

Article

Time–Frequency EPFCN for Fault Warning and Diagnosis of Multi-Phase Interleaved Converters in DC Microgrids

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Abstract

DC microgrids are important platforms for renewable energy integration, energy storage interaction, and bidirectional power exchange. In these systems, multi-phase interleaved parallel DC-DC converters are widely used as key energy-router interfaces, but open-circuit faults in power devices may lead to current imbalance, waveform distortion, ripple redistribution, and system instability. To improve fault warning and diagnosis under variable operating conditions, this paper proposes a time–frequency dual-branch efficient fully convolutional network (EPFCN). The proposed model takes synchronized multi-channel voltage/current signals and their FFT-domain representations as complementary inputs. The time-domain branch extracts transient waveform features, while the FFT-domain branch captures spectral variation and harmonic-related information. An efficient channel attention (ECA) module is introduced to enhance fault-sensitive channel responses while maintaining a lightweight structure. An RT-LAB hardware-in-the-loop platform is established to construct a multi-condition diagnostic dataset covering one normal state and nine fault states. Experimental results show that the proposed EPFCN achieves high diagnostic accuracy, strong noise robustness, clear feature separability, and feasible edge-side inference performance. The proposed method provides an effective data-driven solution for online fault warning and diagnosis of multi-phase interleaved converters in DC microgrids.

Keywords: DC microgrid; multi-phase converter; fault warning and diagnosis; time–frequency feature fusion; efficient fully convolutional network



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1. Introduction

With the continuous advancement of global energy transition, the large-scale integration of distributed photovoltaic systems, energy storage systems and electric vehicles has made DC microgrids an essential form for local consumption of renewable energy and flexible interconnection of multi-energy sources in the new power system [1,2]. Compared with AC microgrids, DC microgrids eliminate the procedures of phase synchronization and reactive power compensation, and possess advantages in power supply efficiency and power quality regulation, serving as an optimal scheme for the nearby utilization of distributed energy resources [3,4]. To satisfy the demand for large-capacity and high-reliability power transmission of DC microgrids, multi-phase interleaved parallel bidirectional DC-DC converters have become the core topology of energy routers by virtue of the current sharing effect and low-frequency ripple suppression capability brought by carrier phase-shift modulation. They are mainly responsible for bidirectional energy interaction of DC power grids, step-up collection of photovoltaic energy, and charge–discharge management

of electric vehicles [5,6]. Power devices in converters such as IGBTs, power diodes and filter inductors operate under harsh working conditions of high-frequency switching and frequent load fluctuation for a long term, resulting in a high occurrence rate of open-circuit faults [7,8]. The initial characteristics of such faults are highly latent. Without timely early warning and localization, these faults will trigger bus voltage distortion and abnormal circulating current, and even lead to system shutdown in severe cases, which directly threatens the safe and stable operation of DC microgrids [9,10]. Therefore, research on accurate, rapid and engineering-applicable fault warning and diagnosis for multi-phase interleaved parallel converters is a key technical support to guarantee the reliable operation of DC microgrids and improve the flexibility of energy dispatching and comprehensive utilization efficiency [11,12].

Fault diagnosis technology for power converters in DC microgrids has been developing continuously around signal feature analysis and intelligent identification. Early diagnosis methods are dominated by signal analysis, which realizes fault judgment by observing time-domain waveforms and extracting voltage and current statistical characteristics. Such methods are easy to implement but susceptible to load fluctuation and photovoltaic output variation, with low fault recognition accuracy [13,14]. Subsequent studies have introduced frequency-domain and time–frequency analysis methods including FFT, wavelet transform and variational mode decomposition into the diagnosis process. These methods can better process non-stationary fault signals and extract harmonic and time–frequency distribution features, yet they still rely on manual parameter setting and empirical feature extraction. When handling high-dimensional and strongly coupled fault waveform data, the feature extraction efficiency fails to meet practical requirements [15,16]. The application of machine learning has provided a new direction for fault diagnosis. Shallow algorithms such as SVM, KNN and Random Forest complete fault classification based on artificial features, which deliver certain performance in small-sample scenarios but cannot mine the deep correlation of fault signals, leaving limited generalization capability of the model [17,18]. The popularization of deep learning has pushed fault diagnosis into the end-to-end era. Models such as CNN, LSTM and FCN can independently complete feature extraction and classification without relying on manual feature design. However, most existing models only adopt single time-domain or frequency-domain signals as input and fail to fully utilize the time–frequency coupling characteristics of fault signals. Under complex working conditions with photovoltaic output fluctuation and frequent load switching, the problem of insufficient robustness remains prominent [19,20].

