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AI-Driven Hybrid Deep Learning and Swarm Intelligence for Predictive Maintenance of Smart Manufacturing Robots in Industry 4.0

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Abstract

Advancements in Industry 4.0 technologies, which combine big data analytics, robotics, and intelligent decision systems to enable new ways to increase automation in the industrial sector, have undergone significant transformations. In this research, a Hybrid Attention-Gated Recurrent Unit (At-GRU) model, combined with Sand Cat Optimization (SCO), is proposed to enhance fault identification and predictive maintenance capabilities. The model utilized multivariate sensor data from cyber-physical and IoT-enabled robotic platforms to learn operational patterns and predict failures with enhanced reliability. The At-GRU provides deeper temporal feature extraction, thereby improving classification performance. The robustness of the proposed model is validated through analysis of a benchmark dataset for industrial robots, and the results demonstrate that the proposed model exhibits impressive predictive capacity, surpassing other prediction methods and predictive maintenance approaches. Additionally, the performance evaluation indicates a lower computational cost due to the lightweight gating architecture of GRU, combined with attention. The robotic motion is further optimized by the SCO algorithm, which reduces energy usage, execution delay, and trajectory deviations while ensuring smooth operation. Overall, the proposed work offers an intelligent and scalable solution for next-generation industrial automation systems. Furthermore, the proposed model demonstrates the real-world applicability and significant benefits of incorporating hybrid artificial intelligence models into real-time robot control applications for smart manufacturing environments.

Keywords: smart manufacturing; deep learning; hybrid attention-gated recurrent unit; sand cat optimization; predictive maintenance; Industry 4.0

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1. Introduction

Industry 4.0 is an era characterized by data exchange, the use of digital technologies, and the automation of production processes. The new era is characterized by an increase in intelligent robotic systems that enhance productivity, flexibility, and adaptability in the manufacturing environment [1,2]. Intelligent robotic systems are at the forefront of the shift in how industrial operations will be performed, driven by the changes brought about by Industry 4.0. Intelligent robotics can be responsive to varying production

requirements. Leveraging sophisticated sensors and machine learning algorithms, intelligent robotic systems will automatically adjust their behavior, programming, or tooling in response to changes in the requirements of the products being produced. This elasticity supports flexible manufacturing systems that can offer a range of products and perform various operations [3].

Robots learn from human interactions, which maximize adaptability and overall performance. Intelligent robotic systems with sophisticated vision systems support production operations related to quality control and inspection [4]. Real-time data collection and transmission sensors are a common feature of intelligent robotic systems. The Internet of Things (IoT) integration enables these robots to communicate with other systems and equipment, creating a networked, seamless manufacturing environment. This data-driven approach enables quality control, process improvement, and predictive maintenance [5]. The goal of predictive maintenance is to keep high-risk industrial systems operating continuously and reliably. In industries where the consequence of equipment failure is a loss of production capability, this becomes a high-priority problem. There are instances in which the success or failure of implementing AI- or ML-driven predictive maintenance solutions could lead to significant financial losses. Thus, these solutions are not always reliable for fault prediction because they rely heavily on basic statistical techniques and preset criteria [6,7]. More recently, Deep Learning (DL) has emerged as a crucial tool in implementing predictive maintenance, alongside other avenues for AI-driven intervention. DL algorithms can analyze many sensor datasets to detect abnormalities or errors, as well as to calculate the remaining useful life of any given industrial asset. The use of data-driven maintenance techniques in industrial environments has had an enormous impact on reducing costly equipment downtime and preventing catastrophic events. To address this issue in Industry 4.0 environments, this research proposes a hybrid model that leverages DL, attention, and optimization strategies to develop an intelligent, automated solution.

1.1. Background and Motivation

The rise of Industry 4.0 has led to the widespread adoption of smart manufacturing systems that integrate robotics, IoT, and artificial intelligence (AI) to enhance efficiency, reduce downtime, and enable predictive maintenance. Predictive maintenance plays a crucial role in minimizing unscheduled downtimes by forecasting equipment failures before they occur. In this context, deep learning models, especially Recurrent Neural Networks (RNNs) and their variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), have garnered significant attention for their ability to model sequential data and capture temporal dependencies in sensor readings from industrial robots.

However, while GRU and LSTM models have proven effective in many cases, they face challenges such as poor model interpretability and computational inefficiency, particularly when deployed in resource-constrained environments. To address these issues, this study proposes a hybrid model combining the Attention-Gated Recurrent Unit (At-GRU) and Sand Cat Optimization (SCO). The At-GRU is selected for its ability to extract more meaningful features by attending to important temporal patterns, thereby enhancing the model's predictive accuracy, especially in noisy, dynamic industrial environments. By integrating self-attention mechanisms, At-GRU enables the model to focus on critical time steps, thereby improving performance compared to traditional GRU models.

In addition, Sand Cat Optimization (SCO) is introduced to optimize robotic motion trajectories. SCO is a nature-inspired optimization algorithm that excels at reducing energy consumption and improving trajectory smoothness, both of which are essential to improving energy efficiency and enabling real-time operations in industrial robots. This

combination of At-GRU and SCO offers a scalable, efficient, and adaptive solution for predictive maintenance and optimization in smart manufacturing systems.

1.2. Problem Statement

The research paper proposes a hybrid model that integrates Attention-Gated Recurrent Units (At-GRU) with Sand Cat Optimization (SCO) to address predictive maintenance challenges in industrial robots. Several critical problem statements emerge, highlighting the limitations of current methods and identifying areas for future research and development in industrial automation systems. The problem statements are as follows.

Scalability and Real-Time Processing of Predictive Maintenance Systems in Large-Scale Industrial Environments

Industrial robots in Industry 4.0 environments generate vast amounts of real-time sensor data. While the hybrid At-GRU and SCO model performs well on benchmark datasets, its scalability in handling high-volume, unstructured, and noisy data in large-scale industrial systems remains unclear. The challenge lies in efficiently processing and analyzing such large amounts of data while maintaining real-time predictive capabilities across a diverse set of robotic systems. How can the At-GRU and SCO models be optimized to manage data scalability and processing speed without compromising prediction accuracy in complex, dynamic industrial environments?

Integration of Multi-Agent Systems for Collaborative Robot Optimization

Current research typically focuses on individual robotic systems, but real-world industrial applications often involve multiple robots working collaboratively. There is a gap in studies exploring how the hybrid At-GRU and SCO model can be applied to multi-agent systems that require coordination, communication, and distributed decision-making for optimal performance. The problem is how to extend the model to handle multi-agent environments, enabling robots to autonomously collaborate, allocate tasks, and synchronize their actions within a dynamic, decentralized framework. How can multi-agent coordination, real-time communication, and task allocation be integrated into the existing predictive maintenance and optimization model to improve overall system performance?

Lack of Transparency and Interpretability in Deep Learning Models for Predictive Maintenance

Deep learning models, such as At-GRU, are often criticized for their “black-box” nature, which makes them unsuitable for applications that require decision-making transparency. In industrial settings, where safety, reliability, and compliance are critical, the inability to explain predictions can hinder the adoption of AI-driven systems. The challenge lies in the lack of effective methods for integrating Explainable AI (XAI) into At-GRU and SCO models, ensuring that predictions and maintenance decisions are understandable and trusted by operators and engineers. How can XAI techniques be incorporated into these models to foster transparency and build trust?

