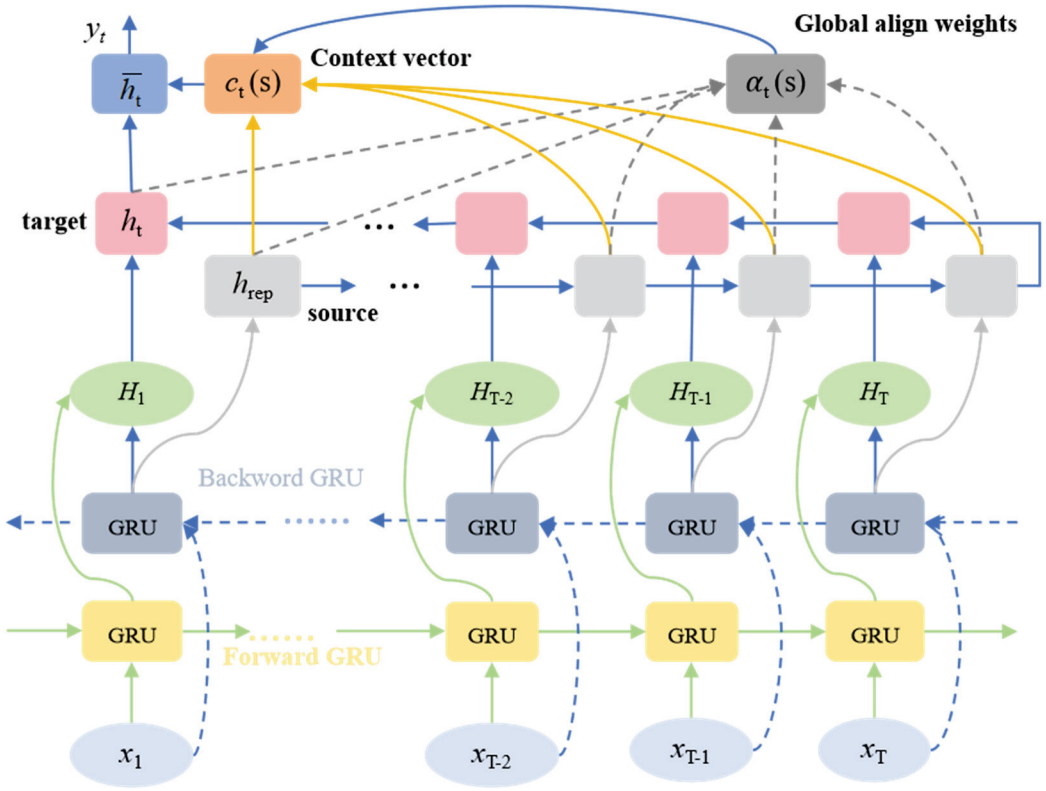


Figure 3. Flowchart of the BiGRU model with the introduction of GlobalAttention.

For a single time step t, the input is $x_t \in \mathbb{R}^{B \times D}$, and the hidden state at the previous time step is $h_{t-1} \in \mathbb{R}^{B \times H}$ (H is the dimension of the hidden layer). In this process, the combination of the new input x_t and the hidden state of the previous time step (which can be understood as the previous memory) h_{t-1} is adjusted by the reset gate r_t. r_t can control the degree to which the information of the previous hidden state is retained at the current time step, thus flexibly determining how much historical information participates in the current calculation. The update gate z_t, on the other hand, is responsible for controlling the retention of the previous hidden state h_{t-1}, thereby determining the degree to which the new hidden state h_t inherits historical information.

The forward GRU unit processes the input sequence to compute the forward hidden state sequence h_t^{fwd} for all time steps, capturing the contextual information from the past to the future. Concurrently, the backward GRU processes the reversed input sequence to generate the backward hidden state sequence h_t^{bwd}, capturing the contextual information from the future to the past. Subsequently, the bidirectional hidden states at each time step t are concatenated as follows:

$$H_t = \left[h_t^{fwd}; h_t^{bwd}\right] \tag{11}$$

Finally, the output of BiGRU is the bidirectional hidden states for all time steps $H = [H_1, H_2, \ldots, H_T] \in \mathbb{R}^{B \times T \times 2H}$. In the TSEBG model, the number of BiGRU layers is greater than one. To calculate the importance weights for each time step and perform weighted aggregation on the hidden state sequence H output by BiGRU, focusing on key temporal features, we introduce a global attention mechanism after BiGRU. Taking the output H of the last BiGRU layer as the target value, and the final hidden state $h_{final} \in \mathbb{R}^{B \times H}$ of the last backward GRU in the last BiGRU layer as the source state (i.e., the query vector). Here, we repeat h_{final} T times along the time step dimension to obtain $h_{rep} \in \mathbb{R}^{B \times T \times 2H}$,

and then concatenate H and h_{rep} to obtain $h_{con} \in \mathbb{R}^{B\times T\times 4H}$. The energy vector is calculated using a linear transformation as follows:

$$e_t = \tanh(W_{attn}h_{con} + b_{attn}) \tag{12}$$

where $W_{attn} \in \mathbb{R}^{2H\times 4H}$ and $e_t \in \mathbb{R}^{B\times T\times 2H}$. The weight vector is calculated using this energy vector e_t as follows:

$$\alpha_t = \text{softmax}\left(w_v^T e_t\right) \tag{13}$$

Here, $w_v \in \mathbb{R}^{2H}$, $\alpha_t \in \mathbb{R}^{B\times T}$, and the sum of the weight vectors across all time steps is 1. This weight vector α_t reflects the degree of importance of each source state for the current target state. Finally, the global context vector is generated as follows:

$$c = \sum_{t=1}^{T} \alpha_t \times H_t \tag{14}$$

When deriving the context vector c_t, all the hidden states of H_t are comprehensively considered. Thus, the final output F_{attn} of this channel is obtained. This process not only effectively focuses on the sequence segments that are most valuable for the current task, but also, through the integration of information across time steps, elevates the local temporal features extracted by the BiGRU to a global feature representation.

3.3. Local Spatial and Global Temporal Feature Fusion Channel

In the final stage of model construction, a dynamic gating feature fusion strategy is adopted. Using learnable gating weights, the contribution ratios of the TCN and BiGRU features are adjusted in real-time, addressing the limitations of static weights in traditional feature fusion methods.

In this module, first, we map the final output features F_{tcn-se} and F_{attn} of the two channels to the same dimension D = embed_dim through linear transformations. The calculation formula is as follows:

$$TSTransformed = W_{tcn} \times F_{tcn-se} + b_{tcn} \tag{15}$$

$$BGTransformed = W_{gru} \times F_{attn} + b_{gru} \tag{16}$$

The output dimensions are $TSTransformed \in \mathbb{R}^{B\times D}$ and $BGTransformed \in \mathbb{R}^{B\times D}$. Then, through a gating mechanism, the original features are concatenated as $gate = Concat(F_{tcn-se}, F_{attn})$ to generate a gating signal, which is used to adaptively determine the importance of the two types of features as follows:

$$gatevalue = \sigma(W_g \times gate + b_g) \tag{17}$$

where $W_g \in \mathbb{R}^{1\times(C_{tcn}+C_{gru})}$ is the weight of the linear layer, $b_g \in \mathbb{R}^1$ is the bias, σ is the Sigmoid function, which compresses the gate value to the range of 0 to 1, and the output dimension is $gatevalue \in \mathbb{R}^{B\times 1}$. Subsequently, the two types of features are weighted and summed using the gate value as follows:

$$F_{fused} = gatevalue \times TSTransformed + (1 - gatevalue) \times BGTransformed \tag{18}$$

When $gatevalue \approx 1$, the fusion result is dominated by the TCN—SENet features; when $gatevalue \approx 0$, the fusion result is dominated by the BiGRU—GlobalAttention features; intermediate values indicate the mixing ratio of the two types of features, which is dynamically determined by the input data.

Finally, the fused features are mapped to the prediction dimension using a linear layer:

$$predict = W_{fc} \times F_{fused} + b_{fc} \tag{19}$$

This feature fusion method achieves efficient fusion of temporal—spatial features and temporal—context features through mathematical linear transformations and non—linear activations, combined with dynamic weight allocation, providing a more discriminative feature representation for subsequent prediction tasks.

The dual—channel feature extraction architecture adopted by the TSEBG model: On the one hand, dilated convolutions are used to mine multi—scale temporal dependency features, and combined with SENet to adaptively calibrate channel weights, extracting important spatial features of time series; on the other hand, by dynamically generating attention weights, it focuses on the temporal features relevant to the prediction step, enhancing the ability to capture long—range temporal dependencies. Finally, after dynamic gating feature fusion, the fully—connected layer completes the prediction. The pseudocode for the TSEBG is described in Algorithm 1.

Algorithm 1 TSEBG

Require: model parameters
initialize the model: Model=TSEBG, sliding window
Input: Time-series $X = (X_1, X_2, X_3, \ldots, X_t)$
While stopping criterion is not satisfied do:
  channel one: temporal-spatial feature extraction
    Dilated Caulsal Conv output: $Y_{conv1,conv2} = \sum_{k=0}^{K-1} w_k \times X_{t-d\times k}$
    WeightNorm, ReLu and Dropout Layer: $\hat{Y}_{conv2}$
    Residual Calculation: $Y_{res} = RELU\left(\hat{Y}_{conv2} + Conv1D_{1\times1}(Y)\right)$
    Squeeze and Excitation: $z_c = \frac{1}{T}\sum_{t=1}^{T} Y_{res,t}\ \ s = \sigma(W_2 \times ReLU(W_1 \times z))$
    Scale: $Y_{se} = Y_{res} \times s$
    Connect SENet after each TCN residual block to compute channel weights:
    $$Y_{tcn-se} = SEBlock(TCN(SEBlock(TCN(X))))$$
    After global average pooling and a fully connected layer: F_{tcn-se}
  channel two: time-domain feature extraction
    The input data passes through the forward and backward GRU units sequentially:
      Update Gate: $z_t = \sigma(W^z x_t + U^z h_{t-1})$
      Reset Gate: $r_t = \sigma(W^r x_t + U^r h_{t-1} + b^r)$
      Candidate State: $h'_t = tan\left(W^{h'} x_t + U^{h'}(r_t \odot h_{t-1}) + b^{h'}\right)$
      Current Hidden State: $h_t = (1 - z_t)h_{t-1} + z_t {h_t}'$
    Concatenate the bidirectional hidden states: $H_t = \left[h_t^{fwd}; h_t^{bwd}\right]$
    Concatenate the output of the BiGRU with the final hidden state of the backward layer from the last BiGRU layer, repeated T times, to obtain h_{con}
    Calculate the energy vector: $e_t = tanh(W_{attn} h_{con} + b_{attn})$
    Calculate the weight vector: $\alpha_t = softmax\left(w_v^T e_t\right)$
    Finally generate the global context vector and ouput F_{attn}: $c = \sum_{t=1}^{T} \alpha_t \times H_t$
  Feature Fusion:
    Feature Mapping: $TSTransformed = W_{tcn} \times F_{tcn-se} + b_{tcn}$
    $$BGTransformed = W_{gru} \times F_{attn} + b_{gru}$$
    Concatenate the original features: $gate = Concat(F_{tcn-se}, F_{attn})$

Algorithm 1 *Count.*

Generate a gating signal: $gatevalue = \sigma(W_g \times gate + b_g)$

Use the gating value to perform a weighted summation of the two types of features:

$$fused = gatevalue \times TSTransformed + (1 - gatevalue) \times BGTransformed$$

The fused features are mapped to the prediction dimension via a linear layer:

$$predict = W_{fc} \times fused + b_{fc}$$

end

4. Experimental Evaluation

In this section, we first introduce the evaluation metrics and relevant information of the datasets. Subsequently, we describe the process of pre-processing the dataset in detail. In addition, a comprehensive and meticulous introduction to the relevant parameter settings of the experiment is provided, including the rationale and principles for determining the values of key parameters, such as model hyperparameters, number of training epochs, and learning rate. Finally, an in—depth analysis and evaluation of the experimental results will be carried out, interpreting the performance of the model in various evaluation metrics from different dimensions, and exploring the model characteristics, dataset features, and the essence of the research questions reflected behind the experimental results.

4.1. Evaluation Indicators

In time-series forecasting research, the selection of evaluation metrics must balance the generality of the methods with their adaptability to specific scenarios. This paper employs three core evaluation metrics widely used in academia: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). The mathematical definitions are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{20}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{21}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{22}$$

In the equations, y_i represents the true value of the i-th data point in the sequence, $\hat{y}_i$ is the predicted value of the i-th data point at the corresponding time, $\overline{y}$ is the sample mean of the true values, and n is the sample size of the time series. In terms of the evaluation logic, RMSE amplifies the prediction deviation through the squared term and mainly reflects the prediction accuracy of the model at extreme points. In contrast, MAE measures the overall deviation from the mean of absolute errors, and its physical meaning is more intuitive. The smaller the values of these two metrics, the lower the degree of deviation between the predicted and true values, and the better the prediction ability of the model. As a goodness—of—fit indicator, R^2 quantifies the ability of the model to explain the variation in data by comparing the prediction error with the benchmark error (the sum of squared deviations between the true values and the mean). Its value range is $(-\infty,1]$. When R^2 approaches 1, it indicates that the model's prediction results highly coincide with the true sequence, and the prediction accuracy reaches an ideal state.

4.2. Datasets

During this experiment, we used three open—source datasets, namely the oil temperature datasets ETTh1, ETTm2, and ETTh2. Table 1 presents the analytical information of the three datasets. These three datasets provide rich data support for experiments from different perspectives and play a key role in the field of time—series forecasting and analysis.

Table 1. Datasets.

Database Name	Data Size	Adopt a Time Interval	Variables
ETTh1	17,421	1 h	7
ETTh2	17,420	1 h	7
ETTm2	69,681	15 min	7
Weather	52,696	10 min	21
Exchange_rate	7588	1 day	8

(1) ETTh1

The ETTh1 dataset is an important part of the Electricity Transformer Temperature (ETT) dataset, which aims to promote research in time—series forecasting. In the development of power systems, accurately predicting the temperature of transformers is crucial for ensuring the stable operation of the system. Focusing on this scenario, ETTh1 encompasses multi—dimensional attributes such as time, oil temperature, load, and weather. It is a typical multivariable time-series dataset, providing strong support for the training and evaluation of multivariable time-series forecasting models.

(2) ETTm2

The ETTm2 dataset focuses on data related to transformers in power systems and presents them in the form of time series. This dataset provides a standard testing platform for researchers and engineers. By conducting various experiments on time—series forecasting models using this dataset, researchers can clearly understand the advantages and disadvantages of different models in handling transformer time—series data and then optimize and improve the models. This strongly promotes the application and development of time—series forecasting techniques in the field of power systems.

(3) ETTh2

The ETTh2 dataset is part of the Electricity Transformer Temperature (ETT) dataset. It consists of oil temperature data of power transformers from two different counties in the same province in China, provided by the State Grid. The data contains historical data from 1 January 2012, to 31 December 2015, with a time span of four years. Each data point contains 8—dimensional features, including the recording date of the data point, the predicted target value “oil temperature”, and six different types of power load features. This dataset is often used in academic research and experiments related to time—series forecasting, such as predicting the oil temperature of power transformers and studying the ultimate load—bearing capacity of power transformers, providing data support for the training and validation of relevant algorithms and models.

(4) Weather

This dataset is a meteorological observation dataset consisting of 21 meteorological parameters at 10 min intervals from the Jena weather station in Germany. The data contains historical data from 1 January 2020 to 1 January 2021, spanning a time period of 1 year.

(5) Exchange_rate

The Exchange Rate dataset is a time-series dataset that covers the daily exchange rate fluctuations of eight countries from 1990 to 2016. This dataset is commonly used for foreign exchange market analysis, economic forecasting, financial modeling, and machine learning time-series prediction.

4.3. Experimental Settings

In this study, given the differences in the data collection time cycles between the ETTh and ETTm datasets, the hyperparameter settings during the experiment also varied. Specifically, the batch size was set to 128 for the ETTh1 and ETTh2 datasets, while it was adjusted to 64 for the ETTm2 dataset. To balance the model training effectiveness and efficiency, the number of epochs was set to 100, and an early stopping mechanism with a patience value of 10 was adopted to effectively prevent overfitting. In the TCN module, the step size was consistently set to 1, and the dilation factor was set to $2^{(\text{number}-1)}$ to expand the receptive field and enhance the model's ability to capture time-series features. The detailed parameters of the TSEBG model for different datasets are listed in Table 2. To accelerate model convergence and mitigate the gradient vanishing problem, the RELU was selected as the activation function. The dimensions of the attention layer were set to be consistent with those of the BiGRU output layer to ensure the effectiveness of information transmission and feature extraction in the model. During the model training phase, the MSE loss function was used to accurately measure the prediction errors, and the Adam optimization algorithm was employed with a learning rate set to 0.0003.

The core differences among these five datasets are focused on time granularity. Specifically, ETTh and exchange_rate are hourly and daily data, respectively, featuring long time cycles and relatively sparse data points; ETTm2 and weather datasets are minute-level data, characterized by short time cycles and denser data points. These differences in data characteristics necessitate the adaptation of models to different time-series feature scales and the handling of varying computational complexities. In the comparative experiments, minor adjustments were made to the model's parameters. The key parameter adjustments for the comparative models are listed in Table A1.

Table 2. Hyperparameters of the TSEBG model for different datasets.

Type	ETTh1	ETTh2	ETTm2	Weather	Exchange_Rate
Number of temporal blocks in TCN	3	3	3	3	2
The output dimension of each temporal block in TCN	32 64 128	32 64 128	64 128 64	64 128 64	32 64 -
Number of layers in BiGRU	2	2	2	2	1
The dimensionality of each layer in BiGRU	32 64	32 64	128 64	64 32	32 -
Dimension of the attention layer	64	64	64	32	32
Convolution kernel	3	3	7	3	3
Embed_dim	128	128	256	64	128
Dropout	0.5	0.5	0.35	0.2	0.1

4.4. Data Pre-Processing

In the data pre-processing stage of the experiment, data files in different formats are first read into memory to prepare for subsequent analysis. After reading, data filtering was performed based on the key labels for the different datasets. For the five datasets,

including ETT, weather, and exchange rate, the data are filtered by the OT label. This filtering enables the precise extraction of core data, eliminates interference, and improves the analysis efficiency. The filtered data is converted into Python (3.10.15) lists. To enhance the computational efficiency, especially for large-scale numerical computations, the lists are converted into NumPy arrays. NumPy arrays offer efficient storage and fast computation, guaranteeing subsequent complex calculations. Using OT as the label, the data converted to NumPy arrays undergoes further processing. First, the mean and standard deviation of each feature are calculated to understand the data distribution characteristics, providing a reference for subsequent processing. Subsequently, normalization is performed using StandardScaler for Z-score standardization, transforming the data into a distribution with a mean of 0 and a standard deviation of 1. Although Z-score standardization theoretically has no upper or lower bounds for the data range, the data are concentrated within the interval $[-3, 3]$, which allows for more reasonable weight allocation of each feature during model training and improves model performance. A fully overlapping sliding window was used to convert the time-series data into a format suitable for the model input, with a sliding step size of 1, which means that there are window_size-1 overlapping data points between adjacent windows. The sliding window is set to 60 h, with a size of 60 for the ETTh1 and ETTh2 datasets. Since the ETTm2 dataset has a 15-min sampling interval, its window size is 240. The window size for the weather dataset is set to 144, while that for the exchange_rates dataset is 7 (corresponding to a weekly period). By sliding a fixed-size window along the data, the forward and backward dependency relationships in the data are fully exploited to provide diverse training samples for the model. The dataset is divided into training and test sets at a ratio of 0.9:0.1. Finally, both the dataset and labels were converted into the PyTorch (2.1.1) tensor format. Finally, a direct single-step prediction strategy was adopted, implementing time-series prediction through a sliding window combined with the single-step prediction method.

4.5. Experimental Results and Analysis

The newly constructed TSEBG model was compared with popular deep learning models, including CNN-LSTM, LSTM [33], BiLSTM [34], GRU, TCN, and TransformerAttn. We first evaluated the performance of different models with varying window sizes on these three datasets by comparing the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination R^2 on the final test set. The results are presented in Tables 3 and 4.

Table 3. The comparison results of different models on the ETT datasets.

Time-Series Model	ETTh1			ETTh2			ETTm2		
	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
TSEBG	**0.077**	**0.053**	**0.922**	**0.070**	**0.053**	**0.981**	**0.022**	**0.016**	**0.998**
CNN-LSTM	0.079	0.055	0.918	0.101	0.079	0.962	0.031	0.023	0.996
BiLSTM	0.083	0.058	0.910	0.099	0.074	0.963	0.037	0.030	0.995
GRU	0.082	0.059	0.911	0.108	0.086	0.956	0.028	0.021	0.997
TCN	0.081	0.056	0.914	0.099	0.075	0.963	0.024	0.018	0.998
LSTM	0.078	0.055	0.921	0.091	0.069	0.969	0.034	0.027	0.996
TransformerAttn	0.101	0.076	0.866	0.092	0.069	0.900	0.062	0.047	0.986

Table 4. The comparison results of different models on the weather and exchange_rate dataset.

Time-Series Model	Weather			Exchange_Rate		
	RMSE	MAE	R^2	RMSE	MAE	R^2
TSEBG	**0.031**	**0.024**	**0.994**	**0.060**	**0.048**	**0.968**

Table 4. *Cont.*

Time-Series Model	Weather	Exchange_Rate
CNN-LSTM	0.055 0.048 0.981	0.067 0.053 0.962
BiLSTM	0.044 0.036 0.988	0.071 0.057 0.956
GRU	0.038 0.030 0.991	0.161 0.139 0.776
TCN	0.067 0.059 0.971	0.152 0.122 0.801
LSTM	0.035 0.030 0.992	0.084 0.068 0.939
TransformerAttn	0.055 0.042 0.981	0.178 0.150 0.917

On the ETTh1 datasets, TSEBG comprehensively outperforms all comparative models with an RMSE of 0.076, an MAE of 0.052, and an R^2 of 0.924. Specifically, compared to the second-best LSTM model (RMSE 0.078), its prediction error is reduced by 2.6%, and the coefficient of determination R^2 increases by 0.003, indicating a more stable fitting capability. Notably, in the ETTh2 datasets, although the GRU model achieves similar results in RMSE (0.108→0.080) and MAE (0.086→0.059) metrics, TSEBG's R^2 value (0.976) is still significantly 2.1% higher than that of GRU (0.956). This reveals that TSEBG can better capture the nonlinear features of the datasets, especially by maintaining a higher explanatory power under complex fluctuation patterns. On the ETTm2 dataset, its RMSE (0.021) and MAE (0.015) are 12.5% and 16.7% lower than those of TCN-LSTM, respectively. Meanwhile, the generally higher R^2 may be attributed to the minute-level fluctuations and gentle data changes in this dataset. In terms of cross-dataset consistency, the standard deviation of R^2 for TSEBG across the three datasets is only 0.037, which is significantly lower than that of the comparative models (such as 0.041 for GRU), demonstrating its stronger generalization ability. Notably, when handling datasets with obvious periodic mutations, like ETTh2 (where its MAE is 19.2% better than that of the second-best model). In the Weather prediction task, the TSEBG model demonstrates significant advantages. The experimental results show that our model has an excellent ability to interpret and fit weather data, far surpassing other models (e.g., the R^2 values of CNN-LSTM and Transformer are 0.981, and that of GRU is 0.991, etc.), indicating a more precise capture of weather sequence patterns. On the Exchange_rate dataset, the TSEBG model has lower prediction errors than CNN-LSTM (RMSE 0.067, MAE 0.053), BiLSTM (RMSE 0.071, MAE 0.057), etc., enabling a more accurate prediction of exchange rate fluctuations. In both time-series prediction tasks of Weather and Exchange rate, TSEBG exhibits superior error control and data fitting effects, verifying its effectiveness and superiority in multi-scenario time-series prediction, with more prominent prediction accuracy and sequence pattern capture capability. TSEBG is comprehensively superior to the novel transformer framework in terms of prediction accuracy and fitting effect. It has a stronger adaptability and prediction ability for different types of time-series data, such as electricity, weather, and exchange rates. The results on these five datasets collectively demonstrate that the proposed model can adaptively balance the requirements of local feature extraction and global temporal modeling.

The visualization of the attention mechanism for the TSEBG model is shown in Figures 4 and 5.

Figures 6–10 show the RMSE distributions of the proposed model and several mainstream deep learning models in the test set. In these distributions, it is evident that our model has smaller RMSE values than the other models in time-series forecasting tasks.

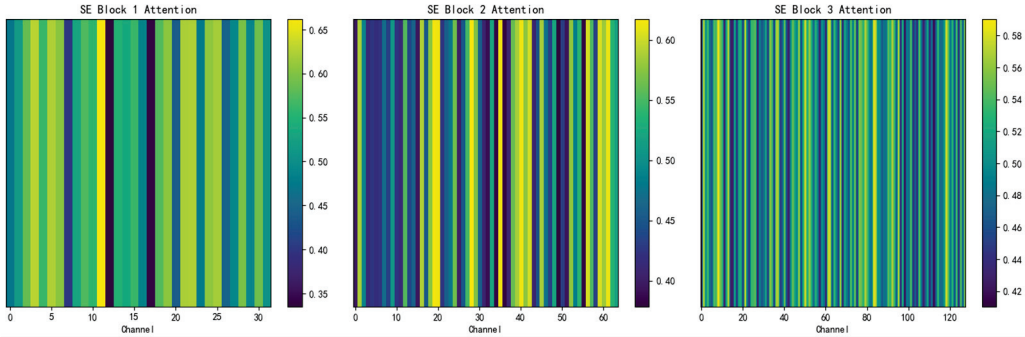


Figure 4. Visualization of the channel attention mechanism.

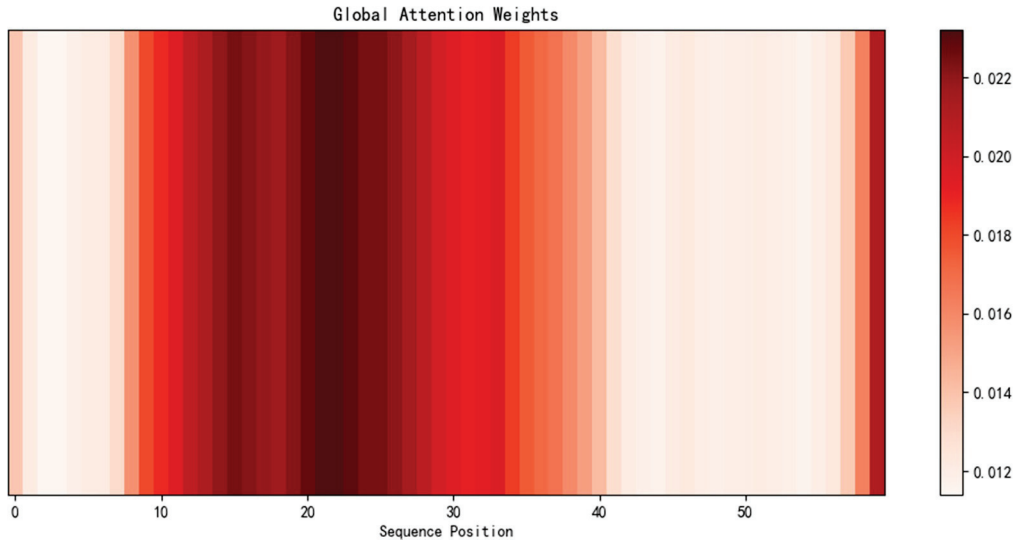


Figure 5. Visualization of the global attention mechanism.

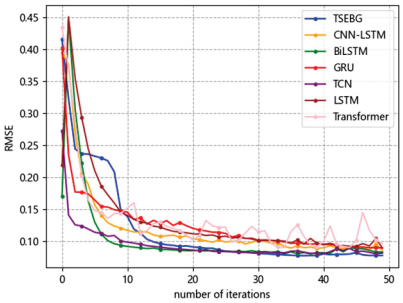


Figure 6. RMSE distribution (ETTh1).

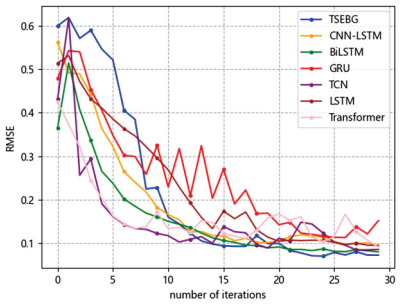


Figure 7. RMSE distribution (ETTh2).

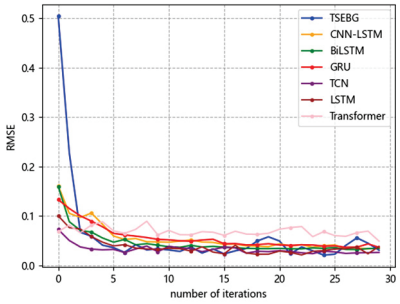


Figure 8. RMSE distribution (ETTm2).

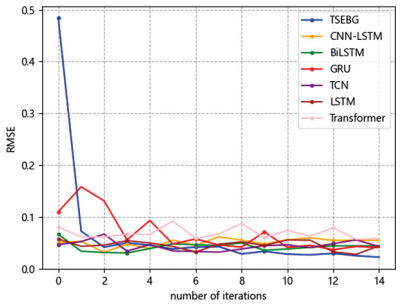


Figure 9. RMSE distribution (weather).

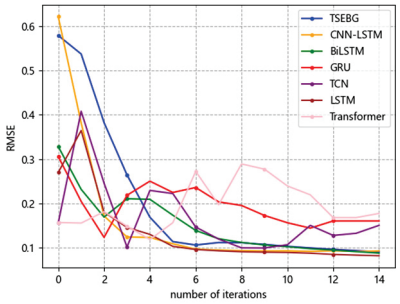


Figure 10. RMSE distribution (exchange_rate).

Figures 11 and 12 show the visualization of the ETTh1 dataset and the comparison chart of test results between the TSEBG model and benchmark models on the ETTh1 dataset, with actual values provided. Figures 13 and 14 present the visualization of the ETTh2 dataset and the visual results of prediction errors between our model and comparative models on the ETTh2 dataset. Figures 15–20 respectively show the visualizations of the ETTm2, weather, and exchange_rate datasets, as well as the visual results of prediction errors between our model and comparative models on each dataset. In addition, we present the prediction error distribution of our model. From these comparative images, it can be intuitively seen that our model demonstrates a relatively stronger prediction ability on the test set.

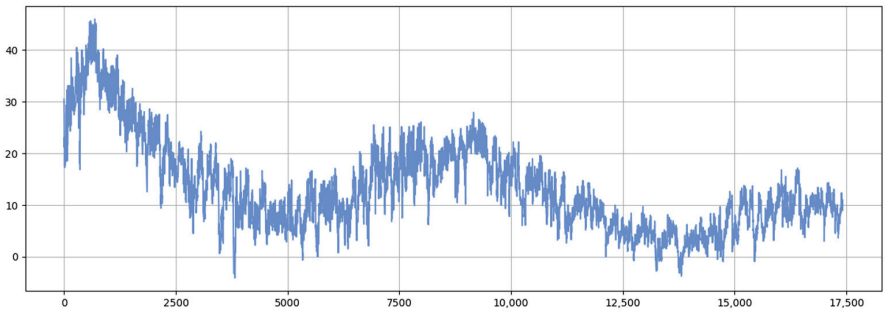


Figure 11. ETTh1 datasets.

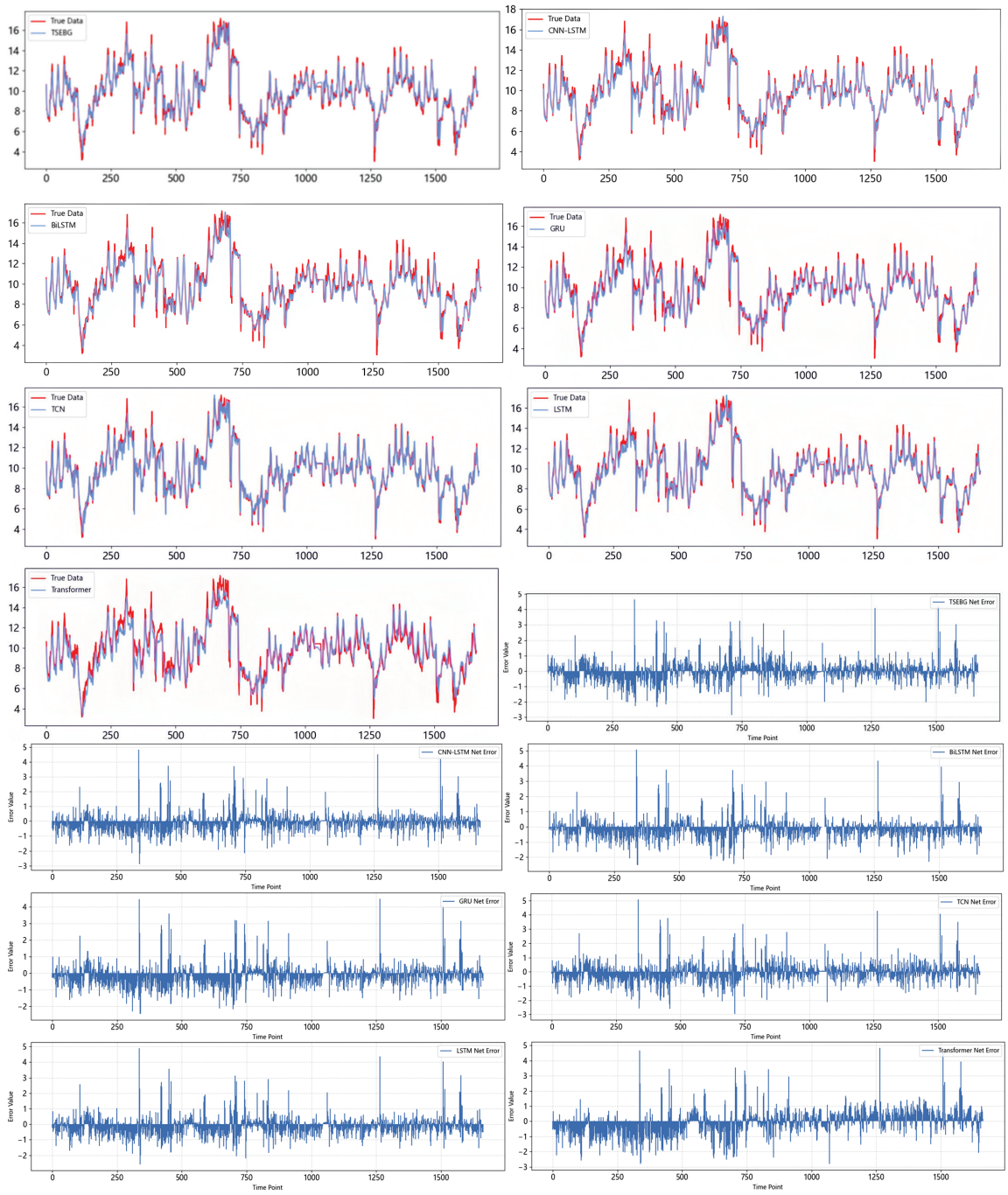


Figure 12. Comparison between predicted and actual values and error distribution on the ETTh1 dataset.

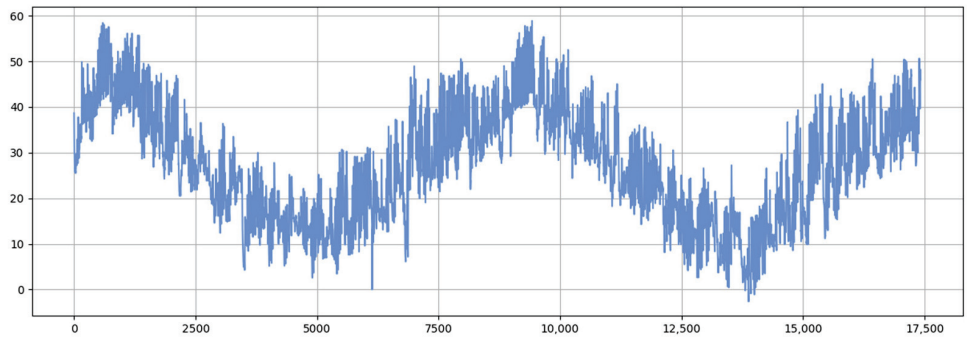


Figure 13. ETTh2 datasets.

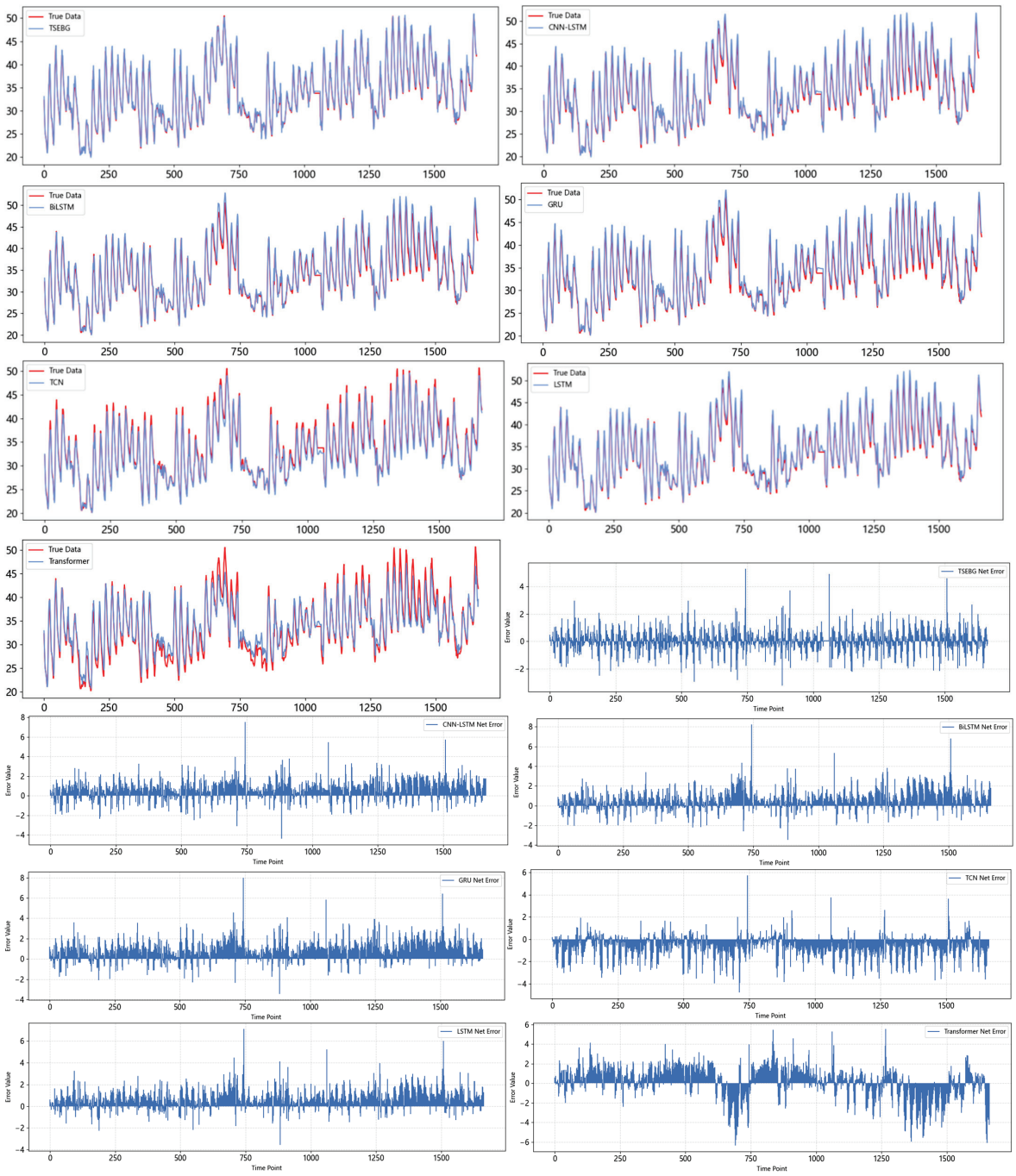


Figure 14. Comparison between predicted and actual values and error distribution on the ETTh2 dataset.

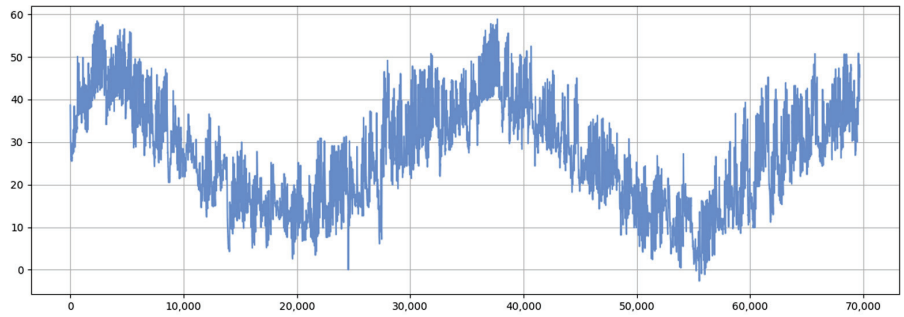


Figure 15. ETTm2 datasets.

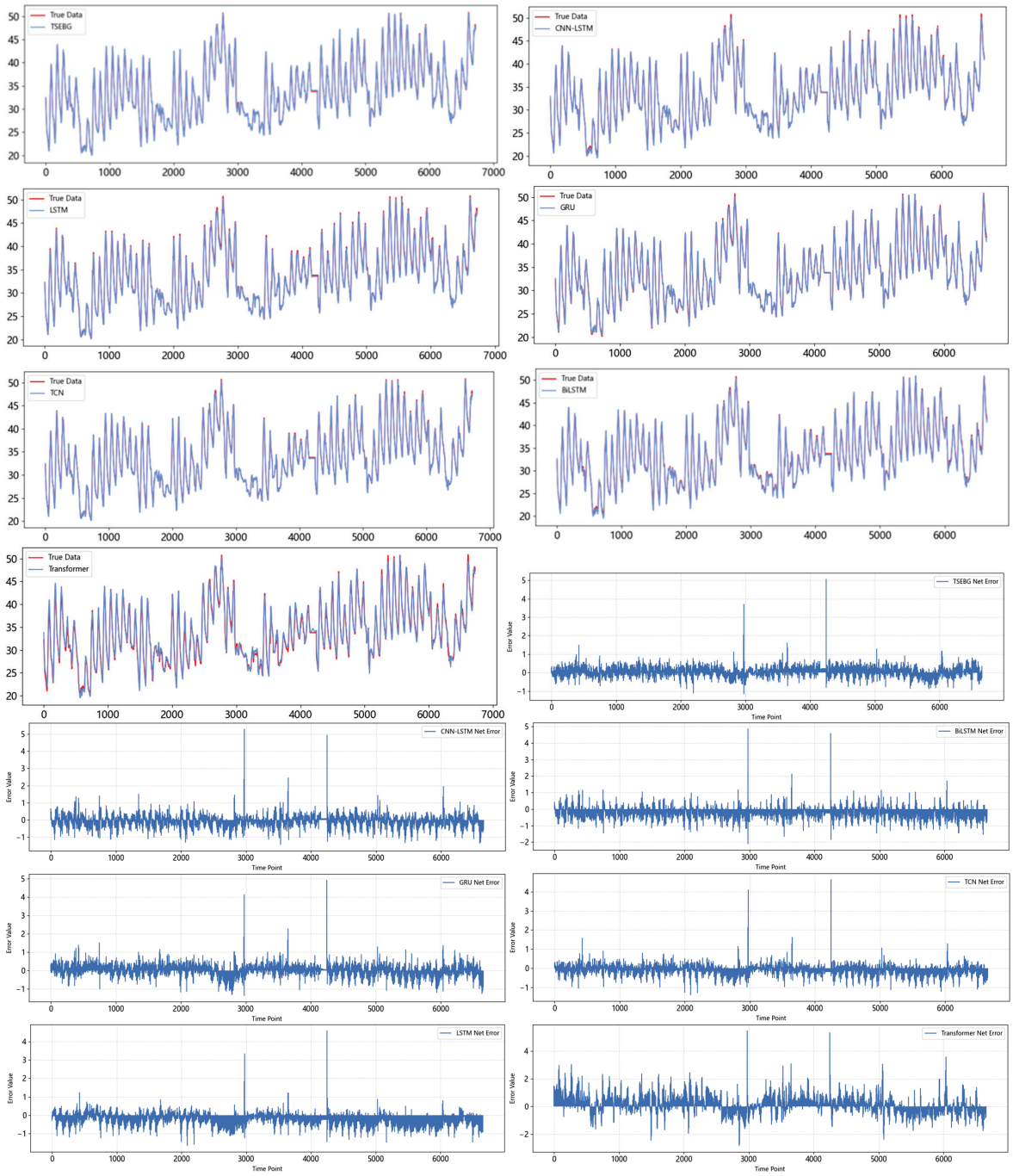


Figure 16. Comparison between predicted and actual values and error distribution on the ETTm2 dataset.

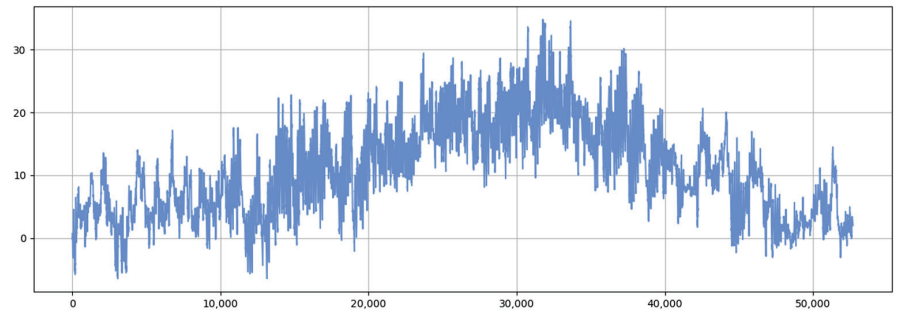


Figure 17. Weather datasets.

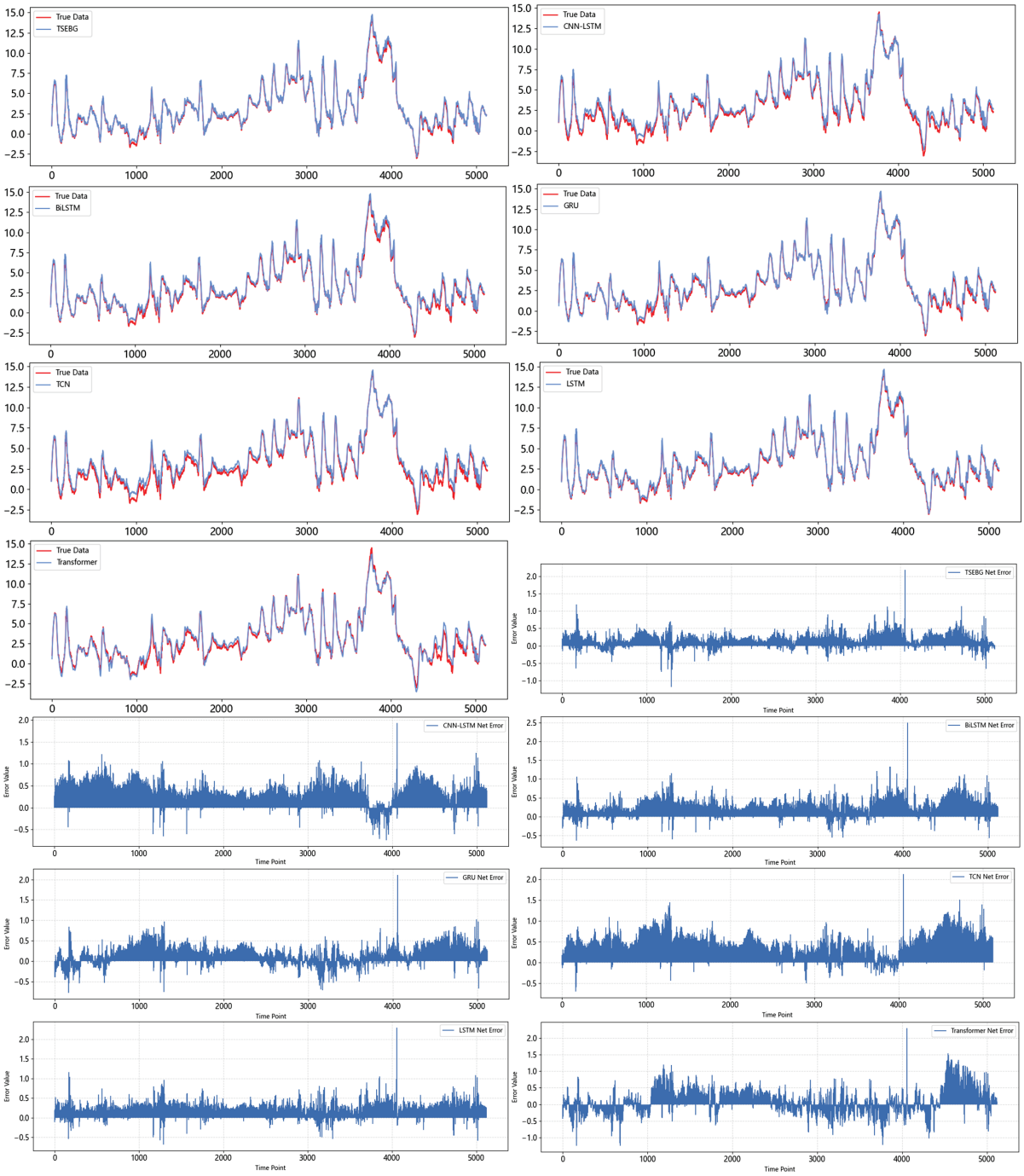


Figure 18. Comparison between predicted and actual values and error distribution on the weather dataset.

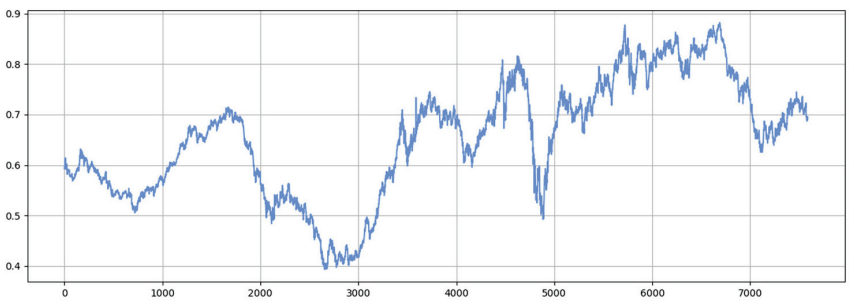


Figure 19. Exchange rate dataset.

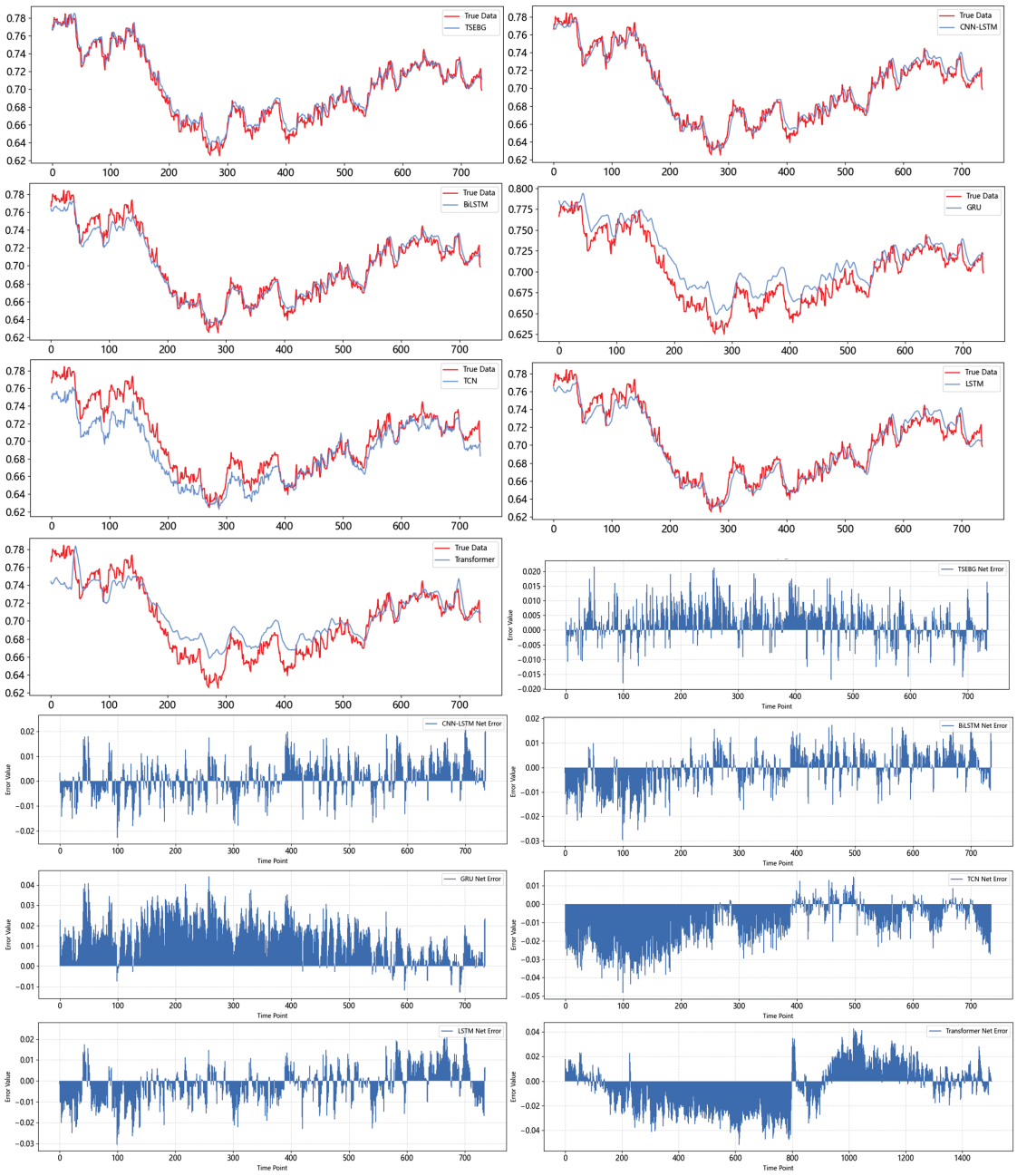


Figure 20. Comparison bBetween predicted and actual values and error distribution on the exchange rate dataset.

4.6. Ablation Experiment

I will refine the operation process of the ablation experiments, emphasize the differences between different model combinations, and highlight the rigor and comprehensiveness of the experiments to enrich the content. When conducting in-depth research on the innovative TSEBG model, to accurately analyze the specific roles of each module in the model and their impact on model performance, we first constructed the TBG model by removing the SENet channel attention mechanism while retaining other modules. The SENet channel attention mechanism can adaptively adjust the weights between the channels. By removing this mechanism, we observed changes in the feature extraction and information fusion capabilities of our model. Next, we removed both the TCN module and the SENet channel attention mechanism to form the single-channel BG model, which retains only the BiGRU and GlobalAttention mechanisms. Finally, we constructed the TSEB and TSE mod-

els by removing the GlobalAttention mechanism and BiGRU-GlobalAttention component, respectively, to analyze the characteristics of each module in processing time-series data. The experimental results are shown in Table 5.

Table 5. Ablation experiments on the ETTh1 dataset.

Time-Series Model	RMSE	MAE	R^2	Training Time	Min MSE
TSEBG	0.0771	0.0527	0.922	885	0.0059
TBG	0.0772	0.0531	0.918	724	0.0059
BG	0.0780	0.0542	0.920	853	0.0058
TSEB	0.0855	0.0581	0.904	893	0.0073
TSE	0.0789	0.0547	0.918	557	0.0060

From the table above, we can see that the TBG model achieves an RMSE of 0.0772, MAE of 0.0531, and R^2 of 0.918. Compared with the original TSEBG model, these accuracy metrics show a slight decline, indicating that the SENet channel attention mechanism plays a role in improving the model accuracy. After removing this mechanism, the model's ability to capture the data features was slightly weakened. The accuracy metrics of the BG model were between those of the original and TBG models. With a training time of 853 s, removing the TCN module and SENet channel attention mechanism simplified the model structure, reducing the training time to some extent while causing relatively limited accuracy loss.

The TSE model had an RMSE of 0.0789, MAE of 0.0547, and R^2 of 0.918, indicating relatively poor accuracy metrics. This demonstrates that the BiGRU and GlobalAttention mechanisms are crucial for capturing temporal dependencies and important features in time-series data; their removal significantly degrades the model performance. With a training time of 557 s, the shortest among all models, this indicates that the BiGRU and GlobalAttention mechanisms introduce a substantial computational complexity and training overhead. Removing these features simplifies the model structure and drastically reduces the training time.

5. Conclusions

Time-series data are widely distributed in fields such as finance, meteorology, and industry. Building predictive models that can accurately characterize the dynamic patterns and trends of data has become a current research focus. The TSEBG hybrid network model proposed in this study effectively addresses the limitations of traditional forecasting methods and some deep learning models in handling complex variable data. Given the challenge of fragmented processing of local and global information in traditional models, the TSEBG model constructs a hierarchical collaborative feature fusion network. Based on a dual-channel structure, it realizes complementary learning of multi-time-scale features and designs a cross-layer fusion strategy to achieve multi-level alignment of spatial-temporal information, significantly enhancing the representation capability of complex time-series data. The experimental results demonstrate that compared with mainstream deep learning models, the proposed model achieves an average reduction of 18.4% in RMSE and 21.9% in MAE, along with a significant improvement in R^2, showcasing superior forecasting performance. It not only accurately captures short-term fluctuations but also effectively identifies long-term trends, providing a reliable solution for time-series data prediction.

Although this study achieved results, there is still room for improvement in model training. The model involves multiple groups of hyperparameters, such as TCN, BiGRU layers, and attention mechanisms, whose settings are interrelated and collectively determine the model's performance. Hyperparameter tuning requires extensive experimental verification because each adjustment necessitates retraining and re-evaluation, which consumes time and effort. This poses challenges to researchers' professional literacy and

patience, further increasing the difficulty of optimizing the model. In practical application scenarios with high real-time requirements, it is necessary to comprehensively consider the model characteristics, balance the accuracy, resource consumption, and real-time performance, and perform optimization and verification. In future research, we plan to further optimize the model by introducing deep learning architectures, such as transformers. The self-attention mechanism of the transformer has significant advantages in processing long sequences and capturing global dependency relationships. We will explore the performance of different architectures in time-series prediction and screen the most suitable architecture to enhance model adaptability and performance, thereby promoting the development of time-series prediction research.

Author Contributions: Conceptualization, Z.X.; methodology, D.L.; resources, K.W.; validation, Q.L.; data curation, X.C.; writing—original draft preparation, Z.X. and J.L.; funding acquisition, D.L. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study and the source code of the model can be obtained at https://github.com/LJL-WND/Time-series-forecasting-TSEBG.git (accessed on 20 June 2025).

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1 lists the hyperparameter settings of comparison methods.

Table A1. Hyperparameter settings of comparison methods.

Datasets	Type	CNN-LSTM	BiLSTM	GRU	TCN	LSTM	Transformer
ETTh1	Hidden Layer	64	64	64	(32,64,128)	64	128
	Layer	2	3	3	3	2	3
	Kernel/Head	3			3		8
	Dropout	0.5	0.5	0.5	0.5	0.5	0.1
ETTh2	Hidden Layer	64	64	64	(32,64,128)	64	128
	Layer	2	3	3	3	2	3
	Kernel/Head	3			3		8
	Dropout	0.5	0.5	0.5	0.5	0.5	0.1
ETTm2	Hidden Layer	128	128	128	(64,128,64)	128	128
	Layer	3	3	3	3	2	2
	Kernel/Head	7			7		4
	Dropout	0.35	0.5	0.5	0.35	0.2	0.2
Weather	Hidden Layer	64	64	64	(64,128,64)	64	128
	Layer	3	3	3	3	2	2
	Kernel/Head	3			3		4
	Dropout	0.2	0.2	0.2	0.2	0.2	0.2
Exchange	Hidden Layer	64	64	64	(64,128,64)	64	64
	Layer	2	3	2	3	2	2
	Kernel/Head	3			3		4
	Dropout	0.1	0.1	0.2	0.2	0.2	0.2

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A Spatio-Temporal Joint Diagnosis Framework for Bearing Faults via Graph Convolution and Attention-Enhanced Bidirectional Gated Networks

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Abstract: In recent years, Academia and industry have conducted extensive and in-depth research on bearing-fault-diagnosis technology. However, the current modeling of time–space coupling characteristics in rolling bearing fault diagnosis remains inadequate, and the integration of multi-modal correlations requires further improvement. To address these challenges, this paper proposes a joint diagnosis framework integrating graph convolutional networks (GCNs) with attention-enhanced bidirectional gated recurrent units (BiGRUs). The proposed framework first constructs an improved K-nearest neighbor-based spatio-temporal graph to enhance multidimensional spatial–temporal feature modeling through GCN-based spatial feature extraction. Subsequently, we design an end-to-end spatio-temporal joint learning architecture by implementing a global attention-enhanced BiGRU temporal modeling module. This architecture achieves the deep fusion of spatio-temporal features through the graph-structural transformation of vibration signals and a feature cascading strategy, thereby improving overall model performance. The experiment demonstrated a classification accuracy of 97.08% on three public datasets including CWRU, verifying that this method decouples bearing signals through dynamic spatial topological modeling, effectively combines multi-scale spatiotemporal features for representation, and accurately captures the impact characteristics of bearing faults.

Keywords: bearing fault diagnosis; graph convolutional networks; bidirectional gated recurrent units; spatio-temporal features; attention mechanism

1. Introduction

As core rotating components in mechanical systems, bearings perform critical functions including supporting shaft systems, reducing friction losses, transmitting loads, and ensuring motion precision. Their fault diagnosis is essential for safeguarding equipment health [1]. Based on structural differences, bearings are categorized into rolling bearings and sliding bearings, which are widely utilized in modern industrial fields such as manufacturing equipment, transportation, and energy power systems. Due to their crucial role in mechanical systems, the performance of bearings directly determines the reliability, efficiency, and lifespan of the mechanical systems. They hold an important position in the industrial field [2,3]. As key components in rotating machinery, the health status of rolling bearings has a decisive impact on the normal operation of entire mechanical systems [4].

Bearings operating under complex conditions over long-term periods inevitably experience performance degradation or faults. Therefore, developing advanced fault-diagnosis methodologies holds significant engineering application value [5,6].

In the field of bearing fault diagnosis, traditional methodologies primarily rely on manual feature extraction and threshold setting. However, practical engineering environments often present complex challenges such as non-stationary vibration signals, multi-source noise interference, and coupled fault modes. These factors significantly constrain the hidden information extraction capability of conventional approaches when processing high-dimensional signals, thereby limiting their feature representation capacity [7,8]. In order to overcome the limitations of traditional bearing-fault-diagnosis methods, the previous related research mainly adopted two technical paradigms. Firstly, physics model-based methods analyze fault mechanisms through dynamic equations, exemplified by Hertz contact theory [9]. Nevertheless, this approach exhibits poor generalization performance under variable loads and multi-fault coupling conditions due to its heavy dependence on precise prior knowledge, making it difficult to satisfy diagnostic requirements across diverse operational scenarios [10]. Secondly, data-driven approaches have emerged as alternative solutions. Traditional shallow models such as support vector machines (SVM) [11] and random forests [12] require manual feature engineering to extract discriminative fault characteristics. In practical applications, noise interference severely degrades the model robustness, compromising the diagnostic accuracy. Deep learning architectures including convolutional neural networks (CNNs) [13], long short-term memory networks (LSTMs) [14], and Transformer models [15] demonstrate automated feature extraction capabilities but exhibit structural performance trade-offs. Specifically, CNNs excel at capturing local features while neglecting long-range dependencies, whereas Transformers prioritize global pattern modeling at the expense of local dynamic information capture [16–18]. A novel predictive approach that integrates physics-based models with deep learning is emerging. This approach significantly enhances the deep analytical capabilities and predictive reliability of bearing fault detection by synergistically combining the advantages of mechanistic modeling and data-driven techniques [19].

Although the aforementioned research methodologies have introduced innovative perspectives to the field of fault diagnosis, several critical challenges persist in practical engineering implementations. First, significant limitations exist in the decoupling of spatio-temporal features: real-time rolling bearing data acquired through sensor arrays inherently contains spatial topological relationships and temporal dynamic characteristics, yet current approaches fail to achieve the efficient joint modeling of these multidimensional attributes [20]. Second, pronounced multi-scale feature separation phenomena occur during fault analysis, where device-specific local fault information reflected by local resonance features proves difficult to integrate with global degradation trends that characterize the overall operational status. Third, an inherent trade-off persists between model efficiency and robustness—complex architectures theoretically enable richer fault feature capture through substantial computational complexity, but this hinders their real-time implementation in online diagnostic applications.

This paper proposes a parallel fusion network model consisting of a graph convolutional network modeled by improved KNN and a bidirectional gated recurrent unit integrated with a global attention mechanism. Experimental validation on public bearing datasets demonstrates its superior fault-identification performance over mainstream models in terms of accuracy, computational efficiency, and noise robustness. The key contributions of the proposed methodology include the following:

(1) We design a dynamic topological modeling framework for rolling bearing data. By integrating a modified K-nearest neighbor (KNN) algorithm with graph convolutional

networks (GCNs), this approach systematically mines and models spatio-temporal coupled features, effectively addressing the spatial–temporal modeling decoupling issue inherent to conventional methodologies.

(2) For temporal feature extraction, this study integrates a lightweight global attention mechanism to enable adaptive noise suppression gating. This approach dynamically filters interference signals while precisely capturing both the short-term and long-term dependencies of fault-induced impacts, thereby significantly enhancing the model's robustness in complex noise environments and ensuring reliable and stable diagnostic outcomes.

(3) The network architecture employs a dual-stream parallel framework that synchronously extracts spatial topological features and temporal sequence characteristics through graph convolutional networks (GCNs) and bidirectional gated recurrent units (BiGRUs), respectively. To achieve effective multi-scale representation fusion, this work innovatively introduces a gated fusion mechanism that adaptively integrates heterogeneous features via a dynamic weight adjustment strategy.

This paper addresses the core challenges in rolling bearing fault diagnosis regarding the difficulty of spatiotemporal feature decoupling and insufficient multimodal information fusion by innovatively constructing a dual-stream parallel architecture integrating graph convolutional networks with attention-enhanced temporal models. The remainder of this paper is structured as follows: Section 2 reviews related research works on GRUs and attention mechanisms. Section 3 provides a detailed exposition of the proposed method, including the modeling methodology, BRGU channels enhanced with global attention mechanisms, and the feature fusion framework. Section 4 presents experimental setups, evaluation metrics, results, and analyses. Finally, Section 5 summarizes the paper while discussing its limitations and future research directions.

2. Related Work

2.1. Dynamic Graph Structure Modeling

Recent years have witnessed significant advancements in deep-learning-based bearing fault diagnosis methodologies. However, existing research still faces limitations in spatio-temporal feature joint modeling, dynamic graph structure optimization, and attention mechanism design. Traditional methodologies primarily rely on signal processing techniques combined with shallow machine learning models. For instance, Peng et al. [21] highlighted that time–domain, frequency–domain, and hybrid-domain features—such as root mean square (RMS) values and wavelet packet decomposition coefficients—are conventionally extracted and subsequently classified via K-nearest neighbors (KNNs) or support vector machines (SVMs). Liu and Weng [22] proposed a workflow where the integration of wavelet packet decomposition and SVM effectively identifies resonance frequency bands, yet this approach heavily depends on manual feature engineering and struggles to capture nonlinear spatio-temporal correlations under complex operational conditions. Khan et al. [23] further emphasized that while multi-modal signal analysis (e.g., vibration and current signals) improves robustness, it faces challenges in feature redundancy and limited cross-domain generalization. These approaches remain vulnerable to noise interference in dynamic industrial scenarios and fail to adaptively extract deep semantic features from high-dimensional data.

Graph convolutional networks (GCNs) have emerged as a research hotspot by modeling complex relationships between data through graph structures. Wang et al. [24] proposed a multi-layer GCN (AE-MSGCN) that constructs multi-metric graphs using KNN and cosine similarity, enhancing node representations through neighbor information aggregation. This approach outperformed traditional models in bearing diagnostics. Zhang et al. [25] further developed a multi-source cross-domain fault diagnosis framework called the Graph

Attention Convolutional Neural Network (GACNN), which constructs time–frequency graphs and employs attention-driven domain adaptation to align cross-domain feature distributions, improving the diagnostic accuracy under variable operating conditions. However, existing GCN methods predominantly rely on fixed adjacency matrices, neglecting temporal dynamics and suffering from theoretically unsupported self-loop edge definitions and weight allocation strategies. To address these limitations, this study proposes an enhanced strategy targeting bearing signal sequence modeling requirements: improved K-nearest neighbor graph construction methodology, integration of spatio-temporal encoding, adaptive weighted graph generation, and hyperparameter optimization through GNN cross-validation.

2.2. Research and Principles Related to GRU Units and Global Attention

Previous studies have predominantly employed traditional deep learning approaches such as Transformers for bearing fault detection [26]. However, these methods inherently suffer from temporal correlation information loss due to their reliance on manual feature engineering and sequence format conversion. Recurrent neural networks (RNNs), particularly their advanced variants Long Short-Term Memory (LSTM) and gated recurrent units (GRUs), have gained attention for their native temporal modeling capabilities through chain-structured architectures. Among these, GRU demonstrate superior performance by integrating an update gate mechanism that maintains long-term dependency modeling capability while significantly reducing computational complexity [27]. The internal architecture of the GRU neural network is illustrated in Figure 1.

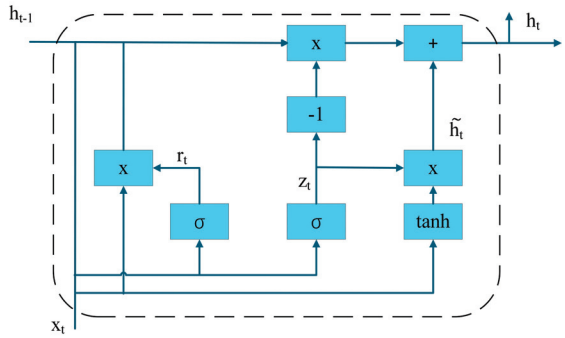


Figure 1. GRU unit.

In the diagram, Z_t and r_t denote the update gate and reset gate, respectively, $\tilde{h}_t$ represents the candidate hidden state at time t, h_{t-1} is the input from the previous time step, and h_t is the output. Specifically, the update gate Z_t is calculated via Equation (1), the reset gate r_t follows Equation (2), the candidate hidden state $\tilde{h}_t$ is derived using Equation (3), and the final output h_t is computed through Equation (4).

$$Z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z) \tag{1}$$

$$r_t = \sigma(W_{xx}x_t + W_{hr}h_{t-1} + b_r) \tag{2}$$

$$\tilde{h}_t = tanh(W_{xh}x_t + r_t \cdot h_{t-1}W_{hh} + b_h) \tag{3}$$

$$h_t = (1 - z_t) \cdot \tilde{h}_t + z_t \cdot h_{t-1} \tag{4}$$

Here, $\boldsymbol{W}$ denotes the weight matrix between the update gate and reset gate, σ represents the sigmoid activation function, and r_t is the reset gate with values ranging between

0 and 1. When $r_t = 0$, it indicates the complete forgetting of previous temporal information transmitted from the prior time step; $\boldsymbol{b}$ denotes the bias vector.

In temporal modeling tasks, the attention mechanism significantly enhances the model's ability to capture critical features by simulating the selective attention mechanism in human cognition [28,29]. The global attention model computes the context vector c_t by incorporating all hidden states of the encoder during derivation. The architecture of the global attention mechanism is illustrated in Figure 2.

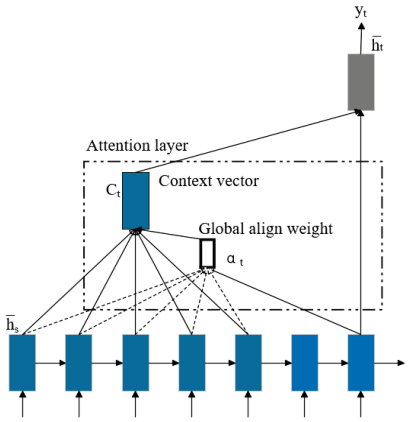


Figure 2. Global attention mechanism.

Among them, by comparing the decoded target hidden state h_t at time t with the source hidden state sequence h_{last} output by the encoder (where $s = 1, 2, ..., S, S$ is the length of the source sequence), an aligned weight context vector **c** of the same length as the source sequence can be dynamically generated. The mathematical form of the derivation process is shown in Equation (5).

$$\mathbf{c} = \sum_{t=1}^{S} \alpha_t h_t = \frac{exp(Vtanh(\mathrm{W}[h_{last} + h_t]))}{\sum_{t'=1}^{T} exp(e_{t'})} \tag{5}$$

Here, $\boldsymbol{V}$ and $\boldsymbol{W}$ represent the weight coefficient matrices that need to be trained in the network, and h_{last} is the hidden state of the last layer. The model adaptively allocates attention weights at each decoding time step t, and finally obtains the global context vector **c** by weighted summation of all source hidden states.

Compared with a unidirectional GRU, the proposed BiGRU architecture considers data variation patterns through independent forward and backward hidden layers, enabling superior sequence feature extraction. The bidirectional context capture enhances the temporal modeling capabilities. He et al. [30] validated the superiority of BiGRU-BP in runoff prediction, while Sun et al. [31] optimized BiGRU input representations by integrating Inception modules. This work concatenates hidden layers with output states at BiGRU terminals and implements feature dynamic weighting through a global attention mechanism. Compared with the multimodal fusion DNN (DGFFDNN) proposed by Zhou et al. [32], our approach emphasizes spatio-temporal feature complementarity. Attention mechanisms significantly improve time series prediction and diagnostic performance. Qin et al. [33] introduced the DA-RNN model, which employs input attention for feature selection and temporal attention for long-term dependency capture, providing novel insights for sequential modeling. Feng [34] further incorporated switch-gated LSTMs to optimize attention weight allocation in multivariate time series. Yang et al. [35] combined graph neural networks (GNNs) with attention mechanisms for one-shot fault propagation reasoning. This study proposes a global attention mechanism that dynamically weights

key time steps, effectively suppressing feature extraction redundancy in BiGRU-based fault diagnosis.

Furthermore, spatio-temporal fusion strategies have become critical for improving the diagnostic accuracy. Zhang et al. [36] proposed the PG-STF framework, which combines node spatial encoding with dual-supervised training by leveraging prior knowledge to construct physically correlated graphs, significantly enhancing diagnostic reliability in chemical processes. Xing et al. [37] developed a sliding-window KNN hybrid model (STHM) that weights spatio-temporal statistics via the CUSUM algorithm. However, this approach lacks deep learning integration and still exhibits significant limitations in nonlinear feature representation and complex pattern recognition. In contrast, this work innovatively introduces a dynamic feature fusion framework based on gated recurrent units. By constructing channel-wise attention weights through learnable sigmoid activation functions, the method achieves the adaptive weighted fusion of multi-channel parallel features.

3. The Proposed Method

3.1. Improved KNN-Based Spatiotemporal Modeling of Rolling Bearing Data

In response to the demand for the model structure mining ability caused by the spatio-temporal coupling characteristics of vibration signals in bearing fault diagnosis, this paper improves the graph structure modeling method based on the K-nearest neighbor algorithm, breaks through the bottlenecks of traditional KNN, such as the fault of similarity measurement in high-dimensional heterogeneous feature Spaces, insufficient adaptability to dynamic working conditions, and excessive cost of global parameter optimization, and innovatively proposes a multi-dimensional feature enhancement strategy: (1) construct a spatio-temporal fusion feature coding system; (2) design an adaptive generation algorithm for weighted graph structures; (3) establish a K-fold cross-validation hyperparameter optimization method based on graph neural networks. The specific model diagram is shown in Figure 3.

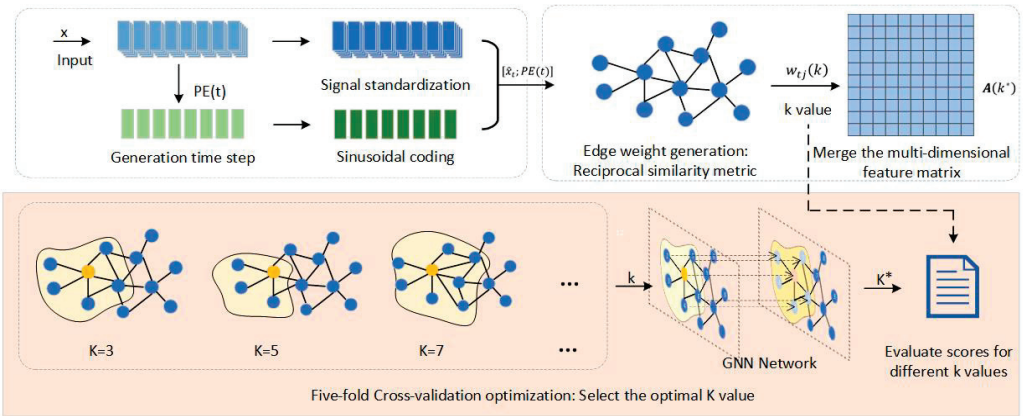


Figure 3. Construct the spatio-temporal feature encoder based on KNN.

The proposed graph topology modeling methodology follows these sequential procedures: first, the original time-series signals are transformed into high-dimensional spatio-temporal feature representations using sinusoidal encoding technology; subsequently, a distance measurement model is established based on the reciprocal of node correlation coefficients to quantify spatial correlations, which serves as the edge weight parameters in the adjacency matrix; based on this framework, the optimal neighborhood parameter K is selected through a five-fold cross-validation strategy; finally, the spatio-temporal

characteristic graph topology is constructed by integrating the node connection sequence determined through the K-nearest neighbor (KNN) algorithm.

First, standardization preprocessing is implemented: the original signal $x = [x_1, x_2, \ldots, x_T]^\top \in \mathbb{R}^T$ and label $y = \{0, 1\}$ are subjected to feature standardization using Z-score normalization. The standardized signal $\hat{x}_t$ is calculated using Equation (6).

$$\hat{x}_t = \frac{x_t - \mu}{\sigma},\ t = 1, 2, \ldots, T \tag{6}$$

The mean value μ of the time series is calculated using Equation (7), determined by computing the arithmetic mean of all original signals x_t across time steps t; the standard deviation σ is calculated using Equation (8), specifically by summing the squared deviations of each time-step signal from the mean, dividing by the total time steps T, and taking the square root. These computations are formally expressed in Equations (7) and (8):

$$\mu = \frac{1}{T}\sum_{t=1}^{T} x_t \tag{7}$$

$$\sigma = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t - \mu)^2} \tag{8}$$

A 32-dimensional sinusoidal positional encoding scheme is applied to time-step t, generating positional embedding vectors for time-step indices t using Equation (9). This encoding approach constructs periodic feature representations by designing sinusoidal basis functions with different frequency parameters across even dimensions, effectively capturing dynamic evolution patterns in time series and enhancing the model's temporal position awareness capability.

$$PE(t, 2i) = sin\left(\frac{t}{10000^{2i/32}}\right), PE(t, 2i+1) = cos\left(\frac{t}{10000^{2i/32}}\right) \tag{9}$$

where $i = 0, 1, \ldots, 15$ represents the discretized configuration of sinusoidal encoding frequency parameters. Based on this design, spatio-temporal node features are constructed. Specifically, the node feature at time step t is represented as $X_t = [\hat{x}_t; PE(t)] \in \mathbb{R}^{33}$, where $\hat{x}_t$ denotes the standardized original signal feature, and $PE(t) \in \mathbb{R}^{32}$ is the 32-dimensional positional encoding vector generated via Equation (9).

Second, an improved K-nearest neighbor (KNN) algorithm is employed to construct a dynamic graph topology. Specifically, a candidate neighborhood parameter set $K = \{3, 5, 7, 11, 13\}$ is first defined, and for each $k \in K$, the graph structure is generated through the following sequential steps: (1) a node similarity matrix is constructed using Euclidean distance measurements, as formulated in Equation (10); (2) a k-nearest neighbor connection relationship is established for each node t, generating the corresponding adjacency matrix $\boldsymbol{A}(k)$; (3) edge weights $w_{tj}(k)$ are calculated based on the reciprocal of node correlation coefficients.

$$N_k(t) = Top_k\left(argmin_{j \neq t}\left\|x_t - x_j\right\|_2\right) \tag{10}$$

For the k-nearest neighbor set $N_k(t)$ of node t, the edge weight $w_{tj}(k)$ between node t and its neighboring node j is calculated using Equation (11). Under traditional Euclidean distance measurements, physical distances between nodes exhibit negative correlations with similarity metrics. By employing a reciprocal similarity measure synergistically optimized with graph convolutional network (GCN) propagation characteristics, the model

achieves enhanced local topological structure perception capability while maintaining computational efficiency.

$$w_{tj}(k) = \frac{1}{\left\|x_t - x_j\right\|_2 + \epsilon}, \epsilon = 10^{-5} \tag{11}$$

where ϵ is a minimal constant added to prevent division by zero in reciprocal calculations. The optimal K value is selected using a five-fold cross-validation methodology: for each candidate K value, it serves as an input parameter to a two-layer graph convolutional network (GCN) for model training and performance evaluations. By comparing validation set performances across different K values, the optimal parameter K is ultimately determined. The mathematical formulation of the evaluation model is defined through a recursive computation in Equation (12).

$$H^{(l)}(k) = \sigma\left(\widetilde{D}(k)^{-1/2}\widetilde{A}(k)\widetilde{D}(k)^{-1/2}H^{(l-1)}W^{(l)}\right) \tag{12}$$

where $H^{(l)}$ denotes the hidden state at layer l, σ is the activation function, $\widetilde{A} = A(k) + \mathbf{I}$ with $\boldsymbol{I}$ as the identity matrix, $\widetilde{D}$ is the degree matrix, and $W^{(l)}$ represents the weight matrix at layer l. The classification accuracy Acc(k) for each candidate k is computed through five-fold cross-validation. The optimal neighborhood parameter is finally selected as $k^* = \text{argmax}Acc(k)$. Based on this optimal parameter, the final adjacency matrix $\boldsymbol{A}(k)$ is reconstructed using Equation (13), completing the parametric modeling of the graph topology.

$$\boldsymbol{A}(k^*) = \begin{cases} \frac{1}{\left\|x_t - x_j\right\|_2 + \epsilon}, j \in N_{k^*}(t) \\ 0 \end{cases} \tag{13}$$

3.2. The Main Procedure of the ST-GABG Diagnostic Model

To address the insufficiency of traditional bearing-fault-diagnosis methods in spatio-temporal feature joint modeling, this study proposes a cross-modal dual-channel diagnostic framework based on graph convolutional-bidirectional gated recurrent units (GCN-BiGRU), termed ST-GABG (Figure 4). By integrating a dynamic K-nearest neighbor algorithm to construct sensor correlation topologies and leveraging GCN for multi-order neighborhood information aggregation, the framework overcomes fixed receptive field limitations. A BiGRU-global attention fusion architecture is designed to strengthen periodic impact signal capture through bidirectional temporal modeling, while dynamically focusing on critical temporal nodes using attention weights. Additionally, a parameter-efficient gated fusion mechanism adaptively regulates interaction weights between spatial topology features and temporal evolution features, achieving synergistic representation of compound fault characteristics.

The specific implementation process of the ST-GABG diagnostic model is as follows:

(1) Graph data modeling and feature extraction network for rolling bearing data. Based on the dynamic graph topology modeling method proposed in Section 3.1, the adjacency matrix $\boldsymbol{A}(k)$ incorporating node feature information is constructed to complete data relationship representation. Subsequently, the graph-structured data is fed into a three-layer graph convolutional network (GCN) module for feature extraction, followed by average pooling that performs row-wise mean operations on the adjacency matrix using Equation (14). This process simultaneously smooths noise interference while enhancing global feature distribution characteristics.

$$z_{gcn} = \frac{1}{N}\sum_{i=1}^{N} h_i^{(L)} \in \mathbb{R}^{256} \tag{14}$$

where z_{gcn} denotes the graph-level feature vector output by the GCN, which serves as input for subsequent tasks. N represents the total number of nodes in the graph, and $h_i^{(L)}$ indicates the hidden state of the i-th node at the L-th layer of the GCN. The final feature vector is mapped through a fully connected layer to generate the ultimate output feature z_{gcn} with dimensions (batch_size,256).

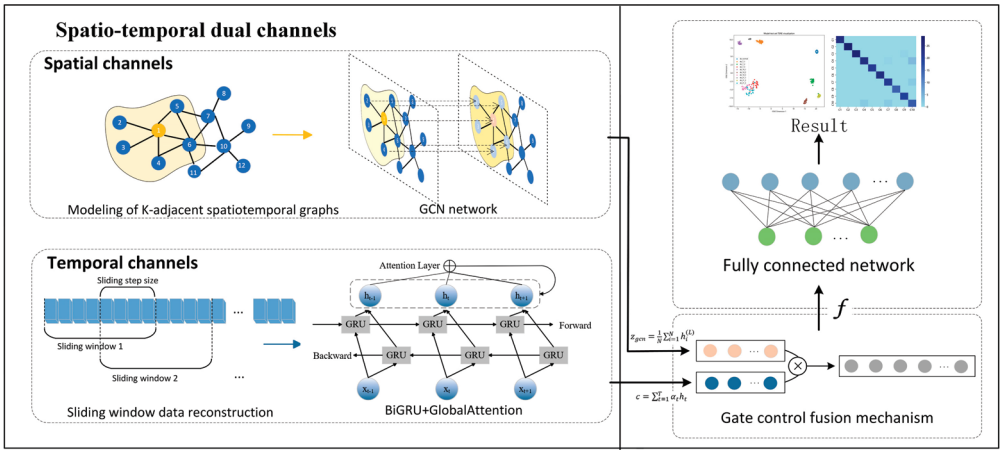


Figure 4. The overall process of the ST-GABG diagnostic model.

(2) Temporal Data Feature Extraction Network Based on Bidirectional Gated Recurrent Units. This module reconstructs the original time-series data, transforming it into a structured training dataset with temporal characteristics. Subsequently, a bidirectional gated recurrent unit (BiGRU) network architecture is constructed to achieve deep feature extraction from input sequences through a synergistic mechanism of forward and backward recursive computation. The network structure is illustrated in Figure 5.

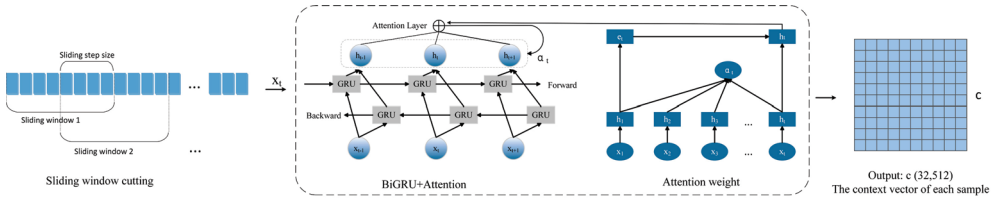


Figure 5. BiGRU and attention fusion architecture.

To address gradient instability and feature extraction challenges in long-sequence signal processing, this module employs a sliding window reconstruction strategy. The original 1024-dimensional time-series signals are partitioned into 32 consecutive temporal windows, each containing 32-dimensional feature points, thereby constructing a 32 × 32 temporal feature tensor.

Subsequently, a bidirectional gated recurrent unit (BiGRU) network architecture is constructed. Through collaborative operations of forward and backward recurrent neurons, this architecture performs deep temporal feature extraction on input sequences to capture bidirectional temporal dependencies in the data. Specifically, the input data x_t is fed into both the forward and backward hidden layers. The forward and backward units receive the input along with the forward hidden state $\overrightarrow{h}_{t-1}$ and backward hidden state $\overleftarrow{h}_{t-1}$ at time $t-1$. The current forward hidden state $\overrightarrow{h}_t$ and backward hidden state $\overleftarrow{h}_t$ at time t are then computed through GRU units. The final hidden state h_t is derived according to Equation (15).

$$h_t = W_{\substack{\rightarrow \\ h_t}} \overrightarrow{h}_t + W_{\substack{\leftarrow \\ h_t}} \overleftarrow{h}_t + b_t \tag{15}$$

Here, $W_{\underset{h_t}{\rightarrow}}$ and $\overrightarrow{h}_t$ denote the weight matrix and hidden state of the forward hidden layer at time t, respectively, while $\overleftarrow{h}_t$ and $W_{\underset{h_t}{\leftarrow}}$ represent the corresponding parameters for the backward hidden layer. b_t denotes the bias term of the hidden state at time t.

The BiGRU architecture enhances the contextual feature extraction capabilities by integrating forward and backward hidden states. Furthermore, this paper proposes embedding a global attention mechanism after the BiGRU framework to generate a context vector c. Through dynamic weight learning, this mechanism enables cross-temporal feature interactions, thereby improving the representation capability of critical fault features and achieving superior global context integration.

(3) Multi-Scale Heterogeneous Feature Fusion Module Based on Channel-Wise Attention Mechanism. In the feature fusion stage, this study proposes a cross-modal feature interaction framework based on a gated mechanism. Considering that different types of faults have varying sensitivities to spatial topological features and temporal dynamic features, this framework introduces a parameter-efficient gated unit to construct a nonlinear feature recombination mechanism to generate multimodal feature representations, which are then inputted into the classifier for fault category identification. On this basis, the system outputs a classification confidence vector and implements a dual-determination mechanism through the preset confidence threshold: when the confidence is higher than the threshold, it is determined as a known fault category; when it is lower than the threshold, the unknown fault identification function is activated. The standard process of online monitoring and offline training verification is shown in Figure 6.

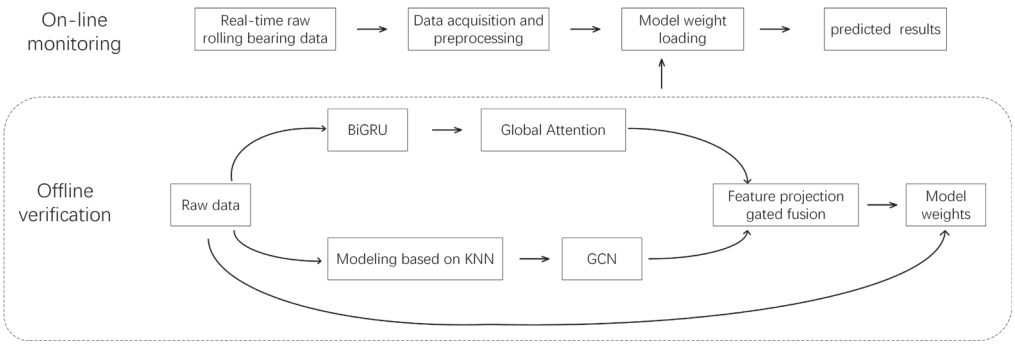


Figure 6. The overall training identification flowchart.

Specifically, the gating mechanism dynamically adjusts interaction weights between graph convolutional features z_{gcn} and attention-enhanced temporal features c, effectively capturing synergistic feature patterns of local graph structure anomalies and global spectral evolution. Firstly, the GCN features are mapped to the category space using Equation (16).

$$z'_{gcn} = W_{gcn} z_{gcn} + b_{gcn} \tag{16}$$

where W_{gcn} denotes the projection matrix and b_{gcn} represents the bias term. Additionally, perform the affine transformation of the context vector c according to Equation (17).

$$c' = W_{att} c + b_{att} \tag{17}$$

where W_{att} denotes the parameter matrix. Finally, the gated weighted fusion is realized by Equation (18).

$$f = W_g \odot z'_{gcn} + \left(1 - \sigma(W_g[z'_{gcn}; c'] + b_g)\right) \odot c' \tag{18}$$

Here, σ denotes the sigmoid activation function, and W_g represents the trainable weight matrix. The fusion feature f outputs the original logits through the classifier and then transforms it into the mathematical form of probability distribution, as shown in Equation (19).

$$P_{i,j} = \text{Softmax}(\text{Wf} + \text{b}) \tag{19}$$

where $P_{i,j}$ is the probability that the *i*th sample belongs to the JTH class, and the confidence is defined as the maximum probability value of each sample $Q_i = Max\left(P_{i,j}\right)$. The unknown category is detected by a confidence threshold τ. If the confidence is lower than the threshold, it is predicted as an unknown category (class C) as detailed in Equation (20).

$$\hat{\boldsymbol{y}}_{\boldsymbol{i}}^{open} = \begin{cases} \hat{\boldsymbol{y}}_i = \arg Max\left(P_{i,j}\right), Q_i \geq \tau \\ C, Q_i < \tau \end{cases} \tag{20}$$

This paper addresses the limitations of traditional bearing fault diagnosis methods in spatiotemporal feature co-modeling by proposing a cross-modal dual-channel diagnostic framework named ST-GABG, based on graph convolutional networks and bidirectional gated recurrent units (GCN-BiGRUs). An improved K-nearest neighbor algorithm is employed to construct graph topological structures, which, combined with three-level graph convolution incorporating post-average pooling, enables multi-order neighborhood information aggregation. Innovatively, a BiGRU-global attention fusion architecture is designed to enhance critical temporal node feature extraction through a dynamic weighting mechanism, while introducing a gating mechanism to achieve dynamic interactions between spatial topological features and temporal features. Systematic experiments are designed in subsequent chapters to comprehensively evaluate the framework's performance from multiple dimensions, including the detection accuracy, robustness, and generalization capability.

4. Experiments

4.1. Experimental Setup and Training Evaluation Metrics

This paper conducts modeling analysis based on the Case Western Reserve University (CWRU) bearing fault dataset [38] and validates the ST-GABG model based on bearing datasets from Southeast University and Jiangnan University. The CWRU bearing test rig introduces single-point faults in test bearings through discharge machining with four different fault diameters: 0.007 inches, 0.014 inches, 0.021 inches, and 0.028 inches [39]. Due to incomplete measurement data for the 0.028-inch diameter condition, this study considers only experimental data from the other three fault sizes. In the CWRU bearing fault dataset, since the outer ring position is relatively fixed, outer race faults are further classified into three categories: 3 o'clock, 6 o'clock, and 12 o'clock positions. This paper employs vibration signals under normal operating conditions and multi-scale damage states as 12 Hz drive bearing faults occurring at 0 horsepower, specifically examining 0.007-inch, 0.014-inch, and 0.021-inch outer race faults (6 o'clock position). The Southeast University bearing dataset includes data types of healthy, rolling element fault, inner race fault, and combined inner-outer race fault under 20 Hz-0V and 30 Hz-3V load conditions. The Jiangnan University bearing dataset contains healthy, inner race fault, outer race fault, and rolling element fault types under variable rotational speeds (600 rpm, 800 rpm, and 1000 rpm). Each dataset comprises 120,000 fault records partitioned into training, testing, and validation sets at a 7:2:1 ratio. Detailed dataset fault information is presented in Table 1.