The carrier phase-shift modulation adopted by multi-phase interleaved parallel converters will further conceal the system ripple variation and harmonic distortion caused by faults, putting forward more stringent requirements for fault diagnosis methods, and the existing research still cannot fully meet the practical engineering needs. The operating conditions of energy routers are strongly random; photovoltaic output and electric vehicle charge–discharge power change all the time, and the system operating state undergoes continuous dynamic adjustment. Traditional diagnosis models and general deep learning architectures have difficulty adaptively matching the variable operating conditions, and the extraction and identification of fault features are highly vulnerable to operating condition disturbances [21,22]. Fault signals contain dual characteristics of time-domain transient distortion and frequency-domain harmonic variation simultaneously. Relying only on single-dimensional information cannot fully depict the essence of faults, and existing models struggle to collaboratively utilize time–frequency information, which restricts the improvement of fault classification accuracy. In addition, fault diagnosis of DC microgrids needs to rely on edge computing nodes to complete online inference. Existing deep learning models generally have large parameter quantities and high computational costs, as well

as high requirements for sampling frequency and hardware platforms, making real-time deployment impossible on low-cost embedded devices. There is an obvious gap between algorithm research and field engineering application, which cannot support the practical operation and maintenance of DC microgrids.

Based on the above research gaps, the aim of this study is to develop and validate an accurate, robust, and edge-deployable fault warning and diagnosis method for multi-phase interleaved parallel converters in DC microgrids. Specifically, this study aims to: (1) analyze the time-domain distortion and frequency-domain harmonic variation characteristics of typical open-circuit faults in the selected converter topology; (2) construct a dual-domain diagnostic dataset based on synchronized multi-channel electrical signals and FFT-domain representations; (3) design an EPFCN model that combines branch-separated time–frequency feature extraction with ECA-based channel response enhancement; and (4) verify the diagnostic accuracy, noise robustness, feature separability, and edge-side inference capability of the proposed method through RT-LAB hardware-in-the-loop experiments and comparative model evaluation. In this study, “early warning” refers to the rapid identification of observable fault-related changes in voltage and current signals at the early fault stage, enabling a warning to be issued before the fault develops into a severe system-level failure.

The remainder of this paper is organized as follows. Section 2 presents the materials and methods, including the converter topology, fault characteristics, dataset construction, signal preprocessing, EPFCN architecture, and training strategy. Section 3 reports and discusses the diagnostic performance, robustness, feature visualization, edge deployment results, and practical limitations. Section 4 concludes the paper and outlines future work.

2. Materials and Methods

2.1. Converter Topology and Fault Characteristic Analysis

Multi-phase interleaved parallel DC-DC converters are adopted in this study as the main research object for fault characteristic analysis and diagnostic verification. This topology is widely used in high-power DC microgrids and energy-router interfaces because multiple parallel branches can share the current stress, while carrier phase-shift modulation reduces the equivalent output ripple and improves modular power conversion capability under variable operating conditions. In the DC microgrid considered in this paper, this structure is used for photovoltaic access, energy storage interaction, and bidirectional power exchange. When an open-circuit fault occurs in one phase or one switching device, the original current-sharing relationship among interleaved branches is disturbed, leading to branch-current imbalance, transient waveform distortion, ripple redistribution, and frequency-domain harmonic variation. These characteristics provide representative multi-channel voltage/current responses for the proposed time–frequency EPFCN-based fault diagnosis framework.

Figure 1 illustrates the integrated application scheme of the DC microgrid system proposed in this paper. The system is structurally equipped with three ports. Port 1 serves as the DC grid port for bidirectional energy transmission. Port 2 is configured as the photovoltaic port, which integrates renewable energy into the DC microgrid. Port 3 acts as a bidirectional power supply port, capable of providing power supply and feeding excess energy back into the DC microgrid system in reverse.