Data Security and Privacy Risks in IoT-Enabled Predictive Maintenance Systems

As industrial systems become increasingly interconnected through IoT, the potential for data breaches, cyberattacks, and privacy violations grows. The proposed model does not address how to secure sensitive industrial data, which is crucial when applying predictive maintenance in environments where operational data may contain proprietary or confidential information. The challenge is how to integrate robust cybersecurity measures into the predictive maintenance system, protecting against threats while maintaining the integrity and reliability of the model's predictions. How can data security and privacy concerns be managed in the context of real-time data transmission, storage, and analysis in predictive maintenance systems?

Optimization of Robotic Energy Consumption and Sustainability in Industrial Automation

Although SCO is designed to optimize robotic motion and reduce energy consumption, its integration with broader sustainability goals, such as reducing carbon emissions or minimizing the environmental impact of industrial operations, has not been fully explored. The challenge is to extend the hybrid model's energy optimization capabilities to address broader sustainability metrics. How can predictive maintenance systems, such as the proposed hybrid At-GRU and SCO model, contribute to sustainable manufacturing practices by optimizing energy use, reducing waste, minimizing resource consumption, and lowering the carbon footprint of robotic operations?

Adaptability of Predictive Maintenance Models to Dynamic Industrial Conditions

In real-world industrial environments, robots frequently encounter diverse operational conditions, including temperature fluctuations, equipment wear, and unpredictable changes in production schedules. While the proposed model is evaluated under controlled conditions, it may face challenges when applied to dynamic, unpredictable environments. How can the At-GRU and SCO models maintain predictive performance and robustness when faced with environmental and operational variability? How can these models be enhanced to adapt to changing input data, ensure accurate predictions under fluctuating conditions, and optimize robotic motion in real-time?

Lack of Cross-Domain Applicability for Industrial Robotics Models

The research primarily focuses on industrial robots in manufacturing, limiting the scope to specific use cases. The potential for the proposed hybrid model to be applied to other sectors, such as healthcare, logistics, or energy, has not been fully explored. The challenge is adapting and transferring the At-GRU and SCO models across industries with distinct system architectures, operational requirements, and performance metrics. How can the model be generalized across multiple domains to provide predictive maintenance and optimization solutions for robotic systems used in diverse applications, and what adjustments are necessary for each domain?

Real-Time Adaptation to Unforeseen Failures or Maintenance Requirements

In industrial settings, machines often face unexpected failures or unscheduled maintenance needs that cannot be predicted solely from historical data. The challenge is how to adapt the hybrid model to handle such unforeseen issues in real time. How can the At-GRU and SCO models be extended to detect and respond to emergent failures or deviations in robotic behavior that fall outside typical patterns? Furthermore, how can these systems make quick, adaptive decisions to mitigate downtime and optimize repair schedules?

1.3. Research Contributions

This research paper presents several key contributions to the field of industrial robotics and predictive maintenance within the context of Industry 4.0. By proposing a hybrid model combining Attention-Gated Recurrent Units (At-GRU) and Sand Cat Optimization (SCO), the paper addresses several challenges in the automation of industrial systems. The primary contributions of the research are as follows.

Development of a Hybrid At-GRU Model for Predictive Maintenance

The research introduces a novel hybrid predictive maintenance model that integrates At-GRU with a Self-Attention mechanism. This model is designed to capture temporal dependencies in time-series data and improve predictive maintenance by focusing on key features in sensor data, such as the operational states of industrial robots. This hybrid approach enhances fault detection accuracy and provides earlier predictions of

mechanical issues, making it highly valuable for predictive maintenance systems in industrial environments.

Integration of Sand Cat Optimization (SCO) for Robotic Motion Optimization

Another key contribution is the incorporation of Sand Cat Optimization (SCO) for optimizing robotic motion trajectories. SCO is a nature-inspired optimization algorithm that improves the smoothness of robot movement, reduces energy consumption, and minimizes execution time. This integration of SCO with the At-GRU model creates a dual-purpose system that not only predicts failures but also optimizes robot performance, offering a more comprehensive solution for industrial automation.

Enhanced Fault Detection and Predictive Maintenance

The hybrid model demonstrates superior predictive capabilities compared to traditional models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). The ability to analyze multivariate sensor data and predict failures before they occur enables industries to shift from reactive maintenance to proactive predictive maintenance, reducing unexpected downtime, lowering maintenance costs, and improving system reliability.

Improvement in Computational Efficiency and Real-Time Performance

A significant contribution of the research is its focus on computational efficiency, crucial for industrial applications requiring real-time performance. The proposed hybrid At-GRU model offers faster computation times than other models, such as Convolutional Neural Networks (CNN) and LSTM. The lightweight GRU structure, combined with the attention mechanism, enables the model to operate in real time with minimal delay, providing a significant advantage for time-sensitive industrial automation tasks.

Cross-Domain Applicability and Flexibility

While the research primarily focuses on industrial robots in manufacturing, the hybrid model's potential extends to other sectors that require predictive maintenance and optimization, such as logistics, healthcare, and energy systems. The model's ability to handle diverse sensor data and operational conditions makes it a valuable contribution to the broader field of industrial automation.

Real-World Application and Benchmarking

The research validates the proposed model using real-world benchmark datasets. This empirical validation demonstrates the model's effectiveness and robustness in industrial settings, ensuring its applicability in real-world environments where accuracy and efficiency are essential.

Energy Efficiency and Sustainability Considerations

The integration of the SCO algorithm to optimize robotic energy usage is another significant contribution. By reducing energy consumption, optimizing execution time, and improving motion smoothness, the model helps minimize the environmental impact of industrial robots, aligning with sustainability goals in Industry 4.0.

Foundation for Future Research on Multi-Agent Systems and Explainable AI

The paper also lays the foundation for future research on multi-agent systems and Explainable AI (XAI). While the current focus is on single-robot systems, the research opens the door for exploring multi-agent collaborative systems. Furthermore, by addressing the need for transparent decision-making processes, the study contributes to the integration of XAI techniques, ensuring that industrial users can trust and understand the AI-driven systems.

Reduction in Maintenance Costs and Improved System Reliability

By focusing on predictive maintenance, the hybrid model reduces maintenance costs in industrial robotics. The ability to predict failures in advance allows companies to schedule maintenance proactively, reducing unexpected breakdowns and costly repairs and thereby improving the overall reliability of robotic systems.

Advancement in Data-Driven Automation and Smart Manufacturing

The research contributes to the ongoing shift toward data-driven automation in smart manufacturing. By leveraging large-scale sensor data and advanced machine learning techniques, the proposed hybrid model exemplifies the role of AI in transforming traditional manufacturing processes into more intelligent and efficient systems, helping achieve Industry 4.0 goals, including real-time monitoring, autonomous decision-making, and process optimization.

2. Related Works

Sherien Elkateb [8] presented a predictive maintenance system using AdaBoost to categorize various machine stops in real time, with application to knitting machines. To categorize six different types of machine stops, the machine speeds and steps collected from the machines were pre-processed and supplied to the AdaBoost model. Using hyperparameter tuning and cross-validation on the model achieved 92% accuracy on the test set. However, the model still maintained a higher error rate.