Table 1. Data set failure situation.

Dataset	Load	Fault Type
CWRU	12 Hertz 0 Mach	Normal 0.007 inner, 0.014 inner, 0.021 inner 0.007 ball, 0.014 ball, 0.021 ball 0.007 outer, 0.014 outer, 0.021 outer
SEU	20 Hz-0V 30 Hz-2V	Normal, ball, comb, inner, outer Normal, ball, comb, inner, outer
JU	600 r/min 800 r/min 1000 r/min	Normal, tb, ib, ob tb, ib, ob tb, ib, ob

The experimental configuration is established as follows: all experiments are implemented on an AMD Ryzen 7 4800U processor with Radeon Graphics operating at 1.80 GHz and 16 GB RAM, utilizing Python 3.8 and the PyTorch-CPU 2.1.0 deep learning framework. This study systematically evaluates the BiGRU network depth through controlled variable analysis: with a fixed GCN layer count (three layers) and learning rate (0.003), performance testing across depths 1–5 reveals optimal accuracy at three BiGRU layers. Further depth increases the trigger gradient explosion risks and results in a 27% extension of the single-epoch training duration. Grid search optimization determines that an initial learning rate of 0.003 stabilizes the validation cross-entropy at ~0.004 by epoch 15, achieving 1.5× faster convergence versus the default (0.001). The implementation of a cosine annealing scheduler enables dynamic learning rate decay to 2.1×10^{-6}, balancing aggressive parameter updates in early epochs with stable optimization in later stages. Parameter configurations are summarized in Table 2.

Table 2. Neural network hyperparameter configuration.

Optimum Model Parameters	Value
BiGRU Hidden Layer	3
GCN Hidden Layer	3
Fully Connected Layer	1
Learning Rate	0.003
Batch	32
Dropout Rate	0.9

This study constructs a multi-dimensional evaluation framework comprising the cross-entropy loss, accuracy, F1 score, and macro-averaged recall. The model performance is systematically characterized through a combination of theoretical derivation and functional validation. The cross-entropy loss quantifies prediction bias based on information entropy theory, calculated in two steps during training: first, the output results are scaled between 0 and 1 using the Sigmoid function as formulated in Equation (21); subsequently, the final loss value is obtained via the negative log-likelihood loss function as defined in Equation (22).

$$sigmoid(x) = \frac{1}{1 + e^{-x}} \tag{21}$$

$$h(p, q) = -\sum_{i=1}^{n} p(x_i)\log(q(x_i)) \tag{22}$$

After each training epoch, the recall is calculated using Equation (23).

$$Recall = \frac{TP}{TP + FN} \tag{23}$$

TP and *FN* denote true positives and false negatives, respectively. Higher recall values and lower cross-entropy loss scores indicate superior model performance. The macro-averaged recall holds particular significance in deep learning multi-class classification tasks. This metric, which treats each class equally, is especially suitable for evaluating model recognition capabilities for minority classes under imbalanced class distributions, with its mathematical formulation derived in Equation (24).

$$Macro - Recall = \frac{1}{m}\sum_{i=1}^{m} Recall_i \tag{24}$$

The F1 score comprehensively considers both model precision and recall. It is particularly applicable to scenarios with class imbalance, such as significant class distribution disparities between positive and negative samples, where it balances precision–recall trade-offs through harmonic mean computation. The mathematical formulation of the F1 score is presented in Equation (25):

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{25}$$

In the performance evaluation of machine learning models, the systematic construction of multi-dimensional indicators has core value. This paper reflects the prediction uncertainty from the perspective of information theory through cross-entropy loss. The accuracy rate provides the overall performance benchmark. The F1 score balance precision rate is in contradiction with the recall rate, while the macro average recall rate focuses on the minority class recognition ability under class imbalance. It is particularly worth noting that in the process of optimizing deep learning models, this multi-dimensional index system can construct a diagnostic analysis graph. Through the collaborative verification among indicators, the precise location of model defects can be achieved, ultimately forming a closed-loop iterative mechanism of "error traceability—performance attribution—strategy optimization", thereby systematically enhancing the generalization ability and decision-making reliability of the model.

4.2. Description of Comparison Methods

To demonstrate the significant advantages of the proposed spatiotemporal joint diagnostic model (ST-GABG) in bearing fault diagnosis tasks, we compare it with various network models including the graph neural networks GAT, GCN, GIN, and SGCN and temporal models TCN, CNLSTM, and TransformerAttn. All methods are evaluated on identical datasets under consistent experimental environments—specific parameter configurations are detailed in Table A1. Diagnostic results across all methods are summarized in Table 3, leading to the following conclusions:

Table 3. Diagnosis accuracies of all the methods.

Methods	Precision	F1 Score	Macro Average Recall Rate
GCN	91.25%	0.9742	0.9724
GIN	83.95%	0.8412	0.8212
GAT	92.08%	0.9356	0.9287
SGCN	92.70%	0.9399	0.9502
TransformAttn	86.91%	0.8798	0.8804
TCN	57.29%	0.5900	0.5800
CNLSTM	66.39%	0.7039	0.7286
Proposed method	**97.08%**	**0.9914**	**0.9906**

(1) Compared with traditional graph neural network models, ST-GABG demonstrates substantially superior performance. Specifically, while GAT and GCN achieve accuracy rates of 92.08% and 91.25%, respectively, ST-GABG attains a remarkable accuracy of 97.08%. This improvement stems from two critical innovations: first, by introducing a global attention mechanism that dynamically weights critical temporal steps after bidirectional GRU-based temporal feature extraction, ST-GABG effectively enhances spatiotemporal feature co-optimization. This approach not only reduces the training time by 9% but also improves the accuracy by 5% compared to the GAT model, which suffers from high computational complexity due to its reliance on single spatial attention mechanisms. Second, unlike GCN's fixed neighborhood aggregation strategy, ST-GABG incorporates an improved KNN temporal-step joint encoding algorithm combined with a self-loop elimination weighted graph construction method. Through cross-validated graph parameter optimization, this approach achieves a 5.83% accuracy improvement. As shown in Figure 7, the proposed method can reach the verification loss convergence level more quickly and achieve a more stable loss curve. Combined with the early stopping strategy, it effectively reduces the training time. These results validate that the integration of bidirectional GRU temporal feature extraction with global attention dynamic weighting, synergistically combined with the improved K-NN algorithm, enables the effective fusion of temporal local–global features and complementary integration of spatiotemporal heterogeneous information.

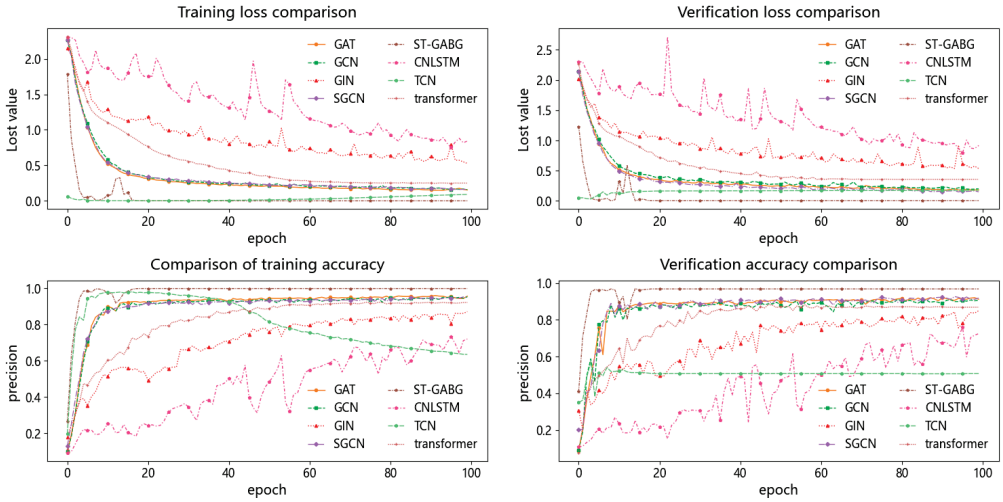


Figure 7. Comparison chart of loss accuracy rates of GCN, GAT, GIN, SGCN, and proposed method.

(2) This study compares ST-GABG with three representative models: TCN, Transformer integrated with attention mechanisms, and CNN-LSTM fusion architectures. Specifically, TCN employs dilated convolutions to expand the receptive field for comprehensive global information capture, but suffers from substantial parameter overhead that increases the computational costs. In contrast, ST-GABG adopts a more lightweight global attention mechanism that significantly improves model efficiency. Compared to Transformer architectures that rely on self-attention for long-range dependency modeling but encounter computational complexity-induced inference latency, ST-GABG implements a cascaded design combining gated recurrent units with global attention. This approach effectively reduces the computational complexity while enhancing dynamic temporal feature capture through BiGRU's memory update mechanism, achieving a 10.17% accuracy improvement. Furthermore, unlike CNN-LSTM's stacked paradigm that sequentially extracts local features followed by sequence dependencies in separate phases, ST-GABG dynamically weights BiGRU hidden states via attention mechanisms to enable the deep fusion of local

detailed features and global semantic information. Figure 8 visually demonstrates these performance advantages through 3D confusion matrix visualization.

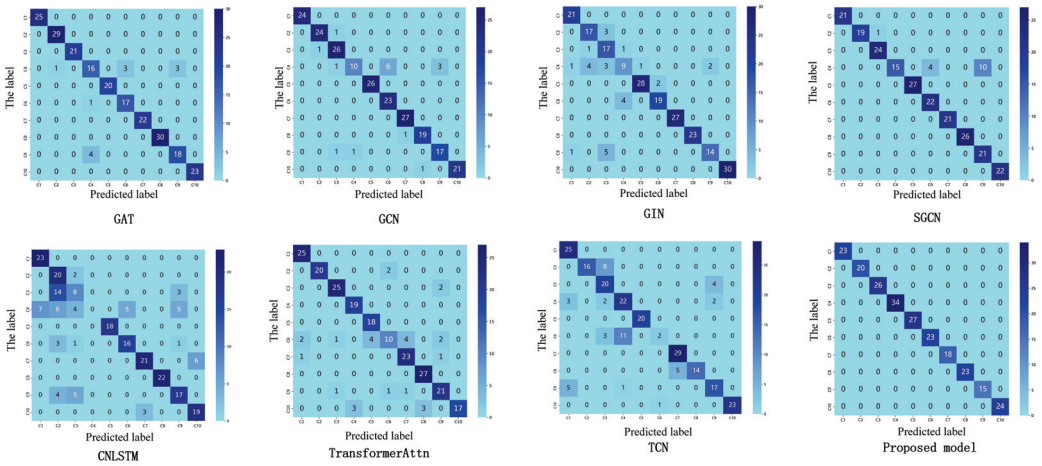


Figure 8. The three-dimensional confusion matrix of the proposed method and the comparison model.

4.3. The Ablation Experiments of the Proposed Method

The proposed multi-modal fusion methodology has demonstrated superior scene-adaptability diagnostic capabilities in preliminary experiments. This section further investigates the effectiveness of each functional module in the proposed model. Based on GCN, BiGRU, and global attention mechanisms, three ablation studies and three single-component control experiments are designed. Experimental results are summarized in Table 4, while Figure 9 compares validation loss curves across ablation groups. Through module combination analysis, this work quantitatively reveals the contributions of individual components to diagnostic performance. Specific quantitative findings lead to the following conclusions:

Table 4. Ablation study on performance comparison of GCN, BiGRU, and attention-based models.

Experiment Number	GCN	BiGRU	Attention	Precision	F1 Score	Macro Average Recall Rate
Ablation1		√	√	90.83%	0.9399	0.9385
Ablation2	√		√	73.12%	0.7253	0.7276
Ablation3	√	√		87.91%	0.9227	0.9233
Ablation4	√			50.62%	0.4850	0.5052
Ablation5		√		89.58%	0.9396	0.9337
Ablation6			√	70.00%	0.6652	0.6643
Proposed method	√	√	√	**97.08%**	**0.9914**	**0.9906**

Compared with Ablation1 (BiGRU and Attention), Ablation2 (GCN and Attention), and Ablation3 (GCN and BiGRU) architectures, Ablation1 achieves 90.83% accuracy, significantly outperforming other configurations. Specifically, it demonstrates a 17.71% improvement over Ablation2 (without temporal modeling) and a 2.92% enhancement compared to Ablation3 (without attention mechanism). Results indicate that equipment degradation processes in industrial scenarios exhibit strong temporal dependencies, which pure spatial modeling struggles to capture. The BiGRU component synchronously captures historical evolution trends and potential future patterns of device states through forward/backward gated recurrent units, while the attention mechanism dynamically enhances critical feature representations and suppresses sensor acquisition noise interference. This synergistic integration of bidirectional temporal modeling and adaptive feature weighting substantially improves complex spatio-temporal pattern recognition capabilities.

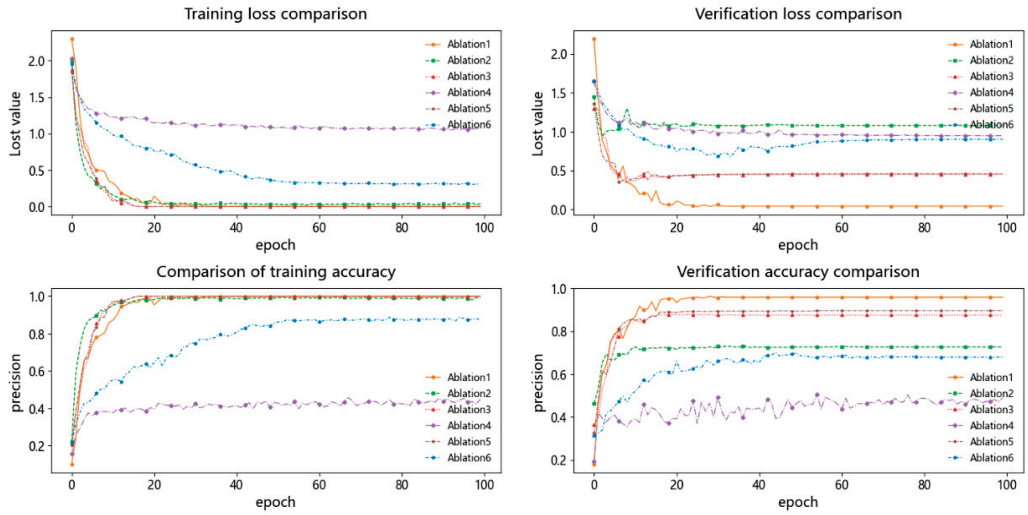


Figure 9. Ablation experiment loss and accuracy comparison chart.

By comparing the proposed method with the BiGRU and attention architecture, the introduction of graph topology structure modeling demonstrates superior feature representation capabilities. Specifically, the proposed approach achieves a 6.25% accuracy improvement over BiGRU and attention, which reveals the necessity of spatio-temporal heterogeneous feature fusion. This performance improvement arises from graph convolutional operations capturing spatial correlations between nodes, complementing BiGRU's temporal dimension modeling. The significant performance gap between Ablation3 (without attention mechanism) and Ablation4 (without any enhancement modules) validates that sole reliance on single-module architectures fails to fully exploit latent information in spatio-temporal data, further substantiating the requirement for joint spatio-temporal reasoning in complex fault pattern analysis.

Through ablation studies comparing GCN and attention, GCN and BiGRU, BiGRU and attention, and the proposed method, the model's ability to maintain high precision while significantly enhancing generalization capabilities in complex scenarios is validated. This advantage stems from the complementary modeling of spatio-temporal features through multi-modal fusion mechanisms. The average accuracy rates of the four architectures are 73.12%, 87.91%, 90.83%, and 97.08%, respectively, demonstrating the progressive performance gains achieved by integrating spatial–temporal heterogeneity and adaptive feature interaction.

4.4. Visualization of the Feature Extraction Results

To validate the deep feature extraction capability of the proposed model under rolling bearing signal-driven few-shot diagnosis scenarios, this study employs the t-distributed stochastic neighbor embedding (T-SNE) algorithm for nonlinear dimensionality reduction and visual analysis of high-dimensional feature spaces [40,41]. Class probability serves as one of the primary perspectives for evaluating model outcomes and identifying problematic samples [42]. As illustrated in Figure 10, conventional methods exhibit significant limitations with severe inter-class overlap and blurred decision boundaries in the projected space. The proposed model (subfigure e) demonstrates superior feature separability: specifically, intra-class compactness is significantly enhanced, inter-class discriminability is strengthened, and fault categories form independent clusters with explicit geometric margins; decision boundaries achieve higher clarity. This visualization validates the proposed model's advantages in rolling bearing signal representation clustering from a geometric-topological perspective. Figure 11 demonstrates that ST-GABG exhibits excellent clustering

representation capability and dataset-adaptability generalization performance across three bearing datasets from CWRU, Southeast University, and Jiangnan University.

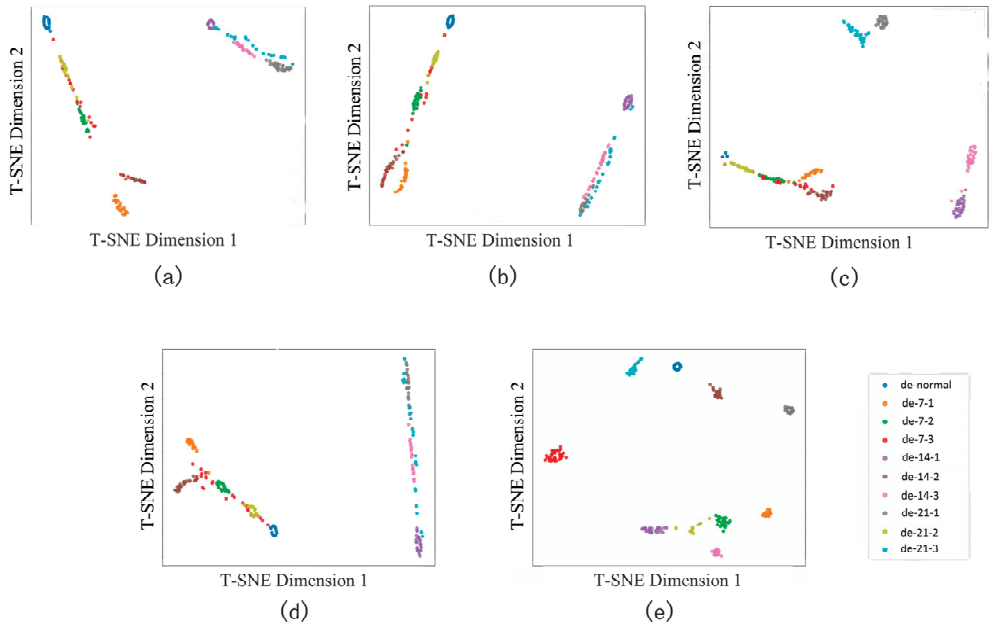


Figure 10. Visualization characteristics of the comparison method of T-SNE in multi-signal scenarios: (**a**) GAT; (**b**) GCN; (**c**) GIN; (**d**) SGCN; (**e**) proposed method.

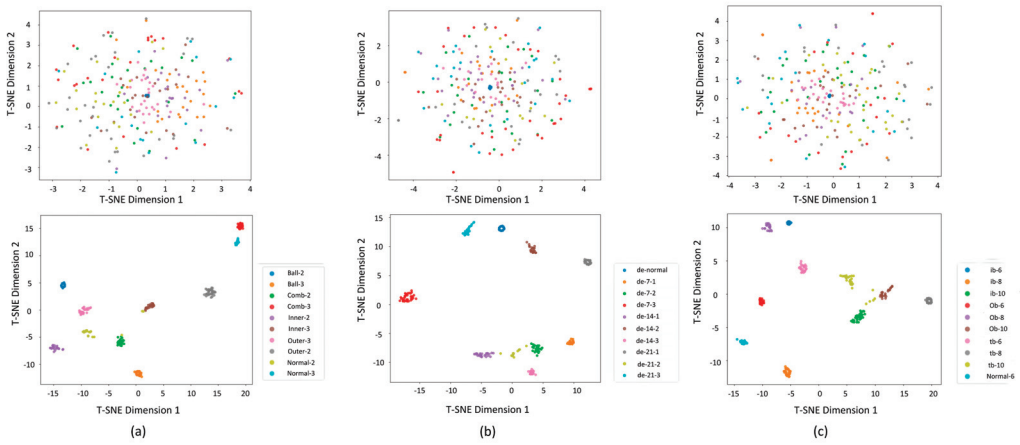


Figure 11. T-SNE scatter plots of the ST-GABG model under the bearing dataset of Southeast University (**a**), Case Western Reserve University bearing dataset (**b**), and Jiangnan University dataset (**c**), respectively.

5. Conclusions

This study proposes a spatiotemporal joint modeling approach for bearing fault diagnosis, addressing critical challenges in traditional diagnostic methods related to multi-dimensional information fusion, dynamic feature capturing, and complex operating condition adaptation. Specifically, a graph topology structure based on a modified K-nearest neighbors (KNNs) algorithm is constructed to deeply explore spatial mutual information correlations among fault signals, enabling the extraction of diagnostic knowledge graphs with cross-condition generalizability. Furthermore, a global attention mechanism is embedded within bidirectional gated recurrent units (BiGRU), where the dynamic allocation of temporal feature weights enhances critical node perception capabilities, significantly improving the model's precision in capturing long-range spatiotemporal context associations. A gated fusion module is ultimately designed to achieve the adaptive integration of

dual-channel features, forming a spatiotemporal joint diagnostic architecture with strong interpretability. Through the experimental part, the effectiveness and universality of the model were fully verified on multiple public datasets. Notably, this work has two primary limitations: first, constrained by experimental conditions, the method has not yet been validated in real industrial scenarios; secondly, the current decision mechanism based on a fixed threshold is difficult to adapt to the change in the category distribution in dynamic scenarios, so we should explore the optimization mechanism of dynamic confidence thresholds.

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Data Availability Statement: The data presented in this study are openly available in kyrr-y/BEARING.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

In the appendix, Table A1 lists the key hyperparameter Settings of the comparison methods in detail, and Table A2 abbreviation table shows the abbreviations in this paper for explanation.

Table A1. Core configuration of the comparison method.

Model	Learn Rate	Weight_Decay	Head/Kernel	Layer
GAT	0.0003		1	3
GCN	0.0003			3
GIN	0.0003			3
SGCN	0.0003		1	3
TCN	0.003		2	2
CNLSTM	0.003		3	2
TransformerAttn	1×10^{-4}	1×10^{-5}	2	2

Table A2. List of abbreviations.

Acronym	Fall Name
BiGRU	The Bidirectional Gated Recurrent Unit
GCN	Graph Convolutional Network
KNN	K-Nearest Neighbor
ST-GABG	The Proposed Spatio-Temporal Joint Diagnosis Model
CWRU	Case Western Reserve University
SEU	Southeast University
JU	Jiangnan University
TransformerAttn	Transformer Attention Fusion Architecture
CNLSTM	CNN and LSTM Fusion Architecture
T-SNE	T-Distributed Stochastic Neighbor Embedding

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Multi-Dimensional Anomaly Detection and Fault Localization in Microservice Architectures: A Dual-Channel Deep Learning Approach with Causal Inference for Intelligent Sensing

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Abstract: Modern data centers face increasing complexity with distributed microservice architectures, making anomaly detection and fault localization challenging yet critical. Traditional monitoring sensor tools struggle with heterogeneous metrics, temporal correlations, and precise root cause analysis in these environments. This paper proposes a dual-channel deep learning framework that integrates Temporal Convolutional Networks with Variational Autoencoders to address these challenges. Our approach employs contrastive learning to create unified representations of diverse service metrics and incorporates causal inference mechanisms to trace fault propagation paths. We evaluated our framework using a semi-supervised learning approach that leveraged both labeled anomalies and abundant normal data, achieving 95.4% detection accuracy, 93.8% F1-score, and 87.6% precision in fault component localization. The system reduced the average troubleshooting time by 43% and false localization rates by 31% compared to state-of-the-art methods, while maintaining a computational efficiency suitable for real-time monitoring. These results demonstrate the effectiveness of our approach in identifying and precisely localizing anomalies in complex microservice environments through intelligent sensing of system metrics, enabling proactive maintenance strategies that minimize service disruptions.

Keywords: anomaly detection; fault localization; microservice architecture; monitoring system; performance sensing

1. Introduction

Modern cloud computing infrastructures are increasingly built on complex microservice architectures, where applications are composed of numerous loosely coupled services that communicate through well-defined interfaces [1]. While this architectural paradigm offers significant advantages in terms of scalability, flexibility, and development efficiency, it also introduces substantial challenges for system monitoring, anomaly detection, and fault diagnosis [2]. The distributed nature of these systems, combined with their dynamic scaling capabilities and intricate service dependencies, creates an environment where the performance issues captured by monitoring sensors can rapidly propagate across the infrastructure, making it difficult to locate the root cause of problems [3]. The complexity of microservice environments is further amplified by the heterogeneous nature of monitoring data. System administrators must track numerous Key Performance Indicators (KPIs) across multiple dimensions, including CPU utilization, memory consumption, network

traffic, response times, error rates, and application-specific metrics sensed from distributed service components [4]. These metrics often exhibit different statistical properties, temporal patterns, and correlation structures, creating significant challenges for traditional anomaly detection approaches [5].

Early detection and precise localization of anomalies through intelligent sensing are critical for maintaining service reliability and minimizing downtime in production environments. According to recent industry reports, the average cost of downtime for enterprise-level services exceeds USD 5600 per minute, with potential financial impacts reaching millions of dollars per hour for major online service providers. Despite these high stakes, existing monitoring solutions frequently struggle with false positives, delayed detection, and imprecise fault localization [6]. Traditional threshold-based methods for anomaly detection lack the sophistication required to handle the dynamic nature of microservice metrics and often fail to capture complex temporal dependencies and inter-service correlations [7]. More advanced machine learning approaches, including isolation forests [8], one-class SVMs [9], and clustering-based methods [10], have demonstrated improved capabilities but typically treat metrics in isolation, overlooking the multi-dimensional relationships that characterize microservice failures.

Recent advancements in deep learning have shown promise for addressing these limitations. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been applied to capture temporal dependencies in monitoring data [11], while autoencoders have proven effective for learning compact representations of normal system behavior [12]. However, most existing deep learning approaches primarily focus on anomaly detection, without addressing the equally important challenge of fault localization—identifying which specific component or service is responsible for an observed anomaly [13]. Furthermore, the causal relationships between metrics and the propagation patterns of failures across services remain largely unexplored in current research. Understanding these causal mechanisms is essential for accurate root cause analysis and effective remediation strategies [14]. The lack of integrated approaches that combine anomaly detection with causal analysis presents a significant gap in the literature and limits the practical utility of existing solutions [15].

To address these challenges, we propose a novel dual-channel deep learning framework that combines Temporal Convolutional Networks (TCNs) with Variational Autoencoders (VAEs) for joint anomaly detection and fault localization in microservice architectures. Our approach leverages contrastive learning to create unified representations of heterogeneous metrics and incorporates causal inference mechanisms to trace fault propagation paths across services. By integrating these components, our framework not only identifies anomalies with high accuracy but also pinpoints their root causes, enabling more efficient troubleshooting and maintenance processes. It is important to clarify that our framework follows a semi-supervised learning paradigm, utilizing both abundant normal operational data and limited labeled anomaly examples from historical incidents during training. While the majority of anomaly detection research focuses on unsupervised approaches that rely solely on normal data patterns, the semi-supervised paradigm is particularly relevant for production microservice environments, where some historical anomaly incidents with known root causes are typically available and the high cost of critical failures justifies leveraging this supervisory signal to improve detection accuracy and reduce false positives. The main contributions of this paper can be summarized as follows:

- We design a dual-channel architecture that combines the temporal modeling capabilities of TCNs with the latent representation power of VAEs, enabling effective anomaly detection across diverse metrics and service types.

- We develop a contrastive learning approach that creates unified representations of heterogeneous monitoring data, addressing the challenge of correlating metrics with different statistical properties and scales.
- We propose a causal inference mechanism that models the dependencies between services and traces fault propagation patterns, significantly improving the precision of root cause localization.
- We conducted extensive experiments on the public MultiDimension-Localization dataset, demonstrating that our framework outperformed state-of-the-art methods in both anomaly detection and fault localization tasks.
- We analyzed the computational efficiency and scalability of our approach, showing that it maintains real-time performance, even with large numbers of services and metrics.

The remainder of this paper is organized as follows: Section 2 reviews related work on anomaly detection, fault localization, and causal inference. Section 3 presents the problem formulation and details our proposed methodology. Section 4 describes the experimental setup, dataset characteristics, and evaluation metrics. Section 5 discusses the experimental results and compares our approach with existing methods. Section 6 concludes our work and outlines directions for future research. concludes the paper.

2. Related Works

This section reviews the existing literature related to anomaly detection and fault localization in distributed systems, with a focus on microservice architectures. We categorize related work into three main areas: (1) traditional anomaly detection methods, (2) deep learning approaches for anomaly detection, and (3) fault localization and root cause analysis techniques.

2.1. Traditional Anomaly Detection Methods

Traditional anomaly detection approaches in distributed systems typically rely on statistical methods, machine learning algorithms, or rule-based techniques. Statistical methods include threshold-based detection [16], moving average processes [17], and time series decomposition [18]. These approaches generally assume that normal behavior follows certain statistical distributions, and they then flag deviations from these sensed patterns as anomalies. Machine-learning-based approaches have gained significant attention due to their ability to learn complex patterns without explicit programming. Supervised methods require labeled anomaly data for training, which are often scarce in real-world scenarios [19]. In contrast, unsupervised methods such as clustering, isolation forests [8], and one-class SVM [9] can identify anomalies without labeled training data by detecting instances that deviate significantly from the majority. Rule-based systems employ domain knowledge to establish detection rules [20]. While effective in well-understood environments, these systems often struggle to adapt to the dynamic nature of microservice architectures, where service behaviors and interactions evolve rapidly [21]. Additionally, the high dimensionality and heterogeneity of monitoring data in microservice environments create significant challenges for traditional methods, which typically process each metric independently and fail to capture complex inter-service dependencies [22].

2.2. Deep Learning for Anomaly Detection

Deep learning approaches have demonstrated superior performance in anomaly detection for complex systems, due to their ability to learn hierarchical representations and capture intricate temporal patterns. Recurrent Neural Networks, particularly Long Short-Term Memory networks, have been widely applied to time series anomaly detection in

various domains, including network traffic [23], cloud computing [24], and IoT systems [25]. Autoencoders represent another popular class of deep learning models for anomaly detection. By learning to reconstruct normal behavior and using reconstruction error as an anomaly indicator, these methods have shown effectiveness in various applications [26]. VAEs extend traditional autoencoders by learning probabilistic latent representations, providing better generalization capabilities for complex data distributions [27]. DONUT [12] applies VAEs for unsupervised anomaly detection in seasonal KPIs of web applications, addressing challenges such as missing data and seasonal patterns. Recent research has explored TCNs for time series modeling, offering advantages over RNN-based architectures through parallel processing, flexible receptive fields, and stable gradients [28]. OmniAnomaly [29] combines stochastic recurrent neural networks with planar normalizing flows for multivariate time series anomaly detection, achieving state-of-the-art performance on various datasets. Despite these advancements, most existing deep learning approaches primarily focus on anomaly detection, without addressing the equally important task of fault localization, particularly in the context of microservice architectures where anomalies can propagate across multiple services [6].

2.3. Fault Localization and Root Cause Analysis

Fault localization in distributed systems aims to identify the root cause of observed anomalies, a challenging task due to complex service dependencies and fault propagation patterns. Traditional approaches rely on expert knowledge and rule-based systems [30], which become increasingly impractical as system complexity grows. Graph-based methods have gained prominence for modeling service dependencies and tracing fault propagation. CloudRanger [31] constructs a service dependency graph and leverages statistical techniques to identify the root cause of performance anomalies. Similarly, MicroScope [4] builds causal graphs to pinpoint performance issues in microservice environments, analyzing request trace data to infer causal relationships between services. Recent advances have incorporated machine learning techniques for more automated fault localization. MicroRCA [7] employs a random forest classifier to identify the root cause component based on anomaly propagation patterns. MIDAS [32] proposes a multi-dimensional anomaly detection and localization framework that combines autoencoders with attention mechanisms to identify faulty services. Causal inference techniques have emerged as a promising direction for more precise root cause analysis. CausalRCA [33] applies causal discovery algorithms to infer causal relationships between metrics and services, enabling more accurate fault localization. ClearCausal [34] leverages structural equation models to capture causal dependencies between services and metrics, demonstrating improved performance in complex microservice environments. Despite these advancements, existing approaches often struggle with the heterogeneity of monitoring data and the dynamic nature of microservice architectures. Most methods either focus on anomaly detection without localization or employ separate models for each task, potentially missing important correlations between them. Additionally, few approaches explicitly model both temporal dependencies and causal relationships, which are crucial for understanding fault propagation in distributed systems [35].

3. Preliminaries

This section introduces key concepts, notations, and problem definitions to establish the foundation for our methodology.

3.1. Problem Formulation

Microservice architectures consist of multiple loosely coupled services that communicate with each other through well-defined interfaces. In this context, we formally define the anomaly detection and fault localization problems as follows: Consider a microservice system with N services, where each service generates M different types of performance metrics over time. Let $X = \{x_1, x_2, \ldots, x_{N\times M}\}$ represent the set of all time series metrics, where each $x_i = \{x_i^1, x_i^2, \ldots, x_i^T\}$ is a sequence of observations for the i-th metric over T timestamps. Given this multivariate time series data, we aim to address two interconnected tasks:

- **Anomaly Detection**: Identify timestamps t where the system exhibits anomalous behavior, represented by a binary indicator function $f_a(X, t) \in \{0, 1\}$, where 1 indicates an anomaly.
- **Fault Localization**: For each detected anomaly at time t, identify the specific service(s) $S_{root} \subseteq \{1, 2, \ldots, N\}$ that represent the root cause of the anomaly through a function $f_l(X, t) = S_{root}$.

In the context of microservice architectures, we define **anomalies** as deviations from normal system behavior observable through monitoring metrics, such as sudden spikes in response time, memory usage exceeding normal ranges, or error rate increases. **Faults** represent the underlying root causes of these anomalies, such as memory leaks in specific services, network congestion between service components, or database connection pool exhaustion. Our framework addresses four primary categories consistent with the dataset: resource contention (CPU/memory exhaustion), network latency issues, application errors (exceptions, timeouts), and dependency failures (service unavailability, cascading failures).

3.2. Key Technical Concepts

3.2.1. Temporal Convolutional Networks

Temporal Convolutional Networks are specialized convolutional architectures designed for sequence modeling. Unlike recurrent networks, TCNs employ causal convolutions that prevent information leakage from future time steps to past ones. A key feature of TCNs is the use of dilated convolutions, which allow the network to effectively capture long-range temporal dependencies by exponentially expanding the receptive field without increasing the computational cost [28]. Formally, a dilated causal convolution operation on a 1D sequence input x is defined as

$$F(s) = (x *_d f)(s) = \sum_{i=0}^{k-1} f(i) \cdot x_{s-d\cdot i} \tag{1}$$

where f is a filter of size k, d is the dilation factor, and $s - d \cdot i$ ensures causality.

3.2.2. Variational Autoencoders

Variational Autoencoders are generative models that learn a probabilistic mapping between the data space and a lower-dimensional latent space [36]. Unlike traditional autoencoders, VAEs model the latent space as a probability distribution, typically a multivariate Gaussian. The VAE consists of an encoder network that maps input x to the parameters of a latent distribution (mean μ and variance σ^2), and a decoder network that reconstructs the input from samples drawn from this distribution. The objective function combines reconstruction quality with a regularization term:

$$L_{VAE} = E_{q(z|x)}[\log p(x|z)] - D_{KL}(q(z|x)||p(z)) \tag{2}$$

where x is the input data, z is the latent variable, $q(z|x)$ is the encoder posterior distribution, $p(x|z)$ is the decoder likelihood, $p(z)$ is the prior distribution (typically standard Gaussian), and D_{KL} denotes the Kullback–Leibler divergence. In practice, the encoder network outputs the mean μ and log-variance $\log \sigma^2$ through two separate fully connected layers that map the input features to the latent dimension. The mean and variance parameters are learned during training through backpropagation, with the encoder automatically determining appropriate latent representations for the input data distribution.

3.2.3. Causal Inference

Causal inference aims to identify cause–effect relationships between variables, going beyond mere statistical correlations [37]. In the context of distributed systems, causal relationships can be represented as a directed acyclic graph (DAG) $G = (V, E)$, where nodes V represent components or metrics, and edges E represent causal dependencies. Several algorithms have been developed to infer causal structures from observational data, including constraint-based methods like the PC algorithm [38] and score-based methods like Greedy Equivalence Search (GES) [39]. These algorithms identify conditional independence relationships between variables to construct or score potential causal graphs.

3.2.4. Contrastive Learning

Contrastive learning is a self-supervised learning technique that learns representations by maximizing the agreement between differently augmented views of the same data point, while minimizing the agreement between views of different data points [40]. The core idea is to pull similar samples closer in the representation space, while pushing dissimilar samples apart. For a given data point x, let x^+ be an augmented view of x (positive sample) and $\{x_1^-, x_2^-, \ldots, x_k^-\}$ be a set of unrelated samples (negative samples). The contrastive loss function can be defined as

$$\mathcal{L}_{contrastive} = -\log \frac{\exp(sim(f(x), f(x^+))/\tau)}{\exp(sim(f(x), f(x^+))/\tau) + \sum_{i=1}^{k} \exp(sim(f(x), f(x_i^-))/\tau)} \quad (3)$$

where $f(\cdot)$ is an encoder network, $sim(\cdot, \cdot)$ is a similarity function (e.g., cosine similarity), and τ is a temperature parameter that controls the sharpness of the distribution.

4. Methodology

This section presents our dual-channel deep learning framework for anomaly detection and fault localization in microservice architectures. We first provide an overview of the framework architecture, followed by detailed explanations of each component and the training procedure.

4.1. Framework Overview

Figure 1 illustrates the overall architecture of our proposed framework, which consists of four main components: (1) a dual-channel encoder comprising a TCN branch and a VAE branch for processing sensed metrics, (2) a contrastive learning module for heterogeneous sensor metric fusion, (3) an anomaly detection module, and (4) a causal inference module for fault localization.

Our framework processes multivariate time series data sensed from multiple microservices, extracting both temporal patterns and latent representations to detect anomalies and identify their root causes. The dual-channel encoder addresses the challenge of heterogeneous metrics by learning both temporal dependencies and compact representations, while the contrastive learning module facilitates the fusion of these diverse metrics into a unified representation. The anomaly detection module identifies timestamps with abnormal sys-

tem behavior, and the causal inference module traces fault propagation paths to localize the root cause services.

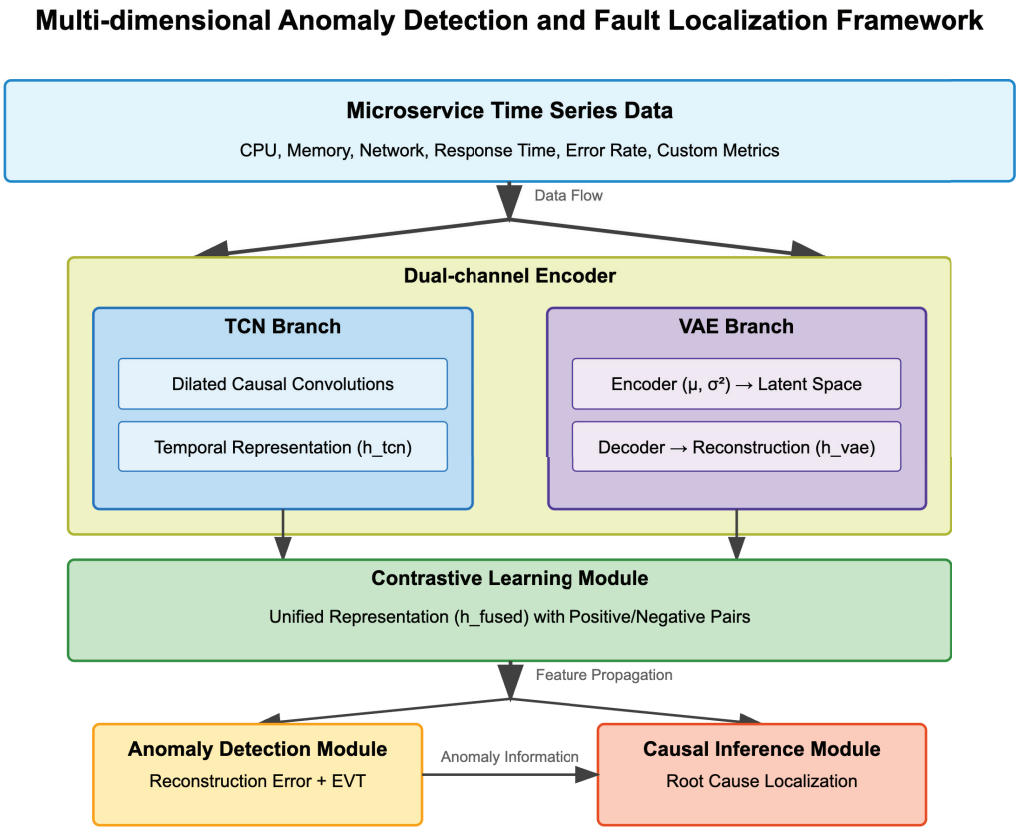


Figure 1. Architecture of the proposed dual-channel framework for anomaly detection and fault localization. The framework consists of a TCN branch that captures temporal dependencies, a VAE branch that learns latent representations, a contrastive learning module that fuses heterogeneous metrics, and a causal inference module that identifies the root cause of anomalies.

4.2. Dual-Channel Encoder for Sensed Time Series

4.2.1. TCN Branch

The TCN branch captures temporal dependencies and sequential patterns in the time series data. For each metric x_i, we construct a sliding window of length w to obtain input segments $\{x_i^{t-w+1}, x_i^{t-w+2}, \ldots, x_i^t\}$ for each timestamp t. These segments are processed by a TCN that consists of multiple residual blocks with dilated causal convolutions. Each residual block contains two dilated causal convolution layers with weight normalization, ReLU activation, and dropout. The dilation factor increases exponentially with the depth of the network ($d = 2^l$ for layer l), enabling the TCN to capture long-range dependencies efficiently. Formally, the output of each residual block is computed as

$$z_l = \text{ReLU}(x_l + F(x_l)) \tag{4}$$

where x_l is the input to the block, $F(\cdot)$ represents the convolution operations, and a skip connection adds the input to the transformed output. The final hidden representation from the TCN branch, denoted as h_{tcn}^t, captures the temporal context and patterns for each timestamp t.

4.2.2. VAE Branch

The VAE branch learns compact latent representations of the input data, capturing the underlying data distribution and relationships between metrics. For each timestamp

t, we encode the current observations $\{x_1^t, x_2^t, \ldots, x_{N\times M}^t\}$ using a variational encoder that maps the input to parameters of a latent distribution. Here, the timestamps t correspond to the regular sampling intervals of the monitoring system (e.g., 1 min intervals in our dataset), with the VAE processing metric observations at each discrete time point during the monitoring window. The encoder consists of multiple fully connected layers with ReLU activations, culminating in two parallel output layers that produce the mean μ and log-variance $\log \sigma^2$ of the latent distribution. We sample latent vectors z using the reparameterization trick:

$$z = \mu + \sigma \odot \epsilon, \quad \epsilon \sim \mathcal{N}(0, I) \tag{5}$$

The decoder reconstructs the input from the latent representation through a series of fully connected layers with ReLU activations. The VAE is trained with the following loss function:

$$\mathcal{L}_{vae} = \|x - \hat{x}\|_2^2 + \beta \cdot D_{KL}(q(z|x)\|p(z)) \tag{6}$$

where $\hat{x}$ is the reconstructed input, $\|\cdot\|_2^2$ is the squared L_2 norm representing the reconstruction error, D_{KL} is the Kullback–Leibler divergence that regularizes the latent space, and β is a hyperparameter that controls the trade-off between reconstruction fidelity and latent space regularity. The latent representation from the VAE branch, denoted as h_{vae}^t, captures the underlying structure and relationships in the multidimensional metric space at timestamp t.

4.3. Contrastive Learning for Heterogeneous Sensed Metric Fusion

To effectively integrate heterogeneous metrics across different services, we employ a contrastive learning approach that creates unified representations by pulling similar patterns closer and pushing dissimilar patterns apart in the embedding space. For each service, we group its related metrics and generate positive pairs by applying different augmentations to the same service's metrics, while treating metrics from other services as negative examples. The augmentations include adding Gaussian noise, scaling, and masking random segments of the time series. Given the embeddings from both the TCN and VAE branches, we compute a fused representation h_{fused}^t for each timestamp t as follows:

$$h_{fused}^t = f_{fusion}([h_{tcn}^t, h_{vae}^t]) \tag{7}$$

where f_{fusion} is a fusion network implemented as a multi-layer perceptron with residual connections, and $[\cdot, \cdot]$ denotes concatenation.

The contrastive loss is computed using the NT-Xent (normalized temperature-scaled cross-entropy) loss function:

$$\mathcal{L}_{contrastive} = -\log \frac{\exp(sim(h_i, h_i^+)/\tau)}{\sum_{j=1}^{2N} \mathbb{1}_{[j\neq i]} \exp(sim(h_i, h_j)/\tau)} \tag{8}$$

where h_i and h_i^+ are the embeddings of a positive pair, $sim(\cdot, \cdot)$ is the cosine similarity, τ is a temperature parameter, and $\mathbb{1}_{[j\neq i]}$ is an indicator function equal to 1 if $j \neq i$. This contrastive learning approach enables the model to learn service-specific patterns, while maintaining awareness of the relationships between different services, which is essential for accurate fault localization.

4.4. Anomaly Detection

Our anomaly detection module leverages both the reconstruction capability of the VAE and the temporal context provided by the TCN to identify anomalies in sensed metrics.

We compute an anomaly score s_a^t for each timestamp t as a weighted combination of the reconstruction error and prediction deviation:

$$s_a^t = \alpha \cdot \|x^t - \hat{x}^t\|_2^2 + (1-\alpha) \cdot \|h_{tcn}^t - \hat{h}_{tcn}^t\|_2^2 \tag{9}$$

where $\hat{x}^t$ is the VAE reconstruction, $\hat{h}_{tcn}^t$ is the predicted TCN embedding for timestamp t based on previous time steps, and $\alpha \in [0,1]$ is a hyperparameter that balances the contribution of each term.

To account for the varying statistical properties of different metrics, we normalize the anomaly scores using a service-specific adaptive threshold based on the Extreme Value Theory (EVT) [41]. Specifically, we fit a Generalized Pareto Distribution (GPD) to the upper tail of the anomaly score distribution for each service during the training phase:

$$F(s) = 1 - (1 + \xi \cdot \frac{s-\mu}{\sigma})^{-1/\xi} \tag{10}$$

where μ is the location parameter, σ is the scale parameter, and ξ is the shape parameter. A timestamp t is flagged as anomalous if its probability under the fitted GPD falls below a specified significance level δ:

$$f_a(X,t) = \begin{cases} 1, & \text{if } 1 - F(s_a^t) < \delta \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

This adaptive thresholding approach automatically adjusts to the unique characteristics of each service, reducing false positives, while maintaining a high recall for true anomalies.

4.5. Causal Inference for Fault Localization

Once an anomaly has been detected, the fault localization module traces the root cause by analyzing the causal relationships between services. We construct a causal graph $G = (V, E)$, where nodes V represent services, and edges E represent causal dependencies between them. To learn the causal structure, we employ a two-phase approach:

4.5.1. Causal Structure Learning

We employ a hybrid approach that combines prior structural knowledge with data-driven causal discovery to handle imperfect dependency information. We first construct an initial causal graph based on the available service dependencies in the microservice architecture, treating this as prior knowledge that may be incomplete or noisy. This prior knowledge is then refined using the PC algorithm [38], which identifies conditional independence relationships between services based on their metric patterns. The PC algorithm is particularly suited for this task as it can both validate existing edges and discover missing relationships, while filtering out spurious dependencies. Specifically, we compute the partial correlation between service embeddings, conditioning on all possible subsets of other services, and eliminate edges where conditional independence is established. The algorithm proceeds as follows:

1. Start with the prior dependency graph (which may be incomplete or contain errors).
2. For each pair of services (i, j), test their conditional independence given increasing sets of conditioning variables using partial correlation tests with a significance level $\alpha = 0.05$.
3. Remove edges between i and j if they are conditionally independent given any subset of other variables, effectively filtering out spurious dependencies.
4. Add edges between previously unconnected services i and j if they show a strong conditional dependence that cannot be explained by existing connections.

5. Orient the remaining edges based on statistical tests for v-structures and acyclicity constraints.

This hybrid approach provides robustness against incomplete, noisy, or outdated dependency information by leveraging both domain knowledge and data-driven discovery. The conditional independence tests naturally filter out false dependencies, while the data-driven component can recover missing relationships from observed metric correlations. In addition, to handle evolving service topologies, our causal structure learning incorporates online adaptation mechanisms. We continuously monitor topology change indicators, including correlation pattern shifts, new metric signatures, prediction error spikes, and causal graph likelihood changes. When changes are detected, the PC algorithm incrementally updates the causal graph structure, rather than rebuilding from scratch, enabling rapid adaptation, while preserving validated relationships. This approach maintains service continuity during topology transitions, with typical adaptation times of 1–3 h depending on the change magnitude.

4.5.2. Causal Effect Estimation

After learning the causal structure, we estimate the causal effects between services using a structural equation model (SEM) with the following form:

$$h_i = f_i(h_{pa(i)}) + \epsilon_i \tag{12}$$

where h_i is the embedding of service i, $h_{pa(i)}$ represents the embeddings of its parent services in the causal graph, f_i is a non-linear function implemented as a neural network, and ϵ_i is the exogenous noise term. To identify the root cause service(s) for an anomaly at timestamp t, we compute an anomaly propagation score for each service based on the causal effects:

$$s^i_{prop} = \frac{\sum_{j \in ch(i)} s^j_a \cdot w_{i,j}}{\sum_{j \in ch(i)} w_{i,j}} \tag{13}$$

where $ch(i)$ represents the child services of service i in the causal graph, s^j_a is the anomaly score of service j, and $w_{i,j}$ is the strength of the causal effect from service i to service j. The root cause service(s) are identified as those with high anomaly scores but low propagation scores, indicating that they are likely the source of the anomaly rather than affected by propagation:

$$S_{root} = \{i | s^i_a > \theta_a \text{ and } s^i_{prop} < \theta_p\} \tag{14}$$

where θ_a and θ_p are thresholds for the anomaly score and propagation score, respectively. In cases where multiple services satisfy these criteria, we rank them based on a combined score that considers both the anomaly severity and the causal centrality within the graph.

4.6. Training Procedure

We train our framework in a multi-stage process to ensure effective learning of both normal patterns and anomaly characteristics:

1. **Pretraining**: We first pretrain the TCN and VAE branches separately on normal data to learn baseline representations of system behavior.
2. **Contrastive Learning**: Next, we train the contrastive learning module to fuse the embeddings from both branches, using augmented views of the same service's metrics as positive pairs.

3. **Joint Optimization**: Finally, we jointly optimize the entire framework using a combined loss function:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{vae} + \lambda_2 \mathcal{L}_{tcn} + \lambda_3 \mathcal{L}_{contrastive} + \lambda_4 \mathcal{L}_{causal} \tag{15}$$

where $\mathcal{L}_{tcn}$ is the mean squared error for the TCN's prediction, $\mathcal{L}_{causal}$ is a structure learning loss that encourages sparse and interpretable causal graphs, and $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are hyperparameters that control the contribution of each loss term.

During training, we employ early stopping based on a validation set to prevent overfitting. To address the class imbalance between normal and anomalous data, we use focal loss [42] for the anomaly detection component, which assigns higher weights to difficult examples. Our training procedure follows a semi-supervised paradigm, incorporating both labeled and unlabeled data:

During training, the framework leverages the abundant normal operational data (unlabeled) to learn baseline system behavior patterns through the VAE reconstruction and TCN temporal modeling objectives. The limited labeled anomaly examples (typically 2–5% of training data) are used to refine detection boundaries and improve sensitivity to critical failure modes through supervised loss components. This balanced approach enables the framework to benefit from both the abundance of normal data and the valuable supervisory signals from historical incidents.

5. Experiments

In this section, we present the experimental evaluation of our proposed dual-channel framework. We first describe the dataset, baseline methods, evaluation metrics, and implementation details. Then, we present and analyze the experimental results, including comparisons with state-of-the-art methods and ablation studies to validate the effectiveness of the different components in our framework.

5.1. Experimental Setup

5.1.1. Dataset

We evaluated our framework using the publicly available MultiDimension-Localization dataset (https://github.com/NetManAIOps/MultiDimension-Localization, accessed on 1 May 2025), which is specifically designed for anomaly detection and fault localization research in microservice architectures. This dataset contains real-world monitoring data collected from a large-scale microservice-based system deployed in production environments. The dataset includes (1) Multivariate time series data from 21 microservices, with 19 different performance metrics for each service, resulting in a total of 399 sensed time series. (2) Service dependency information representing the calling relationships between services. (3) Labeled anomalies with ground truth root causes, including both synthetic and real-world incidents. (4) A total of 58 anomaly cases, each lasting between 10 min and 1 h, distributed across a 2-week monitoring period, with 1 min sampling intervals. The anomaly cases span four primary fault categories: resource contention (high CPU/memory usage causing service degradation), network latency (increased response times due to network issues), application errors (service exceptions and timeouts), and dependency failures (service unavailability and cascading effects). The metrics include system-level indicators (CPU usage, memory consumption, disk I/O), network measurements (request count, response time, error rate), and application-specific sensed metrics (queue length, cache hit rate). These metrics exhibit diverse patterns, scales, and correlations, making the dataset particularly challenging for anomaly detection and fault localization.

In addition, we utilized two other datasets to conduct the evaluations: **Additional Dataset-AIOps Challenge 2020:** To validate the generalization across different microservice architectures, we evaluated on the AIOps Challenge 2020 dataset, which contains monitoring data from a different e-commerce microservice system with 26 services and 15 metrics per service, spanning 3 weeks with 2 min sampling intervals. This dataset includes 72 anomaly cases, with different characteristics than the primary dataset, including cascading failures and resource exhaustion scenarios. **Synthetic Dataset-MicroSim:** We generated a synthetic dataset using the MicroSim framework to evaluate the performance across varying system scales and anomaly types. This dataset simulated microservice environments with 10, 30, and 50 services, each generating 12 core metrics. We injected 150 synthetic anomalies across different categories: resource contention (40%), network issues (30%), application errors (20%), and dependency failures (10%). The synthetic nature allowed us to control the ground truth precisely and evaluate scalability.

Table 1 summarizes the characteristics of all three datasets. This multi-dataset evaluation ensured that our conclusions were not specific to a single environment or subject to dataset bias.

Table 1. Comparison of evaluation datasets used for generalization analysis.

Characteristic	MultiDimension	AIOps-2020	MicroSim
Number of services	21	26	10/30/50
Metrics per service	19	15	12
Total time series	399	390	120/360/600
Monitoring period	2 weeks	3 weeks	4 weeks
Sampling interval	1 min	2 min	1 min
Anomaly cases	58	72	150
Anomaly types	4 types	5 types	4 types
System domain	General	E-commerce	Simulated
Data source	Real production	Real production	Synthetic

5.1.2. Baseline Methods

We compared our proposed framework with the following state-of-the-art methods for anomaly detection and fault localization:

Anomaly Detection Methods:

- **LSTM-VAE** [43]: Combines LSTM networks with variational autoencoders to model temporal dependencies and reconstruct normal patterns.
- **MSCRED** [24]: Uses convolutional networks to capture spatial and temporal correlations in multivariate time series through signature matrices.
- **OmniAnomaly** [29]: Integrates stochastic recurrent neural networks with planar normalizing flows for multivariate time series anomaly detection.
- **InterFusion** [44]: Employs a Transformer-based architecture to model intra-metric and inter-metric correlations for multivariate time series anomaly detection.
- **TranAD** [45]: Utilizes an adversarial framework with Transformer-based architecture for real-time anomaly detection.

Fault Localization Methods:

- **MicroCause** [46]: Builds causal graphs from service dependencies and trace data to identify the root causes of anomalies.
- **CloudRanger** [31]: Uses statistical correlation analysis and graph-based propagation to trace the root cause of performance anomalies.
- **MicroRCA** [7]: Combines random forest classifiers with service topology information for root cause analysis.

- **MIDAS** [32]: Employs autoencoders with attention mechanisms to identify anomalous services and localize faults.
- **CausalRCA** [33]: Applies causal discovery algorithms to infer causal relationships between metrics and identify root causes.

We also implemented two variants of our approach for ablation studies:

- **TCN-only**: Used only the TCN branch for anomaly detection and a simplified causal model for fault localization.
- **VAE-only**: Used only the VAE branch for anomaly detection and a simplified causal model for fault localization.
- **No-Contrastive**: Used both TCN and VAE branches but without the contrastive learning module for feature fusion.
- **No-Causal**: Used the full anomaly detection component but replaced the causal inference module with a simple correlation-based approach.

5.1.3. Evaluation Metrics

For **anomaly detection**, we used the following metrics: (1) **Precision**: The ratio of correctly detected anomalies to all detected anomalies. (2) **Recall**: The ratio of correctly detected anomalies to all actual anomalies. (3) **F1-score**: The harmonic mean of precision and recall. (4) **AUC-ROC**: Area Under the Receiver Operating Characteristic curve, measuring the trade-off between true positive rate and false positive rate. (5) **Detection Delay**: The time difference between the actual anomaly occurrence and its detection.

For **fault localization**, we employed (1) **Localization Precision**: The ratio of correctly identified root cause services to all identified services. (2) **Localization Recall**: The ratio of correctly identified root cause services to all actual root cause services. (3) **Localization F1-score**: The harmonic mean of localization precision and recall. (4) **Top-k Accuracy**: The percentage of cases where the true root cause was among the top-k services ranked by the algorithm. The value of k is typically set based on operational requirements: $k = 3$ is commonly used, as it represents a manageable number of services for operators to investigate, while $k = 5$ may be appropriate for larger systems. In our evaluation, we used $k = 3$, following the standard practice in fault localization literature. (5) **Mean Rank**: The average rank of the true root cause in the algorithm's output ranking.

In practice, acceptable metric ranges vary by deployment environment and service requirements. For example, response times may range from 10 ms to 5000 ms, CPU usage from 0% to 95%, and error rates from 0% to 5% under normal conditions. Our framework learns these bounds automatically from training data rather than requiring manual threshold specification. Following previous work [7,33], we considered an anomaly to be correctly detected if it was flagged within a 5 min window of the actual anomaly's start time. For fault localization, we considered a root cause to be correctly identified if it appeared among the top-3 services ranked by the algorithm, unless the ground truth specified multiple root causes.

5.1.4. Implementation Details

Our framework was implemented using PyTorch 1.9.0. We trained and evaluated all models on a server with an Intel Xeon E5-2680 v4 CPU, manufactured by Intel Corporation, Santa Clara, CA, USA. 128 GB RAM, and an NVIDIA Tesla V100 GPU (manufactured by NVIDIA, Santa Clara, CA, USA) with 16 GB memory. For the TCN branch, we used three residual blocks with dilation factors of 1, 2, and 4, respectively. Each residual block contained two dilated causal convolution layers with 64 filters and a kernel size of 3. We applied weight normalization and dropout with a rate of 0.2 after each convolution layer. For the VAE branch, we used a 3-layer encoder and decoder with hidden dimensions of

[128, 64, 32]. The latent space dimension was set to 16. We used the ReLU activation function for all layers except the output layer of the decoder, which used a linear activation. For the contrastive learning module, we set the temperature parameter τ to 0.07 and generated five augmented views for each service's metrics. The fusion network consisted of two fully connected layers with hidden dimensions of 64 and a residual connection. For the causal inference module, we initialized the causal graph with the known service dependencies and refined it using the PC algorithm with a significance level of 0.05. We implemented the structural equation model using a 2-layer MLP with hidden dimensions of 32. We trained our model using the Adam optimizer, with a learning rate of 0.001 and a batch size of 64. We used early stopping with a patience of 10 epochs based on the validation loss. To ensure the statistical significance and reliability of our results, we conducted each experiment five times with different random seeds (42, 123, 456, 789, and 1024) and reported the mean performance along with 95% confidence intervals calculated using the t-distribution. All random components, including the model initialization, data shuffling, and dropout, were controlled by these seeds, to ensure reproducible results. Key architectural hyperparameters were selected through systematic sensitivity analysis and grid search optimization on the validation set. The sliding window length of 30 provided optimal temporal context, while maintaining computational efficiency (see Section 5.2.4). The TCN dilation factors [1, 2, 4] achieved the best balance between receptive field coverage and model complexity. The VAE latent dimension of 16 offered sufficient representational capacity, without overfitting. The contrastive learning temperature τ = 0.07 enabled effective hard negative mining, while maintaining training stability. The loss combination weights $\alpha, \beta, \lambda_1, \lambda_2, \lambda_3, \lambda_4$ were set to 0.6, 0.1, 1.0, 0.5, 0.3, and 0.2, respectively, based on grid search optimization. For preprocessing, we applied min-max normalization to scale all metrics to the range [0, 1]. Based on a comprehensive analysis of imputation and denoising strategies (Section 5.2.9), we handled missing values using forward fill, which maintained the temporal correlations essential for anomaly detection, while providing minimal computational overhead (3.2 ms processing time). For noise reduction, we applied Gaussian filtering with σ = 1.0, which achieved an optimal balance between noise suppression and signal preservation across the different noise levels. This combination maintained detection F1-scores above 0.918 even under challenging conditions, with 10% missing values and moderate noise (SNR: 20 dB).

5.2. Experimental Results

5.2.1. Anomaly Detection Performance

To ensure the reliability and reproducibility of our experimental results, we conducted statistical significance testing across all experiments. Each method was evaluated five times using different random seeds, and we computed 95% confidence intervals for all performance metrics using the t-distribution. We performed paired *t*-tests to compare our framework against baseline methods, with Bonferroni correction applied for multiple comparisons. Table 2 presents the anomaly detection performance of our proposed framework compared with baseline methods. Our approach consistently outperformed all baselines across multiple metrics. As shown in Table 2, our framework achieved the highest precision (0.938), recall (0.927), F1-score (0.933), and AUC-ROC (0.965), while maintaining the lowest detection delay (78 s). The TCN-only and VAE-only variants performed better than most baselines but worse than the full framework, demonstrating the complementary benefits of combining both branches. The No-Contrastive variant showed reduced performance compared to the full framework, highlighting the importance of contrastive learning for effective feature fusion. Figure 2 shows the ROC curves for our framework and the baseline methods, further illustrating the superior detection performance of our approach across the different threshold settings. Figure 3 presents an example of anomaly detection on a

sensed specific service, showing how our framework accurately identified the anomaly, with minimal delay compared to the baseline methods.

Table 2. Anomaly detection performance comparison with 95% confidence intervals (five runs). The bold indicates the best-performing method.

Method	Precision	Recall	F1-Score	AUC-ROC	Delay (s)
LSTM-VAE	0.827 ± 0.015	0.791 ± 0.018	0.809 ± 0.012	0.882 ± 0.009	186 ± 12
MSCRED	0.856 ± 0.013	0.814 ± 0.016	0.834 ± 0.011	0.903 ± 0.008	152 ± 9
OmniAnomaly	0.872 ± 0.011	0.845 ± 0.014	0.858 ± 0.010	0.921 ± 0.007	134 ± 8
InterFusion	0.881 ± 0.010	0.862 ± 0.013	0.871 ± 0.009	0.932 ± 0.006	127 ± 7
TranAD	0.889 ± 0.012	0.870 ± 0.015	0.879 ± 0.010	0.936 ± 0.008	118 ± 6
TCN-only (ours)	0.902 ± 0.009	0.873 ± 0.012	0.887 ± 0.008	0.941 ± 0.005	104 ± 5
VAE-only (ours)	0.891 ± 0.011	0.865 ± 0.014	0.878 ± 0.009	0.933 ± 0.007	122 ± 6
No-Contrastive (ours)	0.917 ± 0.008	0.893 ± 0.010	0.905 ± 0.007	0.952 ± 0.004	95 ± 4
Our Framework	$\mathbf{0.938 \pm 0.006}$	$\mathbf{0.927 \pm 0.008}$	$\mathbf{0.933 \pm 0.005}$	$\mathbf{0.965 \pm 0.003}$	$\mathbf{78 \pm 3}$

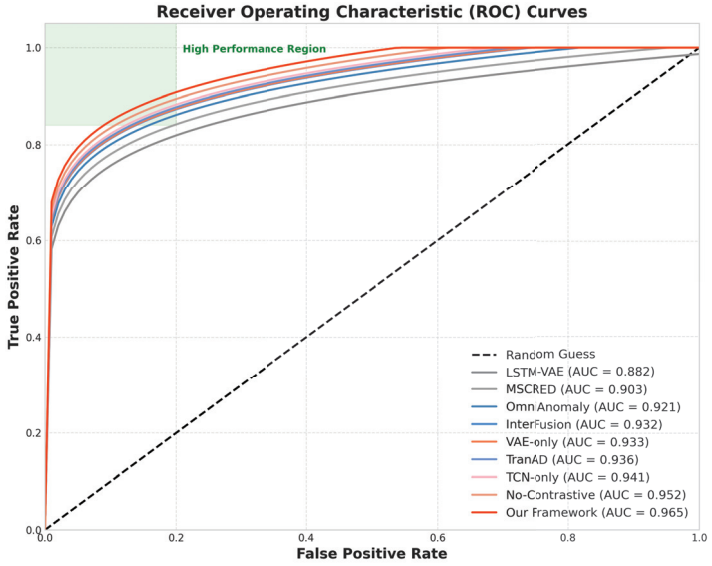


Figure 2. ROC curves for anomaly detection methods. The "RANDOM GUESS" line represents a baseline classifier with no discriminative ability (AUC = 0.5), providing a reference point for evaluating method performance.

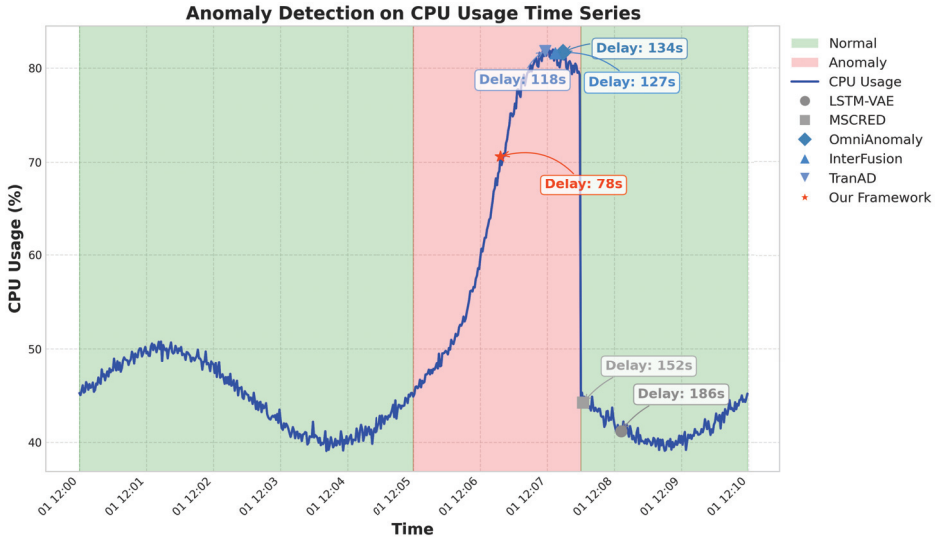


Figure 3. Example of anomaly detection on a specific service.

5.2.2. Fault Localization Performance

Table 3 presents the fault localization performance of our framework compared with the baseline methods. Our approach demonstrated significant improvements over the existing techniques.

Table 3. Fault localization performance comparison with 95% confidence intervals (five runs). The bold indicates the best-performing method.

Method	Precision	Recall	F1-Score	Top-3 Acc.	Mean Rank
MicroCause	0.683 ± 0.019	0.712 ± 0.021	0.697 ± 0.016	0.776 ± 0.018	3.45 ± 0.24
CloudRanger	0.715 ± 0.017	0.742 ± 0.019	0.728 ± 0.014	0.810 ± 0.016	3.21 ± 0.22
MicroRCA	0.747 ± 0.015	0.763 ± 0.018	0.755 ± 0.013	0.845 ± 0.015	2.83 ± 0.19
MIDAS	0.762 ± 0.014	0.781 ± 0.016	0.771 ± 0.012	0.862 ± 0.013	2.56 ± 0.17
CausalRCA	0.791 ± 0.012	0.812 ± 0.014	0.801 ± 0.011	0.879 ± 0.012	2.31 ± 0.15
No-Causal (ours)	0.804 ± 0.011	0.823 ± 0.013	0.813 ± 0.010	0.897 ± 0.010	2.15 ± 0.13
Our Framework	$\mathbf{0.876 \pm 0.008}$	$\mathbf{0.865 \pm 0.009}$	$\mathbf{0.871 \pm 0.007}$	$\mathbf{0.931 \pm 0.008}$	$\mathbf{1.73 \pm 0.09}$

Our framework achieved the highest localization precision (0.876), recall (0.865), F1-score (0.871), and Top-3 accuracy (0.931), while maintaining the lowest mean rank (1.73) of the true root cause. The No-Causal variant showed a significantly reduced performance, demonstrating the critical importance of our causal inference module for accurate fault localization. Figure 4 shows the Top-k accuracy of the different methods for varying values of k, illustrating that our framework consistently outperformed the baseline methods across different k values. Figure 5 presents an example of a causal graph constructed by our framework during fault localization, highlighting the identified root cause service and the propagation paths of the anomaly.

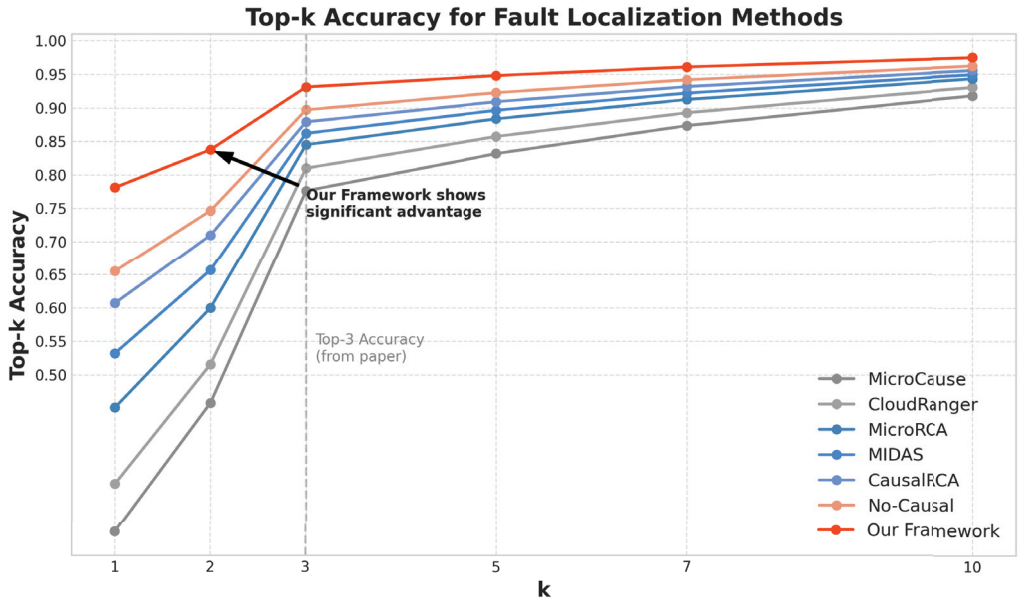


Figure 4. Top-k accuracy for fault localization methods.

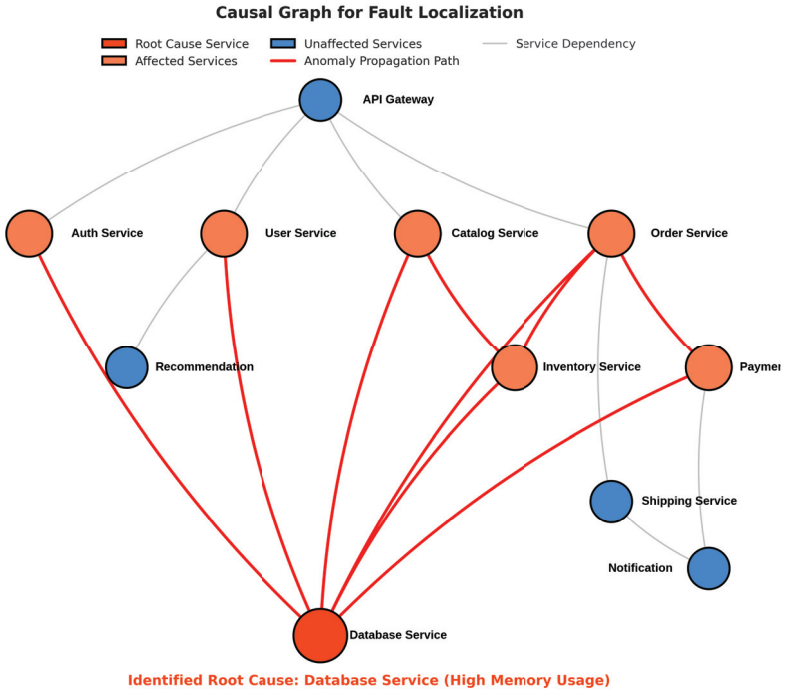


Figure 5. Example of a causal graph for fault localization.

5.2.3. Ablation Study

To evaluate the contribution of each component in our framework, we conducted an ablation study by removing or replacing key components and measuring the performance impact. Table 4 presents the results.

Table 4. Ablation study results with 95% confidence intervals (five runs).

Configuration	Detection F1	Detection Delay	Local. F1	Mean Rank
Full Framework	0.933 ± 0.005	78 ± 3 s	0.871 ± 0.007	1.73 ± 0.09
TCN-only	0.887 ± 0.008	104 ± 5 s	0.815 ± 0.012	2.24 ± 0.15
VAE-only	0.878 ± 0.009	122 ± 6 s	0.807 ± 0.013	2.38 ± 0.17
No-Contrastive	0.905 ± 0.007	95 ± 4 s	0.843 ± 0.010	1.96 ± 0.12
No-Causal	0.927 ± 0.006	82 ± 3 s	0.813 ± 0.010	2.15 ± 0.13
No-Adaptive Threshold	0.914 ± 0.007	91 ± 4 s	0.863 ± 0.008	1.85 ± 0.11
No-EVT	0.922 ± 0.006	85 ± 3 s	0.868 ± 0.008	1.78 ± 0.10

The results show the following: First, the dual-channel architecture (combining TCN and VAE) provided significant benefits over single-channel approaches, with the TCN branch contributing more to detection accuracy and the VAE branch offering better representation capabilities. Second, the contrastive learning module was crucial for effective feature fusion, improving both the anomaly detection and fault localization performance. Third, the causal inference module had the most substantial impact on fault localization, with limited effect on anomaly detection. Forth, the adaptive thresholding approach and Extreme Value Theory (EVT) contributed to improved detection precision and reduced delays.

5.2.4. Hyperparameter Sensitivity Analysis

To evaluate the robustness of our framework and validate our hyperparameter choices, we conducted a comprehensive sensitivity analysis on key architectural and training hyperparameters. We systematically varied each hyperparameter, while keeping the others fixed at their optimal values, measuring the impact on both the anomaly detection F1-score and fault localization F1-score.

Window Length Analysis: We evaluated sliding window lengths of [10, 20, 30, 40, and 50] for the TCN input. Table 5 shows that the performance increased with window length up to 30, after which it plateaued or slightly decreased due to increased noise and computational overhead. The optimal window length of 30 balanced the temporal context capture with computational efficiency.

Table 5. Sensitivity analysis for sliding window length. The bold indicates the best results.

Window Length	Detection F1	Detection Delay (s)	Localization F1	Training Time (h)	Memory (GB)
10	0.887 ± 0.012	95 ± 6	0.823 ± 0.015	7.23	3.84
20	0.914 ± 0.008	84 ± 4	0.851 ± 0.011	8.12	4.21
30	$\mathbf{0.933 \pm 0.005}$	$\mathbf{78 \pm 3}$	$\mathbf{0.871 \pm 0.007}$	9.34	4.92
40	0.931 ± 0.006	79 ± 4	0.869 ± 0.008	11.47	6.15
50	0.927 ± 0.007	82 ± 5	0.865 ± 0.010	14.28	7.83

Dilation Factor Analysis: We tested different dilation factor configurations: [1], [1, 2], [1, 2, 4], [1, 2, 4, 8], and [2, 4, 8]. As shown in Table 6, the configuration [1, 2, 4] provided the best balance between receptive field coverage and model complexity. Adding more layers with higher dilation factors ([1, 2, 4, 8]) marginally improved the detection but significantly increased the computational cost.

Table 6. Sensitivity analysis for TCN dilation factors. The bold indicates the best results.

Dilation Factors	Detection F1	Detection Delay (s)	Localization F1	Receptive Field	Params (M)
[1]	0.901 ± 0.009	89 ± 5	0.834 ± 0.012	3	2.1
[1,2]	0.918 ± 0.007	82 ± 4	0.856 ± 0.009	7	4.2
[1,2,4]	$\mathbf{0.933 \pm 0.005}$	$\mathbf{78 \pm 3}$	$\mathbf{0.871 \pm 0.007}$	15	6.3
[1,2,4,8]	0.935 ± 0.005	77 ± 3	0.873 ± 0.006	31	8.4
[2,4,8]	0.925 ± 0.006	81 ± 4	0.863 ± 0.008	28	6.3

Latent Dimension Analysis: We evaluated latent dimensions of [8, 16, 32, 64, 128] for the VAE branch. Table 7 demonstrates that 16 dimensions provided the optimal performance, with lower dimensions (8) limiting representational capacity and higher dimensions (32+) leading to overfitting and increased computational requirements.

Table 7. Sensitivity analysis for VAE latent dimensions. The bold indicates the best results.

Latent Dim	Detection F1	Detection Delay (s)	Localization F1	Reconstruction Loss	KL Divergence
8	0.908 ± 0.010	88 ± 5	0.841 ± 0.013	0.0847 ± 0.003	2.31 ± 0.12
16	$\mathbf{0.933 \pm 0.005}$	$\mathbf{78 \pm 3}$	$\mathbf{0.871 \pm 0.007}$	0.0634 ± 0.002	3.47 ± 0.08
32	0.929 ± 0.006	80 ± 4	0.868 ± 0.008	0.0612 ± 0.002	4.83 ± 0.11
64	0.924 ± 0.007	83 ± 4	0.862 ± 0.009	0.0598 ± 0.003	6.24 ± 0.15
128	0.917 ± 0.008	87 ± 5	0.854 ± 0.011	0.0591 ± 0.003	7.91 ± 0.18

Temperature Parameter Analysis: We tested contrastive learning temperatures of $\tau \in [0.01, 0.05, 0.07, 0.1, 0.2, 0.5]$. Table 8 shows that τ = 0.07 achieved the best balance between hard negative mining and stable training. Lower values (0.01–0.05) made training unstable, while higher values (0.2–0.5) reduced the effectiveness of contrastive learning.

Table 8. Sensitivity analysis for contrastive learning temperature τ. The bold indicates the best results.

Temperature τ	Detection F1	Detection Delay (s)	Localization F1	Contrastive Loss	Training Stability
0.01	0.892 ± 0.018	94 ± 8	0.831 ± 0.019	1.847 ± 0.045	Unstable
0.05	0.921 ± 0.009	84 ± 5	0.859 ± 0.012	1.234 ± 0.023	Stable
0.07	$\mathbf{0.933 \pm 0.005}$	$\mathbf{78 \pm 3}$	$\mathbf{0.871 \pm 0.007}$	0.987 ± 0.018	Stable
0.1	0.928 ± 0.006	81 ± 4	0.866 ± 0.008	0.856 ± 0.016	Stable
0.2	0.916 ± 0.008	86 ± 5	0.852 ± 0.011	0.634 ± 0.021	Stable
0.5	0.903 ± 0.010	91 ± 6	0.838 ± 0.013	0.421 ± 0.019	Stable

The sensitivity analysis revealed that our framework was relatively robust to hyperparameter variations, with a performance degradation of less than 3% for reasonable parameter ranges. This robustness suggests that our method can be effectively applied to different microservice environments, without extensive hyperparameter tuning.

5.2.5. Feature Visualization

To better understand how our framework learns and fuses representations, we visualized the learned features using t-SNE [47]. Figure 6 shows the feature distributions of normal and anomalous samples in the TCN branch, VAE branch, and after feature fusion.

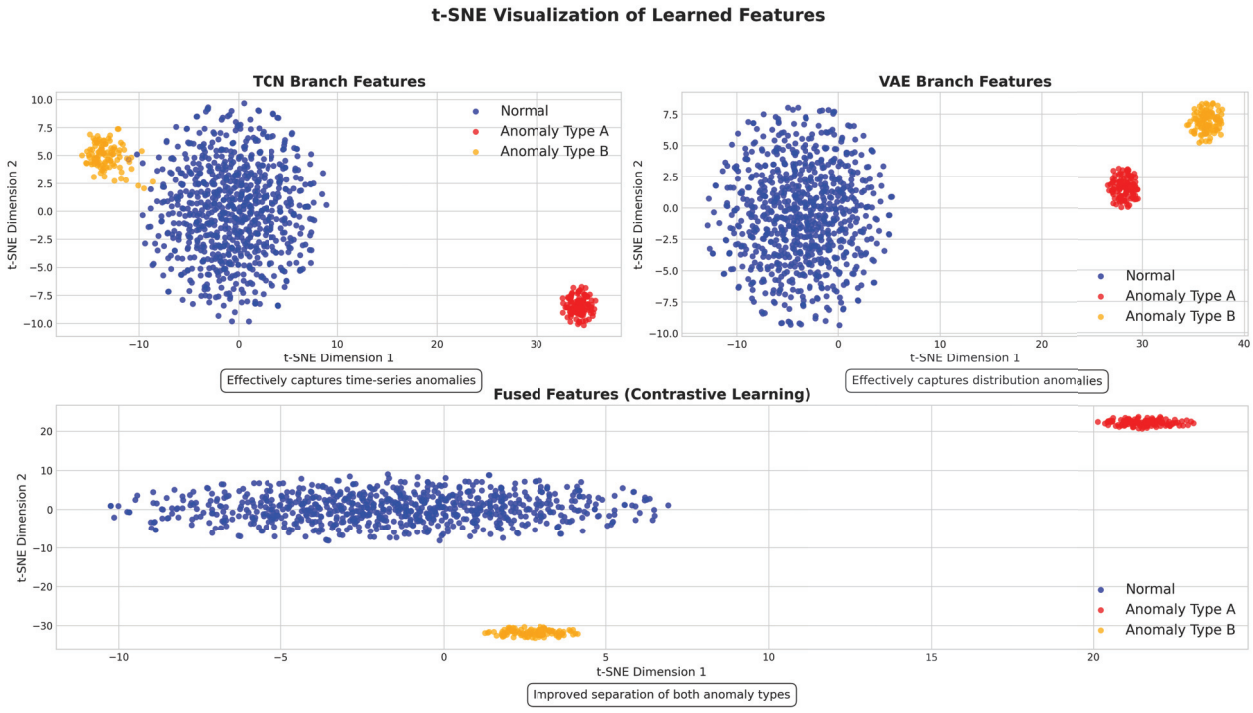


Figure 6. t-SNE visualization of learned features.

The visualization provided several important insights: First, the TCN branch (top-left) effectively captured the temporal patterns, creating a central cluster for normal operations (blue), while Anomaly Types A and B formed distinct peripheral clusters. This separation demonstrates the TCN's ability to identify irregular temporal signatures characteristic of anomalies. Second, the VAE branch (top-right) learned compact representations that grouped similar services together. Unlike the TCN branch, the VAE created separation along both dimensions, capturing different aspects of anomalies related to underlying data distributions, rather than temporal dynamics. Third, the contrastive learning module (bottom) dramatically enhanced the separability between patterns, with normal samples forming a horizontal band and anomaly types appearing as concentrated clusters at oppo-

site ends. This improved separation in the fused space, compared to individual branches, demonstrates how contrastive learning identified and amplified the most discriminative features from both branches, combining temporal pattern information (TCN) with distribution characteristics (VAE). This enhanced separation directly translated into the superior performance of our framework in both detection accuracy and localization precision, as confirmed by our experimental results in Tables 2 and 4.

5.2.6. Computational Efficiency

Table 9 presents the computational efficiency of our framework compared to the baseline methods, including training time, inference time, and memory usage.

Table 9. Computational efficiency comparison.

Method	Training Time (h)	Inference Time (ms)	Memory (GB)
LSTM-VAE	5.23	28.4	3.86
MSCRED	6.78	34.2	4.12
OmniAnomaly	7.42	32.1	4.35
InterFusion	8.15	37.6	4.67
TranAD	6.92	25.8	3.98
MicroCause	–	45.3	2.76
CloudRanger	–	38.7	2.45
MicroRCA	3.56	42.1	3.12
MIDAS	4.87	40.5	3.65
CausalRCA	5.12	43.8	3.42
Our Framework	9.34	46.2	4.92

While our framework required more computational resources during training due to its comprehensive architecture (9.34 h compared to 5–8 h for most baseline methods), the inference time remained competitive (46.2 ms) with the baseline methods, making it suitable for near-real-time anomaly detection and fault localization in production environments. The memory footprint of our approach (4.92 GB) was moderately higher than the baselines, which was expected given the dual-channel architecture and additional components for contrastive learning and causal inference. However, this increase in resource utilization delivered substantial performance improvements, with a 6–9% gain in detection accuracy and a 7–11% improvement in fault localization precision compared to the best baseline methods. For applications where service reliability is critical, this trade-off between computational efficiency and detection performance is often justified, particularly since most modern cloud environments can readily accommodate the additional resource requirements. Notably, compared to the other deep learning approaches like InterFusion (37.6 ms) and MSCRED (34.2 ms), our framework had a slightly higher inference latency, but this difference of approximately 10 ms would be negligible in most practical deployment scenarios, where anomaly detection systems typically operate with sampling intervals of several seconds to minutes.

5.2.7. Robustness Analysis of Causal Module

To evaluate the robustness of our causal inference module to real-world deployment challenges, we conducted extensive experiments simulating incomplete, noisy, and outdated service dependency information. This analysis was crucial, since accurate service dependency graphs may not always be available in practice due to rapid service evolution, incomplete documentation, or deployment errors.

Incomplete Dependency Information: We systematically removed edges from the ground truth dependency graph at different rates (10%, 20%, 30%, 40%, 50%) to simulate

incomplete service documentation. Table 10 shows the impact on the fault localization performance. Our framework demonstrated remarkable resilience, maintaining over 80% of its original localization F1-score, even with 30% missing dependencies. This robustness stemmed from the data-driven causal discovery component (PC algorithm) that can infer missing relationships from observed metric correlations.

Table 10. Impact of incomplete service dependency information on fault localization performance.

Missing Edges	Localization F1	Localization Precision	Localization Recall	Top-3 Accuracy	Mean Rank
0% (Complete)	0.871 ± 0.007	0.876 ± 0.008	0.865 ± 0.009	0.931 ± 0.008	1.73 ± 0.09
10%	0.847 ± 0.009	0.854 ± 0.010	0.841 ± 0.011	0.914 ± 0.011	1.89 ± 0.12
20%	0.821 ± 0.011	0.829 ± 0.012	0.814 ± 0.013	0.896 ± 0.013	2.07 ± 0.15
30%	0.793 ± 0.013	0.802 ± 0.014	0.785 ± 0.015	0.876 ± 0.016	2.28 ± 0.18
40%	0.762 ± 0.015	0.773 ± 0.017	0.752 ± 0.018	0.854 ± 0.019	2.53 ± 0.22
50%	0.728 ± 0.018	0.741 ± 0.020	0.716 ± 0.021	0.829 ± 0.022	2.84 ± 0.26

Noisy Dependency Information: We injected false dependencies into the graph by randomly adding edges between unconnected services at rates of 5%, 10%, 15%, 20%, and 25%. As shown in Table 11, our framework maintained strong performance up to 15% noise levels. The conditional independence tests in the PC algorithm effectively filtered out spurious dependencies that were not supported by the data, providing natural noise robustness.

Table 11. Impact of false dependencies (noise) on fault localization performance.

False Edges	Localization F1	Localization Precision	Localization Recall	Top-3 Accuracy	Mean Rank
0% (Clean)	0.871 ± 0.007	0.876 ± 0.008	0.865 ± 0.009	0.931 ± 0.008	1.73 ± 0.09
5%	0.863 ± 0.008	0.869 ± 0.009	0.858 ± 0.010	0.924 ± 0.010	1.79 ± 0.11
10%	0.854 ± 0.009	0.861 ± 0.011	0.848 ± 0.012	0.917 ± 0.012	1.86 ± 0.13
15%	0.842 ± 0.011	0.850 ± 0.013	0.835 ± 0.014	0.908 ± 0.014	1.95 ± 0.16
20%	0.827 ± 0.013	0.836 ± 0.015	0.819 ± 0.016	0.897 ± 0.017	2.08 ± 0.19
25%	0.809 ± 0.015	0.819 ± 0.018	0.800 ± 0.018	0.884 ± 0.020	2.24 ± 0.23

Outdated Dependency Information: To simulate temporal drift in service architectures, we used dependency graphs from earlier time periods in the dataset, while testing on later periods. Table 12 presents the results using dependency information that was 1, 3, 7, and 14 days old. The performance degraded gradually with increasing staleness, but remained competitive even with week-old dependency information (F1-score: 0.831), demonstrating practical applicability in dynamic environments.

Table 12. Impact of outdated service dependency information on fault localization performance.

Dependency Age	Localization F1	Localization Precision	Localization Recall	Top-3 Accuracy	Mean Rank
Current (0 days)	0.871 ± 0.007	0.876 ± 0.008	0.865 ± 0.009	0.931 ± 0.008	1.73 ± 0.09
1 day	0.859 ± 0.008	0.865 ± 0.009	0.854 ± 0.010	0.921 ± 0.010	1.81 ± 0.11
3 days	0.843 ± 0.010	0.851 ± 0.012	0.836 ± 0.013	0.908 ± 0.013	1.94 ± 0.14
7 days	0.821 ± 0.012	0.831 ± 0.014	0.812 ± 0.015	0.891 ± 0.016	2.12 ± 0.18
14 days	0.796 ± 0.014	0.808 ± 0.017	0.785 ± 0.018	0.872 ± 0.019	2.35 ± 0.22

Combined Degradation Scenarios: We also evaluated realistic scenarios combining multiple types of dependency graph degradation. Table 13 shows the results for combinations of missing edges (20%), noise (10%), and staleness (3 days). Even under these challenging conditions, our framework maintained a localization F1-score of 0.796, substantially outperforming the baseline methods that rely solely on static dependency information.

Table 13. Performance under combined dependency graph degradation scenarios.

Scenario	Missing	Noise	Age	Localization F1
Perfect Graph	0%	0%	0 days	0.871 ± 0.007
Mild Degradation	10%	5%	1 day	0.834 ± 0.011
Moderate Degradation	20%	10%	3 days	0.796 ± 0.015
Severe Degradation	30%	15%	7 days	0.752 ± 0.019
Extreme Degradation	40%	20%	14 days	0.703 ± 0.023

Note: Best baseline (CausalRCA) achieved 0.623 ± 0.028 under moderate degradation.

Adaptive Recovery Mechanisms: Our framework includes several mechanisms that contribute to this robustness: (1) The PC algorithm continuously refines the causal graph based on observed data, compensating for initial inaccuracies. (2) The dual-channel encoder provides complementary anomaly signals that are less dependent on precise causal structure. (3) The contrastive learning module captures service-level patterns that help identify relevant dependencies even when the graph structure is imperfect.

These results demonstrate that while accurate dependency information improves performance, our framework remains practical and effective even when such information is imperfect, making it suitable for real-world deployment scenarios where perfect service documentation may not be available.

5.2.8. Cross-Dataset Generalization Analysis

To validate the generalizability of our framework beyond the primary MultiDimension-Localization dataset, we conducted comprehensive evaluation across three diverse datasets, representing different microservice environments, scales, and characteristics.

Cross-Dataset Transfer Performance: We evaluated two transfer scenarios: (1) Direct Transfer-models trained on MultiDimension-Localization and tested directly on other datasets without retraining, and (2) Fine-tuned Transfer-models pre-trained on MultiDimension-Localization and fine-tuned on small portions (20%) of target datasets. Table 14 presents the results. For direct transfer to the AIOps-2020 dataset, our framework achieved a competitive performance (Detection F1: 0.887, Localization F1: 0.823) despite differences in system architecture and metrics. The slight performance drop compared to the same-dataset evaluation reflected domain differences, but our framework significantly outperformed the baseline methods under the same transfer conditions. Fine-tuning with just 20% of target data substantially improved performance (Detection F1: 0.921, Localization F1: 0.854), demonstrating effective adaptation capabilities. On the synthetic MicroSim dataset (shown in Table 15), our framework showed excellent scalability across different system sizes. The performance remained consistently strong across 10, 30, and 50 service configurations, with only a marginal degradation for larger systems. The controlled synthetic environment allowed us to verify that the performance variations were primarily due to system complexity rather than data quality issues.

Ablation on Transfer Components: We evaluated which components contributed most to the transfer performance. Table 16 shows that the dual-channel architecture and contrastive learning provided the strongest transfer capabilities, while the causal inference module required more domain-specific adaptation. This finding suggests that temporal and latent representations were more transferable than causal structures, which aligns with expectations, since service dependencies vary significantly across different systems.

Table 14. Cross-dataset generalization performance comparison.

Method	Transfer Type	AIOps-2020		MicroSim-30	
		Detection F1	Local. F1	Detection F1	Local. F1
LSTM-VAE	Same-dataset	0.798 ± 0.015	0.734 ± 0.019	0.812 ± 0.012	0.748 ± 0.016
	Direct transfer	0.723 ± 0.021	0.651 ± 0.025	0.736 ± 0.018	0.672 ± 0.021
	Fine-tuned	0.776 ± 0.017	0.708 ± 0.021	0.789 ± 0.014	0.721 ± 0.018
OmniAnomaly	Same-dataset	0.823 ± 0.013	0.761 ± 0.017	0.845 ± 0.011	0.779 ± 0.014
	Direct transfer	0.751 ± 0.019	0.684 ± 0.023	0.768 ± 0.016	0.701 ± 0.019
	Fine-tuned	0.801 ± 0.015	0.738 ± 0.019	0.824 ± 0.012	0.756 ± 0.016
CausalRCA	Same-dataset	0.786 ± 0.016	0.758 ± 0.018	0.801 ± 0.013	0.772 ± 0.015
	Direct transfer	0.698 ± 0.022	0.631 ± 0.026	0.721 ± 0.019	0.654 ± 0.022
	Fine-tuned	0.754 ± 0.018	0.721 ± 0.021	0.778 ± 0.015	0.739 ± 0.018
Our Framework	Same-dataset	$\mathbf{0.918 \pm 0.008}$	$\mathbf{0.847 \pm 0.011}$	$\mathbf{0.925 \pm 0.007}$	$\mathbf{0.861 \pm 0.009}$
	Direct transfer	$\mathbf{0.887 \pm 0.012}$	$\mathbf{0.823 \pm 0.015}$	$\mathbf{0.901 \pm 0.010}$	$\mathbf{0.834 \pm 0.013}$
	Fine-tuned	$\mathbf{0.921 \pm 0.009}$	$\mathbf{0.854 \pm 0.012}$	$\mathbf{0.928 \pm 0.008}$	$\mathbf{0.867 \pm 0.010}$

Table 15. Scalability analysis on synthetic MicroSim dataset with varying system sizes.