This DC microgrid system enables the reliable integration of distributed photovoltaic renewable energy, energy interaction with the main DC grid, and charge–discharge management of electric vehicles (EVs), effectively improving the energy scheduling flexibility and comprehensive utilization efficiency of the microgrid system.

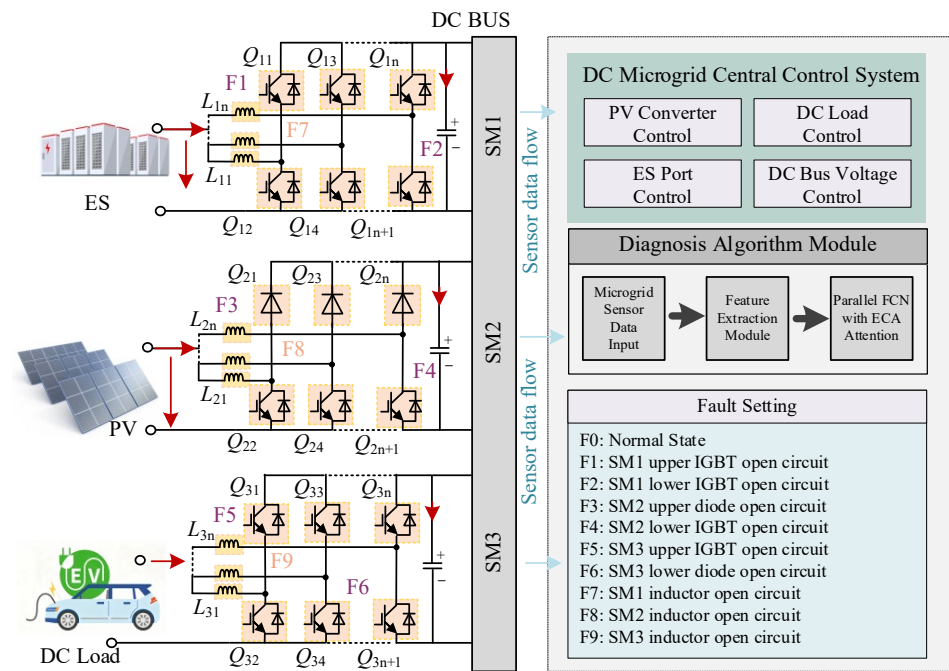


Figure 1. Structure of the DC microgrid system and fault categories.

In this system, the DC grid interface submodule (SM1) adopts a multi-phase interleaved parallel bidirectional DC-DC converter architecture. It consists of filter inductors (L_{11} – L_{1n}), upper-leg IGBTs (Q_{11} – Q_{1n}) and lower-leg IGBTs (Q_{12} – Q_{1n+1}), and is used to realize bidirectional energy transmission between the microgrid and the external main DC grid.

The PV interface submodule (SM2) adopts a multi-phase interleaved parallel unidirectional Boost DC-DC circuit architecture, composed of input inductors (L_{21} – L_{2n}), upper-leg diodes (Q_{21} – Q_{2n}) and lower-leg IGBTs (Q_{22} – Q_{2n+1}), which realizes the unidirectional step-up convergence of photovoltaic energy.

The hardware topology of the electric vehicle interface submodule (SM3) is identical to that of SM1. It also adopts a multi-phase interleaved parallel bidirectional DC-DC converter, including inductors L_{31} – L_{3n} , upper-leg IGBTs Q_{31} – Q_{3n} and lower-leg IGBTs Q_{32} – Q_{3n+1} , to support bidirectional energy management for EV charging and discharging. To simplify the subsequent system-level fault characteristic analysis, this paper selects a typical interleaved parallel structure as a single research object for in-depth deduction and diagnostic verification.

The converters investigated in this study operate under a voltage–current double closed-loop PI control strategy, as shown in Figure 2. The voltage outer loop regulates the DC bus/output voltage and generates the current reference, while the current inner loop regulates the branch current and produces the modulation signal for the interleaved switching devices. The carrier phase-shift modulation is then used to generate the gate signals for different phases, enabling current sharing among parallel branches under normal operating conditions.

The closed-loop controller affects the observed fault signatures after an open-circuit fault occurs. The voltage loop tends to suppress sustained voltage deviation, while the current loop and the remaining healthy branches compensate for the power imbalance. As a result, the fault information is reflected not only in voltage variation, but also in branch-current imbalance, transient waveform distortion, ripple redistribution, and frequency-domain harmonic changes.