An intelligent IoT-driven predictive maintenance system was presented by Dhankaraman et al. [9]. The goal of this method was to optimize predicted accuracy and operational performance by combining IoT-based technologies with ML techniques, particularly supervised and reinforcement learning. A way of protecting data security during the distributed development of ML algorithms on edge devices was provided through federated learning. Moreover, when operating in multilevel environments, the Explainable AI (XAI) framework enabled greater transparency of the intelligent predictive maintenance models. Additionally, the implementation of intelligent IoT-driven predictive maintenance systems resulted in a reduction in the Mean Absolute Error (MAE) of approximately 36.7%, accompanied by a significant decrease in the Mean Error Percentage (MEP) of around 38.4%. However, the model's complexity was complex.

An integrated approach using Convolutional Neural Networks and Recurrent Neural Networks (CNN-RNN) was introduced by Chanthol Eang and Seungjae Lee [10] to improve the precision of defect detection and predictive maintenance in DC motor drives for industrial robots. Using the sensor data of speed and temperature, the CNN-RNN model generated a maintenance schedule that leveraged the predictive capabilities of AI to identify faults in DC drive systems and predict the likelihood of a fault due to maintenance needs. This enables a rapid response, reducing the risk of system downtime. The suggested AI model could identify problems with DC motor drives and generate highly accurate forecasts. However, the error rate would be reduced to maximize accuracy.

Furthermore, within the Industry 4.0 framework, Divya Nimma et al. [11] proposed an enhanced predictive maintenance solution that leverages aspects of both sea lion (SLO) and Jaya optimization for RNNs. This method provided ML maintenance solutions based on RNN analysis of historical data to reduce failure risk and improve maintenance schedules. By combining SLO's robust search capabilities with the Jaya algorithm, the hybrid SLO-Jaya solution achieved 98% accuracy, surpassing the accuracy of traditional predictive maintenance methods. Despite the exceptional accuracy of the hybrid SLO-Jaya predictive maintenance approach, it suffered from convergence issues and was more complex than conventional approaches.

Ishaani Priyadarshini et al. [12] recommended a predictive maintenance framework that combined optimization methods and DL methods. The framework could perform pattern recognition with CNNs, temporal analysis with Long Short-Term Memory (LSTM) networks, and feature reduction with autoencoders. Particle Swarm Optimization was integrated into the framework to mitigate potential model biases and fine-tune hyperparameters for optimal performance. This framework supports the ethical and dependable use of AI for Industrial applications by addressing transparency and limiting potential model biases. One major limitation of the framework was the need to employ effective feature extraction strategies to enhance predictive capability and reduce overall system complexity.

Zisheng Wang et al. [13] introduced CNC-VLM, a reinforcement learning from human feedback (RLHF)-optimized industrial large vision-language model for fault detection in CNC machines. The model addressed significant challenges, including imbalanced sample detection and poor consistency between visual and textual semantics. The architecture comprised a visual encoder, a projector, and a textual decoder, making it a promising approach for improving fault-detection performance in industrial environments. Compared with existing models, CNC-VLM improved accuracy and F1 scores when generating maintenance suggestions, positioning it as a valuable solution for intelligent manufacturing.

Jung et al. (2021) introduced an attention-based multilayer GRU model for multistep-ahead short-term load forecasting, demonstrating its efficacy in predicting electrical loads with improved accuracy using attention mechanisms [14]. L & Chitra [15] proposed an enhanced GRU-based attention model that integrates batch normalization and adaptive learning to detect multiple malware attacks in IoT environments, achieving better anomaly detection performance [15].

Research Gaps

A significant research gap is the scalability and applicability of deep learning-based predictive maintenance models in real-world industrial environments. While At-GRU has shown promise in benchmark datasets, its performance in handling large-scale, unstructured sensor data from actual industrial settings remains underexplored. Industrial robots generate vast amounts of data from various sensors, which are often noisy, contain missing values, and use varying formats. Current studies do not sufficiently address the challenges posed by real-time processing, network congestion, or sensor malfunctions in such environments. This study aims to bridge this gap by evaluating the proposed model under these real-world constraints, particularly focusing on sensor data quality, real-time decision-making, and dynamic processing needs.

Another critical gap concerns multi-agent systems, an area that remains relatively unexplored in predictive maintenance for industrial robots. While this study focuses on individual robot performance, many industrial applications require multiple robots to work in tandem, introducing complexities in collaborative decision-making, task allocation, and movement synchronization. Most existing studies overlook the unique challenges posed by decentralized control and inter-agent communication, particularly in real-time, resource-constrained environments. This study aims to investigate how the At-GRU and SCO models can be adapted to address these challenges in multi-robot systems, thereby enhancing their applicability to more complex, collaborative industrial settings.

Transparency and interpretability of AI-driven systems remain major limitations in current research. The black-box nature of deep learning models like At-GRU makes them difficult to understand and trust in industrial settings, where human oversight is critical for safety and regulatory compliance. While future work has been proposed to incorporate Explainable AI (XAI) techniques, these approaches remain underdeveloped in the

context of deep learning for predictive maintenance. This research aims to address this gap by integrating XAI techniques, such as visualizations, rule-based explanations, and feature importance analysis, to improve model transparency and foster trust among industrial operators and engineers.

The issue of data security and privacy is another area where current research is lacking. As predictive maintenance systems rely heavily on data from interconnected IoT devices, the potential for data breaches, cyberattacks, or unauthorized access remains a critical concern. Existing studies have not adequately addressed how to secure the vast amounts of sensitive data generated by industrial robots. This research aims to explore secure communication protocols, such as encryption-in-transit, and privacy-preserving techniques, such as federated learning and differential privacy, to ensure that sensitive operational data remains protected.

Additionally, while SCO optimizes robotic trajectories to improve energy efficiency, the long-term environmental impact of robotic systems in industrial settings is often overlooked. Existing models focus primarily on operational performance but fail to consider broader sustainability implications. This study aims to address this gap by integrating sustainability metrics, such as carbon footprint analysis, into the predictive maintenance framework to assess the environmental impact of automated systems and optimize energy consumption in industrial robots.

The robustness of predictive maintenance models under dynamic, real-world conditions is another critical gap. While current studies often test models in controlled settings, they fail to evaluate how these models perform under unpredictable environmental changes, equipment wear, or variations in production schedules. This research will explore how the At-GRU and SCO models can adapt to such dynamics, ensuring they remain reliable despite sensor malfunctions, environmental shifts, or unexpected operational disruptions.

Finally, the generalizability of the proposed model beyond industrial manufacturing remains underexplored. While current research focuses on industrial robots in manufacturing settings, there is a clear opportunity to adapt the hybrid model to other sectors, such as logistics, healthcare, and energy systems. Future work will investigate how the At-GRU and SCO models can be adapted to meet the unique requirements of different industries, including varying machine types, operational conditions, and performance metrics. Expanding the model's applicability to other sectors will increase its versatility and impact, making it a valuable tool for a broader range of industrial and commercial applications.