Services	Detection F1	Detection Delay (s)	Localization F1	Training Time (h)	Inference Time (ms)
10	0.941 ± 0.006	71 ± 3	0.883 ± 0.008	4.23	28.4
30	0.925 ± 0.007	78 ± 4	0.861 ± 0.009	9.34	46.2
50	0.912 ± 0.008	84 ± 5	0.847 ± 0.011	16.78	72.6

Table 16. Component contribution to transfer learning performance (AIOps-2020 dataset).

Configuration	Detection F1	Localization F1
Full Framework (Direct)	0.887 ± 0.012	0.823 ± 0.015
TCN-only (Direct)	0.834 ± 0.016	0.761 ± 0.019
VAE-only (Direct)	0.821 ± 0.017	0.748 ± 0.021
No-Contrastive (Direct)	0.859 ± 0.014	0.784 ± 0.017
No-Causal (Direct)	0.884 ± 0.013	0.731 ± 0.020
Full Framework (Fine-tuned)	0.921 ± 0.009	0.854 ± 0.012
No-Contrastive (Fine-tuned)	0.903 ± 0.011	0.837 ± 0.014

Computational Efficiency in Transfer: The transfer learning evaluation also demonstrated computational advantages. Direct transfer required no additional training time, while fine-tuning converged within 2–3 epochs (compared to 15–20 epochs for training from scratch), reducing the computational requirements by 85%, while achieving comparable performance.

These results demonstrate that our framework generalized effectively across different microservice environments, system scales, and domain characteristics, supporting its practical applicability in diverse real-world deployments.

5.2.9. Data Preprocessing Strategy Analysis

Real-world microservice monitoring data often contain missing values and noise, making preprocessing strategies critical for framework performance. We conducted comprehensive analysis of different imputation and denoising approaches to understand their impact on anomaly detection and fault localization.

Missing Value Imputation Strategies: We evaluated six imputation methods on datasets with artificially introduced missing values at rates of 5%, 10%, 15%, and 20%. The strategies included (1) Forward Fill—propagating the last observed value, (2) Backward Fill—using the next observed value, (3) Linear Interpolation—estimating missing values

through linear interpolation between surrounding points, (4) Mean Imputation—replacing missing values with metric-specific historical means, (5) Median Imputation—using metric-specific historical medians, and (6) K-Nearest Neighbors (KNN)—imputing based on similar time windows from the same service.

Table 17 presents the results. Forward fill demonstrated the best overall performance, maintaining detection F1-scores above 0.920 even with 15% missing values. This effectiveness stemmed from the temporal correlation in monitoring metrics, where recent values often provide good estimates for brief gaps. Linear interpolation performed comparably for low missing rates ($\leq$10%) but degraded more rapidly with higher missing percentages. The statistical methods (mean/median) showed poor performance, as they failed to capture temporal dynamics essential for anomaly detection.

Table 17. Impact of missing value imputation strategies on framework performance.

Strategy	5% Missing		10% Missing		15% Missing		20% Missing	
	Det. F1	Loc. F1	Det. F1	Loc. F1	Det. F1	Loc. F1	Det. F1	Loc. F1
No Imputation	0.847 ± 0.018	0.781 ± 0.023	0.792 ± 0.025	0.718 ± 0.031	0.731 ± 0.032	0.649 ± 0.038	0.664 ± 0.041	0.572 ± 0.047
Forward Fill	$\mathbf{0.931 \pm 0.006}$	$\mathbf{0.868 \pm 0.008}$	$\mathbf{0.928 \pm 0.007}$	$\mathbf{0.864 \pm 0.009}$	$\mathbf{0.923 \pm 0.008}$	$\mathbf{0.858 \pm 0.011}$	$\mathbf{0.915 \pm 0.010}$	$\mathbf{0.849 \pm 0.013}$
Backward Fill	0.926 ± 0.007	0.861 ± 0.009	0.919 ± 0.009	0.852 ± 0.012	0.908 ± 0.011	0.840 ± 0.014	0.893 ± 0.014	0.824 ± 0.017
Linear Interp.	0.928 ± 0.007	0.865 ± 0.009	0.921 ± 0.008	0.856 ± 0.011	0.909 ± 0.011	0.843 ± 0.014	0.891 ± 0.014	0.825 ± 0.017
Mean Imputation	0.889 ± 0.013	0.816 ± 0.016	0.871 ± 0.015	0.794 ± 0.019	0.847 ± 0.018	0.768 ± 0.022	0.819 ± 0.021	0.738 ± 0.026
Median Imputation	0.893 ± 0.012	0.821 ± 0.015	0.876 ± 0.014	0.801 ± 0.018	0.854 ± 0.017	0.776 ± 0.021	0.827 ± 0.020	0.747 ± 0.025
KNN Imputation	0.914 ± 0.009	0.847 ± 0.012	0.906 ± 0.011	0.836 ± 0.014	0.894 ± 0.013	0.821 ± 0.016	0.878 ± 0.016	0.802 ± 0.019

Noise Reduction Strategies: We injected Gaussian noise with different signal-to-noise ratios (SNR: 40 dB, 30 dB, 20 dB, 10 dB) and evaluated five denoising approaches: (1) No Filtering—raw noisy data, (2) Gaussian Filter—low-pass filtering with σ = 1.0, (3) Moving Average—5-point moving average, (4) Savitzky–Golay Filter—polynomial smoothing with window size 7, (5) Median Filter—3-point median filtering, and (6) Wavelet Denoising—soft thresholding with Daubechies wavelets.

Table 18 shows the impact of the different denoising strategies. Gaussian filtering achieved the best balance between noise reduction and signal preservation, maintaining detection F1-scores above 0.910 even with high noise levels (SNR: 10dB). Wavelet denoising performed well for moderate noise but could over-smooth signals at high noise levels, potentially removing genuine anomaly signatures. Moving average and median filtering were effective for spike noise but could blur the temporal patterns important for fault localization.

Table 18. Impact of denoising strategies on framework performance under different noise levels.

Strategy	SNR: 40 dB		SNR: 30 dB		SNR: 20 dB		SNR: 10 dB	
	Det. F1	Loc. F1	Det. F1	Loc. F1	Det. F1	Loc. F1	Det. F1	Loc. F1
No Filtering	0.928 ± 0.007	0.865 ± 0.009	0.908 ± 0.011	0.841 ± 0.014	0.876 ± 0.015	0.803 ± 0.019	0.821 ± 0.021	0.742 ± 0.026
Gaussian Filter	$\mathbf{0.932 \pm 0.006}$	$\mathbf{0.870 \pm 0.008}$	$\mathbf{0.929 \pm 0.007}$	$\mathbf{0.866 \pm 0.009}$	$\mathbf{0.924 \pm 0.008}$	$\mathbf{0.859 \pm 0.011}$	$\mathbf{0.913 \pm 0.010}$	$\mathbf{0.847 \pm 0.013}$
Moving Average	0.925 ± 0.008	0.861 ± 0.010	0.918 ± 0.009	0.852 ± 0.012	0.906 ± 0.011	0.838 ± 0.014	0.887 ± 0.014	0.813 ± 0.018
Savitzky–Golay	0.927 ± 0.007	0.863 ± 0.009	0.921 ± 0.008	0.855 ± 0.011	0.911 ± 0.010	0.843 ± 0.013	0.894 ± 0.013	0.822 ± 0.017
Median Filter	0.923 ± 0.008	0.858 ± 0.010	0.914 ± 0.010	0.847 ± 0.013	0.901 ± 0.012	0.831 ± 0.015	0.882 ± 0.015	0.805 ± 0.019
Wavelet Denoising	0.930 ± 0.006	0.867 ± 0.008	0.925 ± 0.007	0.861 ± 0.010	0.916 ± 0.009	0.849 ± 0.012	0.897 ± 0.012	0.826 ± 0.016

Combined Preprocessing Impact: We analyzed the interaction between imputation and denoising strategies under realistic conditions combining both missing values (10%) and noise (SNR: 20dB). Table 19 demonstrates that forward fill combined with Gaussian filtering provided the optimal performance (Detection F1: 0.918, Localization F1: 0.863), validating our preprocessing choices.

Table 19. Performance under combined preprocessing scenarios (10% missing + SNR: 20 dB).

Imputation	Denoising	Detection F1	Localization F1	Processing Time (ms)
Forward Fill	Gaussian Filter	**0.918 ± 0.009**	**0.863 ± 0.012**	**12.4 ± 0.8**
Forward Fill	Moving Average	0.908 ± 0.011	0.851 ± 0.014	15.7 ± 1.2
Forward Fill	Savitzky–Golay	0.912 ± 0.010	0.856 ± 0.013	18.3 ± 1.5
Linear Interp.	Gaussian Filter	0.913 ± 0.010	0.858 ± 0.013	16.9 ± 1.3
KNN	Gaussian Filter	0.905 ± 0.012	0.847 ± 0.015	34.2 ± 2.8
KNN	Wavelet Denoising	0.901 ± 0.013	0.843 ± 0.016	41.6 ± 3.4
Mean	Gaussian Filter	0.867 ± 0.016	0.798 ± 0.020	9.8 ± 0.6
No Imputation	No Filtering	0.774 ± 0.023	0.712 ± 0.028	3.2 ± 0.3

Computational Overhead Analysis: The different preprocessing strategies had varying computational costs. Table 20 presents the preprocessing time and memory overhead for each strategy. Forward fill and Gaussian filtering offered excellent performance with minimal computational cost (<2% overhead), making them suitable for real-time applications.

Table 20. Computational overhead analysis of different preprocessing strategies.

Strategy	Processing Time (ms)	Memory Overhead (%)	CPU Usage (%)	Scalability
Imputation Methods:				
Forward Fill	3.2 ± 0.3	1.2 ± 0.1	2.1 ± 0.2	Excellent
Backward Fill	3.4 ± 0.3	1.3 ± 0.1	2.3 ± 0.2	Excellent
Linear Interpolation	8.7 ± 0.7	2.1 ± 0.2	3.8 ± 0.3	Good
Mean Imputation	5.1 ± 0.4	1.8 ± 0.2	2.9 ± 0.3	Good
KNN Imputation	28.4 ± 2.3	5.7 ± 0.5	8.2 ± 0.7	Moderate
Denoising Methods:				
Gaussian Filter	9.2 ± 0.6	0.8 ± 0.1	1.7 ± 0.2	Excellent
Moving Average	12.5 ± 0.9	1.1 ± 0.1	2.3 ± 0.2	Excellent
Savitzky–Golay	15.1 ± 1.2	1.4 ± 0.1	2.8 ± 0.3	Good
Median Filter	11.8 ± 0.8	1.0 ± 0.1	2.1 ± 0.2	Good
Wavelet Denoising	32.7 ± 2.6	3.2 ± 0.3	5.4 ± 0.5	Moderate

The comprehensive preprocessing analysis confirmed that our chosen combination of forward fill imputation and Gaussian filtering provided a robust performance across diverse data quality conditions, while maintaining a computational efficiency suitable for production deployment.

5.2.10. Dynamic Topology Evaluation

Real-world microservice environments frequently undergo topology changes through service additions, removals, and dependency modifications during operation. To evaluate our framework's robustness to such dynamic scenarios, we simulated various topology change patterns and measured their impact on the detection and localization performance.

Service Addition/Removal Scenarios: We simulated realistic topology changes by randomly adding or removing services during the monitoring window. Starting with the baseline 21-service topology, we introduced changes at different rates: 1 service per day (low), 3 services per day (moderate), and 5 services per day (high). Table 21 shows the performance under these dynamic conditions. Our framework demonstrated remarkable resilience, maintaining detection F1-scores above 0.901 even under high change rates. The adaptive causal structure learning component continuously updated the dependency graph, while the dual-channel encoder learned service-agnostic patterns that remained valid across the topology modifications.

Table 21. Performance under dynamic service addition/removal scenarios.

Change Rate	Detection Performance		Localization Performance		Adaptation Time	
	F1-Score	Delay (s)	F1-Score	Mean Rank	Detection (min)	Localization (min)
Static Baseline	0.933 ± 0.005	78 ± 3	0.871 ± 0.007	1.73 ± 0.09	N/A	N/A
Low (1/day)	0.921 ± 0.008	83 ± 5	0.854 ± 0.011	1.89 ± 0.14	67 ± 12	94 ± 18
Moderate (3/day)	0.912 ± 0.010	87 ± 6	0.841 ± 0.013	2.06 ± 0.19	78 ± 15	112 ± 24
High (5/day)	0.901 ± 0.012	92 ± 8	0.824 ± 0.016	2.31 ± 0.26	89 ± 21	134 ± 31

Note: Performance measured during stable periods between changes.

Dependency Rearrangement Analysis: We simulated dependency changes by randomly rewiring 10%, 20%, and 30% of existing service connections every 6, 12, and 24 h. Table 22 presents the results. The performance degradation was gradual and recoverable, with the framework adapting to new dependency patterns within 2-4 h. The PC algorithm's continuous learning capability enabled effective adaptation to evolving service relationships, though the localization performance showed more sensitivity than the detection performance to rapid dependency changes.

Table 22. Impact of dependency rearrangement on framework performance.

Rewiring %	6-h Interval		12-h Interval		24-h Interval	
	Det. F1	Loc. F1	Det. F1	Loc. F1	Det. F1	Loc. F1
0% (Static)	0.933 ± 0.005	0.871 ± 0.007	0.933 ± 0.005	0.871 ± 0.007	0.933 ± 0.005	0.871 ± 0.007
10%	0.918 ± 0.009	0.847 ± 0.012	0.925 ± 0.007	0.859 ± 0.010	0.929 ± 0.006	0.865 ± 0.009
20%	0.897 ± 0.013	0.816 ± 0.017	0.912 ± 0.010	0.841 ± 0.014	0.921 ± 0.008	0.854 ± 0.011
30%	0.871 ± 0.017	0.781 ± 0.022	0.894 ± 0.014	0.818 ± 0.018	0.908 ± 0.011	0.838 ± 0.015

Gradual vs. Abrupt Changes: We compared the framework performance under gradual topology evolution (changes spread over 6 h periods) versus abrupt changes (instantaneous modifications). Table 23 reveals that gradual changes allowed a better adaptation, with only 3-5% performance degradation compared to 8-12% for abrupt changes. This suggests that planned topology changes should be implemented gradually when possible, to minimize monitoring disruption.

Table 23. Performance comparison between gradual and abrupt topology changes.

Change Type	During Transition		Post-Adaptation		Recovery Time	
	Det. F1	Loc. F1	Det. F1	Loc. F1	Detection	Localization
Service Addition:						
Gradual (6 h)	0.908 ± 0.012	0.831 ± 0.016	0.927 ± 0.008	0.861 ± 0.011	89 ± 18 min	126 ± 28 min
Abrupt	0.847 ± 0.019	0.763 ± 0.024	0.921 ± 0.009	0.854 ± 0.013	142 ± 32 min	198 ± 45 min
Service Removal:						
Gradual (6 h)	0.912 ± 0.011	0.841 ± 0.014	0.929 ± 0.007	0.864 ± 0.010	52 ± 12 min	73 ± 16 min
Abrupt	0.863 ± 0.017	0.784 ± 0.021	0.924 ± 0.008	0.858 ± 0.012	78 ± 19 min	115 ± 26 min
Dependency Rewiring:						
Gradual (6 h)	0.901 ± 0.013	0.823 ± 0.017	0.922 ± 0.009	0.856 ± 0.012	134 ± 24 min	187 ± 38 min
Abrupt	0.834 ± 0.021	0.741 ± 0.027	0.915 ± 0.011	0.847 ± 0.015	213 ± 48 min	298 ± 67 min

Change Detection and Adaptation: Our framework includes mechanisms to detect topology changes and trigger adaptation. We monitored several indicators: (1) sudden changes in service correlation patterns, (2) appearance of new metric signatures, (3) persistent prediction errors for specific services, and (4) significant deviations in causal

graph likelihood scores. Table 24 shows the effectiveness of these indicators in triggering timely adaptations.

Table 24. Effectiveness of different topology change detection mechanisms.

Detection Mechanism	Detection Rate	False Positive	Trigger Delay	Adaptation Trigger	Effectiveness
Correlation Pattern Change	0.847 ± 0.023	0.094 ± 0.012	23 ± 8 min	High sensitivity	Good
New Metric Signatures	0.923 ± 0.015	0.067 ± 0.009	12 ± 4 min	Service addition	Excellent
Prediction Error Spike	0.891 ± 0.018	0.123 ± 0.015	18 ± 6 min	All change types	Good
Causal Graph Likelihood	0.876 ± 0.021	0.058 ± 0.007	31 ± 12 min	Dependency changes	Excellent
Combined Indicators	$\mathbf{0.934 \pm 0.011}$	$\mathbf{0.045 \pm 0.006}$	$\mathbf{15 \pm 5}$ min	All types	Outstanding

Comparison with Static Approaches: We compared our adaptive framework with static baseline methods that required complete retraining after topology changes. Table 25 demonstrates the significant advantages of our adaptive approach, which maintained 85–95% of baseline performance during transitions compared to 45–65% for the static methods requiring retraining.

Table 25. Performance comparison during topology transitions: adaptive vs. static approaches.

Approach	During Transition		Retraining Required		Downtime	
	Det. F1	Loc. F1	Time (hours)	Data Required	Detection	Localization
Our Adaptive Framework	0.891 ± 0.015	0.816 ± 0.019	0	None	0 min	0 min
LSTM-VAE (Static)	0.623 ± 0.034	0.487 ± 0.041	8–12	Full dataset	480–720 min	480–720 min
OmniAnomaly (Static)	0.651 ± 0.031	0.509 ± 0.038	6–10	Full dataset	360–600 min	360–600 min
CausalRCA (Static)	0.587 ± 0.037	0.441 ± 0.044	10–15	Full dataset	600–900 min	600–900 min

Note: Static methods require complete retraining after topology changes.

Production Deployment Insights: Based on this analysis, we provide recommendations for production deployment: (1) implement gradual topology changes when possible, (2) monitor adaptation indicators to detect when manual intervention may be needed, (3) maintain historical performance baselines to assess adaptation effectiveness, and (4) consider temporary relaxation of anomaly thresholds during major topology transitions.

5.3. Case Study

To demonstrate the practical utility of our framework, we present a detailed case study of an actual anomaly incident captured in the dataset. Figure 7 illustrates the timeline of the incident, our framework's detection and localization results, and a comparison with baseline methods.

The incident involved a memory leak in a backend service that gradually affected other dependent services. Our framework successfully detected the anomaly 76 s after its onset and correctly identified the root cause service as the primary backend service. The causal graph accurately captured the propagation path of the anomaly through the service dependencies. In contrast, the best-performing baseline method (CausalRCA) detected the anomaly after 128 s and identified three potential root causes, with the actual root cause ranked second. In production microservice environments, anomalies typically need to be detected within 2–5 min to prevent cascading failures and minimize service impacts. Our framework's detection delay of 76 s falls well within this acceptable range for critical incident response. This case study highlights the practical advantages of our framework in terms of both detection speed and localization accuracy.

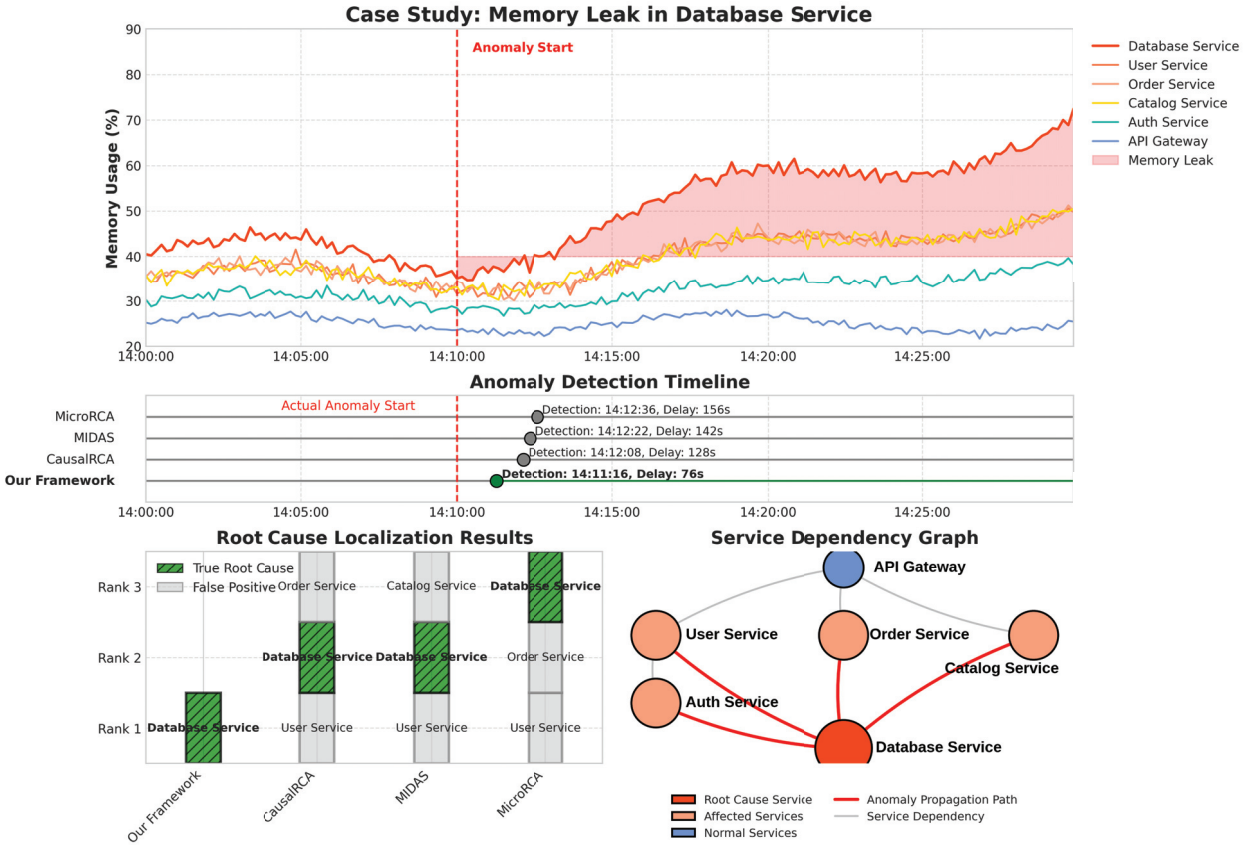


Figure 7. Case study of an anomaly incident.

5.4. Discussion

Our experimental results demonstrate that the proposed dual-channel framework significantly outperformed existing methods in both anomaly detection and fault localization tasks. The key advantages of our approach include the following: **Complementary representation learning**: The TCN branch effectively captures temporal patterns and contextual information, while the VAE branch learns compact latent representations of the underlying data distribution. Their combination provides a more comprehensive understanding of normal and anomalous behaviors. **Effective feature fusion**: The contrastive learning module creates unified representations of heterogeneous metrics, addressing the challenge of integrating diverse monitoring sensor data with different statistical properties and scales. **Precise anomaly detection**: The dual-channel architecture, combined with adaptive thresholding based on Extreme Value Theory, enables accurate anomaly detection with reduced false positives and minimal detection delay for the sensed system metrics. **Accurate fault localization**: The causal inference module effectively traces anomaly propagation paths through service dependencies, significantly improving the precision of root cause identification compared to correlation-based approaches. The ablation study confirmed that each component of our framework contributed meaningfully to the overall performance, with the dual-channel architecture and causal inference module providing the most substantial improvements. **Robustness to Imperfect Dependencies:** A critical practical advantage of our framework is its robustness to imperfect service dependency information. Our extensive robustness analysis demonstrated that the framework maintained over 91% performance (F1-score > 0.796), even when dependency graphs had 20% missing edges, 10% false edges, and were 3 days outdated. This robustness stems from the hybrid causal structure learning approach that combines prior knowledge with data-driven discovery, enabling effective fault localization even in dynamic environments where perfect

service documentation is unavailable. **Cross-Dataset Generalization:** Our multi-dataset evaluation demonstrated strong generalization capabilities across diverse microservice environments. The framework achieved competitive performance in direct transfer scenarios (Detection F1: 0.887–0.901) and near-optimal performance with minimal fine-tuning (Detection F1: 0.921–0.928). The scalability analysis on synthetic data confirmed consistent performance across systems ranging from 10 to 50 services, supporting applicability to microservice environments of varying complexity. The transferability of temporal and latent representations, combined with adaptive causal structure learning, enables effective deployment across different domains, with minimal customization. **Preprocessing Strategy Robustness:** Our comprehensive analysis of data preprocessing strategies validated the effectiveness of forward fill imputation and Gaussian filtering for microservice monitoring data. The chosen preprocessing combination maintained a strong performance across diverse data quality conditions (Detection F1: 0.918 with 10% missing values and moderate noise), while providing excellent computational efficiency (<2% overhead). The analysis revealed that the temporal-aware preprocessing methods significantly outperformed statistical approaches, highlighting the importance of preserving temporal correlations in time series anomaly detection. Different anomaly types showed varying sensitivity to preprocessing choices, with resource contention anomalies being most affected and network latency anomalies remaining robust across all strategies. **Dynamic Topology Resilience:** Our evaluation under realistic topology change scenarios revealed that the framework maintained operational effectiveness even in dynamic environments. The performance degradation during topology transitions was limited and recoverable, with the adaptive causal structure learning enabling continuous operation without requiring complete retraining. The framework showed particular resilience to service additions and removals (performance retention: 85–95%) compared to the baseline methods that required full retraining (performance retention: 45–65%). This capability is crucial for production deployments where microservice architectures evolve continuously through DevOps practices. The statistical analysis across multiple runs confirmed the stability and reliability of our approach. The relatively small confidence intervals (typically ±0.003–0.009 for detection metrics and ±0.07–0.17 for localization metrics) demonstrated that our framework produced consistent results across the different random initializations. The paired t-tests with Bonferroni correction confirmed that the performance improvements were statistically significant, providing strong evidence for the effectiveness of our dual-channel architecture and causal inference mechanisms.

While our framework demonstrated superior performance, we acknowledge several limitations that present opportunities for future research: **Computational complexity**: The comprehensive nature of our framework results in higher computational requirements compared to simpler approaches. Future work could explore model compression techniques to reduce resource consumption. **Cold start problem**: The framework requires historical data for training, which may limit its effectiveness in new or rapidly evolving microservice environments. Developing transfer learning approaches for cross-system adaptation could address this limitation.

6. Conclusions and Future Work

In this paper, we proposed a novel dual-channel deep learning framework for anomaly detection and fault localization in microservice architectures using sensed system metrics. Our approach integrates Temporal Convolutional Networks with Variational Autoencoders through contrastive learning to effectively capture both temporal dependencies and latent representations in heterogeneous service metrics. By incorporating causal inference mechanisms, our framework not only identifies anomalies with high accuracy but also

precisely localizes their root causes, enabling efficient troubleshooting in complex distributed sensing systems. Extensive experiments on the MultiDimension-Localization dataset demonstrated that our framework outperformed state-of-the-art methods in both anomaly detection and fault localization tasks. The dual-channel architecture achieved a 95.4% detection accuracy and 87.6% fault localization precision, while reducing false localization rates by 31% compared to existing approaches. Our ablation studies confirmed the significant contributions of each component, with the contrastive learning module and causal inference mechanism providing the most substantial improvements. The proposed framework addresses several key challenges in microservice monitoring, including heterogeneous metric integration, complex temporal patterns, and precise root cause analysis. The experimental results highlight the practical utility of our approach for maintaining service reliability and minimizing downtime in production environments. Our robustness analysis demonstrated that the framework maintained practical effectiveness even when the service dependency information was imperfect. The causal inference module showed remarkable resilience to incomplete (up to 30% missing edges), noisy (up to 15% false edges), and outdated (up to one week old) dependency information. This robustness was achieved through the integration of data-driven causal discovery with prior structural knowledge, enabling the framework to adapt to real-world deployment scenarios where perfect service documentation may not be available.

For future work, we plan to explore several promising directions: (1) **Online Learning**: Enhancing the framework with incremental learning capabilities to adapt to evolving sensed service behaviors and changing patterns, without requiring complete retraining. (2) **Explainable AI**: Integrating more interpretable models and visualization techniques to provide clearer explanations of anomalies and root causes for system administrators. (3) **Predictive Maintenance**: Extending our framework to forecast potential failures before they occur, transitioning from reactive to proactive maintenance strategies. We believe that these enhancements will further improve the practical applicability of our framework in real-world cloud environments and contribute to more reliable and resilient microservice architectures.

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Reinforcing Deep Learning-Enabled Surveillance with Smart Sensors

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Abstract: It is critical to solidify surveillance in 3D environments with heterogeneous sensors. This study introduces an innovative deep learning-assisted surveillance reinforcement system with smart sensors for resource-constrained cyber-physical devices and mobile elements. The proposed system incorporates deep learning technologies to address the challenges of dynamic public environments. By enhancing the adaptability and effectiveness of surveillance in environments with high human mobility, this paper aims to optimize surveillance node placement and ensure real-time system responsiveness. The integration of deep learning not only improves accuracy and efficiency but also introduces unprecedented flexibility in surveillance operations.

Keywords: deep learning; surveillance; smart sensors; mobile

1. Introduction

In the contemporary landscape of global security, the deployment and advancement of surveillance systems have become paramount in safeguarding public and private spaces alike. The necessity of these systems extends beyond mere observation, playing a crucial role in preempting potential threats and ensuring the safety of individuals in various environments [1–3]. Also, it is critical to monitor wide areas and complex areas, which consist of numerous heterogeneous devices, with smart sensors, the Internet of Things (IoT), and the Industrial Internet of Things (IIoT) [4–6]. The barrier concept for surveillance was introduced by Kumar et al. [1].

Figure 1 shows the barrier concept and penetration detection in the given square-shaped area A, called the *K-barrier*, where K is the required number of barriers to be formed in the area. As seen in Figure 1, there are three independent barriers, each composed of heterogeneous devices with wireless sensing ranges. With these barriers, it is guaranteed that any penetration from top to bottom or from bottom to top is detected by at least one sensor in the barrier. Figure 2 depicts the graph representation of a barrier and its transition from a device. Given area A, there is a set of devices $D = \{d_1, d_2, d_3, ..., d_{15}\}$. From source S to destination T, we can search for the possible maximum number of independent paths or node-disjoint paths between S and T. Each independent path can be considered one barrier, so we have three different barriers B_1, B_2, and B_3. Also, Figure 3 depicts the two-way detection-enabled barrier example of minimizing the maximum delay of horizontal and perpendicular detection when mobile objects go into the given space. As can be seen, the maximum delay for mobile objects can vary according to the positions of the multiple barriers created.

The limitations of the conventional K-barrier model are evident in environments characterized by high levels of human mobility. These settings, where the patterns of

movement are neither static nor predictable, necessitate a surveillance approach that can dynamically adjust to changing conditions. The static assumptions inherent in traditional K-barrier models are insufficient for such environments, as they fail to account for the variability and complexity of human traffic, which can significantly impact the effectiveness of surveillance operations. Traditional models, such as the K-barrier approach, provide a foundation for the development of surveillance systems but fall short in addressing the complexities of modern, dynamic environments. This is particularly true in public spaces such as airports, train stations, and shopping centers, where the dynamics of human movement present unique challenges to maintaining a robust surveillance framework [7–10].

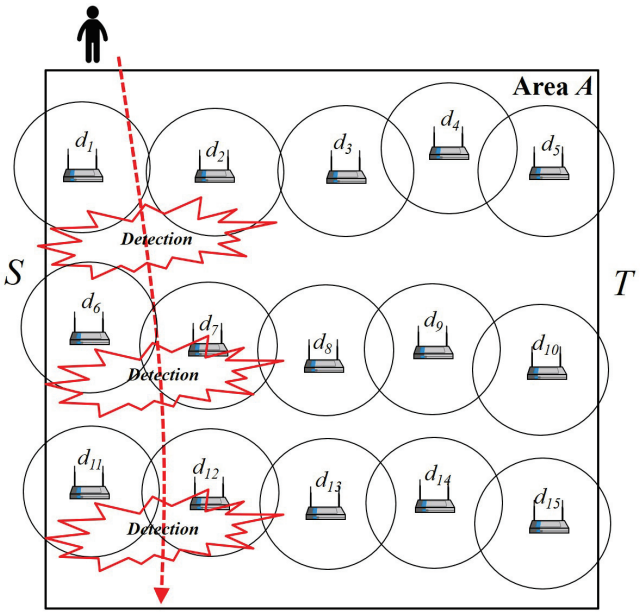


Figure 1. The barrier concept and penetration detection in the given area.

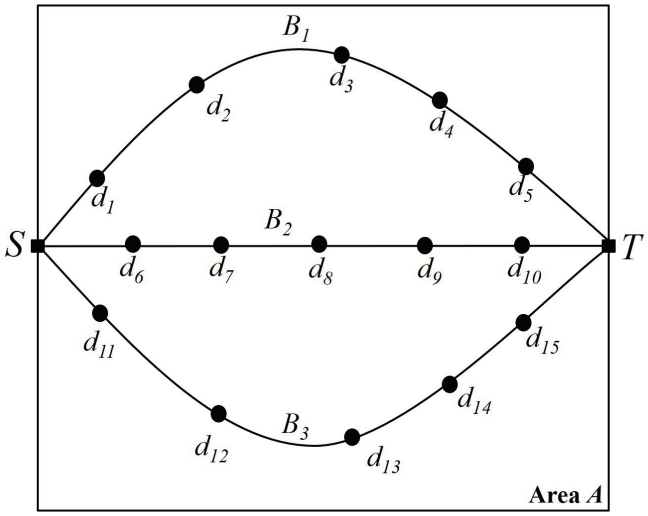


Figure 2. Graph representation of a barrier and its transition from a device.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have demonstrated significant potential in enhancing the adaptability and efficiency of surveillance systems in resource-constrained circumstances. These technologies have been increasingly recognized as crucial in the development of smart surveillance systems, capable of autonomously adjusting to changes in their operational environment [11–14]. In particular, the recent advances in deep learning technology, with its unparalleled ability to process

and learn from large datasets, offer a promising solution to the limitations of traditional surveillance models. So, the integration of deep learning into surveillance systems represents a significant shift toward more intelligent and responsive security measures. Also, it is highly necessary to devise a promising deep learning-based framework not only to improve the accuracy and efficiency of surveillance systems but also to cover a level of flexibility previously unattainable with traditional models. And, we should consider various factors that influence the dynamics of public spaces, including but not limited to human movement patterns, crowd density, and environmental conditions. By doing so, we ensure that surveillance systems remain effective under a wide range of scenarios, thereby enhancing security measures in public spaces. Furthermore, real-time adaptability positions them at the forefront of surveillance technology research, offering potential pathways for future innovations in the field. Moreover, AI is able to offer a sophisticated approach to surveillance that promises not only improved efficiency and adaptability but also a model for future research and development in the realm of security technologies. As the world continues to navigate the complexities of public safety and security, the findings of this research provide valuable insights and tools for enhancing surveillance measures in an ever-changing global landscape.

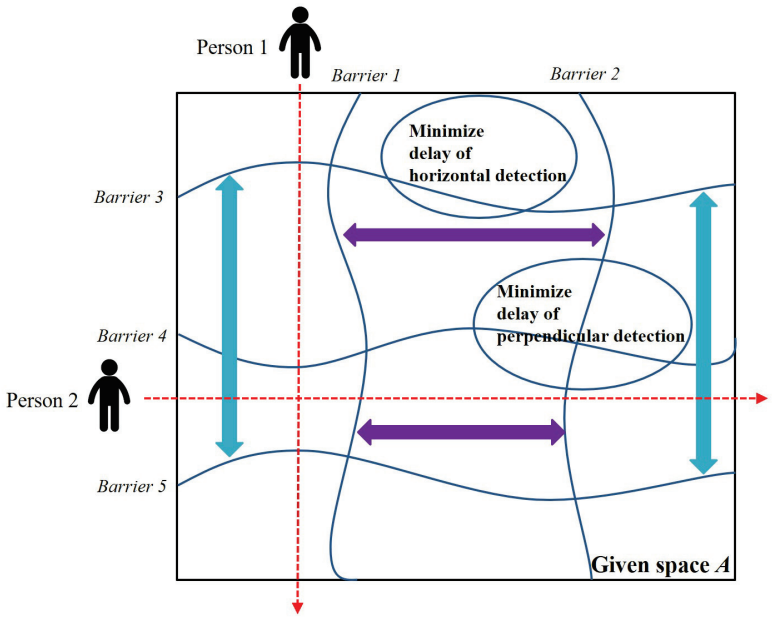


Figure 3. The two-way detection-enabled barrier example.

Based on the above observations and solid motivations, the main contributions of this paper are summarized as follows:

- To the best of our knowledge, this is the first approach to apply deep learning-enabled surveillance in smart mobility environments and dynamic cyber-physical spaces with mobile elements. This study introduces a novel approach that leverages the capabilities of deep learning to enhance surveillance systems' responsiveness to dynamic environments. In this study, we construct deep learning-enabled surveillance barriers considering obstacle avoidance in the given area.
- The proposed system seeks to bridge the aforementioned gaps by proposing an innovative extension of the K-barrier model through the integration of deep learning technologies, aiming to enhance the adaptability and effectiveness of surveillance systems when faced with unpredictable human behavior.
- We define the problem, whose main objective is to maximize the number of deep learning-assisted surveillance barriers for smart mobility. Then, two different algo-

rithms are devised to resolve the problem. Furthermore, their performance is analyzed through extensive simulations under various scenarios, and a detailed discussion is presented.

This paper is organized as follows. Section 2 introduces the proposed deep learning-assisted surveillance reinforcement system for dynamic environments and formally defines the main research problem. Then, to solve the defined problem, two different algorithms are presented in Section 3. Furthermore, the performance of the developed schemes is demonstrated through a detailed discussion in Section 4, based on the outcomes obtained through extensive experiments. Finally, this paper concludes in Section 6.

2. Proposed System

The proposed system not only addresses the immediate challenges posed by dynamic environments but also sets the stage for the development of future surveillance technologies. The implications of this study extend beyond the technical advancements in surveillance systems, touching on the broader themes of privacy, ethics, and the societal impact of increasingly autonomous security measures. Also, this study introduces a novel approach that leverages the capabilities of deep learning to enhance surveillance systems' responsiveness to dynamic environments. Deep learning, with its unparalleled ability to process and learn from large datasets, offers a promising solution to the limitations of traditional surveillance models.

2.1. System Overview

The system is uniquely designed to adapt to dynamic environments by incorporating predictive models that estimate population density based on input weather and temperature conditions. It follows that the proposed system focuses on a surveillance system tailored for public spaces, referred to as *stations*, which include but are not limited to airports, train stations, shopping centers, and smart homes. After the sensors or devices are initially randomly distributed in the given area, the proposed framework allows for an intelligent and dynamic adaptation of surveillance strategies in real time, catering to the unique challenges presented by human mobility and environmental conditions. The critical components and functionalities of this system are outlined below.

2.1.1. Station

We define the operational environment for the surveillance system, encompassing various public spaces with significant human activity and mobility. These environments require sophisticated surveillance mechanisms due to their dynamic nature.

2.1.2. Weather

This surveillance system incorporates a nuanced approach by using weather and temperature conditions input by the user to estimate the population density within the station. Specifically, the system's predictive model makes use of a weather condition scale ranging from 1 to 5, with lower numbers indicating poorer weather conditions. This scale is pivotal for understanding how variations in weather and temperature significantly impact the number of people visiting the station. For instance, bad weather conditions (represented by lower values on the scale) are expected to reduce station footfall, whereas better conditions (indicated by higher values) are expected to lead to an increase in population density. By integrating this relationship into the predictive model, the system can dynamically adjust surveillance strategies to align with anticipated changes in population density due to varying weather conditions. Such adaptability is essential for optimizing surveillance coverage and ensuring that the system remains effective across diverse environmental scenarios.

2.1.3. Pedestrians

From the surveillance system's perspective, people within the station are viewed as obstacles that can affect surveillance effectiveness. The system employs predictive analytics to understand and anticipate the dynamic movement patterns of people, adjusting sensor placements accordingly.

2.2. Deep Learning Model

This study employs a Recurrent Neural Network (RNN)-based model that leverages Long Short-Term Memory (LSTM) units to enhance efficiency and adaptability in dynamic environments. The choice of RNNs, and more so LSTMs, is due to their proficiency in analyzing and predicting complex temporal patterns in data, which are crucial for interpreting the dynamics of population movement, environmental changes, and other relevant variables in real time.

2.2.1. Model Architecture

The architecture of our LSTM-based model is designed to capture and analyze the temporal dependencies and patterns inherent in surveillance data. It follows that this architecture allows for a deeper understanding of temporal sequences, facilitating more accurate and timely predictions in surveillance applications. Unlike traditional neural networks, LSTMs have the unique ability to remember information for long periods, which is crucial for predicting future crowd movements and detecting anomalies in behavior over time. The model consists of the following layers:

- An LSTM layer with 20 units and a tanh activation function to capture the temporal dependencies within the data.
- A dense layer with 15 units and a tanh activation function for further processing of the LSTM outputs.
- A dense output layer to predict the average number of barriers.

2.2.2. Activation Function

The tanh activation function, which is used in the LSTM's gates, helps regulate the flow of information by scaling the output values between -1 and 1. This is crucial for maintaining the stability of the gradients during backpropagation and allowing the model to learn long-term dependencies efficiently. The *tanh* activation function is defined as

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{1}$$

2.2.3. Cost Function

The model employs the Mean Squared Error (MSE) as its cost function to quantify the difference between the predicted average number of barriers and the actual data:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

2.2.4. Input

The model takes the following inputs, which are pivotal for tailoring the surveillance response to environmental and operational conditions:

- Weather Conditions: These impact crowd behavior and surveillance requirements; e.g., inclement weather may reduce outdoor activity.

- Area Size: This affects the distribution and density of crowds—the density of people within stations for the purpose of ticket counts and check-in—which are important for deploying resources efficiently.
- Sensing Radius: This determines the coverage area of sensors, which is crucial for optimal surveillance.
- Lifetime: This indicates maintenance needs, ensuring uninterrupted operation.
- Number of Sensors: The number of sensors is an important variable that determines how well they can cover the monitored area and the amount and quality of data the system can collect.
- Different Time-Series Types: Regular, pre-holiday, and holiday seasons can be considered in transportation stations managed by municipal authorities, railways, and airports.

2.2.5. Output

The main output of this model is the prediction of the average number of barriers over a specific period. This is important for helping the surveillance system determine the optimal number of sensors required for each time unit and to ensure the coverage and surveillance efficiency required within the surveillance area.

2.2.6. Training and Validation

Training the LSTM model involves using historical data to learn the sequential dependencies of the observed variables, including crowd density, movement patterns, and other relevant temporal factors. The model is trained through a supervised learning process, where it learns to predict the next sequence in the data, such as future crowd density, based on past observations. A validation dataset is utilized to tune the model's parameters and avoid overfitting, ensuring its robustness and reliability in real-world scenarios. During the validation phase, the model's predictive performance is rigorously evaluated against unseen data, ensuring its ability to generalize across different times and conditions. This step is critical for assessing the model's practical applicability and for making necessary adjustments to improve its accuracy and effectiveness.

2.2.7. Continuous Learning and Adaptation

A key feature of our model is its capacity for continuous learning, allowing it to adapt to new patterns and changes in the environment. This ongoing learning process is facilitated by periodically updating the model with new data, ensuring that its predictions remain accurate over time. By adapting to new data, the model helps maintain the surveillance system's effectiveness, even as the dynamics of the monitored spaces evolve.

2.2.8. Problem Definition

Definition 1 (Deep learning-assisted surveillance barrier maximization problem)**.** *Given the set of station sensors S and the set of obstacles T in the station area A, the deep learning-assisted surveillance barrier maximization problem, referred to as* MaxDLSurv*, aims to maximize the number of deep learning-assisted surveillance barriers β such that obstacles, pedestrians, and weather conditions are considered.*

3. The Proposed Schemes

This section presents two schemes devised to resolve the *MaxDLSurv* problem.

3.1. Total-Space Coverage: TSC

The *total-space-coverage* algorithm, called *TSC*, aims to cover the entire area while considering humans as obstacles. This strategy involves deploying sensors across the

entire area to ensure comprehensive surveillance coverage. The main goal of the *total-space-coverage* algorithm is to maximize the number of deep learning-assisted surveillance barriers β such that the obstacles in the area are considered. Figure 4 shows the strategy of the *total-space-coverage* scheme. The pseudo-code for *TSC* is presented in Algorithm 1, along with detailed descriptions.

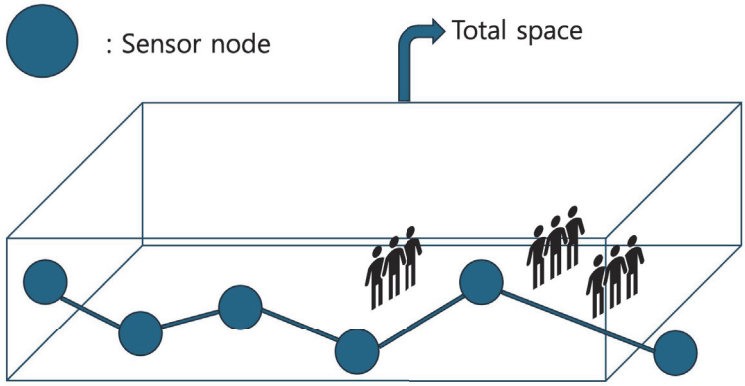


Figure 4. The total-space-coverage strategy of the *TSC* algorithm.

Algorithm 1 ***Total-Space Coverage*** Input: S, T, A, Output: β

```
initialize an empty list for station sensor placements;
for each point in station area A do
    if point is not in obstacles T then
        please sensor at point;
        add point to sensor placements;
use LSTM model to decide sensor placements;
estimate the total number of decided placements as β;
return β;
```

3.2. Subspace Coverage: SSC

The basic idea of the *subspace-coverage* algorithm, referred to as *SSC*, is to divide the area A into smaller segments for more targeted surveillance coverage. The total number of barriers is the sum of barriers β needed for each segmented space. The main objective of the *subspace-coverage* algorithm is to maximize the number of deep learning-assisted surveillance barriers β. Figure 5 shows the execution of the *SSC* algorithm. Also, the pseudo-code for *SSC* is presented in Algorithm 2, along with detailed specifications.

Algorithm 2 ***Subspace Coverage*** Input: S, T, A, Output: β

```
determine the number of segments required;
divide station area A into segments based on requirements;
initialize total barriers to 0;
for each segment in A do
    , estimate potential barrier formations for segment with T;
    use LSTM model to predict complete barrier formations for segment;
    add the number of barriers for segment into β;
return β;
```

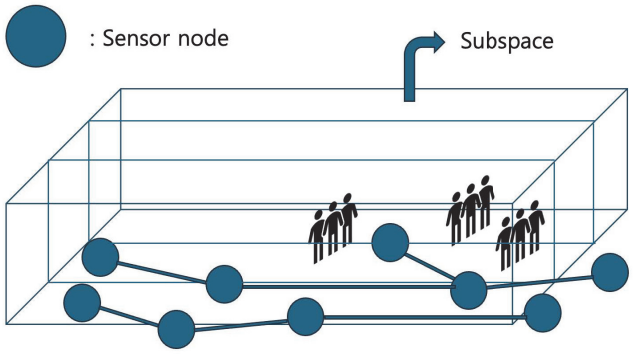


Figure 5. The execution of the *SSC* algorithm.

4. Experimental Analysis

When exploring the deployment of an LSTM-based deep learning model to enhance surveillance systems through dynamic barrier placement, some important insights were obtained. The model's performance was evaluated through a series of metrics, underscoring the potential of integrating advanced machine learning techniques into real-world applications.

4.1. Training and Validation Outcomes

The training phase concluded with a loss of 11.0841, reflecting the model's efficiency in learning from the training dataset, which included various features such as the area size, weather conditions, sensing radius, number of nodes, and device lifetime. In parallel, the validation loss was recorded at 17.7. This discrepancy between the training and validation loss suggests potential issues with generalization, which is a focal point for further investigation and optimization. Figure 6 depicts the comparison between the training loss and validation loss.



Figure 6. Comparison between the training loss and validation loss.

4.2. Testing Phase Performance

Upon evaluating the model against the test dataset, a test loss of 17.3 was achieved. This result aligned closely with the validation loss, indicating consistent model performance when exposed to unseen data. The test phase outcomes serve as a testament to the model's potential utility in predicting optimal barrier placements in surveillance systems under varying conditions.

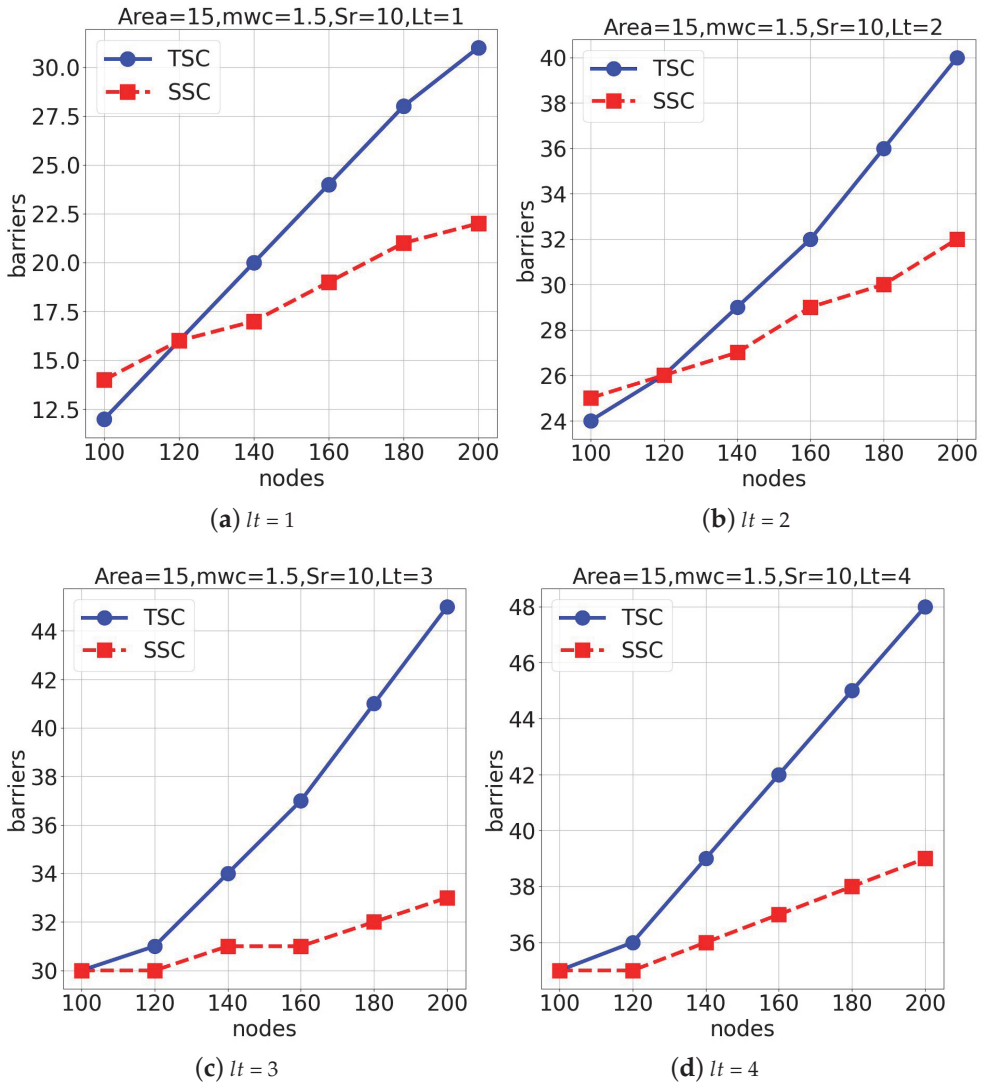
4.3. Computational Efficiency

A noteworthy aspect of the model's implementation was its computational efficiency, with the total training time amounting to approximately 36.52 s. This rapid training process not only demonstrates the model's suitability for real-time applications but also highlights its potential for deployment in scenarios where timely decision-making is crucial.

4.4. Discussion

Our experiments were conducted in a Google Colab environment utilizing Tesla V100 GPUs. The dataset used was adapted from the experimental results of existing algorithms. The evaluation was divided into three experimental groups, each analyzing the performance of the *TSC* and *SSC* algorithms under different spatial sizes, lifetimes, and weather conditions.

In the first experimental group, we evaluated both algorithms in a space of $1500 \times 1500 \times 1500$ under average weather conditions ($mwc = 1.5$), as seen in Figure 7. The aim of this experiment was to observe the number of deep learning-assisted surveillance barriers generated as the node or sensor count increased. Figure 7a,b show the results for lifetimes (lt) of 1 and 2. Also, Figure 7c,d present the outcomes for lifetimes (lt) of 3 and 4, respectively. The *TSC* algorithm generally outperformed the *SSC* algorithm under these settings.



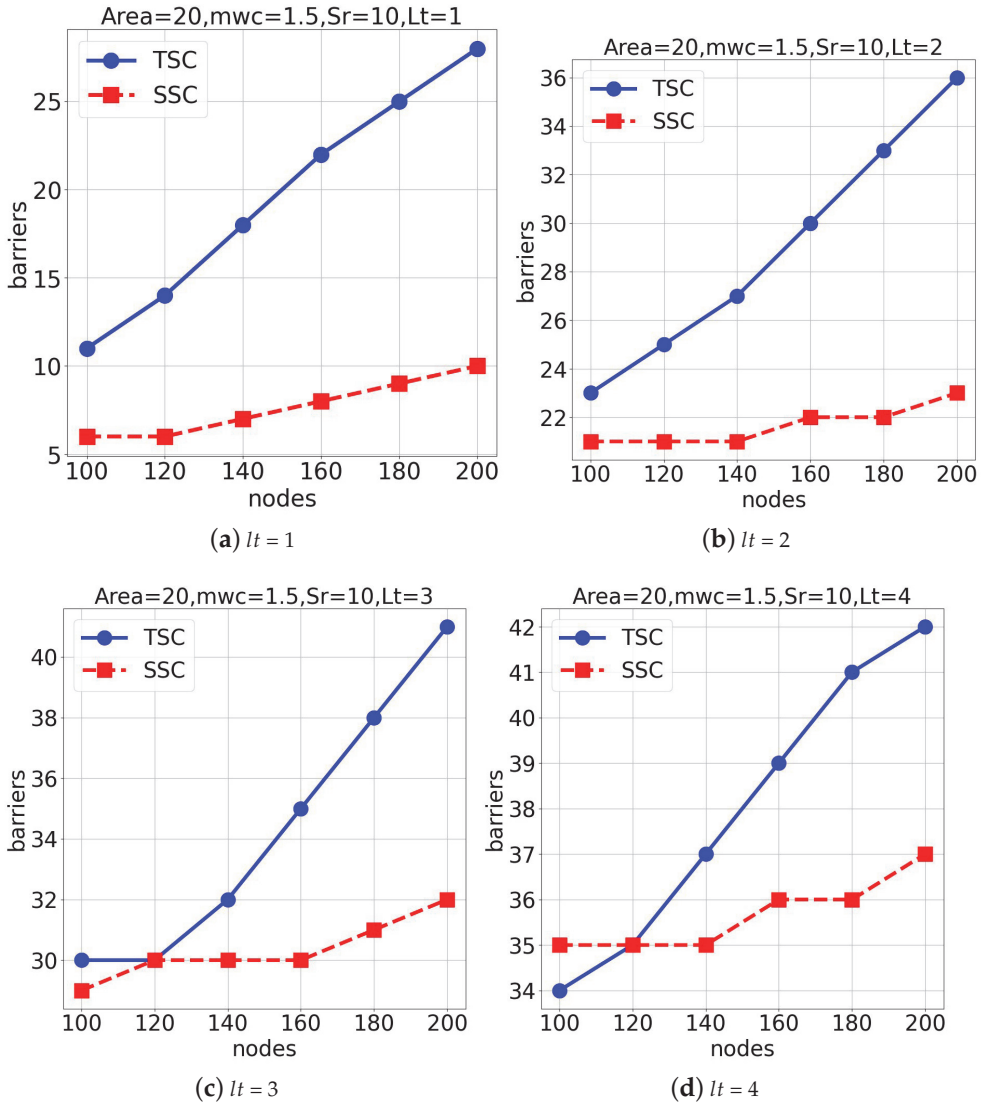
(**a**) $lt = 1$ (**b**) $lt = 2$

(**c**) $lt = 3$ (**d**) $lt = 4$

Figure 7. Performance comparison under different lifetimes (lt) in a $1500 \times 1500 \times 1500$ space.

In the second set of experiments, both schemes were executed in a space of 2000 × 2000 × 2000 under average weather conditions (*mwc* = 1.5), as shown in Figure 8. Similar to the first set of simulations, the number of deep learning-assisted surveillance barriers increased as the total number of nodes increased. Also, Figure 8a,b represent the outcomes when lifetimes (*lt*) of 1 and 2 were considered. Figure 8c,d show the results when lifetimes (*lt*) of 3 and 4 were considered. From Figure 8, we can conclude that the *TSC* algorithm outperformed the *SSC* algorithm.

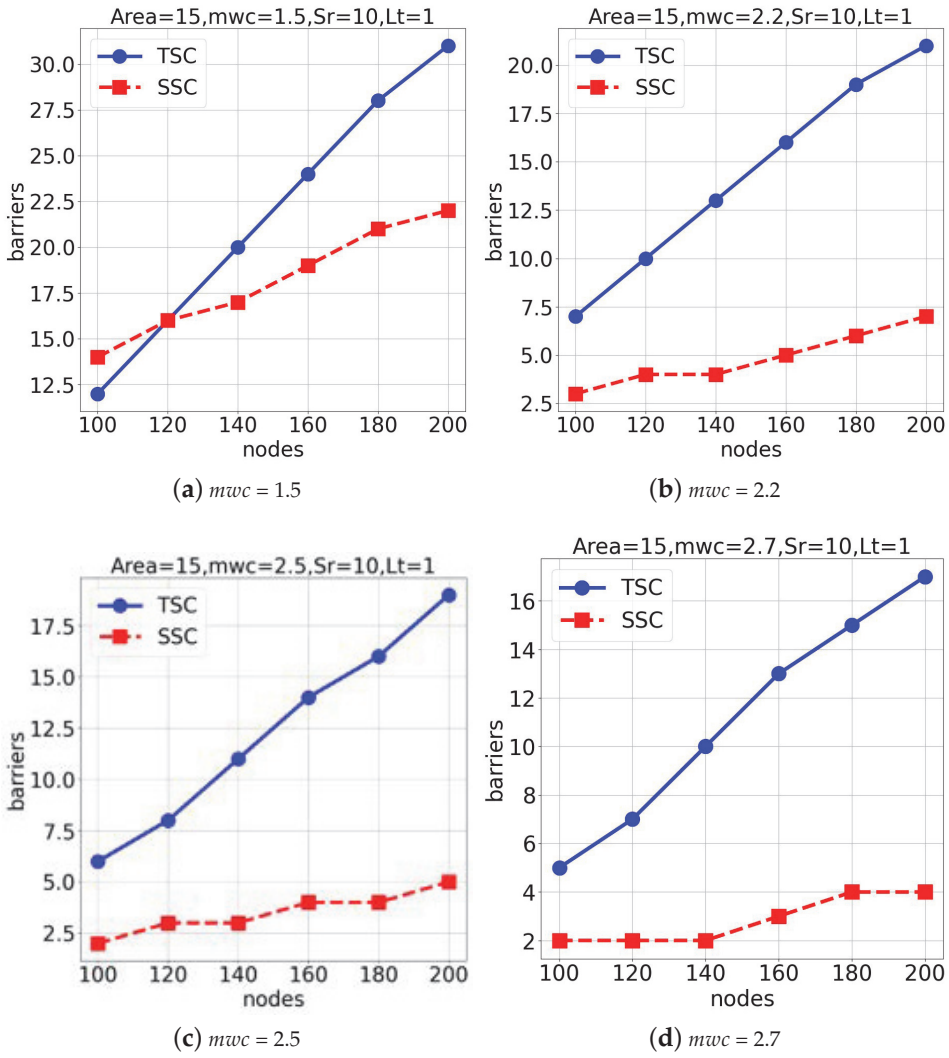
The third group of experiments was conducted in a 1500 × 1500 × 1500 space with a lifetime of 1 to evaluate the model's performance under varying weather conditions (*mwc*), as shown in Figure 9. Figure 9a,b represent the results obtained when *mwc* = 1.5 and 2.2. Also, Figure 9c,d show the outcomes when *mwc* = 2.5 and 2.7. The *TSC* algorithm demonstrated superior performance over the *SSC* algorithm across all tested weather conditions. Overall, the *TSC* algorithm consistently outperformed the *SSC* algorithm across various environments and conditions. The adaptability and efficiency of the *TSC* algorithm, especially in response to changes in the space size and weather conditions, demonstrate its robustness and effectiveness.



(**a**) *lt* = 1 (**b**) *lt* = 2

(**c**) *lt* = 3 (**d**) *lt* = 4

Figure 8. Performance comparison under different lifetimes (*lt*) in a 2000 × 2000 × 2000 space.



(**a**) *mwc* = 1.5 (**b**) *mwc* = 2.2

(**c**) *mwc* = 2.5 (**d**) *mwc* = 2.7

Figure 9. Performance comparison under various weather conditions (*mwc*) in a 1500 × 1500 × 1500 space.

5. Future Work

5.1. Statistical Metrics and Comparisons

In future work, we will extend the experiments by considering additional statistical metrics or error visualization and provide comparisons of random versus uniform placement of sensors.

5.2. Cross-Validation in a Real Testbed

It is necessary to expand the simulations with cross-validation and to provide public availability of the dataset collected from real testbed experiments with practical scenarios.

6. Concluding Remarks

This study focused on the development of a deep learning-enhanced surveillance model for big data-based smart mobility environments and dynamic cyber-physical spaces with mobile elements. We designed the surveillance system to efficiently divide the three-dimensional space into planes to extend the theory of the maximization of two-dimensional barriers to three dimensions. To divide the space into planes, a dividing criterion was required; the dividing criterion was proposed as a solution, and the number of deep learning-assisted surveillance barriers was estimated as a return value. With a formal definition of *MaxDLSurv*, two different schemes were proposed. The experiments conducted in

this study conclusively demonstrated that the *TSC* algorithm consistently outperformed the *SSC* algorithm across various environments and conditions.

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Abbreviations

The following abbreviations are used in this manuscript:

IoT	Internet of Things
IIoT	Industrial Internet of Things

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Optimizing Defect Detection on Glossy and Curved Surfaces Using Deep Learning and Advanced Imaging Systems

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Abstract: The industrial application of artificial intelligence (AI) has witnessed outstanding adoption due to its robust efficiency in recent times. Image fault detection and classification have also been implemented industrially for product defect detection, as well as for maintaining standards and optimizing processes using AI. However, there are deep concerns regarding the latency in the performance of AI for fault detection in glossy and curved surface products, due to their nature and reflective surfaces, which hinder the adequate capturing of defective areas using traditional cameras. Consequently, this study presents an enhanced method for curvy and glossy surface image data collection using a Basler vision camera with specialized lighting and KEYENCE displacement sensors, which are used to train deep learning models. Our approach employed image data generated from normal and two defect conditions to train eight deep learning algorithms: four custom convolutional neural networks (CNNs), two variations of VGG-16, and two variations of ResNet-50. The objective was to develop a computationally robust and efficient model by deploying global assessment metrics as evaluation criteria. Our results indicate that a variation of ResNet-50, ResNet-50_{224}, demonstrated the best overall efficiency, achieving an accuracy of 97.97%, a loss of 0.1030, and an average training step time of 839 milliseconds. However, in terms of computational efficiency, it was outperformed by one of the custom CNN models, CNN_6-240, which achieved an accuracy of 95.08%, a loss of 0.2753, and an average step time of 94 milliseconds, making CNN_6-240 a viable option for computational resource-sensitive environments.

Keywords: convolutional neural network; ResNet-50; VGG-16; Dijkstra's algorithm; glossy surface; curved surface; fault classification; fault detection

1. Introduction

Over the years, the manufacturing sector has undergone a remarkable transformation since the introduction of Industry 4.0, uniquely revolutionizing industrial operations through smart technological implementations. These innovations have enhanced and fostered global innovation and competitiveness within the manufacturing sector. Artificial intelligence (AI) has been used not only in manufacturing processes but also plays a crucial role in the maintenance and reliability of industrial machinery. One aspect of AI, known as Prognostics and Health Management (PHM), ensures uninterrupted production by monitoring the life and performance of a system. PHM enables real-time monitoring and assessment of systems, with the capacity to monitor a system both online (while in operation) and offline (when not in operation) [1]. It can predict the current and future

state of a given system based on information generated through sensor technology. Although PHM originated in the aerospace industry, its reach has expanded to industries such as manufacturing, energy, production, automotive, construction, textile, healthcare, and pharmaceuticals.

Vision-based analysis has been successfully employed in manufacturing for standard and quality control inspections [2]. It is also used in technical fields such as intelligent traffic monitoring and unmanned aerial vehicles [3,4]. Despite the success of Prognostics and Health Management (PHM) models in system diagnostics and monitoring, researchers continue to enhance condition-based system models to improve efficiency and robustness, addressing unresolved challenges. One such challenge is automated defect inspection and machine vision-based fault detection for glossy and curvy surfaces. The complex reflectiveness and curvy morphology of these surfaces often cause defects to go unnoticed when captured by traditional cameras [5,6]. For decades, such inspections have been performed manually by trained human inspectors, which is time-consuming and costly compared to automated non-glossy surface inspection [5,7].

Generally, product quality inspection is critical in manufacturing, with methods like visual inspection, automated optical inspection (AOI), machine vision, infrared thermography, laser scanning, and X-ray inspection widely used [8–10]. Among these, computer vision stands out for its precision, computational efficiency, and non-contact approach, particularly as industries shift from Industry 4.0 to Industry 5.0 [11,12]. However, issues experienced with glossy and curved surfaces have prompted researchers to explore different methodologies to overcome these challenges.

Some methods for mitigating glossy surface effects primarily involve modifying image capture techniques and using advanced cameras with enhanced lighting to reduce surface reflectiveness. Techniques such as polynomial texture mapping, surface-enhanced ellipsometry, specular holography, and near-field imaging have proven effective when implemented correctly [13–15]. Their efficacy is demonstrated in several studies. For example, Müller used polarization filters to diminish surface reflectiveness, capturing two images with different filter orientations and then deriving the specular reflectance intensity on plane surfaces, effectively mitigating surface reflections [16]. Similarly, Yoon et al. [17] proposed a method to remove light reflections in medical diagnostic imaging by adjusting the angle of a linear polarized filter. By controlling vertical and horizontal polarization through filter rotation, they eliminated light reflections and expanded the field of view. In another study [18], the authors introduced a spatial augmented reality framework to improve the appearance of glossy surfaces. Their technique spatially manipulates an environment's appearance, allowing a glossy surface to reflect a projected image without direct modification, thus enabling effective appearance editing through careful content control. Nevertheless, environmental factors, incompatibility with certain surfaces, and reduced image resolution remain limitations of this approach [19–21].

Another unique method often utilized involves implementing advanced algorithms and unique image processing deep learning models, robust enough to handle glossy surfaces. The study by Yuan et al. [22] proposed a dual-mask-guided deep learning model specifically designed to detect surface defects on highly reflective leather materials. Their model enhances defect detection accuracy by effectively removing surface specular highlights in images while preserving bright defects. Although leather surfaces may not be perfectly reflective, this technique could be effective on highly glossy surfaces when implemented with robust models. In another notable study [23], the authors presented an object detection and classification model of polished metal shaft surface defect using a deep learning method based on convolutional neural network feature extraction. Their method was achieved through image segmentation, architecture setup, and parameter optimization

of a Fast-R-CNN object detection framework. According to the assessment, their model proved to be implementable in practical production; hence, their model can also be extended to other fields of large image micro-fine defects with large light surfaces. However, model performance can decline in real-life applications involving intense reflections or varying levels of reflectiveness. For example, a glass defect detection method proposed in [20] struggled when the background image closely resembled the reflected image.

For curved surfaces in fault detection—especially with fixed cameras—researchers have developed various techniques to address the challenges. Among these, robotic arms stand out for their flexibility in navigating curved geometries. Wang et al. [24] demonstrated a robotic arm equipped with a 3D micro X-ray fluorescence (μXRF) spectrometer and a depth camera for high-precision scanning of curved surfaces. They emphasized that maintaining consistent X-ray incident angles and scanning distances minimizes counting errors and improves accuracy. The arm's flexible six-axis design enables comprehensive surface inspections from multiple perspectives, enhancing its industrial utility. Similarly, Huo et al. [25] highlighted the advantages of robotic arms by employing a six-degree-of-freedom manipulator integrated with a line scan camera and high-intensity lighting. This setup successfully inspected convex, free-form, and specular surfaces by dynamically adapting the region of interest, ensuring robust defect detection on complex geometries.

Regardless of the technique used to establish a robust image fault detection or classification model, the classifier or fault detection algorithm remains critical to achieving accurate results. Among deep learning algorithms, convolutional neural networks (CNNs) stand out as one of the most powerful. They have dominated the field of computer vision since their remarkable performance in the ImageNet Large Scale Visual Recognition Competition in 2012 and are widely employed in diverse areas, including medical imaging for tumor detection and fault identification using MRI and X-ray images [26–28]. A typical example can be seen in this study by Rajeshkumar et al. [29]; they used CNNs to diagnose brain tumors via MRI scans, emphasizing prompt and efficient defect detection in medical practice. Their methodology demonstrated the flexibility of CNNs; by employing a grid search optimization technique, they enhanced the performance of three CNN models for multi-classification tasks involving brain tumor images. While the models exhibited varying performance levels, they demonstrated the flexibility and adaptability of CNNs. The high accuracy achieved in identifying and classifying brain tumors further underscores the reliability and effectiveness of CNNs in medical image analysis.

Over the years, convolutional neural networks (CNNs) have branched into various specialized architectures to tackle specific challenges in computer vision—including segmentation, object detection, fault detection, and more. For instance, the Visual Geometry Group (VGG) architecture is a standard CNN model with multiple sequential layers, emphasizing simplicity in design to enhance feature extraction [30,31]. However, this comes at a high computational cost due to its depth. The Residual Neural Network (ResNet) architecture revolutionized deep networks by introducing residual connections, which address the vanishing gradient issue and enable much deeper architectures [32].

The strength of ResNet was demonstrated in [33], where several CNN architectures—including Inception V3, VGG-16, VGG-19, and a conventional CNN—were compared for early fault detection in rice leaf blast disease. ResNet-50 achieved a top accuracy of 99.75%, highlighting the importance of deep feature extraction in agricultural applications. In some cases, combining multiple CNN architectures can yield better results. For example, in [34], the authors employed a combination of CNN subtypes for COVID-19 detection and classification. They used Faster R-CNN with a VGG-16 backbone to detect and classify COVID-19 infections in computed tomography (CT) images, achieving an accuracy of 93.86%. This further validates the utility of region-based CNNs in medical image analysis. CNN has also

been integrated into various advanced models to create more sophisticated frameworks. For instance, the authors in [35] proposed a novel transformer network enhanced with a CNN cross-attention mechanism for hyperspectral image (HSI) classification. Despite the constraint of limited data samples, their framework demonstrated exceptional classification performance. In another study, He et al. [36] utilized a cross-fusion of CNN and transformer architectures for high-speed railway dropper defect detection. Their robust framework achieved accurate defect detection even under challenging weather conditions, such as rain, fog, sunlight, and nighttime. Deployed across over 300 high-speed trains, their system successfully detected more than 10,000 dropper defects, outperforming most state-of-the-art networks in terms of competence and reliability.

The motivation behind this study stems from the pressing demand within a manufacturing company to create a reliable classification model for products with glossy and curved surfaces. Figure 1 illustrates a product sample: a uniquely designed hairbrush case cover tailored for women. This product merges aesthetic appeal with practical functionality, catering to a specific consumer need. Its distinctiveness arises not only from its visual design but also from its ergonomic construction, material durability, and comfortable palm fit. Beyond its user-centric features, the case enhances the hairbrush's longevity by providing protection and portability. Its versatile design ensures adaptability to diverse settings and uses, further solidifying its value in everyday life.

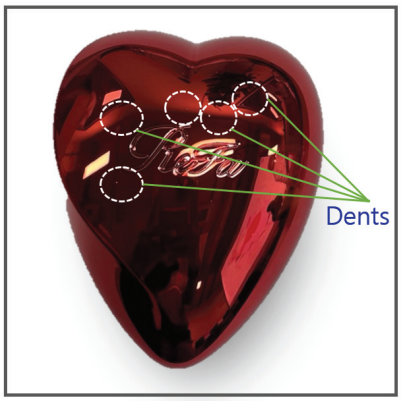


Figure 1. Heart case product sample.

Nevertheless, the product's aesthetic nature not only attracts customers but also poses challenges. Its glossy and curved design complicates traditional machine-vision inspection techniques. For example, as shown in Figure 1, the white circles highlight dent locations that are difficult to detect visually due to surface reflectivity. Quality inspection is critical for this product, as the target demographic demands flawless items, and even minor defects like cracks, dents, or scratches lead to rejection. This stringent requirement has prompted online platforms to automatically flag and reject listings with such imperfections.

To ensure that fault classification is effectively carried out on glossy and curved surfaces in the manufacturing industry, this study makes the following contributions:

- A proposal for integrating a Basler vision camera with enhanced lighting to achieve clear, high-quality image acquisition of glossy surfaces. This integration is aimed to facilitate the development of a robust fault detection and classification framework specifically designed for reflective surfaces.
- The utilization of a KEYENCE laser displacement sensor in combination with a Motoman-GP7 Yaskawa robotic arm to enable the precise and effective acquisition of curved geometries. Additionally, the integration of images from the Basler vision camera and the laser displacement sensor is proposed as an ideal approach for developing a fault classification framework for glossy and curved surface image products.

- A thorough comparative assessment of robust deep learning algorithms for image-based fault detection, with global assessment metrics such as accuracy, loss, computational efficiency, recall, F1 score, specificity, mAP, and confusion matrix, to validate the performance of our model and identify an efficient algorithm that is also computationally cost efficient.

The rest of the paper is structured as follows: Section 2 explains the theoretical background of the core techniques employed in the study. Section 3 details the proposed system framework and methodologies used to achieve the study's objectives. Section 4 presents the experimental setup and visualizations. Section 5 discusses and evaluates the results, while Section 6 concludes the study.

2. Theoretical Background

This section discusses the theoretical background of CNN architecture and its subtypes as employed in the study. It also explores key techniques utilized in the development of the proposed framework.

2.1. Convolutional Neural Network

Convolutional neural networks (CNNs), or ConvNets, are a class of deep learning models with multi-layered neural network architectures. They excel in tasks such as image classification, object detection, segmentation, natural language processing, and time series analysis, and are widely used in fields like computer vision and fault detection [37,38]. Their ability to learn directly from raw data, eliminating manual feature extraction, enhances their efficiency in complex tasks with minimal human intervention.

First conceptualized by Hubel and Wiesel in the 1950s–1960s through studies of the visual cortex, CNNs gained prominence in 2012 after dominating the ImageNet Large Scale Visual Recognition Competition [37,39]. CNNs are categorized by input dimensionality: 1D CNNs are used for sequential data such as audio and time series, 2D CNNs excel in image-related tasks like classification and segmentation, and 3D CNNs handle volumetric datasets such as CT scans and video [40–42]. Each category employs specialized kernels to extract task-specific features, making CNNs versatile for applications like fault detection and signal processing.

CNN Architectural Overview

A typical CNN architecture is composed primarily of six layers, namely:

- Input layer;
- Convolutional layer;
- Pooling layer;
- Flatten layer;
- Fully connected layer;
- Output layer.

A typical convolutional neural network (CNN) consists of specialized layers, each performing distinct tasks, making it a powerful algorithm for image understanding tasks such as processing, classification, and fault detection. The architecture begins with the input layer, which determines the nature and format of the input. For image inputs, pixels represent numerical color grades (0–255), forming a matrix that the CNN processes. The brightness, shade, and tint of an image are determined by pixel value grading, which is sequentially organized into a digital layout [37,38]. The input layer is critical as it defines the raw data structure, influencing model performance. Factors such as image resolution, data augmentation, normalization, and input channels (e.g., grayscale, RGB, or RGBA) must align with the input layer format to ensure optimal performance [43,44]. Normalization

scales pixel values from 0–255 to 0–1, ensuring dataset consistency and training stability. Mathematically, normalization is expressed as follows:

$$I_{norm}(x, y, c) = \frac{I(x, y, c)}{255} \tag{1}$$

where I_{norm} stands for the normalized image pixel value, I presents the original pixel value. The output of the input layer, a tensor, is passed to the convolutional layer for feature extraction. This layer uses filters (kernels), small matrices of learnable weights, to convolve through the input array, producing feature maps [45]. The convolution operation is defined as follows:

$$f_{ij}^{k} = \sum_{u=1}^{U} \sum_{v=1}^{V} \sum_{c=1}^{C} I_{(i+u)(j+v)c} \cdot K_{uvc}^{k} + b^{k} \tag{2}$$

where f_{ij}^{k} stands for the output values at positions i and j in the k-th feature map. U, V, and V represent the filter's height, width, and input channels, respectively; K_{uvc}^{k} stands for the filter weight at positions u and v for the c-th channel of the k-th filter; and b^{k} is bias.

Filter size (e.g., 3 × 3, 5 × 5, or 7 × 7) determines the level of detail captured, with smaller filters extracting finer details and larger filters capturing broader context. Convolutional layers are stacked to progressively extract low-level (edges, corners), mid-level (shapes, patterns), and high-level (complex patterns) features, enabling hierarchical representation learning [46]. The number of filters in a layer determines the variety of features learned; for example, 16 filters generate 16 feature maps. Strides and padding further influence the output: strides control the filter's step size (e.g., stride 1 processes all pixels), while padding (e.g., Same or Valid) determines whether input edges are included in computations, affecting output dimensions [43,47].

The pooling layer, also known as downsampling, refines the features extracted by the convolutional layer by reducing the dimensionality of the feature map while retaining the most significant features. This process enhances the network's performance by maintaining accuracy and computational efficiency [37,43]. Pooling operations include max pooling, average pooling, and global pooling. Max pooling selects the maximum value within a pooling window, while average pooling computes the average value in the window. Global pooling applies max or average pooling over the entire feature map, reducing it to a single value per channel [37,48].

The pooling window size is a critical parameter, as it determines the region over which the pooling operation is applied and influences the nature of downsampling. Smaller window sizes, such as 2 × 2, preserve finer details in the feature map, whereas larger windows, like 3 × 3, provide more aggressive dimensionality reduction, potentially sacrificing fine details but capturing broader contextual features. The stride, which controls the movement of the pooling window, also plays a significant role. Larger strides result in greater dimensionality reduction, while smaller strides retain more spatial details in the output feature map. Mathematically, the output dimensions of the pooling layer can be expressed as follows:

$$O_d = \frac{I_d - T_d + 2P}{S} + 1 \tag{3}$$

where O_d represents the output and its dimensions; I_d represents the input and its dimensions; and T_d stands for the pooling window and its dimensions. P and S represent padding and strides, respectively.

Additionally, the operations for max pooling and average pooling are defined as follows:

$$P_{ij} = \max\left(I_{(i:i+h-1, j:j+w-1)}\right) \tag{4}$$

$$P_{ij} = \frac{1}{h \cdot w} \sum_{x=i}^{i+h-1} \sum_{y=j}^{j+w-1} I_{xy} \tag{5}$$

Generally, the pooling layer's effectiveness depends on the careful selection of window size and stride, which together determine the balance between dimensionality reduction and feature retention [37,43,48].

The flatten layer serves as a critical transition between the convolutional/pooling layers and the fully connected layer, reshaping the multidimensional feature maps from the pooling layer into a one-dimensional vector. This transformation ensures that spatial features extracted by earlier layers are preserved and formatted for processing in the fully connected layer [49,50]. For instance, a pooling layer output of size 3 × 3 with 64 feature maps is flattened into a vector of size 576 (3 × 3 × 64). Once flattened, the data is passed to the fully connected layer, where every neuron connects to every neuron in the previous layer, enabling dense connectivity. This layer aggregates the extracted features and processes them for tasks such as classification, regression, or prediction [37,43]. Each neuron in the fully connected layer computes a weighted sum of its inputs, adds a bias, and applies an activation function to introduce non-linearity, as described in Equation (6):

$$F = \sigma\left(\sum_{i=1}^{n} W_i x_i + b\right) \tag{6}$$

where F is the output of the neuron; σ is the activation function; $\sum_{i=1}^{n}$ represents the summation of all input; and W_i is the weight of the i-th input. x_i and b represent the input vector and bias, respectively.

The activation function plays a vital role in both convolutional and fully connected layers, enabling neurons to detect complex patterns and hierarchies in the input data. In convolutional layers, activation functions process and retain spatial features extracted by filters, while in fully connected layers, they introduce non-linearity, allowing the network to learn and understand the complexity of the data. Without activation functions, neurons would only perform linear transformations, limiting the network's ability to model intricate relationships [51,52]. Commonly used activation functions include ReLU, Softmax, and Sigmoid, each serving specific purposes; these are represented mathematically in Equation Equations (7)–(9) below.

$$ReLU(x) = \max(0, x) \tag{7}$$

$$Softmax(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}} \tag{8}$$

$$Sigmoid(x) = \frac{1}{1 + e^{-x}} \tag{9}$$

where x is the input and e represents Euler's number.

ReLU is widely used in intermediate layers to prevent vanishing gradients and ensure efficient training, as it activates neurons only for positive inputs. Softmax is typically employed in multi-class classification tasks, converting outputs into probabilities, while Sigmoid is used for binary classification, mapping outputs to a range between 0 and 1. The choice of activation function depends on the task and defines the output layer of the CNN architecture [37,53].

Despite their effectiveness, fully connected layers have limitations, such as high computational costs and susceptibility to overfitting. These challenges can be mitigated through

proper parameter tuning, including the selection of optimal layer sizes, filters, padding, and strides, as well as the use of regularization techniques. Regularization methods—such as batch normalization, L1/L2 regularization, early stopping, and dropout—improve a model's ability to generalize to unseen data by adding constraints that prevent overfitting [54]. Batch normalization stabilizes the learning process by normalizing inputs to each layer, while L1 regularization encourages sparsity by penalizing the absolute values of weights. L2 regularization, on the other hand, penalizes squared weights, ensuring even weight distribution without driving them to zero. Elastic Net combines L1 and L2 penalties, balancing sparsity and weight stability [37,43,54]. Early stopping monitors validation performance during training and halts the process when improvements plateau, while dropout randomly deactivates neurons during training, forcing the model to learn robust and redundant features. Additionally, data augmentation is a powerful technique to combat overfitting, especially with limited datasets. It generates additional training samples by applying transformations such as zooming, flipping, and adjusting brightness or intensity. These transformations increase data variability and complexity, ensuring the model generalizes better to real-world variations, regardless of dataset size [37].

2.2. Visual Geometry Group 16 Layer CNN (VGG-16)

VGG-16 is one of the most popular CNN architectures, developed by the Visual Geometry Group (VGG) at the University of Oxford. It was first implemented in 2014 by Simonyan and Zisserman for large-scale image recognition, as described in their study [55]. The name VGG-16 comes from the number of trainable layers in the network, which totals sixteen trainable layers comprising thirteen convolutional layers and three fully connected layers. Although the network contains a total of twenty-one layers, some of these are non-trainable (e.g., pooling layers).

The architecture was designed to deepen the structure of traditional CNNs while maintaining simplicity in the network design. One of its standout features is the use of 3×3 convolutional kernels, which help capture local patterns in the input data while maintaining computational efficiency. To further increase its depth, VGG-16 utilizes a stack of these small filters, enabling the model to train on and learn more complex features. Another key feature of VGG-16 is the application of max-pooling layers after every 2–3 convolutional layers. These pooling layers use a 2×2 filter size with a stride of 2 to reduce the spatial dimensions of the feature maps, making the model computationally efficient while preserving the most important features. At the end of the convolutional stack, the network outputs a feature map passed through fully connected layers, followed by a Softmax layer for multi-class classification. However, though it is highly efficient for feature extraction and transfer learning, VGG-16 is notable for being more computationally demanding than traditional CNN due to its large number of parameters [56]. For instance, it has two dense layers with 4096 neurons each, with an output layer of 1000 neurons in the case of Imagenet classification, and it has a total of 138 million parameters.

2.3. Residual Network (ResNet)

ResNet is a distinctive CNN architecture first introduced by He et al. in their study [32]. It was specifically designed to address the vanishing gradient problem, a common issue in deep neural networks where gradients become increasingly small during backpropagation, hindering effective learning. This problem is particularly evident in architectures like VGG-16. ResNet resolves this issue through residual learning and skip connections, which ensure smoother gradient flow and mitigate the vanishing gradient problem. As the name suggests, ResNet consists of various layers, including convolutional layers, activation functions, normalization layers, and bottleneck residual blocks [32].

The skip connection and bottleneck residual block are key characteristics of ResNet-50 that enable it to achieve high efficiency and lower computational costs compared to similar CNN architectures. Skip connections allow the input to bypass certain layers and be added directly to the output, enabling the network to learn residual functions. These residual functions are generally easier to optimize than direct mappings. On the other hand, the bottleneck structure, which uses 1×1 convolutions to reduce and then restore dimensionality, ensures smoother gradient flow during backpropagation, reducing computational requirements [32].

ResNet architectures come in various depths, with the most popular models being ResNet-18, ResNet-50, ResNet-101, and ResNet-152, each differing in the number of layers. Due to its unique architecture, ResNet—particularly ResNet-50—has been successfully employed in a variety of fields due to its efficiency and robust performance in image classification, object detection, and numerous computer vision tasks [32,33].

2.4. Dijkstra's Algorithm Overview

Dijkstra's algorithm is one of the popular algorithms introduced by Edsger W. Dijkstra that can be employed to determine the shortest paths in weighted graph instances where edges have non-negative weights [57,58]. This technique, known for its simplicity and efficiency, has been widely used in solving graph-based shortest path problems and has found applications in various domains such as GPS navigation, network routing, and optimization problems. The core principle of Dijkstra's algorithm works by exploring the paths from nodes to the source node, selecting the shortest possible path among them. Dijkstra's algorithm employs a greedy approach, enabling it to make a locally optimal choice at every step, aiming to achieve the global optimum [57,58]. The algorithm begins by initializing all nodes with a tentative distance of infinity, except for the source node. This process is repeated until the shortest distance is determined. In practice, the initial distance of the source node is set to zero, and the other nodes are set to infinity. The algorithm marks all nodes as unvisited and, for each unvisited neighbor, calculates their tentative distances by adding the weight of the edge connecting the current node to the neighbor. Once all neighbors of the current node are processed, the node is marked as visited, and the algorithm moves to the next unvisited node with the smallest tentative distance. This process is repeated until all nodes have been visited, or the remaining unvisited nodes are not connected to the source. As the algorithm terminates, each node will have the shortest distance from the source node, providing the solution to the problem.

In the context of graph theory, given that $G = (V, E)$ where V and E represent the vertices and edges of a given graph, and assuming each edge (u, v) has a weight of $w(u, v)$, then $d[v]$ stands for the shortest distance from a source node s to the node v, and $p[v]$ represents the previous node in the shortest path from the source node s to node v. Dijkstra's algorithm initializes using Equation (10).

$$\text{Set:} \quad d[s] = 0, \quad d[v] = \infty \quad \text{for all} \quad v \neq s \tag{10}$$

where u is the current node and v is the neighbor node.

At this point, all nodes are marked as unvisited. While the nodes are unvisited, each neighboring node v, updates its distance using Equation (11):

$$d[v] = \min(d[v], d[u] + w(u, v)) \tag{11}$$

After this, node n is marked as visited, and the algorithm moves to the next unvisited node with the shortest distance of $d[v]$.

3. Proposed System Framework and Methodology

The proposed framework, illustrated in Figure 2, outlines the steps and methodologies used in our study to achieve fault diagnostic classification for glossy and curved surfaces. A heart-shaped brush case with a glossy and curved surface was selected as the reference sample.

Our methodology consisted of three key steps. The first step involved image data collection, where two robust pieces of equipment were used to ensure the datasets were suitable for deep learning-based fault classification. A Basler vision camera with lighting was employed to capture images of the flat top surface, while a KEYENCE laser displacement sensor, mounted on a robotic arm, was used to efficiently scan the curved surface. The second step focused on data processing, which included data merging, data augmentation, labeling, and dataset splitting. In the final step, the processed datasets were fed into various deep learning image classification models. Validation assessments were conducted to identify the best-performing model and ensure it met the required performance standards.

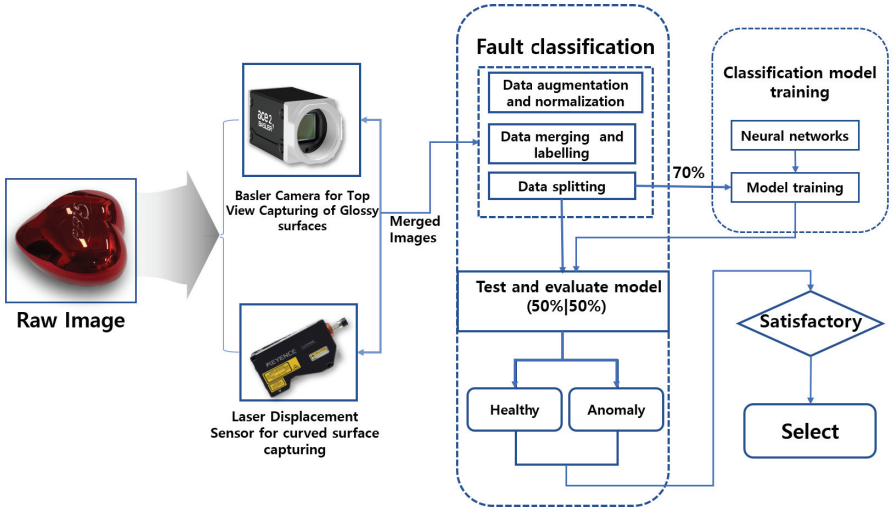


Figure 2. Proposed system framework.

These stages are implemented to ensure that issues encountered with glossy and curved surfaces are mitigated, thereby providing a reliable framework capable of achieving the desired efficiency for overall model validation. Given the nature of our dataset, which originates from glossy and curved surfaces, we applied specific data augmentation techniques to further enhance the images and ensure optimal adaptation.

3.1. Data Augmentation

The primary aim of data augmentation is to introduce variability into the dataset, simulating real-world instances such as zoom, lighting changes, and flipping. This ensures that the model does not rely on overly simplistic patterns, which could lead to overfitting. Data augmentation is particularly crucial when working with unbalanced or small datasets, as it serves as an efficient way to enhance and increase training data without the need to acquire additional samples. In our study, the augmentation techniques employed were brightness, zoom, and custom pixel multiplication, and their mathematical representation is presented thus:

Brightness:

$$\hat{X}(i,j) = X(i,j) + \Delta b \tag{12}$$

where (i,j) stands for the pixel value at position (i,j), Δb is the brightness adjustment constant.

Zoom:

$$\hat{X}(i',j') = X\left(\frac{i}{Z_s}, \frac{j}{Z_s}\right) \tag{13}$$

Z_s stands for the zoom factor.

Contrast:

$$\hat{X}(i,j) = \alpha \cdot (X(i,j) - \mu_X) + \mu_X \tag{14}$$

Custom Pixel Multiplication:

$$\hat{X}(i,j) = k \cdot X(i,j) \tag{15}$$

where k is the scaling factor for each pixel value.

In this study, brightness and contrast were adjusted by ±30% and ±20%, respectively, while zoom was adjusted by ±10%. Additionally, a random multiplier of 3.0 was applied.

3.2. Model Performance Evaluation Criteria

Model evaluation is important to ensure that the model performs up to a given standard. In this study, these metrics were implemented to help evaluate, validate, and determine the best-performing deep neural network for our framework. Thus, some of the core global performance metrics implemented in this study include accuracy (A_{cc}), precision (P_{rc}), F1-score (F_{sc}), sensitivity (S_{nv}), specificity (S_{pc}), and mean average precision (mAP), and their mathematical representations are shown in (16)–(20).

$$A_{cc} = \frac{TP}{TP + FP + TN + FN} \tag{16}$$

$$P_{rc} = \frac{TP}{TP + FP} \tag{17}$$

$$F_{sc} = \frac{2 * \text{Sensitivity} * \text{Precision}}{\text{Precision} + \text{sensitivity}} \tag{18}$$

$$S_{nv} = \frac{TP}{TP + FN} \tag{19}$$

$$S_{pc} = \frac{TN}{TN + FP} \tag{20}$$

$$\text{mAP} = \frac{1}{N} \sum_{x=1}^{N} AP_x \tag{21}$$

TP, FP, TN, and FN stand for true positive, false positive, true negative, and false negative, respectively. AP_x represents the average precision of class x, while N is the total number of classes.

TP represents the number of positive samples that a model accurately classified as belonging to the positive class, while FP indicates the number of non-positive samples

that the model falsely classified as belonging to the positive class. On the other hand, TN represents the number of negative samples that the model accurately classified as belonging to the negative class, and FN stands for the number of negative samples that the model falsely classified as belonging to the positive class.

mAP measures the accuracy of a model in classifying within a dataset. It evaluates the model's performance across all classes and provides a single score for overall assessment, indicating the model's quality. Furthermore, a confusion matrix was implemented in our study to provide a detailed analysis of the actual classification performance, represented in percentages with respect to TP, FP, TN, and FN.

4. Experimental Setup and Visualization

The experimental data collection was conducted at the Defense Reliability Laboratory of the National Institute of Technology Kumoh, Gumi, Republic of Korea. The procedure involved two stages. In the first stage, high-vision imaging combined with appropriate lighting was used to capture a detailed front view of the image data. In the second stage, a laser displacement sensor mounted on a robotic arm was utilized to scan and reconstruct 3D surface data of the curved sections of the dataset.

4.1. Data Collection Using Basler Vision Camera

The Basler vision camera equipped with lighting was initially employed to generate image data from our samples in this study. The setup for image data collection using the Basler vision camera and lighting is shown in Figure 3. This setup was used exclusively to capture the front glossy view of the heart-case samples, as it was unable to capture the curved glossy portions of the samples. The curved surfaces were instead captured using laser displacement sensors.

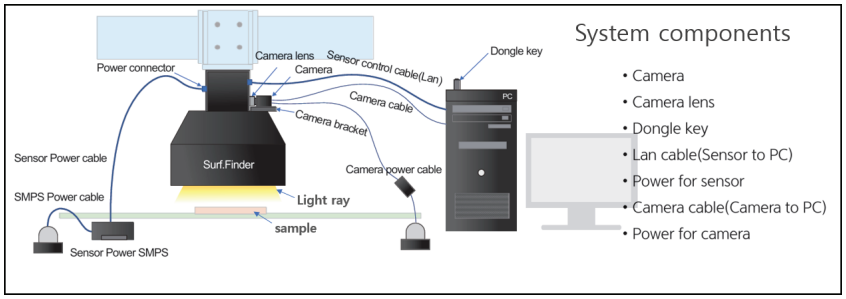


Figure 3. Basler vision and lighting usage overview.

Due to the glossy nature of the heart case samples, a lighting device, Surf.Finder-SF, was introduced to minimize glare and enhance image quality. Tables 1 and 2 present the specifications of the camera and lighting equipment used. Figure 3 illustrates the schematic diagram of the Basler vision camera setup with the lighting system. When the lighting equipment is powered on through the sensor power SMPS, the Surf.Finder light activates. This lighting system includes adjustable settings to reduce glare, ensuring optimal illumination for the heart case samples. These settings can be modified through a dedicated program, which requires a dongle key to be connected to the computer for access. The camera is powered separately via the camera power SMPS. Focus adjustments can be made using a screw attached to the camera lens. The camera is connected to the PC through a dedicated cable, enabling parameter adjustments and facilitating the transmission of captured images to the CPU for processing, storage, and further analysis.

Three core input parameters implemented include reference (REF), roughness (RGH), and raw gray vertical (RGV).

- REF: This parameter sets the lighting to capture photos by projecting light in all directions. Three shots are taken at 1 ms intervals to minimize reflections caused by brightness.
- RGH: This parameter configures the lighting to check horizontal roughness. Lighting is directed at a 45-degree angle to the vertical direction, and three shots are taken at 1 ms intervals to assess horizontal roughness or changes.
- RGV: This parameter configures the lighting to check vertical roughness. Lighting is set at a 45-degree angle to the horizontal direction, and three shots are taken at 1 ms intervals to assess vertical roughness or changes.

The Surf.Finder lighting system is designed to operate in a controlled environment, minimizing the impact of external lighting variations. Its enclosed casing ensures a consistent illumination field, reducing interference from ambient light sources. Additionally, the adjustability of the REF, RGH, and RGV parameters allows for fine-tuned lighting conditions that adapt to different surface reflectivities, ensuring robust and high-quality image acquisition under varying conditions.

These three setups were used to capture our samples, which were then transferred to a PC for review and selection of the desired data samples for implementation.

Table 1. Camera Specification.

Camera Specification Details	
Product Name	Hikvision MV-CA050-20UM
Lens	f 35 mm
Working Distance	20 mm
Pixel	5 MP
Field of view (FOV)	91 mm × 72 mm
Manufacturer	Hangzhou Hikvision Digital Technology Co., Ltd., headquartered in Hangzhou, Zhejiang, China.

Table 2. Lighting specification.

Lighting Specification Details	
Product Name	surf.Finder-SF
Dimension	335 × 325 × 330 mm^3
(FOV)	60 × 60 mm^2
Weight	6.9 kg
Other Accessories	Built-in Controller, S/W Package (SDK, Viewer), Lan cable, SMPS, Dongle key
Manufacturer	Didim Sensor Co., Ltd. Seoul, South Korea.

4.2. Data Collection Using KEYENCE Laser Displacement Sensor

In our setup, we employed a Basler vision camera with controlled lighting to capture front-view image data samples. However, the curved surfaces of the data samples posed challenges for the Basler camera, as its point of view (POV) was not optimal for effectively imaging curved geometries. To overcome this, a laser displacement sensor was introduced. For curved surfaces with glossy finishes, using the laser displacement sensor alone introduced noise due to the diffuse reflection of light during surface scanning, as illustrated in Figure 4. To mitigate this issue, a YASKAWA robotic arm was utilized to scan the surface in a curved motion with the laser displacement sensor. Table 3 summarizes the specifications of the laser displacement sensor used in this study.

Table 3. Laser displacement specification.

Laser Specification Details	
Product Name	LJX-8080
Measuring range Z-axis (height)	73 mm (±20.5 mm)
(Measuring range X-axis (width))	35.0 mm
Repeatability Z-axis (height)	0.5 µm
Repeatability X-axis (width)	1.0 µm

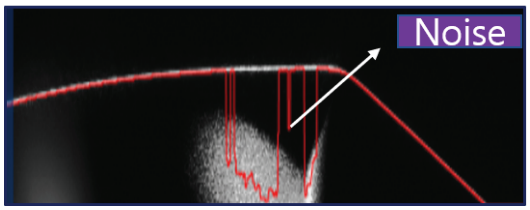


Figure 4. Laser noise overview.

Traditionally, visual inspection is performed at least three times for the appearance inspection of glossy products, with an average inspection time of about 15 s. However, to measure a defect of 0.1 mm or more on a curved surface, it takes an average of 60 s for a laser displacement sensor with a precision of about 12.5 µm, operating at a speed of 1.15 cm per second, to scan the entire shape. Therefore, it is necessary to maintain a time period similar to that of visual inspection to avoid disrupting production speed. To address this issue, a vision camera is first used to quickly photograph the front part of the heart case, which has many flat areas, and a laser displacement sensor is used for the side parts to reduce the overall measurement time. The more laser displacement sensors there are, the shorter the measurement time, but the higher the initial cost purchase of the robotic arm and laser displacement sensors. To solve this, the study developed a technology that moves the optimal path at an angle that minimizes reflection using one robotic arm and one laser displacement sensor. Our goal was to achieve an average inspection time of about 15 s. An overview of the setup is shown in Figure 5.

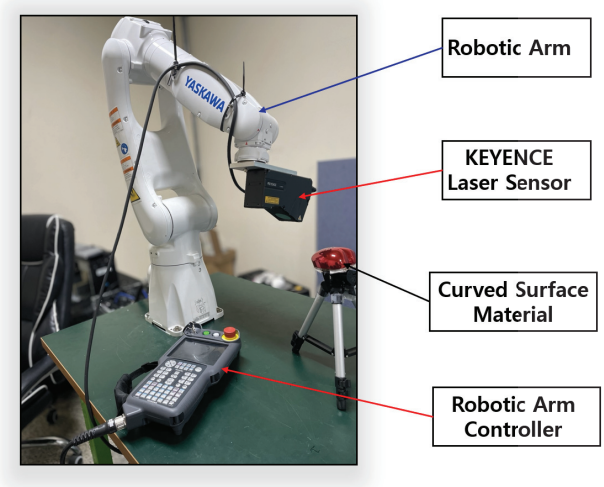


Figure 5. Robotic arm.

Data Generation Using the Laser Displacement Sensor and Robotic Arm

To minimize glare caused by the glossy surface of the materials, the primary objective was to determine the normal vectors of all sample surfaces. This was achieved by aligning the vertical relationship between the surface of the heart case samples and the measurement

setup, thereby reducing light reflection. To obtain the normal vector coordinates of the heart case-shaped samples, CATIA's NC (Numerical Control Machining) module was utilized. This module automatically generates tool movement paths and optimizes the machining process by preventing collisions between the tool and the machined object. This optimization is based on the shape of the designed 3D model. Using the NC module, coordinates offset from the surface of the heart case were obtained. To ensure accurate measurement, the laser displacement sensor was set to an identification distance of 70 mm, meaning coordinates were collected 70 mm vertically above the heart case surface. Figure 6 provides an overview of the obtained coordinates.

The collected coordinates represent areas that theoretically minimize diffuse reflection. However, many of these coordinates included overlapping measurement regions. To address this, the teaching function of YASKAWA—which refers to a mode allowing the operator to define tasks, movements, or paths for the robot to follow and execute—was utilized to first identify and select the coordinates that minimized diffuse reflection. Next, overlapping areas among the selected coordinates were eliminated, and the remaining coordinates were further refined through a second selection process. Using the coordinates generated through the NC module and the process of minimizing diffuse reflection while removing duplicates, 10 measurement paths for the sides of the heart case were created. The inspection results, as shown in Table 4, indicate a measurement time ranging from approximately 20 to 26 s.

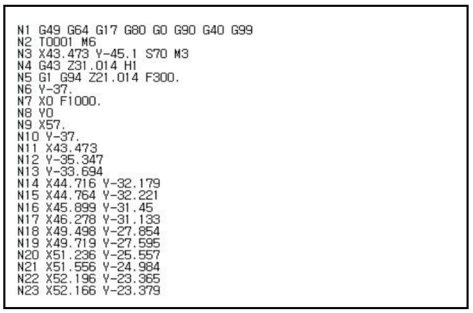


Figure 6. Coordinates obtained through NC module.

Table 4. Measurement results for shooting from the side

Number of Inspections	Number of Coordinates Moved	Time (s)	Inspection Speed (mm/s)
1	22	21.2	11.5
2	23	20.8	11.5
3	23	23.4	11.5
4	24	25.1	11.5
5	23	24.2	11.5
6	23	25.1	11.5
7	23	23.1	11.5
8	23	22.9	11.5
9	23	22.9	11.5
10	23	26.0	11.5

Since the selected coordinates include several paths, the shortest optimal path among them must be determined. However, before introducing the Dijkstra algorithm, the coordinates of the heart case were selected by manually choosing the areas with the least light reflection on the curved surface from the coordinates extracted through the NC code. The coordinates were selected at 2 cm intervals. In the case of the inspection time, the left side of the heart case was photographed in the order of the front, right side, and back. It

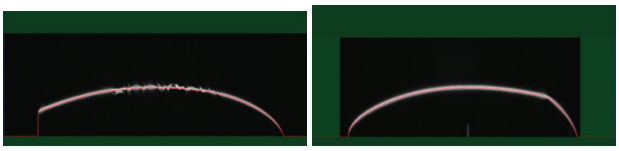
took 21 s based on the 11 mm/s movement of the Yaskawa robotic arm that received the coordinates and moved. This was because there were many instances where the same scene was filmed repeatedly, as the focus was on minimizing diffuse reflection. By excluding the overlapping areas through the Dijkstra algorithm, the result was reduced to 15 s based on the 11 mm/s movement. It is observed that the movement path was optimized while excluding overlapping filming scenes. For this purpose, the Dijkstra algorithm was used to determine the shortest path the robotic arm could follow for fast execution. The input data were obtained by calculating the travel time for each coordinate using the 3D coordinates, and one path was selected through the algorithm. The information about the path is summarized in Table 5 below.

Table 5. Selected path information when shooting from the side.

Number of Coordinates Moved	Measurement Time (s)	Inspection Speed (mm/s)
23	18.2	11.5

The inspection speed is set to 11.5 mm/s because the amount of data collected per unit of time is fixed due to the characteristics of the laser displacement sensor. The amount of data collected during measurement is inversely proportional to the range to be measured. Thus, if the inspection speed exceeds 11.5 mm/s, the shape to be measured is compressed, and if the inspection speed is slower than 11.5 mm/s, the shape to be measured is expanded. Therefore, to measure the heart case shape without distortion, the inspection speed must be set to 11.5 mm/s.

To match the inspection time to 15 s, a method is required to increase the inspection speed while minimizing distortion in the results. To achieve this, images were captured under conditions where the heart-shaped case measured 90 mm × 90 mm, ensuring that the side could be fully observed in a single pass during measurement. This approach increases the inspection speed by reducing the collection area while simultaneously increasing the amount of data collected within a confined space. As a result, the inspection speed improved from 11.1 mm/s at 500 Hz to 13.2 mm/s at 750 Hz, as shown in Figure 7. The results are summarized in Table 6.



(**a**) (**b**)

Figure 7. Laser displacement sensor measurable range based on (**a**) data collection speed of 500 Hz; (**b**) data collection speed of 750 Hz.

Table 6. Selected path information while shooting from the side.

Number of Coordinates Moved	Measurement Time (s)	Inspection Speed (mm/s)
23	14.6	13.2

Using the 2D CSV file acquired through a laser displacement sensor, a 2D matrix is generated based on the sensor's movement trajectory and measurement conditions. The horizontal axis is defined as x, the vertical axis as y, and the measured values as z. The generated matrix is expressed by the following function:

$$z(x, y) = \text{Results from height measurement} \quad (22)$$

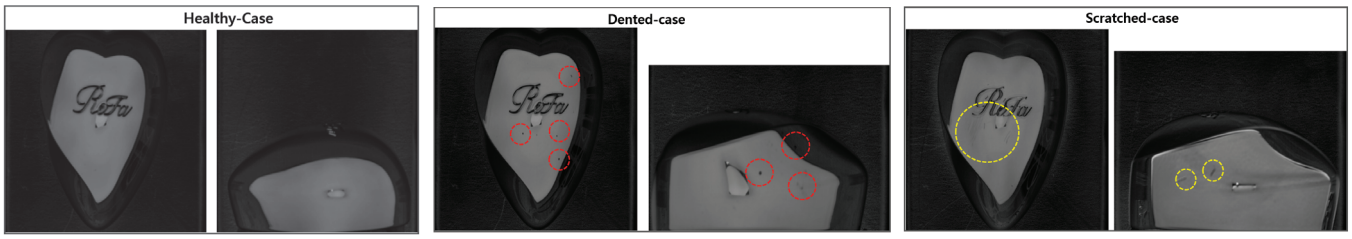
There may be unmeasured areas within the data collection range, and these gaps are filled using interpolation methods such as linear interpolation or spline interpolation. Through this process, a continuous 3D data structure is formed. Subsequently, the matrix is input into 3D graphics software or a visualization tool to generate a 3D surface image. During rendering, tools such as OpenGL 4.6, Matplotlib 3.7.1, or other 3D libraries are utilized to visualize the data in three dimensions.

4.3. Dataset Description

As previously highlighted, the study utilized two data acquisition techniques: a Basler vision camera with lighting and a laser displacement sensor. Each technique generated two image samples per data point—one from the camera and one from the laser sensor. Data labeling and model selection in this study were guided by customer requirements, including alignment with historical rejection patterns and a target accuracy of 95% or higher. The dataset, derived from production records, was labeled to reflect defect types and severity levels critical to the customer's quality standards, ensuring the model was trained on operationally meaningful data. The data samples were categorized into three classes, as summarized in Table 7. As a result, six distinct data classes were generated from these three classes using the two techniques: HCC Basler camera images, HCC laser sensor images, DC Basler camera images, DCC laser sensor images, SCC Basler camera images, and SCC laser sensor images. To ensure consistency and reduce data complexity, similar data classes were merged. For instance, HCC Basler camera images and HCC laser sensor images were combined into a single HCC dataset. Pictorial samples of the merged images are shown in Figure 8.

Table 7. Summary of different classes of images involved in the study.

Label	Image Class	Description
HCC	Healthy-case class	The healthy cases of the image samples.
DCC	Dented-case class	The dented cases of the image samples.
SCC	Scratched-case class	The scratched cases of the image samples.



(**a**) (**b**) (**c**)

Figure 8. Combined image class samples: (**a**) Healthy class; (**b**) Dent class showing dent portion in red circles; (**c**) Scratch class showing scratch portion in yellow circles.

After the combination, a total of 6902 images—2452 HCC images, 2414 DCC images, and 2037 SCC images—were generated, approximately in a ratio of 35.52%, 34.97%, and 29.51%, respectively. In terms of dataset distribution, the data were relatively balanced across categories. However, to mitigate potential bias due to slight class size differences, data augmentation techniques such as brightness adjustment, zooming, contrast enhancement, and custom pixel multiplication—as discussed in Section 3.1—were applied to enhance model generalization. This approach ensured that the model learned meaningful features from all defect types effectively while preventing overfitting to dominant categories.

4.4. Deep Learning Algorithms Parameters

The performance of any fault classification model largely depends on the choice of classifier algorithm. To address this, we evaluated four custom CNN architectures alongside four pre-trained models: two variants of VGG-16 and two variants of ResNet-50. Our objective was to develop an efficient model optimized for low computational energy consumption. To achieve this, we designed streamlined architectures that balance performance and efficiency, prioritizing minimal resource usage without compromising accuracy. Additionally, the hyperparameters of the deep learning algorithms were optimized empirically. A summary of the models is provided in Table 8.

Table 8. Summary of the models used in the study.

Model Name	Input Image Resolution	Number of Layers	Description
CNN_5-128	128 × 128	Five (5)	A traditional CNN model with 128 × 128 image input dimension and five layers.
CNN_5-240	240 × 240	Five (5)	A traditional CNN model with 240 × 240 image input dimension and five layers
CNN_6-128	128 × 128	Six (6)	A traditional CNN model with 128 × 128 image input dimension and six layers
CNN_6-240	240 × 240	Six (6)	A traditional CNN model with 240 × 240 image input dimension and six layers
$VGG\text{-}16_{128}$	128 × 128	Default with one dense layer	A typical VGG-16 algorithm with 128 × 128 image input dimension and a dense layer
$VGG\text{-}16_{224}$	224 × 224	Default with one dense layer	A typical VGG-16 algorithm with 224 × 224 image input dimension and a dense layer
$ResNet\text{-}50_{128}$	128 × 128	Default with one dense layer	A typical ResNet-50 algorithm with 128 × 128 image input dimension and a dense layer
$ResNet\text{-}50_{224}$	224 × 224	Default with one dense layer	A typical ResNet-50 algorithm with 224 × 224 image input dimension and a dense layer

4.4.1. Custom CNN Parameters

The study evaluated four custom CNN architectures—CNN_5-128, CNN_5-240, CNN_6-128, and CNN_6-240—each subjected to varying hyperparameter configurations, including the number of convolutional layers, strides, pooling layers, and fully connected layers. These configurations were optimized to evaluate fault classification performance while minimizing computational demands. A summary of the architecture details and the n-layer structure of the custom CNN framework is presented in Table 9 and Figure 9.

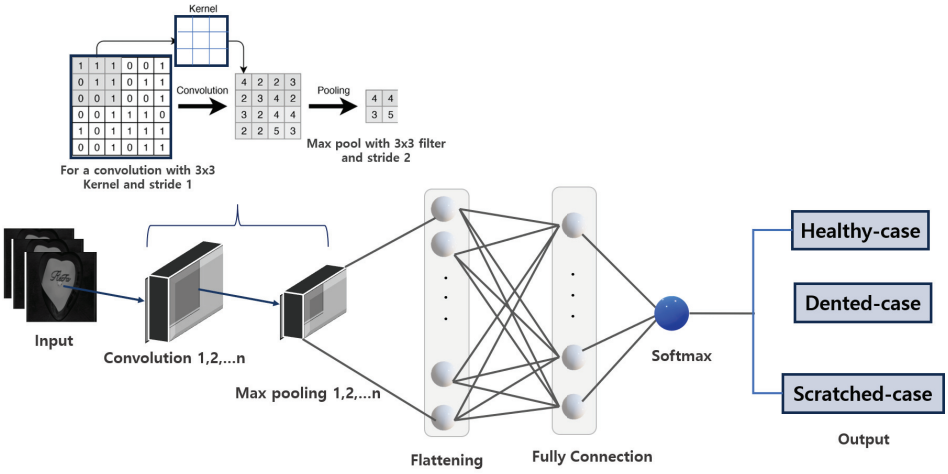


Figure 9. The n-layer structure of the custom CNN architecture with 3 × 3 filter and a stride of 2.

Table 9. Architectures of the custom CNN models.

Model Name	Number of Conv Layers/Stride	Kernel Sizes/Learning Rate	Pooling Layer/Size	Activation Functions	Fully Connected Layers/Dropout	Image Dimension	Batch Size/Epochs
CNN_5-128	3/1	3 × 3/0.001	3/2 × 2	Relu/Softmax	2/0.1	128 × 128	16/200
CNN_5-240	3/1	3 × 3/0.001	3/2 × 2	Relu/Softmax	2/0.1	240 × 240	16/200
CNN_6-128	4/1	3 × 3/0.001	3/2 × 2	Relu/Softmax	2/0.1	128 × 128	16/200
CNN_6-240	4/1	3 × 3/0.001	3/2 × 2	Relu/Softmax	2/0.1	240 × 240	16/200

The custom CNNs with three convolutional layers (CNN_5-128 and CNN_5-240) include 32, 64, and 128 kernels across their respective layers, while the custom CNNs with four convolutional layers (CNN_6-128 and CNN_6-240) contain 16, 32, 64, and 128 kernels. All custom CNN models also feature dense layers with 128 kernels. To optimize efficiency and minimize computational energy, the input image dimensions were carefully chosen, as they significantly affect the speed and resource requirements of the CNN models. Common input dimensions for CNNs include 128 × 128, 224 × 224, 256 × 256, or their multiples. While larger dimensions can improve performance by offering more detailed images, they also increase the computational resource demands.

Consequently, we explored image pixel sizes of 128 × 128 and 240 × 240 during training. Dimensions of 256 × 256 and larger were avoided due to their high computational demands. However, we chose 240 × 240 as it provided better image clarity than 224 × 224 while maintaining reasonable computational requirements.

4.4.2. Other Deep Learning Models' Parameters

VGG-16 was introduced in this study due to its compatibility with our dataset, despite not being the most advanced architecture compared to robust image classification models like Inception, ResNet, and EfficientNet. Although the optimal input size for VGG-16 is typically 224 × 224, we trained VGG-16 variants using two image dimensions: 128 × 128 ($VGG\text{-}16_{128}$) and 224 × 224 ($VGG\text{-}16_{224}$) to evaluate the best balance between performance and computational requirements. This approach aimed to assess whether comparable results could be achieved with a lower resolution.

Similarly, ResNet-50 was included to ensure the selection of the most suitable neural network for the dataset through performance comparisons. Known for its efficiency and lower computational demands compared to VGG-16, ResNet-50 was chosen to provide a practical assessment of model performance, rather than relying solely on assumptions. Although ResNet-50 often outperforms VGG-16 in many applications, the effectiveness of any model depends heavily on its adaptability to the specific dataset. To further optimize ResNet-50 for low computational energy, we trained it using two image dimensions: 128 × 128 ($ResNet\text{-}50_{128}$) and 224 × 224 ($ResNet\text{-}50_{224}$) to identify the best performing configuration. A summary of the VGG-16 and ResNet-50 architectures used in this study is provided in Table 10.

Table 10. Summary of the modified VGG-16 and ResNet-50 architecture employed in the study.

Model Name	Pre-Trained VGG-16 Model	Image Dimension	Dense Layer	Dropout Rate	Output Layer	Optimizer/Learning Rate
$VGG\text{-}16_{128}$	ImageNet weights	128 × 128	256, ReLU	0.2	Softmax	Adam/0.0001
$VGG\text{-}16_{224}$	ImageNet weights	224 × 224	256, ReLU	0.2	Softmax	Adam/0.0001
$ResNet\text{-}50_{128}$	ImageNet weights	128 × 128	256, ReLU	0.2	Softmax	Adam/0.0001
$ResNet\text{-}50_{224}$	ImageNet weights	224 × 224	256, ReLU	0.2	Softmax	Adam/0.0001

The models were executed with unfrozen layers to achieve the desired results. This approach allows for weight updates during the training process, enabling the model to adapt to the specific dataset.

5. Result Evaluation and Discussion

The eight neural networks were empirically evaluated and assessed using three image classes, with the evaluation based on global metrics outlined in the previous section. This approach ensured the selection of the best model for our fault classifier. In addition to performance metrics, computational cost and the confusion matrix were also considered to guarantee a comprehensive evaluation of the models. A total of 6902 images were used, consisting of 2452 HHC, 2414 DCC, and 2037 SCC images. The dataset was divided

into training, validation, and testing sets. For VGG-16 and ResNet-50, a 70:15:15 ratio (training:validation:testing) was used, while custom CNN models were trained with an 80:10:10 ratio, based on their respective adaptation requirements. For VGG-16 and ResNet-50, both the 70:15:15 and 80:10:10 splits produced similar results. However, the 70:15:15 ratio was chosen because it allocated fewer resources to training, reducing computational demands while maintaining performance. In contrast, for the custom CNN models, the 80:10:10 ratio yielded better performance, as evidenced by higher accuracy and lower loss values compared to the 70:15:15 split, making it the preferred choice.

The experiments were conducted on a system configured with an Intel Core i7-11700 processor (8 cores, 16 threads, 2.50 GHz base frequency), 32 GB of DDR4 RAM, and running the Windows 10 operating system. The hardware was manufactured by Gigabyte Technology Co., Ltd., New Taipei City, Taiwan, featuring the B560M AORUS ELITE motherboard. The system designation is DESKTOP-J1TP30L, operating on a 64-bit architecture (x64-based PC). The deep learning models were trained using TensorFlow 2.x and NumPy 1.23.4 without GPU acceleration. The decision to use only the CPU was intentional, as the goal was to establish a resource-aware framework that could be deployed on systems without GPU acceleration, making it more accessible for practical applications. Consequently, some state-of-the-art algorithms, such as R-CNN, Mask R-CNN, and YOLO, were not feasible due to their high computational demands, which stem from their reliance on large-scale feature extraction and real-time processing capabilities. Figure 10 presents the training and loss curves for all models, illustrating their convergence behavior and performance during training.

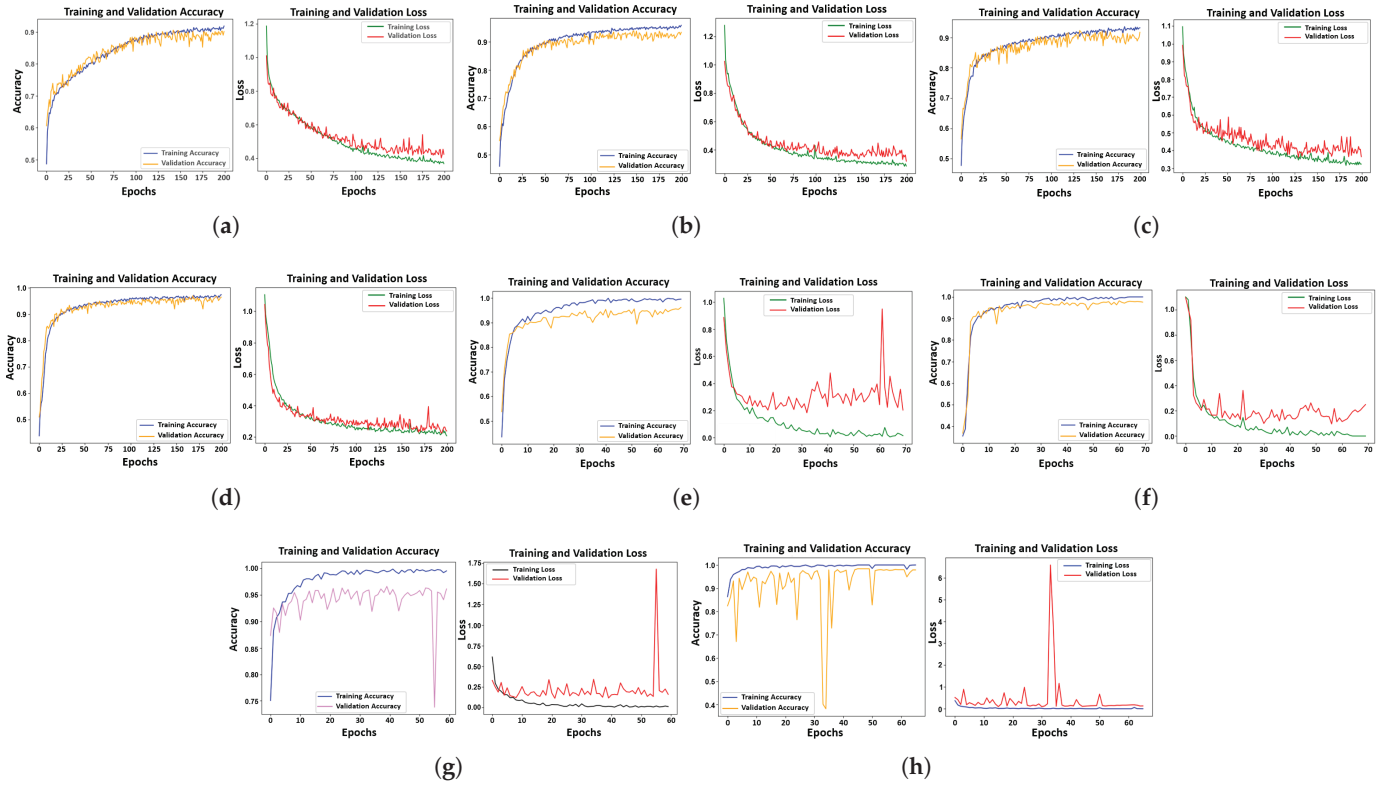


Figure 10. Accuracy and loss curve: (**a**) CNN_5-128; (**b**) CNN_5-240; (**c**) CNN_6-128; (**d**) CNN_6-240; (**e**) VGG-16_{128}; (**f**) VGG-16_{224}; (**g**) ResNet-50_{128}; (**h**) ResNet-50_{224}.

As shown in the plots, the training accuracy and loss curves of all eight neural network models used in this study reveal key insights into their performance. The results demonstrate that higher image resolution improved model efficiency, emphasizing the importance of resolution in enhancing training outcomes. In general, all models displayed strong

learning capacity, as reflected in their accuracy curves, with the exception of ResNet-50_{128} and ResNet-50_{224}, which experienced some instability during the early stages of training.

However, this instability was not observed in the loss curves, where the validation curves for VGG-16_{128}, VGG-16_{224}, ResNet-50_{128}, and ResNet-50_{224} struggled to converge, despite the models' inherent robustness. This could be attributed to the input image dimensions, as the VGG-16_{224} and ResNet-50_{224} models showed greater stability than their 128 × 128 counterparts. Additionally, the high learning rate used due to the complexity of the dataset may have contributed to the observed fluctuations. While early fluctuations in accuracy and loss curves do not necessarily indicate poor performance, they suggest potential challenges in model convergence. Upon closer inspection, despite the fluctuations, ResNet-50_{224} demonstrated the ability to adapt and stabilize towards the end of the training process, showcasing its robustness and capacity to efficiently optimize and generalize from the data.

To provide a more comprehensive evaluation, the models were further assessed using the test dataset, and the results are summarized in Table 11 below.

Table 11. Performance Eevaluation summary.

Model	Test Accuracy	Test Loss	Precision	Recall	F1 Score	Specificity	mAP
CNN_5-128	91.03	0.4064	91.47	90.82	91.07	95.30	0.9697
CNN_5-240	93.63	0.3651	91.41	91.33	91.36	95.62	0.9723
CNN_6-128	91.75	0.3459	92.58	91.64	91.86	95.72	0.9795
CNN_6-240	95.08	0.2753	95.09	95.21	95.14	97.53	0.9878
VGG-16_{128}	95.66	0.1981	95.91	95.79	95.85	97.75	0.9906
VGG-16_{224}	97.49	0.1911	97.61	97.61	97.52	98.71	0.9963
ResNet-50_{128}	95.85	0.2073	96.21	96.21	96.12	97.83	0.9869
ResNet-50_{224}	97.97	0.1030	98.16	97.99	98.05	97.78	0.9942

In our assessment, macro-averaging was preferred over weighted averaging for the evaluation metrics to ensure that the models were evaluated based on their performance across each individual class. Given the slight imbalance in our dataset classes, macro-averaging was chosen to provide a more balanced evaluation. As shown in Table 11, VGG-16_{224} and ResNet-50_{224} outperformed the other models across various metrics. Specifically, ResNet-50_{224} achieved the best performance in most cases, including accuracy, loss, precision, recall, and F1-score. On the other hand, VGG-16_{224} excelled in specificity and mean average precision (mAP).

While ResNet-50_{224} can be considered the best classifier based on these results, it is important to note that specificity and mAP are also critical metrics. In particular, mAP is often the most important metric for evaluation, especially in multi-class and imbalanced data scenarios. Notably, ResNet-50_{224} did not achieve the highest mAP score, suggesting that other models, such as VGG-16_{224}, may offer better performance in certain aspects.

To gain deeper insights into the models' performance, the confusion matrix was also employed to evaluate the actual class classification performance, focusing on TP, FP, TN, and FN.

Figure 11 displays the confusion matrix for all models. The reduced performance of most models can be attributed to the high FN values in the dent class, with many datasets incorrectly predicted as belonging to the normal class. Overall, the dent class had the highest FN, while the scratch class had the lowest FN on average across all models. The normal class consistently showed the highest percentage of TP, whereas the dent class had the lowest percentage of TP.

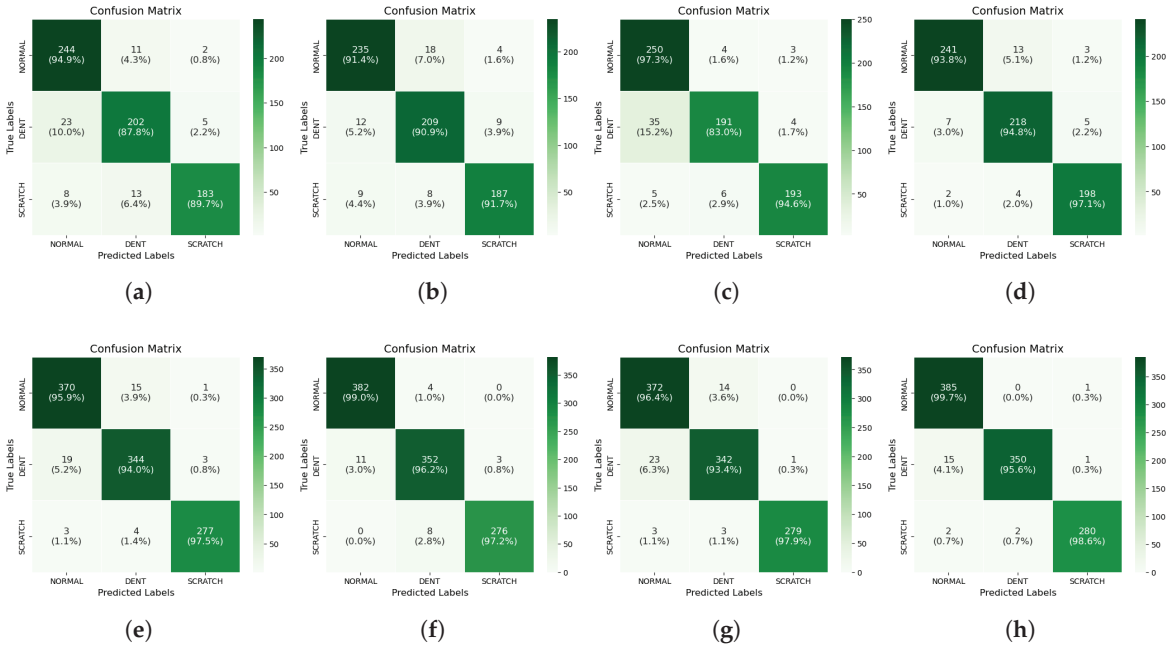


Figure 11. Confusion matrix: (**a**) CNN_5-128; (**b**) CNN_5-240; (**c**) CNN_6-128; (**d**) CNN_6-240; (**e**) VGG-16_{128}; (**f**) VGG-16_{224}; (**g**) ResNet-50_{128}; (**h**) ResNet-50_{224}.

A comparative analysis of the performance of VGG-16_{224} and ResNet-50_{224}—based on their confusion matrix evaluations shown in Figures 11f and 11h, respectively—was conducted to determine the superior model, as these two emerged as the top performers. The performance of each model across all classes was evaluated to identify their respective strengths and weaknesses in class prediction. ResNet-50_{224} demonstrated superior TP performance for the normal and scratch classes, while VGG-16_{224} excelled in the dent class. Furthermore, ResNet-50_{224} achieved lower FN scores in two classes (normal and scratch), while VGG-16_{224} recorded a lower FN only for the dent class. A similar pattern was observed in the FP assessment, where ResNet-50_{224} exhibited lower scores for the dent and scratch classes, whereas VGG-16_{224} had a lower score for the normal class.

These findings suggest that ResNet-50_{224} demonstrated greater data adaptability and overall efficiency compared to VGG-16_{224} in this study.

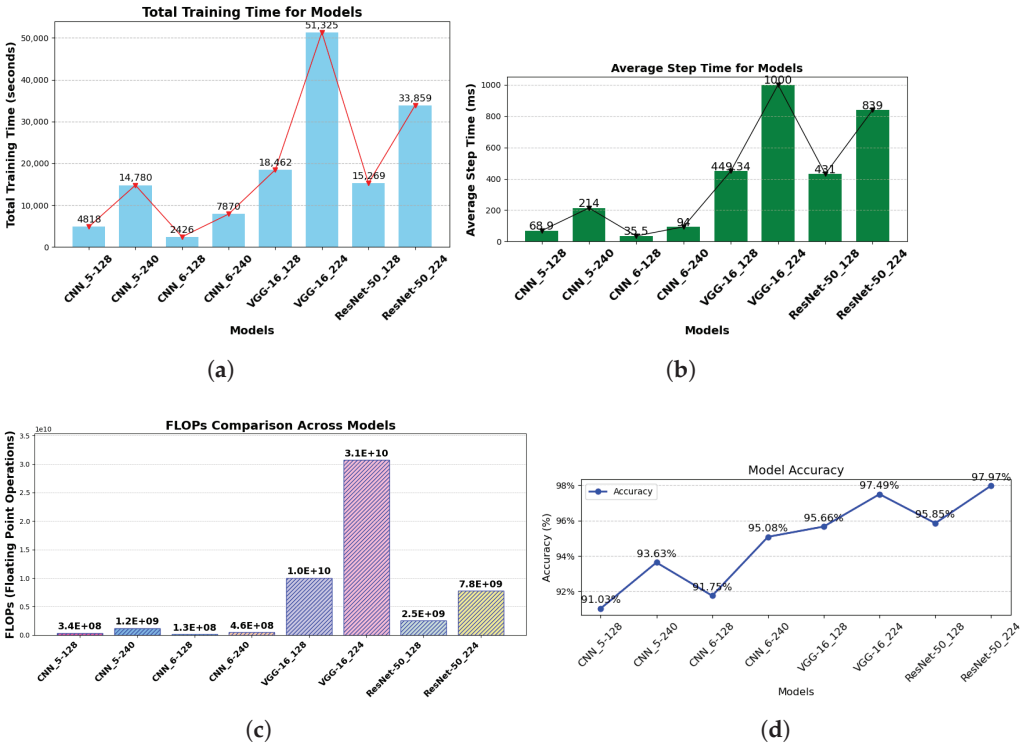
5.1. Computation Efficiency Evaluation

One of the key factors in determining an optimal model is its computational efficiency. Therefore, this section discusses the selection of an adequate model and offers suggestions for alternative models that could be considered when computational efficiency is a critical factor.

For a more in-depth analysis, floating point operations (FLOPs) are introduced to concisely determine the computational energy requirements of each model. FLOPs are a key metric for assessing model complexity, especially in deep learning models. They provide valuable insights into the computational requirement of a model, which is key for model optimization, hardware implementation, and real-time performance.

Figure 12a–c provide a comprehensive computational analysis of the models implemented in this study. The plots clearly show that the custom CNN models outperformed the pre-trained models (VGG-16 and ResNet-50 variants) in terms of computational efficiency. An interesting observation from the computational analysis is that the CNN_5 models exhibited higher computational energy demands for their respective input pixel dimensions, despite having shallower architectures compared to the CNN_6 models. This

behavior may be attributed to the complexity of the dataset, which likely challenges the CNN_5 architectures in fully capturing and learning its features.



(**a**) (**b**)

(**c**) (**d**)

Figure 12. (**a**) Models' total training time; (**b**) Models' average training step for one image data; (**c**) Models' floating points operations; (**d**) Models' accuracy.

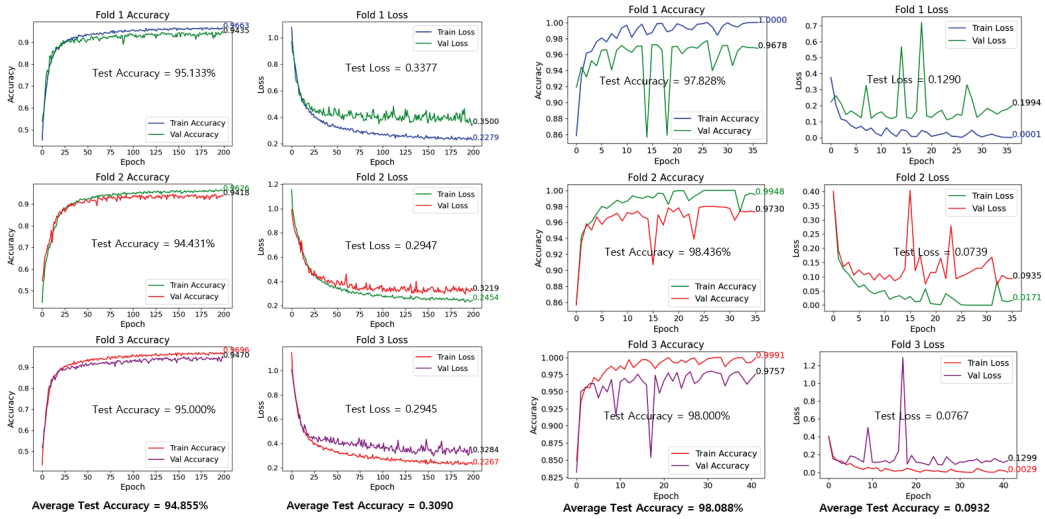
While ResNet-50_{224} demonstrated exceptional performance across various evaluation metrics, its significant computational energy demand raises concerns for applications where computational efficiency is a key factor, as shown in Figure 12a,b. Furthermore, Figure 12c, which displays the FLOPs of the models, revealed similar findings. ResNet-50_{224}—with a total of 7,751,510,674 FLOPs—may not be the ideal choice for real-time system applications due to its computational complexity. In contrast, CNN_6-240 presents itself as a more desirable option. Its accuracy—reaching up to 95% as shown in Figure 12d—though lower than that of ResNet-50_{224}, requires significantly less computational energy and has FLOPs of 459,072,914, suggesting suitability for real-time system implementation. This can be attributed to its lighter architecture, making it a practical alternative despite its slightly lower accuracy compared to ResNet-50_{224}. Moreover, its computational efficiency offers an opportunity for further hyperparameter tuning, which could enhance its accuracy. This makes the CNN_6-240 model adaptable, cost-effective, and well-suited for resource-sensitive environments without compromising performance.

5.2. K-Fold Model Evaluation

To validate the two best-performing models—ResNet-50_{224} (best overall) and CNN_6-240 (most computationally efficient)—we implemented a 3-fold cross-validation. This technique partitions the dataset into three folds, using two folds for training and one for validation in each iteration. By rotating the validation fold, we ensure every data point contributes to both training and evaluation, reducing bias from a single split, hence providing a more generalized performance assessment. Stratified sampling was implemented to ensure robust evaluation.

Figure 13 illustrate the outcomes of the 3-fold cross-validation, showing both models' accuracy and loss curves, alongside their respective test accuracies and losses. CNN_6-240

maintained an average k-fold test accuracy of 94.86%, closely mirroring its initial test accuracy of 95.08%. This reflects its strong efficiency and reliability in maintaining performance across different splits. Meanwhile, ResNet-50_{224} demonstrated superior accuracy, achieving an average of 98.088% with a reduced average loss of 0.0932, outperforming its original test results of 97.97% accuracy and 0.1030 loss. These findings highlight ResNet-50_{224}'s advantage in generalization and accuracy, while CNN_6-240 remains an effective, computationally efficient alternative.



(**a**) (**b**)

Figure 13. 3-Fold validation curves: (**a**) CNN_6-240; (**b**) ResNet-50_{224}.

6. Conclusions and Further Works

In this study, we proposed a framework for image data generation and fault classification on glossy and curved surfaces. Data collection was achieved using two complementary techniques: a Basler vision camera with specialized lighting to capture front-view images of heart case glossy surface samples while minimizing reflectiveness, and a laser displacement sensor paired with a robotic arm to accurately capture the curved surfaces of the samples.

Our dataset—consisting of three classes (HCC, DCC, and SCC)—was used to train eight deep neural networks. These networks were selected for their adaptability to the data and lower computational energy requirements. The architectures included four custom traditional CNNs (CNN_5-128, CNN_5-240, CNN_6-128, CNN_6-240) trained on image dimensions of 128 × 128 and 240 × 240 pixels, as well as four pre-established models: two variations of VGG-16 (VGG-16_{128}, VGG-16_{224}) and two variations of ResNet-50 (ResNet-50_{128}, ResNet-50_{224}), which were trained on images of 128 × 128 and 224 × 224 pixels, respectively. From our evaluation results, ResNet-50_{224} achieved the highest accuracy at 97.97%, followed closely by VGG-16_{224} with an accuracy of 97.49%. However, ResNet-50_{224}'s computational demands were less efficient compared to some of the custom traditional CNN architectures. Notably, CNN_6-240 delivered an accuracy of 95.08% with an average step time of 94 milliseconds, compared to ResNet-50_{224}'s 839 milliseconds, making CNN_6-240 a viable choice in scenarios where computational efficiency is paramount.

Our framework significantly advances glossy and curved surface defect detection by integrating specialized imaging hardware with tailored deep learning models. Using a Basler camera with custom lighting minimizes reflections on glossy surfaces, while a laser displacement sensor with a robotic arm precisely captures curved surfaces—yielding high-quality, reliable data. Beyond technical metrics, our framework also has significant industrial implications. Its deployment in manufacturing could lead to substantial cost

savings by reducing defect rates and minimizing downtime, ultimately improving product quality and competitiveness.

For future work, we plan to further optimize and enhance the custom CNN models to achieve higher accuracy while reducing energy consumption. The lag observed in most models can likely be attributed to the high FN rate of the dent class, as indicated by the confusion matrix. This issue is more likely caused by feature overlap with normal surfaces rather than class imbalance. To address this, targeted data augmentation like CLACHE (Contrast Limited Adaptive Histogram Equalization), feature engineering, and loss function modifications can be employed to enhance detection accuracy. In addition, systematic optimization techniques such as grid search and Bayesian optimization can be introduced to fine-tune hyperparameters for improved model performance. Furthermore, we aim to explore federated learning for multi-factory deployment, enabling collaborative, privacy-preserving model training across distributed production sites. We also plan to investigate lightweight model distillation techniques to facilitate real-time, energy-efficient deployment in industrial settings, potentially achievable through fine-tuning the custom CNN.

However, a key limitation of our approach is its reliance on controlled lighting conditions and specific robotic arm configurations. The reliance on controlled lighting conditions may limit the framework's applicability in environments with no lighting, variable lighting, or uncontrolled lighting, such as outdoor or poorly lit industrial settings. For example, in environments with uncontrolled lighting, the system's accuracy could drop significantly due to increased reflections and noise. Furthermore, the use of a robotic arm for precise positioning introduces scalability limitations and challenges in integrating with other automated systems. Additionally, its deployment is heavily dependent on expert knowledge, which may restrict widespread adoption. Future work will focus on mitigating these limitations by improving adaptability to diverse lighting conditions and exploring alternative data acquisition methods.

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Conflicts of Interest: All authors declare no conflicts of interest.

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State-Based Fault Diagnosis of Finite-State Vector Discrete-Event Systems via Integer Linear Programming

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Abstract: This paper presents a state-based method to address the verification of $\mathcal{K}$-diagnosability and fault diagnosis of a finite-state vector discrete-event system (Vector DES) with partially observable state outputs due to limited sensors. Vector DES models consist of an arithmetic additive structure in both the state space and state transition function. This work offers a necessary and sufficient condition for verifying the $\mathcal{K}$-diagnosability of a finite-state Vector DES based on state sensor outputs, employing integer linear programming and the mathematical representation of a Vector DES. Predicates are employed to diagnose faults in a Vector DES online. Specifically, we use three different kinds of predicates to divide system state outputs into different subsets, and the fault occurrence in a system is detected by checking a subset of outputs. Online diagnosis is achieved via solving integer linear programming problems. The conclusions obtained in this work are explained by means of several examples.

Keywords: vector discrete-event system; fault diagnosis; $\mathcal{K}$-diagnosability; predicate; integer linear programming

1. Introduction

As discrete-event systems (DESs) grow increasingly complex, fault diagnosis becomes a challenging endeavor that cannot solely resort to trial-and-error or experience. Adopting a systematic approach is vital for efficiently addressing diagnostic challenges. Diagnosability in DESs, as studied in prior works [1,2], refers to the probability to detect a fault within a limited delay once it occurs. Fault detection acts as a monitoring mechanism, revealing potential faults by observing the behavior of a DES.

The formal definition of diagnosability for DESs is initially introduced in [3], where a fault detection method based on events is introduced for regular languages that are represented by finite-state machine (FSM) models [4]. Wonham and Lin [5,6] touch upon the supervisory control problem of partially observed FSMs. A diagnoser is constructed to detect a set of possibly occurring faults [3] or a collection of fault states that a system can reach [7] after an observed event. A diagnoser is used to extend the diagnosability concept to stochastic automata in [8] and to the decentralized case in [9,10]. A coordinated decentralized architecture consisting of local sites communicating with a coordinator that is responsible for diagnosing the failures occurring in a DES is proposed in [9]. The study in [10] presents a model-based technique for the diagnosis of large-scale active systems that are treated as distributed DESs with events being received asynchronously. In the literature, the diagnosability concept is extended to the centralized cases [11–14], to the decentralized cases [9,10,15], and to the distributed cases [16,17].

The problem of the verification of diagnosability has also been solved within the framework of Petri nets (PNs) [18,19] with two representations: graphical and mathematical. In [20], assuming that not every place of a PN is observable, every transition is unobservable, and a fault is represented by a transition, a diagnoser is constructed to verify the diagnosability of the system. One may determine whether a model is a member of a specified net subclass by the graphical representation of a PN. High-efficiency algorithms are developed for verifying the diagnosability of a specified PN subclass by investigating its peculiarity. Assuming that all places are not observable, the diagnosability of a PN is verified by constructing its diagnoser in [21]. The mathematical representation of a PN makes it possible to verify its diagnosability using common mathematical techniques like integer linear programming (ILP). The *K*-diagnosability of a PN is verified via ILP in [22]. An approach [23] using ILP achieves online diagnosis by recording observed transition sequences.

In general, only partial observation of events and states can be obtained since real systems have a limited number of sensors. Modeling faults as unobservable state transitions [20,24,25] or unobservable events [3,26] is one of the fault models that has been studied extensively. Fault diagnosers of DESs or PNs are constructed to verify the fault diagnosability or diagnose faults in some research based on states (i.e., state-based) [27,28], or markings in observed places [29,30]. In [27], a state-based methodology for fault diagnosis in a fully observable DES is introduced. This approach assumes a categorization of the system state set, distinguishing between failure and normal states. The objective of the diagnosis problem is to ascertain whether the current state is faulty or normal upon receiving the most recent observation.

Compared with traditional automata and PNs, a vector discrete-event system (Vector DES) offers greater flexibility. This structured model is particularly effective for representing systems with inherent additive structures, such as smart manufacturing systems. Vector DESs provide a modeling approach, particularly to systems that contain groups of entities with the same characteristics. When the internal system shares similar structural characteristics, it is logical to improve the model of an abstract automaton by leveraging its regularity in algebra. Compared to Petri nets (PNs), Vector DESs offer the advantage of more compact modeling. Within the framework of Vector DESs, PNs are simply used as a graphical tool for illustration, and the mathematical theory of PNs is not utilized [31–35]. This is because the primary aim of developing Vector DESs is to apply Ramadge–Wonham (R-W) methods to structured systems with vector addition. Moreover, since a state vector of a Vector DES is composed of integers, the definition of states becomes more flexible, and it is also crucial for the state feedback control [35]. An event-based approach to verifying the diagnosability property of Vector DES is presented in [31]. Particularly, predicates are proposed to partition system states into different subsets, based on which the fault diagnosability is verified.

This research investigates the problem of state-based $\mathcal{K}$-diagnosability analysis and state-based fault diagnosis in a finite-state Vector DES, particularly in scenarios where sensors are embedded within specific state components. The idea of this paper is generated to characterize all the state output sequences corresponding to an event sequence $u\varepsilon_f v$, where v sustains the system evolution after the fault ε_f occurs, while u enables a fault ε_f from the initial state. The following is a summary of this work's primary contributions.

1. We first investigate and formulate the definition of the state-based $\mathcal{K}$-diagnosability in a Vector DES. For the verification of state-based $\mathcal{K}$-diagnosability, a necessary and sufficient condition is introduced.
2. A standard mathematical tool is utilized to verify state-based $\mathcal{K}$-diagnosability and diagnose, preventing a full state enumeration. The presented method does not depend on the construction of a diagnoser, because it solves ILP problems to verify the state-based $\mathcal{K}$-diagnosability and achieve online diagnosis.

The rest of this paper is arranged as follows. Section 2 provides the preliminaries on system models. Section 3 describes the problem statement, together with the definitions of the state-based diagnosability and state-based $\mathcal{K}$-diagnosability. For the verification of state-based $\mathcal{K}$-diagnosability, a necessary and sufficient condition is introduced in Section 4. Section 5 develops an algorithm to achieve online diagnosis. An example of a production line repairing damaged parts is presented to illustrate the proposed methods in Section 6. In the end, conclusions are provided in Section 7.

2. Preliminaries

A DES plant is a *generator* $G = (D, \Sigma, \xi, d_0, D_m)$, where D stands for the state set, Σ for the alphabet, ξ: $D \times \Sigma \to D$ for the (partial) transition function, d_0 for the initial state, and $D_m \subseteq D$ for the marker state set. Σ^+ and Σ^* are used to represent the set of all finite sequences of symbols defined over Σ and the Kleene closure of Σ, respectively, i.e., $\Sigma^* := \Sigma^+ \cup \{\epsilon\}$, where $\Sigma^+ = \Sigma \cup \Sigma^2 \cup \Sigma^3 \cup \cdots$, and ϵ is the empty sequence [35]. An element $w \in \Sigma^*$ is called a *string*, with $|w|$ representing the length of w. Given $\sigma \in \Sigma$, we follow the notations in [35], and use $\xi(d, \sigma)!$ to represent that the transition $\xi(d, \sigma)$ is defined. The *closed behavior* of G is

$$L(G) := \{w \in \Sigma^* | \xi(d_0, w)!\}, \tag{1}$$

and the *marked behavior* is

$$L_m(G) := \{w \in L(G) | \xi(d_0, w) \in D_m\} \subseteq L(G). \tag{2}$$

Given a DES G, a state $d \in D$ is *reachable* if there exists a string $w \in \Sigma^*$ such that $\xi(d_0, w)!$ and $d = \xi(d_0, w)$. For any state $d \in D$,

$$L(G, d) := \{w \in \Sigma^* | \xi(d, w)!\}. \tag{3}$$

Define

$$L/w := \{v \in \Sigma^* | w \in L(G), wv \in L(G)\}. \tag{4}$$

The space of n-vectors (i.e., ordered n-tuples) with components in $\mathbb{Z}$ (resp., $\mathbb{N}$) is represented by $\mathbb{Z}^n$ (resp., $\mathbb{N}^n$), where $\mathbb{Z}$ and $\mathbb{N}$ stand for the sets of integers and natural numbers, respectively. The "direct sum" operation $\bigoplus$ is used to form structures similar to $\mathbb{N}^n \bigoplus \mathbb{Z}^m$ or $\mathbb{Z}^n \bigoplus \mathbb{Z}^m$. A Vector DES [33–35] is defined as $\mathbf{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{D}_m)$, but with a vector structure. Generally speaking, $\boldsymbol{D}! = \mathbb{N}^n \bigoplus \mathbb{Z}^m$, while ξ: $\boldsymbol{D} \times \Sigma \to \boldsymbol{D}$ satisfies the following form:

$$\xi(\boldsymbol{d}, \sigma) = \boldsymbol{d} + \boldsymbol{e}_\sigma, \tag{5}$$

where $\boldsymbol{e}_\sigma \in \mathbb{Z}^{n+m}$ and $\sigma \in \Sigma$. Let $\Sigma = \{\sigma_1, \ldots, \sigma_k\}$ and write $\boldsymbol{e}_i$ for $\boldsymbol{e}_{\sigma_i}$. Define

$$E := [\boldsymbol{e}_1 \ldots \boldsymbol{e}_k] \in \mathbb{Z}^{p \times k} \tag{6}$$

as the displacement matrix for $\mathbf{G}$. Let $|\boldsymbol{D}|$ represent the size of state set.

Let $E(\cdot, \boldsymbol{e}_i)$ represent the column of E corresponding to event e_i. Define

$$\boldsymbol{V} : \Sigma^* \to \mathbb{N}^k : w \mapsto [\boldsymbol{v}_1(w) \dots \boldsymbol{v}_k(w)] \in \mathbb{N}^{k \times 1}, \tag{7}$$

where $v_j(w)$ is the number of occurrences of σ_j in w. A more general definition of a Vector DES would add the following enabling conditions. Assume $\boldsymbol{D} = \mathbb{N}^n$. Given $\boldsymbol{e}_\sigma \in \mathbb{Z}^n$ and $\boldsymbol{f}_\sigma \in \mathbb{N}^n$, let $\boldsymbol{e}_\sigma := \boldsymbol{e}_\sigma^+ - \boldsymbol{e}_\sigma^-$, $\boldsymbol{f}_\sigma := \boldsymbol{e}_\sigma^-$, where $\boldsymbol{e}_\sigma^+, \boldsymbol{e}_\sigma^- \in \mathbb{N}^n$. Define

$$E^+ := [\boldsymbol{e}_1^+ \dots \boldsymbol{e}_k^+] \in \mathbb{N}^{p \times k} \tag{8}$$

and

$$E^- := [\boldsymbol{e}_1^- \dots \boldsymbol{e}_k^-] \in \mathbb{N}^{p \times k}. \tag{9}$$

Example 1. *Consider a Vector DES $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{D}_m)$ in Figure 1, where the state vector is $\boldsymbol{d} := [\boldsymbol{d}(1), \boldsymbol{d}(2), \boldsymbol{d}(3), \boldsymbol{d}(4)]^T \in \mathbb{N}^{4 \times 1}$, alphabet is $\Sigma = \{a_1, a_2, a_3, a_4\}$, and the initial state is $\boldsymbol{d}_0 = [1, 0, 0, 0]^T$.*

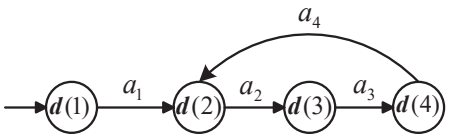


Figure 1. Vector DES model in Example 1.

Displacement matrix $E \in \mathbb{Z}^{4 \times 4}$ and $E^- \in \mathbb{Z}^{4 \times 4}$ are given as follows:

$$\begin{array}{c} \\ \boldsymbol{d}(1) \\ \boldsymbol{d}(2) \\ \boldsymbol{d}(3) \\ \boldsymbol{d}(4) \end{array} \begin{array}{c} \begin{array}{cccc} a_1 & a_2 & a_3 & a_4 \end{array} \\ \begin{pmatrix} -1 & 0 & 0 & 0 \\ 1 & -1 & 0 & 1 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & -1 \end{pmatrix} \end{array}$$

$$\begin{array}{c} \\ \boldsymbol{d}(1) \\ \boldsymbol{d}(2) \\ \boldsymbol{d}(3) \\ \boldsymbol{d}(4) \end{array} \begin{array}{c} \begin{array}{cccc} a_1 & a_2 & a_3 & a_4 \end{array} \\ \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \end{array}$$

All states of $\boldsymbol{G}$ are listed in Table 1.

Table 1. All states of Vector DES **G** in Example 1.

State	State Vector
$\boldsymbol{d}_0$	$[1, 0, 0, 0]^T$
$\boldsymbol{d}_1$	$[0, 1, 0, 0]^T$
$\boldsymbol{d}_2$	$[0, 0, 1, 0]^T$
$\boldsymbol{d}_3$	$[0, 0, 0, 1]^T$

Consider a Vector DES $\mathbf{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{D}_m)$. A predicate P, as defined in [33,34], operates on $\boldsymbol{D}$ and is represented as a function $P : \boldsymbol{D} \to \{0, 1\}$. In essence, P can be viewed as denoting the corresponding state subset associated with it, i.e.,

$$\boldsymbol{D}_P = \{\boldsymbol{d} \in \boldsymbol{D} | P(\boldsymbol{d}) = 1\} \subseteq \boldsymbol{D}. \tag{10}$$

$P(\boldsymbol{d}) = 1$ is often written as $\boldsymbol{d} \models P$ ("$\boldsymbol{d}$ satisfies P"). For the Vector DES $\mathbf{G}$ presented in Example 1, a predicate P can be defined as

$$\boldsymbol{D}_P = \{\boldsymbol{d} \in \boldsymbol{D} | \boldsymbol{d}(1) = 0\}$$

or equivalently,

$$\boldsymbol{d} \models P \text{ iff } \boldsymbol{d}(1) = 0.$$

3. Problem Formulation

States and events may be partially observable in a real system that can be modeled by a Vector DES. This paper considers the scenario in which all events of a Vector DES are unobservable and the states are partially observable. Alternatively, this setup implies that sensors are solely equipped in specific components of a state, which has been studied in the framework of state-based partially observed automata [27,36]. Consider a Vector DES designated for diagnosis, modeled as a reachable deterministic finite-state Moore automaton $\mathbf{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, \lambda)$. Here, $\boldsymbol{D}$, Σ, and $\boldsymbol{Y}$ represent the finite state, event, and output sets, respectively. The notation $\boldsymbol{d}_0$ denotes the initial state, ξ stands for the transition function, and λ: $\boldsymbol{D} \to \boldsymbol{Y}$ is defined as the output map [27] (this output map can be formulated by taking into account the requirements of a specific physical system). Formally, suppose that a state $\boldsymbol{d} \in \boldsymbol{D}$'s component elements are separated into two sets: observable components set $\boldsymbol{d}_o$ and unobservable components set $\boldsymbol{d}_{uo}$, and $\boldsymbol{D} = \boldsymbol{D}_o \bigoplus \boldsymbol{D}_{uo}$.

We shall concentrate on the diagnosability and diagnosis of a single fault ε_f instead of the diagnosability and diagnosis of a type of fault without sacrificing generality. Set $\boldsymbol{D} = \boldsymbol{D}_n \cup \boldsymbol{D}_f$ can be classified into a normal state subset $\boldsymbol{D}_n$ and faulty state subset $\boldsymbol{D}_f$ including the states that are reachable from $\boldsymbol{d}_0$ via a fault event represented by ε_f.

Definition 1 (Output projection)**.** *Given a Vector DES $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{D}_m)$, $\boldsymbol{D} = \boldsymbol{D}_o \bigoplus \boldsymbol{D}_{uo}$, and $\boldsymbol{d} = [\boldsymbol{d}(1), \boldsymbol{d}(2), \ldots, \boldsymbol{d}(k)]^T \in \boldsymbol{D}$ $(k \in \mathbb{N})$, the output projection $Pr : \boldsymbol{D} \to \boldsymbol{D}_o$ is defined as*

$$Pr(\boldsymbol{d}) = [\boldsymbol{d}(i)]^T, \boldsymbol{d}(i) \in \boldsymbol{d}_o \ (i \leq k \in \mathbb{N}). \tag{11}$$

The output projection Pr just "erases" the unobservable state components of a state.

Example 2. *Continuing to Example 1, we briefly explain the output projection as follows. Assume $\boldsymbol{d}_{uo} := \{\boldsymbol{d}(4)\}$. For instance, given $\boldsymbol{d}_1 = [0, 1, 0, 0]^T$, it comes $Pr(\boldsymbol{d}_1) = [0, 1, 0]^T$.*

Definition 2. *Given a Vector DES $\boldsymbol{G}$, a vector $\boldsymbol{h} \in \mathbb{N}^n$ is called an E-invariant if $E \cdot \boldsymbol{h} = \mathbf{0}$.*

Similar to the definition of the *support* of a T-invariant in net theory [22], we define the *support* of an E-invariant $\boldsymbol{h}$ as the set of events that corresponds to entries of $\boldsymbol{h}$ that are not zero. If no suitable nonempty subset of a support can be a support, then the support is considered as being minimal. $\mathcal{T}(\mathbf{G})$ stands for the set of minimal support E-invariants of $\mathbf{G}$.

In this work, the output map is defined as the output projection and Pr: $\boldsymbol{D} \to \boldsymbol{Y}$. From now on, let us write a reachable nondeterministic finite-state Moore automaton $\mathbf{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$ in place of $\mathbf{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, \lambda)$. We adopt the following assumptions in the remainder of the paper.

Assumption 1. *The state set of a Vector DES can be classified according to the condition (normal or failure) of the system.*

Assumption 2. *The system* $\boldsymbol{G}$ *is deadlock-free, i.e.,* $(\forall \boldsymbol{d} \in \boldsymbol{D})(\exists \sigma \in \Sigma)\ \xi(\boldsymbol{d}, \sigma)!$

Assumption 3. *The fault modes are permanent, i.e., the system stays in the faulty condition indefinitely after a fault occurs.*

Assumption 4. *The initial state* $\boldsymbol{d}_0$ *is unique.*

The notion of diagnosability guarantees that, upon the occurrence of a fault in a system, it must be detected within a limited delay. The formal descriptions of *state-based diagnosability* and *state-based $\mathcal{K}$-diagnosability* are presented in what follows.

Definition 3. *Given a Vector DES* $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$ *and a fault* ε_f, $\boldsymbol{G}$ *is state-based diagnosable if*

$$(\exists h \in \mathbb{N})(\forall \boldsymbol{d}_f \in \boldsymbol{D}_f)(\forall v \geq h)(\forall \boldsymbol{d}_e^v \in \mathcal{X}(\boldsymbol{d}_f, v))\boldsymbol{d}_e^v \subseteq \boldsymbol{D}_f, \tag{12}$$

where $\mathcal{X}(\boldsymbol{d}_f, v)$ *represents the set of all state estimations provided after* v *events occurring from* $\boldsymbol{d}_f$.

Let $\boldsymbol{d}_f$ be any faulty state. Condition (12) indicates that there exists $h \in \mathbb{N}$ such that, once $v \geq h$, the set of all state estimations provided after v events occurring from $\boldsymbol{d}_f$ is the subset of the faulty state subset $\boldsymbol{D}_f$.

Definition 4. *Given a Vector DES* $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, *a fault* ε_f, *and* $\mathcal{K} \in \mathbb{N}$, $\boldsymbol{G}$ *is state-based $\mathcal{K}$-diagnosable if*

$$(\forall \boldsymbol{d}_f \in \boldsymbol{D}_f)(\forall v \geq \mathcal{K})(\forall \boldsymbol{d}_e^v \in \mathcal{X}(\boldsymbol{d}_f, v))\boldsymbol{d}_e^v \subseteq \boldsymbol{D}_f, \tag{13}$$

where $\mathcal{X}(\boldsymbol{d}_f, v)$ *represents the set of all state estimations provided after* v *events occurring from* $\boldsymbol{d}_f$.

The notion of $\mathcal{K}$-diagnosability provides a means to specify an upper limit on the number of events required to detect a fault. If a system is considered to be state-based $\mathcal{K}$-diagnosable, it implies that the system is also state-based diagnosable. However, the converse is not necessarily true. According to Definitions 3 and 4, if a system is state-based diagnosable, then there exists another integer value $\mathcal{K}'$ for which the system is also state-based $\mathcal{K}'$-diagnosable.

The fault detection problem discussed in this work employs a sequence of state output $(\boldsymbol{y}_1\boldsymbol{y}_2\boldsymbol{y}_3\cdots)$ to determine the condition of a Vector DES. It should be noted that it is assumed that just alterations in the output are observable. It indicates that, if the system goes from one state to another state with an identical state output, such transition will be unnoticed, i.e., the transition is not observable. In an output sequence, $\boldsymbol{y}_i \neq \boldsymbol{y}_{i+1}$ for $i \geq 1$. Given an output $\boldsymbol{y}$, an upper limit for the number of states corresponding to the output $\boldsymbol{y}$ is given by $\mathcal{H}$, which can be computed by Netlab [37]. For instance, in Example 2, we can obtain that $\mathcal{H} = 2$, implying that one state output corresponds to up to two system states.

Given a finite-state Vector DES $\mathbf{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$ and a fault ε_f, our goal is to realize the online diagnosis of a Vector DES by checking the subsets of states. When a new state output is generated, whether the faults occurred can be derived, the system can be in only one of the following states: normal, faulty, and uncertain. Enhancing the fault detection algorithm's efficiency can be achieved at the expense of a slight rise in memory usage. Therefore, we just record the current state output. Of course, if we record the complete state output sequence, there will be a more accurate diagnosis decision. We need to find a specific predicate for a Vector DES such that, if a current state output satisfies this specific predicate, we can detect the fault. The primary issues to be investigated in this work are presented as follows.

Problem 1. *Given a finite-state Vector DES $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$, and a fault ε_f, verify the state-based $\mathcal{K}$-diagnosability of $\boldsymbol{G}$ via solving an ILP problem.*

Problem 2. *Given a finite-state Vector DES $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$, and a fault ε_f, find a predicate P for $\boldsymbol{G}$ such that, if the current state output of the system satisfies P, one can determine the occurrence of ε_f.*

4. Verification of State-Based $\mathcal{K}$-Diagnosability

4.1. Necessary and Sufficient Condition for State-Based $\mathcal{K}$-Diagnosability of Finite-State Vector DESs

The primary outcome discussed in this section is to provide a necessary and sufficient condition for state-based $\mathcal{K}$-diagnosability of a fault in a Vector DES. This condition is established as the solution to an ILP problem. Prior to introducing Lemma 1, a brief review of fundamental Petri net concepts and additional notations is provided.

A *Petri net* (PN) is a four-tuple $N = (\widehat{P}, T, Pre, Post)$, where $\widehat{P}$ is a finite set of *places*, T is a finite set of *transitions*, Pre: $\widehat{P} \times T \to \mathbb{N}$, and $Post$: $\widehat{P} \times T \to \mathbb{N}$. A *marking* of a PN is a vector $\boldsymbol{m}$: $\widehat{P} \to \mathbb{N}$. For further information on the fundamental concepts of PNs, the reader is directed to [22].

Lemma 1 ([38])**.** *Given a PN $(N, \boldsymbol{m}_0)$ with a marking $\boldsymbol{m}$ and a sequence $\sigma \in T^*$, there exists a set of ρ non-negative integer vectors $\boldsymbol{w}_1, \ldots, \boldsymbol{w}_\rho$ with $\rho \leq |\sigma|$ such that the linear constraints listed below are satisfied*

$$\begin{cases} \boldsymbol{m} \geq Pre \cdot \boldsymbol{w}_1, \\ \boldsymbol{m} + C \cdot \boldsymbol{w}_1 \geq Pre \cdot \boldsymbol{w}_2, \\ \cdots, \\ \boldsymbol{m} + C \cdot \sum\limits_{i=1}^{\rho-1} \boldsymbol{w}_i \geq Pre \cdot \boldsymbol{w}_\rho, \\ \sum\limits_{i=1}^{\rho} \boldsymbol{w}_i = \boldsymbol{\sigma}, \end{cases} \tag{14}$$

if and only if σ is enabled at the marking $\boldsymbol{m}$.

A finite-length transition sequence that is enabled at a marking $\boldsymbol{m}$ in a PN must meet the necessary and sufficient condition given by Lemma 1. Based on Lemma 1, Lemma 2 is presented.

Lemma 2. *Given a finite-state Vector DES $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$ and $\boldsymbol{D} \subseteq \mathbb{N}^n$, an output sequence $\boldsymbol{y}_1\boldsymbol{y}_2 \cdots \boldsymbol{y}_\gamma$ is generated at the initial state $\boldsymbol{d}_0$, if and only if there exist $\mathcal{H}^2 \cdot \gamma$ vectors $\boldsymbol{s}_1, \ldots, \boldsymbol{s}_{\mathcal{H}^2 \cdot \gamma} \in \mathbb{N}^n$ that satisfy the set of constraints listed below, represented by $\mathcal{E}(\boldsymbol{d}_0, \boldsymbol{y}_1\boldsymbol{y}_2 \cdots \boldsymbol{y}_\gamma)$,*

$$
\begin{cases}
\left.\begin{array}{l}
\boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{s}_1 \\
\boldsymbol{d}_0 + E \cdot \boldsymbol{s}_1 \geq E^- \cdot \boldsymbol{s}_2 \\
Pr(\boldsymbol{d}_0) = \boldsymbol{y}_1 \\
Pr(\boldsymbol{d}_0 + E \cdot \boldsymbol{s}_1) = \boldsymbol{y}_1 \\
\cdots \\
\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{H}^2-1} \boldsymbol{s}_i \geq E^- \cdot \boldsymbol{s}_{\mathcal{H}^2} \\
Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{H}^2} \boldsymbol{s}_i) = \boldsymbol{y}_1
\end{array}\right\}(a) \\
\cdots \\
\left.\begin{array}{l}
\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{H}^2\cdot(\gamma-1)} \boldsymbol{s}_i \geq E^- \cdot \boldsymbol{s}_{\mathcal{H}^2\cdot(\gamma-1)+1} \\
Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{H}^2\cdot(\gamma-1)} \boldsymbol{s}_i) = \boldsymbol{y}_\gamma \\
\cdots \\
\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{H}^2\cdot\gamma-1} \boldsymbol{s}_i \geq E^- \cdot \boldsymbol{s}_{\mathcal{H}^2\cdot\gamma} \\
Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{H}^2\cdot\gamma-1} \boldsymbol{s}_i) = \boldsymbol{y}_\gamma \\
Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{H}^2\cdot\gamma} \boldsymbol{s}_i) = \boldsymbol{y}_\gamma.
\end{array}\right\}(b) \\
||\boldsymbol{s}_i||_1 = 1,\ i = 1, \ldots, \mathcal{H}^2 \cdot \gamma \qquad (c)
\end{cases}
\tag{15}
$$

Proof of Lemma 2. (if) Since one state output corresponds to up to $\mathcal{H}$ system states, there are at most $\mathcal{H}^2$ events between $\mathcal{H}$ states. By Lemma 1, if there exist $\mathcal{H}^2$ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_{\mathcal{H}^2}$ satisfying constraints (15) (a), then at least one event sequence is generated from the initial state $\boldsymbol{d}_0$ with the output $\boldsymbol{y}_1$. Constraints (15) (b) have the same meaning as constraints (15) (a). Therefore, if there exist $\mathcal{H}^2 \cdot \gamma$ vectors $\boldsymbol{s}_1, \ldots, \boldsymbol{s}_{\mathcal{H}^2\cdot\gamma}$ satisfying constraints $\mathcal{E}(\boldsymbol{d}_0, \boldsymbol{y}_1\boldsymbol{y}_2 \cdots \boldsymbol{y}_\gamma)$, an output sequence $\boldsymbol{y}_1\boldsymbol{y}_2 \cdots \boldsymbol{y}_\gamma$ is generated at the initial state $\boldsymbol{d}_0$.

(only if) Let us suppose that an output sequence $\boldsymbol{y}_1\boldsymbol{y}_2 \cdots \boldsymbol{y}_\gamma$ is generated at the initial state $\boldsymbol{d}_0$. According to Lemma 1, there exist $\mathcal{H}^2 \cdot \gamma$ vectors $\boldsymbol{s}_1, \ldots, \boldsymbol{s}_{\mathcal{H}^2\cdot\gamma}$ corresponding to an event sequence yielding the output sequence $\boldsymbol{y}_1\boldsymbol{y}_2 \cdots \boldsymbol{y}_\gamma$ starting from the initial state $\boldsymbol{d}_0$, such that constraints (15) (a), (b), and (c) are satisfied. □

Theorem 1. *Consider a finite-state Vector DES $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$, and a fault ε_f. Let $\mathcal{J}$ be a positive integer such that $\mathcal{J} \geq \mathcal{J}_{min}$ (Implicitly, the value of $\mathcal{J}$ establishes the longest event sequence that can provide a generic state that enables ε_f. In [22], the minimum $\mathcal{J}_{min}$ is presented to fully describe all states reachable from $\boldsymbol{d}_0$ that enable ε_f, and these states are reached via a sequence not including ε_f. The system is supposed to be finite-state, which implies that the integer $\mathcal{J}_{min}$ exists. An overestimation of $\mathcal{J}_{min}$ [22] is given by $|\boldsymbol{D}| - 1$. Given an integer $\mathcal{K}$ that is positive, ε_f is state-based $\mathcal{K}$-diagnosable if and only if there exist $((\mathcal{H}^2 + 1) \cdot (\mathcal{J} + \mathcal{K}) + 2\mathcal{H}^2) \in \mathbb{N}$ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\mathcal{J}$, $\boldsymbol{v}_1, \ldots, \boldsymbol{v}_\mathcal{K}$,$\boldsymbol{s}_1, \ldots, \boldsymbol{s}_{\mathcal{H}^2\cdot(\mathcal{J}+\mathcal{K}+2)} \in \mathbb{N}^n$ such that*

$$
\min_{s.t. \mathcal{D}(\boldsymbol{d}_0, \varepsilon_f, \mathcal{J}, \mathcal{K})} \sum_{r=1}^{\mathcal{H}^2\cdot(\mathcal{J}+\mathcal{K}+2)} \boldsymbol{s}_r(\varepsilon_f) \neq 0,
$$

where the set of constraints $\mathcal{D}(\boldsymbol{d}_0, \varepsilon_f, \mathcal{J}, \mathcal{K})$ is given in (16):

$$\left\{\begin{array}{l}\left.\begin{array}{l}\boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1\\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2\\ \cdots\\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{J}-1} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_{\mathcal{J}}\\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{J}} \boldsymbol{u}_i \geq E^-(\varepsilon_f)\\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{J}} \boldsymbol{u}_i + E(\cdot, \varepsilon_f) \geq E^- \cdot \boldsymbol{v}_1\\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{J}} \boldsymbol{u}_i + E(\cdot, \varepsilon_f) + E \cdot \boldsymbol{v}_1 \geq E^- \cdot \boldsymbol{v}_2\\ \cdots\\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{J}} \boldsymbol{u}_i + E(\cdot, \varepsilon_f) + E \cdot \sum\limits_{j=1}^{\mathcal{K}-1} \boldsymbol{v}_j \geq E^- \cdot \boldsymbol{v}_{\mathcal{K}}\\ \sum\limits_{i=1}^{\mathcal{J}} \boldsymbol{u}_i(\varepsilon_f) = 0\\ ||\boldsymbol{u}_i||_1 = 1,\ i = 1, \ldots, \mathcal{J}\\ ||\boldsymbol{v}_j||_1 = 1,\ j = 1, \ldots, \mathcal{K}\\ ||\sum\limits_{j=1}^{\mathcal{K}} \boldsymbol{v}_j||_1 \geq \mathcal{K}\end{array}\right\}(a)\\ \\ \left.\begin{array}{l}\mathcal{E}(\boldsymbol{d}_0, Pr(\boldsymbol{d}_0) \cdots Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\mathcal{J}} \boldsymbol{u}_i + E(\cdot, \varepsilon_f) + E \cdot \sum\limits_{j=1}^{\mathcal{K}} \boldsymbol{v}_j)\end{array}\right\}(b)\end{array}\right. \tag{16}$$

Proof of Theorem 1. (if) By $\mathcal{J} \geq \mathcal{J}_{min}$, the constraints (16) (a) describe all states reachable from $\boldsymbol{d}_0$ that enable fault event ε_f. It follows that, if there exist $((\mathcal{H}^2+1)\cdot(\mathcal{J}+\mathcal{K})+2\mathcal{H}^2) \in \mathbb{N}$ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_{\mathcal{J}}, \boldsymbol{v}_1, \ldots, \boldsymbol{v}_{\mathcal{K}}, \boldsymbol{s}_1, \ldots, \boldsymbol{s}_{\mathcal{H}^2\cdot(\mathcal{J}+\mathcal{K}+2)} \in \mathbb{N}^n$ fulfilling constraints (16) and

$$\min_{s.t. \mathcal{D}(\boldsymbol{d}_0, \varepsilon_f, \mathcal{J}, \mathcal{K})} \sum_{r=1}^{\mathcal{H}^2\cdot(\mathcal{J}+\mathcal{K}+2)} \boldsymbol{s}_r(\varepsilon_f) \neq 0,$$

then every faulty event sequence $u\varepsilon_f v$ with $\varepsilon_f \notin u$ of an output sequence includes the fault event ε_f, such that there are at least $\mathcal{K}$ events in the postfix following the fault ε_f. Therefore, ε_f is state-based $\mathcal{K}$-diagnosable according to Definition 4.

(only if) Let us suppose that ε_f is state-based $\mathcal{K}$-diagnosable. According to Definition 4, for each state estimation $\boldsymbol{D}_e$, which is provided after sufficient steps of state transition from $\boldsymbol{d}_{fi}$, if $\boldsymbol{D}_e \subseteq \boldsymbol{D}_{fi}$, then the fault can be accurately identified in a limited delay.

Now, let us assume *ad absurdum* that

$$\min_{s.t. \mathcal{D}(\boldsymbol{d}_0, \varepsilon_f, \mathcal{J}, \mathcal{K})} \sum_{r=1}^{\mathcal{H}^2\cdot(\mathcal{J}+\mathcal{K}+2)} \boldsymbol{s}_r(\varepsilon_f) = 0.$$

Then, there should exist at least one output sequence and the corresponding event sequences that are $u\varepsilon_f v$ with $\varepsilon_f \notin u$ and $u'v'$ not containing ε_f, such that $|v|, |v'| \geq \mathcal{K}$. This implies that ε_f is not state-based $\mathcal{K}$-diagnosable, which contradicts that ε_f is state-based $\mathcal{K}$-diagnosable. □

The constraint (16) (b) will return the occurrence vectors of an event sequence generating the same output sequence with $u\varepsilon_f v$.

For a huge value of $\mathcal{K}$, being state-based $\mathcal{K}$-diagnosable could imply being practically undiagnosable. In practice, being state-based $\mathcal{K}$-diagnosable for $\mathcal{K} \ll |\boldsymbol{D}|$ is essential when the number of states is high. Utilizing Theorem 1, the minimal $\mathcal{K}$ required for a diagnosable fault to be state-based $\mathcal{K}$-diagnosable can be calculated by conducting a binary search on $\mathcal{K}$, beginning at $\mathcal{K} = |\boldsymbol{D}|/2$.

4.2. Illustrative Example

Example 3. *Consider a Vector DES* $\boldsymbol{G}$ *visualized in Figure 2 with alphabet* $\Sigma = \{a_1, a_2, a_3, a_4, a_5, \varepsilon_f\}$, *where* ε_f *represents the fault. The state vector* $\boldsymbol{d}$ *is defined as* $\boldsymbol{d} := [\boldsymbol{d}(1), \boldsymbol{d}(2), \boldsymbol{d}(3), \boldsymbol{d}(4), \boldsymbol{d}(5)]^T \in \mathbb{N}^{5\times 1}$. $\boldsymbol{d}_o := \{\boldsymbol{d}(1), \boldsymbol{d}(2), \boldsymbol{d}(3), \boldsymbol{d}(4)\}$, *and* $\boldsymbol{d}_{uo} := \{\boldsymbol{d}(5)\}$. *The initial state* $\boldsymbol{d}_0$ *is* $[1, 0, 0, 0, 0]^T$. *Displacement matrix* $E \in \mathbb{Z}^{5\times 6}$ *and* $E^- \in \mathbb{Z}^{5\times 6}$ *are given as follows:*

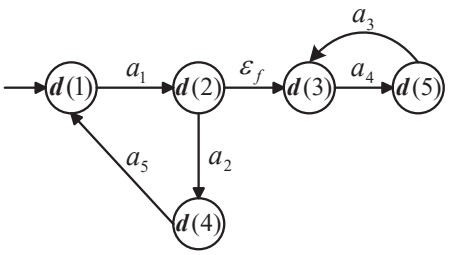


Figure 2. Vector DES model in Example 3.

$$E = \begin{array}{c} \\ \boldsymbol{d}(1) \\ \boldsymbol{d}(2) \\ \boldsymbol{d}(3) \\ \boldsymbol{d}(4) \\ \boldsymbol{d}(5) \end{array} \begin{array}{c} \begin{array}{cccccc} a_1 & a_2 & a_3 & a_4 & \varepsilon_f & a_5 \end{array} \\ \begin{pmatrix} -1 & 0 & 0 & 0 & 0 & 1 \\ 1 & -1 & 0 & 0 & -1 & 0 \\ 0 & 0 & 1 & -1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & -1 \\ 0 & 0 & -1 & 1 & 0 & 0 \end{pmatrix} \end{array}$$

$$E^- = \begin{array}{c} \\ \boldsymbol{d}(1) \\ \boldsymbol{d}(2) \\ \boldsymbol{d}(3) \\ \boldsymbol{d}(4) \\ \boldsymbol{d}(5) \end{array} \begin{array}{c} \begin{array}{cccccc} a_1 & a_2 & a_3 & a_4 & \varepsilon_f & a_5 \end{array} \\ \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \end{array}$$

All states of $\boldsymbol{G}$ *are listed in Table 2. In this system,* $\boldsymbol{D}_n = \{\boldsymbol{d}_0, \boldsymbol{d}_1, \boldsymbol{d}_3\}$ *and* $\boldsymbol{D}_f = \{\boldsymbol{d}_2, \boldsymbol{d}_4\}$. *We solve an ILP problem and a full state enumeration is avoided. The* $|\boldsymbol{D}|$ *is calculated using Netlab software 1.75 and it equals 5. We set* $\mathcal{J} = 5$ *and* $\mathcal{H} = 2$. *If we select* $\mathcal{K} = 1$, *then*

$$\min_{s.t. \mathcal{D}(\boldsymbol{d}_0, \varepsilon_f, 5, 1)} \sum_{r=1}^{32} \boldsymbol{s}_r(\varepsilon_f) \neq 0,$$

where the set of constraints $\mathcal{D}(\boldsymbol{d}_0, \varepsilon_f, 5, 1)$ *is given in (17):*

$$\left\{ \begin{array}{l} \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{5} \boldsymbol{u}_i \geq E^-(\varepsilon_f) \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{5} \boldsymbol{u}_i + E(\cdot, \varepsilon_f) \geq E^- \cdot \boldsymbol{v}_1 \\ \sum\limits_{i=1}^{5} \boldsymbol{u}_i(\varepsilon_f) = 0 \\ ||\boldsymbol{u}_i||_1 = 1, \ i = 1, \ldots, 5 \\ ||\boldsymbol{v}_j||_1 = 1, \ j = 1 \\ ||\sum\limits_{j=1}^{1} \boldsymbol{v}_j||_1 \geq 1 \end{array}\right\}(a) \\ \\ \left.\mathcal{E}(\boldsymbol{d}_0, Pr(\boldsymbol{d}_0) \cdots Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{5} \boldsymbol{u}_i + E(\cdot, \varepsilon_f) + E \cdot \boldsymbol{v}_1). \right\}(b) \end{array} \right. \tag{17}$$

If we select $\mathcal{K} = 2$*, then*

$$\min_{s.t.\mathcal{D}(\boldsymbol{d}_0,\varepsilon_f,5,2)} \sum_{r=1}^{36} \boldsymbol{s}_r(\varepsilon_f) \neq 0.$$

Therefore, ε_f *is state-based* 1*-diagnosable. We have validated this result by employing the YALMIP software tool R20180612 [39] to solve the ILP problem.*

Table 2. All states of Vector DES **G** in Example 3.

State	State Vector
$\boldsymbol{d}_0$	$[1,0,0,0,0]^T$
$\boldsymbol{d}_1$	$[0,1,0,0,0]^T$
$\boldsymbol{d}_2$	$[0,0,1,0,0]^T$
$\boldsymbol{d}_3$	$[0,0,0,1,0]^T$
$\boldsymbol{d}_4$	$[0,0,0,0,1]^T$

4.3. Complexity Analysis

The primary computational burden of the proposed method lies in solving Equation (16), which can be reformulated as an ILP model. It is widely acknowledged that ILP problems are generally NP-hard. Notably, the computational complexity of solving an ILP problem is heavily influenced by the number of constraints and variables involved. Assuming that $\mathcal{J}$ is provided, it is easy to deduce that (16) (a) contains $(\mathcal{J}+\mathcal{K})\cdot|\Sigma|$ variables, while (16) (a) contains $(2\mathcal{J}+2\mathcal{K}+2)\cdot n+1$ constraints. The number of variables in (16) (b) is $\mathcal{H}^2\cdot(\mathcal{J}+\mathcal{K}+2)\cdot|\Sigma|$, while that of constraints in (16) (b) is $\mathcal{H}^2\cdot(2\mathcal{J}+2\mathcal{K}+2)$. The total number of variables in (16) is $(\mathcal{J}+\mathcal{K}+\mathcal{H}^2\cdot(\mathcal{J}+\mathcal{K}+2))\cdot|\Sigma|$, while the total number of constraints is $2(\mathcal{J}+\mathcal{K}+1)\cdot(\mathcal{H}^2+n)+1$. Furthermore, if $\mathcal{J}$ and $\mathcal{K}$ are given, regardless of the initial state, the numbers of constraints and variables rise linearly with the size of a Vector DES.

5. State-Based Fault Online Diagnosis

5.1. State-Based Fault Online Diagnosis of Finite-State Vector DESs

For online diagnosis, the current condition of a system is determined by the recorded state output. We do not rely on a diagnoser-based approach to achieve online diagnosis. The following predicates are presented to divide the outputs of current states based on the condition of a system.

Definition 5 (Faulty predicate P_f)**.** *Given a Vector DES* $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$*,* $\boldsymbol{D} \subseteq \mathbb{N}^n$*, and a fault* ε_f*, the faulty predicate* P_f *with regard to* $\boldsymbol{G}$ *identifies a state subset* $\boldsymbol{D}_{P_f} \subseteq \boldsymbol{D}_o$ *by defining*

$$\boldsymbol{D}_{P_f} := \{\boldsymbol{d}_o \in \boldsymbol{D}_o | \forall s \in L(\boldsymbol{G}, \boldsymbol{d}_0) : Pr(\xi(\boldsymbol{d}_0, s)) = \boldsymbol{d}_o \wedge \boldsymbol{v}_{\varepsilon_f}(s) \neq 0\},$$

or equivalently,

$$\boldsymbol{d}_o \models P_f \ \textit{iff}\ \forall s \in L(\boldsymbol{G}, \boldsymbol{d}_0) : Pr(\xi(\boldsymbol{d}_0, s)) = \boldsymbol{d}_o \wedge \boldsymbol{v}_{\varepsilon_f}(s) \neq 0.$$

The following provides an illustration of the definition of faulty predicate P_f. Given a state output satisfying P_f, all states in the set of estimation are reachable via the sequences containing a fault, and the current condition of **G** is faulty.

Definition 6 (Normal predicate P_n)**.** *Given a Vector DES* $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$, *and a fault* ε_f, *the normal predicate* P_n *with regard to* $\boldsymbol{G}$ *identifies a state subset* $\boldsymbol{D}_{P_n} \subseteq \boldsymbol{D}_o$ *by defining*

$$\boldsymbol{D}_{P_n} := \{\boldsymbol{d}_o \in \boldsymbol{D}_o | \forall s \in L(\boldsymbol{G}, \boldsymbol{d}_0) : Pr(\xi(\boldsymbol{d}_0, s)) = \boldsymbol{d}_o \wedge \boldsymbol{v}_{\varepsilon_f}(s) = 0\},$$

or equivalently,

$$\boldsymbol{d}_o \models P_n \ \textit{iff} \ \forall s \in L(\boldsymbol{G}, \boldsymbol{d}_0) : Pr(\xi(\boldsymbol{d}_0, s)) = \boldsymbol{d}_o \wedge \boldsymbol{v}_{\varepsilon_f}(s) = 0.$$

The following provides an illustration of the definition of normal predicate P_n. Given a state output satisfying P_n, all states in the set of estimation are reachable via the sequences not containing a fault, and the current condition of **G** is normal.

Definition 7 (Uncertain predicate P_{un})**.** *Given a Vector DES* $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$, *and a fault* ε_f, *the uncertain predicate* P_{un} *with regard to* $\boldsymbol{G}$ *identifies a state subset* $\boldsymbol{D}_{P_{un}} \subseteq \boldsymbol{D}_o$ *by defining*

$\boldsymbol{D}_{P_{un}} := \{\boldsymbol{d}_o \in \boldsymbol{D}_o | \exists s, s' \in L(\boldsymbol{G}, \boldsymbol{d}_0) : Pr(\xi(\boldsymbol{d}_0, s)) = \boldsymbol{d}_o \wedge Pr(\xi(\boldsymbol{d}_0, s')) = \boldsymbol{d}_o \wedge \boldsymbol{v}_{\varepsilon_f}(s) = 0 \wedge \boldsymbol{v}_{\varepsilon_f}(s') \neq 0\}$,
or equivalently,

$\boldsymbol{d}_o \models P_{un}$ *iff* $\exists s, s' \in L(\boldsymbol{G}, \boldsymbol{d}_0) : Pr(\xi(\boldsymbol{d}_0, s)) = \boldsymbol{d}_o \wedge Pr(\xi(\boldsymbol{d}_0, s')) = \boldsymbol{d}_o \wedge \boldsymbol{v}_{\varepsilon_f}(s) = 0 \wedge \boldsymbol{v}_{\varepsilon_f}(s') \neq 0$.

For any state output $\boldsymbol{d}_o \models P_{un}$, there exist at least two states $\boldsymbol{d}, \boldsymbol{d}' \in \boldsymbol{D}$ with the identical observation, such that $\boldsymbol{d}$ is reachable via a sequence containing a fault, and $\boldsymbol{d}'$ is reachable via a sequence not containing a fault. The current condition of **G** is uncertain.

Example 4. *For Example 3, if* $[0,1,0,0]^T$ *is observed, the corresponding state estimation set is* $\{[0,1,0,0,1]^T\}$. *Each state in this set is reachable via the sequences containing a fault and* $[0,1,0,0]^T$ *satisfies* P_f, *implying that a fault occurs.*

Proposition 1. *Given a finite-state Vector DES* $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$, *a fault* ε_f, *and the current state output* $\boldsymbol{d}_c \in \boldsymbol{D}_o$, $\boldsymbol{d}_c \models P_f$ *if and only if there exist* ρ *vectors* $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\rho \in \mathbb{N}^n$, *such that*

$$\textit{ILPP 1}: \min_{s.t. \mathcal{F}(\boldsymbol{d}_0, \rho, \boldsymbol{d}_c)} \sum_{i=1}^{\rho} \boldsymbol{u}_i(\varepsilon_f) \neq 0,$$

where the set of constraints $\mathcal{F}(\boldsymbol{d}_0, \rho, \boldsymbol{d}_c)$ *is given in (18):*

$$\begin{cases} \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\rho-1} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_\rho \end{array}\right\} (a) \\ \left.\begin{array}{l} Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\rho} \boldsymbol{u}_i) = \boldsymbol{d}_c. \end{array}\right\} (b) \end{cases} \tag{18}$$

Proof of Proposition 1. (if) By Lemma 1, if there exist ρ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\rho$ satisfying constraints (18) (a), then at least one event sequence is generated from the initial state $\boldsymbol{d}_0$. Suppose that there exist ρ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\rho$, such that $\min\limits_{s.t. \mathcal{F}(\boldsymbol{d}_0, \rho, \boldsymbol{d}_c)} \sum\limits_{i=1}^{\rho} \boldsymbol{u}_i(\varepsilon_f) \neq 0$, which

implies that any state $\boldsymbol{d}$ in the state estimation set of $\boldsymbol{d}_c$ according to the constraint (18) (b) is reachable via fault ε_f. By Definition 5, $\boldsymbol{d}_c \models P_f$ and the fault occurs.