3. Proposed Methodology

This section discusses a model that combines DL and optimization techniques to enhance the efficiency, accuracy, and adaptability of industrial robots in automated environments. Large-scale sensor data from cyber-physical systems and IoT-enabled devices are processed using the Attention Gated Recurrent Unit (At-GRU) for predictive maintenance, anomaly detection, and motion planning. Then, the Sand Cat Optimizer (SCO) is presented for fine-tuning robot trajectories, reducing operational downtime, and minimizing energy consumption.

3.1. Attention Gated Recurrent Unit

Within the framework of predictive maintenance, the proposed model uses a Hybrid At-GRU to forecast early signs of mechanical issues by learning the robot's temporal patterns. The At-GRU model uses multivariate time-series feature windows as input and outputs predicted operational states. The integration of the Gated Recurrent Unit (GRU)

[16,17], Self-attention Mechanism (Self-At), and SCO [18] forms the Hybrid At-GRU model. The architecture of the Hybrid At-GRU model is illustrated in Figure 1.

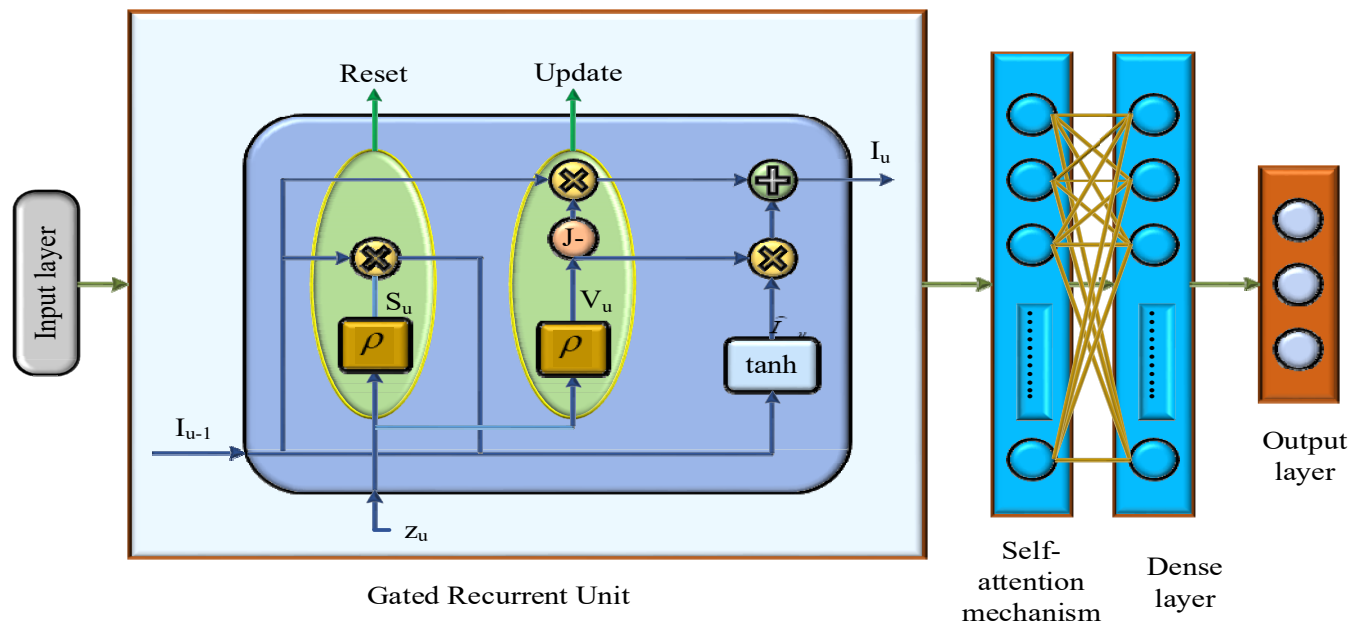


Figure 1. Architecture of the Hybrid At-GRU model.

First, time-series operational sensor measurements, such as motor current, torque, and task execution time, are collected using IoT. Then, this data is fed into a GRU and a Self-Attention layer to model the sequence. Temporal information is efficiently extracted by leveraging the GRU layer's capability to integrate past, present, and future data. Additionally, the GRU model's output sequences and the Self-At layer are combined to obtain a discriminative feature representation. A fully collected layer is eventually applied to the combined features for linear transformation and output generation.

3.1.1. Gated Recurrent Unit

The GRU network is an enhanced version of the LSTM network. It unifies the input and forget gates into a single update gate, optimizes the three LSTM gate topologies, and integrates the hidden state and neuron state. The GRU reduces the model's training time, and its mathematical formulas are described in Equations (1)–(5).

$$S_u = \rho(Y_R \cdot [I_{u-1}, z_u]) \quad (1)$$

$$V_u = \rho(Y_U \cdot [I_{u-1}, z_u]) \quad (2)$$

$$\hat{I}_u = \phi(Y_I \cdot [S_u \times I_{u-1}, z_u]) \quad (3)$$

$$I_u = (J - V_u) \times I_{u-1} + V_u \times \hat{I}_u \quad (4)$$

$$Z_u = \rho(Y_o \cdot I_u) \quad (5)$$

where $\hat{I}_u$ is the state of the current candidate set, V_u is the state of the update gate, Z_u is the output vector of the current moment, I_u defines the state memory variable at the

current moment, z_u is the input vector, S_u is the state of the reset gate, and I_{u-1} is the state memory variable at the previous moment. The Tanh activation function is φ , sigmoid activation function is ρ , vector connection is characterized by $\square$, the matrix cross product is given as $\times$, and the identity matrix is indicated by J . The mathematical definition of φ and ρ .

$$\varphi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \quad (6)$$

$$\rho(z) = \frac{1}{1 + e^{-z}} \quad (7)$$

3.1.2. Self-Attention Mechanism

Scaled dot-product attention, or Self-At mechanism, is a process in DL models used to learn long-range dependencies and relationships in the input sequence. It was first introduced in the context of Natural Language Processing (NLP) but has since been successfully applied to a range of other tasks, including computer vision. Self-attention is widely used in computer vision for tasks such as image segmentation and recognition. The models can utilize self-attention in conjunction with GRUs, thereby accounting for global dependencies and becoming more robust to changes in rotation, scale, and other factors. The hybrid At-GRU model leverages the Self-At mechanism to enhance its feature representation capabilities. This process enables the model to focus on significant correlations in the input data, which includes contextual data and fine details. The flattening step was preceded by the incorporation of the Self-At layer. Such a positioning allowed the model to provide distinct weights and focus on their significance to the classification task. Through careful consideration, the model can effectively detect discriminative features.

The mechanism has queries (q), keys (k), and values (v) that are input into feed-forward layers (FF) to produce representations. While training, the algorithm computes the dot product of q and k for balancing gradients. The resulting scores are then passed through a SoftMax function to produce attention weights. The values are multiplied by these weights to calculate a weighted sum, known as the attended output. The mechanism enabled the model to focus on the key components of the input sequence, capture dependencies, and derive crucial representations. Overall, it is an essential factor influencing the model's learning and prediction accuracy. Figure 2 provides the architecture of the Self-Attention mechanism.