(only if) Assume $\boldsymbol{d}_c \models P_f$. It follows that, by Definition 5, all states in the set of estimation of $\boldsymbol{d}_c$ are reachable via sequences containing a fault.

Now, let us assume *ad absurdum* that

$$\min_{s.t.\mathcal{F}(\boldsymbol{d}_0,\rho,\boldsymbol{d}_c)} \sum_{i=1}^{\rho} \boldsymbol{u}_i(\varepsilon_f) = 0.$$

Then, there should exist at least one state $\boldsymbol{d}$ in the state estimation set of $\boldsymbol{d}_c$ that is reachable not via fault ε_f. This implies that $\boldsymbol{d}_c$ does not satisfy P_f, which contradicts that $\boldsymbol{d}_c \models P_f$. □

Proposition 2. *Given a finite-state Vector DES $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$, a fault ε_f, and the current state output $\boldsymbol{d}_c \in \boldsymbol{D}_o$, $\boldsymbol{d}_c \models P_n$ if and only if there exist ρ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\rho \in \mathbb{N}^n$, such that*

$$ILPP\ 2: \max_{s.t.\mathcal{N}(\boldsymbol{d}_0,\rho,\boldsymbol{d}_c)} \sum_{i=1}^{\rho} \boldsymbol{u}_i(\varepsilon_f) = 0,$$

where the set of constraints $\mathcal{N}(\boldsymbol{d}_0, \rho, \boldsymbol{d}_c)$ is presented in (19):

$$\begin{cases} \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\rho-1} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_\rho \end{array}\right\}(a) \\ \\ \left.\begin{array}{l} Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\rho} \boldsymbol{u}_i) = \boldsymbol{d}_c. \end{array}\right\}(b) \end{cases} \tag{19}$$

Proof of Proposition 2. (if) By Lemma 1, if there exist ρ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\rho$ satisfying constraints (19) (a), then at least one event sequence is generated from the initial state $\boldsymbol{d}_0$. Suppose that there exist ρ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\rho$, such that $\max\limits_{s.t.\mathcal{N}(\boldsymbol{d}_0,\rho,\boldsymbol{d}_c)} \sum\limits_{i=1}^{\rho} \boldsymbol{u}_i(\varepsilon_f) = 0$, which implies that any state $\boldsymbol{d}$ in the state estimation set of $\boldsymbol{d}_c$ according to the constraint (19) (b) is reachable not via fault ε_f. By Definition 6, $\boldsymbol{d}_c \models P_n$ and the fault does not occur.

(only if) Assume $\boldsymbol{d}_c \models P_n$. It follows that, by Definition 6, all states in the set of estimation of $\boldsymbol{d}_c$ are reachable via sequences not containing a fault.

Now, let us assume *ad absurdum* that

$$\max_{s.t.\mathcal{N}(\boldsymbol{d}_0,\rho,\boldsymbol{d}_c)} \sum_{i=1}^{\rho} \boldsymbol{u}_i(\varepsilon_f) \neq 0.$$

Then, there should exist at least one state $\boldsymbol{d}$ in the state estimation set of $\boldsymbol{d}_c$ that is reachable via fault ε_f. This implies that $\boldsymbol{d}_c$ does not satisfy P_n, which contradicts that $\boldsymbol{d}_c \models P_n$. □

Proposition 3. *Given a finite-state Vector DES $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$, a fault ε_f, and the current state output $\boldsymbol{d}_c \in \boldsymbol{D}_o$, $\boldsymbol{d}_c \models P_{un}$ if and only if there exist $\rho + \lambda$ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\rho$, $\boldsymbol{v}_1, \ldots, \boldsymbol{v}_\lambda \in \mathbb{N}^n$ such that*

$$ILPP\ 3: \min_{s.t.\mathcal{U}(\boldsymbol{d}_0,\lambda,\rho,\boldsymbol{d}_c)} \sum_{j=1}^{\lambda} \boldsymbol{v}_j(\varepsilon_f) = 0,$$

where the set of constraints $\mathcal{U}(\boldsymbol{d}_0, \lambda, \rho, \boldsymbol{d}_c)$ is given in (20):

$$\begin{cases} \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\rho-1} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_\rho \end{array}\right\}(a) \\ \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{v}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{v}_1 \geq E^- \cdot \boldsymbol{v}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{j=1}^{\lambda-1} \boldsymbol{v}_j \geq E^- \cdot \boldsymbol{v}_\lambda \end{array}\right\}(b) \\ \left.\sum\limits_{i=1}^{\rho} \boldsymbol{u}_i(\varepsilon_f) \neq 0 \right\}(c) \\ \left.\begin{array}{l} Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{\rho} \boldsymbol{u}_i) = \boldsymbol{d}_c \\ Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{j=1}^{\lambda} \boldsymbol{v}_j) = \boldsymbol{d}_c. \end{array}\right\}(d) \end{cases} \tag{20}$$

Proof of Proposition 3. (if) By Lemma 1, if there exist $\rho + \lambda$ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\rho, \boldsymbol{v}_1, \ldots, \boldsymbol{v}_\lambda$ satisfying constraints (20) (a) and (b), then at least one event sequence is generated from the initial state $\boldsymbol{d}_0$. Suppose that there exist $\rho + \lambda$ vectors $\boldsymbol{u}_1, \ldots, \boldsymbol{u}_\rho, \boldsymbol{v}_1, \ldots, \boldsymbol{v}_\lambda \in \mathbb{N}^n$ such that $\min\limits_{s.t.\mathcal{U}(\boldsymbol{d}_0,\lambda,\rho,\boldsymbol{d}_c)} \sum\limits_{j=1}^{\lambda} \boldsymbol{v}_j(\varepsilon_f) = 0$. Then, there exist two states with the same state output $\boldsymbol{d}_c$ according to constraints (20) (d), for which one state is not generated via a fault but another is generated via at least one fault according to the constraint (20) (c). By Definition 7, $\boldsymbol{d}_c \models P_{un}$ and the system condition is uncertain.

(only if) Assume $\boldsymbol{d}_c \models P_{un}$. It follows that, by Definition 7, for any state $\boldsymbol{d}$ in the state estimation set of $\boldsymbol{d}_c$, there exists another state $\boldsymbol{d}'$ such that these two states have the same output $\boldsymbol{d}_c$. However, $\boldsymbol{d}$ is reachable via a sequence containing a fault, and $\boldsymbol{d}'$ is reachable via a sequence not containing a fault.

Now, let us assume *ad absurdum* that

$$\min_{s.t.\mathcal{U}(\boldsymbol{d}_0,\lambda,\rho,\boldsymbol{d}_c)} \sum_{j=1}^{\lambda} \boldsymbol{v}_j(\varepsilon_f) \neq 0.$$

Then, each state in the state estimation set of $\boldsymbol{d}_c$ is reachable via fault ε_f. This implies that $\boldsymbol{d}_c$ does not satisfy P_{un}, which contradicts that $\boldsymbol{d}_c \models P_{un}$. □

Proposition 4. *Given a finite-state Vector DES* $\boldsymbol{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$, *and a fault* ε_f, *the upper bounds of* ρ *and* λ *satisfy*

$$\rho, \lambda \leq \| \sum_{\boldsymbol{h} \in \mathcal{T}(\boldsymbol{G})} \boldsymbol{h} \|_1 + (|\boldsymbol{D}| - 1). \tag{21}$$

Proof of Proposition 4. Denote by $\sigma = \sigma_1 \sigma_2 \ldots \sigma_k$ the longest sequence. In a finite-state Vector DES **G**, the length of σ can be arbitrarily long. Here, we just need to compare the projections of states. The states of **G** are finite, whose number is $|\boldsymbol{D}|$. The farthest state can be reached from $\boldsymbol{d}_0$ via σ by the occurrence of the maximum number of events without reaching two times the same intermediate state. $\| \sum_{\boldsymbol{h} \in \mathcal{T}(\mathbf{G})} \boldsymbol{h} \|_1$ covers all minimal support

E-invariants. Therefore, the length of σ is less than $(\| \sum_{\boldsymbol{h} \in \mathcal{T}(\mathbf{G})} \boldsymbol{h} \|_1 + (|\boldsymbol{D}| - 1))$, i.e., ρ and λ are less than $(\| \sum_{\boldsymbol{h} \in \mathcal{T}(\mathbf{G})} \boldsymbol{h} \|_1 + (|\boldsymbol{D}| - 1))$. □

Now, an online procedure for Problem 2 is ready to be developed. The basic procedures for performing state-based diagnosis in a finite-state Vector DES using the ILP approach only are outlined in Algorithm 1, where is guaranteed to be correct by Propositions 1–4.

Algorithm 1: State-based online fault diagnosis of a finite-state Vector DES

Input: A finite-state Vector DES $\mathbf{G} = (\boldsymbol{D}, \Sigma, \xi, \boldsymbol{d}_0, \boldsymbol{Y}, Pr)$, $\boldsymbol{D} \subseteq \mathbb{N}^n$
Output: faulty, normal, or uncertain

1 Wait until a new output $\boldsymbol{y}$ is observed;
2 Let $\boldsymbol{d}_c = \boldsymbol{y}$;
3 Let τ_1 be ILPP 1's minimal objective value;
4 **if** $(\tau_1 \neq 0)$ **then**
5 | return faulty and go to line 1 ;
6 **else**
7 | continue;
8 Let τ_2 be ILPP 2's maximal objective value;
9 **if** $(\tau_2 = 0)$ **then**
10 | return normal and go to line 1;
11 **else**
12 | continue;
13 Let τ_3 be ILPP 3's minimal objective value;
14 **if** $(\tau_3 = 0)$ **then**
15 | return uncertain and go to line 1;
16 **else**
17 | go to line 1.

5.2. Illustrative Example

Example 5. *Consider the Vector DES* $\boldsymbol{G}$ *presented in Example 3. The variable* $|\boldsymbol{D}|$ *is calculated with Netlab software 1.75 and it equals 5. Then, the minimal support E-invariants are calculated with Netlab:* $\boldsymbol{h}_1 = [1, 1, 0, 0, 0, 1]^T$, $\boldsymbol{h}_2 = [0, 0, 1, 1, 0, 0]^T$.
Proposition 4 gives the upper bounds of ρ *and* λ, *i.e.,*
$\rho, \lambda \leq \| \boldsymbol{h}_1 + \boldsymbol{h}_2 \|_1 + (|\boldsymbol{D}| - 1) = 5 + 4 = 9$.
Before applying Algorithm 1 to the Vector DES $\boldsymbol{G}$, *the corresponding ILPPs 1, 2, and 3 are obtained as follows.*

$$\textit{ILPP 1}: \min_{s.t. \mathcal{F}(\boldsymbol{d}_0, 9, \boldsymbol{d}_c)} \sum_{i=1}^{9} \boldsymbol{u}_i(\varepsilon_f) \neq 0,$$

where the set of constraints $\mathcal{F}(\boldsymbol{d}_0, 9, \boldsymbol{d}_c)$ *is given in (22):*

$$\begin{cases} \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum_{i=1}^{8} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_9 \end{array}\right\} (a) \\ \left.\begin{array}{l} Pr(\boldsymbol{d}_0 + E \cdot \sum_{i=1}^{9} \boldsymbol{u}_i) = \boldsymbol{d}_c. \end{array}\right\} (b) \end{cases} \tag{22}$$

$$\textit{ILPP 2}: \max_{s.t. \mathcal{N}(\boldsymbol{d}_0, 9, \boldsymbol{d}_c)} \sum_{i=1}^{9} \boldsymbol{u}_i(\varepsilon_f) = 0,$$

where the set of constraints $\mathcal{N}(\boldsymbol{d}_0, 9, \boldsymbol{d}_c)$ *is presented in (23):*

$$\left\{\begin{array}{l} \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{8} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_9 \end{array}\right\}(a) \\ \\ \left.\begin{array}{l} Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{9} \boldsymbol{u}_i) = \boldsymbol{d}_c. \end{array}\right\}(b) \end{array}\right. \tag{23}$$

ILPP 3 : $\min\limits_{s.t.\mathcal{U}(\boldsymbol{d}_0,9,9,\boldsymbol{d}_c)} \sum\limits_{j=1}^{9} \boldsymbol{v}_j(\varepsilon_f) = 0,$
where the set of constraints $\mathcal{U}(\boldsymbol{d}_0, 9, 9, \boldsymbol{d}_c)$ *is given in (24):*

$$\left\{\begin{array}{l} \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{8} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_9 \end{array}\right\}(a) \\ \\ \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{v}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{v}_1 \geq E^- \cdot \boldsymbol{v}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{j=1}^{8} \boldsymbol{v}_j \geq E^- \cdot \boldsymbol{v}_9 \end{array}\right\}(b) \\ \\ \left.\begin{array}{l} \sum\limits_{i=1}^{9} \boldsymbol{u}_i(\varepsilon_f) \neq 0 \end{array}\right\}(c) \\ \\ \left.\begin{array}{l} Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{9} \boldsymbol{u}_i) = \boldsymbol{d}_c \\ Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{j=1}^{9} \boldsymbol{v}_j) = \boldsymbol{d}_c. \end{array}\right\}(d) \end{array}\right. \tag{24}$$

When $\boldsymbol{d}_c = \boldsymbol{y} = [0,1,0,0]^T$ *is observed, the output of Algorithm 1 is "normal". When* $\boldsymbol{d}_c = \boldsymbol{y} = [0,0,1,0]^T$ *is observed, the output of Algorithm 1 is "faulty".*

5.3. Complexity Analysis

The solutions to ILPPs 1, 2, and 3 are the primary source of Algorithm 1's computational expense. An ILP problem is believed to be NP-hard in general. Let us assume that ρ and λ are given; it is easy to deduce that ILPP 1 contains $\rho \cdot |\Sigma|$ variables, while ILPP 1 contains $(\rho + 1) \cdot n$ constraints. ILPP 2 contains $\rho \cdot |\Sigma|$ variables, while ILPP 2 contains $(\rho + 1) \cdot n$ constraints. ILPP 3 contains $(\rho + \lambda) \cdot |\Sigma|$ variables, while ILPP 3 contains $(\rho + \lambda + 3) \cdot n$ constraints.

6. Example: A Production Line Repairing Damaged Parts

Consider a production line repairing damaged parts as shown in Figure 3, namely metallic slabs where a plate and a slab have been placed in decentralized positions. The production line consists of two lines, and each line consists of four parts, i.e., a numerically controlled grinding machine, a numerically controlled milling machine, a painting machine, and a numerically controlled fitter. Slabs and plates are separated when a damaged metallic

slab is ready for repair, with the slab going in the left line and the plate in the right. Parts are fixed in the two lines consisting of ground, milled, painting, and fitted. Ultimately, the robot correctly positions a single metallic plate in the slab. The whole process is repeated. A new damaged metallic slab enters the production line as input. Slabs and plates are separated when a new damaged metallic slab is ready for repair, with the slab going in the left line and the plate in the right.

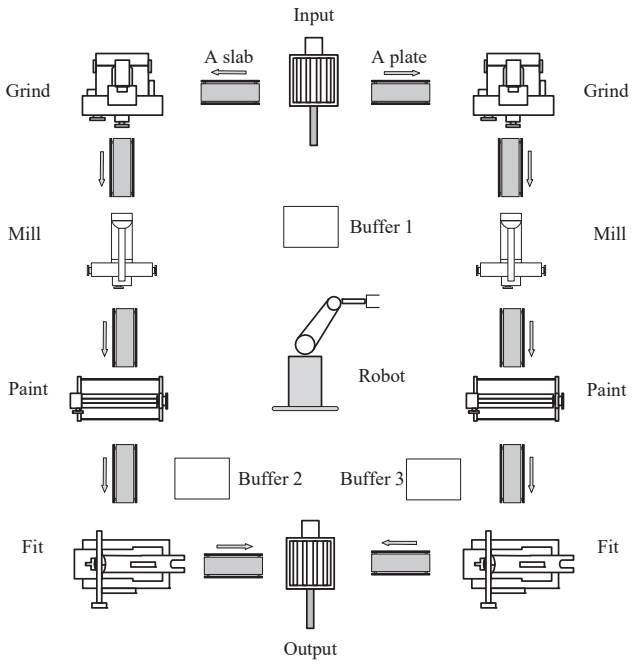


Figure 3. Schematic of the production line repairing damaged parts.

The Vector DES model of the production line is visualized in Figure 4, where the meanings of events and state components are shown in Tables 3 and 4, respectively. We define the state vector $\boldsymbol{d}$ as $\boldsymbol{d} := [\boldsymbol{d}(1), \boldsymbol{d}(2), \boldsymbol{d}(3), \boldsymbol{d}(4), \boldsymbol{d}(5), \boldsymbol{d}(6), \boldsymbol{d}(7), \boldsymbol{d}(8), \boldsymbol{d}(9), \boldsymbol{d}(10), \boldsymbol{d}(11), \boldsymbol{d}(12), \boldsymbol{d}(13), \boldsymbol{d}(14), \boldsymbol{d}(15), \boldsymbol{d}(16), \boldsymbol{d}(17)]^T \in \mathbb{N}^{17\times 1}$, $\boldsymbol{d}_o := \{\boldsymbol{d}(1), \boldsymbol{d}(2), \boldsymbol{d}(3), \boldsymbol{d}(4), \boldsymbol{d}(5), \boldsymbol{d}(6), \boldsymbol{d}(7), \boldsymbol{d}(8), \boldsymbol{d}(9), \boldsymbol{d}(10), \boldsymbol{d}(11), \boldsymbol{d}(12), \boldsymbol{d}(13), \boldsymbol{d}(14), \boldsymbol{d}(15), \boldsymbol{d}(17)\}$, and $\boldsymbol{d}_{uo} := \{\boldsymbol{d}(16)\}$. $\Sigma = \{a_1, a_2, b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8, b_9, b_{10}, b_{11}, b_{12}, c, e_1, e_2, \varepsilon_f\}$, where ε_f represents the fault. The initial state $\boldsymbol{d}_0$ is $[1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1]^T$.

Table 3. Event of Figure 4.

Event	Meaning	Fault
a_1	*A damaged part is separated*	*No*
a_2	*A metallic plate is inserted in the slab*	*No*
b_1	*Right line is grinding*	*No*
b_2	*Right line is milling*	*No*
b_3	*Right line is painting*	*No*
b_4	*Right line is fitting*	*No*
b_5	*Left line is grinding*	*No*
b_6	*Left line is milling*	*No*
b_7	*Left line is painting*	*No*
b_8	*Left line is fitting*	*No*
b_9	*Load a supplementary slab from Buffer 1*	*No*
b_{10}	*Load a supplementary plate from Buffer 1*	*No*
b_{11}	*Load a supplementary plate from Buffer 3*	*No*
b_{12}	*Load a supplementary slab from Buffer 2*	*No*
c	*Repeat the whole process*	*No*
e_1	*Self-replenish pigment*	*No*
e_2	*Pigment deficiency response*	*No*
ε_f	*There is not enough pigment to paint*	*Yes*

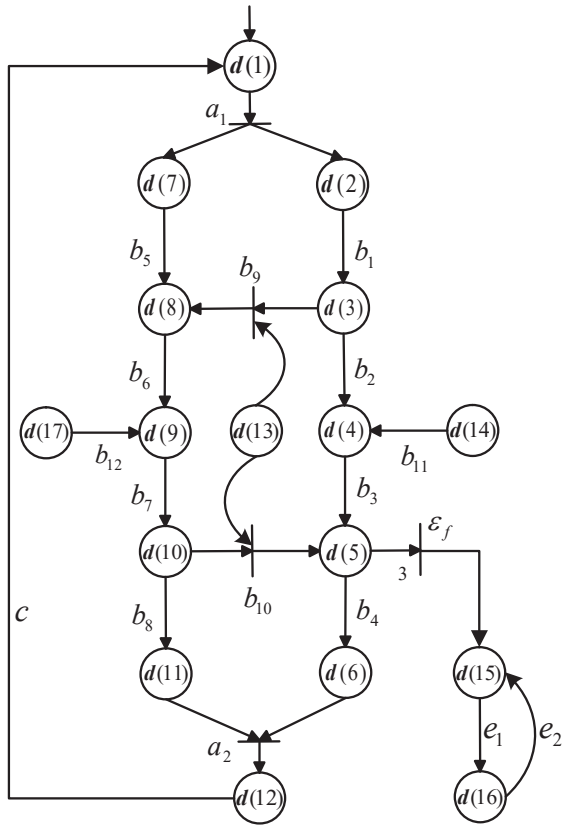


Figure 4. A Vector DES model of the production line repairing damaged parts in Figure 3.

Table 4. State component of Figure 4.

State Component	Meaning	Observability
$\boldsymbol{d}(1)$	*A damaged part is ready to be repaired*	*Observable*
$\boldsymbol{d}(2)$	*A plate separated from the damaged part*	*Observable*
$\boldsymbol{d}(3)$	*Grinding is finished in the right line*	*Observable*
$\boldsymbol{d}(4)$	*Milling is finished in the right line*	*Observable*
$\boldsymbol{d}(5)$	*Painting is finished in the right line*	*Observable*
$\boldsymbol{d}(6)$	*Fitting is finished in the right line*	*Observable*
$\boldsymbol{d}(7)$	*A slab separated from the damaged part*	*Observable*
$\boldsymbol{d}(8)$	*Grinding is finished in the left line*	*Observable*
$\boldsymbol{d}(9)$	*Milling is finished in the left line*	*Observable*
$\boldsymbol{d}(10)$	*Painting is finished in the left line*	*Observable*
$\boldsymbol{d}(11)$	*Fitting is finished in the left line*	*Observable*
$\boldsymbol{d}(12)$	*One metallic plate inserted in the slab*	*Observable*
$\boldsymbol{d}(13)$	*Buffer 1 is available*	*Observable*
$\boldsymbol{d}(14)$	*Buffer 3 is available*	*Observable*
$\boldsymbol{d}(15)$	*Painting is unavailable*	*Observable*
$\boldsymbol{d}(16)$	*Pigment deficiency*	*Unobservable*
$\boldsymbol{d}(17)$	*Buffer 2 is available*	*Observable*

The Vector DES model of the production line is finite-state and has a total of 1149 states, which has been successfully verified by Netlab. We set $\mathcal{J} = 1148$ and $\mathcal{H} = 2$. If we select $\mathcal{K} = 1$, then

$$\min_{s.t.\mathcal{D}(\boldsymbol{d}_0,\varepsilon_f,1148,1)} \sum_{r=1}^{4604} \boldsymbol{s}_r(\varepsilon_f) = 1 \neq 0,$$

where the set of constraints $\mathcal{D}(\boldsymbol{d}_0, \varepsilon_f, 1148, 1)$ is given in (25):

$$\left\{\begin{array}{l}\left.\begin{array}{l}\boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1\\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2\\ \cdots\\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{1148} \boldsymbol{u}_i \geq E^-(\varepsilon_f)\\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{1148} \boldsymbol{u}_i + E(\cdot, \varepsilon_f) \geq E^- \cdot \boldsymbol{v}_1\\ \sum\limits_{i=1}^{1148} \boldsymbol{u}_i(\varepsilon_f) = 0\\ ||\boldsymbol{u}_i||_1 = 1,\ i = 1, \ldots, 1148\\ ||\boldsymbol{v}_j||_1 = 1,\ j = 1\\ ||\sum\limits_{j=1}^{1} \boldsymbol{v}_j||_1 \geq 1\end{array}\right\}(a)\\ \\ \left.\mathcal{E}(\boldsymbol{d}_0, Pr(\boldsymbol{d}_0) \cdots Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{1148} \boldsymbol{u}_i + E(\cdot, \varepsilon_f) + E \cdot \boldsymbol{v}_1).\right\}(b)\end{array}\right. \tag{25}$$

Therefore, ε_f is state-based 1-diagnosable.

Then, the minimal support E-invariants are calculated with Netlab:
$\boldsymbol{h}_1 = [1,1,1,1,1,1,1,1,1,0,0,0,1,0,1,0,0]^T$,
$\boldsymbol{h}_2 = [0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1]^T$.
Proposition 4 gives the upper bounds of ρ and λ, i.e.,
$\rho, \lambda \leq \| \boldsymbol{h}_1 + \boldsymbol{h}_2 \|_1 + (|\boldsymbol{D}| - 1) = 1161$.
Before applying Algorithm 1 to the Vector DES model of the production line, the corresponding ILPPs 1, 2, and 3 are obtained as follows.

ILPP 1 : $\min\limits_{s.t. \mathcal{F}(\boldsymbol{d}_0, 1161, \boldsymbol{d}_c)} \sum\limits_{i=1}^{1161} \boldsymbol{u}_i(\varepsilon_f) \neq 0$,
where the set of constraints $\mathcal{F}(\boldsymbol{d}_0, 1161, \boldsymbol{d}_c)$ is given in (26):

$$\left\{\begin{array}{l}\left.\begin{array}{l}\boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1\\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2\\ \cdots\\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{1160} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_{1161}\end{array}\right\}(a)\\ \\ \left.Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{1161} \boldsymbol{u}_i) = \boldsymbol{d}_c.\right\}(b)\end{array}\right. \tag{26}$$

ILPP 2 : $\max\limits_{s.t. \mathcal{N}(\boldsymbol{d}_0, 1161, \boldsymbol{d}_c)} \sum\limits_{i=1}^{1161} \boldsymbol{u}_i(\varepsilon_f) = 0$,
where the set of constraints $\mathcal{N}(\boldsymbol{d}_0, 1161, \boldsymbol{d}_c)$ is presented in (27):

$$\left\{\begin{array}{l}\left.\begin{array}{l}\boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1\\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2\\ \cdots\\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{1160} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_{1161}\end{array}\right\}(a)\\ \\ \left.Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{1161} \boldsymbol{u}_i) = \boldsymbol{d}_c.\right\}(b)\end{array}\right. \tag{27}$$

ILPP 3 : $\min\limits_{s.t.\mathcal{U}(\boldsymbol{d}_0,1161,1161,\boldsymbol{d}_c)} \sum\limits_{j=1}^{1161} \boldsymbol{v}_j(\varepsilon_f) = 0,$

where the set of constraints $\mathcal{U}(\boldsymbol{d}_0, 1161, 1161, \boldsymbol{d}_c)$ is given in (28):

$$\begin{cases} \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{u}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{u}_1 \geq E^- \cdot \boldsymbol{u}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{1160} \boldsymbol{u}_i \geq E^- \cdot \boldsymbol{u}_{1161} \end{array}\right\}(a) \\ \left.\begin{array}{l} \boldsymbol{d}_0 \geq E^- \cdot \boldsymbol{v}_1 \\ \boldsymbol{d}_0 + E \cdot \boldsymbol{v}_1 \geq E^- \cdot \boldsymbol{v}_2 \\ \cdots \\ \boldsymbol{d}_0 + E \cdot \sum\limits_{j=1}^{1160} \boldsymbol{v}_j \geq E^- \cdot \boldsymbol{v}_{1161} \end{array}\right\}(b) \\ \left.\begin{array}{l} \sum\limits_{i=1}^{1161} \boldsymbol{u}_i(\varepsilon_f) \neq 0 \end{array}\right\}(c) \\ \left.\begin{array}{l} Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{i=1}^{1161} \boldsymbol{u}_i) = \boldsymbol{d}_c \\ Pr(\boldsymbol{d}_0 + E \cdot \sum\limits_{j=1}^{1161} \boldsymbol{v}_j) = \boldsymbol{d}_c. \end{array}\right\}(d) \end{cases} \tag{28}$$

When $\boldsymbol{d}_c = \boldsymbol{y} = [0,1,0,0,0,0,1,0,0,0,0,0,1,1,0]^T$ is observed, the output of Algorithm 1 is "normal". We have validated these results by employing the YALMIP software tool to solve the ILP problems.

7. Conclusions

This paper addresses a state-based approach to solving the problems of the verification of $\mathcal{K}$-diagnosability and online diagnosis of a Vector DES by formulating and solving ILP problems. A necessary and sufficient condition for verifying $\mathcal{K}$-diagnosability of a finite-state Vector DES is presented. Several ILP problems are built according to a state output. The online diagnosis result is obtained by giving distinct objective functions to the ILP problem. The proposed approach requires neither any search of paths in graphs nor any estimation of the reachability set. By changing the structure of input of the Vector DES to the suggested ILP problems, it can therefore be applied to other Vector DESs. In future work, we will optimize parameters $\mathcal{J}_{min}$, λ, and ρ of the ILP problems to make the procedure more efficient.

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Abbreviations

The following abbreviations are used in this manuscript:

DES	Discrete-event system
FSM	Finite-state machine
PN	Petri net
ILP	Integer linear programming
ILPP	Integer linear programming problem

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Remaining Useful Life Prediction Method for Stochastic Degrading Devices Considering Predictive Maintenance

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Abstract: Predictive maintenance, recognized as an effective health management strategy for extending the lifetime of devices, has emerged as a hot research topic in recent years. A general method is to execute two separate steps: data-driven remaining useful life (RUL) prediction and a maintenance strategy. However, among the numerous studies that conducted maintenance and replacement activities based on the results of RUL prediction, little attention has been paid to the impact of preventive maintenance on sensor-based monitoring data, which further affects the RUL for repairable degrading devices. In this paper, an adaptive RUL prediction method is proposed for repairable degrading devices in order to improve the accuracy of prediction results and achieve adaptability to future degradation processes. Firstly, a phased degradation model based on an adaptive Wiener process is established, taking into account the impact of imperfect maintenance. Meanwhile, integrating the impact of maintenance activities on the degradation rate and state, the probability distribution of RUL can be derived based on the concept of first hitting time (FHT). Secondly, a method is proposed for model parameter identification and updating that incorporates the individual variation among devices, integrating maximum likelihood estimation and Bayesian inference. Finally, the effectiveness of the RUL prediction method is ultimately validated through numerical simulation and its application to repairable gyroscope degradation data.

Keywords: predictive maintenance; remaining useful life; repairable degrading devices; imperfect maintenance; adaptive Wiener; sensor-based monitoring

1. Introduction

The emergence of Industry 4.0 has facilitated the advancement of sophisticated devices, such as aviation industry machinery, missile weapon systems, and high-speed trains, toward intelligence and integration. Consequently, the timely and effective maintenance of devices is imperative to ensure their safe and reliable operation [1,2]. Prognostic and health management technology, as a health management activity involving monitoring, prediction, and maintenance, has garnered substantial attention from both academia and industry in recent years [3–5]. In comparison to traditional failure maintenance and planned maintenance approaches, predictive maintenance (PdM) leverages forecasted information of remaining useful life (RUL) to implement maintenance strategies, thereby reducing operation and maintenance costs while ensuring the safe and reliable operation of devices [6].

The data-driven method serves as the fundamental and pivotal component for PdM decision-making, encompassing both statistical data-driven methods and machine learning-based methods [7,8]. By leveraging extensive monitoring data pertaining to the health

status of systems, the machine learning-based method can obtain the predictive information of devices' RUL, thereby formulating more efficient maintenance strategies [9]. For instance, Nguyen et al. [10] initially presented a dynamic PdM framework that utilizes deep learning for failure prognostics. In this framework, a long short-term memory network is employed to estimate the probability of system failure, enabling real-time decision-making by promptly evaluating maintenance and spare parts costs. To elucidate prognostic uncertainties, Zhuang et al. [11] proposed a Bayesian deep learning-based prognostic driven dynamic PdM framework that incorporates the latest predictive RUL information to update maintenance and spare part ordering decisions. This method exhibits the advantages of excellent universality and low implementation costs, but it is difficult to quantify the inherent uncertainty associated with the degradation process.

The statistical data-driven method aims to utilize statistical processes, such as the Wiener process, Gamma process, and inverse Gaussian process, to construct a degradation model that describes the trajectory of devices' degradation [10,12,13]. In contrast to the machine learning-based method, it can derive the probability density function (PDF) of RUL and facilitate subsequent maintenance activities. Specifically, due to its mathematical properties and nonmonotonicity, the degradation model based on the Wiener process has attracted widespread attention from academia and industry [14–16]. However, in the aforementioned PdM studies, it is commonly assumed that prediction and maintenance are relatively independent components, i.e., that the prediction results only serve as guidance for maintenance activities, while neglecting the influence of maintenance activities on RUL prediction throughout the entire lifecycle. If preventive maintenance is carried out before the device's failure, it can effectively reduce the operational risk of devices and extend their RUL. Therefore, it is imperative to study the RUL prediction problem while incorporating maintenance activities.

Based on the description of maintenance activities in previous work [17], they can typically be categorized as perfect maintenance, minor repair, and imperfect maintenance. Specifically, perfect maintenance reinstates degraded indicators that reflect the device's health condition to the pristine state, which is difficult to achieve in practical engineering. Minor repairs can only slightly improve the health condition of devices to a certain extent. Imperfect maintenance can partially mitigate the device's degraded condition but falls short of fully restoring it to an optimal state, occupying a position between minor repairs and perfect maintenance. Compared to perfect maintenance and minor repairs, the majority of preventive maintenance in practical engineering is classified as imperfect maintenance based on industry standards, which has attracted extensive attention from researchers. For example, Kijima [18] and Nakagawa [19] utilized the virtual age model and the risk increase model, respectively, to depict the impact of imperfect maintenance on degradation processes. Based on this foundation, Zhou et al. [20] integrated the aforementioned models to develop a hybrid model that incorporates imperfect maintenance, thereby substantiating the rationality of the proposed model through numerical illustrations.

However, the aforementioned model fails to incorporate the performance degradation data acquired during the device's operation, thereby compromising the accuracy of decision optimization. To address this issue, statistical data-driven methods incorporating imperfect maintenance are widely employed. Guo et al. [21] first established a maintenance decision model based on the Wiener process, which introduces a residual degradation model to characterize the impact of imperfect maintenance on degrading devices. To account for the impact of imperfect maintenance on the degradation rate, Zhang et al. [22] introduced a stochastic enhancement factor to establish a novel model that incorporates the effects of imperfect maintenance. Wang et al. [23] proposed a Wiener process model that incorporates negative jumps to predict the device's RUL during maintenance activities, which solely

considers the impact of maintenance activities on the degradation state, without taking into account their influence on the degradation rate. The accurate description of the degradation process for repairable degrading devices necessitates considering the influence of maintenance activities on both the degradation state and rate. Hu et al. [24,25] established a degradation model that incorporates the impact of imperfect maintenance activities on both the rate and state of degradation. Based on this foundation, Ma et al. [26] constructed a multi-phase Wiener-process-based degradation model to characterize the degradation process subjected to imperfect maintenance activities. Pang et al. [27] proposed an adaptive RUL prediction method by employing a multi-stage diffusion process to address the challenge of individual variability among degraded devices with imperfect maintenance.

However, the aforementioned methods typically employ an autoregressive model of order 1, i.e., AR(1), to accomplish the adaptive drift of degradation modeling, which is primarily applicable to scenarios of equispaced monitoring of degraded devices. Furthermore, it is important to note that this model fails to account for the variability in adaptive drift during future degradation processes, which consequently affects the accuracy of RUL predictions [28]. To address this problem, this paper proposes an adaptive-Wiener-process-based method for RUL prediction with imperfect maintenance activities. Firstly, an adaptive Wiener process model is developed to depict the multi-stage degradation process incorporating imperfect maintenance. The PDFs of RUL can be derived based on the concept of first hitting time (FHT) and a convolution operator. Subsequently, taking into account the impact of imperfect maintenance on the degradation state and rate, the maximum likelihood estimation (MLE) method is employed for the offline estimation of model parameters, while Bayesian inference is utilized for online parameter updating. Finally, the effectiveness of the proposed method is verified by simulation examples and case studies of repairable gyroscopes. Compared to the work in [25], the primary innovation of this paper is the implementation of an online updating mechanism for model parameters that explicitly accounts for individual variation. Compared with [27], the main innovation of this paper lies in achieving the adaptive drift of future degradation processes. In summary, the primary contribution of this paper is the integration of the adaptive Wiener model with imperfect maintenance strategies, resulting in a comprehensive composite degradation model that incorporates individual variations and enables online updates of model parameters, thereby enhancing the accuracy of RUL prediction.

The remaining parts of this paper are organized as follows. Section 2 demonstrates the study's motivation and provides the general framework of the degradation model. In Section 3, we introduce the RUL prediction method incorporating imperfect maintenance. Section 4 provides the main results of model parameter identification and updating. Section 5 validates the proposed method by simulation examples and case studies of repairable gyroscopes. Section 6 summarizes the whole paper.

2. Motivation and Degradation Modeling

2.1. Motivation

In engineering practice, there are typically two categories of thresholds in PdM activities. The first category is the preventive maintenance threshold ω_p, which can be optimized and determined using the maintenance decision model. The second category is the failure threshold ω, which is typically established through the device's design manuals, industry standards, and expert knowledge. In order to determine appropriate maintenance activities, we can compare the degradation state $X(t)$ with both the preventive maintenance threshold ω_p and failure threshold ω. When the degradation state is below the preventive maintenance threshold, i.e., $X(t) < \omega_p$, the devices operate normally and require no preventive maintenance. When the degradation state falls within the range between the preventive

maintenance threshold and the failure threshold, i.e., $\omega_p \leq X(t) < \omega$, it indicates that the devices require preventive maintenance. When the degradation state $X(t)$ exceeds the failure threshold ω, device failure will occur, and preventive maintenance needs to involve replacement with spare parts.

The cost of preventive maintenance activities is usually influenced by the number of maintenance activities. To ensure the reliability and cost-effectiveness of device operation, maintenance activities are typically constrained in number. Preventive replacement will be implemented instead of preventive maintenance if the degradation state $X(t)$ exceeds the preventive threshold ω_p after the Nth imperfect maintenance activity. The degradation trajectory for repairable degrading devices is illustrated in Figure 1 [24–27].

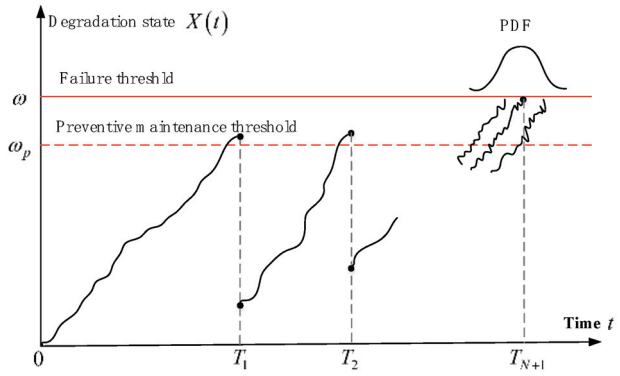


Figure 1. The degradation trajectory in the presence of imperfect maintenance. Where, ω_p and ω represent the preventive maintenance threshold and failure threshold, respectively. T_i denotes the time of the ith imperfect maintenance activity, while N indicates the number of imperfect maintenance activities. It can be observed from Figure 1 that the state and rate of the degradation process are affected by imperfect maintenance.

It is worth noting that the degradation rate undergoes changes as the working time continuously accumulates. Nevertheless, existing methods often ignore the adaptive drift variability in future degradation processes, which may affect the accuracy of RUL prediction. Therefore, the focus of this study is to derive the analytical form of the RUL distribution and estimate unknown parameters of the degradation model while considering the impact of imperfect maintenance activities on the degradation state and rate. Based on the actual project requirements, the following reasonable assumptions are made regarding the current situation:

(1) The assumption is made that the same batch of degrading devices consists of M components, with each component functioning independently and exhibiting individual variability in the degradation process. Δt denotes the detection interval, which is usually considered negligible.
(2) The preventive maintenance activities for devices are imperfect maintenance activities, and the number of such activities is limited.
(3) The lifetime and RUL discussed in this study are mainly concerned with the working time of the devices, without taking into account the downtime resulting from preventive maintenance activities.
(4) The degradation processes of components, both prior to and following preventive maintenance activities, are assumed to be statistically independent.

2.2. Degradation Model Incorporating Imperfect Maintenance

The degradation model based on the Wiener process is a stochastic model with non-monotonic properties, which has been employed in the fields of RUL prediction and

reliability assessment [29,30]. The adaptive Wiener process, as an improved version of the Wiener process, offers significant advantages in dealing with nonuniform measurements and adaptive drift problems. Therefore, it has been widely employed for degradation modeling, aiming to enhance the generality of the degradation model. In particular, an adaptive Wiener process satisfies [28]

$$\begin{aligned} &\lambda(t) = \lambda_0 + \kappa W(t) \\ &X(t) = X(0) + \int_0^t \lambda(\tau) d\mu(\tau, \theta) + \sigma_B B(t) \end{aligned} \tag{1}$$

where $\lambda(t)$ represents a time-varying drift term that follows a Wiener process. λ_0 denotes the initial drift rate, and κ signifies the diffusion coefficient of the adaptive drift term. $\mu(\tau, \theta)$ is a nonlinear function with time t, $W(t)$ corresponds to a standard Brownian motion independent of $B(t)$, and σ_B indicates the diffusion coefficient. If $\kappa = 0$, the model in Equation (1) can be transformed into a Wiener process model with AR(1).

Under the framework of stochastic degradation modeling, the lifetime T in the concept of FHT can be defined as [31]

$$T = \inf\{t : X(t) \geq w | X(0) < w) \tag{2}$$

where w denotes the failure threshold of the devices, and $X(0)$ is the initial degradation state.

Owing to the impact of imperfect maintenance activities, the degradation model of repairable devices is conducted based on the multi-stage Wiener process. When the devices undergo $i-1$ preventive maintenance activities, the degradation process in the ith stage $X_i(t)$ satisfies

$$\begin{cases} \lambda_i = \lambda_{i0} + \kappa_i W(\Delta T_i) \\ X_i(t) = z_i + \lambda_i \mu(\Delta T_i, \theta) + \kappa_i \int_{T_{i-1}}^t W(\tau) d\mu(\tau, \theta) + \sigma_B B(\Delta T_i) \end{cases} \tag{3}$$

where T_i indicates the time of the ith preventive maintenance activity. $0 \leq i \leq N$ is the number of maintenance activities performed on the devices before time T_i, and $\Delta T_i = t - T_{i-1}$. N denotes the upper limited number of preventive maintenance activities. z_i represents the residual degradation state after $i-1$ maintenance activities, that is, the initial value of the ith degradation stage. λ_i represents the drift term of the ith degradation stage, λ_{i0} is the initial drift rate, κ_i is the diffusion coefficient of the adaptive drift term, and $W(\cdot)$ is a standard Brownian motion independent of $B(\cdot)$. σ_B represents the diffusion coefficient of the whole degradation stage. If residual degradation $z_i = 0$, Equation (3) can be regarded as perfect maintenance; i.e., the special case of imperfect maintenance can still be carried out for parameter identification and RUL prediction.

In this paper, the impacts of preventive maintenance on the degradation state and rate are primarily considered. Specifically, the impact on the degradation state can be represented by the residual degradation state z_i, while the impact on the degradation rate is denoted as the stage degradation rate λ_i. Firstly, to depict the impact of maintenance activities on the degradation state, the residual degradation state z_i is commonly assumed to follow a Gaussian distribution. After $i-1$ maintenance activities, the probability density function (PDF) of the residual degradation state z_i can be defined as [25]

$$f(z_i) = \frac{a^{i-1}b}{1 - \exp\left(-ba^{i-1}\right) w_p} \times \exp\left[-\frac{a^{i-1}b\left(w_p - z_i\right)}{w_p} \right] \mathbb{I}(z_i) \tag{4}$$

where a and b represent hyperparameters. $\mathbb{I}(z_i)$ denotes a value function, and

$$\mathbb{I}(z_i) = \begin{cases} 1, & z_i \in [0, w_p] \\ 0, & \text{else} \end{cases} \tag{5}$$

If $z_i < 0$, it indicates a negative degradation state of the device after maintenance activities, which contradicts the fundamental law governing the degradation process of devices. If $z_i = 0$, it signifies that the device reverts to a new degradation state following perfect maintenance activities, which deviates from the research in this paper. If $z_i \geq \omega_p$, it indicates that the degradation state of the component remains unchanged or even exceeds the preventive maintenance threshold after maintenance activities. This means that these maintenance activities lose their significance in ensuring the safe and reliable operation of the devices and extending their service life, which contradicts objective reality.

Subsequently, to accurately depict the influence of maintenance activities on the degradation rate λ_i, a change coefficient of the degradation rate ζ_i was introduced to facilitate subsequent derivation of the RUL distribution under conditions where the degradation model aligns with objective reality, which can be defined by

$$\lambda_i = \zeta_i \lambda_1 \tag{6}$$

where ζ_i is the change coefficient after $i-1$ maintenance activities, i.e., $\zeta_i \sim \left(i\mu_\zeta, \sigma_\zeta^2\right)$. The degradation rate of the first stage, denoted by λ_1, represents the inherent degradation rate in the absence of any maintenance activities, i.e., $\zeta_1 = 1$. In the $2 \leq i \leq N$ stage degradation process, the degradation rate of the devices satisfies $\lambda_i \sim N\left(\mu_{\lambda_i}, \sigma_{\lambda_i}^2\right)$, where $\mu_{\lambda_i} = i\mu_\zeta \lambda_{10}$ and $\sigma_{\lambda_i}^2 = \sigma_\zeta^2 \lambda_{10}^2$.

3. RUL Prediction Incorporating Imperfect Maintenance

Let $\boldsymbol{X}_{i,0:t_k} = \{x_{i,0}, x_{i,1}, \cdots, x_{i,t_k}\}$ represent the condition monitoring (CM) data in the ith degradation stage. According to the definition of FHT, the lifetimes R_{i,ω_p} and $R_{i,\omega}$ when degradation first reaches the thresholds for preventive maintenance and failure can be defined as

$$\begin{aligned} R_{i,w_p} &= \inf\left(r_{i,w_p} | X(t_{i,0} + r_i) \geq w_p | X(t_{i,0}) < w_p\right) \\ R_{i,w} &= \inf(r_{i,w} | X(t_{i,0} + r_i) \geq w | X(t_{i,0}) < w) \end{aligned} \tag{7}$$

where r_{i,w_p} represents the working time after $i-1$ preventive maintenance activities which the preventive maintenance threshold ω_p is first reached. $r_{i,w}$ represents the working time after $i-1$ preventive maintenance activities which the failure threshold ω is first reached. Considering the individual variability in the same batch of devices, the adaptive drift term λ_i is randomized and satisfies $\lambda_i \sim N\left(\mu_{\lambda_i}, \sigma_{\lambda_i}^2\right)$.

Owing to the inherent stochastic nature of Brownian motion, the lifetime $R_{i,\omega}$ can be identified as a random variable that follows an inverse Gaussian distribution. Thus, the conditional PDF of the predicted lifetime can be expressed as

$$\begin{aligned} &f_{R_{i,\omega}|\lambda_i}(r_{i,\omega}|\lambda_i) = \frac{1}{\sqrt{2\pi\varphi(r_{i,\omega})}} \times \exp\left\{ -\frac{\left[\omega - \int_0^{r_{i,\omega}} \lambda_i d\mu(\tau,\theta)\right]^2}{2\varphi(r_{i,\omega})} \right\} \\ &\left[\frac{\omega - \int_0^{r_{i,\omega}} \lambda_i d\mu(\tau,\theta)}{\varphi(r_{i,\omega})} \varphi'(r_{i,\omega}) + \lambda_i \mu'(r_{i,\omega},\theta) \right] \\ &\varphi(r_{i,\omega}) = \kappa^2 \int_0^{r_{i,\omega}} \left(\mu(r_{i,\omega},\theta) - \mu(\tau,\theta)\right)^2 d\tau + \sigma_B^2 r_{i,\omega} \\ &\varphi'(r_{i,\omega}) = d\varphi(r_{i,\omega})/dr_{i,\omega} = 2\kappa^2 \int_0^{r_{i,\omega}} \left(\mu(r_{i,\omega},\theta) - \mu(\tau,\theta)\right) d\tau + \sigma_B^2 \end{aligned} \tag{8}$$

To consider the individual variation in devices, we introduce Lemma 1, as presented in our previous work [32], to tackle the aforementioned integral.

Lemma 1 [32]. *If* $p \sim N(u, \sigma^2)$, $A, B \in \mathbb{R}$, *and* $C \in \mathbb{R}^+$, *then the following formula holds:*

$$E_p\left[(A-p)\exp\left(-\frac{(B-p)^2}{2C}\right)\right] = \sqrt{\frac{C}{\sigma^2+C}}\left(A-\frac{\sigma^2 B+uC}{\sigma^2+C}\right)\cdot\exp\left(-\frac{(B-u)^2}{2(\sigma^2+C)}\right) \quad (9)$$

Therefore, owing to Lemma 1 and the full probability formula, the PDF and cumulative density function (CDF) for lifetimes R_{i,ω_p} and $R_{i,\omega}$ that consider the influence of imperfect maintenance activities can be derived, respectively:

$$\begin{aligned}
&f_{R_{i,\omega_p}}\left(r_{i,\omega_p} \mid z_i\right) = \frac{1}{\sqrt{2\pi\left(\varphi(r_{i,\omega_p})+\sigma_{\lambda_i}^2\mu^2\left(r_{i,\omega_p},\theta\right)\right)}} \times \exp\left\{-\frac{\left(\omega_p - z_i - \mu_{\lambda_i}\mu\left(r_{i,\omega_p},\theta\right)\right)^2}{2\left(\varphi(r_{i,\omega_p})+\sigma_{\lambda_i}^2\mu^2\left(r_{i,\omega_p},\theta\right)\right)}\right\} \\
&\left(\frac{\varphi'(r_{i,\omega_p})}{\varphi(r_{i,\omega_p})}(\omega_p - z_i) + \left(\mu'\left(r_{i,\omega_p},\theta\right) - \frac{\varphi'(r_{i,\omega_p})}{\varphi(r_{i,\omega_p})}\mu\left(r_{i,\omega_p},\theta\right)\right)\frac{\varphi(r_{i,\omega_p})\mu_{\lambda_i} + (\omega_p - z_i)\sigma_{\lambda_i}^2\mu\left(r_{i,\omega_p},\theta\right)}{\varphi(r_{i,\omega_p})+\sigma_{\lambda i}^2\mu^2\left(r_{i,\omega_p},\theta\right)}\right) \\
&\mu_{\lambda_i} = i\mu_\zeta\lambda_{10}, \sigma_{\lambda_i}^2 = \sigma_\zeta^2\lambda_{10}^2 \\
&\varphi(r_{i,\omega_p}) = \kappa^2\int_0^{r_{i,\omega_p}}\left(\mu\left(r_{i,\omega_p},\theta\right) - \mu(\tau,\theta)\right)^2 d\tau + \sigma_B^2 r_{i,\omega_p} \\
&\varphi'(r_{i,\omega_p}) = \frac{d\varphi(r_{i,\omega_p})}{dr_{i,\omega_p}} = 2\kappa^2\int_0^{r_{i,\omega_p}}\left(\mu\left(r_{i,\omega_p},\theta\right) - \mu(\tau,\theta)\right)d\tau + \sigma_B^2
\end{aligned} \quad (10)$$

$$\begin{aligned}
F_{i,w_p}\left(r_{i,w_p} \mid z_i\right) &= P\left\{R_{i,w_p} < r_i \mid z_i\right\} \\
&= \Phi\left(\frac{-(w_p - z_i)+\mu_{\lambda_i}\mu\left(r_{i,\omega_p},\theta\right)}{\sqrt{\varphi'(r_{i,\omega_p})+\sigma_{\lambda_i}^2\mu^2\left(r_{i,\omega_p},\theta\right)}}\right) + \exp\left(\frac{2\mu_{\lambda_i}(w_p - z_i)}{\varphi'(r_{i,\omega_p})} + \frac{2\sigma_{\lambda_i}^2(w_p - z_i)}{\varphi'(r_{i,\omega_p})^2}\right) \\
&\times\Phi\left(-\frac{2\sigma_{\lambda_i}^2(w_p - z_i)\mu\left(r_{i,\omega_p},\theta\right)+\varphi'(r_{i,\omega_p})^2\left(\mu_{\lambda_i}\mu\left(r_{i,\omega_p},\theta\right)+w_p\right)}{\varphi'(r_{i,\omega_p})\sqrt{\varphi(r_{i,\omega_p})+\sigma_{\lambda_i}^2\mu^2\left(r_{i,\omega_p},\theta\right)}}\right)
\end{aligned} \quad (11)$$

Furthermore, the PDF and CDF for lifetime $R_{i,\omega}$ exhibit similar mathematical forms. On the basis of deducing the lifetime distribution in the $i-1$ th stage of imperfect maintenance, it can be observed from the previous assumptions that when considering the impact of imperfect maintenance, the lifetime mainly consists of two parts. One is the cumulative working time in stage $1 \le i \le N$, which refers to the duration until the degradation state reaches the preventive maintenance threshold for the first time after each imperfect maintenance activity. The other one is the working time when the degradation state first reaches the failure threshold in stage $N+1$. In this case, the whole lifetime T can be expressed as follows:

$$T = \sum_{i=1}^{N} R_{i,\omega_p} + R_{N+1,\omega} \quad (12)$$

When the degradation state $X_{i,k}$ at time $t_{i,k}$ is provided in the ith stage, the corresponding RUL can be defined as

$$R_{i,k} = \inf\left(r_{i,k} \middle| X(t_{i,k}+r_i) \ge w_p \middle| X(t_{i,k}) < w_p\right) \quad (13)$$

where $f_{R_{i,k}|\boldsymbol{X}_{i,0:k}}\left(r_{i,k}\middle|\boldsymbol{X}_{i,0:k}\right)$ denotes the PDF of stage RUL at time $t_{i,k}$.

Similarly, the whole RUL corresponding to the component at time $t_{i,k}$ satisfies

$$L_{i,k} = R_{i,k} + \mathbb{I}(i) \sum_{m=1}^{N-i+1} R_{i+m} \tag{14}$$

where $\mathbb{I}(i)$ is the value function, satisfying

$$\mathbb{I}(i) = \begin{cases} 1, & 1 \le i \le N \\ 0, & i = N+1 \end{cases} \tag{15}$$

Let $f_{L_{i,k}|\boldsymbol{X}_{1:i,0:k}}(l_{i,k}|\boldsymbol{X}_{1:i,0:k})$ denote the PDF of the whole RUL at time $t_{i,k}$. According to the knowledge of probability theory and the convolution operator, the PDF of the device's RUL incorporating imperfect maintenance can be specifically expressed as follows:

$$\begin{cases} f_{L_{i,k}|\boldsymbol{X}_{1:i,0:k}}(l_{i,j} \mid \boldsymbol{X}_{1:i,0:k}) = f_{L_{N+1,k}|X_{N+1,0:k}}(l_{N+1,k} \mid \boldsymbol{X}_{N+1,0:k}), \quad i = N+1 \\ f_{L_{i,k}|\boldsymbol{X}_{1:i,0:k}}(l_{i,j} \mid \boldsymbol{X}_{1:i,0:k}) = f_{R_{i,k}|X_{i,0:k}}(r_{i,k} \mid \boldsymbol{X}_{i,0:k}) \otimes f_{R_{i+1,\omega_p}|X_{i+1,0:K_{i+1}}}\left(r_{i+1,\omega_p} \mid \boldsymbol{X}_{i+1,0:K_{i+1}}\right) \\ \otimes \cdots \otimes f_{R_{N+1,\omega}|X_{N+1,0:K_{N+1}}}\left(r_{N+1,\omega} \mid \boldsymbol{X}_{N+1,0:K_{N+1}}\right), \quad 1 \leqslant i \leqslant N \end{cases} \tag{16}$$

where $\otimes$ represents the convolution symbol. Based on the aforementioned analysis, the RUL prediction of degrading devices incorporating imperfect maintenance can be divided into two cases, i.e., $i = N+1$ and $1 \le i \le N$.

(1). If $i = N+1$, it indicates that the device has undergone Nth imperfect maintenance activities. In this case, the stage RUL in the $N+1$ th stage $R_{N+1,k}$ is equivalent to the whole RUL of devices $L_{N+1,k}$, and the PDFs of RUL can be further expressed as

$$\begin{aligned} &f_{L_{N+1,k}|\lambda_{N+1,k}}(l_{N+1,k} \mid \lambda_{N+1,k}) \\ &= \frac{1}{\sqrt{2\pi\left(\varphi(l_{N+1,k}) + \sigma^2_{\lambda_{N+1}}\mu^2(l_{N+1,k},\theta)\right)}} \exp\left\{ -\frac{\left(\omega - x_{N+1,k} - \mu_{\lambda_{N+1}}\mu(l_{N+1,k},\theta)\right)^2}{2\left(\varphi(l_{N+1,k}) + \sigma^2_{\lambda_{N+1}}\mu^2(l_{N+1,k},\theta)\right)} \right\} \\ &\times \begin{pmatrix} \dfrac{\varphi'(l_{N+1,k})}{\varphi(l_{N+1,k})}(\omega - x_{N+1,k}) + \left(\mu'(l_{N+1,k},\theta) - \dfrac{\varphi'(l_{N+1,k})}{\varphi(l_{N+1,k})}\mu(l_{N+1,k},\theta)\right) \\ \dfrac{\varphi(l_{N+1,k})\mu_{\lambda_{N+1}} + (\omega - x_{N+1,k})\sigma^2_{\lambda_{N+1}}\mu(l_{N+1,k},\theta)}{\varphi(l_{N+1,k}) + \sigma^2_{\lambda_{N+1}}\mu^2(l_{N+1,k},\theta)} \end{pmatrix} \\ &\mu_{\lambda_{N+1}} = (N+1)\mu_\zeta\lambda_{10}, \sigma^2_{\lambda_{N+1}} = \sigma^2_\zeta\lambda^2_{10} \\ &\varphi(l_{N+1,k}) = \kappa^2\int_0^{l_{N+1,k}} [\mu(l_{N+1,k},\theta) - \mu(\tau,\theta)]^2 d\tau + \sigma^2_B l_{N+1,k} \\ &\varphi'(l_{N+1,k}) = \frac{d\varphi(l_{N+1,k})}{dl_{N+1,k}} = 2\kappa^2\int_0^{l_{N+1,k}} [\mu(l_{N+1,k},\theta) - \mu(\tau,\theta)]d\tau + \sigma^2_B \end{aligned} \tag{17}$$

(2). If $1 \le i \le N$, $f_{R_{i,k}|\lambda_{i,k}}(r_{i,k} \mid \lambda_{i,k})$, $f_{R_{i+j}|\lambda_{i+j,k}}\left(r_{i+j} \mid \lambda_{i+j,k}\right)$, and $f_{R_{N+1}|\lambda_{N+1,k}}(r_{N+1} \mid \lambda_{N+1,k})$ represent the PDF of the stage RUL at time $t_{i,k}$, the PDF of operational time R_{i+j} in the $i+j$ $(1 \le j \le N-i)$ th stage, and the PDF of operational time in the $N+1$ th stage, respectively. Based on the RUL distribution in an adaptive Wiener process, the PDFs of RUL can be derived as

$$f_{R_{i,k}|\lambda_{i,k}}(r_{i,k} \mid \lambda_{i,k}) = \frac{1}{\sqrt{2\pi\left(\varphi(r_{i,k}) + \sigma_{\lambda_i}^2 \mu^2(r_{i,k},\theta)\right)}} \times \exp\left\{ -\frac{\left(\omega_p - x_{i,k} - \mu_{\lambda_i}\mu(r_{i,k},\theta)\right)^2}{2\left(\varphi(r_{i,k}) + \sigma_{\lambda_i}^2 \mu^2(r_{i,k},\theta)\right)} \right\}$$
$$\left(\frac{\varphi'(r_{i,k})}{\varphi(r_{i,k})}(\omega_p - x_{i,k}) + \left(\mu'(r_{i,k},\theta) - \frac{\varphi'(r_{i,k})}{\varphi(r_{i,k})}\mu(r_{i,k},\theta) \right) \frac{\varphi(r_{i,k})\mu_{\lambda_i} + (\omega - x_{i,k})\sigma_{\lambda_{N+1}}^2 \mu(r_{i,k},\theta)}{\varphi(r_{i,k}) + \sigma_{\lambda_i}^2 \mu^2(r_{i,k},\theta)} \right) \tag{18}$$
$$\mu_{\lambda_i} = i\mu_\zeta \lambda_{10}, \sigma_{\lambda_i}^2 = \sigma_\zeta^2 \lambda_{10}^2$$
$$\varphi(r_{i,k}) = \kappa^2 \int_0^{r_{i,k}} [\mu(r_{i,k},\theta) - \mu(\tau,\theta)]^2 d\tau + \sigma_B^2 r_{i,k}$$
$$\varphi'(r_{i,k}) = \frac{d\varphi(r_{i,k})}{dr_{i,k}} = 2\kappa^2 \int_0^{r_{i,k}} [\mu(r_{i,k},\theta) - \mu(\tau,\theta)] d\tau + \sigma_B^2$$

$$f_{R_{i+j}|\lambda_{i+j,k}}\left(r_{i+j} \mid \lambda_{i+j,k}\right) = \frac{1}{\sqrt{2\pi\left(\varphi(r_{i+j}) + \sigma_{\lambda_{i+j}}^2 \mu^2(r_{i+j},\theta)\right)}} \times \exp\left\{ -\frac{\left(\omega_p - z_{i+j} - \mu_{\lambda_{i+j}}\mu(r_{i+j},\theta)\right)^2}{2\left(\varphi(r_{i+j}) + \sigma_{\lambda_{i+j}}^2 \mu^2(r_{i+j},\theta)\right)} \right\}$$
$$\left(\frac{\varphi'(r_{i+j})}{\varphi(r_{i+j})}(\omega_p - z_{i+j}) + \left(\mu'(r_{i+j},\theta) - \frac{\varphi'(r_{i+j})}{\varphi(r_{i+j})}\mu(r_{i+j},\theta) \right) \frac{\varphi(r_{i+j})\mu_{\lambda_i+j} + (\omega - z_{i+j})\sigma_{\lambda_{i+j}}^2 \mu(r_{i+j},\theta)}{\varphi(r_{i+j}) + \sigma_{\lambda_{i+j}}^2 \mu^2(r_{i+j},\theta)} \right) \tag{19}$$
$$\mu_{\lambda_{i+j}} = (i+j)\mu_\zeta \lambda_{10}, \sigma_{\lambda_{i+j}}^2 = \sigma_\zeta^2 \kappa^2 r_{i+j}$$
$$\varphi(r_{i+j}) = \kappa^2 \int_0^{r_{i+j}} \left[\mu(r_{i+j},\theta) - \mu(\tau,\theta)\right]^2 d\tau + \sigma_B^2 r_{i+j}$$
$$\varphi'(r_{i+j}) = \frac{d\varphi(r_{i+j})}{dr_{i+j}} = 2\kappa^2 \int_0^{r_{i+j}} \left[\mu(r_{i+j},\theta) - \mu(\tau,\theta)\right] d\tau + \sigma_B^2$$

$$f_{R_{N+1}|\lambda_{N+1,k}}(r_{N+1} \mid \lambda_{N+1,k}) = \frac{1}{\sqrt{2\pi\left(\varphi(r_{N+1}) + \sigma_{\lambda_{N+1}}^2 \mu^2(r_{N+1},\theta)\right)}} \times \exp\left\{ -\frac{\left(\omega - z_{N+1} - \mu_{\lambda_{N+1}}\mu(r_{N+1},\theta)\right)^2}{2\left(\varphi(r_{N+1}) + \sigma_{\lambda_{N+1}}^2 \mu^2(r_{N+1},\theta)\right)} \right\}$$
$$\left(\frac{\varphi'(r_{N+1})}{\varphi(r_{N+1})}(\omega - z_{N+1}) + \left(\mu'(r_{N+1},\theta) - \frac{\varphi'(r_{N+1})}{\varphi(r_{N+1})}\mu(r_{N+1},\theta) \right) \frac{\varphi(r_{N+1})\mu_{\lambda_{N+1}} + (\omega - z_{N+1})\sigma_{\lambda_{N+1}}^2 \mu(r_{N+1},\theta)}{\varphi(r_{N+1}) + \sigma_{\lambda_{N+1}}^2 \mu^2(r_{N+1},\theta)} \right) \tag{20}$$
$$\mu_{\lambda_{N+1}} = (N+1)\mu_\zeta \lambda_{10}, \sigma_{\lambda_{N+1}}^2 = \sigma_\zeta^2 \lambda_{10}^2$$
$$\varphi(r_{N+1}) = \kappa^2 \int_0^{r_{N+1}} [\mu(r_{N+1},\theta) - \mu(\tau,\theta)]^2 d\tau + \sigma_B^2 r_{N+1}$$
$$\varphi'(r_{N+1}) = \frac{d\varphi(r_{N+1})}{dr_{N+1}} = 2\kappa^2 \int_0^{r_{N+1}} [\mu(r_{N+1},\theta) - \mu(\tau,\theta)] d\tau + \sigma_B^2$$

4. Model Parameter Identification and Updating

Based on the degradation model (3) incorporating imperfect maintenance, the estimated parameters are denoted by $\boldsymbol{\Theta} = \left\{a, b, \lambda_{10}, \mu_\zeta, \sigma_\zeta^2, \kappa, \sigma_B^2, \theta\right\}$, where $\boldsymbol{\Theta_1} = \{a, b\}$ represents the hyperparameters of the residual degradation state z_i, and $\boldsymbol{\Theta_2} = \left\{\lambda_{10}, \mu_\zeta, \sigma_\zeta^2, \kappa, \sigma_B^2, \theta\right\}$ denotes the unknown parameters of the operational degradation model.

4.1. Parameter Estimation of Residual Degradation State

The estimation of residual degradation hyperparameters $\boldsymbol{\Theta_1} = \{a, b\}$ requires the collection of historical data on residual degradation after each imperfect maintenance activity. Assume that we have gathered the CM data from M devices and that each device has undergone N imperfect maintenance activities. Subsequently, let $\boldsymbol{Z}_{1:N}^j = \left\{z_1^j, z_2^j, \cdots z_N^j\right\}$ denote the historical residual degradation data of the jth device, where $1 \le j \le M$, $j \in \mathbb{N}^+$.

According to the definition of the residual degradation state in (4), the residual degradation coefficient of the ith stage can be expressed as

$$\gamma_i^j = z_i^j / \omega_p \tag{21}$$

where $1 \le i \le N$, and $\gamma_{1:N}^{j} = \left\{\gamma_1^j, \gamma_2^j, \cdots \gamma_N^j\right\}$ represents the residual coefficient of the jth device. Furthermore, the hyperparameter $\boldsymbol{\Theta_1} = \{a, b\}$ of the residual degradation state can be estimated utilizing the MLE algorithm, and its likelihood function can be presented as

$$\hat{\boldsymbol{\Theta}}_{\mathbf{1}} = \underset{\boldsymbol{\Theta_1}}{\operatorname{argmax}} \ell(\boldsymbol{\Theta_1}) = \underset{\boldsymbol{\Theta_1}}{\operatorname{argmax}} \left[-\frac{MN}{2}\ln 2\pi - \frac{MN}{2}\ln b - \frac{\sum_{j=1}^{M}\sum_{i=1}^{N}\left(\gamma_i^j - (1-\exp(-ai))\right)^2}{2b} \right] \tag{22}$$

where $\ell(\boldsymbol{\Theta_1})$ represents the log-likelihood function. The relationship between a and b can be derived by maximizing the likelihood function in (22).

$$b = \frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}\left(\gamma_i^j - (1-\exp(-ai))\right)^2 \tag{23}$$

Then, substituting the estimated value of b into Equation (23) can provide the maximum likelihood estimation result of parameter a.

4.2. Parameter Estimation of Degradation Model

The parameters $\boldsymbol{\Theta_2} = \left\{\lambda_{10}, \mu_\zeta, \sigma_\zeta^2, \kappa, \sigma_B^2, \theta\right\}$ can be estimated through the historical degradation data of repairable degrading devices. Let $\boldsymbol{X}_{0:N,k}^{j} = \left\{x_{0,0}^j, x_{0,1}^j, \cdots x_{N,k-1}^j, x_{N,k}^j\right\}$ denote the CM data of the jth device. Owing to the impact of the change coefficient $\zeta_i \sim N\left(i\mu_\zeta, \sigma_\zeta^2\right)$, the estimation of model parameters needs to be divided into two cases for analysis, i.e., $i = 1$ and $2 \le i \le N+1$.

(1). If $i = 1$, based on the degradation model (3) and the characteristics of the diffusion process, $\boldsymbol{X}_{0:N,k}^{j}$ is assumed to follow a multidimensional normal distribution, and its mean and covariance should be expressed.

$$\begin{aligned}&\left\{x_{1,k}^j \mid x_{1,k-1}^j, \lambda_{10}, \kappa, \sigma_B^2, \theta\right\} \sim \\ &N\left(x_{1,k-1}^j + \lambda_{10}\mu\left(t_{1,k}^j - t_{1,k-1}^j, \theta\right), \kappa^2\int_0^{t_{1,k}^j - t_{1,k-1}^j}\left[\mu\left(t_{1,k}^j - t_{1,k-1}^j, \theta\right) - \mu(\tau,\theta)\right]^2 d\tau + \sigma_B^2\left(t_{1,k}^j - t_{1,k-1}^j\right)\right)\end{aligned} \tag{24}$$

Therefore, the conditional probability distribution of $\left\{x_{1,k}^j \mid x_{1,k-1}^j, \lambda_{10}, \kappa, \sigma_B^2, \theta\right\}$ can be expressed as

$$\begin{aligned}p\left(x_{1,k}^j \mid x_{1,k-1}^j, \lambda_{10}, \sigma_B^2, \kappa\right) &= \frac{1}{\sqrt{2\pi\varphi\left(t_{1,k}^j - t_{1,k-1}^j\right)}}\left[\begin{array}{l}\frac{x_{1,k}^j - x_{1,k-1}^j - \lambda_{10}\mu\left(t_{1,k}^j - t_{1,k-1}^j, \theta\right)}{\varphi\left(t_{1,k}^j - t_{1,k-1}^j\right)} \\ \times\varphi'\left(t_{1,k}^j - t_{1,k-1}^j\right) + \lambda_{10}\mu'\left(t_{1,k}^j - t_{1,k-1}^j, \theta\right)\end{array}\right] \\ &\quad \times \exp\left\{-\frac{\left[x_{1,k}^j - x_{1,k-1}^j - \lambda_{10}\mu\left(t_{1,k}^j - t_{1,k-1}^j, \theta\right)\right]^2}{2\varphi\left(t_{1,k}^j - t_{1,k-1}^j\right)}\right\}\end{aligned} \tag{25}$$

where
$$\begin{aligned}&\varphi(t_{1,k}^j - t_{1,k-1}^j) = \kappa^2\int_0^{t_{1,k}^j - t_{1,k-1}^j}\left[\mu\left(t_{1,k}^j - t_{1,k-1}^j, \theta\right) - \mu(\tau,\theta)\right]^2 d\tau + \sigma_B^2\left(t_{1,k}^j - t_{1,k-1}^j\right) \\ &\varphi'(t_{1,k}^j - t_{1,k-1}^j) = \frac{d\varphi(t_{1,k}^j - t_{1,k-1}^j)}{d\left(t_{1,k}^j - t_{1,k-1}^j\right)} = 2\kappa^2\int_0^{t_{1,k}^j - t_{1,k-1}^j}\left[\mu\left(t_{1,k}^j - t_{1,k-1}^j, \theta\right) - \mu(\tau,\theta)\right]d\tau + \sigma_B^2\end{aligned}.$$

Based on the chain rule and the Markov property, the likelihood function of the degradation model can be derived from the CM data of the first stage as follows:

$$L\left(\lambda_{10},\sigma_B^2,\kappa,\theta\right) = \prod_{j=1}^{M}\prod_{k=1}^{k_i}\frac{1}{\sqrt{2\pi\varphi\left(t_{1,k}^j-t_{1,k-1}^j\right)}}\left[\begin{array}{c}\dfrac{x_{1,k}^j-x_{1,k-1}^j-\lambda_{10}\mu\left(t_{1,k}^j-t_{1,k-1}^j,\theta\right)}{\varphi\left(t_{1,k}^j-t_{1,k-1}^j\right)}\\ \times\varphi'\left(t_{1,k}^j-t_{1,k-1}^j\right)+\lambda_{10}\mu'\left(t_{1,k}^j-t_{1,k-1}^j,\theta\right)\end{array}\right] \times\exp\left\{-\frac{\left[x_{1,k}^j-x_{1,k-1}^j-\lambda_{10}\mu\left(t_{1,k}^j-t_{1,k-1}^j,\theta\right)\right]^2}{2\varphi\left(t_{1,k}^j-t_{1,k-1}^j\right)}\right\} \tag{26}$$

(2). If $2\le i\le N+1$, based on $\lambda_i=\zeta_i\lambda_1$ and $\zeta_i\sim N\left(i\mu_\xi,\sigma_\zeta^2\right)$, the conditional probability distribution of $\left\{x_{i,k}^j\mid x_{i,k-1}^j,\lambda_{10},\mu_\zeta,\sigma_\zeta^2,\kappa,\sigma_B^2\right\}$ can be obtained.

$$\begin{array}{l}p\left(x_{i,k}^j\mid x_{i,k-1}^j,\lambda_{10},\mu_\zeta,\sigma_\zeta^2,\kappa,\sigma_B^2\right)\\ =\frac{1}{\sqrt{2\pi G}}\left[\frac{x_{i,k}^j-x_{i,k-1}^j-i\mu_\zeta\lambda_{10}\mu\left(t_{i,k}^j-t_{i,k-1}^j,\theta\right)}{G}\varphi'\left(t_{i,k}^j-t_{i,k-1}^j\right)+i\mu_\zeta\lambda_{10}\mu'\left(t_{i,k}^j-t_{i,k-1}^j,\theta\right)\right]\\ \times\exp\left\{-\frac{\left[x_{i,k}^j-x_{i,k-1}^j-i\mu_\zeta\lambda_{10}\mu\left(t_{i,k}^j-t_{i,k-1}^j,\theta\right)\right]^2}{2G}\right\}\end{array} \tag{27}$$

where $G=\kappa^2\int_0^{t_{i,k}^j-t_{i,k-1}^j}\left[\mu\left(t_{i,k}^j-t_{i,k-1}^j,\theta\right)-\mu(\tau,\theta)\right]^2d\tau+\sigma_B^2\left(t_{i,k}^j-t_{i,k-1}^j\right)+\sigma_\zeta^2\int_{t_{i,k-1}^j}^{t_{i,k}^j}\lambda_{10}d\mu(\tau,\theta)$.

$\varphi'(t_{i,k}^j-t_{i,k-1}^j)=2\kappa^2\int_0^{t_{i,k}^j-t_{i,k-1}^j}\left[\mu\left(t_{i,k}^j-t_{i,k-1}^j,\theta\right)-\mu(\tau,\theta)\right]d\tau+\sigma_B^2$

Similarly, based on the chain rule and the Markov property, the likelihood function of the degradation model can be derived from the CM data of the ith stage as follows:

$$\begin{array}{l}L_i\left(\lambda_{10},\mu_{\zeta,}\sigma_\zeta^2,\kappa,\sigma_B^2\right)\\ =\prod_{j=1}^{M}\prod_{k=1}^{k_i}\frac{1}{\sqrt{2\pi G}}\left[\frac{x_{i,k}^j-x_{i,k-1}^j-i\mu_\zeta\lambda_{10}\mu\left(t_{i,k}^j-t_{i,k-1}^j,\theta\right)}{G}\varphi'\left(t_{i,k}^j-t_{i,k-1}^j\right)+i\mu_\zeta\lambda_{10}\mu'\left(t_{i,k}^j-t_{i,k-1}^j,\theta\right)\right]\\ \times\exp\left\{-\frac{\left[x_{i,k}^j-x_{i,k-1}^j-i\mu_\zeta\lambda_{10}\mu\left(t_{i,k}^j-t_{i,k-1}^j,\theta\right)\right]^2}{2G}\right\}\end{array} \tag{28}$$

According to the assumed condition, the degradation processes of devices at each stage are assumed to be mutually independent. Therefore, the likelihood function can be further constructed based on historical degradation data from M devices within the same batch.

$$L\left(\lambda_{10},\mu_{\zeta,}\sigma_\zeta^2,\kappa,\sigma_B^2,\theta\right)=L\left(\lambda_{10},\sigma_B^2,\kappa,\theta\right)\prod_{i=2}^{N+1}L_i\left(\lambda_{10},\mu_{\zeta,}\sigma_\zeta^2,\kappa,\sigma_B^2,\theta\right) \tag{29}$$

By maximizing the aforementioned Equation (29), we can obtain the maximum likelihood estimation of the unknown parameters $\boldsymbol{\Theta_2}=\left\{\lambda_{10},\mu_{\zeta,}\sigma_\zeta^2,\kappa,\sigma_B^2,\theta\right\}$ in the degradation model.

In addition, considering the random characteristics of the parameter ζ_i, after experiencing i instances of imperfect maintenance, the degradation data $\boldsymbol{X}_{i,0:k}=\left\{x_{i,0},x_{i,1},\cdots x_{i,k-1},x_{i,k}\right\}$ can be obtained at the current time $t_{i,k}$. Owing to the imper-

fect degradation model established in Equation (3) and the Bayesian chain rule, the joint probability density function of the degradation data $\boldsymbol{X}_{i,0:k}$ can be derived as follows:

$$p(X_{i,0:k} \mid \zeta_i) = \prod_{j=1}^{k} \frac{1}{\sqrt{2\pi\varphi(\Delta)}} \cdot \exp\left(-\frac{\left(X(t_{i,j}) - X(t_{i,j-1}) - \zeta_i\lambda_{10}\Delta\right)^2}{2\varphi(\Delta)}\right) \left[\frac{\left(X(t_{i,j}) - X(t_{i,j-1}) - \zeta_i\lambda_{10}\Delta\right)}{\varphi(\Delta)}\varphi'(\Delta) + \zeta_i\lambda_{10}\Delta'\right] \tag{30}$$

where $\Delta = \mu(t_{i,j} - t_{i,j-1}, \theta)$. Let the prior distribution of ζ_i be denoted by $p(\zeta_i)$, and $\zeta_i \sim \left(i\mu_{\zeta,i0}, \sigma^2_{\zeta,i0}\right)$ can be obtained by parameter updating after $i-1$ imperfect maintenance activities. Based on the Bayesian theorem, the posterior distribution of the random parameter ζ_i can be calculated as follows:

$$p(\zeta_i \mid X_{i,0:k}) \propto p(X_{i,0:k} \mid \zeta_i)p(\zeta_i) = p(X_{i,0:k} \mid \zeta_i) \cdot \frac{1}{\sqrt{2\pi\sigma^2_{\zeta,i0}}} \cdot \exp\left(-\frac{\left(\zeta_i - i\mu_{\zeta,i0}\right)^2}{2\sigma^2_{\zeta,i0}}\right) \tag{31}$$

5. Case Study

In this section, simulation cases and degradation data of repairable gyroscopes are employed to verify the validity of the proposed model. For the sake of experimental convenience, we designate the proposed method as M0, while we refer to the imperfect maintenance degradation model presented in previous work [25,27] as M1 and the degradation model that neglects the influence of imperfect maintenance discussed in [29] as M2. Although method M1 incorporates the impact of preventive maintenance activities on the device's degradation state and rate, it often fails to account for the variability in future degradation caused by adaptive drift.

5.1. Numerical Simulation

The degradation trajectory for the model described in Equation (6) can be generated through simulation using the Euler discretization method [33], while the model parameters are specified in Table 1. Firstly, let $\mu(\tau, \theta)$ denote the power-law function t^θ. By incorporating the model parameters from Table 1 into the degradation model, we can obtain four degradation trajectories, as depicted in Figure 2. The black solid line, #1, indicates the online test data, which are employed to verify the effect of the proposed method. The other dotted lines, #2–4, represent the historical degradation data that are employed for the offline estimation of model parameters.

Table 1. The values of model parameters.

Parameter	Values	Parameter	Values
Initial drift term λ_{10}	1.8	Residual degradation hyperparameter α	2
Diffusion coefficient of drift term κ	0.1	Residual degradation hyperparameter β	5
Change coefficient means μ_ζ	1.2	Maintenance frequency N	3
Standard deviation of coefficient change σ_ζ	0.3	Failure threshold ω	3.5
Diffusion coefficient σ_B	0.35	Preventive maintenance threshold ω_p	3
Time interval Δt	0.01	Nonlinear parameter θ	1.2

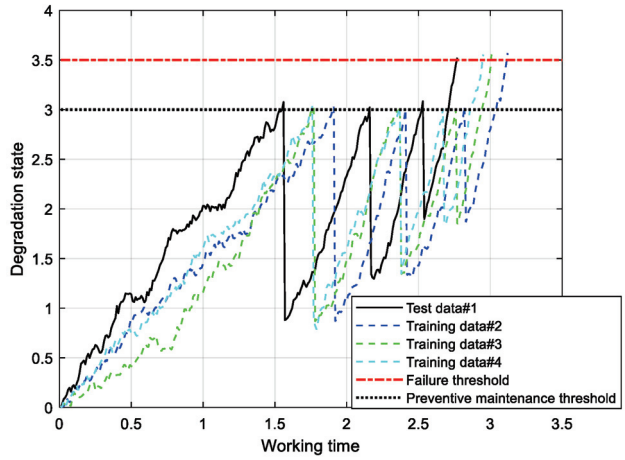


Figure 2. The degradation trajectory from numerical simulation.

Based on the degradation data from the numerical simulation, the results of RUL prediction can be obtained by M0, M1, and M2. In this study, four monitoring points ($t_k = 0.6$, $t_k = 1.8$, $t_k = 2.2$, and $t_k = 2.6$) were carefully selected for RUL prediction in the four degradation stages. In order to compare the accuracy of prediction results, Figure 3 provides the PDFs of RUL obtained from different methods. The solid black line represents the PDF of RUL obtained from M0, while the dotted green line corresponds to the PDF of RUL for M1, which is an imperfect maintenance method discussed in [25,27]. Additionally, the dotted blue line illustrates the PDF of RUL for M2, which does not account for any influence from maintenance activities.

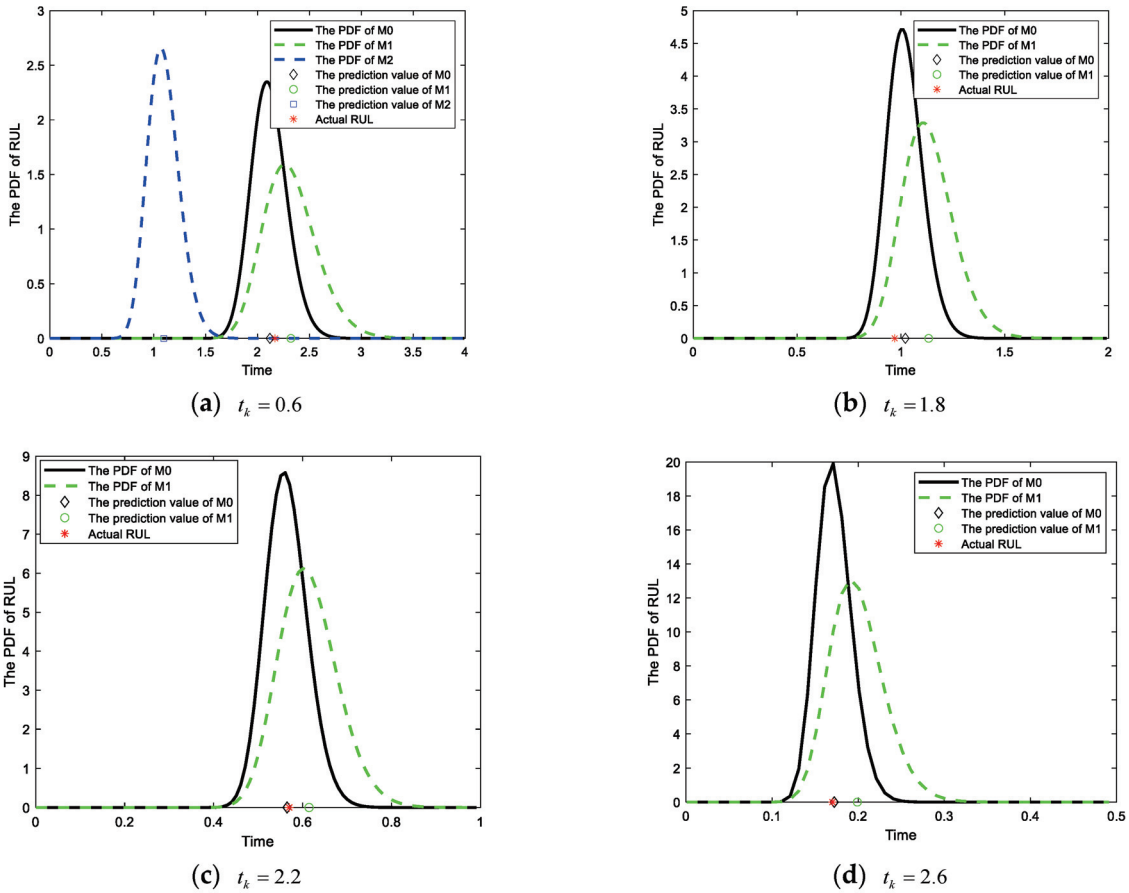


Figure 3. The PDFs and prediction results of RUL at the various time points.

When the monitoring time $t_k = 0.6$, the device has not undergone any maintenance activities, and the RUL at the corresponding time can be obtained from M0, M1, and M2. It can be observed from Figure 3a that M2 has disregarded the impact of subsequent maintenance activities on the degradation process. From the initial stage until reaching the failure threshold ω, there is a significant disparity between the predicted RUL and the actual RUL. The analysis of Figure 3 reveals that, in comparison with method M1, the proposed method M0 not only incorporates the influence of maintenance activities on the degradation process but also accounts for the variability in adaptive drift terms in future degradation processes. Consequently, the PDF of M0 exhibits a narrower and more pronounced shape, indicating reduced uncertainty in prediction results and closer alignment between the predicted RUL and the actual RUL. With the accumulation of degradation data on test samples, M0 can ensure the model parameters are continuously updated so that the RUL results always maintain a high prediction accuracy. In addition, to demonstrate the superiority of the adaptive Wiener process in the proposed method M0 over the AR(1) model in M1, the RUL distribution was obtained through Monte Carlo simulations of 2000 degenerate trajectories. The resulting distributions were then compared with the PDFs of methods M0 and M1, as illustrated in Figure 4. It is evident from the figure that the PDF of RUL obtained using method M0 aligns more closely with the RUL distribution derived from the Monte Carlo method. This suggests that the adaptive Wiener process model employed in M0 is more effective than the AR(1) model used in M1 for degradation modeling.

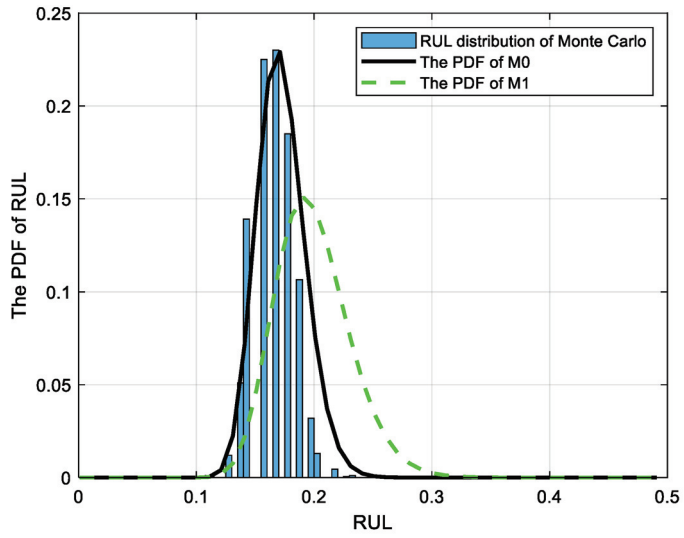


Figure 4. The comparison of RUL distributions.

To quantitatively analyze the RUL prediction results of these three methods, this paper presents the relative error (RE) and mean squared error (MSE) [34] of different methods at four monitoring points, as shown in Table 2. It can be observed from Table 2 that the proposed method M0 consistently exhibits superior prediction accuracy for RUL compared to method M1, with the former closely approximating the actual RUL. As a crucial metric for quantifying the uncertainty of prediction results, the smaller MSE corresponds to better-predicted results. The results presented in Table 2 demonstrate that the MSE of the proposed method M0 is consistently smaller than those of methods M1 and M2, thereby indicating superior prediction uncertainty.

Table 2. Relative error and mean squared error of RUL prediction.

Time t_k	RE of RUL Prediction			MSE of RUL Prediction		
	M0	**M1**	**M2**	**M0**	**M1**	**M2**
0.6	2.30%	11.62%	44.74%	0.0025	0.0626	0.9424
1.8	5.31%	16.87%	\	0.0026	0.0268	\
2.2	0.85%	7.82%	\	2.34×10^{-5}	0.002	\
2.6	1.27%	17.05%	\	4.67×10^{-6}	8.40×10^{-4}	\

After conducting three preventive maintenance activities, M0 and M1 were employed to predict the RUL of the device during the fourth stage, with detailed outcomes presented in Figure 5. It is not difficult to find from Figure 4 that, compared with the RUL prediction result obtained from M1, the RUL expectation of the proposed method M0 is closer to the actual RUL, and M0 demonstrates reduced uncertainty in the PDF of RUL. Through the aforementioned comparison, it is evident that, in contrast to method M1, the proposed method M0 incorporates considerations for the adaptive drift variability of the model, resulting in enhanced precision and reduced uncertainty in predicting RUL.

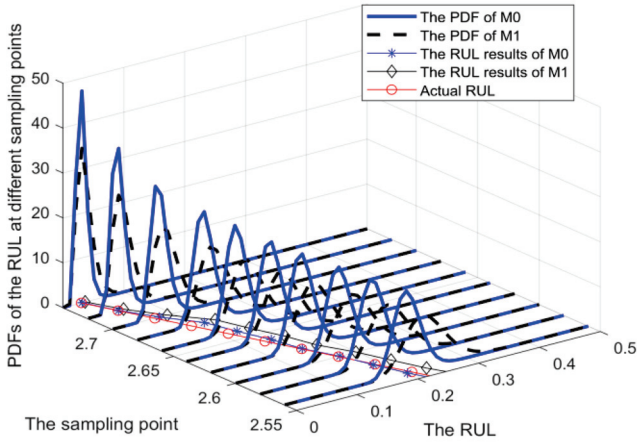


Figure 5. The PDFs and prediction results of RUL.

5.2. A Case Study of the Gyroscope

The performance of a gyroscope, which is the core component of an inertial navigation system (INS), directly affects the guidance accuracy and even the overall performance of the control system. During the operation of an INS, the high-speed rotation of the gyroscope rotor inevitably induces motor shaft wear. With the accumulation of working time, the drift coefficient of the gyroscope will increase from the deformation of the motor bearing. When the drift coefficient exceeds the threshold, it indicates the gyroscope's degradation and failure.

In order to prolong the operational duration of the gyroscope and ensure the secure and stable functioning of the INS, preventive maintenance activities are typically scheduled as follows. When the gyro drift coefficient exceeds the predetermined threshold for preventive maintenance, the hardware compensation circuit is utilized to effectively mitigate both the constant and primary terms of gyro drift. Considering that the majority of maintenance activities in practical engineering are characterized by imperfections, it is expected that the residual degradation state and degradation rate of devices will progressively increase following maintenance activities. When the maintenance effect fails to meet the operational requirements, the gyroscope will be replaced with spare parts. However, there is a limited number of maintenance activities throughout the entire degradation process.

The proposed method is verified in a practical case using the degradation data of an electromechanical gyroscope, as depicted in Figure 6. The degradation monitoring data of two gyroscopes are provided, which were monitored at a time interval of 2.5 h. According to the technical specifications of this type of inertial navigation system, the gyroscope drift coefficient failure threshold should be 0.37 (°)/h, while the preventive maintenance threshold should be set at 0.3 (°)/h. The degradation process, as depicted in Figure 6, underwent three rounds of correction and maintenance. Specifically, gyroscope #1 was monitored at 117 points, with an actual operational life of 282.5 h, while gyroscope #2 was monitored at 115 points, with an actual operational life of 277.5 h. The degradation data of the gyroscope gradually increase over time, and proactive maintenance activities should be conducted on the gyroscope when it reaches the preventive maintenance threshold to enhance its degradation state through compensation correction and other measures. However, residual degradation still persists, and the rate of degradation escalates further in subsequent stages. Further maintenance activities will not be conducted until the failure threshold is reached after completing the predetermined number of proactive maintenance tasks.

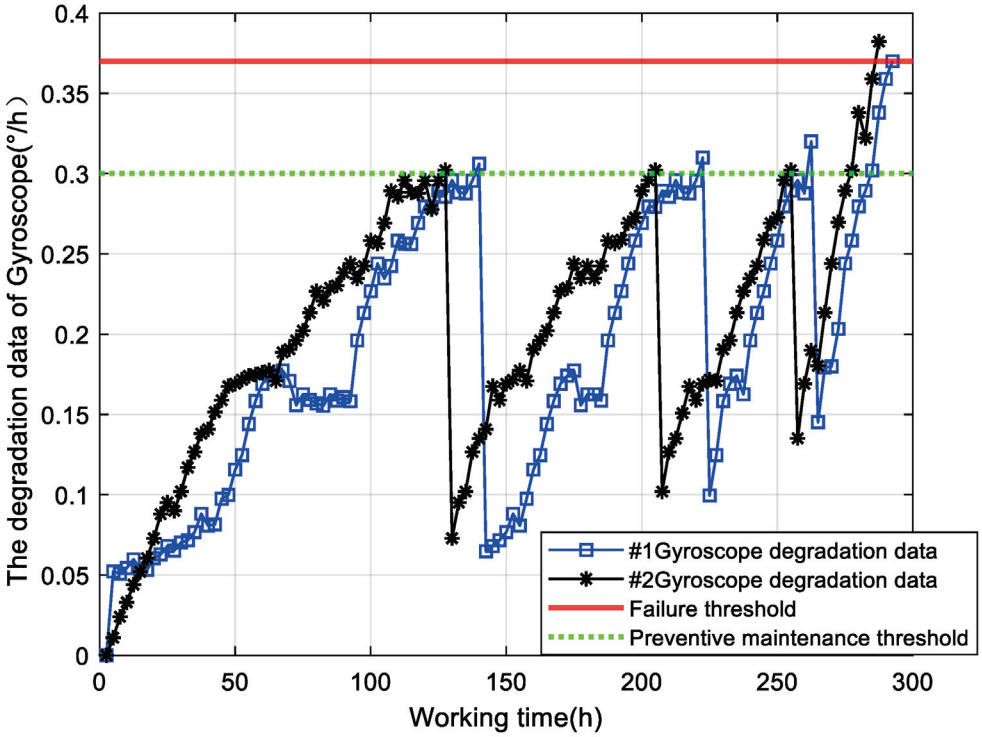


Figure 6. The degradation data under maintenance activities.