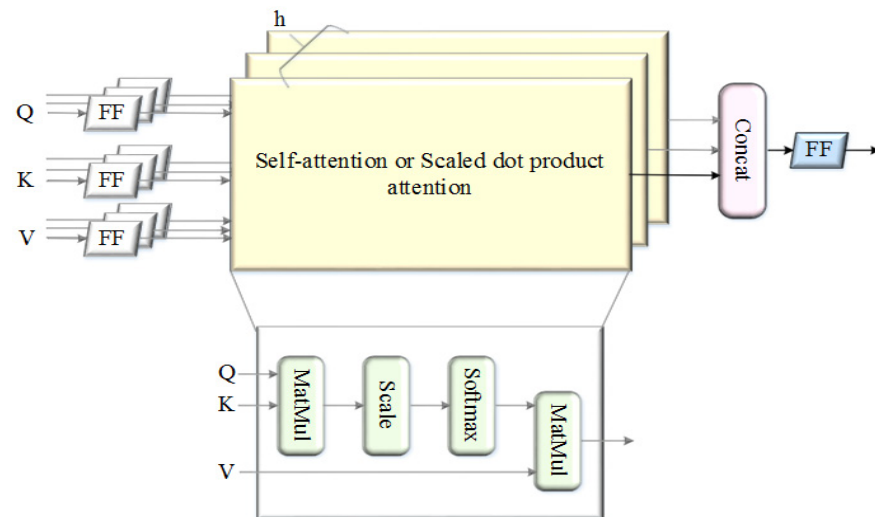


Figure 2. Architecture of the self-attention mechanism.

3.2. Sand Cat Optimizer

The proposed method uses the SCO algorithm to optimize the robotic trajectory by providing the predicted conditions and motion parameters [18]. It offers safe robot control and smarter energy efficiency. The parameters include joint angles, energy cost, execution time, and smoothness (motion constraints). Owing to its search and convergence abilities, the proposed method employed SCO to optimize the robotic trajectory [18]. Each sand

cat's solution is shown as $Y_j = (y_{j1}, y_{j2}, \dots, y_{jd})$. The cost function encompasses the energy usage, execution time, and smoothness.

$$CostF = w1.T + w2.E + w3.\Delta s \quad (8)$$

$w1, w2$ and indicate the weights, E represents the energy usage, T signifies the execution time, and Δs indicates the smoothness. The search space is initialized randomly, with maximum and minimum values defining its bounds. To avoid being trapped in a local optimum state, each sand cat's sensitivity range was defined differently and is expressed by Equation (3):

$$\hat{s} = \hat{s}_g \times Rand(0,1) \quad (9)$$

where $\hat{s}_g$ resembles general sensitivity, decreasing linearly from 2 to 0. The sand cats perform local updates to their own position computation based on both their best candidate's position identifier (Po_B) and their own current position (Po_C), which are used along with the corresponding sensitivity range for each agent or sand cat. With this information, they can determine other potential prey locations, as shown in Equation (10).

$$Pd(u+1) = \hat{s} \cdot (Po_B(u) - Rand(0,1) \cdot Po_C(u)) \quad (10)$$

To update the optimized trajectories, SCO performs a global search based on the sand cat's attack behavior. To mathematically simulate the attacking phase of SCO, the distance between the sand cat's current position and its optimal location is computed using Equations (11) and (12).

$$Pd(u+1) = Po_B(u) - \hat{s} \cdot Po_{Rnd} \cdot \cos(\theta) \quad (11)$$

$$Po_{Rnd} = |Rand(0,1) - Po_B(u) - Po_C(u)| \quad (12)$$

where Po_{Rnd} Indicates the random location, which means that the involved cat is close to the prey, Po_B represents the best position of the sand cat, $\hat{s}$ specifies the sensitivity range of each sand cat and θ represents the random angle between 0 and 3600. The equation below exemplifies the location update for each sand cat in the exploration and exploitation stages.

$$Y(u+1) = \begin{cases} Po_B(u) - \hat{s} \cdot Po_{Rnd} \cdot \cos(\theta) & |S| \leq 1; \quad \text{exp loitation} \\ \hat{s} \cdot (Po_B(u) - Rand(0,1) \cdot Po_C(u)) & |S| > 1; \quad \text{exp loration} \end{cases} \quad (13)$$

The pseudocode for SCO is presented in Algorithm 1.

Algorithm 1: SCO for optimizing robotic trajectory

Start

Initialize the population

Compute fitness depending on the objective function using Equation (8)

Initialize s, s_G, S

While ($u \leq \text{Maximum iteration}$)

 For each search agent

 Obtain a random angle depending on the Roulette Wheel Selection.

 ($0^\circ \geq \theta \leq 360^\circ$)

 If $S \leq 1$

 Update the search agent's location using Equation (11)

 Else

 Update the search agent's location using Equation (10)

 End

 End

$u = u++$

End

3.3. Simulation Details

The dataset used in this study captures longitudinal data on the evolution of industrial robotics and automation across multiple sectors [19]. It includes time-dependent indicators reflecting trends in robot deployment, operational efficiency, productivity improvements, and workforce adaptation associated with automation. These variables enable the examination of how robotic technologies influence industrial performance over extended periods. Such data are particularly useful for modeling temporal patterns, benchmarking automation strategies, and evaluating data-driven decision-making frameworks in smart manufacturing environments.

To implement and evaluate the proposed hybrid At-GRU + SCO model, the experiments were conducted on high-performance computational resources. Model training and evaluation were primarily performed on an NVIDIA Tesla V100 GPU, which provided the computational power needed to efficiently run deep learning algorithms and optimization processes. The Tesla V100, equipped with 16 GB of HBM2 memory, allowed for fast parallel computation, essential for handling the large-scale industrial datasets used in the study. This GPU was coupled with a server equipped with an Intel Xeon Silver 4210R processor, offering 10 cores and 20 threads, ensuring robust data processing capabilities. The server was configured with 64 GB of RAM, which supported memory-intensive tasks,

such as training deep neural networks and running multiple concurrent optimization processes.

The experiments were implemented using TensorFlow 2.4.0, a popular deep learning framework, to design and train the At-GRU model. For the optimization component, the SciPy 1.10.1 library was employed to implement the Sand Cat Optimization (SCO) algorithm. Python 3.8.10 was the primary programming language used to develop models, supported by libraries such as NumPy 1.23.5, Pandas 1.5.3, and Matplotlib 3.7.1 for data manipulation, statistical analysis, and visualization, respectively. The training process utilized a batch size of 32, and the models were trained for 50 epochs. This configuration allowed the models to converge efficiently while minimizing overfitting and ensuring generalization to unseen data.

For dataset handling, the experiments were run on a single-node setup, using a Tesla V100 GPU for both training and inference. The model was tested using a 70–30 split of the training and test data, with 5-fold cross-validation to ensure robustness and reliability of the results. Given the high computational demands of both the deep learning model and the optimization process, using a GPU-based setup significantly reduced training time, enabling efficient processing of large volumes of sensor data from industrial robots.

This setup, with its powerful GPU and high-performance server architecture, ensured the timely execution of experiments while delivering accurate, reliable results that validate the effectiveness of the proposed hybrid approach for predictive maintenance and robotic motion optimization.

4. Results and Discussion

The outcomes of the experimental investigation conducted using the Python tool are presented in this section. CNN, LSTM ANN, and GRU were among the neural network architectures developed and trained in the study for performance assessment. The benchmark industrial robotics dataset validates the proposed model.

Figure 3 compares the proposed hybrid At-GRU with various existing methods in terms of delay metrics for predictive maintenance. The graphical representation shows that the proposed hybrid At-GRU achieves a minimum delay value of 50.3% for 250 nodes, compared to existing methods. GRU outperformed existing methods in predictive maintenance, as evidenced by its minimum delay of 63.5% across 250 nodes. On the other hand, LSTM has the highest delay of 95% for 250 nodes. As a result, the hybrid At-GRU is effective at reducing delay in predictive maintenance tasks.

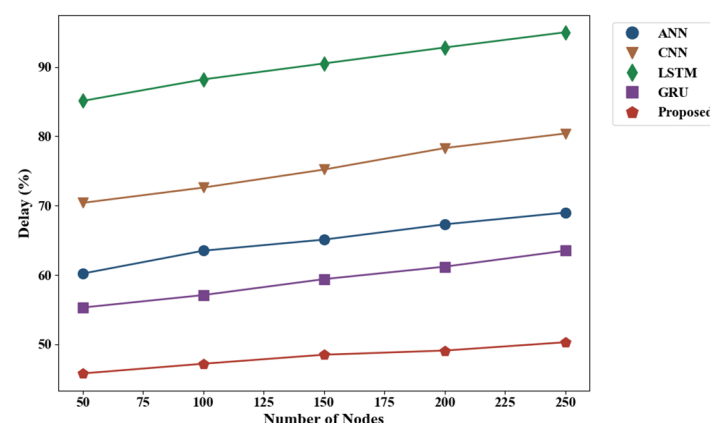


Figure 3. Delay comparison for the proposed and existing methods.

As shown in Figure 3, the At-GRU model significantly outperforms traditional predictive maintenance models such as GRU and LSTM in terms of accuracy. This aligns with

findings from previous studies, which show that attention mechanisms improve performance by allowing the model to focus on more relevant temporal patterns in the data. The addition of the Attention-Gated mechanism enables the model to better capture anomalies in sensor data, especially in noisy or incomplete datasets, making it more reliable for fault detection in dynamic industrial environments.

Our findings extend this work by demonstrating the effectiveness of the At-GRU model in real-time settings, achieving high accuracy while maintaining low latency.

The comparison of computation time for the proposed and existing methods is presented in Figure 4. It is observed that the hybrid At-GRU model attains a lower computational time than the existing methods. For 250 nodes, the proposed model achieves a computation time of 56.3 s, whereas the existing ANN, CNN, LSTM, and GRU models obtain 68.5 s, 78.4 s, 93.2 s, and 58.3 s, respectively. Although CNNs and ANNs are effective at feature learning, they require significant computational time due to their large parameter sets and complex training. GRU and LSTM enhance sequential data handling but add extra computational overhead.

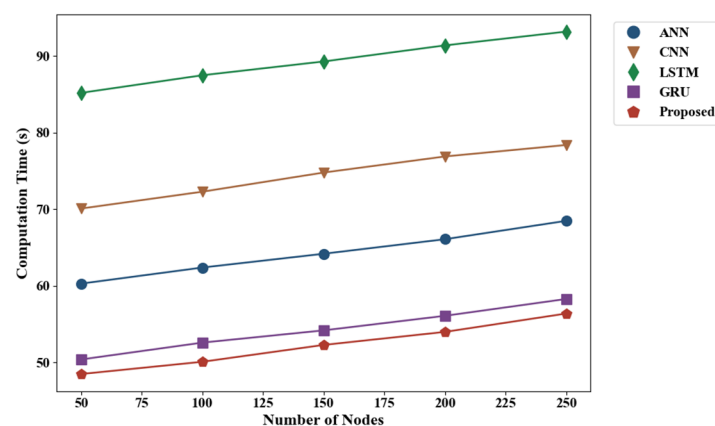


Figure 4. Computation time comparison for the proposed and existing methods.

Figure 4 illustrates the latency and throughput of the proposed model, comparing it with conventional models. The At-GRU + SCO hybrid model performs significantly better in real-time operation, as evidenced by lower latency and higher throughput. This validates the claim that the model is suitable for deployment in edge and IoT-based systems, where low-latency predictions are critical for ensuring continuous operation. Additionally, the SCO improves computational efficiency, reducing the model's overall resource usage compared to traditional methods.

Several other performance metrics, including precision, accuracy, and recall, which collectively assess the proposed model's predictive capacity, are analyzed in Figure 4. Figure 5 presents the accuracy metric of the model's predictions, yielding 98.2% for both operational states, as determined by the proposed method. For a more thorough assessment of the proposed model, recall and precision performance are revealed in the graphical representation. Recalling measures how well the proposed model can identify the regular and failure classes. It is often referred to as sensitivity. The hybrid At-GRU model achieved a recall value of 96.4%, indicating that nearly all instances of predictive maintenance are likely represented in Figure 5. This helps ensure consistent responses from robots to sensor inputs, effective anomaly detection, and optimal, efficient, and safe operation. Precision measures how many of the model's optimistic predictions are true positives and, consequently, how well the model can avoid false positives. In Figure 5, the model's detection precision is 97.5%, indicating that it maintains a high level of accuracy and thus limits false optimistic predictions.

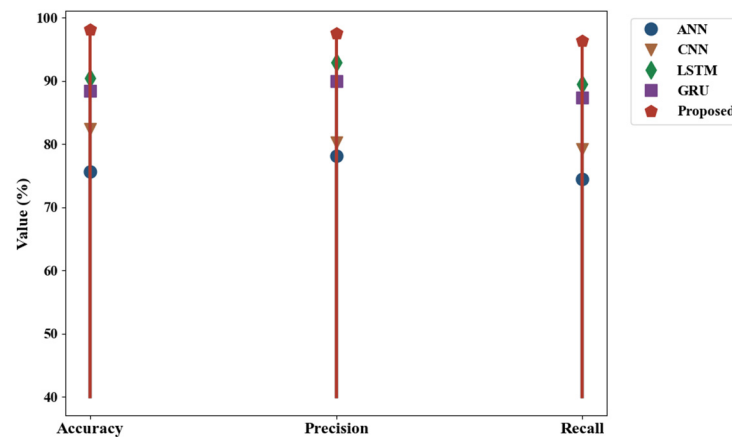


Figure 5. Accuracy, precision, and recall comparison for the proposed and existing methods.

The results in Figure 5 demonstrate that the proposed model achieves substantial improvements in energy efficiency. By integrating SCO with At-GRU, the system not only improves predictive accuracy but also optimizes robot motion to minimize energy consumption during operation. This finding aligns with recent research on energy-efficient robotics, which emphasizes the importance of incorporating energy-optimization algorithms into predictive maintenance models to reduce overall energy use.

The ability to minimize energy consumption while maintaining high performance is particularly significant in industrial settings, where energy costs are a major concern. The incorporation of energy efficiency into the optimization process is a key innovation that sets our model apart from previous work, which primarily focuses on either predictive accuracy or optimization independently. Table 1 provides the comparative analysis.