The degradation data of gyroscope #1 were employed as test samples in this paper to validate the proposed method M0. The RUL prediction results of the M0 and M1 methods can be compared after obtaining the model parameters $\boldsymbol{\Theta} = \left\{ a, b, \lambda_{10}, \mu_\zeta, \sigma_\zeta^2, \kappa, \sigma_B^2 \right\}$ through the parameter estimation method outlined in Section 4. Firstly, a monitoring point is selected in each of the first three stages to predict the RUL of gyroscope #1. The PDFs and prediction results of RUL are depicted in Figure 7.

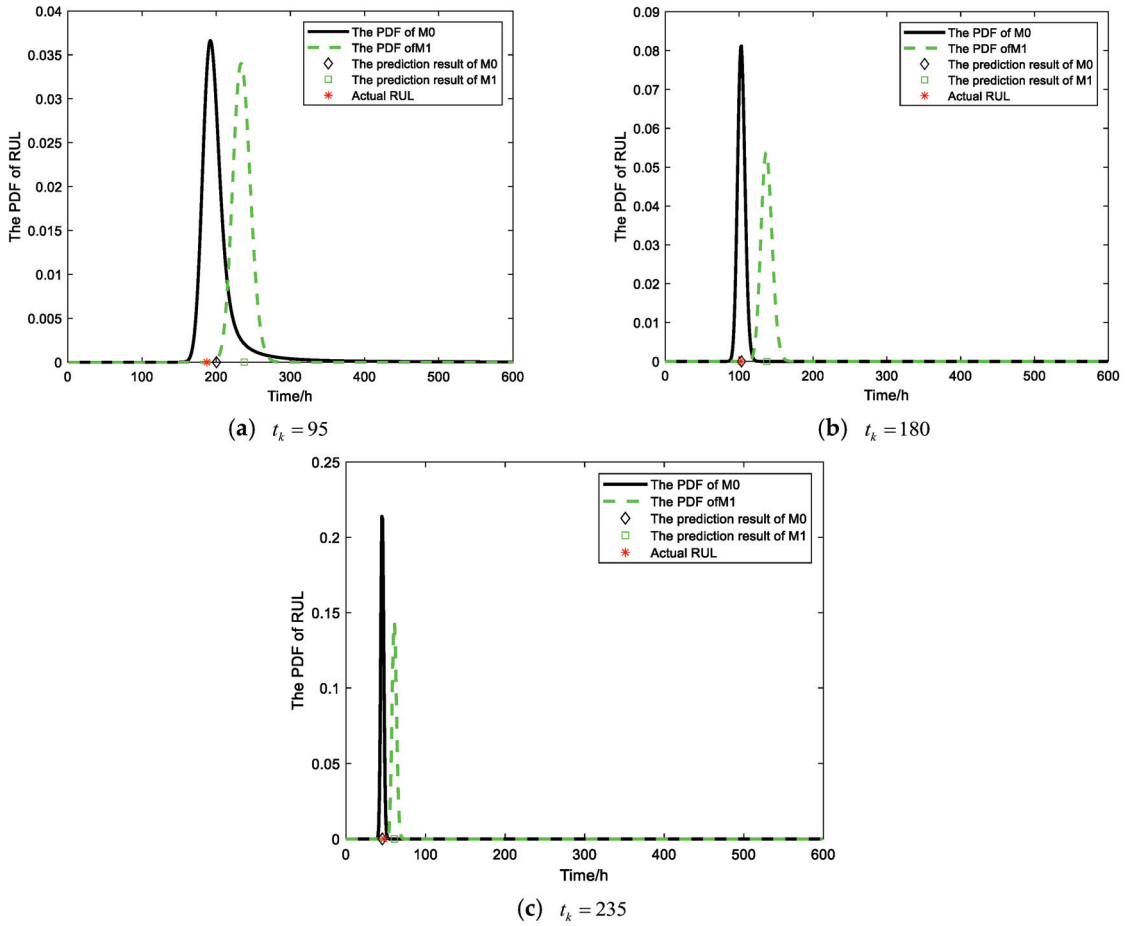


Figure 7. The PDFs and prediction results of RUL for gyroscope #1.

The PDF of RUL for the proposed method M0 exhibits a narrower and sharper distribution compared to method M1, as depicted in Figure 7, across various monitoring points during the initial three stages. Moreover, the prediction results of M0 demonstrate a closer proximity to the actual RUL. These findings collectively indicate that method M0 offers higher prediction accuracy and reduced uncertainty in RUL prediction. After three rounds of maintenance activities, two prediction methods were employed to predict the RUL of the gyroscope during its final degradation stage. The PDF generated by the proposed method M0 for predicting RUL at various monitoring points is illustrated in Figure 8.

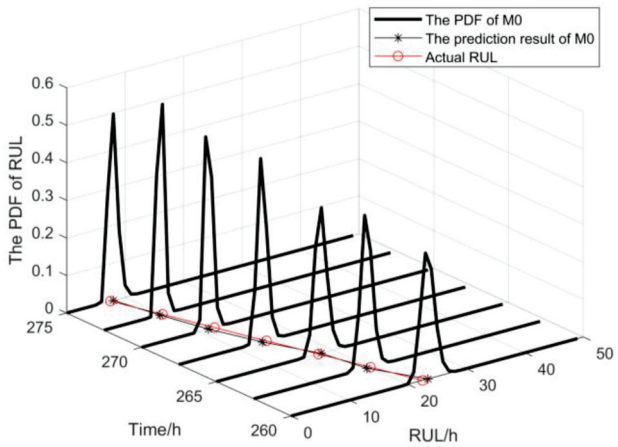


Figure 8. The PDF of RUL in the last stage.

As shown in Figure 8, the proposed method M0 takes into account the variability in the adaptive drift term in the future, and its RUL prediction is close to the actual RUL of the device. The specific RUL prediction results, MSE, and the prediction Score corresponding to the two methods at different monitoring points are provided in this paper for qualitative and quantitative comparison of their prediction performance. The comparison between the two methods is illustrated in Figure 9 and Table 3. In practical engineering applications, underestimating the predicted RUL value may result in a relatively conservative maintenance strategy, while overestimating the predicted RUL value may lead to catastrophic accidents caused by sudden device failure. The MSE and Score are two crucial metrics for evaluating the accuracy and distribution uncertainty of RUL prediction outcomes. A smaller MSE value indicates a more concentrated distribution of RUL predictions around the actual values, implying reduced uncertainty in the predicted RUL. It can be clearly observed from Table 3 that compared with the prediction result of the M1 method, the proposed method M0 has a smaller Score value, and the deviation and MSE of the prediction result of the M0 method are significantly smaller than those of the M1 method at several monitoring points. Therefore, the proposed method M0 exhibits higher accuracy in predicting the RUL and lower uncertainty in its predictions.

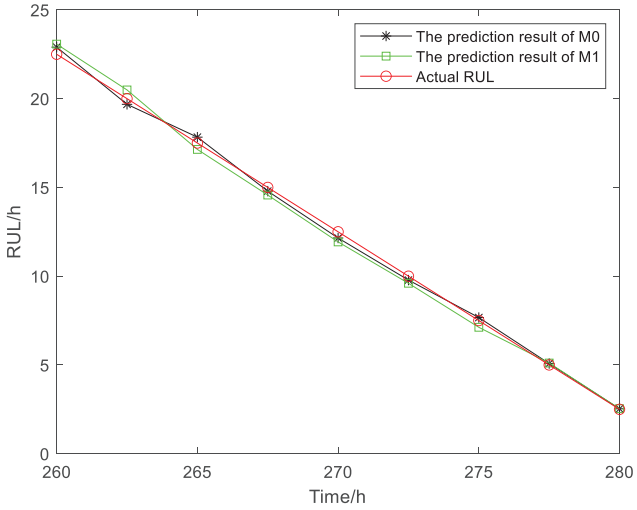


Figure 9. The RUL prediction results of gyroscope # 1.

Table 3. The MSE and Score of the RUL prediction.

Monitoring Point/h	M0	M1	Actual RUL/h
	MSE	MSE	
260	0.1600	0.3260	22.5
262.5	0.1024	0.2401	20
265	0.1089	0.1296	17.5
267.5	0.0441	0.1849	15
270	0.1225	0.3249	12.5
272.5	0.0484	0.1600	10
275	0.0289	0.1444	7.5
277.5	0.0062	0.0115	5
280	0.00089	0.0014	2.5
Score	5.2228	5.6447	\

6. Conclusions

The RUL prediction problem for repairable degrading devices considering the impact of imperfect maintenance activities has been investigated in this paper. An adaptive degradation model incorporating the impact of imperfect maintenance was established by utilizing Brownian motion for adaptive drift. It not only integrated maintenance activities into degradation modeling but also facilitated adaptive dynamic prediction during future processes. Subsequently, the RUL expression of the proposed model was derived based on the concept of FHT, which achieved real-time RUL prediction under imperfect maintenance. Furthermore, an algorithm for parameter identification was introduced that employs MLE for offline estimation, while a Bayesian posterior estimation was developed for online updating. Finally, the effectiveness of the proposed method was verified through cases of numerical simulation and gyroscopes. Furthermore, several directions warrant further exploration in future research. Firstly, it is imperative to investigate the impact of condition monitoring to facilitate wider application scenarios. Secondly, researching optimal health management strategies is crucial, including joint decisions for preventive maintenance and spare parts inventory.

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Acronyms, Abbreviations and Nomenclatures

Acronyms and Abbreviations

PdM	predictive maintenance
RUL	remaining useful life
PDF	probability density function
CDF	cumulative density function
AR(1)	autoregressive model of order 1
FHT	first hitting time
CM	condition monitoring
MLE	maximum likelihood estimation
RE	relative error
MSE	mean squared error
INS	inertial navigation system

Nomenclatures

ω	failure threshold
ω_p	preventive maintenance threshold
$X(t)$	degradation state

$\lambda(t)$	drift term
σ_B	diffusion coefficient
$B(t)$	standard Brownian motion
z_i	residual degradation state
ζ_i	change coefficient

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Maintenance Decision-Making Using Intelligent Prognostics Within a Single Spare Parts Support System

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Abstract: Health management is the foothold of remaining useful life (RUL) prediction, known as 'prognostics'. However, sudden failures in complex systems can lead to increased downtime and maintenance costs, ultimately diminishing system health and availability. Considering intelligent prognostics of components, maintenance decision-making for spare parts ordering and replacement is proposed within a spare parts support system. The decision-making process aims to minimize costs while maximizing availability as its primary objective. It considers spare parts ordering time and replacement time as key decision variables. By developing a maintenance decision-making model, it aims to determine the optimal time for ordering and replacing spare parts. This maintenance approach is designed to provide technical support for effective and rational equipment management decision-making.

Keywords: maintenance decision-making; single spare parts support system; spare parts ordering; replacement

1. Introduction

In the era of the Industrial Revolution 4.0, new concepts have emerged alongside this technological shift, particularly predictive maintenance (PM). PM plays a crucial role in sustainable manufacturing and production systems by introducing a digital model for machine maintenance [1–9]. The advancement of sensing technology and artificial intelligence has led to an exponential increase in data extracted from production processes. PM effectively minimizes machine downtime and associated costs, maximizes machine life cycles, and enhances the overall quality and pace of production. This method typically involves a precise workflow that begins with understanding the project and collecting data and concludes with the decision-making stage [10–19].

2. Literature Review

The previous work of PM focuses on a large number of monitoring data generated during the operation of complex systems, and much information can be obtained through fault diagnosis and intelligent prognostics. Among them, the prediction information includes the probability density function (PDF), cumulative distribution function (CDF), and reliability function (RF) of RUL. Based on RUL prediction information, maintenance staff can carry out condition-based maintenance for complex systems, formulate reasonable health management activities in advance for problems that may occur during operation, and implement preventive and remedial measures in advance [20–24].

In the industrial sector, particularly in the field of aircraft key equipment (such as engines and gyroscopes), numerous researchers have conducted comprehensive studies.

Zheng et al. [25] introduced an adaptive maintenance decision-making approach that utilizes RUL prediction information for nonlinear degraded systems. This method effectively determines the optimal replacement time and dynamic monitoring intervals while considering constraints such as operating costs and system availability. Building on this foundation, Mu et al. [26] integrated spare parts ordering time as a variable within the maintenance decision-making process, optimizing both spare parts replacement and ordering times. This approach facilitates more sophisticated maintenance activities compared to focusing on a single objective. Following this, Zheng et al. [27] expanded the maintenance decision-making model by incorporating the influence of condition monitoring for condition-based maintenance and spare parts ordering of individual component systems. They employed a normal distribution to characterize the effects of periodic condition assessments on equipment degradation. Using RUL prediction information, they established a maintenance decision-making model aimed at minimizing the long-term average costs associated with component maintenance.

Recent studies have also explored various methodologies for maintenance decision-making. For instance, Errandonea et al. [28] conducted a literature review on digital twins for maintenance, highlighting the potential of digital twins in enhancing predictive maintenance strategies. Similarly, Fink et al. [29] discussed the potential, challenges, and future directions for deep learning in prognostics and health management applications, emphasizing the importance of advanced machine learning techniques in improving maintenance decision-making. These studies demonstrate the potential of integrating advanced machine learning techniques into maintenance decision-making processes.

In the context of spare parts inventory management, research has shown that optimizing inventory strategies can significantly reduce downtime and maintenance costs. For example, Meddaoui et al. [30] established reliable methods for predicting failures in manufacturing excellence, demonstrating the benefits of predictive maintenance in reducing downtime and improving system reliability. Additionally, Molęda et al. [31] reviewed maintenance approaches for the power industry, highlighting the transition from corrective to predictive maintenance and its impact on system reliability.

The C-MAPSS dataset has been widely used in the field of predictive maintenance to validate the effectiveness of various models. Li et al. [32] proposed a new data-driven prediction method based on deep convolutional neural networks, which achieved high prediction accuracy for RUL estimation on the C-MAPSS dataset. This study highlights the potential of deep learning techniques in handling large-scale industrial data for predictive maintenance.

Despite these advancements, current research primarily focuses on scenarios without spare parts inventory support. It emphasizes multiple constraints, such as operating costs and availability, as objectives for making maintenance decisions and ordering spare parts [33,34]. However, real-world situations often involve sudden failures of complex system components, which can significantly increase the risk of downtime and maintenance costs, putting the system in an unhealthy state. To minimize the time required for component replacement, reduce downtime risks, and enhance system availability, there is a pressing need for an operational strategy for spare parts inventory management. This strategy aims to extend the operational lifespan of the system.

This article presents a maintenance decision-making method designed to operate within a single spare parts support system. The aim is to prevent prolonged system shutdowns caused by unexpected failures and to ensure system availability. The proposed method utilizes intelligent prognostics from the well-known C-MAPSS dataset. It establishes a multi-objective joint decision-making model that takes cost and availability into account simultaneously. The goal is to maximize the availability of components while

minimizing maintenance costs. This approach helps determine the optimal time for spare parts ordering and component replacement.

The structure of this article is organized as follows: Section 1 provides a brief introduction, while Section 2 provides a more detailed literature review. Section 3 defines the single spare parts support system and discusses the associated challenges. Section 4 introduces the proposed maintenance decision-making model. In Section 5, a numerical verification analysis is conducted. Finally, Section 6 summarizes the key points of the article.

3. Problem Description and Definition

To ensure the high availability of the entire system, this article investigates a decision-making method for maintenance concerning the ordering and replacement of spare parts. It focuses on a single spare parts support system that relies on intelligent prognostics. The discussion includes an overview of the single spare parts support system within the context of a single inventory spare parts component operation system, as well as various maintenance decision-making scenarios related to replacement and spare parts ordering based on specific scenarios.

3.1. Single Spare Parts Support System

The single spare parts support system, often referred to as the single inventory spare parts single component operation system, is designed for a solitary large, valuable, and replaceable service component with the capability for single inventory management. To minimize system downtime and enhance overall operational efficiency, the inventory of spare parts should be maintained at a minimum of one.

As illustrated in Figure 1, during the actual operating cycle, two components of the same model are initially purchased at the same time. One component is designated for active use, while the other serves as an inventory spare. The inventory component is stored in the warehouse and can be swiftly deployed to replace the operational component in the event of an unexpected failure, thereby restoring the system's normal operation. At any given time, one component is actively in use, accompanied by an additional redundant part in storage. Furthermore, considering the pre-ordering of spare parts for inventory components is essential. This approach ensures that even if the original component fails and is replaced by an inventory spare, a backup spare part remains available in stock, preventing a shortage due to potential failures of newly replaced components.

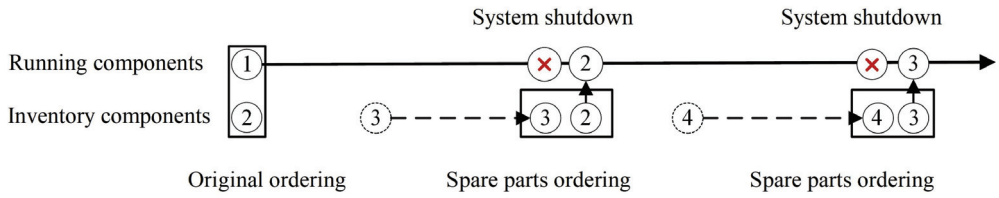


Figure 1. Single spare parts support system.

Within the operational life cycle of a component, the minimum single spare parts inventory system primarily focuses on the cost associated with ordering spare parts. It considers ordering just one component in the later stages, with the exception of ordering two components simultaneously during the initial stage. To clarify, the operation of ordering two components for the first time is referred to as the 'original ordering', while the subsequent ordering of a single component is termed the 'spare parts ordering'.

3.2. Intelligent Prognostics

Obtaining the RUL is essential for making informed maintenance decisions regarding degraded equipment. For effective intelligent prognostics, it is important to provide interval estimates of prediction results. In recent years, traditional deep learning models that incorporate dropouts have proven capable of capturing the uncertainty inherent in prediction results, allowing for the provision of interval estimates. By training the RUL prediction network using a training set and subsequently inputting new condition monitoring (CM) data, we can derive the corresponding RUL prediction results. For convenience, the PDF of the predicted RUL is simplified as $f(l_k|\mathbf{X}_{1:k})$, where l_k is the predicted RUL at time t_k and $\mathbf{X}_{1:k}$ is the input CM data. According to the PDF of predicted RUL, the cumulative distribution function (CDF) and reliability function (RF) of predicted RUL can be obtained as follows:

$$\begin{aligned} F(l_k|\mathbf{X}_{1:k}) &= \int_0^{l_k} f(\tau|\mathbf{X}_{1:k})d\tau \\ R(l_k|\mathbf{X}_{1:k}) &= 1 - F(l_k|\mathbf{X}_{1:k}) \end{aligned} \tag{1}$$

3.3. Maintenance Description

According to the information above, two potential scenarios may arise throughout the entire lifecycle of the components, as illustrated in Figure 2. Let t_k be the current CM time and t_{k+1} be the next CM time. t_o and t_p are the predicted spare part ordering time and replacement time, respectively. L is the delivery time for spare parts. Replacement is divided into failure replacement f_f and preventive replacement f_p, and $f_f < f_p$.

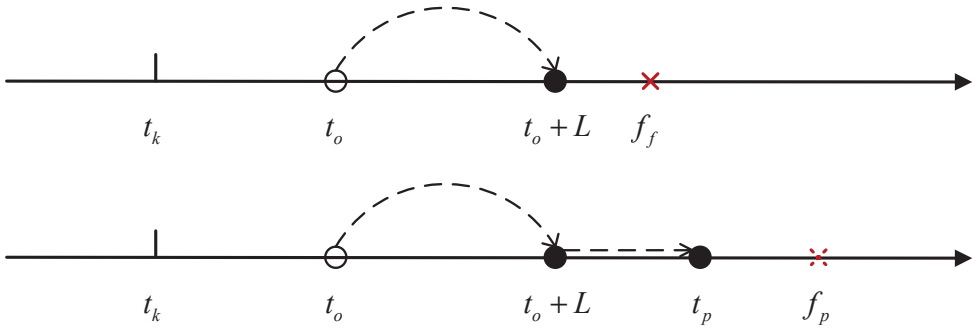


Figure 2. Two possible scenarios throughout the life cycle.

Scenario 1: If the component has been ordered according to the predicted ordering time and has arrived, but it fails before the predicted replacement time, the existing spare parts must be replaced immediately. This means that if the component suddenly fails, there will be costs associated with maintaining the inventory of spare parts as well as costs for ordering new spare parts.

Scenario 2: If the parts have been ordered according to the predicted ordering time and have arrived, and the original parts have not reached their predicted replacement time, then the existing spare parts will be replaced according to the scheduled replacement time. In this case, if the parts suddenly fail, there will again be costs related to maintaining the inventory of spare parts and costs associated with ordering new ones.

4. Methodology

The flowchart illustrating the maintenance decision-making method is presented in Figure 3. Initially, within the single spare parts support system, intelligent prognostics utilizing condition monitoring (CM) data can extract information such as the probability density function (PDF), cumulative distribution function (CDF), and reliability function (RF). Subsequently, a long-term average cost model and a long-term average availability model are collaboratively developed to determine the optimal time for ordering spare parts. Finally, a replacement time point is identified, taking into account both failure replacement and preventive replacement scenarios.

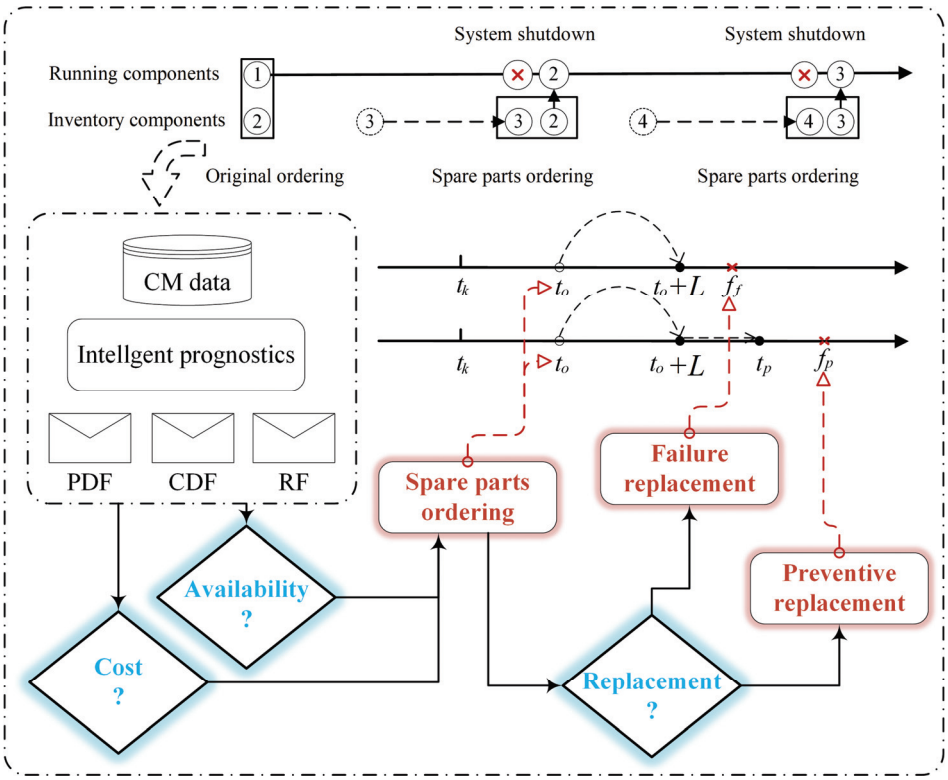


Figure 3. The flowchart of the maintenance decision-making method.

It is necessary to make the following assumptions based on the two scenarios described in the previous section.

(1) The condition monitoring interval is fixed, and the cost of a single monitoring is C_m. The equipment requires preventive replacement with a cost C_p and failure replacement with a cost C_f. We assume $C_m < C_p < C_f$.

(2) The state monitoring behavior of the original spare parts service will not affect parts of residual life, and redundancy of spare parts storage in warehouse degradation is negligible. The time that completes the failure replacement and preventive replacement is T_f and T_p, respectively.

(3) A period of time L between ordering and arrival of a spare part is considered to be fixed.

(4) Let C_o be the ordering cost of the spare part, C_h be the cost of maintaining inventory per unit time, and C_c be the the total cost of maintaining inventory parts.

(5) Let CH be the inventory cost, TH be the inventory time, and CR be the replacement cost, including the failure replacement cost and preventive replacement cost.

4.1. Long-Term Average Cost Model

Based on the model assumptions in the previous section and the renewal–reward theorem [35,36], the long-term average cost model can be expressed as

$$C_k(t_o, t_p) = \frac{EU}{EV} \tag{2}$$

where the EU represents the expected cycle cost, the EV represents the expected cycle length, and t_o and t_p are the spare parts ordering and parts replacement time to be optimized, respectively.

The first step is to derive the EU, which can be expressed as

$$EU = C_o + C_c + C_H + C_R + kC_m \tag{3}$$

Total cost of spare parts ordering: since the quantity of spare parts to be ordered in a life cycle is 1, the total cost of spare parts ordering is C_o.

Total maintenance cost of inventory parts: there are long-term maintenance costs of inventory parts in the early stages of scenario 1 and scenario 2. The total inventory time is divided into two parts, which are calculated as follows:

$$C_c = t_k \times C_h + (t_k - t_o - L) \times C_h = (2t_k - t_o - L) \times C_h \tag{4}$$

where the inventory maintenance time of spare parts is from the start of operation to the current monitoring time t_k. Similarly, the inventory maintenance time of ordered spare parts is $t_k - (t_o + L)$.

In order to get the total cost of inventory, you need to derive the corresponding inventory time first. Inventory time exists in scenario 1 and scenario 2.

$$\begin{aligned} T_H &= \int_{t_o+L}^{t_p} [l_k - (t_o + L)] \cdot f(l_k|\mathbf{X}_{1:k})dl_k + \int_{t_p}^{\infty} [t_p - (t_o + L)] \cdot f(l_k|\mathbf{X}_{1:k})dl_k \\ &= \int_{t_o+L}^{t_p} [l_k - (t_o + L)]dF(l_k|\mathbf{X}_{1:k}) + \int_{t_p}^{\infty} [t_p - (t_o + L)]dF(l_k|\mathbf{X}_{1:k}) \\ &= [l_k - (t_o + L)] \cdot F(l_k|\mathbf{X}_{1:k}) \,|_{t_o+L}^{t_p} \\ &- \int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k + [t_p - (t_o + L)] \cdot [1 - F(t_p|\mathbf{X}_{1:k})] \\ &= [t_p - (t_o + L)] - \int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k \\ &= \int_{t_o+L}^{t_p} [1 - F(l_k|\mathbf{X}_{1:k})]dl_k \\ &= \int_{t_o+L}^{t_p} R(l_k|\mathbf{X}_{1:k})dl_k \end{aligned} \tag{5}$$

Therefore, the inventory cost is

$$C_H = C_h \cdot T_H = C_h \int_{t_o+L}^{t_p} R(l_k|\mathbf{X}_{1:k})dl_k \tag{6}$$

The replacement cost includes preventive replacement cost and ineffective replacement cost, which can be expressed as

$$C_R = C_p \left[1 - \int_0^{t_p} f(l_k|\mathbf{X}_{1:k})dl_k\right] + C_f \int_0^{t_p} f(l_k|\mathbf{X}_{1:k})dl_k \tag{7}$$

Overall, the expected cycle cost is

$$\begin{aligned} EU &= C_o + C_c + C_H + C_R + kC_m \\ &= C_o + t_k \times C_h + (t_k - t_o - L) \times C_h + C_h \int_{t_o+L}^{t_p} R(l_k|\mathbf{X}_{1:k})dl_k \\ &+ C_p\left[1 - \int_0^{t_p} f(l_k|\mathbf{X}_{1:k})dl_k\right] + C_f \int_0^{t_p} f(l_k|\mathbf{X}_{1:k})dl_k + kC_m \\ &= C_o + (2t_k - t_o - L) \times C_h + C_h \int_{t_o+L}^{t_p} R(l_k|\mathbf{X}_{1:k})dl_k \\ &+ C_p\left[1 - \int_0^{t_p} f(l_k|\mathbf{X}_{1:k})dl_k\right] + C_f \int_0^{t_p} f(l_k|\mathbf{X}_{1:k})dl_k + kC_m \end{aligned} \tag{8}$$

Step two, derive the EV. In the two possible scenarios that may occur throughout the entire life cycle of the component, scenario 1 involves the spare parts arriving but the component failing before the predicted preventive replacement time; therefore, immediate failure replacement is carried out. Scenario 2 involved the spare parts arriving and the components failing within the predicted replacement time, in which case, preventive replacement should be carried out at the predicted replacement time. Based on the above analysis, the EV can be expressed as

$$\begin{aligned} EV &= t_k + \int_{t_o+L}^{t_p} \left(l_k + T_f\right) \cdot f(l_k|\mathbf{X}_{1:k})dl_k + \int_{t_p}^{\infty} \left(t_p + T_p\right) \cdot f(l_k|\mathbf{X}_{1:k})dl_k \\ &= t_k + \left(t_p + T_f\right) \cdot F\left(t_p|\mathbf{X}_{1:k}\right) - \\ &\int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k + \left(t_p + T_p\right) - \left(t_p + T_p\right)F\left(t_p|\mathbf{X}_{1:k}\right) \\ &= t_k + \left(T_f - T_p\right) \cdot F\left(t_p|\mathbf{X}_{1:k}\right) - \int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k \end{aligned} \tag{9}$$

By combining Formulas (8) and (9), the long-term average cost model can be obtained as follows:

$$\begin{aligned} C_k(t_o, t_p) &= \frac{EU}{EV} \\ &= \frac{C_o + (2t_k - t_o - L) \times C_h + C_h \int_{t_o+L}^{t_p} R(l_k|\mathbf{X}_{1:k})dl_k}{t_k + \left(T_f - T_p\right) \cdot F\left(t_p|\mathbf{X}_{1:k}\right) - \int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k} \\ &+ \frac{C_p\left[1 - \int_0^{t_p} f(l_k|\mathbf{X}_{1:k})dl_k\right] + C_f \int_0^{t_p} f(l_k|\mathbf{X}_{1:k})dl_k + kC_m}{t_k + \left(T_f - T_p\right) \cdot F\left(t_p|\mathbf{X}_{1:k}\right) - \int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k} \end{aligned} \tag{10}$$

4.2. Long-Term Average Availability Model

Availability is an important indicator for measuring the actual operational efficiency of a component, used to describe the probability or expected time occupancy of the component being able to operate normally within a certain period of time. The construction form is as follows:

$$A_k(t_o, t_p) = \frac{EO}{EV} \tag{11}$$

where the EO represents the expected running time of the component, and the EV represents the expected cycle length, which is the sum of the running time and downtime of the component. Among the four possible scenarios in the whole life cycle of components, scenario 1 and scenario 2 have downtime caused by out-of-stock and replacement activities because spare parts have not arrived at the time of component failure. Scenario 1 has downtime due to failure replacement, and scenario 2 has downtime due to preventive replacement.

The first step is to derive the expected running time, which can be expressed as

$$\begin{aligned} EO &= t_k + \int_{t_o+L}^{t_p} l_k \cdot f(l_k|\mathbf{X}_{1:k})dl_k + \int_{t_p}^{\infty} t_p \cdot f(l_k|\mathbf{X}_{1:k})dl_k \\ &= t_k + t_p \cdot F\left(t_p|\mathbf{X}_{1:k}\right) - (t_o + L) \cdot F(t_o + L|\mathbf{X}_{1:k}) \\ &- \int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k + t_p - t_p \cdot F\left(t_p|\mathbf{X}_{1:k}\right) \\ &= t_k + t_p - (t_o + L) \cdot F(t_o + L|\mathbf{X}_{1:k}) - \int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k \end{aligned} \tag{12}$$

By combining Formula (9) and Formula (12), the long-term average availability can be obtained:

$$\begin{aligned} A_k\left(t_o, t_p\right) &= \frac{EO}{EV} \\ &= \frac{t_k + t_p - (t_o+L) \cdot F(t_o+L|\mathbf{X}_{1:k}) - \int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k}{t_k + \left(T_f - T_p\right) \cdot F\left(t_p|\mathbf{X}_{1:k}\right) - \int_{t_o+L}^{t_p} F(l_k|\mathbf{X}_{1:k})dl_k} \end{aligned} \tag{13}$$

4.3. Multi-Objective Maintenance Decision-Making Model

In order to solve the multi-objective optimization problem, a decision boundary is constructed. Specifically, let the long-term average availability meet the requirements of component use efficiency in engineering practice and let the long-term average cost be minimized on this basis. Then, the multi-objective maintenance decision-making model can be rewritten as

$$\begin{aligned} &\textit{Minimize} && C_k\left(t_o, t_p\right) \\ &\textit{Subject to} && A_k\left(t_o, t_p\right) \geq \zeta \\ & && t_k \leq t_o \leq t_p \end{aligned} \tag{14}$$

where ζ is the availability threshold, which is usually set according to the actual operation requirements of the project. In order to ensure that the parts meet the availability requirements, the spare parts ordering and parts replacement time are within a certain value range. The optimal spare parts ordering and component replacement time can be calculated using Equation (15).

$$\begin{aligned} t_o{}^*, t_p{}^* &= \arg\min C_k\left(t_o, t_p\right) \\ t_o, t_p &\in [t_{\min}, t_{\max}] \end{aligned} \tag{15}$$

5. Numerical Verification

5.1. Data Description on C-MAPSS Dataset and Intelligent Prognostics

This section selects a well-known C-MAPSS dataset released by NASA to verify the method. The dataset consists of multiple multivariate time series, including three operating settings and 21 types of sensors that have a significant impact on engine performance. The specific information is shown in Table 1. This dataset has four sub-datasets, and the sub-dataset named FD001 is used for our case study. Each sub-dataset is further divided into training engines and testing engines. In the training engines, the entire time series of each engine from normal operation until system failure is recorded. Conversely, in the test engines, the time series for each engine ends sometime before the system fails.

Table 1. C-MAPSS dataset.

Sub-Dataset	Training Engines	Testing Engines	Scenarios	Fault Modes
FD001	100	100	1	1
FD002	260	260	6	1
FD003	100	100	1	2
FD004	249	249	6	2

This article presents the results of a new deep learning prediction method based on the Temporal Convolutional Network (TCN) and Bidirectional Long Short-term Memory

(BiLSTM) neural networks, as referenced in [37]. Among them, TCN mainly undertakes feature extraction and captures short-term local dependencies, while BiLSTM mainly undertakes long-term memory and captures long-term macro dependencies. Figure 4 illustrates the PDF for the 76th engine among the tested engines. The RUL prediction method demonstrates strong predictive performance and offers practical reference value.

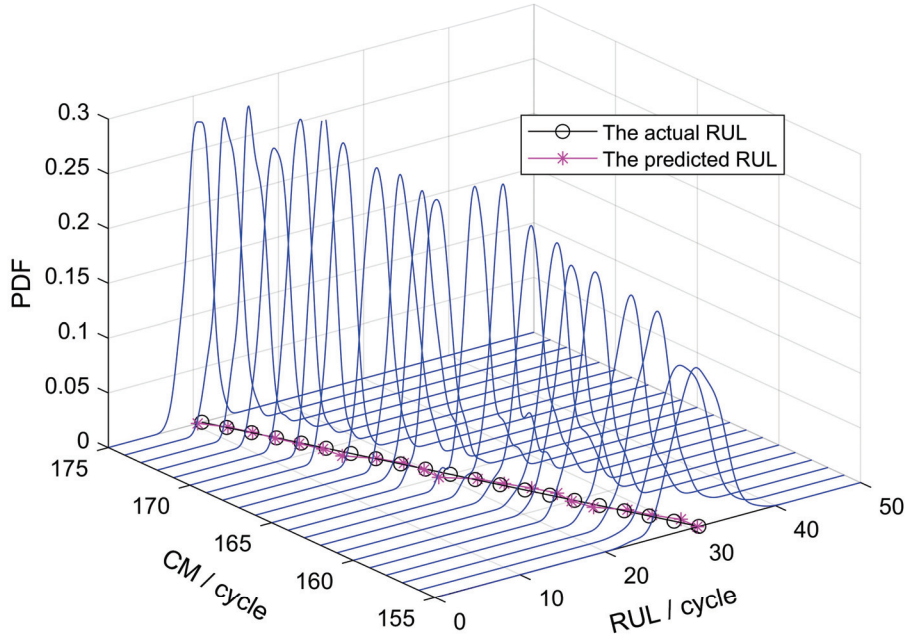
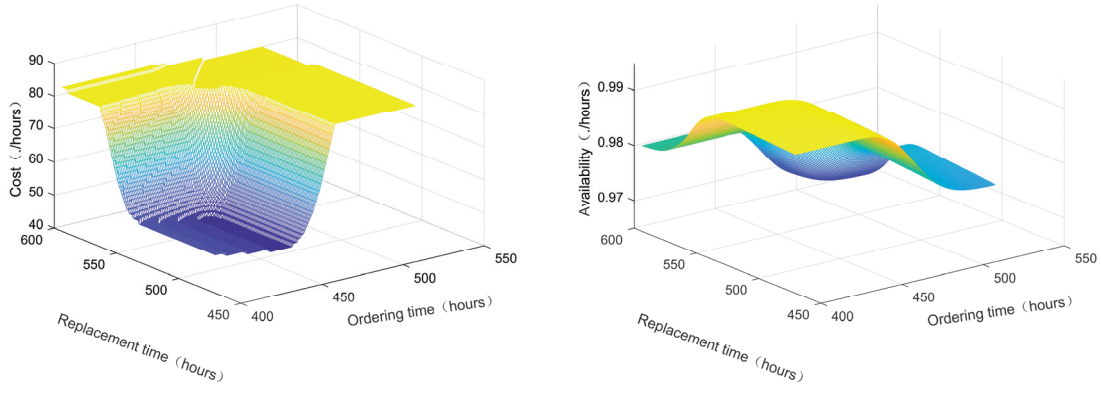


Figure 4. PDF for different CM cycles of RUL cycles.

5.2. Results on the Testing Data of FD001 at the 76th Engine

Based on the above intelligent prognostics, the parameters in the multi-objective maintenance decision-making model are set as $C_p = 10000\$$, $C_f = 30000\$$, $C_m = 30\$$, $C_o = 1000\$$, $C_i = 10\$$, $T_f = 15$ h, $T_p = 9$ h and availability threshold $\zeta = 0.98$. The No. 76 engine has CM data for 176 CM cycles. It is assumed that the interval between each CM cycle is 3 h, and the lead time noted L of spare parts is 72 h.

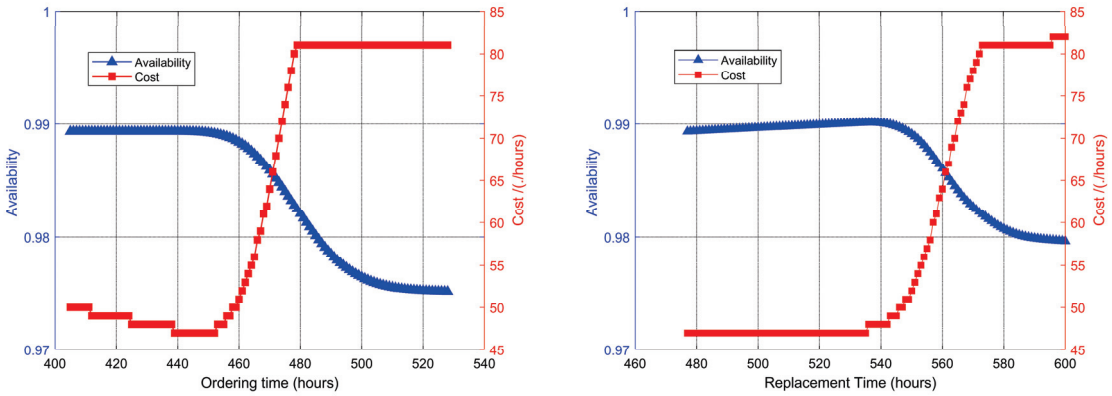
According to the proposed method in Section 3, taking the 135th monitoring cycle at the current monitoring time point, i.e., the 405th hour, the constraint function graphs of long-term average cost and long-term average availability as a function of spare parts ordering and replacement time are plotted in Figure 5a and Figure 5b, respectively.



(**a**) (**b**)

Figure 5. Constraints: (**a**) Long-term average cost model; (**b**) Long-term average availability model.

To enhance the intuitiveness of the proposed maintenance decision-making results, Figure 6 presents these results. The blue line indicates the long-term average availability, while the red line represents the long-term average cost.



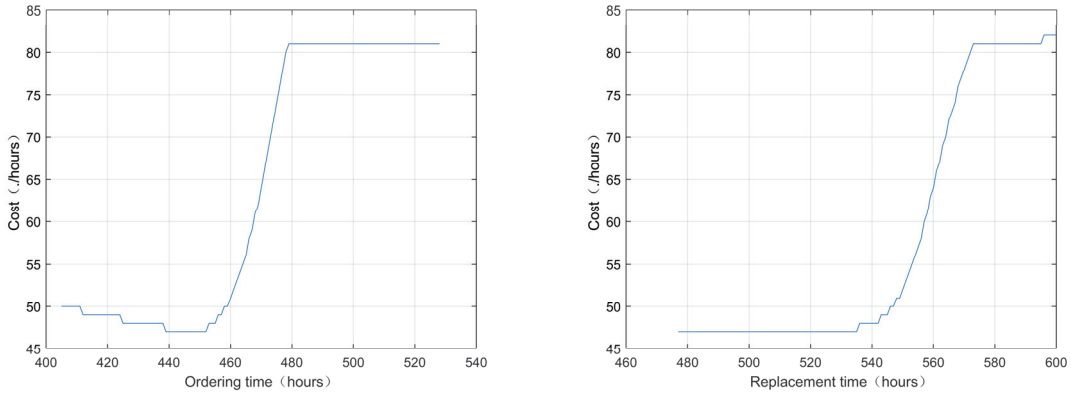
(**a**) (**b**)

Figure 6. Maintenance decision-making: (**a**) ordering time; (**b**) replacement time.

Figure 6 illustrates that the maintenance decision-making model identifies the optimal times for ordering spare parts and replacing components as the 439th hour and the 477th hour, respectively. This is attributed to the fact that the degradation of components tends to accelerate with increased operating time, leading to a gradual decline in their availability. The model developed in this article incorporates both cost and availability as key decision objectives, constructing a multi-objective decision function based on intelligent prognostics to determine the ideal times for spare parts ordering and component replacement.

5.3. Compared with Single Cost Decision-Making

To illustrate the importance of availability, only cost is chosen as the decision variable under identical conditions. Figure 7a,b present two-dimensional schematic diagrams of the decision outcomes from the single-cost decision-making model.



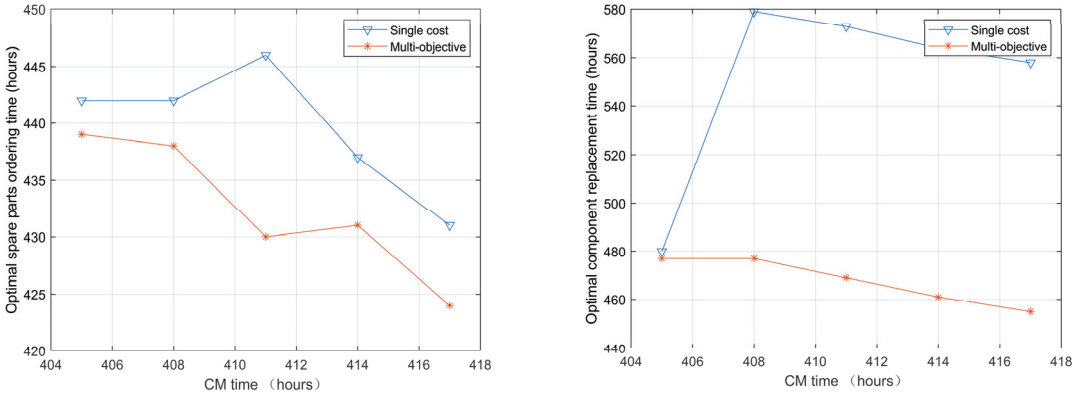
(**a**) (**b**)

Figure 7. Single-cost decision: (**a**) ordering time; (**b**) replacement time.

From Figure 7, it is evident that at the current monitoring time point of the 405th hour, if the objective is solely to minimize costs, the optimal times for ordering spare parts and replacing components are the 442nd and 480th hours, respectively. As the components continue to operate and accumulate running time, their degradation characteristics intensify, leading to a gradual decrease in availability as they near failure. Therefore, to ensure

compliance with the required availability thresholds, it is essential to schedule spare parts ordering and replacement times in advance.

Similarly, in order to evaluate the generalization ability of the proposed model, a comparative analysis was conducted at different CM time points (e.g., 405, 408, 411, 414, and 417), and the results are shown in Figure 8 and recorded in Table 2. Compared with the single-cost decision-making model that aims to minimize a single cost, the optimal spare parts ordering and replacement time obtained through the proposed multi-objective maintenance decision-making model in this article are both in advance, which can help operation and maintenance personnel arrange spare parts ordering and replacement activities in a timely manner, ensuring that components can efficiently and stably complete tasks.



(**a**) (**b**)

Figure 8. Optimal time: (**a**) spare parts ordering time; (**b**) component replacement time.

Table 2. Decision results of the two methods at different condition monitoring time points.

Model	Condition Monitoring Time	Optimal Spare Parts Ordering Time	Optimal Component Replacement Time	Maintenance Cost
Single-cost maintenance decision-making model	405	442	480	47
	408	442	579	47
	411	446	573	47
	414	437	564	47
	417	431	558	47
The proposed multi-objective maintenance decision-making model	405	439	477	47
	408	438	477	47
	411	430	469	47
	414	431	461	47
	417	424	455	47

6. Conclusions

This article presents a maintenance decision-making method that utilizes intelligent prognostics to address the practical needs of maintenance costs and the actual performance of components in a system that relies on a single inventory of spare parts during operation and maintenance processes. The primary focus of this study includes

1. Utilizing the predicted remaining useful life information to develop a maintenance decision-making method for spare parts ordering and component replacement that balances high availability with low cost.
2. Considering both cost and availability as key decision objectives, while treating spare parts ordering and component replacement time as decision variables. The

method addresses the trade-off between these two objectives by establishing a decision boundary.
3. Aiming to minimize costs while still meeting availability requirements, the method determines the optimal time for ordering spare parts and replacing multiple degraded components.

Finally, the effectiveness of the proposed method was validated using an aircraft engine dataset. The decision-making results can assist operation and maintenance personnel in effectively planning spare parts and replacement activities, demonstrating a valuable application in engineering. In the future, we will further consider providing feedback on the decision-making results of intelligent prognostics.

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Abbreviations

The following abbreviations are used in this manuscript:

RUL	Remaining useful life
PM	Predictive maintenance
PDF	Probability density function
CM	Condition monitoring
CDF	Cumulative distribution function
RF	Reliability function

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Triboelectric Nanogenerator-Embedded Intelligent Self-Aligning Roller Bearing with the Capability of Self-Sensing, Monitoring, and Fault Diagnosis

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Abstract: Monitoring the dynamic behaviors of self-aligning roller bearings (SABs) is vital to guarantee the stability of various mechanical systems. This study presents a novel self-powered, intelligent, and self-aligning roller bearing (I-SAB) with which to monitor rotational speeds and bias angles; it also has an application in fault diagnosis. The designed I-SAB is compactly embedded with a novel sweep-type triboelectric nanogenerator (TENG). The TENG is realized within the proposed I-SAB using a comb–finger electrode pair and a flannelette triboelectric layer. A floating, sweeping, and freestanding mode is utilized, which can prevent collisions and considerably enhance the operational life of the embedded TENG. Experiments are subsequently conducted to optimize the output performance and sensing sensitivity of the proposed I-SAB. The results of a speed-sensing experiment show that the characteristic frequencies of triboelectric current and voltage signals are both perfectly proportional to the rotational speed, indicating that the designed I-SAB has the self-sensing capability for rotational speed. Additionally, as both the bias angle and rotational speed of the SAB increase, the envelope amplitudes of the triboelectric voltage signals generated by the I-SAB rise at a rate of 0.0057 $V \cdot deg^{-1} \cdot rpm^{-1}$. To further demonstrate the effectiveness of the triboelectric signals emitted from the designed I-SAB in terms of self-powered fault diagnosis, a Multi-Scale Discrimination Network (MSDN), based on the ResNet18 architecture, is proposed in order to classify the various fault conditions of the SAB. Using the triboelectric voltage and current signals emitted from the designed I-SAB as inputs, the proposed MSDN model yields excellent average diagnosis accuracies of 99.8% and 99.1%, respectively, indicating its potential for self-powered fault diagnosis.

Keywords: triboelectric nanogenerator; intelligent bearing; speed sensing; bias angle monitoring; fault diagnosis; deep learning

1. Introduction

Self-aligning roller bearings (SABs) are designed to withstand significant radial loads and relatively low axial loads, making them ideal for various applications, including in wind turbines, construction machinery, and power transmission systems. SABs can withstand axial loads, even when the shaft and the bearing housing are misaligned, enabling them to operate efficiently when there is a bias angle between their inner and outer rings.

The bias angle results in a change in the contact angle, and the value of the change is called the self-aligning contact (SAC) angle [1]. An overweight SAC angle leads to weakened stiffness and intensified friction and internal clearance, thus shortening the operational life of the SAB [2–4]. Furthermore, SABs are prone to various faults due to the harsh working environment [5]. To avoid industrial disasters caused by mechanical faults, it is necessary to develop an efficient way of monitoring the health condition of SABs. Traditionally, the bias angle of SABs is measured with a coordinate measuring machine, which is expensive and cannot be used during real-time operations. Moreover, vibration-based fault diagnosis techniques usually require extra radial space for the installation of acceleration sensors. Therefore, there is a significant need to develop a self-powered and self-sensing method to monitor the dynamic behaviors and health conditions of SABs.

Triboelectric nanogenerators (TENGs) have recently provided an elegant and promising solution to the self-sensing monitoring tasks of mechanical systems. Based on the periodic transfer of triboelectric charges during mechanical motion, TENGs can convert mechanical energy into electrical energy at a certain power density [6]. TENGs have attracted considerable attention in the field of energy harvesting and self-powered sensing owing to the advantages of high structural integration, small volume, and low cost [7–12]. Self-powered sensors based on TENGs can be manufactured with a small size [13] and are capable of performing self-sensing tasks within a limited space. Meng et al. developed a TENG-based self-powered sensor that is integrated into glasses and the brake and accelerator pedals of a car, aiming to monitor driver behaviors [14]. Jin et al. implemented a wireless sensor based on a TENG and embedded it into a train chassis to monitor vibrations during the running process [15]. Xie et al. designed a novel TENG by pasting electrode and triboelectric layers onto gear teeth and carried out online fault monitoring using TENG triboelectric signals and a deep learning model [16]. Being sensitive to many physical quantities, TENGs are widely applied in mechanical systems for acceleration, distance, and speed sensing. Liu et al. observed that the output amplitude of a contact–separation TENG is proportional to the triboelectric–electrode displacement, which led to the design of a self-powered acceleration sensor for vibration monitoring [17]. Similarly, Pang et al. combined three TENG sensors for 3D acceleration monitoring [18]. Owing to their high integration degree, flexibility, and great sensitivity, TENG sensors have also been widely applied in self-powered intelligent bearings for the surveillance of rotational speed, slip rate, and health conditions. Gao et al. used the spherical ceramic rollers of bearings as a triboelectric material and developed an embedded TENG inside the bearing without causing damage, achieving real-time behavior monitoring [19]. Moreover, the authors proposed a compact intelligent bearing for skidding rate monitoring using an embedded freestanding-mode TENG [20]. Xie et al. studied the influence of triboelectric–electrode separation on the TENG output performance and proposed a long-life intelligent bearing with non-contact triboelectric layers, which was applied to monitor the speed and skidding rate of bearings [21]. Jiang et al. proposed a compact-mode self-powered smart bearing [22] and a smart bearing embedded with a membrane-based disk-type TENG [23], both of which were verified as being capable of fault diagnosis. The experiments showed that diagnostic accuracy could reach 90%, demonstrating that TENG-based smart bearings are promising for self-powered and self-sensing condition monitoring.

Though TENG-based smart bearings have shown considerable potential for self-powered and self-sensing condition-monitoring applications, there remains a research gap between intelligent bearings embedded with TENGs and the capability of simultaneously monitoring the dynamic behaviors and health conditions of SABs. To this end, we propose a novel-type self-powered intelligent SAB embedded with a TENG (I-SAB) in this study and verify its applications in self-powered rotational speed sensing, bias angle monitoring, and fault diagnosis. Specifically, a compact prototype of the I-SAB based on freestanding-mode triboelectric layers and a comb–electrode pair is fabricated. Three triboelectric layers are attached to an acrylic disk, which is fastened to the inner ring of the bearing using a nut. The disk, coated with triboelectric layers, serves as the rotor part of the TENG since it

rotates simultaneously with the inner ring. Steel cushions are placed between the inner ring and acrylic disk in order to control the dielectric–electrode separation. Pairs tin electrodes with comb shapes are printed on a ring-shaped PCB via the hot-air solder leveling (HASL) process. The PCB is inlaid in acrylic housing that is adhered to the outer ring using neodymium magnets. Based on the designed I-SAB prototype, detailed design parameters, including the triboelectric layer material, comb–finger pair number, the distance between the electrode and triboelectric layer surface, and the triboelectric layer number, are discussed. Moreover, the variations in the triboelectric voltage and current with load resistance are measured to evaluate the output power of the I-SAB. The characteristic frequencies of the triboelectric current and voltage acquired at different speeds are validated as accurate indicators of rotational speeds. A test bench is constructed based on optical systems to conduct experiments on the I-SAB from various bias angles. Bias angle monitoring is performed by analyzing the envelope amplitude of the triboelectric voltage signals emitted from the I-SAB. A strong linear relationship between the triboelectric voltage envelope amplitude and bias angle is discovered; thus, the newly designed I-SAB is found to be reliable in bias angle monitoring. The triboelectric voltage and current signals emitted from I-SABs under different health conditions are also assessed and analyzed. We propose a novel Multi-Scale Discrimination Network (MSDN), based on the ResNet18 architecture, to extract and classify the weak fault features hidden in the signals emitted from the designed I-SAB with various faults. Both the triboelectric current and voltage signals emitted from the I-SABs are processed and used to train and evaluate the MSDN. The evaluation results of fault diagnosis show that the MSDN model trained using the triboelectric voltage and current signals emitted from the I-SAB achieves average diagnostic accuracies of 99.8% and 99.1%, respectively, outperforming the classical convolutional neural network (CNN) and ResNet18.

The main contributions of this study can be summarized as follows: firstly, we designed the first compact TENG that can be embedded to create an intelligent SAB with excellent self-powered rotational speed sensing and bias angle monitoring; secondly, with the aid of deep learning, we developed a novel MSDN model and achieved self-sensing fault diagnosis with superior diagnostic accuracy based on weak fault features.

2. Design and Implementation of I-SAB

2.1. Structure and Principle of I-SAB

The sectional view of the designed I-SAB, which comprises an SAB (B21308CA/W33 type), an acrylic disk, acrylic housing, an epoxy resin PCB board, and cushions, is illustrated in Figure 1a. The designed I-SAB is embedded with a compact TENG, which is configured with an acrylic disk as the rotor and an epoxy resin PCB as the stator. Three flannelette layers, pasted on three adjacent bosses present on the disk, serve as the triboelectric layers of the TENG; meanwhile, a 12-tooth tin comb–electrode pair sprayed on the epoxy resin PCB forms the TENG electrode. The acrylic disk, acrylic housing, and 0.5 mm thick #45 steel cushions are processed by CNC machining. A pair of tin electrodes, approximately 2 μm thick, are created on a 1.5 mm thick PCB board using the hot-air leveling process. The PCB is fixed to the inner surface of the housing. The I-SAB is fixed onto the #45 steel stepped shaft and fastened with a standard M35 nut. The assembly process is illustrated in the explosion diagram in Figure 1b. Firstly, we inlaid the PCB and neodymium magnets into the acrylic housing; secondly, we threaded the bearing, the cushions, and the acrylic disk onto the stepped shaft; and thirdly, we screwed the tightening nut to fix the disk onto the inner ring of the SAB. Finally, we magnetically adhered the acrylic housing to the outer ring of the SAB. The I-SAB prototype is illustrated in Figure 1c.

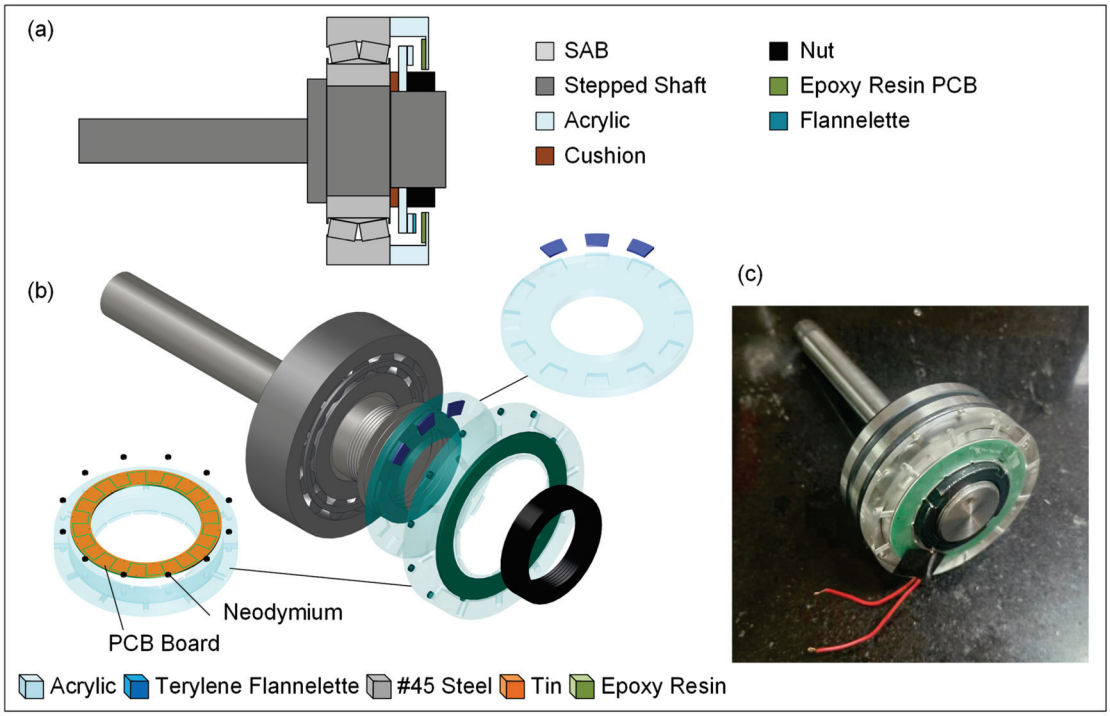


Figure 1. (**a**) Sectional view of I-SAB; (**b**) explosion diagram of I-SAB; (**c**) I-SAB prototype.

The full working cycle for the TENG embedded into the I-SAB is illustrated in Figure 2a. As the shaft rotates, the flannelette triboelectric layers on the acrylic disk sweep along the circumferential direction of the comb fingers on the electrodes. A constant negative charge accumulates on the surface of the triboelectric layer. As the triboelectric layer moves between the combs of the different electrodes, electrons are periodically driven between the electrodes by the electrostatic forces. Initially, the triboelectric layer faces electrode A, whose negative charges cause an equal number of positive charges to accumulate on the electrode. In this state, as shown in Figure 2(a1), electrostatic equilibrium is established, and no charge transfer occurs between the two electrodes; thus, no current is observed. As the acrylic disk rotates along with the inner ring of the SAB, the triboelectric layer moves toward electrode B. Simultaneously, some positive charges transfer from electrode A to electrode B through the load circuit between the two electrodes. The transfer of charge between the electrodes results in there being a detectable transient current in the same direction, as shown in Figure 2(a2). When the triboelectric layer aligns with electrode B, a new electrostatic equilibrium is established, with positive charges accumulating on electrode B, as shown in Figure 2(a3). Then, the triboelectric layer sweeps back toward electrode A, causing the positive charges to transfer back to electrode A, as shown in Figure 2(a4). After the flannelette triboelectric layer moves back to the initial state, one complete cycle of power generation finishes. The continuous movements of the triboelectric layer repeat these stages (a1–a4), producing a continuous alternating triboelectric current (AC) signal between the two electrodes in the TENG. The open-circuit potential distribution corresponding to the four stages of one power generation cycle is shown in the image in Figure 2b, which was obtained using the finite element method (FEM) with COMSOL. The simulation results confirmed the power generation mechanism of the TENG inside the I-SAB, thereby demonstrating that an AC signal can be generated between the two electrodes of the TENG within the I-SAB when the inner ring of the SAB rotates. The short-circuit current and open-circuit voltage of the I-SAB under different speeds are acquired and are displayed in Figure 2(c1) and Figure 2(c2), respectively. It can be observed that both the peak current and the peak voltage increase from 0.2 nA and $\pm$1.7 V to $\pm$0.55 nA and $\pm$6.2 V, respectively, with the rotational speed increasing from 400 rpm to 900 rpm.

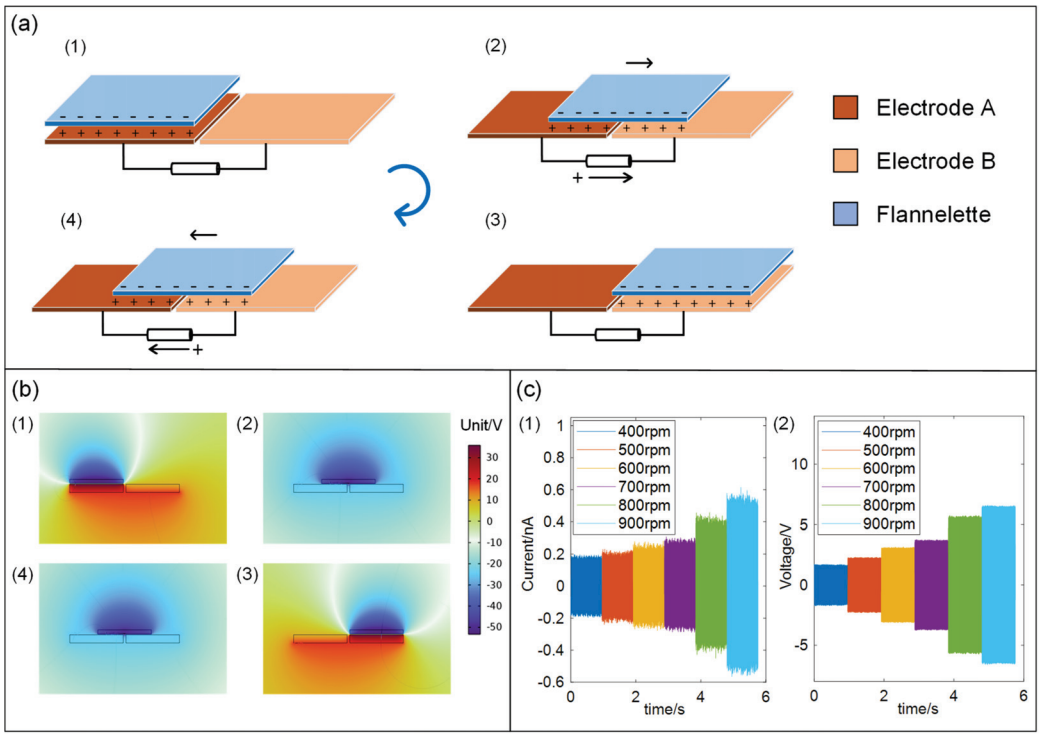


Figure 2. (**a**) Power generation mechanism of I-SAB; (**b**) simulation results of electrostatic field using COMSOL; (**c**) (1) short-circuit current and (2) open-circuit voltage from I-SAB under different rotational speeds.

2.2. Output Characteristics and Parameter Optimization

To optimize the structural design of the I-SAB, we conducted the following experiments to examine the impact of structural parameters on the output characteristics of the TENG. Firstly, we sampled the output performance of TENGs in two different working modes, namely, a single-electrode mode and double-electrode mode. Figure 3a shows a comparison of the short-circuit current and open-circuit voltage of the I-SAB embedded with TENGs in two working modes. The results indicated that the short-circuit current and open-circuit voltage of TENG in the double-electrode mode reached peak-to-peak values of approximately 2.7 nA and 3 V, respectively, which are nearly 20 times and 10 times greater than those obtained in the single-electrode mode. For the single-electrode mode, the charge only accumulated at one electrode; thus, no additional charge gathered when the triboelectric layer moved away from the electrode comb. As a result, the electrode was only charged during half of the cycle, limiting the charge density and, consequently, reducing the output. This finding supports the selection of a double-electrode mode for our I-SAB design. Secondly, to identify the most suitable material for the triboelectric layer of the TENG in our I-SAB, we selected three different materials—flannelette, nylon-flocked cloth, and EPE—and acquired the triboelectric current and voltage at a rotational speed of 600 rpm. As shown in Figure 3b, the flannelette produced the highest short-circuit current and open-circuit voltage, with peak-to-peak values of 0.3 nA and 3.1 V, respectively. Based on its superior output performance, flannelette was selected as the triboelectric layer material in this study. Thirdly, another crucial design parameter, namely, the separation distance (as illustrated in Figure 3c) between the triboelectric layer and electrode, was optimized. The short-circuit current and open-circuit voltage from the I-SAB were measured at different separation distances under a rotational speed of 400 rpm, and the results are shown in Figure 3d. It is evident that both the short-circuit current and open-circuit voltage increase as the separation distance decreases. Specifically, the peak values of the short-circuit current and open-circuit voltage increase from 0.1 nA and 1.1 V at a 2 mm distance to 0.3 nA and 2.7 V at a 0.5 mm distance. Thus, a closer separation distance can enhance the output

performance of the I-SAB. It should be noted that the separation distance should not be too small, as collisions between the electrode and triboelectric layer shorten the device's lifespan. Considering the possible tilting of the acrylic shell under self-aligning conditions, a separation distance of 1.5 mm was determined to prevent collisions during tests within the allowable tilt range. Finally, the relationship between the output performance of the I-SAB and the number of comb–finger pairs was also analyzed and optimized. The short-circuit current and open-circuit voltage with different numbers of comb–finger pairs on the electrodes were acquired at a rotation speed of 600 rpm, and the experimental results are illustrated in Figure 3e. The results indicate that increasing the number of comb–finger pairs can result in triboelectric signals with greater signal amplitudes generated from the I-SAB. Thereby, to maximize the triboelectric signal amplitudes, we incorporated a 12-finger comb–electrode pair into the designed I-SAB.

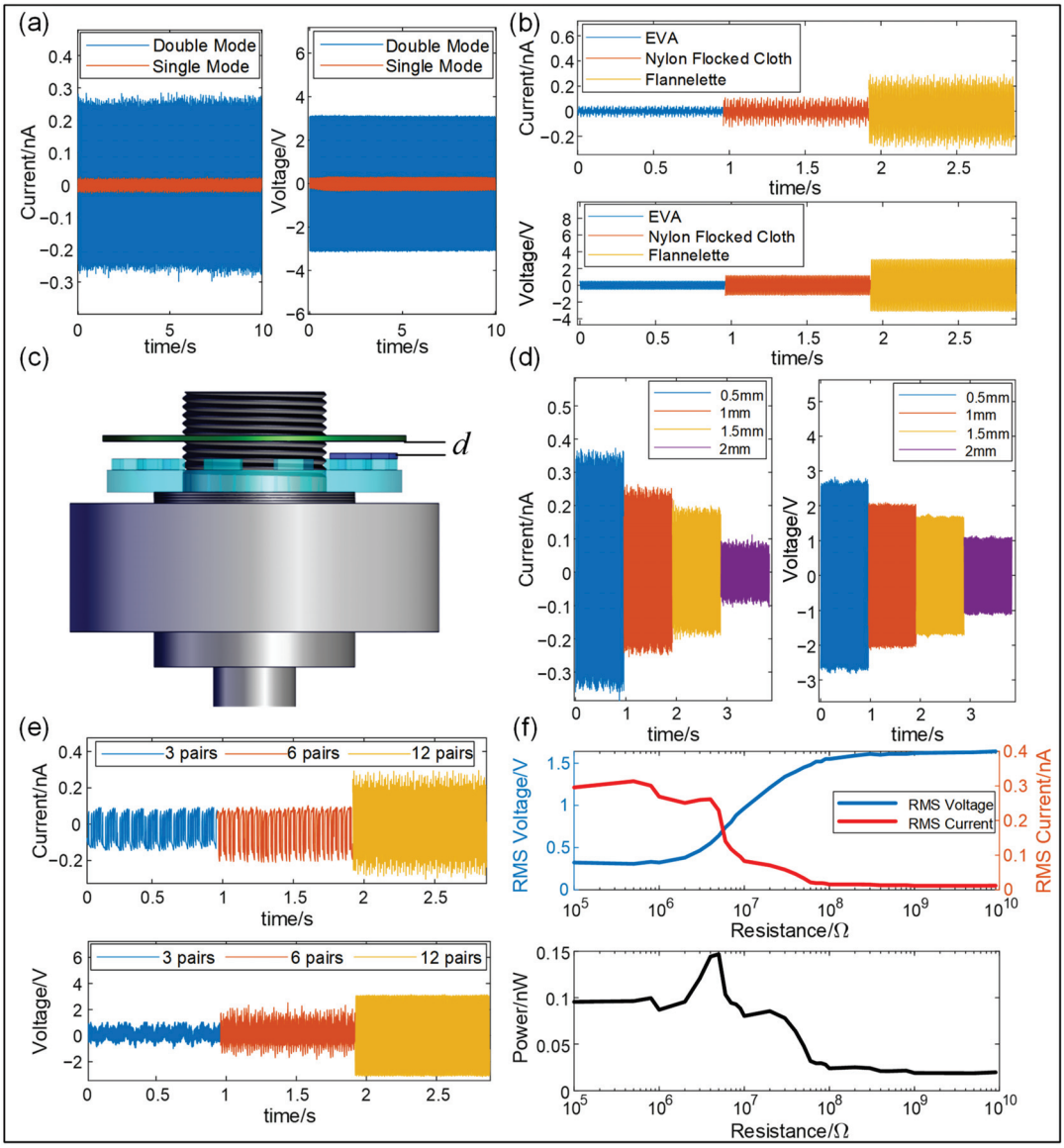


Figure 3. The output performance of the I-SAB with different design parameters. (**a**) The short-circuit current and open-circuit voltage in two working modes; (**b**) the short-circuit current and open-circuit voltage for different dielectric materials; (**c**) an illustration of the separation distance in the I-SAB; (**d**) a short-circuit current and open-circuit voltage with different separation distances; (**e**) a short-circuit current and open-circuit voltage with different comb–finger numbers; (**f**) variation in output power as load resistance changes.

With the optimized structural parameters, the output performance of the I-SAB under varying load resistances was also acquired under a rotational speed of 600 rpm. As shown in Figure 3f, as the load resistance increases from 100 KΩ to 9 GΩ the root-mean-square (RMS) value of the triboelectric voltage from the I-SAB increases from 0.3 V to 1.6 V, while the RMS value of the triboelectric current decreases from 0.3 nA to 0.012 A. As a result, a peak power of 0.15 nW is achieved at a load resistance of 5 MΩ.

3. Self-Sensing Applications

The newly designed I-SAB embedded with a TENG is an intelligent bearing with multiple functionalities. To illustrate its self-sensing performance, we constructed the test bench shown in Figure 4a. During the experiment, the triboelectric voltage signal was detected using a Tektronix DPO-2024B Digital Phosphor Oscilloscope (Tektronix, Portland, OR, USA), while the triboelectric current signal was measured using a Keithley 6514 System Electrometer (Tektronix, Portland, OR, USA). All data were collected with an NI Data Acquisition Card and recorded on an ASUS laptop. The inner ring of the I-SAB was fastened to a stepped shaft and connected to a brushless motor (AM-370L, Adlee Servo Motor Manufacturer, Taichung City, Taiwan), and the motor's rotational speed was adjusted using a BL2-IPM controller.

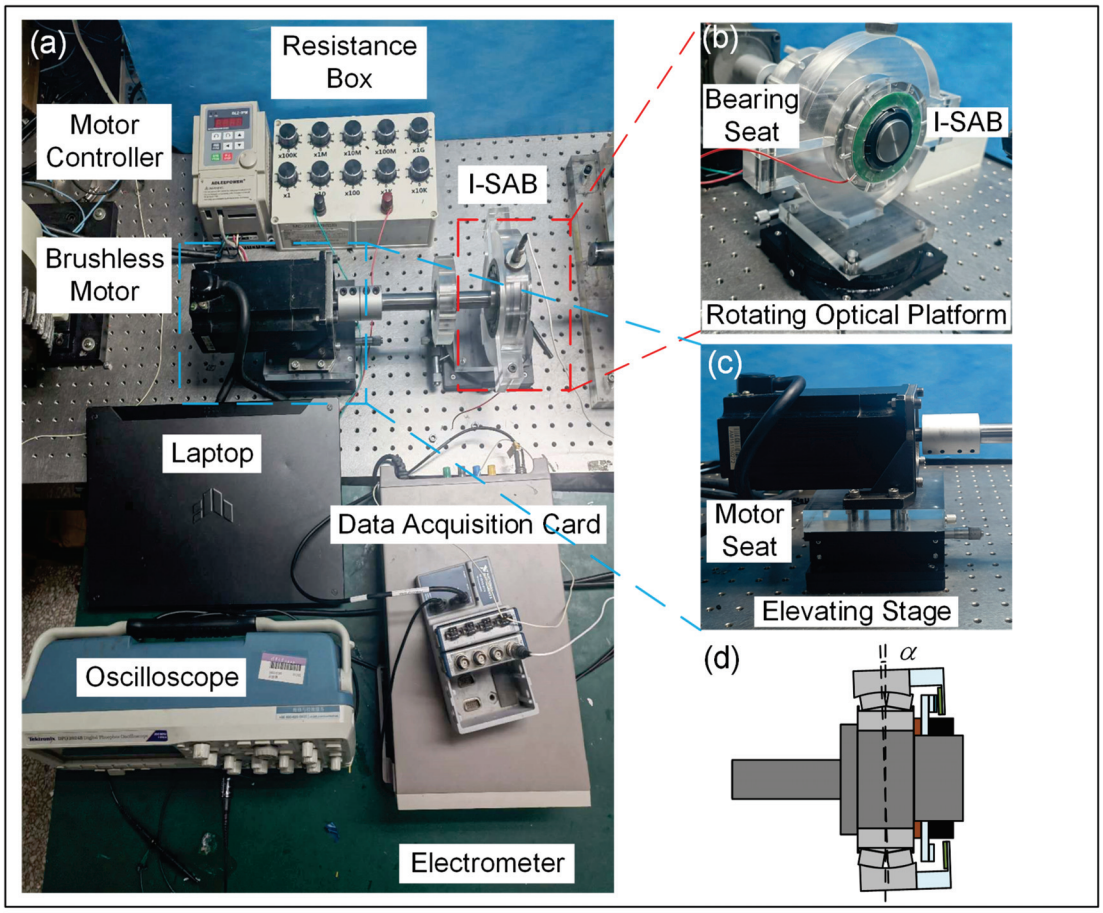


Figure 4. (**a**) Photograph of test bench; (**b**) structure of bearing seat; (**c**) installation of motor; (**d**) bias angle applied to I-SAB.

As shown in Figure 4b, the I-SAB was mounted on a specially designed acrylic bearing seat, which was fixed to an RSP125-L rotational optical platform. The rotational optical platform can be adjusted to tilt the bearing seat and simulate the application of different bias angles to the I-SAB. Specifically, the outer ring of the I-SAB was secured to the bearing seat and could be tilted when the optical platform was adjusted, as illustrated in Figure 4d.

Meanwhile, the inner ring of the I-SAB remained fixed to the rigid stepped shaft, ensuring that it was unaffected by the adjustments to the outer ring. This setup can simulate a controllable bias angle between the inner and outer ring of the I-SAB. For the adjustment of coaxiality, the motor was also fixed onto another LZ125-2-N, elevating the motor seat using an optical stage (shown as Figure 4c). This delivered one translational degree of freedom along the Z-axis. Additionally, the motor's positioning hole diameter was 0.3 mm greater than tthe screw diameter, providing two translational degrees of freedom in the horizontal plane (X and Y) and a small rotational degree of freedom, enabling fine angular adjustments within roughly $\pm$ 0.5°. This design grants the motor three translational degrees of freedom and one rotational degree of freedom, allowing for the precise alignment of its axis with the bearing's axis. Once aligned, the limit screws are tightened, and we use metal flat washers to minimize the load on the hole walls and to ensure the stability of the entire test bench. It is worthy of note that this configuration only ensures stability at relatively low speeds, restricting the rotational speeds in this study to under 1000 rpm.

3.1. Rotational Speed Sensing

One key functionality of the newly designed I-SAB is its self-sensing capability in terms of rotational speed. The waveforms of the open-circuit voltage and short-circuit current from the I-SAB at a rotational speed of 600 rpm are displayed in Figure 5a, and their corresponding spectra are presented in Figure 5b. The spectra show that both the triboelectric current and voltage signals have a prominent frequency of 120 Hz. Theoretically, the prominent frequency f_s of the triboelectric signal of the TENG can be expressed using the number of comb–finger pairs N and the rotational frequency f_r as follows:

$$f_s = Nf_r/60 \tag{1}$$

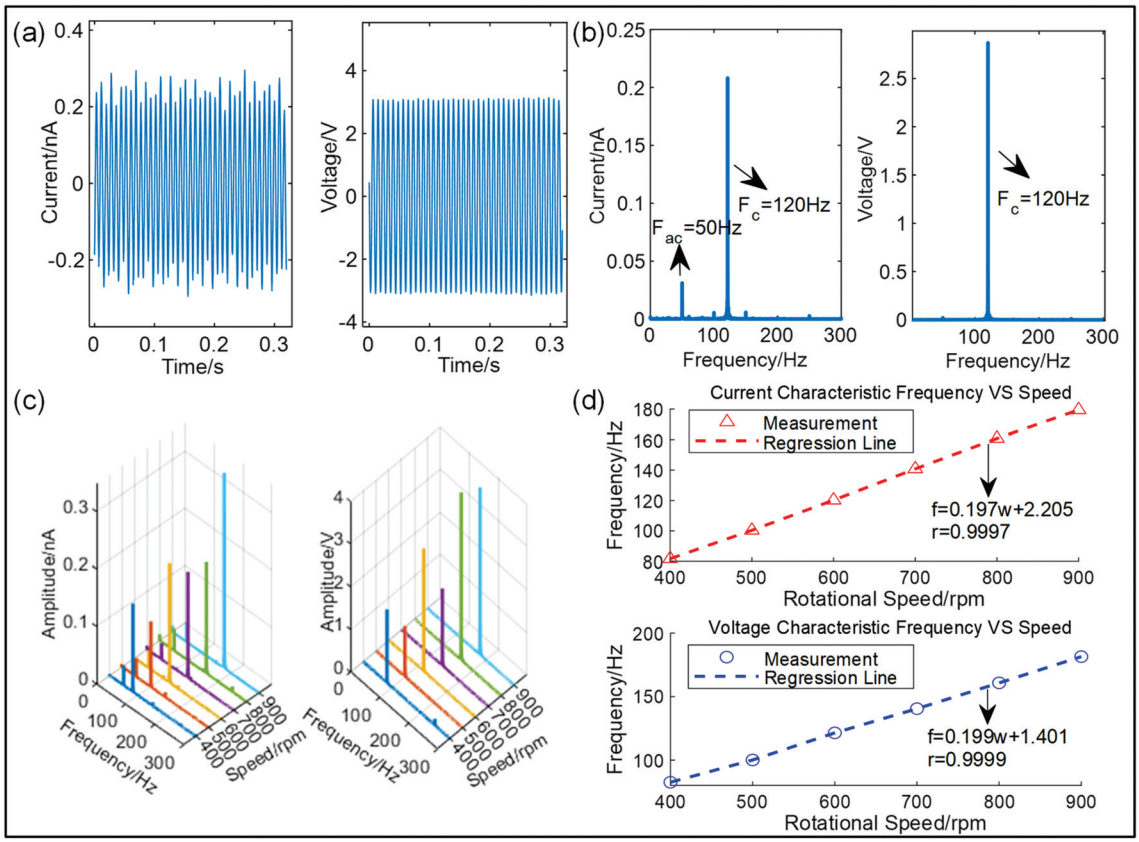


Figure 5. (**a**) Voltage and current signals under a rotational speed of 600 rpm; (**b**) spectra of voltage and current signals; (**c**) a waterfall plot of voltage and current signals; (**d**) a linear relationship between the prominent frequency and rotational speed.

In our experiment, the number of comb–finger pairs N is 12; thus, the theoretical signal frequency corresponding to a rotational speed of 600 rpm should be 120 Hz, which is consistent with the experimental result. To further explore the relationship between the signal frequency and rotational speed, we acquired 20 s long triboelectric current and voltage signals emitted from the I-SAB at various speeds ranging from 400 rpm to 900 rpm. Furthermore, the fast Fourier transform (FFT) algorithm was applied for signal analysis to investigate the characteristic frequencies, as shown in Figure 5c. Figure 5d illustrates the relationship between the characteristic frequencies of the signals and the rotational speed. From these results, we found a strong linear relationship between the prominent signal frequency and the rotational speed. After calculation, the linear correlation coefficients for the current and voltage signals were 0.9997 and 0.9999, respectively, indicating that the prominent frequency of triboelectric signals can be an excellent indicator for the self-sensing and measurement of the rotational speed. The slopes of the linear regression lines for the current and voltage signals were calculated to be 0.197 and 0.199, respectively, which are very close to the theoretical value given by Equation (3), namely, 0.2.

3.2. Bias Angle Monitoring and Sensing Performance Optimization

Another key functionality of the I-SAB is its self-sensing capability to monitor the bias angle. An illustration of the bias angle and varying triboelectric–electrode distances in the operating I-SAB is depicted in Figure 6a. When a bias angle is introduced to the self-aligning bearing, the separation distance between the flannelette triboelectric layer and the electrode varies at different circumferential positions. The distance between the triboelectric layer and electrode during operation can be formulated as follows:

$$d(t) = d_0 + R\sin(\alpha)\sin(\omega t + \varphi) \tag{2}$$

where d_0 represents the initial separation distance between the triboelectric layer and the electrode in the scenario of zero bias angle, R denotes the distance from the center of the triboelectric layer to the geometric center of the acrylic disk, α is the bias angle, ω is the rotational speed, and φ is the initial phase of rotation. Supposing that the self-aligning bearing (21308CA/W33 model) has a nominal maximum bias angle limitation of 1°, Equation (2) can be approximated as follows:

$$\mathrm{d(t)} \approx \mathrm{d_0} + \mathrm{R}\alpha\sin(\omega\mathrm{t} + \varphi) \tag{3}$$

From Equation (3), it is evident that the distance between the triboelectric layer surface and the electrode varies during rotational motions. The induced charge on the electrode decreases with an increasing triboelectric–electrode distance, leading to a reduction in the transferred charge. Conversely, the transferred charge increases as the triboelectric–electrode distance decreases. The variations in the triboelectric–electrode distance are more significant when the bias angle of the I-SAB increases. Given that the distance between the triboelectric layer and the electrode layer varies periodically at an angular frequency of ω, the output signals exhibit a sinusoidal envelope, modulated by this periodic variation. The modulation of the signals' envelopes can be expressed via the following equations:

$$Q_i = \int\int \varepsilon_0 E(x, y, d(t))cos(\theta_n)\mathrm{d}x\mathrm{d}y \tag{4}$$

$$I_{sc} = \frac{Q_i}{\Delta t} = \frac{\int\int \varepsilon_0 E(x, y, d(t))cos(\theta_n)\mathrm{d}x\mathrm{d}y}{\Delta t} \tag{5}$$

$$V_{oc} = \frac{Q_i}{\Delta t}Z = \frac{\int\int \varepsilon_0 ZE(x, y, d(t))cos(\theta_n)\mathrm{d}x\mathrm{d}y}{\Delta t} \tag{6}$$

where Q_i represents the induced charge accumulated on the electrode, E(x,y,θ) is the electric field strength at a point on the electrode surface with the location of (x,y), d(t) denotes the triboelectric–electrode distance, ε_0 is the dielectric constant of the vacuum, θ_n is the

angle between the electric field and the electrode surface, Δt is the time duration of one rotation cycle, and Z is the internal impedance of the I-SAB. Due to the fringe effects of the electric field, the strength of the electric field on the electrode surface decreases with increasing triboelectric–electrode distance. Thus, a reduction in the triboelectric–electrode distance will increase the induced charge density. As a result, a larger bias angle will result in more significant variations in the triboelectric–electrode distance, thus leading to both an increase in voltage variation and a greater envelope amplitude on the triboelectric voltage signal. The analysis of the envelope of output triboelectric signals can provide critical insights into bias angle monitoring.

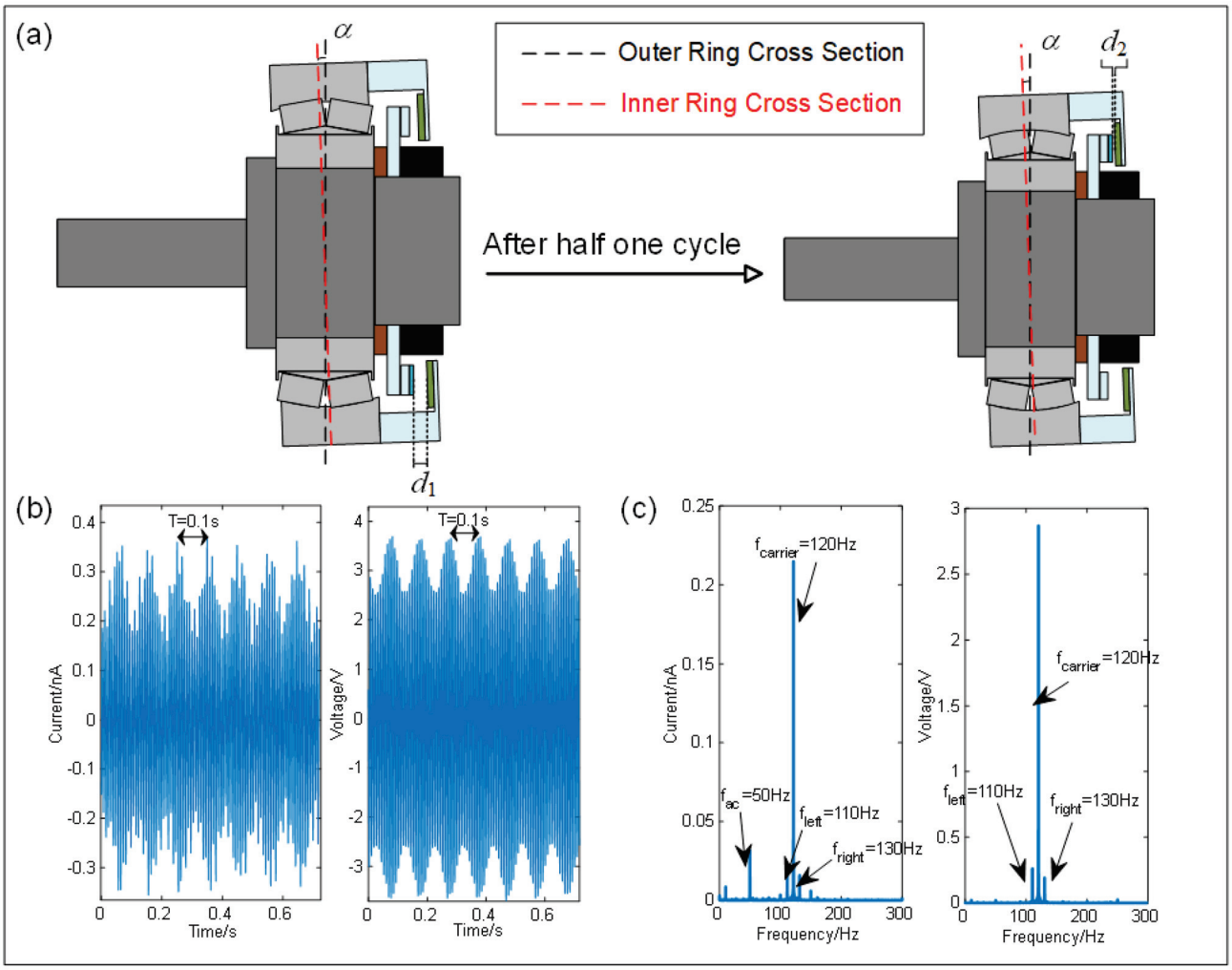


Figure 6. (**a**) Illustrations of the bias angle and the triboelectric–electrode distance during one half rotation; (**b**) the waveform of the triboelectric current and voltage signals of the I-SAB with a bias angle of 0.6° under a rotational speed of 600 rpm; (**c**) spectra of the triboelectric current and voltage signals.

Figure 6b exhibits the waveforms of the triboelectric current and voltage signals emitted from the designed I-SAB with a bias angle of 0.6° at a speed of 600 rpm, with their corresponding spectra presented in Figure 6c. The clear periodic envelopes can be identified in both the triboelectric current and voltage signals. These envelopes have a period of approximately 0.1 s, which corresponds to one rotation period. Theoretically, the voltage signal shown in the figure can be regarded as an amplitude modulation (AM) signal, as shown in the following equations:

$$V(t) = (V_0 + A\cos(2\pi f_r t))\cos(2\pi f_s t) \quad (7)$$

$$\mathrm{V(t)} = \mathrm{V_0cos}(2\pi f_s \mathrm{t}) + \frac{\mathrm{A}}{2}\mathrm{cos}(2\pi(f_\mathrm{r} - f_\mathrm{s})) + \frac{\mathrm{A}}{2}\mathrm{cos}(2\pi(f_\mathrm{r} + f_\mathrm{s})) \quad (8)$$

where $\mathrm{V_0}$ is the carrier amplitude, A denotes the envelope amplitude, f_r represents the rotational frequency, and f_s is the carrier frequency ($f_r << f_s$). Similarly, the triboelectric current signal can also be rewritten in the same form. Working from the equivalent Equation (8), it can be stated that the three prominent frequencies in the triboelectric signals are f_s, $f_s - f_r$, and $f_s + f_r$. In the case of the I-SAB with a bias angle of 0.5° under a rotational speed of 600 rpm, the three prominent frequencies of the triboelectric signals are 110, 120, and 130 Hz, which are clearly identified in the spectra. However, there exists an apparent difference between the current and voltage envelope waveforms: only the voltage envelope is perfectly sinusoidal. The current spectra show a noticeable 50 Hz ambient interference, namely, the power frequency, which may seriously affect the monitoring of the bias angle. To ensure reliability, the triboelectric voltage signal was analyzed via the bias angle monitoring using the I-SAB.

To analyze the envelope of the triboelectric voltage signal, the signal processing procedure was designed, as shown in Figure 7a. The Hilbert transform is a robust and computationally efficient algorithm used for analyzing the instantaneous amplitude of non-stationary signals [24], including the triboelectric voltages generated by the proposed I-SAB. In this study, the Hilbert transform was utilized to extract the envelope of the voltage signals. Firstly, the Hilbert transformation, defined in Equation (9), was applied to the voltage signal $\mathrm{V(t)}$, which yields the imaginary part $\hat{\mathrm{V}}(\mathrm{t})$ of the analytic signal:

$$\hat{\mathrm{V}}(\mathrm{t}) = \mathrm{H(V(t))} = \mathrm{V(t)} * \frac{1}{\pi \mathrm{t}} \quad (9)$$

The analytical signal $\widetilde{V(t)}$ of the voltage signal $\mathrm{V(t)}$ is defined as follows:

$$\widetilde{V(t)} = V(t) + j\hat{V}(t) \quad (10)$$

Since $f_s = 12f_r$ in Equation (7), which ensures no overlap between the spectrum of the carrier and the envelope, the Hilbert transformation of the triboelectric voltage signal can be written in the following form according to the Bedrosian Theorem [25]:

$$\hat{V}(t) = \mathrm{H}((\mathrm{V_0} + \mathrm{Acos}(2\pi f_\mathrm{r}\mathrm{t}))\mathrm{cos}(2\pi f_\mathrm{s}\mathrm{t})) = (\mathrm{V_0} + \mathrm{Acos}(2\pi f_\mathrm{r}\mathrm{t}))\mathrm{H}(\mathrm{cos}(2\pi f_\mathrm{s}\mathrm{t})) \quad (11)$$

By substituting Equations (7) and (11) into Equation (10), the following equation can be yielded:

$$\widetilde{V(t)} = (V_0 + A\mathrm{cos}(2\pi f_r t))(\mathrm{cos}(2\pi f_s t) + j\mathrm{sin}(2\pi f_s t)) \quad (12)$$

Furthermore, the envelope amplitude of the analytic signal can be written as follows:

$$\left|\widetilde{V(\mathrm{t})}\right| = V_0 + A\mathrm{cos}(2\pi f_\mathrm{r} t) \quad (13)$$

According to Equation (13), the magnitude of the analytic signal can directly represent the envelope amplitude when there is a DC component that can be easily removed by subtracting the mean value.