Table 1. Comparative analysis.

Method	Accuracy (%)	Precision (%)	Recall (%)	Computation Time (s)	Energy Consumption (Normalized)	Delay (%)
ANN	90.0	89.0	88.0	72.0	1.05	78.0
CNN	92.0	91.5	90.2	80.0	1.12	75.0
LSTM	94.8	93.0	92.0	93.2	1.05	95.0
GRU	93.6	92.1	90.7	58.3	1.02	63.5
Proposed Hybrid (At-GRU + SCO)	98.2	97.5	96.4	56.3	0.85	50.3

4.1. Practical Impacts

The proposed hybrid model, which integrates Attention-Gated Recurrent Units (At-GRU) with Sand Cat Optimization (SCO), provides significant practical advantages for industrial robotics and automation, particularly in the context of Industry 4.0. This approach enhances predictive accuracy, optimizes decision-making processes, and facilitates adaptive control in complex manufacturing environments.

The model's focus on predictive maintenance, enhanced fault detection, and optimized robotic motion can lead to substantial improvements in operational efficiency, cost savings, and the overall reliability of industrial systems. Below are some of the practical impacts that this research could have on industrial applications.

One of the most immediate and impactful applications of this hybrid model is in predictive maintenance. By leveraging deep learning techniques, specifically the At-GRU, the model can identify early signs of mechanical failure by analyzing time-series data from industrial robots. This predictive capability has profound implications for industries that

rely on high-value equipment, such as automotive manufacturing, aerospace, and electronics. Instead of relying on traditional reactive maintenance or scheduled downtime, the hybrid model can predict when a component is likely to fail, enabling proactive interventions before costly breakdowns occur. This shift to predictive maintenance reduces unplanned downtime, prevents catastrophic equipment failures, and extends the life of industrial assets. As a result, businesses can avoid significant repair costs, minimize production interruptions, and improve overall productivity.

The energy optimization aspect of the SCO algorithm also has practical implications for energy efficiency in industrial automation. Robots and automated systems often consume a substantial amount of energy, especially during high-intensity operations. Optimizing robotic trajectories and minimizing energy use without compromising performance can lead to cost savings and reduced environmental impact. By refining motion paths and minimizing energy wastage, the model contributes to both operational cost reductions and sustainability goals. In an era of increasing pressure to reduce carbon footprints, the energy-efficient solutions proposed by this model can play a critical role in meeting sustainability targets while maintaining competitiveness in the global market.

Moreover, the ability to optimize execution time and trajectory smoothness is crucial for improving the overall efficiency of industrial robots. In manufacturing environments, time is often a critical factor, and even minor improvements in execution time can result in substantial increases in throughput. The SCO's ability to reduce delays and optimize motion paths enables robots to perform tasks faster and with greater precision. This enhancement is particularly valuable in high-throughput environments such as assembly lines or packaging operations, where minimizing cycle times directly translates into higher production volumes and increased revenue. The smoothness of motion also contributes to better wear and tear management, leading to less frequent maintenance and fewer mechanical issues over time.

The proposed model also has the potential to transform how industrial robots interact with other systems into an innovative manufacturing environment. The integration of IoT-enabled devices and sensors with the hybrid predictive maintenance model allows robots to continuously monitor their operational conditions and communicate with other machines in the network. This connection facilitates more informed decision-making across the entire manufacturing system, enabling real-time adjustments based on sensor data. For example, if one robot detects a malfunction or performance degradation, it can alert other robots or central control systems to adjust operations accordingly, minimizing disruption and ensuring smoother workflows. The seamless exchange and communication of data between machines in an Industry 4.0 framework helps optimize resource utilization, reduce bottlenecks, and enhance overall system efficiency.

In terms of operational flexibility, the hybrid model enhances robots' adaptability in dynamic production environments. As industrial processes become more complex and customized, the ability of robots to adapt their behavior and operations to changing production requirements becomes increasingly important. The At-GRU, with its attention mechanism and temporal feature extraction capabilities, enables robots to better adapt to fluctuations in task complexity, machine wear, or environmental conditions. This adaptability makes the system more resilient and better able to handle unexpected changes without compromising performance. In industries where demand variability and product customization are high, this increased flexibility can significantly enhance customer satisfaction by enabling companies to deliver products more quickly and to be more accurately tailored to their needs.

Another practical impact is the model's potential to improve safety in industrial environments. Robots equipped with predictive maintenance capabilities can detect early signs of malfunction that may pose safety risks to human workers. By identifying and

addressing potential failures before they escalate, the model helps ensure a safer working environment. In industries where robots work alongside humans, such as collaborative robots (cobots) in manufacturing and healthcare, minimizing risks from equipment failure is essential to preventing accidents and ensuring worker safety. The combination of predictive maintenance and motion optimization can, therefore, play a crucial role in reducing safety hazards associated with robotic operations.

Furthermore, the hybrid model contributes to the overall digital transformation of industrial operations. By incorporating advanced AI techniques, such as deep learning and optimization algorithms, industries can move beyond traditional automation systems toward more intelligent, data-driven decision-making. This shift not only enhances productivity but also enables companies to gather and analyze vast amounts of operational data, which can be used to further optimize performance. Over time, insights from these systems can drive continuous improvements in manufacturing processes, product quality, and overall business operations. As more companies adopt digitalization and automation, the ability to integrate AI-driven solutions, such as the one proposed in this research, will be crucial for maintaining competitiveness in the rapidly evolving Industry 4.0 landscape.

Lastly, the model's application in robotics can extend beyond manufacturing, opening opportunities in other industries such as logistics, healthcare, and energy. For instance, in logistics, robotic systems used for warehousing or distribution can benefit from the hybrid model's predictive maintenance and optimization features, enhancing operational efficiency and reducing downtime. Similarly, in healthcare, robotic systems used in surgeries or patient care could rely on such predictive systems to ensure continuous, reliable operation, minimizing the risk of system failures that could jeopardize patient safety. The model's versatility across different sectors highlights its potential to drive widespread improvements in automation and decision-making across various industries.

In conclusion, the practical implications of the proposed hybrid model in industrial automation are far-reaching, with significant effects on cost savings, energy efficiency, safety, flexibility, and the overall performance of robotic systems. By improving predictive maintenance, optimizing energy use, and enhancing robots' adaptability to dynamic environments, this research offers valuable contributions that can directly benefit industries by reducing costs, improving safety, and increasing productivity. The integration of this model into real-world industrial operations can help businesses meet Industry 4.0 demands and accelerate the adoption of intelligent, autonomous systems.

4.2. Future Research Scopes

The proposed hybrid model, which combines Attention-Gated Recurrent Units (At-GRU) and Sand Cat Optimization (SCO), represents a significant advancement in predictive maintenance and optimization for industrial robotics. However, several avenues for future research remain unexplored, offering substantial opportunities to expand the model's capabilities and enhance its practical application across various domains. Future research could explore the following directions.