As illustrated in Figure 7a, the presence of high-frequency noise can still be observed in the envelope signal with the removal of the DC component. Therefore, the low-pass filtering operation was further applied to mitigate the noise interference. Eventually, the extracted envelope signal exhibited a perfect sinusoidal form, as illustrated in Figure 7a. To further explore the influence of the bias angle on the envelope signal, we acquired triboelectric voltage signals with various bias angles. The resulting original waveforms are shown in Figure 7b, with the corresponding demodulated envelope signals shown in Figure 7c. It is evident that the envelope amplitude increases with the increasing bias angle,

showing that the AM voltage signal from the I-SAB can serve as an excellent indicator of the self-sensing of the I-SAB's bias angle. Figure 7d illustrates the relationship between the peak-to-peak value of the envelope voltage signal and the bias angle at various rotational speeds. This was determined using the linear regression method. The results in Figure 7d show that the sensitivity of the peak-to-peak voltage to the bias angle increases with the rotational speed, rising from 0.8092 V/deg at 400 rpm to 3.6067 V/deg at 900 rpm. In addition, the results also reveal a strong linear correlation between the peak-to-peak value of the envelope voltage and bias angle, with the Pearson correlation coefficients all exceeding 0.99. Eventually, to determine the relationship between the line slope K and the rotational speed ω, the linear regression method was applied. The formulation obtained is as follows:

$$K = 0.0057\omega - 1.6279 \quad (14)$$

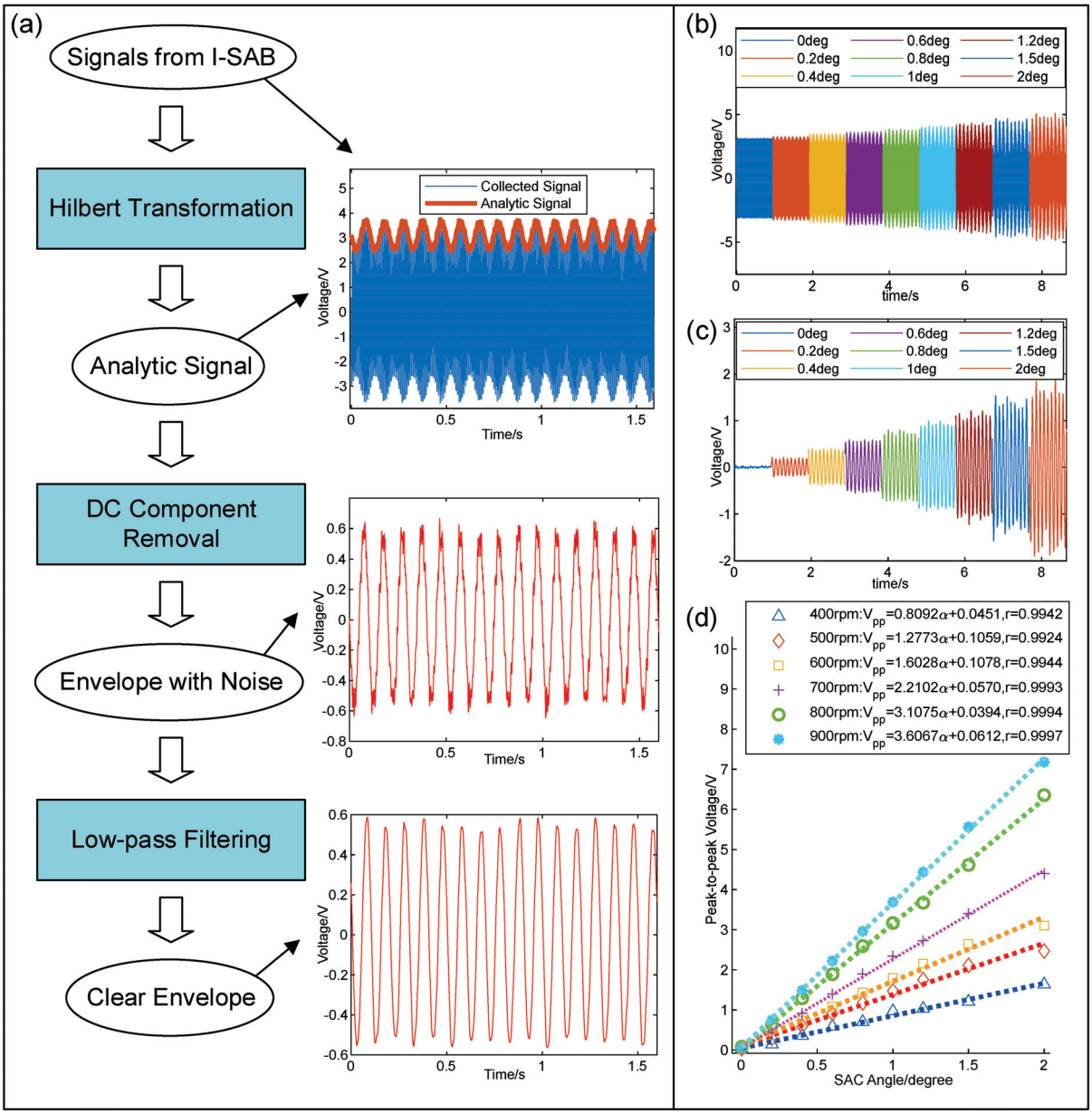


Figure 7. (**a**) Signal processing procedure; (**b**) voltage signals with different bias angles under speed of 600 rpm; (**c**) demodulated envelope signals with different bias angles under speed of 600 rpm; (**d**) relationship between peak-to-peak value of envelope signal and bias angle at various rotational speeds.

The Pearson correlation coefficient of the linear regression in Equation (14) is 0.9894, which indicates the existence of a strong linear relationship between the sensing sensitivity and rotational speed. According to Equation (14), we can rewrite the relationship between the bias angle and peak-to-peak value V_{pp} of the voltage envelope as follows:

$$\hat{\alpha} = \frac{V_{pp}}{(0.0057\omega - 1.6279)} \tag{15}$$

where $\hat{\alpha}$ denotes the estimated bias angle. To demonstrate the accuracy of the bias angle monitoring, we calculated the deviation value and deviation rate under different bias angles, given by Equation (15), using the following formulae:

$$\text{Deviation} = |\hat{\alpha} - \alpha| \tag{16}$$

$$\text{Deviation Rate} = \frac{\text{Deviation}}{\alpha} \times 100\% \tag{17}$$

The calculated results are shown in Figure 8a, indicating that the deviation and deviation rates of bias angle sensing are the most pronounced at the rotational speed of 400 rpm; meanwhile, the deviation rate reaches its highest value of approximately 50% at bias angles of 0.6° and 1°. However, as the rotational speed increases, both the deviation and deviation rate decrease significantly. When the rotational speed exceeds 600 rpm, the deviation rate can be maintained within the range of ±10%.

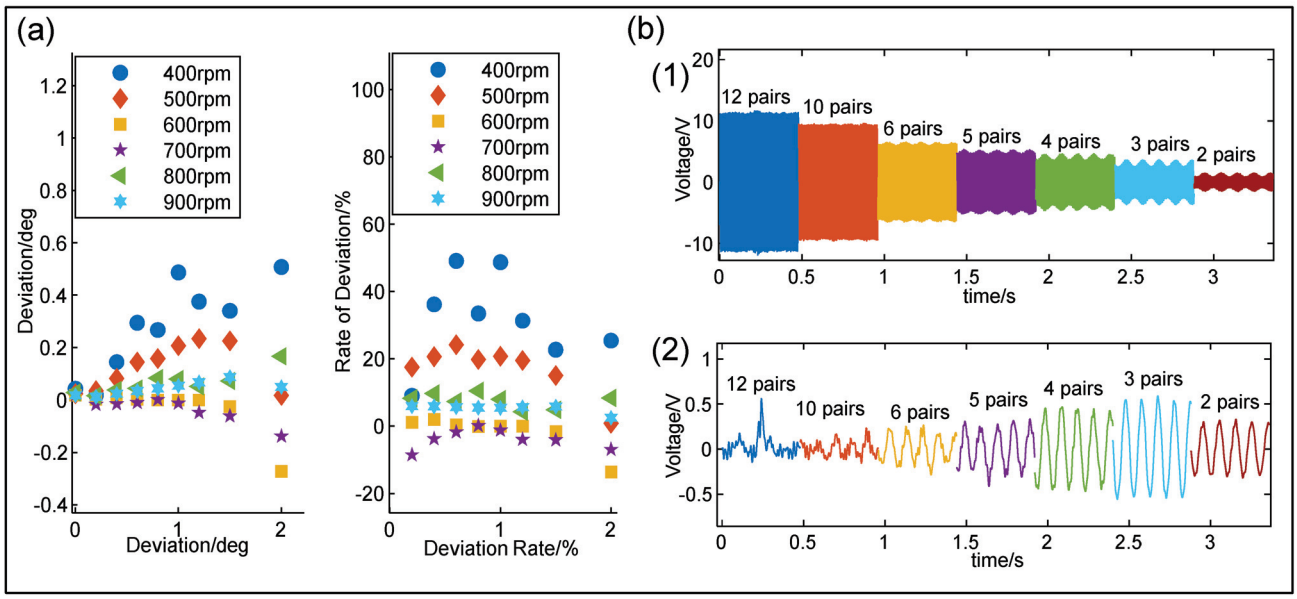


Figure 8. (**a**) Deviation and deviation rate given by the linear regression algorithm; (**b**) voltage (1) and envelope signals (2) given by the I-SABs containing different numbers of flannelette triboelectric layers.

To maximize the voltage signal amplitude and improve the capability of bias angle monitoring, the number of dielectric patches was further optimized. Specifically, different numbers of flannelette triboelectric layers were adhered to the acrylic disk and voltage signals were acquired from the designed I-SAB with a bias angle of 0.6° at a rotational speed of 600 rpm. As shown in Figure 8b, the disk with 12 dielectric patches produced a maximum voltage peak-to-peak value of 22 V; however, no recognizable envelope exists under this condition. With a decreasing number of dielectric patches, the envelope amplitude increases and reaches a maximum peak-to-peak value of 1.07 V with three dielectric patches, although the voltage signal amplitude decreases continuously. The main reason for this is that reducing the number of dielectric patches decreases the total charge induced

on the electrode, but it increases the variations in the induced charges during each rotation cycle, leading to an increase in the envelope amplitude. Ultimately, to yield the maximum envelope amplitude and a superior capability in terms of bias angle monitoring, three pairs of flannelette triboelectric layers were adhered to the acrylic disk.

4. Fault Diagnosis Application

Due to the harsh working conditions, the key components of self-aligning bearings are prone to faults after prolonged operation; therefore, it is necessary to monitor and diagnose the condition of the bearings. To address this issue, we explored the usage of triboelectric signals emitted from the newly designed I-SAB for self-powered fault diagnosis. In detail, the output triboelectric signals emitted from the I-SAB were collected under various conditions including ones with no fault, an inner ring fault, an outer ring fault, a roller fault, and a rotor imbalance fault. All datasets were acquired across six different rotational speeds. Moreover, we developed an end-to-end deep learning model, namely, the Multi-Scale Discrimination Network (MSDN), based on the ResNet18 architecture, to implement the automatic fault diagnosis application. The developed MSDN is a promising method used to extract the hidden fault features embedded in the triboelectric signals emitted from our designed I-SAB.

A data processing flowchart showing the self-powered fault diagnosis application is presented in Figure 9a. Since bearing fault features are modulated onto a carrier signal through amplitude modulation [23], the envelope signals are first obtained through the Hilbert transform for feature enhancement. Taking the triboelectric voltage signals under the condition of an inner ring fault at a rotational speed of 600 rpm as an example, the waveforms of the envelope signal and the corresponding spectrum are displayed in Figure 9b. The envelope spectrum in Figure 9b indicates that the frequency components related to fault features are overshadowed by the sinusoidal component produced by the bias angle. To extract and enhance the weak fault features related to different health conditions, singular spectrum analysis (SSA) [23] was further applied to the envelope signal. This SSA technique decomposes the envelope signal into three different scales—the trend term, the seasonal term, and the residual term—thus enabling feature extraction in these three scales. As for the implementation details of SSA, firstly, the envelope signal x with a length of N is embedded into a trajectory matrix using slide-window sampling with the window length L. This is performed as follows:

$$\mathrm{X} = \begin{bmatrix} x\,[0] & x\,[1] & & x[N-L] \\ \vdots & \vdots & \cdots & \vdots \\ x[L-1] & x[L] & & x[N-1] \end{bmatrix} \tag{18}$$

Secondly, by applying the singular value decomposition (SVD) to the trajectory matrix X, we obtain the following:

$$\mathrm{X} = \mathrm{U}\Sigma\mathrm{V}^{\mathrm{T}} = \left[\vec{\mathrm{u}}_0, \vec{\mathrm{u}}_1, \ldots, \vec{\mathrm{u}}_i, \ldots, \vec{\mathrm{u}}_{L-1}\right] \begin{bmatrix} \sqrt{\lambda_0} & 0 & 0 & 0 & \cdots & 0 \\ 0 & \ddots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \sqrt{\lambda_{\mathrm{L}-1}} & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} \vec{\mathrm{v}}_0 \\ \vdots \\ \vec{\mathrm{v}}_{\mathrm{N}-\mathrm{L}} \end{bmatrix}_{(\mathrm{N}-\mathrm{L}+1)\times(\mathrm{N}-\mathrm{L}+1)} \tag{19}$$

where $\vec{\mathrm{u}}_i \in R^{\mathrm{L}\times 1}$ is the i^{th} column vector in orthogonal matrix U, $\sqrt{\lambda_j} \in R$ is the j^{th} eigenvalue, and $\vec{\mathrm{v}}_k \in R^{1\times(\mathrm{N}-\mathrm{L}+1)}$ is the k^{th} row vector in the orthogonal matrix V^T. The i^{th} component of the trajectory matrix can also be represented as follows:

$$X^i = \sqrt{\lambda_i}\,\vec{u}_i\,\vec{v}_i,\ i \in [0, L-1] \tag{20}$$

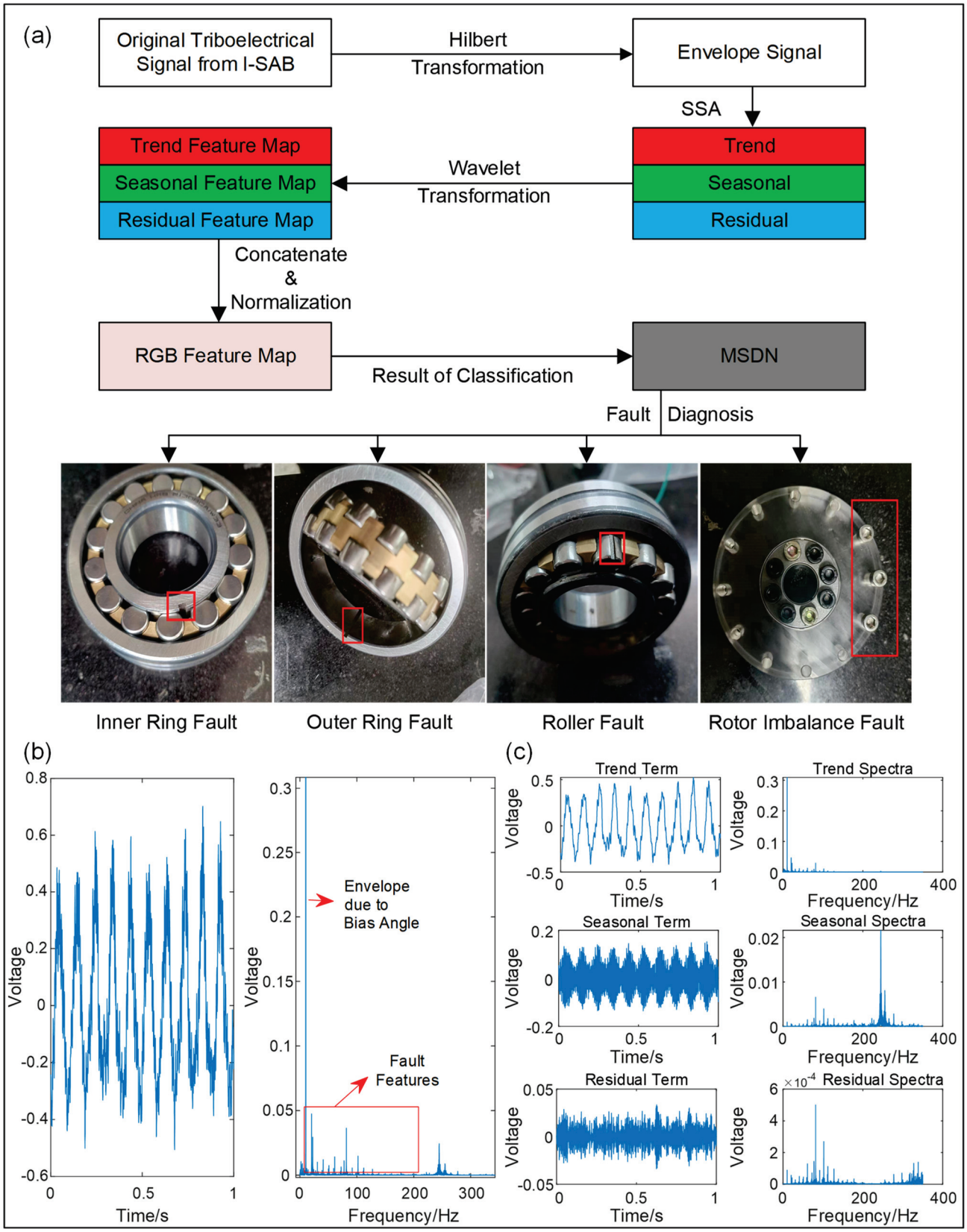


Figure 9. (**a**) The data processing flowchart; (**b**) the waveform and spectrum of the voltage envelope signal under the health condition of an inner ring fault and a rotational speed of 600 rpm; (**c**) waveforms and spectra for the trend term, seasonal term, and residual term given by the singular spectrum analysis.

Thirdly, the i^{th} signal component, $\hat{x}^i$, is recovered from the corresponding component matrix by calculating the average of the reverse diagonal elements:

$$\hat{x}^i[d] = \frac{1}{n_d}\sum_{m+n=d} X^i[m,n] \tag{21}$$

where n_d denotes the element number in the d $^{\text{th}}$ reverse diagonal. In our study, N = 125,000 and L = 10. To reconstruct the signal components in the three different scales, we categorized the components into three groups based on their eigenvalue magnitude and then superposed the discrete sequences within each group. The reconstructed sequences in three different scales and their spectrum are displayed in Figure 9c.

As deep learning models require a large sample size, data augmentation was conducted using sliding window sampling; this enables deep learning models to learn local invariant features and enhances the model's generalization capability. The sample number obtained from each component of the fault signal, S, can be calculated as follows:

$$\mathrm{S} = \frac{N-M}{\text{Slide}} + 1 \tag{22}$$

where N is the length of the signal components, Slide refers to the overlap length, and M is the window length. The wavelet transformation effectively captures local features such as transients, discontinuities, and singularities [26]. In this study, the Morlet wavelet was selected as the mother wavelet for the wavelet transformation, as formulated below:

$$\psi(\mathrm{t}) = \mathrm{e}^{\mathrm{j}\omega_0 \mathrm{t}}\mathrm{e}^{-\frac{\mathrm{t}^2}{2}}, \mathrm{t}\epsilon[-4,4] \tag{23}$$

where ω_0 is the center frequency of the mother wavelet. The Morlet wavelet can be viewed as a complex sinusoidal wave modulated by a Gaussian envelope. This unique structure enables the Morlet wavelet to exhibit high sensitivity to time-variant features. Consequently, the continuous wavelet transformation based on the Morlet wavelet was further applied to the signal components to obtain component spectrograms at three different scales. The component spectrograms in the three scales were then concatenated into three-channel feature maps that were subsequently stored as RGB jpeg images. It is worthy of note that channel normalization was also applied to each feature map before saving. These RGB images were then fed into the deep learning models for end-to-end fault diagnosis.

To address the task of end-to-end fault diagnosis with weak fault features in the RGB images of triboelectric signals, we developed a novel deep learning model, the MSDN. The structure of the MSDN is shown in Figure 10a. The developed MSDN model consists of three feature extractor modules and a decision layer, aiming to extract weak fault features from the perspective of time–frequency spectrograms and achieve fault diagnosis with high diagnosis accuracy. To accurately extract fault features at different scales, ResNet18 [27] was selected as the baseline of the feature extractor modules in our developed MSDN model. The architecture of the ResNet18-based feature extractor module is shown in Figure 10b. It is worthy of note that the features from different channels in traditional convolution layers are summed up after the convolution operations; hence, the weak features would be overshadowed by the stronger ones. As a result of the premature feature mixing, some important features disappear due to this inter-channel superposition. To mitigate this, we introduced three independent feature extractor modules to process the three-channel spectrogram separately at each scale. This strategy ensures that each feature extractor can specially extract features for one single feature map. The features from one scale do not sum up with those from other scales until reaching the decision layer, where the final feature fusion based on the fully connected layer occurs. This delayed fusion helps the model to extract weak fault features from each channel in turn [28]. The fused features are finally reduced to a 5D vector, which is then input into a SoftMax classifier for fault classification.

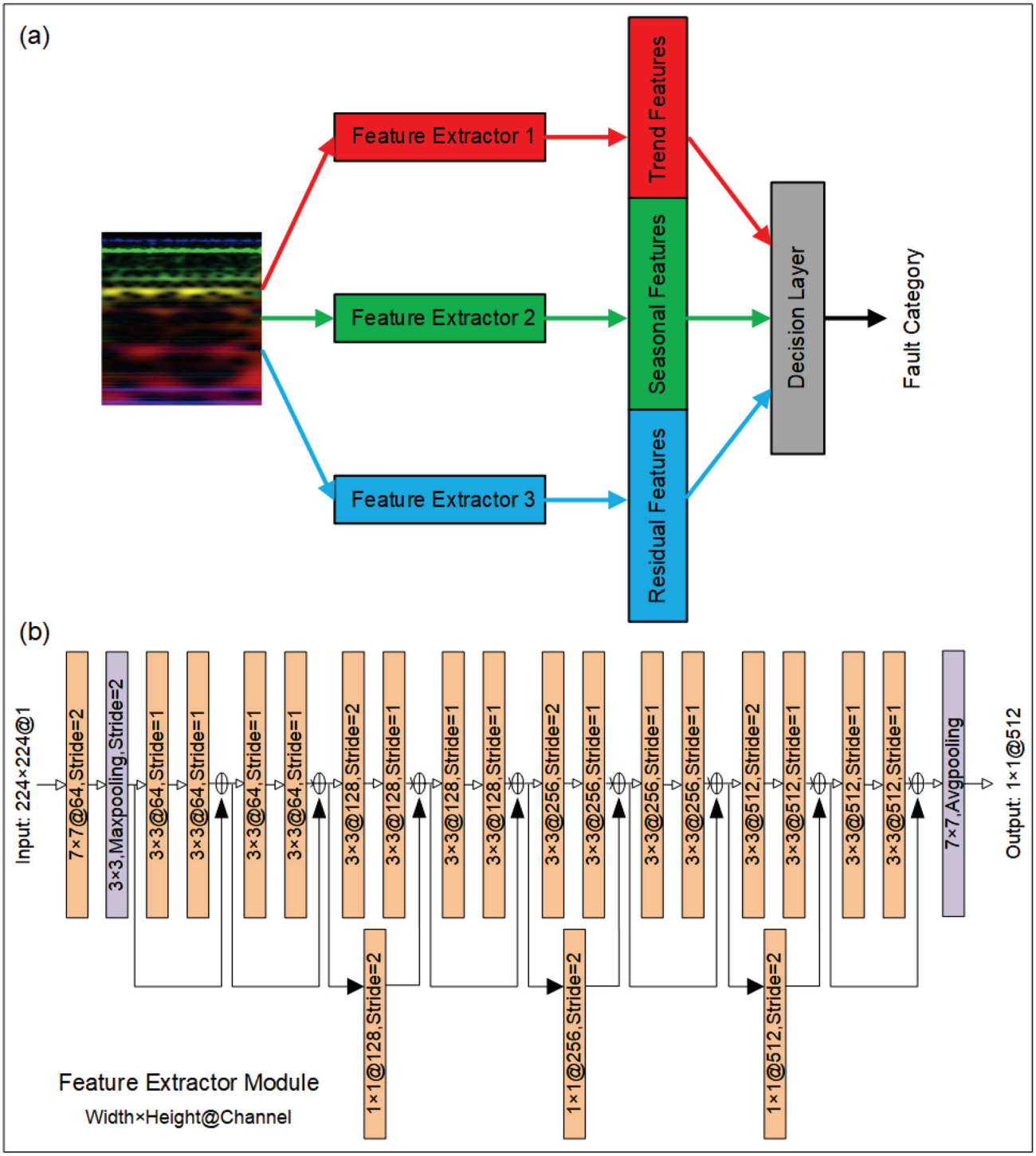


Figure 10. (**a**) Structure of MSDN; (**b**) architecture of feature extractor module based on ResNet18.

In our fault diagnosis experiments, the triboelectric signals emitted from the I-SAB were sampled in each condition for 40 s, and the total length of these signals was 125,000. The sliding window length M was 3125, and the Slide was 625. Both of these values were further applied to segment the components into smaller pieces. According to Equation (22), the number of samples obtained from one scale under one working condition was 196. Since the complete dataset consists of samples from six different rotational speeds (400 rpm, 500 rpm, 600 rpm, 700 rpm, 800 rpm, and 900 rpm), each with five different working conditions, the complete dataset consisted of 5880 samples. In our experiment, 60% of the

samples from each working condition were used in the training set, 20% were used in the validation set, and the remaining 20% were used in the testing set. To avoid the overfitting issue, the learning rate was set to 10^{-5}, and the stochastic gradient descent optimizer was used for model training. The loss function was cross-entropy, and deep learning models were built using Pytorch 1.12.0 on a Python 3.9 interpreter.

The fault diagnostic results of the proposed MSDN model built using triboelectric voltage and current signals emitted from the newly designed I-SAB are illustrated in Figure 11. The confusion matrix in Figure 11a demonstrates that the proposed MSDN model built using triboelectric voltage signals can exhibit superior diagnostic accuracy with a maximum level of 100%. To evaluate the robustness of the proposed model, five independent repeated experiments were carried out, resulting in a high average accuracy of 99.8% with a standard deviation of 0.23%. By contrast, the proposed MSDN model designed using the triboelectric current signals emitted from the I-SAB also yielded an optimal diagnostic accuracy of 99.7%, as shown in Figure 11b. The average accuracy derived from the triboelectric current signals emitted from the I-SAB reached 99.1% with a standard deviation of 0.71%. Additionally, the t-distributed stochastic neighbor embedding (t-SNE) algorithm was further applied to visualize the features of the final layer in the proposed MSDN model. The t-SNE feature visualization results shown in Figure 11c,d indicate that the output features of the MSDN using the triboelectric voltage and current signals emitted from the I-SAB can be perfectly separated, thus further validating the robustness of the proposed MSDN model.

In order to compare the newly proposed MSDN with classical deep learning models, the diagnostic performances of the CNN and ResNet18 using triboelectric voltage signals, including the training loss, confusion matrix, and feature visualization results, were further comprehensively analyzed. The training loss and accuracy during the training stage for the three different methods are displayed in Figures 12a and 12b, respectively. It can be observed that, after 15 training epochs, the best accuracy of the MSDN was maintained at 100%. To verify the possibility of overfitting, the proposed MSDN model was further examined on the validation set and the optimal diagnostic accuracy also reached 100%. These results confirm that the proposed MSDN model has a higher convergence speed and superior diagnostic accuracy compared to classical CNN and ResNet18 models, whose average diagnostic accuracies are 85.4% and 96.6%, respectively. Furthermore, the confusion matrices for CNN and ResNet18 are shown in Figure 12c,d, which indicate that neither CNN nor ResNet18 could perfectly distinguish between inner ring faults and roller faults. In addition, the t-SNE feature visualization results for the CNN and ResNet18 in Figure 12e,f show that the output features are overlapped, illustrating their weakness in terms of inter-channel feature extraction. By contrast, the MSDN has the least feature overlaps, indicating that it has excellent potential in feature separation. These comparison results solidly confirmed that the proposed MSDN model, which uses the triboelectric signals emitted from the I-SAB, exhibits superior convergence speed, diagnostic accuracy, and feature separation capability for self-powered fault diagnosis. Moreover, with the aid of the proposed MSDN model, triboelectric signals emitted from the I-SAB can be used as accurate and reliable indicators in self-powered fault diagnosis.

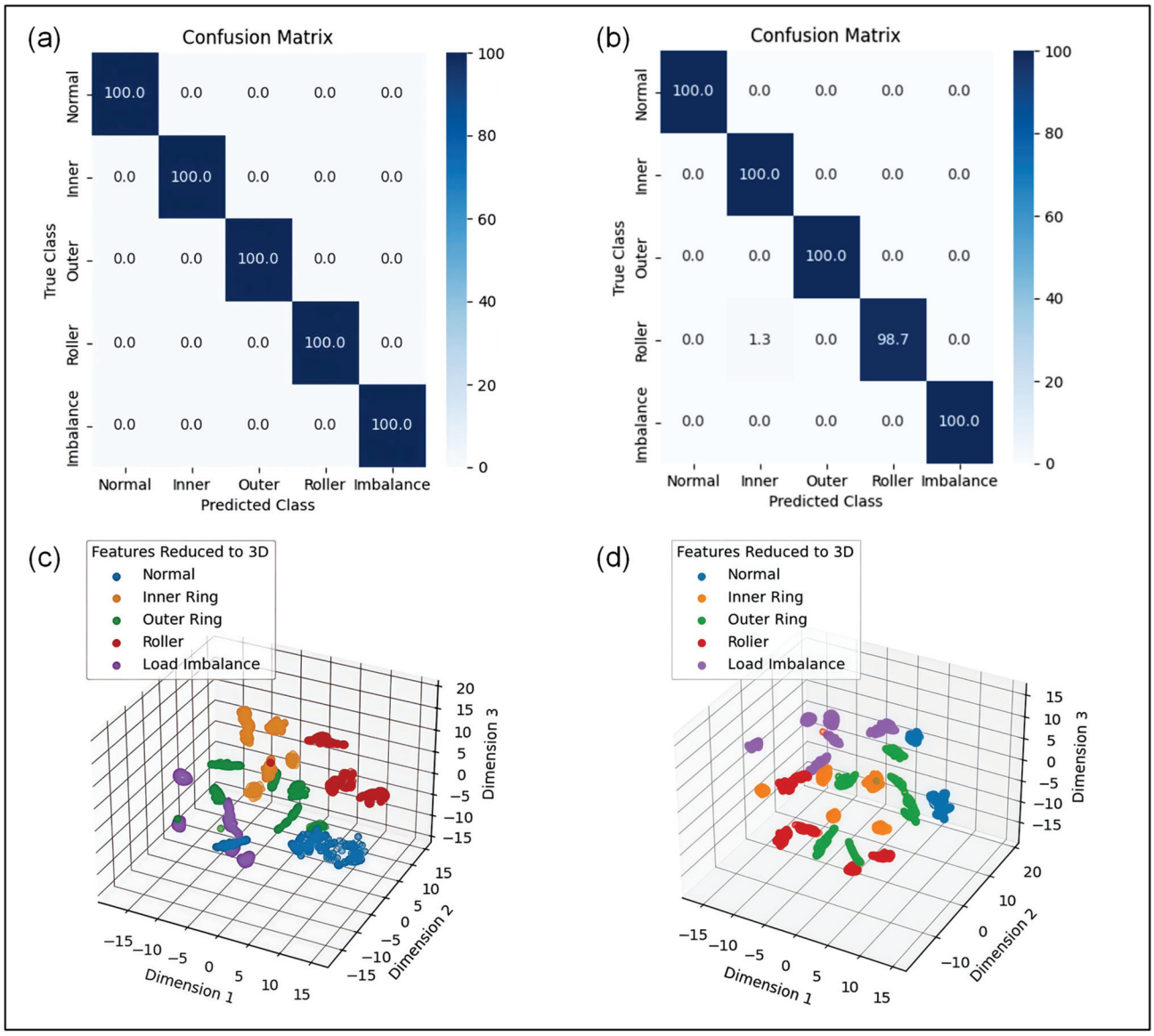


Figure 11. Fault diagnostic results of the proposed MSDN model. (**a**) Optimal confusion matrix using triboelectric voltage signals; (**b**) optimal confusion matrix using triboelectric current signals; (**c**) t-SNE feature visualization using triboelectric voltage signals; (**d**) t-SNE feature visualization using triboelectric current signals.

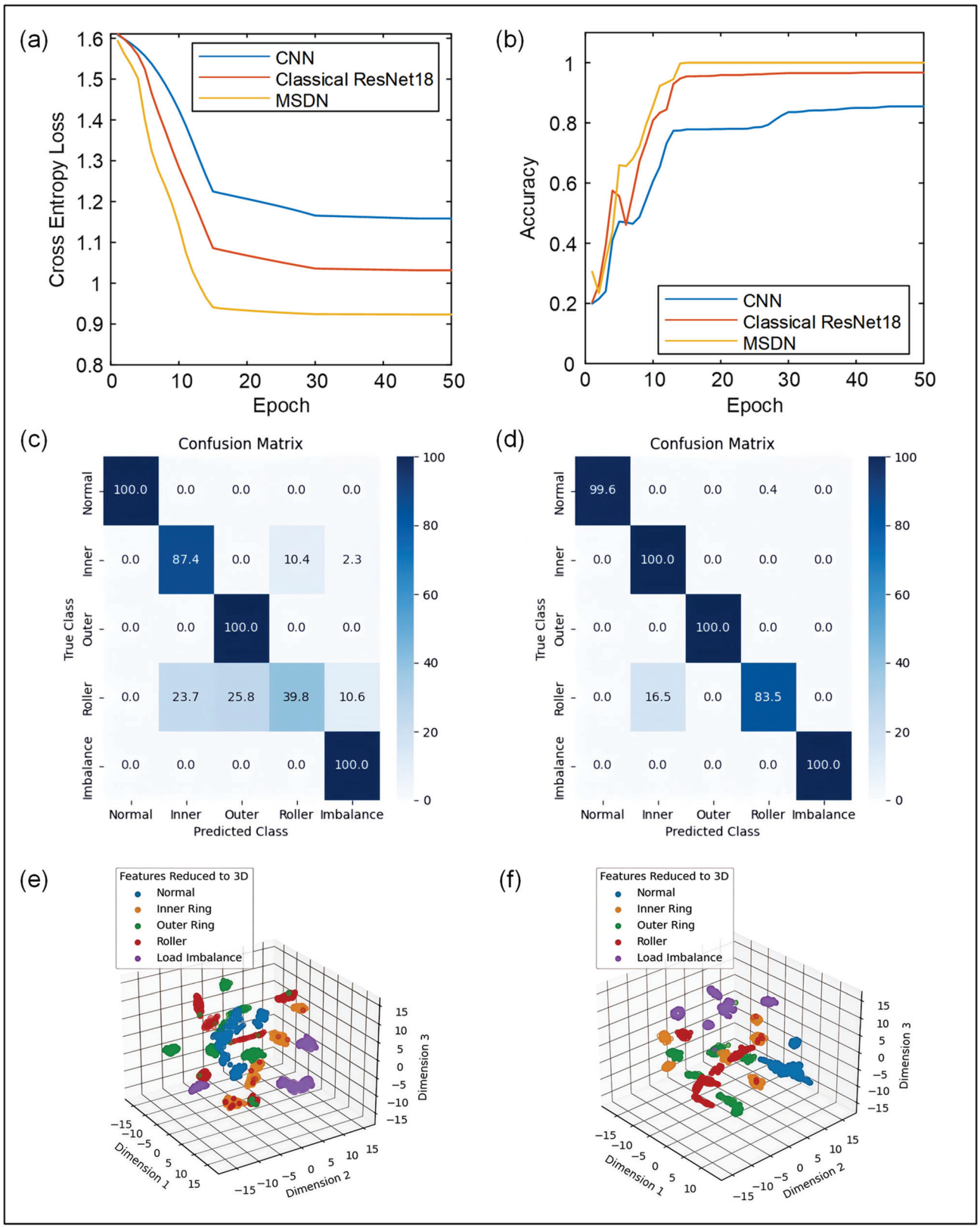


Figure 12. (**a**) The variation in training losses seen for three different methods. (**b**) The variation in training accuracies seen for three different methods. (**c**) The confusion matrix for CNN using triboelectric voltage signals, where accuracy = 85.4%. (**d**) The confusion matrix for ResNet18 using triboelectric voltage signals, where accuracy = 96.6%. (**e**) T-SNE feature visualization for the output features of CNN. (**f**) T-SNE feature visualization for output features of ResNet18.

5. Conclusions

In this study, a novel self-powered, intelligent, and self-aligning bearing (I-SAB) embedded with a triboelectric nanogenerator (TENG) was designed and implemented. This innovative smart bearing demonstrated extremely high accuracy in rotational speed sensing. Most notably, the newly designed I-SAB performed the first ever example of self-powered bias angle monitoring in a rotating machinery system. Benefiting from its unique design, the triboelectric voltage signal from the I-SAB exhibits an amplitude-modulated envelope, which occurs when a bias angle is present in the designed SAB device. A strong linear relationship was observed between the envelope amplitude of the triboelectric voltage signals and the bias angle. Moreover, the sensitivity of the bias angle sensing exhibited a linear correlation with the rotational speed. These two strong linearities enabled the proposed I-SAB to achieve self-powered and reliable bias angle sensing. To facilitate fault diagnosis using the I-SAB, a new neural network framework, namely, the Multi-Scale Discrimination Network (MSDN), was developed for weak feature extraction and self-powered fault diagnosis. The proposed MSDN trained using the triboelectric voltage and current signals yielded excellent average diagnosis accuracies of 99.8% and 99.1%, respectively, surpassing traditional deep learning models, including CNN and ResNet18. In summary, the newly designed I-SAB has shown considerable potential for self-powered rotational speed sensing, reliable bias angle monitoring, and accurate fault diagnosis. Furthermore, this work pioneers self-powered bias angle monitoring and fault diagnosis in rotating machinery systems supported by self-aligning bearings.

However, due to equipment limitations, the performance of the I-SAB under variable temperatures and high-speed conditions and during long-term operation was not investigated in this study. In the future, we plan to examine the performance of the I-SAB under extreme conditions and further optimize its design to ensure adaptability to harsh environments and to fault diagnosis applications under varying speed conditions.

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Effect of Dielectric Layer on Miniaturized Patch Antenna Sensor

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Abstract: Miniature patch antenna sensors have great potential in the field of structural health monitoring for crack propagation detection due to their small size and high sensitivity. A primary research focus has been achieving efficient miniaturization, with the performance of the dielectric layer playing a pivotal role. Studies have demonstrated that increasing the relative dielectric constant (ε_r) of the dielectric layer can reduce antenna size, but higher dielectric losses (tanδ) can lower radiation efficiency. This study identifies the optimal dielectric properties by examining the interplay between ε_r and tanδ to balance size reduction and radiation efficiency. Additionally, while increasing the dielectric layer's thickness improves bandwidth and radiation efficiency, a thinner layer is preferred to maintain overall performance without compromising radiation efficiency. Furthermore, the resonant frequency of the smaller-sized patch antenna sensor exhibits greater detection sensitivity to crack propagation. These insights provide useful guidance for selecting effective dielectric layers and assist in the miniaturization design of antenna sensors.

Keywords: antennas; dielectric constant; dielectric losses; dielectric layer

1. Introduction

In industrial applications such as aircraft and industrial robots, components often endure harsh conditions that lead to strain concentration and eventual damage accumulation, initiating cracks that can result in catastrophic structural failures and significant losses [1,2]. Real-time strain measurement of critical structures is therefore crucial for detecting potential crack initiation areas promptly, ensuring the safety of essential equipment and engineering facilities. Traditional strain sensor networks typically involve extensive cabling, which adds weight, complexity, installation costs, and vulnerability to system failures during disasters due to damaged leads [3]. Antenna sensors offer a promising solution by integrating wireless capabilities with sensing functions [4,5]. Their simple installation and structure have expanded the application across various fields. Recent research has demonstrated the reliability of antenna sensors in detecting crack propagation in structural components [6,7]. For example, Mohammad et al. proposed the basic structure and operational principles of antenna sensors for crack propagation detection [8]. Sofi et al. studied the feasibility of a wireless patch antenna sensor network for structural health monitoring [9,10]. Xue et al. designed a double-layer slotted circular patch antenna to measure the maximum strain of components according to the relationship between strain and antenna resonance frequency [11]. However, challenges persist when applying antenna sensors to detect damage in complex micro-components, potentially compromising the safety and reliability assessments of precision engineering structures due to size mismatches. Thus, there is an urgent need for sensor miniaturization.

To address this, researchers have proposed many structural improvements for the miniaturization of antenna sensors. Zhou et al. proposed an effective design method for compact bandpass filters with extensible orders/channels on a modified patch resonator [12]. Santhanam et al. found that digging holes in the ground plate can also reduce the antenna resonance frequency, thus realizing the miniaturization of the sensor size [13].

Merlin et al. achieved sensor miniaturization by slotting the patch antenna surface. Although this approach reduces the antenna's radiation surface area, it complicates antenna manufacturing and impedance matching [14]. Goswami utilized fractal antenna principles to reduce size while introducing multi-frequency characteristics, though increasing fractal complexity can compromise radiation efficiency and other antenna performance metrics [15]. Therefore, these structural improvements will reduce the radiation surface area of the antenna and affect the performance.

Recently, Singh et al. established a relationship between dielectric layer materials and antenna sensor size, showing that a higher dielectric constant of the dielectric layer results in smaller antenna sizes under required initial frequencies [16]. Miniaturized patch antenna sensors can be achieved by adjusting the dielectric layer material without modifying the antenna structure. However, dielectric materials with high dielectric constants often exhibit high dielectric losses, which can negatively impact the radiation efficiency of the antenna sensor [17,18]. Currently, the specific effects of dielectric layer properties on radiation efficiency remain underexplored. Although the implementation of miniaturized antenna sensors is feasible, it is still a challenge to ensure the performance of the dielectric electrical layer to meet the demand for crack propagation detection in small-sized antenna sensors. This work analyzes the effects of the dielectric layer on patch antenna size and radiation efficiency through simulations. This study aims to optimize dielectric layer materials to achieve antenna sensor miniaturization while enhancing operational efficiency.

2. Size Calculation of Antenna Sensor

The structure of the rectangular patch antenna sensor is shown in Figure 1, including the patch antenna on the upper surface, the dielectric layer in the middle, and the metal ground plane below. Through the action of the dielectric layer, an electromagnetic resonance cavity is formed between the patch antenna and the metal ground plate to receive external microwave frequency modulation signals. The electromagnetic waves form stable oscillations in the antenna and reflect the signals to obtain the return loss curve and center frequency. The center frequency of the patch antenna sensor is related to its structure, and the center frequency will also shift when the grounding plane has crack propagation. Therefore, the measured metal structure can be used as the metal ground plate, and then the strain can be characterized by the change in the center frequency of the patch antenna to detect crack propagation.

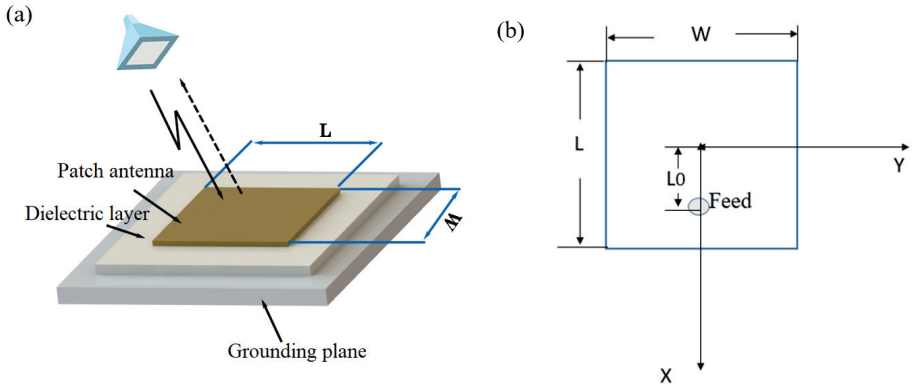


Figure 1. Structure of a coaxial antenna sensor: (**a**) size of the antenna; (**b**) position of the feed point.

Based on the transmission model of the antenna, the length L and width W of the rectangular radiation patch were designed using Equations (1)–(4) [19].

$$L = c/(2f\sqrt{\varepsilon_e}) - 2\Delta L \quad (1)$$

$$W = (c/2f)((\varepsilon_r + 1)/2)^{-1/2} \quad (2)$$

$$\varepsilon_e = (\varepsilon_r + 1)/2 + (\varepsilon_r - 1)/2(1 + 12h/w)^{(-1/2)} \quad (3)$$

$$\Delta L = 0.412h(\varepsilon_e + 0.3)(W/h + 0.264)/(\varepsilon_e - 0.258)(W/h + 0.8) \quad (4)$$

where c is the speed of light in vacuum, f is the operating frequency, h is the thickness of the dielectric layer, ε_r is the relative dielectric constant of the dielectric layer, ε_e is the effective dielectric constant, and ΔL is the extension length.

Take the coordinate origin as the center of the patch antenna. The antenna length is along the *x*-axis and the width is along the *y*-axis. The central feeding method is used in this study, and it is only necessary to keep the feeding point on the *x*-axis. The distance of the feed point from the center of the patch (L_0) will affect the impedance matching of the antenna. The position of the feeding point (L_0, 0) can be calculated by Equation (5) [20].

$$L_0 = L/(2\sqrt{\varepsilon_e}) \quad (5)$$

Arlon CuClad233, Krempel AKaflex kcl, Rogers TMM4, Rogers TMM6, and Arlon AR1000 were used as dielectric layer materials for the patch antenna sensor. The values of the relative dielectric constant (ε_r) and dielectric losses (tanδ) are shown in Table 1.

Table 1. Relative dielectric constant (ε_r) and dielectric losses (tanδ) of dielectric layer materials.

Material	Arlon CuClad233	Krempel AKaflex kcl	Rogers TMM4	Rogers TMM6	Arlon AR1000
ε_r	2.33	3.40	4.50	6.00	10.00
tanδ	0.0013	0.0018	0.0020	0.0023	0.0030

The center frequency is set to 3 GHz, and the thickness of the dielectric layer is 1.5 mm. The antenna dimensions are calculated using Equations (1)–(5), followed by optimization using the commercial software Ansys High Frequency Structure Simulator (HFSS version 15.0). The optimization process aims to refine the antenna dimensions. The return loss curve (S_{11}), standing wave ratio curve (VSWR), and radiation efficiency are derived for the antenna.

3. Results and Discussion

3.1. Effect of Relative Dielectric Constant of Dielectric Layer on Miniaturization of Antenna Sensor

The dimensions of the coaxial patch antenna sensor can be calculated by the above five kinds of dielectric layer materials with different relative dielectric constants, and the optimized dimensions are shown in Table 2.

Table 2. Calculated and optimized values of antenna sensor dimensions.

Dielectric Layer Materials	Calculation		Optimization				
	L/mm	W/mm	L/mm	W/mm	L_0/mm	Antenna Area/mm^2	Radiation Efficiency/%
Arlon CuClad233	33.16	38.75	31.00	38.75	5.5	1201.25	98.02
Krempel AKaflex kcl	27.25	33.71	25.75	33.71	4.2	868.03	94.97
Rogers TMM4	23.88	30.15	22.40	30.15	3.6	675.36	93.14
Rogers TMM6	21.45	26.73	19.38	26.73	2.8	518.03	90.05
Arlon AR1000	17.11	21.32	14.95	21.32	2.0	318.73	81.57

As can be seen from Table 2, the size of the antenna is inversely proportional to the ε_r value of the dielectric lay materials. When the ε_r value increases from 2.33 to 10, the area of the patch antenna sharply decreases from 1201.25 mm^2 to 318.73 mm^2. Since the coaxial antenna sensor uses a center feed, the resonant frequency of the antenna sensor is mainly affected by the antenna length L and the feed position L_0, and it is unnecessary to

change the antenna width W during optimization. Thus, compared with the calculated value, the optimized antenna length (L) is slightly reduced, while the width (W) is still consistent with the calculated value. However, Table 2 also shows that as the area of the antenna shrinks, the radiation efficiency of the antenna decreases from 98.02% to 81.57%.

From Table 2, it can also be seen that the antenna's feeding point positions (L_0) were determined to be 5.5, 4.2, 3.6, 2.8, and 2.0 mm, respectively. As the size of the antenna sensor decreases, the L_0 value decreases accordingly. The location of the L_0 mainly affects the antenna's input impedance. Through optimization, the optimal L_0 value is determined to achieve impedance matching with the input impedance of the antenna sensor (Z_0 is 50 Ω), as described in reference [21].

Figure 2 shows the optimized reflection coefficient of the sensor using five kinds of materials with different relative dielectric constants of the dielectric layer, including the return loss curve (S_{11}) and the standing wave ratio curve (VSWR). Figure 2a demonstrates that after optimization, the center frequency of the antenna aligns with the calculated resonant frequency of 3 GHz. The bandwidth is defined as the frequency range of the S_{11} curve within −10 dB. It can be seen from the figure that as the value of ε_r increases, the bandwidth gradually becomes narrower. Figure 2b displays VSWR curves of different dielectric layer materials that are relatively close, and the highest value is not more than 1.2. It means that the antenna dimensions optimized according to Table 2 satisfy the specified requirements, achieving excellent impedance matching.

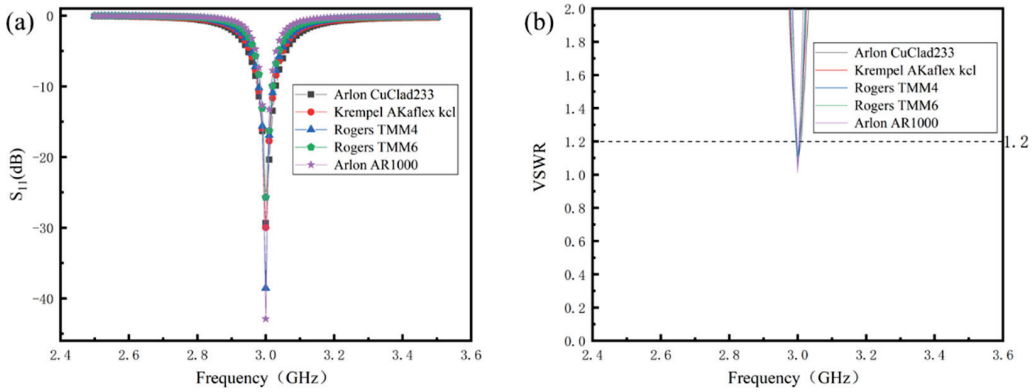


Figure 2. The optimized reflection coefficient of antenna sensors with varying relative dielectric constants of the dielectric layer: (**a**) S_{11}; (**b**) VSWR.

It can be concluded that a high relative dielectric constant of the dielectric layer significantly impacts the size of the antenna sensor, effectively reducing the antenna's area. However, this also results in a narrower bandwidth and decreased radiation efficiency.

3.2. Effect of Dielectric Loss of Dielectric Layer on Miniaturized Antenna Sensor

To further investigate the effect of dielectric losses of the dielectric layer on the size and performance of antenna sensors, we used the same relative dielectric constant to simulate and analyze the performance of antenna sensors by changing the dielectric losses of the dielectric layer. Figure 3 shows the optimized reflection coefficient of the antenna sensor after optimization. Table 3 shows the dimensions, radiation efficiency, and bandwidth of these patch antenna sensors.

Figure 3a illustrates that an increase in dielectric losses can improve the bandwidth of the antenna, and Figure 3b shows that the antenna impedance has reached a good match. Combined with Figure 3, as may be seen from Table 3, the change in dielectric loss does not affect the dimensions of the antenna sensor. However, when the relative dielectric constant of the dielectric layer is the same, the radiation efficiency of the antenna sensor decreases from 59.25% to 40.65% as the dielectric losses increase. This confirms that the dielectric layer with large dielectric losses cannot efficiently utilize the energy of the incident signal. As the dielectric losses increase, the peak gain of the antenna sensor decreases from 3.39

dB to 2.34 dB, indicating that increasing the dielectric losses is also not conducive to the long-distance application of the antenna sensor.

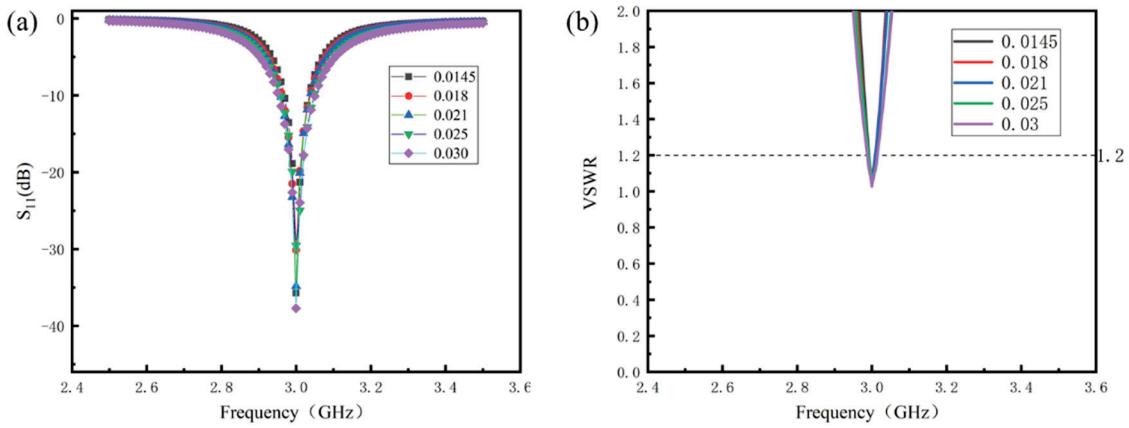


Figure 3. The optimized reflection coefficient of antenna sensors with varying dielectric losses of the dielectric layer: (**a**) S_{11}; (**b**) VSWR.

Table 3. Effect of dielectric layer with varying dielectric losses on antenna sensor dimensions and performance.

ε_r	tanδ	W/mm	L/mm	L_0/mm	Radiation Efficiency/%	Peak Gain/dB
4.5	0.0145	30.15	22.50	4.6	59.25	3.39
4.5	0.0180	30.15	22.56	5.0	53.77	3.08
4.5	0.0210	30.15	22.59	5.1	49.58	2.84
4.5	0.0250	30.15	22.60	5.5	45.14	2.59
4.5	0.0300	30.15	22.65	5.8	40.65	2.34

Therefore, we know that high ε_r values of dielectric layers are mainly beneficial to the miniaturization of the antenna sensor size, but the dielectric losses affect the antenna bandwidth, peak gain, and radiation efficiency. Selecting appropriate dielectric layer materials with appropriate ε_r and tanδ values can not only miniaturize the size of the antenna sensor but also obtain good performance.

3.3. Relationship Between Relative Dielectric Constant and Dielectric Losses of Dielectric Layer at Specific Radiation Efficiency

The relationship between the radiation efficiency (η), relative dielectric constant (ε_r), and dielectric losses (tanδ) of antenna sensors can be explained by Equations (6) and (7) [22].

$$\eta = \frac{P_{rad}}{P_{rad} + P_{loss}} \tag{6}$$

$$P_{loss} = \frac{1}{2}|E|^2 \frac{Wh\tan\delta}{240}\sqrt{\varepsilon_r} \tag{7}$$

where P_{rad} is the radiation efficiency of the antenna, P_{loss} is the loss power of the antenna, $|E|$ is the electric field strength, W is the width of the antenna, and h is the thickness of the dielectric layer. As may be seen from the above equation, radiation efficiency (η) is inversely proportional to dielectric loss (tanδ). Specifically, an increase in dielectric loss usually leads to a decrease in radiation efficiency. Therefore, by optimizing the relative dielectric constant and loss factor of the dielectric layer, the radiation efficiency of the antenna can be improved. The following is the actual verification process.

By changing the relative dielectric constant and dielectric losses of the dielectric layer material, the specific radiation efficiency of the antenna sensor is maintained at 40%, 50%,

and 60%, respectively. Table 4 shows the optimized parameters of the antenna for different layer materials.

Table 4. Antenna sensor dimensions and relationship between the relative dielectric constant and required dielectric loss at the specified radiation efficiencies.

ε_r	Radiation Efficiency								
	40%			50%			60%		
	L/mm	L_0/mm	Required tanδ	L/mm	L_0/mm	tanδ	L/mm	L_0/mm	Required tanδ
2.33	31.45	8.30	0.039	31.30	7.20	0.0270	31.20	7.00	0.0190
3.40	26.10	7.10	0.036	26.00	6.00	0.0240	25.90	5.80	0.0163
4.50	22.65	6.00	0.030	22.55	5.10	0.0210	22.50	4.60	0.0145
6.00	19.60	4.80	0.025	19.50	4.00	0.0180	19.50	3.80	0.0120
9.26	15.65	2.90	0.019	15.65	2.70	0.0130	15.60	2.60	0.0090
11.67	13.90	2.42	0.016	13.87	2.36	0.0110	13.85	2.10	0.0070
14.17	12.58	2.10	0.014	12.55	2.00	0.0095	12.52	1.70	0.0065
16.00	11.78	1.90	0.013	11.76	1.80	0.0083	11.75	1.40	0.0055
18.00	11.09	1.70	0.011	11.08	1.60	0.0076	11.05	1.45	0.0052
20.00	10.48	1.50	0.010	10.45	1.40	0.0070	10.45	1.20	0.0050

It can be seen from Table 4 that the varying relative dielectric constant and dielectric losses of the dielectric layer will affect the length (L) of the antenna and the position of the feeding point at different specified radiation efficiencies. In contrast, the width (W) of the antenna is independent of the dielectric losses of the dielectric material. As the relative dielectric constant of the dielectric layer increases, lower dielectric losses are required to achieve the same radiation efficiency. Therefore, when determining the radiation efficiency, there may be a certain relationship between the relative dielectric constant of the dielectric layer and the required dielectric losses.

Figure 4 illustrates the S_{11} curve and VSWR curve of antenna sensors with varying specified radiation efficiency. The size optimization of the patch antenna results in impedance matching, with values consistently below 1.2 for VSWR. The S_{11} curve further indicates that as the relative dielectric constant of the substrate material increases, the bandwidth of the antenna sensor decreases. This observation aligns with the findings from simulations discussed in the preceding section.

Figure 5a–c show the data and fitting curves for the predetermined radiation efficiency of 40%, 50%, and 60%, respectively. By linear fitting, the relationship between the relative dielectric constant and critical required dielectric losses is obtained, as shown in Equations (8)–(10).

$$y = 1.04 \times 10^{-4} \times X^2 - 3.85 \times 10^{-3} \times X + 0.0464 \quad (8)$$

$$y = 7.2 \times 10^{-5} \times X^2 - 2.66 \times 10^{-3} \times X + 0.0321 \quad (9)$$

$$y = 5.6 \times 10^{-5} \times X^2 - 1.97 \times 10^{-3} \times X + 0.0225 \quad (10)$$

The fitting degrees for Equations (8)–(10) are 98.6%, 99.4%, and 99.1%, respectively. It indicates that the fitting equation has high accuracy.

To further verify the accuracy of fitting equations (8)–(10) shown above, three materials with relative dielectric constants of 5, 10, and 15 were used for validation. Table 5 shows the verify parameters.

From the simulation results presented in Table 5, the critical required dielectric losses of the antenna layer material can be calculated, and the obtained radiation efficiency closely matches the specified radiation efficiency, labeled as "R" in Table 5. Thereby, the accuracy of the fitting Equations (6)–(8) is verified.

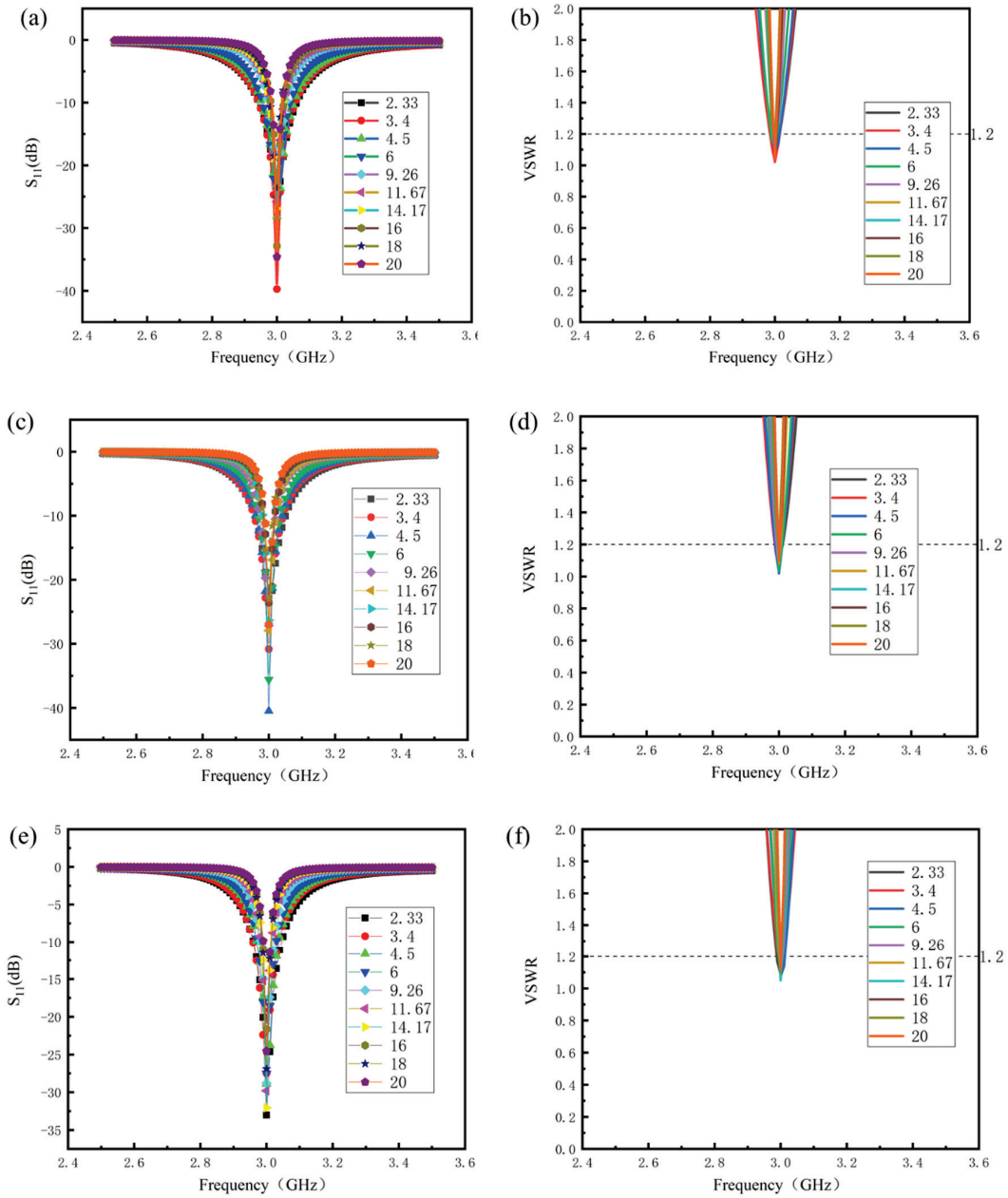


Figure 4. S_{11} and VSWR curves of antenna sensors with varying relative dielectric constant of the dielectric layer at different specified radiation efficiencies: (**a**,**b**) 40%; (**c**,**d**) 50%; (**e**,**f**) 60%.

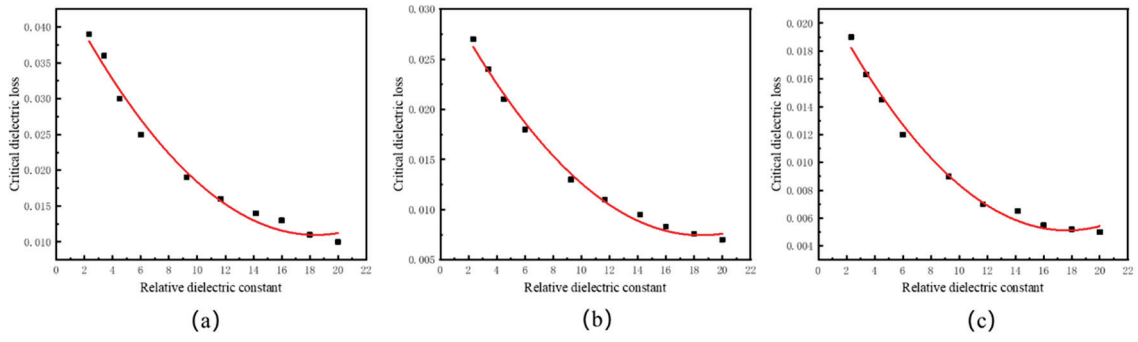


Figure 5. Relationship between relative dielectric constant and critical dielectric loss under predetermined radiation efficiencies: (**a**) 40%; (**b**) 50%; (**c**) 60%.

Table 5. Matching of the relative dielectric constant of the dielectric layer with the critical dielectric loss at different specified radiation efficiencies.

ε_r	Rated Radiation Efficiency/%					
	40%		50%		60%	
	Required tanδ	R	Required tanδ	R	Required tanδ	R
5	0.0298	39.2	0.0206	47.9	0.0141	58.1
10	0.0183	39.7	0.0127	49.1	0.0084	59.4
15	0.0121	42.3	0.0084	51.6	0.0056	62.1

3.4. Effect of Dielectric Layer Thickness on Miniaturized Antenna Sensor

Figure 6 presents the S_{11} and VSWR curves of the antenna sensors with Rogers TMM4 dielectric layer thicknesses of 1 mm, 1.5 mm, 2 mm, 3 mm, and 5 mm, respectively. As illustrated in Figure 6a,b, the optimization process has successfully aligned the resonant frequencies with the predetermined operating frequency of 3 GHz, while the VSWR values remain below 1.2. This indicates a strong impedance match for the antenna across the various dielectric layer thicknesses, suggesting that the antenna design can achieve optimal performance. Furthermore, Figure 6a reveals that the bandwidth of the antenna increases obviously as the thickness of the dielectric layer increases.

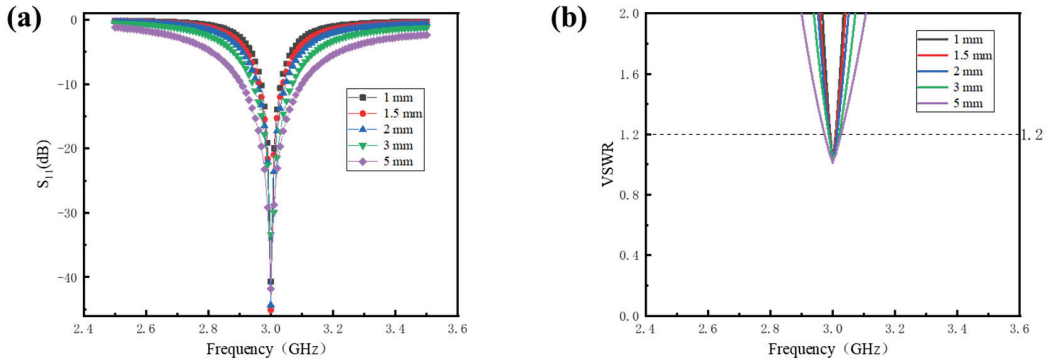


Figure 6. The optimized reflection coefficient of antenna sensors with varying dielectric layer thicknesses: (**a**) S_{11}; (**b**) VSWR.

Table 6 presents the optimized antenna dimensions for varying dielectric layer thicknesses. It can be observed that the thickness of the dielectric layer has a minimal impact on the antenna length. Specifically, as the thickness increases from 1 mm to 5 mm, the length decreases only from 23.20 mm to 21.05 mm. And the dielectric layer thickness does not influence the antenna width, which is further supported by Equation (2), demonstrating that the width remains independent of the dielectric thickness. Consequently, while the overall size of the antenna decreases slightly with increasing dielectric layer thickness, the reduction is limited. This suggests that although increasing the thickness of the dielectric layer has little effect on antenna size, it can enhance the antenna's bandwidth obviously.

Table 6. Optimized antenna sensor dimensions with different dielectric layer thicknesses.

Layer Thickness /mm	Antenna Sensor Dimensions/mm		
	W	L	L_0
1	30.43	23.20	5.6
1.5	30.43	22.80	5.0
2	30.43	22.45	4.8
3	30.43	21.80	4.8
5	30.43	21.05	5.8

Figure 7a shows the relationship between dielectric layer thickness and antenna radiation efficiency. The data clearly indicate that as the thickness of the dielectric layer decreases, the antenna's radiation efficiency declines significantly. When the thickness is reduced from 5 mm to 1 mm, the radiation efficiency decreases from 80% to 40%. The magnitude of radiation efficiency is closely linked to the distribution of the electric field within the dielectric layer [23]. Figure 7b illustrates the electric field distribution across dielectric layers of varying thicknesses. As may be seen from the figure, the electric field in the thick dielectric layer is more evenly and widely distributed, whereas the electric field in the thin dielectric layer is relatively concentrated in a small area. A wide electric field distribution within the dielectric layer enhances the radiation of the sensor through the edge effect of the patch antenna [24,25]. Consequently, the thick dielectric layer maintains a high radiation efficiency. However, as the dielectric layer thickness continues to increase, antenna losses rise due to the generation of surface waves [26,27], causing the growth of radiation efficiency to decelerate, as depicted by the arrow in Figure 7a.

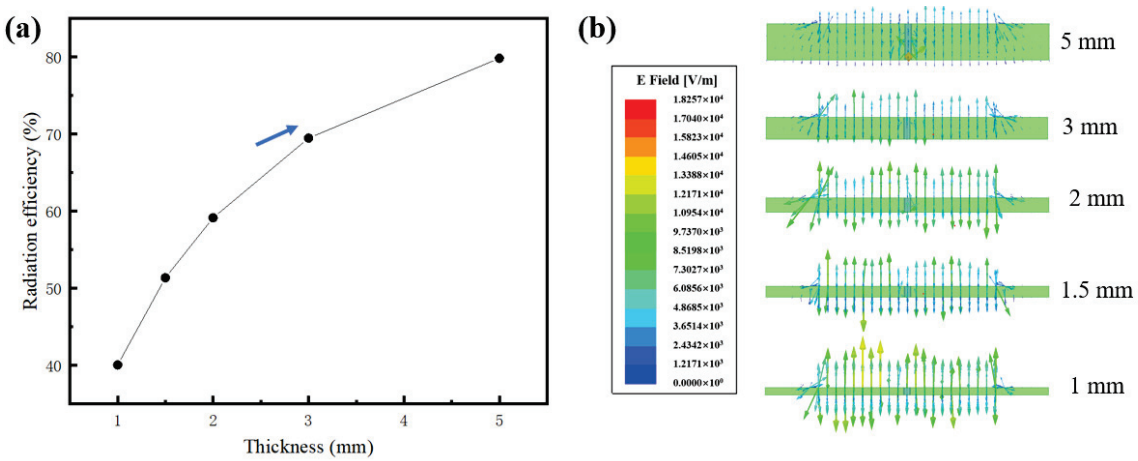


Figure 7. (**a**) Relationship between dielectric layer thickness and antenna radiation efficiency; (**b**) electric field distribution and intensity within dielectric layers of varying thicknesses.

As the thickness of the dielectric layer decreases, the electric field distribution becomes more concentrated, but the electric field intensity increases, as illustrated in Figure 7b. The high electric field intensity contributes to the generation of stable electromagnetic waves. This stability is crucial for enhancing the overall performance of the antenna, particularly in applications requiring high sensitivity. Therefore, although antenna sensors with thinner dielectric layers exhibit lower radiation efficiency, they are more capable of generating stable electromagnetic waves. For antenna sensors, it is advisable to select the thinnest possible dielectric layer while ensuring adequate radiation efficiency.

3.5. Effect of Crack Propagation on Miniaturized Antenna Sensor

Figure 8a–c illustrate three antenna sensors of different sizes with Arlon CuClad233, Rogers TMM4, and Arlon AR1000 dielectric layers, respectively. Their operating frequency is at 3 GHz. The relative dielectric constant of the three dielectric layers is 2.33, 4.50, and 10.00, respectively, as detailed in Table 1. The figures demonstrate a clear reduction in antenna size as the relative dielectric constant of the dielectric layer increases. Figure 8d–f present the relationship between the resonant frequencies of the three antenna sensors and crack propagation along the width direction of the metal ground plane. These figures show that as the crack expands from 0 mm to 10 mm, the resonant frequency shifts from 3 GHz towards lower frequencies.

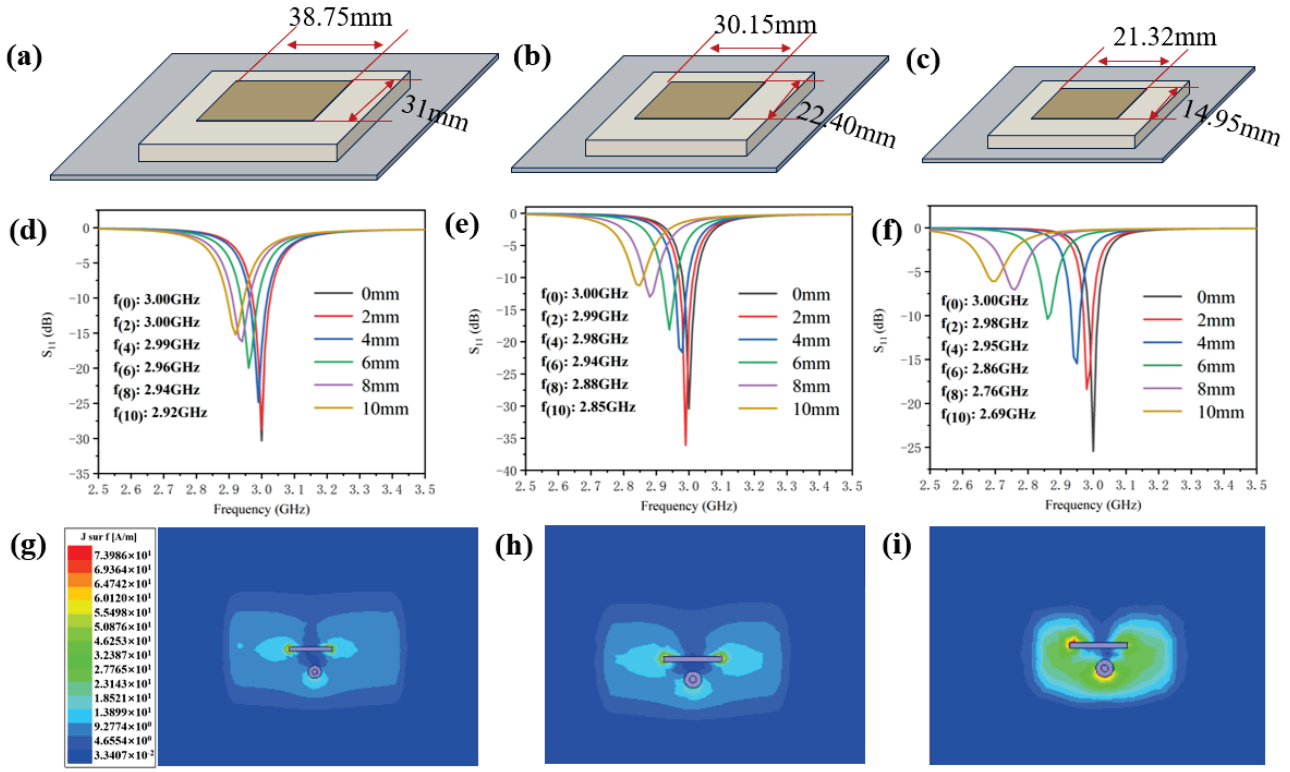


Figure 8. Three different-sized antenna sensors: (**a**) large-sized with Arlon CuClad233 as the dielectric layer; (**b**) medium-sized with Rogers TMM4 as the dielectric layer; and (**c**) small-sized with Arlon AR1000 as the dielectric layer. Relationship between resonant frequency and crack propagation for antenna sensors: (**d**) large-sized; (**e**) medium-sized; and (**f**) small-sized. Surface current density profiles on the ground plane of the antenna sensors: (**g**) large-sized; (**h**) medium-sized; and (**i**) small-sized.

The presence of cracks in the metal ground plane alters the current distribution within the antenna sensor, thereby impacting its electromagnetic characteristics. When a crack exists in the metal ground plane, the resonant frequency of the antenna sensor can be expressed as follows [28]:

$$f_{(crack)} = \frac{c}{2\sqrt{\varepsilon_e}} \frac{1}{L + 2\Delta L + \Delta L_{(crack)}} \tag{11}$$

Here, c represents the speed of light in a vacuum, ε_e denotes the effective dielectric constant, L is the length of the antenna sensor, ΔL is the extension length, and $\Delta L_{(crack)}$ is the additional length of the current path caused by the presence of the crack.

As shown in Equation (11), crack propagation reduces the resonant frequency ($f_{(crack)}$) of the antenna sensor, resulting in a leftward shift of the curve, as illustrated in Figure 8d–f. Notably, smaller antenna sensors exhibit greater sensitivity to changes in resonant frequency when the crack on the metal ground plane extends beyond a certain threshold. As observed in Figure 8f, the resonant frequency of the small-sized sensor decreases significantly from 3 GHz at $f_{(0)}$ to 2.69 GHz at $f_{(10)}$ as the crack expands from 0 mm to 10 mm. In contrast, the resonant frequency of the large-sized sensor shows minimal change with crack growth. In Figure 8d, its resonant frequency ($f_{(10)}$) is 2.92 GHz when the crack length extends to 10 mm. This indicates that the smaller-sized antenna sensor demonstrates improved detection sensitivity.

Figure 8g–i present the surface current density profiles on the ground planes of antenna sensors with varying sizes. It can be observed that the smaller-sized sensor exhibits stronger and more uniform current density in its central region. This heightened current density leads to a more pronounced change in the electromagnetic field distribution

around the ground plane. When a crack appears, the interaction between this intensified electromagnetic field and the crack generates more significant signal changes, enabling the antenna sensor to detect the presence of the crack with greater sensitivity.

4. Conclusions

The dielectric properties of the dielectric layer are crucial for the miniaturization and performance of antenna sensors, as demonstrated through simulations and analyses. Increasing the relative dielectric constant (ε_r) of the dielectric layer significantly reduces the size of the antenna sensor and narrows the bandwidth. However, higher dielectric losses (tanδ) in the dielectric layer reduce radiation efficiency and antenna gain. Establishing a precise relationship between ε_r and tanδ enables accurate prediction of both antenna size and radiation efficiency. For radiation efficiencies of 40%, 50%, and 60%, the relationship between the relative dielectric constant and critical dielectric losses aligns with Equations (8)–(10), with validation under critical conditions confirming the accuracy of this relationship. Understanding this dynamic facilitates the selection of appropriate dielectric layer materials, thereby enhancing the performance of miniaturized patch antenna sensors. Additionally, increasing the thickness of the dielectric layer improves both bandwidth and radiation efficiency, though it has minimal impact on the antenna size. On the premise of ensuring the radiation efficiency, a thinner dielectric layer can be selected as far as possible. When crack propagation occurs in the metal ground plane, smaller-sized sensors exhibit higher sensitivity to changes in resonant frequency. These insights provide valuable guidance for designing miniaturized patch antennas using suitable dielectric materials. This advancement not only broadens the application potential of high-performance antenna sensors in structural health monitoring for crack propagation detection but also extends their use to fields such as wireless communication, radar, electronic countermeasures, and more.

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sensors

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Review

Coaxial Cable Distributed Strain Sensing: Methods, Applications and Challenges

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Abstract: Distributed strain sensing is a powerful tool for in situ structural health monitoring for a wide range of critical engineering infrastructures. Strain information from a single sensing device can be captured from multiple locations simultaneously, offering a reduction in hardware, wiring, installation costs, and signal analysis complexity. Fiber optic distributed strain sensors have been the widely adopted approach in this field, but their use is limited to lower strain applications due to the fragile nature of silica fiber. Coaxial cable sensors offer a robust structure that can be adapted into a distributed strain sensor. They can withstand greater strain events and offer greater resilience in harsh environments. This paper presents the developments in methodology for coaxial cable distributed strain sensors. It explores the two main approaches of coaxial cable distributed strain sensing such as time domain reflectometry and frequency domain reflectometry with applications. Furthermore, this paper highlights further areas of research challenges in this field, such as the deconvolution of strain and temperature effects from coaxial cable distributed strain sensor measurements, mitigating the effect of dielectric permittivity on the accuracy of strain measurements, addressing manufacturing challenges with the partial reflectors for a robust coaxial cable sensor, and the adoption of data-driven analysis techniques for interrogating the interferogram to eliminate concomitant measurement effects with respect to temperature, dielectric permittivity, and signal-to-noise ratio, amongst others

Keywords: distributed sensing; structural health monitoring; coaxial cable Fabry–Perot interferometry; time domain reflectometry; coaxial cable Bragg grating

1. Introduction

Data on parameters such as strain provide reassurance that structural assets are working within their design limits and provide an early warning if safe levels are exceeded [1]. This information enables structural failure avoidance, which can prevent heavy human and financial costs [2]. Structural health monitoring (SHM) plays a critical role across a breadth of industries, such as civil infrastructure, energy production, aerospace, and automotive, in the management of existing and future structures [3]. Growth industries such as offshore wind present new challenges for SHM due to the range of operating environments and structural requirements on the various turbine components [4]. Information gathered by the Caithness Windfarm Information Forum 2014 [5] reported that there is a clear trend in the number of accidents increasing as more wind turbines are being built. Blade failure and structural failure were cited as two of the main causes of accidents.

As well as avoiding accidents by pre-empting failures, in situ condition monitoring decreases the volume of routine manual inspection work that is often carried out in exposed

environments with awkward access. Reducing the regularity of human interaction with the structure would be a secondary route to lowering accident rates. Remotely tracking the operation and health of assets can feed into scheduling risk-based inspections where inspections and maintenance efforts are focused on areas deemed to carry the highest risk. This optimizes the time and cost efficiency of operation and maintenance (O&M) labor, which is vital for remote, difficult-to-access assets exposed to challenging environmental conditions [6].

Furthermore, real-time, in situ condition monitoring can be used to optimize the operation of the assets, ensuring that the system is not driven beyond limits which could incite structural 'wear and tear'. This extends the lifetime of the structures and ultimately reduces the need to prematurely dispose of components, minimizing costs, and material waste detrimental to the planet.

Structural health monitoring is an extensive field of research and technology development. In the context of trains sensing, there are several incumbent and emerging technologies summarized in Table 1. This summarized information provides a broader perspective to set the scene for how optical fiber and coaxial cable strain sensing technologies, the key focus of this paper, compare with other strain sensing techniques.

Table 1. A summarized comparison of existing and emerging strain sensing technologies for structural health monitoring.

In Situ Strain Sensor Technology	Basic Principle of Operation, Key Attributes, and Limitations	Quantified Performance Values	Reference
DOFSs (Brillouin or Rayleigh scattering)	• Optical time domain reflectometry. Based on time-of-flight methodology, reflections of light propagating along the fiber are analyzed for components of higher or lower wavelengths than the source light that provide information on changes to the optical fiber such as strain or temperature. • Distributed sensing over many kilometers due to low power loss. Resistant to electromagnetic interference. Small diameter and lightweight. Broad bandwidth enables high-speed data transmission and high spatial resolution, and the signal can contain significantly more information than is possible with metallic conductors. • Fragile optical fibers limit maximum strain to <1%. Sensitive to strain and temperature.	Sensing range up to 10 s of km Spatial resolution down to ~1 m. (trade-off between sensing range and spatial resolution). Maximum strain capability < 1%	[7–9]
FBG	• Periodic modifications in the refractive index of the optical fiber are manufactured. This creates narrow-band reflections and discrete resonant frequencies. Changes in environmental conditions such as strain or temperature cause the distance between the periodic refractive index modifications to change, shifting the resonant frequencies. This shift is analyzed to infer the change in environmental conditions that has occurred. • Many of the same attributes as DOF technology are still based on optical fibers. Can be embedded into composite fiber structures. Capable of single-point or multi-point sensing. Approximately 13–14 sensors can be multiplexed on a single fiber. • Quasi-distributed as multiplexed Bragg gratings are spaced out along a fiber optic length. Fragile optical fibers limit maximum strain to <1%. Sensitive to strain and temperature.	Sensing range up to 10 s of km. Spatial resolution of ~2 mm. Maximum strain capability < 1%.	[2,10–12]

Table 1. *Cont.*

In Situ Strain Sensor Technology	Basic Principle of Operation, Key Attributes, and Limitations	Quantified Performance Values	Reference
CCTDR	• Time domain reflectometry. A time-of-flight measurement based on reflected signals from a coaxial cable. Defects along the line create new reflections. • Coaxial cables are robust structures that can withstand rough environments. • Only relatively large-scale deformation/defects will generate a new reflection that can be deflected. Lower strain events cannot be monitored. Coaxial cable heavier compared to fiber optics.	Sensing range ~10 s–100 s m	[13]
CCFPI	• A pair of partial reflectors created by a change in cable impedance are manufactured on the cable. Reflections interfere to create a series of resonant frequencies that can be tracked. If the distance between the pair of partial reflectors changes due to strain or thermal expansion, the frequency of the resonances shift. • Option for single-zone or fully distributed sensing. Coaxial cable is a robust structure. • Further work to be carried out on the longevity and reliability before employed in the field. Coaxial cable heavier compared to fiber optics.	Maximum reported sensing range ~1m. Spatial resolution reported ~order of cm's. Large strain capability (>5%).	[14–16]
Electrical resistance strain gauges	• The resistance of a wire is dependent on the length and cross-sectional area. When a strain is applied to a wire, these dimensions change, altering the resistance which can be measured. • Very established technology, low cost, and can be wired for temperature compensation in a bridge configuration. • Point sensors. Installing many strain gauges results in complex wiring arrays. Impractical for measuring long distance structures.	3–5% maximum strain	[17]
RFID antenna	• A rectangular micro-strip patch antenna constructed of a metallic patch on a substrate with a ground plane has a resonant frequency. If strain is applied to patch, changing the length of the structure, the resonant frequency shifts. A handheld stand-alone RFID reader is used to measure this change from which the change in strain can be inferred. • Wireless, low-cost. Each RFID tag has a unique identifier so strain measurements can easily be linked to an exact location. • Must be accessible for a reader to interrogate the device. Point sensors. Does not provide continuous monitoring.	Maximum strains of up to 10 s of %.	[18–20]

It becomes impractical to use arrays of discrete sensors to measure strains over large or extensive structures due to the costs of installation, wiring, and analysis of a multitude of sensor devices [7]. Also, discrete sensors measure localized events and can miss important behaviors occurring on non-instrumented sections of the structure [10].

Fiber optic technology can provide distributed strain data, where a single device (the fiber optic cable) can report on the conditions at continuous locations over an entire length. Due to the relatively low strain limit of the silica in fiber optics, there is a limit on the magnitude of strain this technology can monitor [15,21]. Fiber optic technology is therefore not

capable of capturing high-strain events. There is also a challenge around the installation of fiber optics. The fragile fibers must be handled carefully, which presents challenges during installation procedures and operation in exposed or extreme conditions [10]. However, there are techniques used in fiber optic sensing that can be applied to other media such as coaxial cables [15,21–23].

Coaxial cables are more robust than fiber optics and can also provide distributed strain information. There has been significant interest and development in the field of coaxial cable distributed sensing in recent years [16]. This paper outlines the development of coaxial cable distributed sensing for strain applications, from the origins of fiber optic sensing techniques through to time domain and frequency domain methods employed on coaxial cables, and reviews the latest developments in coaxial cables as distributed strain sensors.

The development of coaxial cable distributed sensing is, to some extent, analogous to the development of fiber optic distributed sensing. Figure 1 illustrates the similarities in the two fields and shows the structure of this paper.

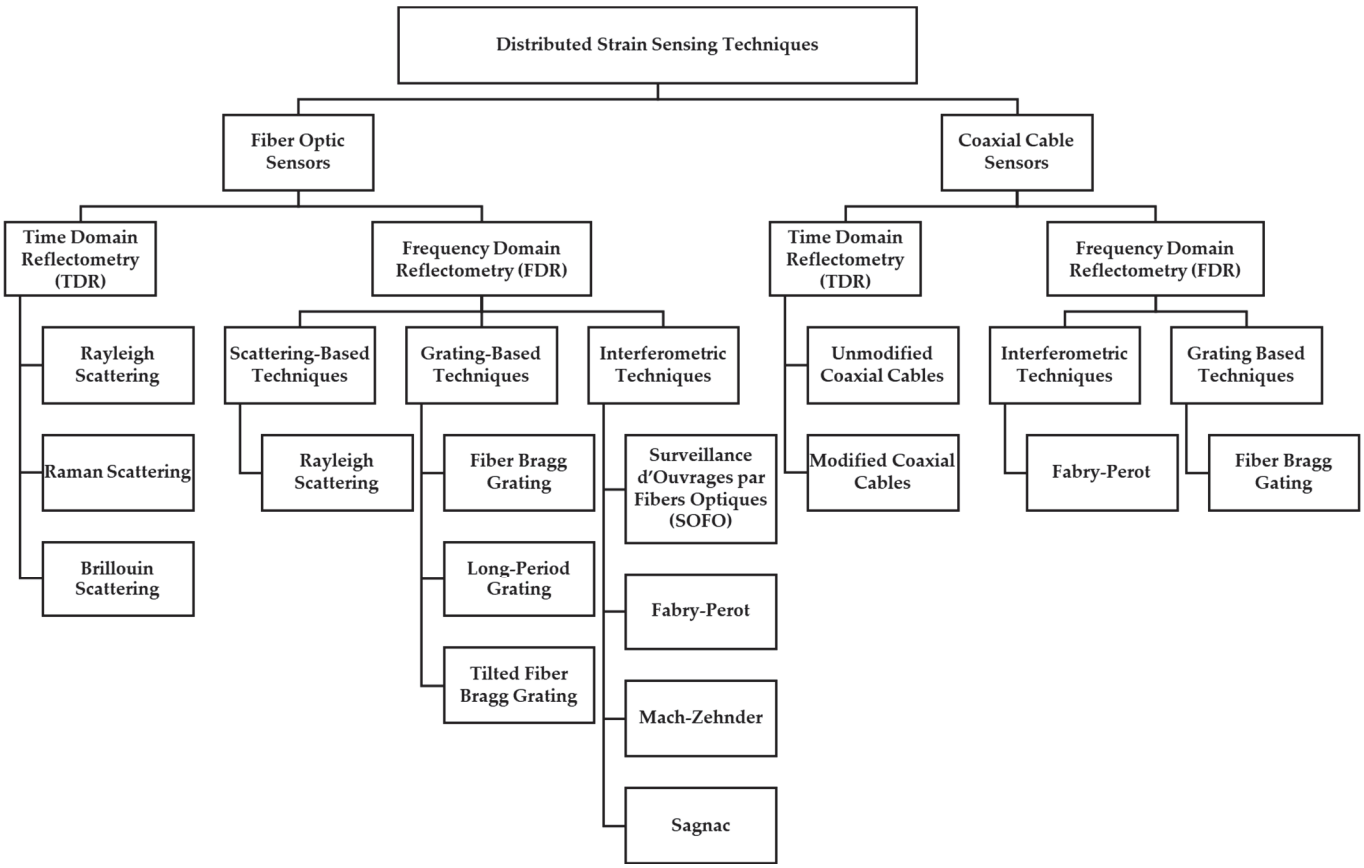


Figure 1. Overview of techniques employed in distributed strain sensing.

This paper provides an overview of the research progress in the development and application of distributed strain sensing with a specific focus on coaxial cable sensors. To enable the reader to navigate this paper efficiently, it has been split into the following sections:

- Section 2. Background on fiber optical distributed sensing:
  - Section 2.1. Time domain reflectometry in fiber optical sensing;
  - Section 2.2. Frequency domain reflectometry in fiber optical sensing.

- Section 3. Coaxial cable distributed strain sensing:
  - Section 3.1. Time domain reflectometry in coaxial cable distributed strain sensing;
  - Section 3.2. Frequency domain reflectometry in coaxial cable distributed sensing.
- Section 4. Future research challenges in frequency domain coaxial cable strain sensing.

2. Background on Fiber Optical Distributed Sensing

The development of extremely low-loss optical fibers in the late 1970s opened up the field of optical fiber sensors (OFSs). By 1982, a range of sensing applications were under research and development, including magnetic, acoustic, temperature, and strain, among others [10]. The applications are wide-ranging, including seismology [24], biomechanics [25], shape sensing [26], and structural health monitoring (SHM) [2]. Details on the working principles and applications of fiber optic sensors are well documented [27]. There are three main branches of OFSs: grating-based sensors, interferometric sensors, and distributed sensors, as described in Figure 2.

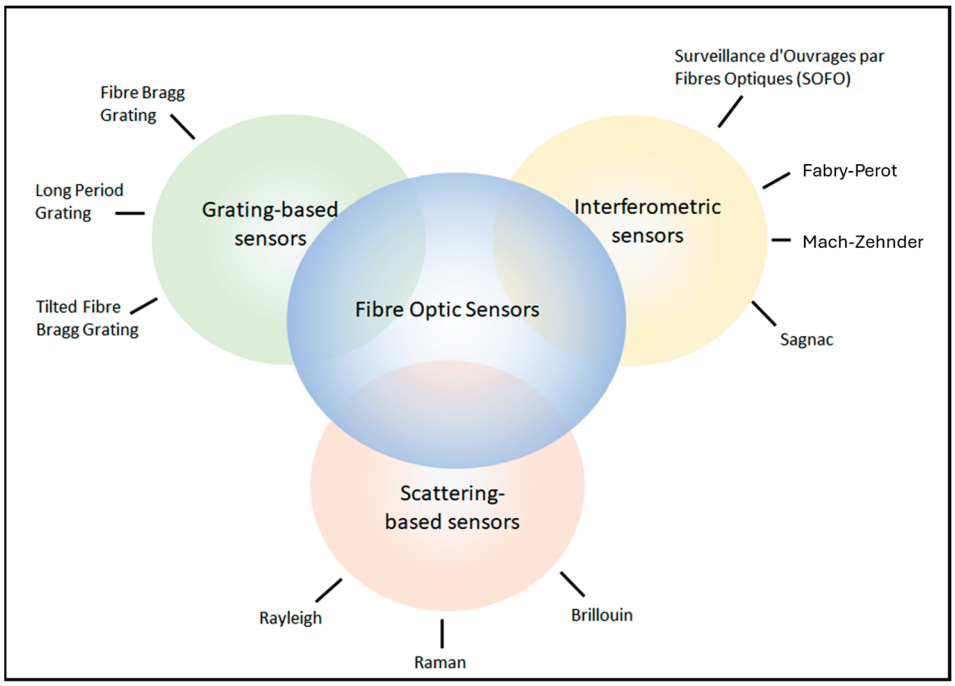


Figure 2. Types of fiber optic sensors (adapted from [10]).

As a very basic description, time and frequency domain reflectometry-based fiber optical sensing works by sending a pulse of light along a fiber and collecting the reflected light signal. An image of a distributed fiber optic sensor is shown in Figure 3. Optical fibers are bonded to, or embedded in, the structure of interest. A change in strain in the structure transfers to the optical fiber, altering the way in which the light is reflected. By studying the reflected light, it is therefore possible to infer the change in strain [10]. Some of these techniques utilize time domain reflectometry (TDR), whereby the arrival times of the reflected light are analyzed. The alternative is frequency domain reflectometry (FDR), whereby the frequencies of the reflected light are used to interpret strain events in the structure. Figure 1 describes the classification of the different fiber optical sensors into time domain or frequency domain techniques [8].

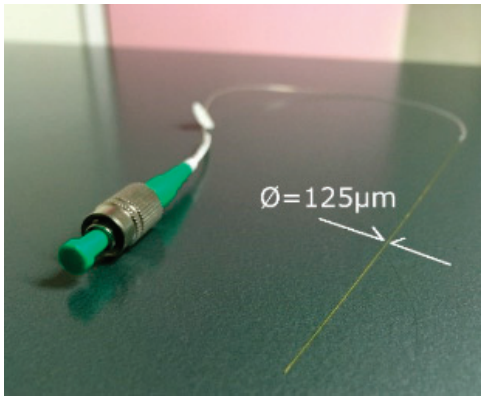


Figure 3. A distributed optical fiber sensor (DOFS) manufacture by LUNA technologies [8].