One significant avenue for future research is the model's scalability in large-scale industrial environments. While this study demonstrates the model's effectiveness on benchmark datasets, real-world industrial settings typically involve more complex data sources, such as large-scale sensor networks with varying data quality. Investigating how the hybrid At-GRU and SCO model can handle vast amounts of unstructured data, perform real-time processing under high throughput conditions, and maintain its predictive accuracy across diverse systems is crucial. Future research could involve testing the model on industrial-scale datasets, developing methods to handle incomplete or noisy data, and optimizing computational efficiency for large-scale deployment. By addressing these

challenges, the model can be scaled to meet the demands of modern industrial environments that generate massive volumes of real-time sensor data.

Another promising area for future research is the integration of multi-agent systems within the framework. The current model focuses on optimizing individual robotic systems, but many industrial applications rely on teams of robots working collaboratively. Future research could explore how the hybrid model can be extended to multi-agent environments, where robots must not only optimize their own performance but also coordinate with other agents to achieve shared goals. Such an extension requires addressing challenges such as decentralized decision-making, communication protocols, task allocation, and synchronization in dynamic environments. By developing algorithms that enable efficient multi-agent coordination, the model can be made suitable for a broader range of industrial applications, including automated warehouses, assembly lines, and autonomous fleets. Multi-agent systems would enable a more flexible, scalable approach, allowing multiple robots to work together autonomously and improving efficiency and task completion times.

The explainability of AI models is another critical area that demands attention in future research. While deep learning models like At-GRU are highly effective, their black-box nature limits their acceptance in critical industrial applications where transparency is essential for safety and regulatory compliance. Incorporating Explainable AI (XAI) techniques into the hybrid model would not only increase user trust but also facilitate its adoption in industries where decision accountability is required. Future work could focus on developing interpretable models or hybrid approaches that combine deep learning's performance with transparent decision-making processes. Incorporating Explainable AI techniques may involve methods such as attention-based visualizations, rule extraction, or surrogate modeling to provide insight into the model's decision-making process. The ability to explain the decision-making process is especially crucial for applications in fields such as healthcare and aerospace, where the stakes are high and regulatory oversight is rigorous.

As cybersecurity concerns become increasingly crucial in connected industrial systems, data security and privacy should be a key focus of future research. The IoT integration within the proposed model makes it susceptible to data breaches, cyberattacks, and unauthorized access to sensitive operational data. Future research could explore how the model can incorporate robust cybersecurity measures, such as encryption techniques, federated learning, or differential privacy, to protect data in transit and ensure the integrity of predictive maintenance decisions. In highly sensitive industries, such as defense, healthcare, or energy, the inclusion of these security features is essential to ensure that predictive maintenance systems do not become a vector for cyber threats. Addressing these concerns will enhance the model's robustness and reliability, particularly in mission-critical applications.

Future work could also explore the environmental and sustainability impacts of robotic systems in industrial settings. While the SCO algorithm already optimizes energy efficiency, the broader environmental impact of industrial automation systems remains an important consideration. Research could investigate how the proposed model can contribute to sustainable manufacturing by reducing energy consumption, minimizing waste, and optimizing resource utilization. Additionally, integrating sustainability metrics, such as carbon footprint analysis, into the predictive maintenance framework could help industries meet their environmental goals while maintaining operational efficiency. This aligns with growing global efforts to reduce carbon emissions and improve the sustainability of industrial operations. As industries move toward more environmentally conscious practices, embedding sustainability within automation systems will be an increasingly important research goal.

The model's adaptability to dynamic and unpredictable industrial environments is another critical area for future research. Industrial robots often operate in environments subject to variations in temperature, humidity, equipment wear, and fluctuating production demands. These factors can influence the performance of predictive maintenance models. Future research could explore how the At-GRU and SCO models can be enhanced to maintain their effectiveness under such dynamic conditions. This could involve developing models that can adapt to changing input data over time, ensuring that predictive maintenance tasks remain accurate even when the system undergoes operational shifts. Improving the model's ability to adapt in real time would make it more robust in environments where conditions are constantly changing.

Another critical area for future investigation is the integration of reinforcement learning (RL) to further improve decision-making in robotic systems. While the hybrid At-GRU and SCO model addresses fault detection and motion optimization, incorporating RL could further enhance the model's ability to make continuous, real-time adjustments in response to evolving environmental factors and operational conditions. By allowing robots to learn optimal policies through interactions with their environment, RL could further improve decision-making in complex, unpredictable industrial scenarios. This approach would enable the system to self-optimize over time, ensuring that robots continuously adapt to new tasks and environmental conditions without requiring manual reprogramming. Integrating RL with the hybrid model could enable robots to learn from past experiences, improving their decision-making capabilities as they encounter new challenges in the industrial environment.

Furthermore, the cross-domain applications of the hybrid model present exciting prospects for future research. Although the current study focuses on industrial robots in manufacturing environments, the methodology could be extended to other domains such as healthcare robotics, logistics, and energy systems. For instance, in healthcare, robots used in surgical procedures or patient care could benefit from predictive maintenance models that ensure continuous, reliable operation. In logistics, autonomous vehicles and drones can utilize similar models to predict and prevent failures before they impact service delivery. Exploring how the proposed hybrid model can be adapted to different industry requirements, operating conditions, and machine types will provide further insights into its versatility and potential for broader application. Expanding the model's scope to other industries could unlock its potential in sectors that require highly reliable and efficient robotic systems.

Lastly, integrating hybrid models with advanced sensor technologies and digital twin frameworks could provide a deeper understanding of the robot's health and performance. Digital twin virtual representations of physical systems can be used in conjunction with the At-GRU and SCO models to simulate real-time operational data and test predictive maintenance strategies under various scenarios. This would enable a more detailed and comprehensive approach to fault prediction, trajectory optimization, and system reliability. The combination of digital twins with predictive maintenance systems could lead to more proactive maintenance strategies, improving the efficiency and lifespan of robotic systems.

In conclusion, the future research directions for the hybrid At-GRU and SCO model are diverse and multifaceted, spanning from scalability in real-world environments to the integration of multi-agent systems, explainable AI, and sustainability measures. By addressing these gaps, the model can be further refined to meet the growing demands of Industry 4.0 and beyond, ensuring its relevance and applicability across a wide range of industrial and commercial sectors. As these research directions are explored, the hybrid model will become a more comprehensive and adaptable solution, capable of transforming industrial robotics and predictive maintenance across multiple domains.

5. Conclusions

The proposed hybrid model, incorporating At-GRU and SCO, demonstrates significant potential to enhance intelligent automation in Industry 4.0 environments. At-GRU effectively identifies operational anomalies and predicts system health by utilizing multi-variate sensor signals, outperforming conventional LSTM and GRU models. Meanwhile, the SCO improves robotic motion by optimizing execution time, trajectory smoothness, and energy efficiency. The combined system enables predictive maintenance while simultaneously refining the robot's behavior. The experimental findings demonstrate that this hybrid approach minimizes equipment failures, enhances overall performance compared to prevailing methods, and facilitates adaptive decision-making. Moreover, the results indicate that the DL model, enriched with an attention mechanism and paired with an optimization strategy, forms a strong foundation for autonomous robotic operations in smart manufacturing equipment. Future work focuses on expanding the proposed work to multi-agent robotic systems. Also, incorporating explainable AI models will help foster transparency and trust in industrial applications.

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