2.1. Time Domain Reflectometry in Fiber Optical Sensing

Scattering-based techniques (Rayleigh scattering, Raman scattering, and Brillouin scattering) are used for time domain reflectometry in optical fibers [28]. The entire continuous length of the fiber optic cable is turned into a sensor, achieving truly distributed sensing down to approximately 1 mm spatial resolution [8]. Scattering is the process by which the directional energy in a propagating wave is transferred to other directions. Light undergoing linear scattering has no change in frequency, whereas light experiencing nonlinear scattering will undergo a frequency shift.

Optical time domain reflectometry (OTDR) is a technique that was developed in the 1980s to test optical telecommunication fibers. Essentially, a short optical pulse is transmitted down the fiber, and the backscatter is monitored, which provides information on the condition of the fiber from which environmental conditions external to the fiber, but acting on it, can be inferred. This method was developed for all three types of scattering (Raman, Rayleigh, Brillouin), with each providing different advantages and disadvantages.

- Rayleigh scattering describes the elastic scattering of light by inhomogeneities much smaller than the wavelength of the incident light [29,30]. Under normal conditions in a fiber optic, as light interacts with the fiber, scattered light remains at an angle that supports forwards propagation. On interaction with a discontinuity, some of the light will be scattered at an angle which does not support forwards propagation, or scattered backwards, towards the light source, which is the principle behind OTDR. Rayleigh scattering is used to analyze attenuation associated with breaks, splices, connectors, and the general health of a fiber [2,31]. Other applications explored include measuring landslide activity [32] and detecting cracks in concrete structures [33]. This technique offers the highest spatial resolution of the three scattering methods [8], but it is highly sensitive to vibrations [34], so it also finds applications in acoustic sensing. The sensing range of Rayleigh scattering is limited to around 70 m.
- Raman scattering is nonlinear and arises from the interaction between light and the vibrational and rotational transitions of the atoms within the fiber material structure. Depending on the exact transitions, the scattered light will shift in frequency to two discrete bands; anti-Stokes transmission describes the shift to a higher frequency, and Stokes transmission describes the shift to a lower frequency. The ratio of the magnitude of these peaks provides data on the temperature of the fiber [2]. This technique provides temperature information independent of strain, but it does have a poor signal-to-noise-ratio [35].
- Brillouin scattering is nonlinear and associated with electrostriction, which couples electromagnetic waves with material structure-scale waves and phonons. Incident electromagnetic energy interacts with the optical fiber material to create backscat-

tered electromagnetic energy of a lower frequency and a phonon of a low-frequency vibrational energy. The thermal energy within the fiber will influence the Brillouin scattering [29,30]. This technique is used for temperature sensing and also strain sensing (if a separate temperature measurement independent of strain can be taken, enabling strain to be inferred). One notable advantage, in the context of this paper, is the development of Brillouin optical time domain reflectometry (BOTDR), through which monitoring could be achieved from one end of the fiber. Single-ended sensing is an attractive practical advantage when considering the deployment of distributed sensors in engineering structures [10]. This has led to Brillouin scattering being the most common technique used in civil applications of structural health monitoring [36]. This method enables a long measurement range (kilometers (kms)) but with limitations on the spatial resolution to around 1 m [8].

The trade-off between spatial resolution and range drove the development of the techniques and then led to Optical Frequency Domain Reflectometry (OFDR). The equipment required to obtain high spatial resolutions with OTDR techniques is complex and therefore expensive; a narrow light pulse is necessary, but this generates a poor signal-to-noise ratio, which necessitates a receiver with an increased bandwidth for any signal detection [10]. Huang et al. [23] also cites the poor signal-to-noise ratio (SNR) as a limitation of OTDR. In order to address these disadvantages, frequency domain reflectometry was developed for fiber optical sensing.

2.2. Frequency Domain Reflectometry in Fiber Optical Sensing

In OFDR, the backscatter is monitored in the frequency domain; the interference fringes of the backscattered signals are monitored, and a shift in the interference pattern infers an environmental change that can be located through the phase information of the frequency signal. This technique is employed for grating-based sensors, interferometric sensors, and some scattering-based sensors.

2.2.1. Scattering-Based Sensors

The natural impurities in the silica of the fiber optic give rise to an inherent variation in the refractive index along the length of the fiber. Rayleigh scattering occurs at each variation in the refractive index and gives each optical fiber a unique 'fingerprint' from which changes can be monitored. Raman scattering is a result of incident light interacting with the rotational and vibrational atomic transitions within the fiber optic material. Brillouin scattering is the interaction of incident light with the larger-scale material structure vibrational modes of the fiber.

The three scattering mechanisms (Raman, Rayleigh, Brillouin) all offer different advantages and disadvantages, as outlined in Section 2.1. Recent work has explored the possibility of combining all three techniques for an optimized solution [37].

2.2.2. Grating-Based Sensors

Grating-based sensors such as Fiber Bragg Gratings (FBGs) enable parameters such as strain to be measured along fiber optic cables. Periodic modifications in the refractive index of the fiber in the axial direction create narrow-band reflections at discrete resonant frequencies [21]. The exact resonant frequencies can be monitored. A change in environmental conditions will change the optical length of the grating features, shifting the resonances.

FBGs can either be used as point sensors or quasi-distributed sensors through the ability to multiplex gratings along the fiber length; several gratings of different periods can be inscribed on a single fiber [2,11]. The strain sensing capability of FBGs has made them suitable for a wide range of applications: strain analysis of power transmission lines [38],

soil strain sensing [39], corrosion sensor based on strain measurements [40], and leakage monitoring via hoop strain sensing [41].

2.2.3. Interferometric Sensors

Optical interferometric techniques (Fabry–Perot, Mach–Zehnder, Sagnac) all work on the principle of recombining two optical signals that have experienced different optical paths and analyzing the resultant interference pattern [42]. Each technique uses a different arrangement to generate the two optical beams [43,44]. Fabry–Perot interferometry holds the advantage that it is an in-line arrangement, so it can be employed on a single cable. Other interferometric techniques utilize two cables: one experiencing environmental change, the other remaining in steady-state acting as a reference. The Surveillance d'Ouvrages par Fibres Optiques technique is one of the more successful approaches to obtaining integrated measurements; a single elongation value is determined from the integration of behavior along the length of the fiber [2].

Whilst the OFDR methods are more cost-effective and achieve higher spatial resolution than the OTDR techniques, the sensing range is more limited. Table 2 summarizes the advantages and disadvantages of the various distributed optical fiber sensors techniques.

Table 2. Performance of distributed and quasi-distributed fiber optic sensing techniques (adapted from [10]).

Sensing Technology	Transducer Type	Sensing Range	Spatial Resolution	Main Measurands	Single-Ended Monitoring
Raman OTDR	Distributed	1 km 37 km	1 cm 17 m	Temperature	NO
Brillouin OTDR	Distributed	20–50 km	~1 m	Temperature and Strain	YES
Rayleigh OFDR	Distributed	50–70 m	~1 mm	Temperature and Strain	YES (needs a reference fiber)
Fiber Bragg Grating	Quasi-distributed	~100 channels	2 mm (Bragg length)	Temperature, Strain, and Displacement	YES

Fiber optics distributed sensing finds applications in monitoring buildings, bridges, tunnels and roads, crack growth in concrete structures, strain measurements in wind turbine blades and pile foundations, monitoring land slope stability, soil and rock deformations and monitoring the stability of ground anchors, oil and gas pipeline degradation, and the detection of failure in hydraulic engineering structures, amongst others, as illustrated in Figure 4 [8,10].

However, fiber optics distributed strain sensing presents the following challenges:

- The inherent weakness of the fiber optic material limits its application to lower strain events. In order to realize a wider range of measurable strain and monitor structures up to failure, a more robust 'carrier' would be necessary [10,45].
- There are several references quoting the strain limits of optical fibers:
  - 10,000 με (1%) [7,9];
  - 4000 με (0.4%) [21,46].
- The fragility of the fiber optics makes installation difficult, and great care must be taken not to damage the sensor itself. Bending stresses should be avoided during installation as this can impact the weakly scattered signals necessary for monitoring [10].
- There is concern that the fragility implies a strong limitation on the long-term exposure to harsh environments [10,21,45].

- The expense of fiber optic systems can limit their use to applications only where reliability is critical [2,47]. A more cost-effective solution could see SHM techniques applied where reliability or safety is less critical but nonetheless would benefit from the economic advantages in targeted O&M activities, or the optimization of system operating parameters.



(**a**)

(**b**)

(**c**)

Figure 4. Photographs of distributed optical fiber sensor applications: (**a**) monitoring bridge integrity, (**b**) tracking the stability of ground anchors, and (**c**) measuring strains in a wind turbine pile [8].

3. Coaxial Cable Distributed Strain Sensing

Coaxial cables and optical fibers follow similar principles of electromagnetic theory and signal propagation, albeit at different frequencies of the electromagnetic spectrum. Similar techniques developed for DOFSs can be applied to the medium of coaxial cables. However, coaxial cables are advantageous as they are more robust, can withstand larger strain, and present a lower cost [15,21,45,46]. The coaxial configuration of the conductors also provides shielding from electromagnetic interference [48,49].

The background of the development of coaxial cables as distributed strain sensors follows an analogous path to that already outlined for fiber optics, and this is presented in the following Sections 3.1 and 3.2.

3.1. Coaxial Cable Time Domain Reflectometry

Time domain reflectometry for fault location is a well-established technique [50]. A short pulse signal propagating along a waveguide will create a reflection at an impedance discontinuity (change in cross-sectional area) caused by a physical fault [51,52]. The arrival time of this reflection identifies the location of the fault. The principle of this technique is depicted in Figure 5.

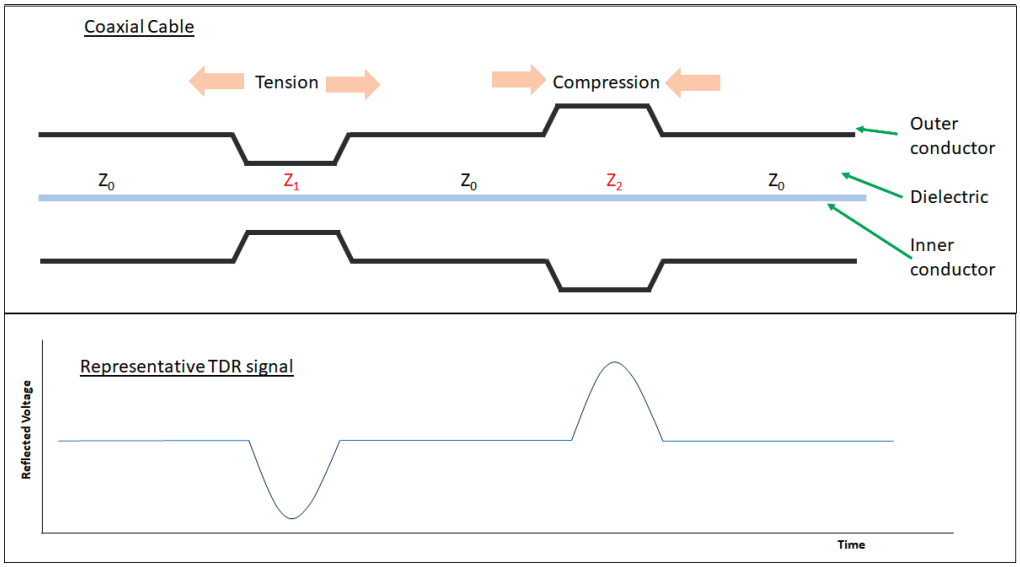


Figure 5. Illustration of the principles of coaxial cable time domain reflectometry (CCTDR) adapted from [48,53], showing a cross-section of a coaxial cable experiencing tension and compression and the associated time domain reflectometry signal.

For a lossless transmission line, the characteristic impedance Z_0 is described as follows:

$$Z_0 = \sqrt{\frac{L}{C}} = \frac{1}{2\pi}\sqrt{\frac{\mu_0\mu_r}{\varepsilon_0\varepsilon_r}}\ln\left(\frac{D_o}{D_i}\right), \quad (1)$$

where Z_0 is the characteristic impedance of the cable, L is the inductance per unit length, and C is the capacitance per unit length. The properties of the dielectric are given by ε_0 the permittivity of free space, ε_r the relative permittivity of the dielectric in the coaxial cable, μ_0 the permeability of free space, and μ_r the permeability of the dielectric in the coaxial cable. The cable dimensions are D_i the outer diameter of the inner conductor and D_o the inner diameter of the outer conductor.

Varying any of these parameters will change the impedance Z_0. Where there is an impedance discontinuity, a reflection will occur in accordance with the below equation:

$$\rho = \frac{Z_0 - Z_1}{Z_0 + Z_1}, \quad (2)$$

where ρ is the reflection coefficient, Z_0 is the impedance before the discontinuity, and Z_1 is the impedance after the discontinuity. If Z_0 is different to Z_1 (in a region where the material properties or physical geometries differ), then a reflection will occur.

This technique has been used to monitor the health of cables themselves and identify wiring faults [13,52,54]. The ability of TDR to locate geological discontinuities has been

reported, where changes and fractures in rock following a sub-terranean nuclear explosion were monitored by way of monitoring the change in unbroken cable length [55]. Initially, coaxial cable TDR could only monitor events and not provide measurements due to challenges relating the TDR reflections to the true deformation. Work has been undertaken to quantify the relationships between shear deformation and change in impedance, axial and transverse loads and impedance change, and axial strain and reflected voltage, as well as assess the accuracy of using TDR to measure impedance [48,56–59]. This work means that the TDR method could be extended to infer environmental conditions external to, but impacting on, the cable, giving rise to localized impedance variations [56]. Monitoring the reflections provides information on the location of damage or environmental change acting on the cable, such as strain [60]. In this way, coaxial cables can become distributed sensors using TDR to interrogate the cable.

A number of papers cite the use of coaxial cables as distributed structural health sensors using TDR in applications such as monitoring the integrity of large-diameter wire rope [61], rock and soil movement in mining activities [22,61], the prediction of slope failure in open-cast mines [51], landslide monitoring [62], bridge scour monitoring [63,64], and crack detection in reinforced concrete structures such as bridges and buildings [7,47,65].

A challenge associated with using TDR for distributed strain sensing includes the lack of sensitivity of the technique [47,56,65]. There is also an associated difficulty in ascertaining the relationship between the voltage of reflected signals and the associated impedance change when the impedance has changed gradually over a length of cable and is not a sharp discontinuity [56]. The short pulse required for TDR spectrally spreads with transmitted distance, reducing the accuracy of the technique over long distances [52,54,66–68].

Coaxial cable time domain reflectometry is a single-ended technique that can be employed on any coaxial cable without the need for modifications to that cable. It can therefore be used to analyze an existing, in situ cable from any point in the cable's lifetime without prior requirement to anticipate future TDR measurements. The potential of the technique has been pursued since 1971 [55]. A summary of published work reporting the most recent advances in TDR for strain sensing/mechanical movement monitoring using unmodified coaxial cables is provided in Section 3.1.1.

3.1.1. TDR Using Unmodified Coaxial Cables

Guidelines to optimize TDR for landslide monitoring were deduced in an effort to encourage the adoption of this technique to geological applications [62]. The scenario under investigation is illustrated in Figure 6. Three types of coaxial cable were tested: RG-8, P3-500CA, and P3-500 JCASS in a custom-built shear box designed to simulate landslide events. Various soil types and cable grout arrangements were tested. Removal of the cable jacket is advised to avoid slippage, which reduces the sensitivity of the technique, but the increased exposure to corrosion was noted. A standardized grout mixture was recommended to simplify installation and also aid signal interpretation as the known grout interaction could be accounted for via signal analysis.

This study built on work published in where TDR was investigated to predict slope failure in open-cast mines [51]. This research involved testing two different coaxial cable types, RG-6 and RG-213, first in lab-based equipment and then in a 5-month field trial at the Manganese Ore India Limited Dongri Buzurg mines. The experimental tests related the reflection coefficient of the TDR signal to the shear deformation of the cable. For RG-6, the average highest deformity by shear failure was 11 mm, and for RG213, it was 14 mm. There was insufficient ground movement in the field trials to register a notable change in the reflection coefficient of the TDR response. RG-6 was recommended due to its increased sensitivity and cost-effectiveness.

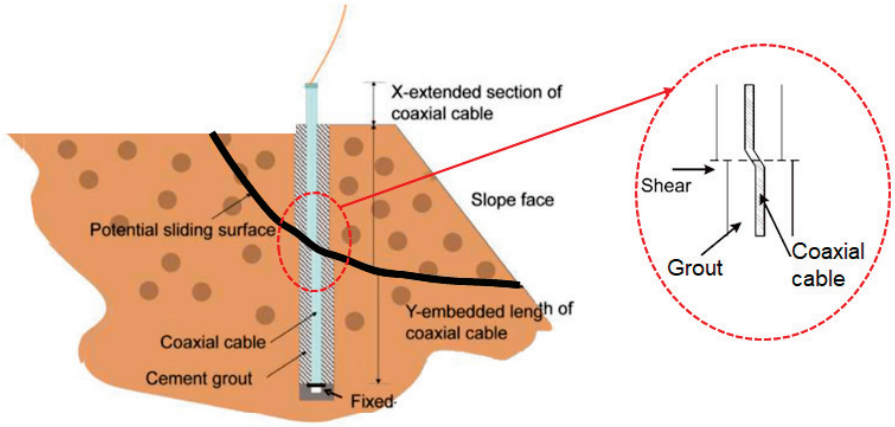


Figure 6. Modeling of shear displacement time domain reflectometry sensing (adapted from [69]).

Recent work has shown that random reflections intrinsic to an unmodified coaxial cable can be tracked to monitor more subtle changes in environmental conditions [22,70]. Whilst this work focused on tracking changes in temperature using random reflections on an unmodified coaxial cable, the principle is analogous when applied to tracking changes in strain. Essentially, a change in temperature causes a change in physical distance between sites of random reflections due to the coefficient of the thermal expansion of the materials in the cable. The electrical path length would also change with temperature due to the change in dielectric permittivity. Similarly, a change in strain would cause a change in physical distance between sites of random reflections, and it would also cause a change in the electrical path length due to the photoelastic effect altering the permittivity of the dielectric with strain [46]. A novel method using the random reflections of a coaxial cable to enable temperature monitoring in this way is presented in [22]. A cross-correlation analysis of TDR S11 signals before and after heating was applied to establish the location and magnitude of a temperature change along a 14 m length of the RG58 cable. The cross-correlation identifies a shift in the S11 signal using the random reflections as position markers to align the S11 signals before and after heating. A misalignment in the signals indicates a change in temperature through a change in the arrival time of the random reflections. An analogous result could be achieved through the application of strain instead of temperature.

Fundamental research into using a coaxial cable as a distributed strain sensor using TDR was conducted using the standard RG-174 coaxial cable. A standard RG-174 coaxial cable was subjected to a localized lateral compression at a fixed distance. The TDR signal of the uncompressed cable was first baselined so that the impact of the application of the lateral force could clearly be observed. This loading condition resulted in a sharp impedance change at the location of the applied force. The cable was also subjected to axial tension tests with a fixed section of the cable being stretched in controlled increments. The increased tensile strain reduced the cross-sectional area of the cable, decreasing the impedance of the stretched cable section and increasing the reflected voltage level. A prototype sensor, similar in geometry and size to RG-174 but with a rubber dielectric, was tested alongside the RG-174 cable for comparison. The prototype sensor (diagram shown in Figure 7) demonstrated the greater sensitivity of the applied loads compared with the RG-174 cable due to the more compliant dielectric material [48]. The level of random noise in the TDR measurements was noted and, whilst the load levels tested were clearly visible above the noise level, could be problematic when monitoring lower levels of strain.

These practical works build on an analytical study that was conducted to assess the theoretical possibility of using TDR to purpose a coaxial cable as a distributed strain sensor [56]. The purpose of the analysis was to ascertain a relationship between reflected voltage measured through TDR and axial strain. Without this type of investigation, and

other similar work conducted on deducing direct relationships between TDR response and shear and tensile deformations, coaxial cable TDR could only monitor events, not provide direct measurements of strain or loading conditions [48,57,58].

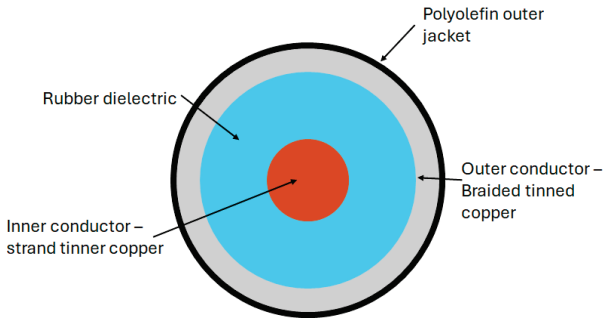


Figure 7. Diagram of a prototype coaxial cable designed for enhanced TDR capability through inclusion of a compliant rubber dielectric.

3.1.2. TDR Using Modified Coaxial Cables

There are several ways in which coaxial cables have been modified in the pursuit of coaxial cable strain/mechanical movement sensing using TDR. The intended purpose of the different modifications varies and is summarized in Table 3.

- Lack of sensitivity using coaxial cable for strain sensing remains a challenge using TDR [47,56,65]. As described earlier in this paper, reviewing the progress of the unmodified coaxial cable, Lin et al. [48] explored the use of a more compliant rubber as the dielectric in a coaxial cable structure by way of increasing the sensitivity to strain. The sensitivity of a prototype rubber-based dielectric cable was shown, through experiments, to be approximately five to ten times that of the standard RG-174 coaxial cable. This approach still relies on a geometric change with strain, whereas a change in the topology of the outer coaxial cable conductor with strain could inherently offer increased sensitivity.
- Several published reports describe the use of helical wound outer conductors as a technique to induce a change in outer conductor topology with strain [7,9,47,71,72]. A lot of this work focused on crack detection in reinforced concrete beams. In 2004, Chen et al. tested a prototype coaxial cable sensor constructed with helically wound adhesive copper tape forming the outer conductor (Figure 8) [7].

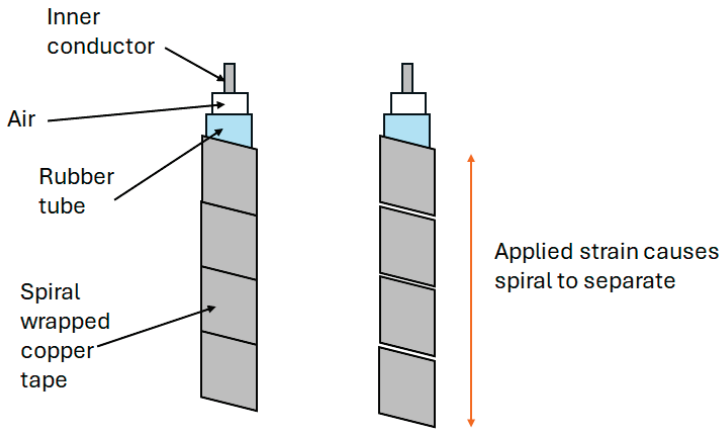


Figure 8. Diagram showing helically wound outer conductor topology.

Table 3. Summary of work on modified coaxial cables to enhance TDR capabilities.

Type of Modification	Purpose of Modification	Citation
Dielectric material selection	Increased sensitivity to strain	[48]
Topology of outer conductor	Increased sensitivity to strain	[7,9,47,71,72]
Intentional creation of impedance changes	Tracking point to measure distance changes/act as 'location tags'	[61]
Inclusion of small in-line sensors	Increase sensitivity to strain, or increase functionality of cable	[53,73]

When compared with the coaxial cable with a regular copper braided outer conductor, it was found that the prototype sensors were 15–80 times more sensitive than sensors based on an off-the-shelf coaxial cable and could offer a spatial resolution of 50 mm. This work verified that the change in the topology of the outer conductor has a greater impact on sensitivity to strain than relying on a geometric change. Subsequent developments to improve consistency in the sensor performance of this approach included the inclusion of a Teflon dielectric with a commercial steel spiral wrapper covered with a thin solder layer to improve electrical continuity between adjacent spirals [71]; the replacement of the solder layer with a plasma-sprayed coating to create a more uniform, reproducible sensor [47]; performance validation of the copper tape spiral and Teflon/steel spiral devices through field trials in a highway bridge over a 5-year period [72] (Figure 9) and replacement of the spiral-wound outer conductor with a solid outer conductor inscribed with a shallow helical groove [9]; and with the purpose of maintaining the topographic contribution to strain sensitivity but avoiding the problem of poor electrical continuity seen in spiral-wrap configurations. This impacted signal attenuation and limited the length of the sensors. The results from this work suggested that this sensor design could detect cracks of 0.02 mm and identify multiple cracks with a minimum of 3 mm spatial resolution, although further work was noted regarding the assessment of the improved signal attenuation of spiral-wound topologies [9].

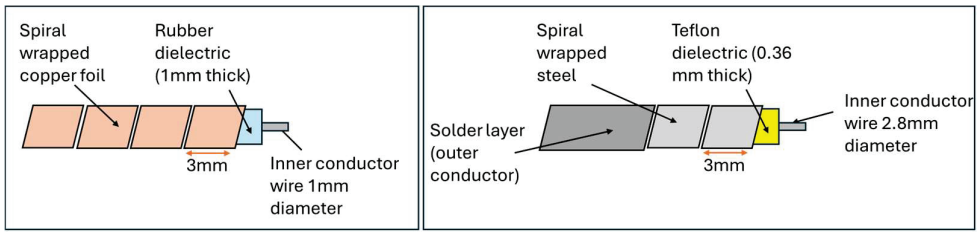


Figure 9. Schematic of a rubber dielectric coaxial cable structure and a Teflon dielectric coaxial cable, both with spiral-wound outer conductors for increased TDR sensitivity [72].

Through winding two parallel conductors helically around a central silicone core, a different approach to harnessing the change in topology to increase the TDR coaxial cable's sensitivity to strain was researched [60,74]. This alternative configuration is illustrated in Figure 10. The work concluded that this different 'coaxial' design could be used for the distributed monitoring of deformation.

- The techniques described above rely on the creation of a new reflection point being generated, alerting the user to a source of increased strain or mechanical movement. A different approach, whereby a coaxial cable is crimped prior to installation, is referred to in [61]. The crimps create reflections at known distances along the cable, so they act as location reference points to improve the spatial accuracy of CCTDR. Crimping coaxial cables to improve the location tracking of ground movements are also mentioned in the 2020 research into investigating TDR as a means of predicting

slope failure in open-cast mines [51]. 'Denting' the coaxial cable to increase the SNR of reflected signals, making it easier to track with changing conditions, was mentioned in [70] but dismissed due to the impact on the mechanical strength of the cable.

- More extreme modifications of cables to enhance the distributed strain sensing using TDR have involved the inclusion of discreet sensors along the cable. Novel sensing elements created from piezoresistive multi-walled carbon nanotubes were incorporated along the standard speaker cable. Separate lengths of the speaker wire were joined via one or more sensing elements, with a reflection in the time domain occurring at these inclusions (Figure 11). The nanocomposite exhibits an increased response to strain, which could enhance the sensitivity of the technique. Challenges were faced with multiple sensing elements where signal attenuation and reflections at prior sensing elements resulted in very small signal levels in the sensing elements at the end of the cable [53].

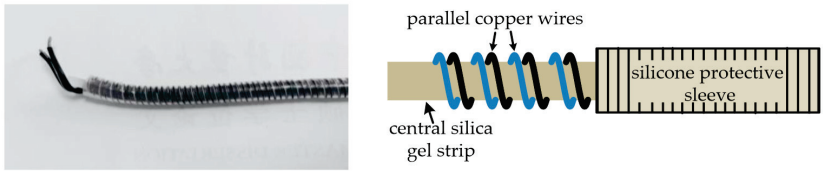


Figure 10. Two parallel conductors helically wound around a central core for TDR tensile deformation monitoring [74].

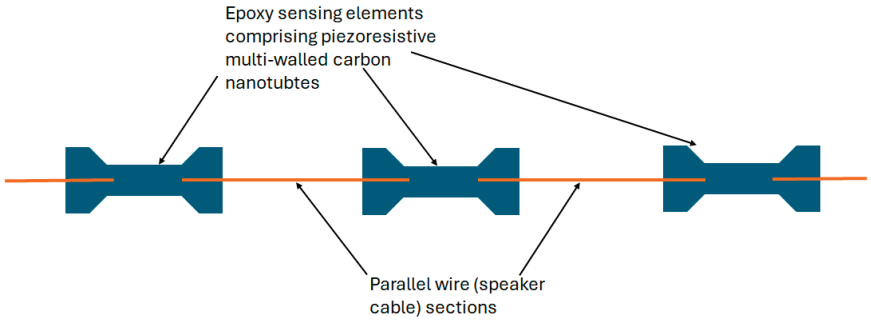


Figure 11. Schematic of novel piezoresistive multi-walled carbon nanotube sensing elements placed in-line with a cable to create a distributed strain sensor [53].

A similar idea was evaluated in the context of incorporating capacitive tilt sensors along a coaxial cable for TDR measurements to monitor 'crosslevel' or difference in height between adjacent train tracks. The device tested is shown in Figure 12, with a single in-line sensor present. This was scaled up to test up to three in-line sensors. Ground movements can cause the top surface of the tracks to come out of alignment, causing derailments. Testing validated the operation of the tilt sensors themselves and confirmed that TDR accurately measured the physical location of the tilt sensors. TDR could be used to analyze in-line tilt sensors, but again challenges were faced with multiple sensors and signal degradation with additional sensors [73].

There are some remaining challenges with the TDR method for distributed sensing that could not be fully addressed by modifying the design of the coaxial cable.

- Poor SNR and low sensitivity limit the technique [9,56,75].
- Multiple discontinuities give rise to secondary reflections, complicating signal deconstruction for analysis [58].
- Cable attenuation and energy lost through partial reflection at each impedance change result in the degradation of signal clarity for additional faults along the cable [76].
- Spatial resolution degenerates along the cable as the excitation signal distorts due to frequency-dependent cable attenuation [52,54,58,66,76].



Figure 12. A tilt sensor placed in-line with RG-6 coaxial cables to form distributed sensing [73].

To overcome the shortcomings of TDR, a multitude of signal analysis techniques have been developed. These aim to refine the TDR technique beyond the advances previously described, which were achieved through a modification of the physical cable design.

A reconstruction method, developed to overcome the limitation of inaccuracies when multiple discontinuities are present on a TDR system, was proposed [77]. The impedance of a transmission line was reconstructed from the waveshape of a reflected signal by dividing the reflected wave into equal subintervals for analysis. This model did not account for dispersion or loss.

State-of-the-art signal analysis techniques include spread spectrum time domain reflectometry, noise domain reflectometry, and their derivatives. An overview of these is explained well in [52,54,78]. State-of-the-art systems such as Viper Innovations products [79] utilize some of these methods. The key objective of these techniques is to enable monitoring on live cables and in high-noise environments. Joint time–frequency analysis (JTFA) or time–frequency domain reflectometry (TFDR) bring an added advantage to analyzing multiple faults along a cable [76]. Conventional TDR struggles to detect multiple faults due to the inherent frequency-dependent attenuation of coaxial cables, distorting the signals of more distant faults. The partial reflection of energy at each fault also means that the clarity of the discontinuity recedes along a sequence of faults. JTFA utilizes an excitation signal carefully characterized by time and frequency content to address this challenge [13,76,80]. Applications of JTFA in nuclear power plant cables, high-temperature superconductor cables, and in high-voltage direct-current submarine cables have been explored [75]. Pure FDR is another variation in this field, forming a large body of work. Working in the frequency domain, strain sensing at multiple locations along a cable and greater resolution on strain measurements could be achieved. This is apparent on a comparison of specifications of TDR analysis equipment and FDR analysis equipment (Vector Network Analyzer (VNA)) [81,82]. The sampling rate of the TDR instruments limit resolution and the TDR electronics are more complex and expensive than the equipment needed for FDR [52,76]. The technique of frequency domain coaxial cable strain sensing is described in the next section along with a review of the work conducted in this field and state-of-the-art results.

3.2. Coaxial Cable Frequency Domain Reflectometry

Traditionally, FDR was developed for fault diagnosis in electrical systems. A transmitted sine wave is used as a reference against which reflected sine waves, arising from reflectors caused by impedance changes along the cable, are compared and analyzed. A fault, caused by strain or mechanical movement creating a localized change in cable impedance, can be identified and located by analyzing a shift in frequency or phase between the input signal and reflected signal [52,54]. This technique could be susceptible to a high error rate due to the sensitivity of phase to noise [76]. Interferometric techniques, first

developed for fiber optic cable distributed sensing, can be applied to coaxial cables, utilizing a different part of the electromagnetic spectrum [15,21]. These methods use artificially created partial reflectors to track changes in the cable and infer environmental conditions such as strain or temperature. By placing partial reflectors along the cable, the magnitude of the partially reflected signals can be controlled through manufacturing and therefore the SNR can be improved, optimizing the FDR technique for condition sensing.

In this report, coaxial cable frequency domain reflectometry is split into two types of sensors, interferometric sensors and grating-based sensors, as outlined in Figure 1. An introduction is given to each technique, followed by a review of the work in that field.

3.2.1. Interferometric Coaxial Cable Frequency Domain Reflectometry

A Fabry–Perot interferometer is an optical instrument constructed from two parallel, partially reflective surfaces or reflectors as shown in Figure 13 [83]. Reflections from each surface interfere, creating a fringed pattern of maxima (at constructive interference) and minima (at destructive interference), as illustrated in Figure 14. The frequency location of these maxima and minima is determined by the electromagnetic path length difference between the reflection from the first partial reflector and the reflection from the second partial reflector. The technique is not constrained to optical frequencies but can work across the electromagnetic spectrum. A Fabry–Perot interferometer is created on a coaxial cable by making a pair of partial reflectors through a localized change in impedance from either a variation in geometry, as illustrated in Figure 13, or material property, such as permittivity or permeability. The theory of using a coaxial cable Fabry–Perot interferometer (CCFPI) as a strain sensor is well documented [14,16,45,46] and outlined here.

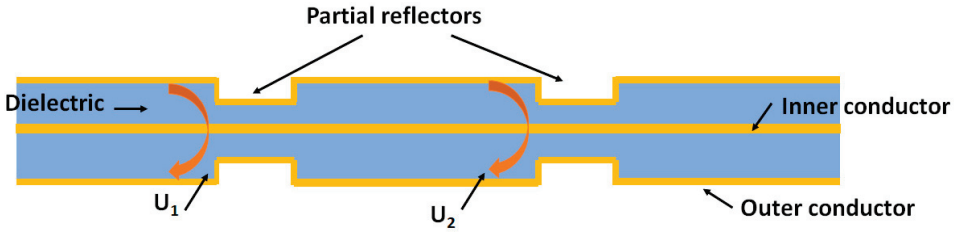


Figure 13. Schematic of coaxial cable Fabry–Perot interferometry.

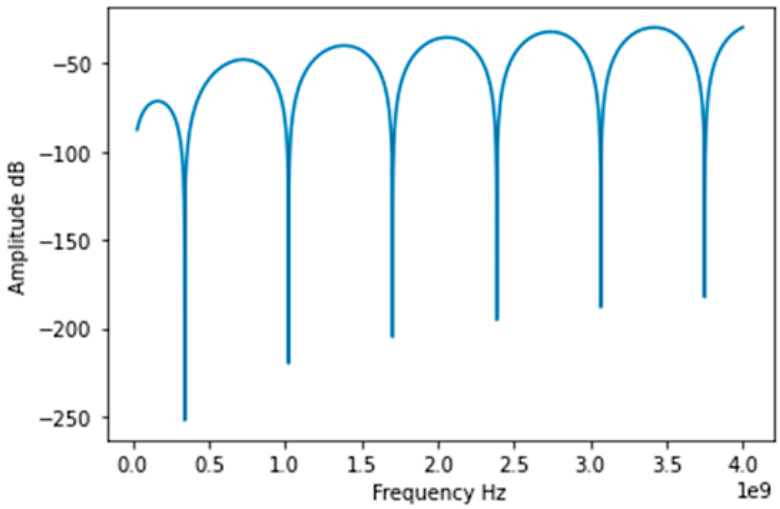


Figure 14. Example interference pattern (interferogram) from a CCFPI.

The interferogram is created by the superposition of the two reflected waves U_1 and U_2, described as follows [46]:

$$U_1 = \Gamma(f)e^{-\alpha z}cos(2\pi ft), \tag{3}$$

$$U_2 = \Gamma(f)e^{-\alpha z}cos[2\pi f(t+\tau)], \tag{4}$$

$$\tau = \frac{2d\sqrt{\varepsilon_r}}{c}. \tag{5}$$

The addition of U_1 and U_2 creates an interference pattern of the following form, as illustrated in Figure 14:

$$U = 2\Gamma(f)e^{-\alpha z}cos(2\pi f\tau)cos[2\pi f(t+\tau)], \tag{6}$$

where Γ is the reflection coefficient of the partial reflectors, f is the frequency of the electromagnetic wave, α is the attenuation of the cable, z is the axial cable direction, t is the arrival time at the first partial reflector, τ is the time delay between the two reflected waves, ε_r is the relative permittivity of the dielectric in the coaxial cable, d is the distance between the two partial reflectors, and c is the speed of light.

The fundamental frequency is given by $(1/\tau)$ and is dependent on the spacing of the two partial reflectors, as shown below:

$$fundamental\ frequency = \frac{c}{2d\sqrt{\varepsilon_r}}, \tag{7}$$

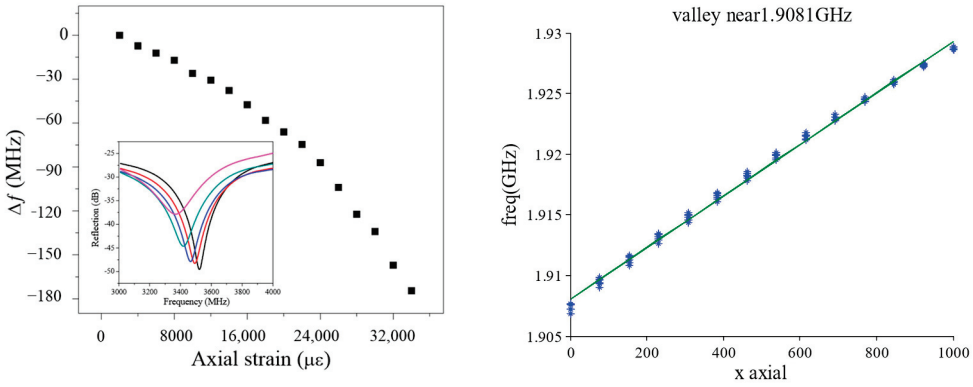
where c is the speed of light, d is the distance between the two partial reflectors, and ε_r is the relative permittivity of the dielectric in the coaxial cable.

With increased strain, d will increase through elongation and ε_r will vary due to the photoelastic effect of dielectrics [46]. This will change the fundamental frequency, shifting the interferogram pattern. The frequency location of key features such as the minima or maxima is tracked to infer the change in strain.

The principle of using a CCFPI in a strain sensing application was reported in [46]. Two partial reflectors, with 70 mm spacing, were manufactured onto an RG58 coaxial cable by a hole-drilling method. The reflection spectrum was captured by a VNA, and the frequency of the dips of the interferogram was tracked. As strain was applied, the distance between the two partial reflectors changed and so the resonant frequency changed. A total strain of ~34,000 με was applied to the cable in 18 steps of 2000 microstrains (0.2%). The frequency demonstrated a quasi-linear response to strain with a relationship of approximately −3.3 kHz/με, suggesting that a CCFPI had sufficient sensitivity for use as a strain sensor and demonstrating the superior maximum strain capability over fiber optics. The results are shown in Figure 15a. The spatial resolution of the CCFPI is determined by the distance between the partial reflectors, which is 70 mm in this study.

Cheng [14] also studied the application of CCFPI as a strain sensor. The coaxial cable type used in this testing was not stated, but the applied strain was between 0 and 1000 microstrains over 14 steps, and the tracked frequency minima was around 1.91 GHz. The data presented in [46] demonstrate a decrease in resonant frequency as strain increases, implying that the physical elongation with the applied axial strain dominated the response, as illustrated in Figure 15a. Conversely, data presented in [14] demonstrated an increase in resonant frequency with increasing strain, as shown in Figure 15b. The reasons for the conflicting reported results could be due to the differing responses of the cable dielectric permittivity to strain. The variation in the results highlights that the response to strain is complex, and greater research is needed in order to achieve a single-valued, repeatable

response to strain that will be required for a successful manifestation of a CCFPI as a distributed strain sensor in industrial applications.



(**a**) (**b**)

Figure 15. Response of a CCFPI to strain from two different sets of published data showing that the impact of strain on a CCFPI resonant frequency can produce different results. (**a**) Resonant frequency shift as a function of strain with inset showing shift in reflection spectra as strain increases [46]; (**b**) interference resonant frequency shift as a function of applied strain [14].

Through different topological configurations of the coaxial cable, the potential of using RG58 as a torsion sensor based on cascaded CCFPIs (Figure 16) [84] and beam shape sensors through strain sensing was demonstrated [85]. For both of these references, testing occurred in the GHz region [14].

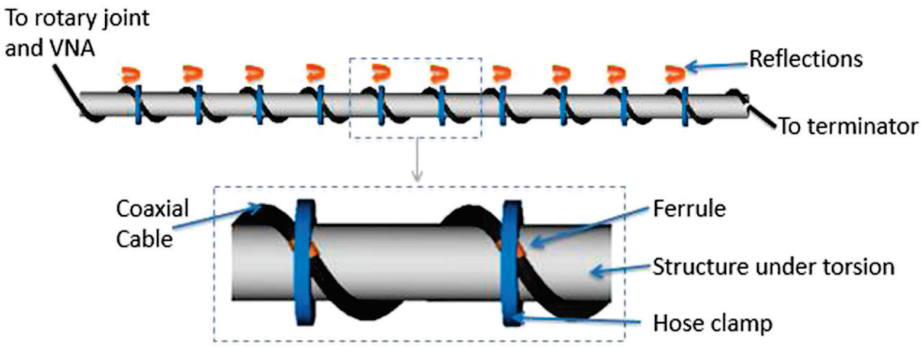


Figure 16. Schematic of using an RG58 CCFPI as a torsion sensor [14].

A large strain-tolerated Fabry–Perot interferometer smart steel strand has been developed [45], making a CCFPI on SF047 coaxial cable and embedding it into glass fiber-reinforced polymer (GFRP) before replacing the core wire of a steel strand with this GRFP-CCFPI, as depicted in Figure 17. The intention was that this sensor could replace a steel strand in a structural component such as a bridge cable or anchor rod for continuous health monitoring.

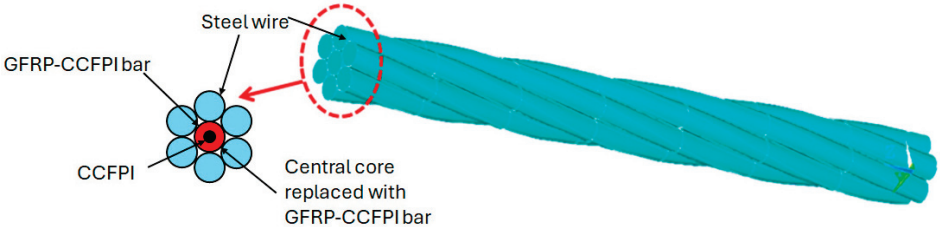


Figure 17. Schematic of the CCFPI SF407 cable embedded in GFRP and replacing the core wire of a steel strand (adapted from [86]).

The bare SF047 CCFPI demonstrated a measuring range up to 140,000 με. When embedded in GRFP, the dynamic range was shown to be 16,000 με. The partial reflectors for this work were created by crimping metal ferrules onto the SF047 cable at two specific locations 200 mm apart. A resonant frequency near 3 GHz was tracked during the strain tests and a strain sensitivity of −3.7 kHz/με was recorded. This work concluded that the GRFP-CCFPI could replace a previously developed optical fiber sensor-based smart steel strand, offering a much larger measurement range as it can withstand a greater maximum strain. The GRFP-CCFPI sensor response to strain also demonstrated good sensitivity and linearity. Further work in this field was reported in 2024 [87], where a coaxial cable Bragg grating (CCBG) structure was integrated with GFRP into a steel strand. SF047 cable with a diameter of 1.19 mm was used to create a sensing structure comprising 41 discontinuities spaced at 20 mm intervals (total sensing section 800 mm). The increased number of partial reflectors, created by crimping metal ferrules to generate an impedance change, ensured that the SNR was sufficient. The CCBG was then embedded within GRFP before being incorporated into a steel strand. As well as testing to ensure that the CCBG did not compromise the mechanical strength of the GFRP or the steel strand, the strain sensing performance was compared with linear variable differential transformer measurements. The results suggested the CCBG embedded in GFRP could measure strains up to the ultimate limit of GFRP, 20,000 με. Similar work looking at embedding FBG could only monitor strains up to 6000 με. The embedded CCBG in GFRP in the steel strand only slightly reduced the mechanical properties of the steel strand, with the tensile strength at 87.9% and elastic modulus at 88.7%. The CCBG structure was reported to demonstrate strain resolution of at least 100 με and a range of 150,000 με.

A series of partial reflectors could be manufactured along the entire length of a coaxial cable. Any two consecutive partial reflectors create a Fabry–Perot interferometer (FPI), as illustrated in Figure 18.

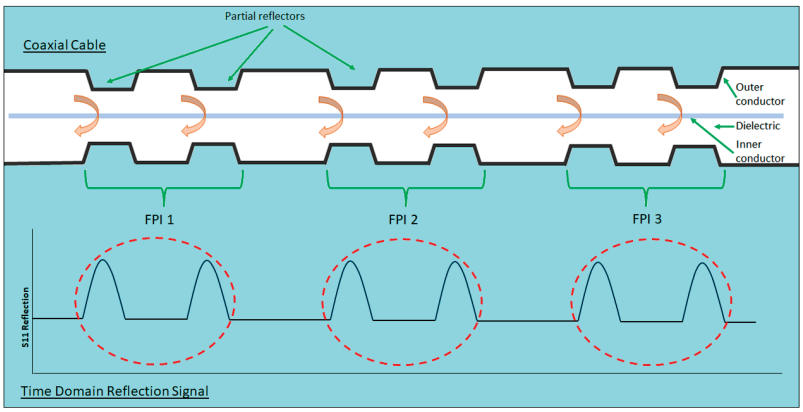


Figure 18. Diagram to illustrate the principles of multiplexing FPIs along entire cable length, forming a distributed sensor.

In this way, a coaxial cable could become a distributed sensor. Cascading a series of FPIs is possible due to the way in which the VNA captures the S11 reflection spectrum [23]. The entire frequency information, including magnitude and phase, is recorded, which enables the interferogram of each FPI to be uniquely associated with a physical location along the cable [14]. The value of this feature is apparent considering a CCFPI in a monitoring application; this means that the part of the structure experiencing a significant strain event can be identified, and remedial effort can be focused on the area of concern, optimizing efficiency of any maintenance work required.

Several signal processing methods are cited to analyze the CCFPI interferogram signal. The technique that appears to be employed in a lot of the references cited in this paper uses

a form of JTFA [14,23,46]. The method of JTFA used in the CCFPI analysis is detailed in the following signal processing steps.

1. A VNA is used to send a frequency swept signal and capture the S11 signal amplitude and phase information from the entire CCFPI cable length.
2. In the time domain, the gating function on the VNA is applied to a single pair of partial reflectors, creating an individual CCFPI. The time span of this gate is designed to encompass the two reflections but must be wide enough to avoid breach of the minimum time gate span rules specified in the VNA documentation, which is dependent on the bandwidth of the swept frequency signal. Applying the time gate to a single CCFPI sufficiently isolates it from the rest of the cable features for analysis. With reference to Figure 18, the red dashed line indicates the principle of time domain gating, isolating a single CCFPI.
3. Fourier transform is used to convert the gated time domain signal of a single CCFPI into the frequency domain; this feature is often built in to the VNA functionality. In the frequency domain, the interferogram of the isolated CCFPI under analysis will be apparent, such as the interferogram given in Figure 19.

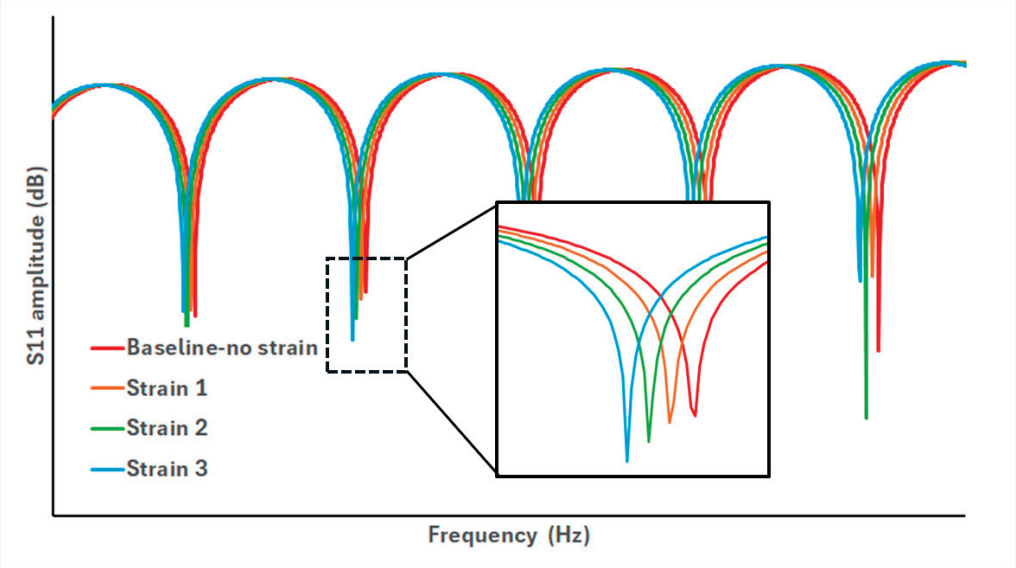


Figure 19. Example interference pattern of a CCFPI sensor varying with applied strain. The zoomed-in section illustrates how strain can be inferred from tracking the frequency of the interferogram minima [45].

4. This action is repeated for all pairs of reflectors along the cable, sliding the time domain gating window along the cable, isolating each individual CCPFI in turn for analysis. This is a method of short-form Fourier transform and enables each CCFPI to be monitored and, crucially, the physical location of each CCFPI on the cable is known, through the time gate, allowing parameters such as strain along the cable to be monitored and mapped along the cable length.

Using this technique, different features of the interferogram can be tracked, although the main feature to be tracked appears to be the resonant frequencies or interferogram minima, illustrated below in Figure 19. In their development of a CCFPI for sensing applications, Huang et al. report tracking the dips in the interferogram and also observe that the Q-factor of the dips decreased as strain increased, which could indicate an increase in the propagation loss between the two reflectors [46]. A similar approach was taken in the development of a smart steel strand with built-in CCFPI, illustrated below in Figure 19. The sharpness of the dips compared to the peaks could provide greater resolution.

A different joint time–frequency analysis method, time–frequency domain reflectometry (TFDR), was proposed by Song et al. [76]. This was presented as a method of overcoming the challenges of TDR and FDR on unmodified coaxial cables. The argument was that for accurate TDR, a sharp rise in the time pulse is required, but this incurs distortions. Conversely, FDR is very sensitive to noise and so carries a high error rate. By performing the analysis jointly in the time and the frequency domains, this method aims to overcome the challenges incurred when analyzing in a single domain. This is linked to the uncertainty principle, giving rise to the trade-off between the time duration and the frequency bandwidth of the same signal. In order to analyze both the time and frequency domains simultaneously, the reference signal launched down the cable was chosen to be a Gaussian waveform envelope (frequency domain) and a chirp signal (time domain), as illustrated in Figure 20.

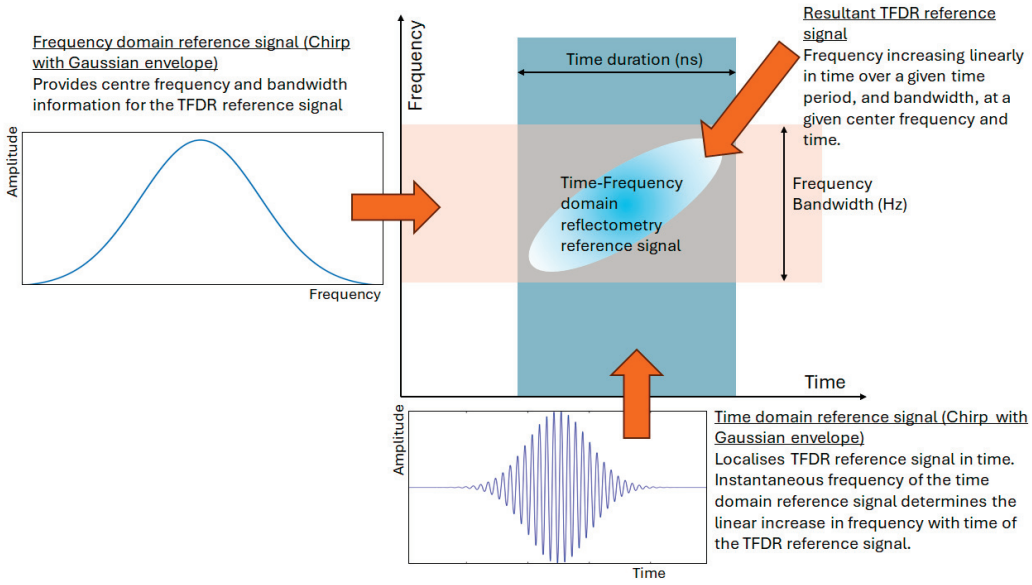


Figure 20. The design of a reference signal for TFDR method (modified from [13,76]).

The reflected signal is then cross-correlated with the reference signal to reveal the location of faults along the cable. This method was shown to offer improved fault location accuracy on unmodified coaxial cables, but the inherent attenuation of the coaxial cable resulted in decreasing accuracy and sensitivity with increased fault distance [76]. This reference does not document the sensitivity of this technique to lower strain events and only considers identifying the location of significant cable damage (absence of outer conductor material) on an otherwise unmodified coaxial cable.

A novel signal processing technique of using a sliding time gate and cross-correlating spectral data is well described in [88], where a series of cascaded partial reflectors formed the sensing region of a coaxial cable. Time domain plots of the technique demonstrate the limited measurement resolution and clarify the need to perform frequency domain analysis. The correlation technique is interesting in this context and is combined with a structure comprising a series of 100 randomly spaced weakly reflecting holes to create a 2 m long strain sensor that could have applications to CCFPI.

The spatial resolution that can be achieved with CCFPI is dependent on the spacing between the two partial reflectors constituting the FPI. There is an inherent trade-off between the frequency bandwidth and spacing, with a higher bandwidth required to achieve greater spatial resolution. The bandwidth required to measure the interferogram

varies with the spacing of the partial reflectors. The partial reflectors cannot be resolved unless they are greater than x distance apart [14]:

$$x\ must\ be\ \geq \frac{c}{(\omega_{max} - \omega_{min}) * 2 * \sqrt{\varepsilon_r}}, \tag{8}$$

where x is the distance between the two partial reflectors making up the FPI, ω_{max} is the maximum frequency and ω_{min} is the minimum frequency, ε_r is the permittivity of the coaxial cable dielectric, and c is the speed of light.

Whilst the focus of this report is on coaxial cable distributed strain sensing, there are several derivatives of this technique providing a single discreet measurement, or tailored to track a parameter different to strain, which are worthy of note.

- On creating a pair of highly reflective reflectors in a coaxial structure, a Fabry–Perot resonator (CCFPR) is constructed. Whilst only a single measurement can be made from this device, multiplexing is not possible as insufficient energy passes the reflectors and the multiple round trips of the energy within the cavity increase the Q-factor of the device, increasing the measurement resolution. The second reflector forming the resonant cavity can be placed beyond the open end of the coaxial structure, thereby forming 'open-ended coaxial probes' which are widely available for measuring material properties in the microwave range of the electromagnetic spectrum [89–96]. By adapting this arrangement, it was shown that the second reflector in the CCFPR could be formed by a metal plate positioned beyond the end of the coaxial structure. The lateral position of the plate could be measured to resolutions of the order of 1 nm, comparable with the resolutions of analogous fiber optic techniques [97,98]. A diagram of this open-ended hollow coaxial cable resonator (OE-HCCR) is shown in Figure 21.

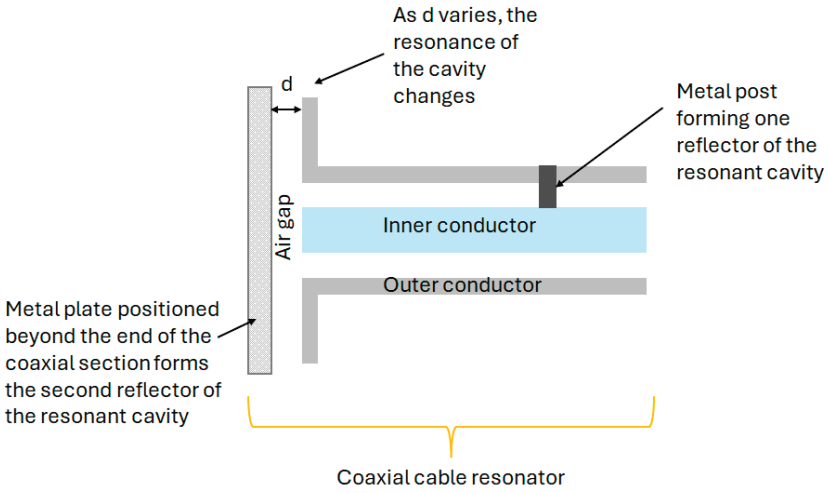


Figure 21. Schematic of the OE-HCCR structure for measuring lateral displacements. The metal post forms the first reflector of the resonant cavity and the metal plate beyond the end of the coaxial structure forms the second reflector of the cavity.

As a further extension of this work, the coaxial resonator was adapted to measure vibrations and impacts and, combined with machine learning techniques, the cause of the impact could be identified [99]. A diagram of this OE-HCCR impact sensor is shown in Figure 22.

A humidity sensor has also been developed based on this technique, harnessing the sensitivity of the device to detect the moisture content of exhaled air. The potential applications include chemical sensing and the analysis of gaseous contents [100].

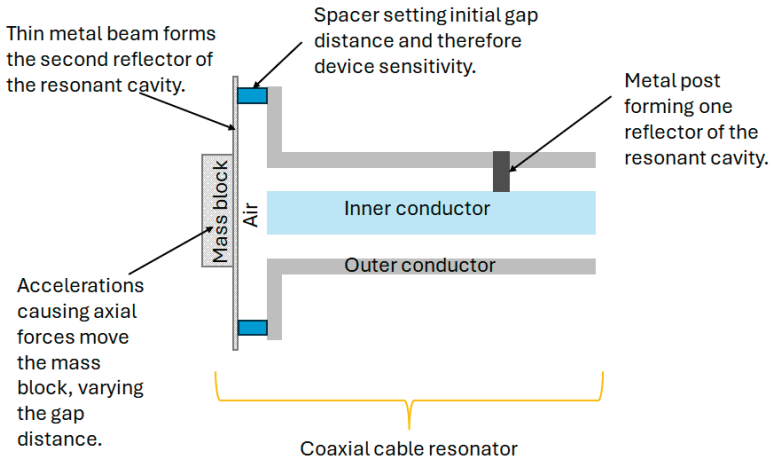


Figure 22. A diagram of an open-ended hollow coaxial cable resonator impact sensor [99].

A similar OE-HCCR construction was devised as a strain sensor for nanoscale precision [101]. The premise of the operation was to track a frequency shift occurring from a change in the reflection coefficient of the open end of the OE-HCCR. The reflection coefficient was dependent on the signature from a gap and a flange. With varying strain, the gap width changed, altering the capacitance and leading to a reflection coefficient change. Sensitivities of 2.5 GHz/mm were achieved. An application to measure shrinkage strain during the mortar drying process was demonstrated.

- A displacement sensor based on a hollow coaxial cable Fabry–Perot resonator (HCC-FPR) was developed and tested in 2018 [102]. A solid stainless-steel inner conductor (6 mm diameter) and a tubular stainless-steel outer conductor (14 mm diameter) form the basis of an air-dielectric coaxial structure. A single pair of highly reflective partial reflectors exist, with one on the moveable handgrip, forming a resonant cavity. When the handgrip is moved, the reflector moves, changing the length of the resonant cavity and causing a shift in frequency. The device, shown in Figure 23, could measure displacement to a resolution of 10 µm.

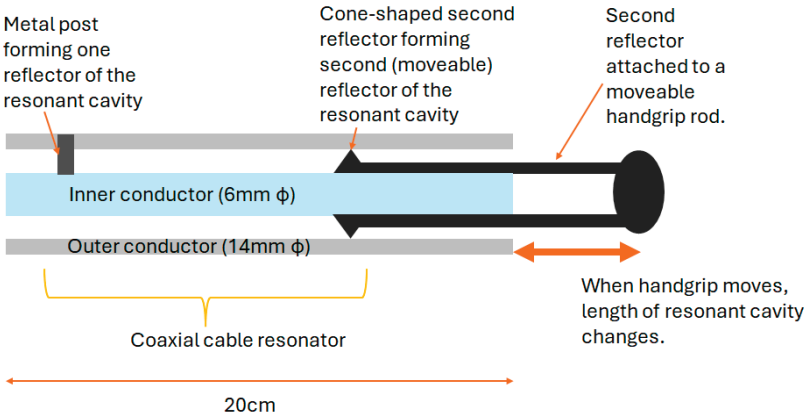


Figure 23. Schematic of the HCC-FPR displacement sensor [102].

- Further developments on the HCC-FPR proved the principle of this device as a strain sensor for high-temperature environments, up to 1000 °C. The movable hand grip was replaced with weld points (limit disks) to attach the device to a test steel plate. Now, as the steel plate expands with temperature, the cavity length of the FPR changes, shifting the resonant frequency, from which strain can be deduced. The nested arrangement of the coaxial structure is intended to remove the effects of the thermal expansion of

the sensor itself [103]. The principle of the operation of this device is illustrated in Figure 24, along with photographs of the tested sensor.

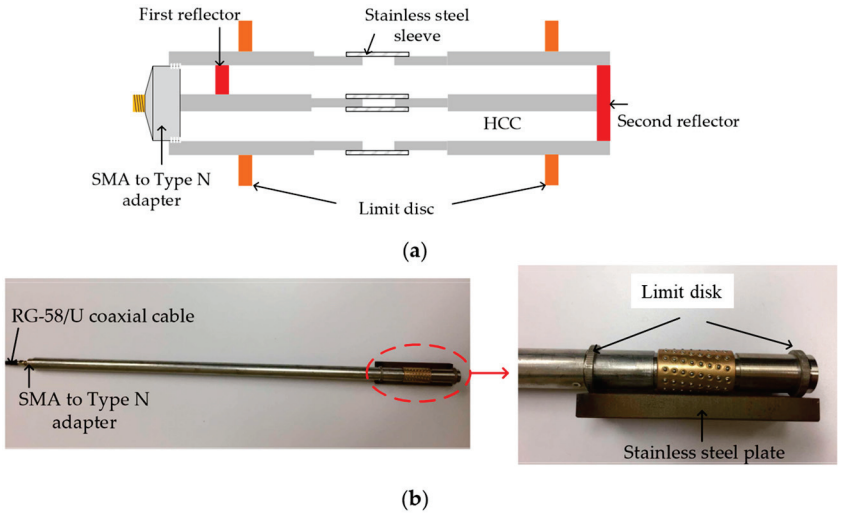


Figure 24. (**a**) Schematic of the HCC-FPR strain sensor. (**b**) Photographs showing the two limit disks welded to the stainless-steel plate for high-temperature strain sensing. The distance between the two limit disks was ~11.5 cm [103].

- Adapting a coaxial cable into a CCFPR for temperature measurements was described in 2017 [104]. In contrast to utilizing partial reflectors in distributed sensing using FPI arrangements along the entire length of the cable, CCFPRs use a single pair of highly reflective points, in this case constructed by filling drilled cavities in a coaxial cable with copper powder to form a short circuit (Figure 25). The high reflectivity results in increased measurement resolution [105] but limits the number of sensing points. This investigation noted the adaptability of the technique to strain sensing.

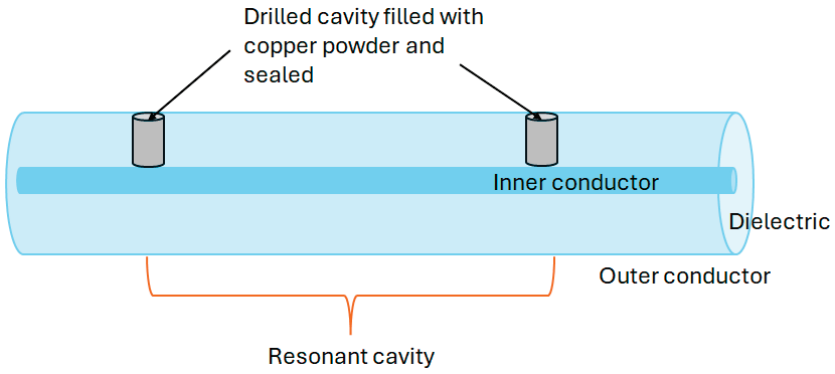


Figure 25. Diagram showing cut-through schematic of the high-quality factor coaxial cable Fabry–Perot resonator [104].

- The application of an HCC-FPR as a liquid-level sensor was researched in [106]. In this configuration, illustrated in Figure 26, the liquid forms the second reflector creating the resonant cavity, and hence the level of the liquid determines the frequencies of resonance. The sensor could measure liquid levels over a ~20 cm range to resolutions in the order of micrometers.

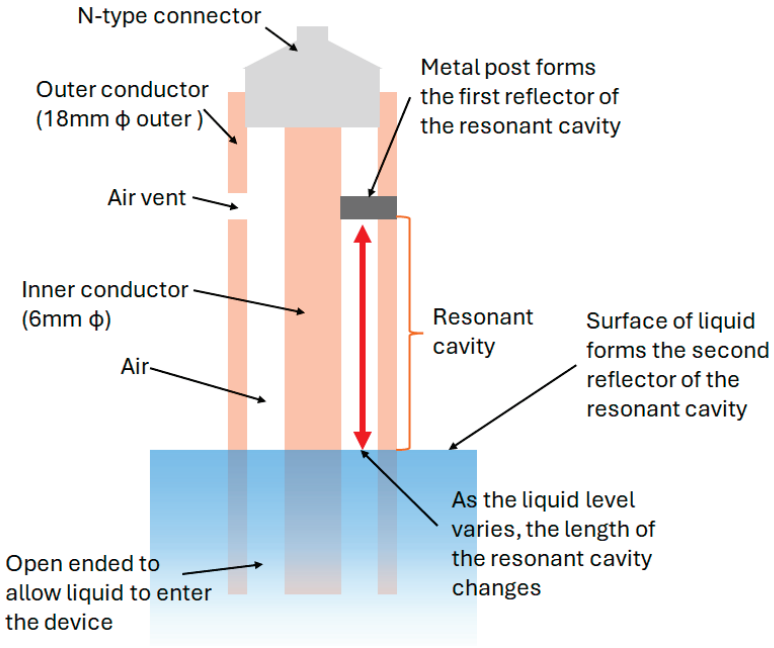


Figure 26. Diagram and of the HCC-FPR device as a liquid-level sensor [106].

- Characterizing liquids through the measurement of their dielectric properties is important for a range of functions such as food processing, biological analysis, and the design of microwave communication systems. A sensor based on a CCFPI construction was developed for this application in 2017 [107]. A bespoke coaxial structure was manufactured using a stainless-steel tube and wire as the outer and inner conductors and ceramic (Al_2O_3) as the dielectric. Two Teflon disks formed the partial reflectors either side of a cavity formed by the omission of the ceramic dielectric for a ~10 cm proportion of the structure. The construction of the device is shown in Figure 27. Different fluids were pumped through this cavity, in turn, and the resultant interferogram was shown to be dependent on the dielectric properties of the different fluids.

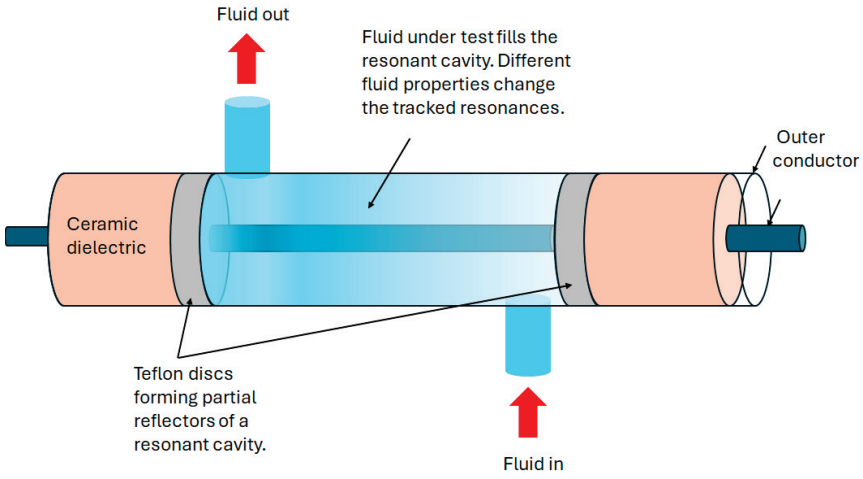


Figure 27. Diagram of the metal–ceramic CCFPI for the measurement of dielectric properties of liquids [107].

- A metal–ceramic coaxial cable design was proposed for high-temperature monitoring using the Fabry–Perot interferometric technique [108]. The high-temperature properties of the ceramic replace the temperature-limited conventional polymer dielectrics. Successful operation was reported between 200 °C and 500 °C, although thermal stability over longer time frames at these temperatures was yet to be explored. Two different

partial reflector designs were tested: full-circle air gaps and half-circle air gaps, as shown in Figure 28.

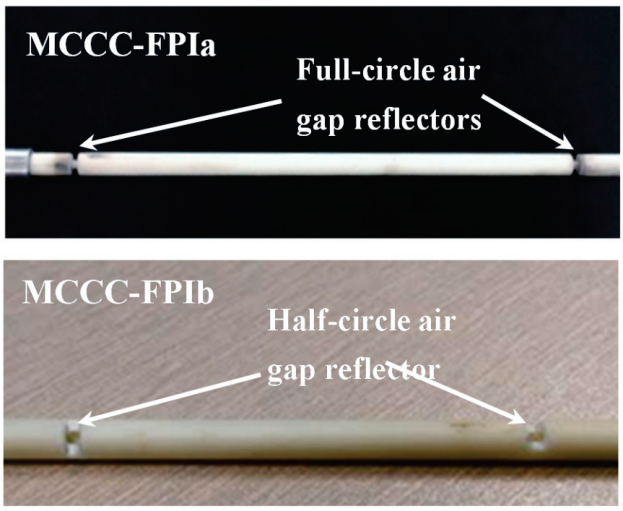


Figure 28. Photograph of the metal–ceramic coaxial cable Fabry–Perot interferometer design with two different configurations for the partial reflectors [108].

- The use of CCFPI for temperature monitoring is also described in [109], where copper crimp rings are compressed onto a conventional coaxial cable to form an FPI (~10 cm) long. The objective of this research was to design a sensor capable of monitoring temperatures' downhole in order to indicate leakages in CO_2 storage.

3.2.2. Grating-Based Coaxial Cable Frequency Domain Reflectometry

Fiber Bragg gratings are well established in the field of fiber optic sensing, as discussed in Section 2.2.2 of this paper. There are wide-ranging examples of optical FBGs as sensors [110–114]. However, the inherent weakness of the fiber optic material limits its application to lower strain events. To realize a wider range of measurable strain and monitor structures up to failure, a more robust FBG 'carrier' would be necessary. The application of an FBG structure on a coaxial cable achieves this [15,21]. Whereas a CCFPI is constructed from a pair of partial reflectors, a coaxial cable Bragg grating consists of a group of equally spaced partial reflectors (as shown in Figure 29), all forming an interferogram that tracks with changing environmental conditions.

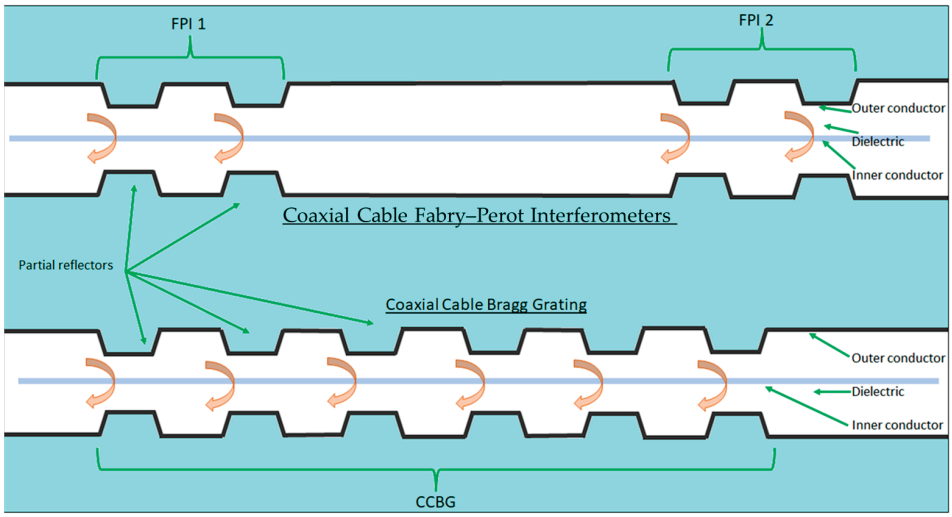


Figure 29. Diagram to illustrate the difference between a CCFPI and CCBG configuration.

The proposed benefit of CCBG over CCFPI is the higher Q-factor of the interferogram, which should offer increased measurement resolution [104,105,115]. The CCBG interferogram clearly shows sharper maxima, indicating a higher Q-factor, over the broader peaks of the CCFPI interferogram, as illustrated in Figure 30.

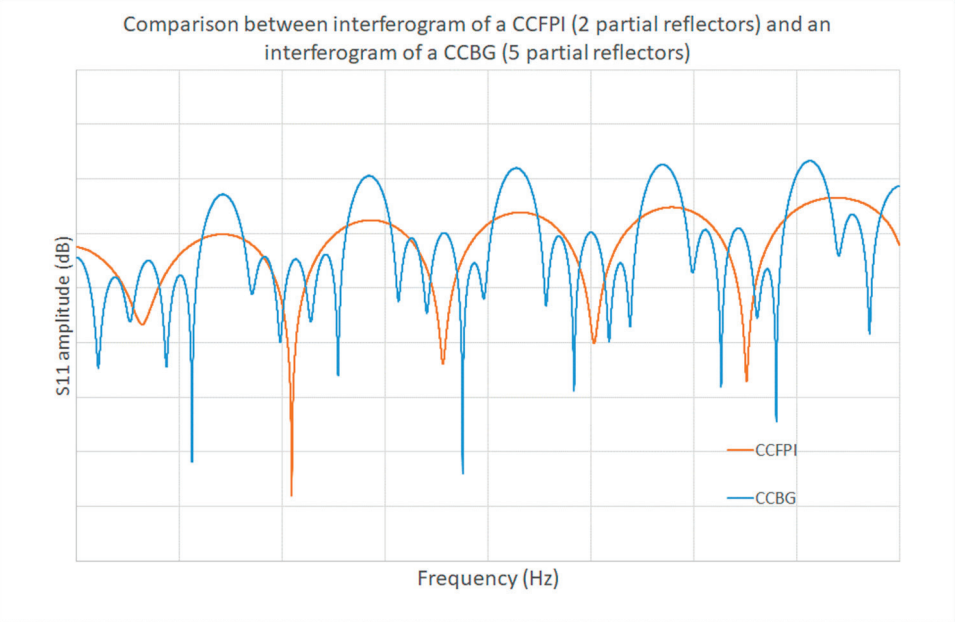


Figure 30. The higher Q-factor of a CCBG over a CCFPI is apparent on studying the interferograms from the respective structures.

Wei, Wu, and Huang et al. reported on fabricating a CCBG in 2011 [21]. A series of 46 holes, 2.5 cm apart, were drilled onto an RG58 cable, penetrating the dielectric layer, to create a series of partial reflectors (analogous to the changes in refractive index manufactured into FBGs). The holes present a localized change in impedance, which gives rise to a reflection as the discontinuity is encountered, whilst still allowing for most of the signal to propagate along the cable. A VNA was used to measure the S11 return loss in the frequency domain configured to capture the first resonance peak. A load frame was used to apply a total axial strain of 20,000 με in 16 steps. The frequency of the first resonant peak showed a linear response to the applied axial strain. The maximum strain applied (20 mε) was significantly greater than a typical fiber optic could withstand (about 4 mε), proving the principle that a coaxial cable is a more robust alternative to fiber optic technology for strain sensing in challenging environmental conditions [21].

A similar investigation was conducted using an FBG of 41 discontinuities (holes) with a gating period of 25 mm to measure a 1 m length of RG58 cable subjected to axial strain [15]. This CCBG again demonstrated a large dynamic strain of around 5% with a linear response to strain and a resolution of 100 με. From the results, it was observed that the Q-factor decreased as the strain increased. This was explained due to the change in impedance mismatch at the site of the Bragg gratings as the cable dimensions change with increased strain. In this paper, a cross-correlation method was applied between the interferogram before and after applied strain to detect the small shift in resonant frequency.

A disadvantage of a Bragg grating is the reduced spatial resolution that can be achieved [14,45]. Monitoring a Bragg grating of 46 periods of 2.5 cm distance covers a total distance of 1.125 m. Information on the strain deduced from tracking the interferogram of this Bragg grating could therefore only be assigned to a location covering a 1.125 m span.

At the 2012 workshop on civil structure health monitoring, the results on the development of a CCBG strain sensor were presented. A variety of cable types were tested, and it was demonstrated that the dynamic range of the sensors was up to 7% (70,000 με), measuring strain to a resolution of 100 με. The signal analysis techniques included a cross-correlation method to improve the sensitivity of the device. Furthermore, a positive feedback oscillator analog system was developed and shown to increase the Q-factor of the data from the device by ~3500 times. This improved the strain resolution by almost a factor of 10, from 100 με to 11.4 με [115].

Further work and details of the positive feedback oscillator to increase the sensitivity to strain were explored and reported in 2017 [116]. An RG58 cable formed the basis of the CCBG sensor under test. A series of ~8 partial reflectors were created by milling out the outer conductor and dielectric in discreet locations ~11 cm apart. This manufacturing method is shown in Figure 31.

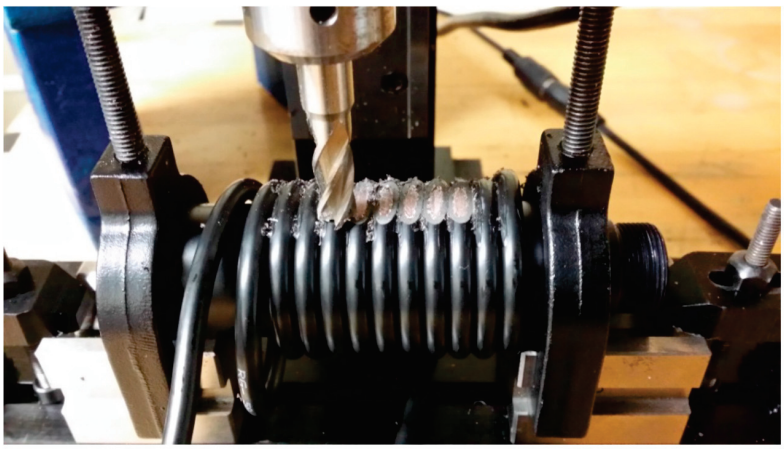


Figure 31. Photograph illustrating the process by which the CCBG was created on RG58 cable [116].

The emphasis of this research was to make a cost-effective geodetic strain sensor. The proposed solution was to use a pair of CCBGs: one detecting strain, the other detecting environmental noise. Integrating the two signals in a mixer allowed for measurements to be taken at a lower frequency, which reduced the complexity and cost of the electronic components needed for signal propagation and analysis. A cost-effective portable spectrum analyzer could therefore be used for data processing, eliminating the need for an expensive VNA.

Recent work in the field of CCBG (2023) investigated designing and constructing a bespoke coaxial cable, with a regularly undulating dielectric layer forming the grating feature, to operate as a strain sensor via the CCBG technique. A thermoplastic polymer was chosen as the dielectric layer, offering greater elongation and tensile strength over conventional polyethylene dielectric, to increase the range over which a CCBG strain sensor could operate before undergoing plastic deformation and become unusable. The grating feature was constructed from a regularly fluctuating cross-section of the dielectric, as illustrated in Figure 32. This idea built on work conducted in 2013 which proposed creating partial reflectors on a CCBG structure by modifying the cross-section of the coaxial cable instead of hole drilling [117]. The proposed benefit of this approach was to eliminate sharp impedance discontinuities formed by crimping or drilling a coaxial cable, which introduces a mechanical weakness [118]. HFSS modeling was employed to determine the optimum shapes of the dielectric before a variety of dielectric designs were 3D-printed, and the bespoke cables were constructed for the test. The most sensitive CCBG had the most extreme variation in the dielectric cross-section and demonstrated a resonant frequency shift of ~3.075 kHz/με [118].

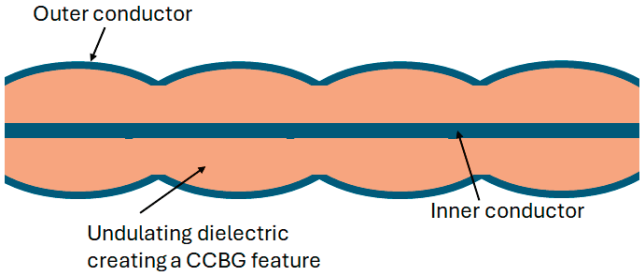


Figure 32. Diagram of bespoke CCBG with regularly undulating dielectric layer forming the grating feature [118].

Through the inclusion of a series of weak partial reflectors along a coaxial cable, the entire structure can be converted into a sensor. Recent work in 2024 [88] demonstrated the promising performance of a coaxial cable sensor, made from a series of 100 randomly spaced holes creating partial reflectors. This forms a type of irregular Bragg grating. The random arrangement generated a multibeam interference pattern. Combined with a signal analysis technique utilizing a sliding time gate and cross-correlation techniques, strain data were inferred across a 2 m section of a 15 m long MIL-C-17 coaxial cable. Strains up to 18,000 με were measured. The resolution of the strain measurement was shown to be dependent on the spatial resolution (spatial width of the time gate). Increasing the time gate width (inclusion of more partial reflectors in the measurement) improved the SNR and measurement resolution. For higher-spatial-resolution measurements, where the time gate was narrower, fewer partial reflectors were included in the measurement, lowering the SNR and measurement resolution. The trade-off between reflector size, signal-to-noise ratio, and successful transmission distance was noted. Larger reflectors improve the SNR but reduce the total distance over which signals can propagate along the device.

A summary of the key results from published works on the development of coaxial cable strain/displacement sensing is given in Table 4.

Table 4. Summary of published information on development of coaxial cable strain/displacement sensors.

Coaxial Cable Sensor Type	Application	Cable Type	Partial Reflector	Sensor Active Length	Frequency	Key Results	Reference
CCFPI	Axial strain sensor	RG58	Holes	70 mm	~3.5 GHz	−3.3 kHz/με	[46]
CCFPI	Axial strain sensor	Not stated	Not stated	Not stated	~1.9 GHz	22.5 kHz/με	[14]
CCFPI	Torsion sensor (cascaded FPIs)	RG58	Crimping metal ferrules	227 mm (wrapped)	~4.2 GHz	1.834 MHz $(rad/m)^{-1}$	[84]
CCFPI	Embedded in GFRP for core in steel stranded cable	SF047	Crimping metal ferrules	200 mm	~3 GHz	−3.7 kHz/με	[45]
CCFPR	Measure lateral displacements	Bespoke structure	Metal post and metal plate	75 mm	~1 GHz	Lateral position resolutions measured to order of 1nm	[98]
CCFPR	Strain, e.g., shrinkage strain	Bespoke structure	Metal post and gap/flange	80 mm	~0.6 GHz	Sensitivity of 2.5 GHz/mm—nanoscale precision	[101]
CCFPR	Displacement sensor	Bespoke structure	Metal post and metal cone	20 cm	~1.2 GHz	Displacement to resolution of 10 μm	[102]
CCFPR	Strain sensor for high-temperature environments	Bespoke structure	Metal inserts	11.8 cm	~1 GHz	Monitored thermal strain between 100 and 900 °C	[103]

Table 4. *Cont.*

Coaxial Cable Sensor Type	Application	Cable Type	Partial Reflector	Sensor Active Length	Frequency	Key Results	Reference
CCBG	Axial strain sensor	RG58	Holes	1.408 m (22 periods)	~4.25 GHz	−3 kHz/με	[21]
CCBG	Axial strain sensor	RG58	Holes	1 m (40 periods)	~4 GHz	−2.1 kHz/με	[15]
CCBG	Strain sensor	Bespoke	Undulating dielectric	200 mm (10 periods)	~4.5 GHz	~3.075 kHz/με	[118]
Irregular CCBG	Strain sensor	MIL-C_17	Holes	2 m	0–6 GHz	−5.068 kHz/με	[88]

4. Future Research Challenges in Coaxial Cable Strain Sensing

An extensive range of exciting developments in the field of CCFPI strain sensing have been investigated under laboratory-scale tests designed for practical applications. However, CCFPI is not yet a standard, industrial SHM tool, and further work remains to promote this technology to a workable product. Understanding the longevity and stability of CCFPI-based devices is necessary before their deployment in field applications [16]. Fiber optic technologies have long since provided an industrial solution to a large range of SHM requirements. CCFPI needs to prove that it can provide additional value to complement the DOFS before it can become a viable, commercial alternative. The potential advantages of utilizing coaxial cables as distributed strains sensors, complementing or replacing incumbent fiber optic technologies, are several-fold.

- Higher strain events can be monitored due to the strength of the materials of coaxial cable construction [9,46].
- Coaxial cables can withstand greater exposure to challenging, harsh environments [21,45].
- The robust coaxial cable structure means that they can withstand installation procedures which are too severe for delicate fiber optics [10].
- The construction and manufacturing techniques and signal excitation and analysis methods are all simplified compared to fiber optic technology, offering the potential for a more economical alternative [2,47].

However, from the reviewed literature, it is apparent that for the concept to progress to a usable technology, there are several research challenges remaining, including the following:

1. A CCFPI response to strain is dependent on several factors, not just the physical distance between the two partial reflectors comprising the FPI. The response of the dielectric permittivity to strain has a significant influence on the performance of a coaxial cable as a strain sensor using FPI features. Characterizing the dielectric permittivity with strain is an area for further work. This would enable the likely response of different coaxial cables as strain sensors, using FPI features, to be understood and predicted.
2. CCFPI-distributed sensing measurements can be a result of the convolution of strain and temperature effects on the device. Both environmental factors influence the interferogram. Suggestions on how this challenge may be addressed, and the effects of the proposed decoupling methods, are summarized below and in Table 5:
    a. Inference is made that the convolution of strain and temperature effects can be minimized by selecting dielectric materials that show preferential sensitivity to strain or temperature, depending on which condition is to be monitored [14]. There is a further reference to this technique in [7] where instead of using a commercially available coaxial cable with a Teflon or polyethylene dielectric, a coaxial cable with a low-stiffness rubber dielectric was designed in an attempt to increase the sensitivity of the cable to strain.

b. Another approach taken has been to use a reference CCFPI alongside the CCFPI monitoring the strain to act as temperature compensation [14]. This is similar to the well-established practice of utilizing conventional electrical resistance strain sensors in a bridge arrangement to provide temperature compensation [119].
c. Depending on the application and CCFPI design, temperature variations could be accounted for by presentation as an error on the strain reading, within reason.
d. Lessons could be learned from fiber optic techniques and are worth future assessment and investigation [40,120–125].
e. Signal analysis methods to monitor different characteristics of the interferogram might hold the key to inferring temperature effects on strain measurements. The latest developments in machine learning could more rapidly classify interferogram changes due to temperature and changes due to strain, deconvolving the environmental effects.
f. Recent work on FBG sensors has applied machine learning techniques to discriminate between strain and temperature variations [126]. It would be interesting to pursue the role machine learning could play in advanced signal processing techniques for CCFPI.

3. Significant experimental works need to be conducted to test the CCFPI operation when subjected to combinations of environmental parameters and assess operational limits under conditions of high humidity, high pressure, and high temperature. The impact of cumulative and combined environment effects needs to be understood to make sure CCFPI is reliable and robust for real-world applications.
4. In the reviewed work, there have been two main methods for creating the partial reflectors in the FPI arrangement: crimps/localized deformation and hole drilling [15,21,45,46]. For the measurement of strain, it was cited that localized deformations with metal ferrules ensure that cable strength is retained, whereas hole drilling would create undesirable weaknesses [115]. One purpose of the development of the undulating cross-section CCBG was to propose a design that could be realistically fabricated [118]. The practicality and engineering challenges of manufacturing partial reflectors on a large scale, integrated with coaxial cable manufacturing processes, should not be overlooked to realize the full commercial potential of this technology. This is another aspect worthy of further work.
5. Optimal signal analysis techniques would further enhance the CCFPI technology for commercial success. Some techniques reviewed under this paper, but not necessarily applied yet to CCFPI devices, include the following:
    a. JTFA method applied to date to unmodified cables [76].
    b. Increased sensitivity of CCBG device achieved through cross-correlation analysis and a feedback oscillator [115].
6. Deeper investigation into key features of the interferogram to track would be interesting, such as amplitude, Q-factor, as well as the position of frequency maxima and minima. The inclusion of machine learning methods into the signal analysis would be a novel approach to extracting greater information from the interferogram data. The objectives of more sophisticated signal analysis techniques would include the following:
    - Increased sensitivity;
    - Improvement in the SNR;
    - Rapid analysis of multiple FPIs for real-time monitoring;
    - Potential to de-convolve strain and temperature.

Table 5. Summary and comparison of strain–temperature deconvolution methods.

Temperature–Strain Decoupling Method	Sensor Technology Which Method Has Been Tested	Description/Comments	Strain Sensitivity	Temperature Sensitivity	Reference
None	FBG	Baseline for understanding potential impact of temperature on strain measurements.	7.72 ppm/με	−101.62 ppm/°C	[120]
None	CCFPI		For a CCFPI with thermal expansion dominated by the dielectric (PTFE of 150 ppm), a 1 °C shift would result in a strain measurement of 150 με.		
Design preferential response to strain	CCFPI	In a CCFPI, select a dielectric material that demonstrates a greater change in response to strain and had reduced reaction to temperature. Topology of the coaxial cable designed to enhance response to strain. May only serve to reduce sensitivity to temperature, not eliminate it.	A coaxial cable with a silicon rubber dielectric (instead of PTFE) and a spiral wrapped outer conductor showed 15–80 times increase in sensitivity to strain. Silicon rubber has a modulus of elasticity approximately 10 times lower than that of PTFE, so on that basis, it would theoretically provide a 10-fold increase in sensitivity to strain.		[7]
Inclusion of uncoupled/relaxed sections along CCFPI	CCFPI	Along the length of a CCFPI, several sections could be left uncoupled to the structure under strain. These 'relaxed' sections should then only be subjected to temperature fluctuations, and analysis of these sections can be used to calibrate the strained sections to remove unwanted temperature effects. Relaxed sections used for temperature compensation are not co-located with the strain sensing sections and could therefore be subjected to different temperature fluctuations, so calibration to eliminate temperature effects may not be accurate.	In theory, an 'inactive' co-located section of a CCFPI should provide full temperature compensation, subject to precise material composition and manufacturing variations, resulting in slightly different temperature response between active and 'inactive' sections.		[14]
Wheatstone bridge configuration	Electrical resistance strain gauges	Arrange multiple sensors in a half or full Wheatstone bridge configuration. One branch of the bridge monitors strain; other branches aid temperature compensation. A full Wheatstone bridge offers a more complete solution, but this does involve a greater number of sensor devices.	For a single electrical resistance strain gauge, sensitivity to strain is approximately 2 ppm/με, and sensitivity to temperature is approximately 150 ppm/°C. A full Wheatstone bridge should eliminate the temperature response.		[119,127]
Active/dummy section	FBG	One active strain sensor, coupled to structure to be monitored, works with a 'dummy' strain sensor that is not coupled for strain monitoring, and therefore solely tracks temperature fluctuations. Active and dummy sections could be co-located for optimum temperature compensation.	In theory, a 'dummy' co-located section of an FBG should provide near-full-temperature compensation (subject to precise material composition and manufacturing variations resulting in slightly different temperature response between active and dummy sections).		[40]
FPI based on a bubble	Fiber optic	Bubble filled with air forms an FPI cavity. The low thermal conductivity of air reduces impact of temperature on strain measurements. Including as a baseline for comparison with Vernier method.	7.75 ppm/με 6.0 ppm/με	1.2 ppm/°C 1.1 ppm/°C	[120]
Two parallel FPIs and Vernier effect	Fiber optic	Using two FPI fiber optic sensors in parallel. One active and sensing strain and one acting as a reference. The joint parallel response from the two sensors is used for analysis, with the Vernier effect aiding to enhance the sensitivity to strain.	−14.9 ppm/με	0	[120]

5. Conclusions

Sensors for structural health monitoring provide vital information to ensure the safety and economic viability of engineering assets. Novel technologies in this field are of interest to keep pace with engineering developments, as well as improve current sensing devices. This paper introduced the concept and principles of distributed sensing for SHM by providing a brief overview and history of the development of optical fiber sensing. Time domain reflectometry was the first technique utilized to infer parameters such as strain from fiber optics, with frequency domain reflectometry arising to address some of the limitations of TDR, such as measurement resolution. A parallel development journey is echoed in the emergence of coaxial cable distributed sensing techniques. Initial work on TDR on coaxial cables demonstrated the principle that such cables could be adapted into distributed sensors able to withstand greater strains than delicate optical fibers. Through the adaptation of interferometric and grating techniques first used on fiber optics, coaxial cables have been transformed into distributed sensors, capable of high measurement resolution up to strains beyond fiber optic limits. Furthermore, the construction and materials of a coaxial structure can be selected and adapted to a wide range of topologies. A standard cable form factor can provide strain information when embedded in a steel rope for anchoring, and a shorter more rigid coaxial structure can form a displacement sensor for high-temperature environments. Coaxial cable frequency domain measurement techniques could therefore offer advantages over distributed optical fiber sensors for the given applications. This paper has documented the state of the art in this promising technology.

Optimizing the design and construction of the features required for CCFPI and CCBG structures is a focus for further research. Some novel manufacturing techniques, reported in this paper, have been devised and tested, and research on these, as well as the underlying physics of the techniques, is necessary to elevate this concept into a successful product, rivaling DOFSs. Enhanced signal analysis techniques could further develop the full potential of coaxial cable frequency domain-based sensors and, as before, inspiration could come from mirroring DOFS techniques and emerging methods.

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