This paper investigates the fault diagnosis of devices in energy routers. Considering that the probability of simultaneous faults in multiple devices is extremely low, only single-circuit device faults are taken into account.

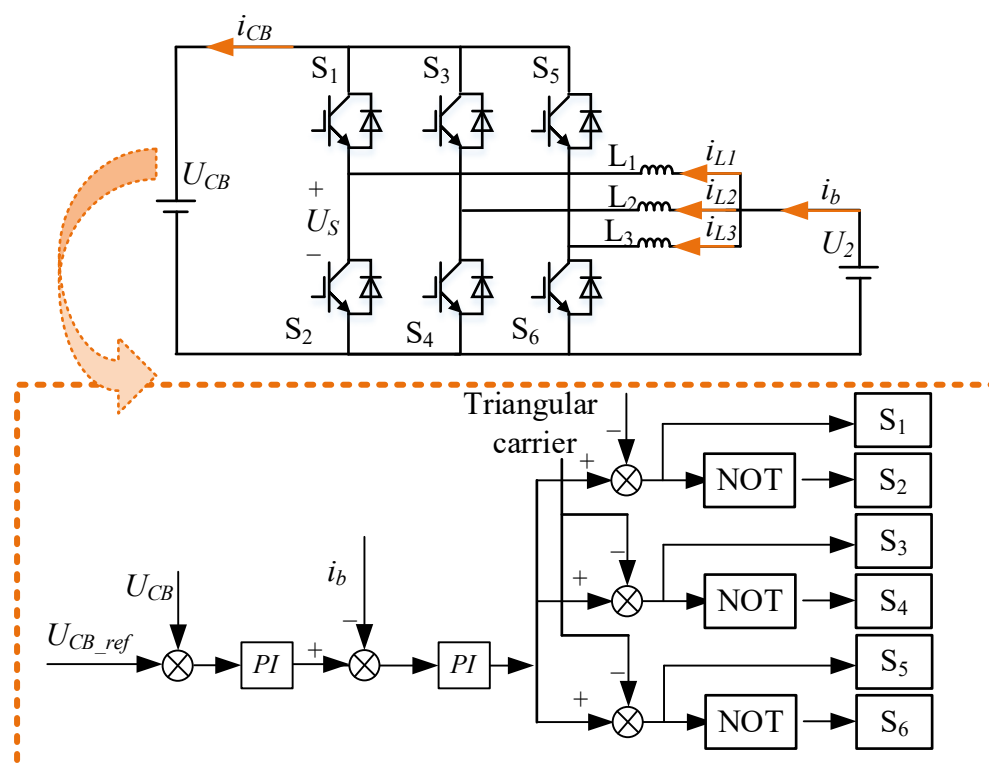


Figure 2. Voltage-current double closed-loop PI control strategy of the interleaved converter.

In view of the failure modes and topological locations of different devices in the system, ten operational mode labels covering the steady state (F0) and nine abnormal states are defined in this study. Regarding the measuring point deployment strategy, comprehensively considering full-dimensional state perception and hardware deployment cost, the system finally acquires six channels of electrical signals, including the DC bus capacitor voltage, the voltage and current of the energy storage port (ES) and DC grid port, as well as the terminal voltage of the photovoltaic (PV) access side.

To meet the demand for large-capacity power transmission, the main circuit of the system generally adopts a multi-phase interleaved parallel architecture, with a carrier phase-shift modulation strategy adopted to share the current stress of each bridge arm. This control architecture can effectively cancel the low-frequency ripple of the bus current and multiply its characteristic frequency according to the number of parallel circuit branches, which greatly reduces the volume and design margin of passive filter components.

Under the ideal fault-free steady-state operating condition, for an interleaved DC-DC converter with n parallel branches, the analytical model of the inductor current for any single phase can be derived as follows.

$$i_{L_k}(t) = I_{dc} + \sum_{m=1}^{\infty} \frac{V_{in} T_s}{L(1-D)(\pi m)^2} \sin(m\pi D) \cos(m\omega_s t - \theta_k) \quad (1)$$

In the formula, I_{dc} represents the DC bias component of single-phase current; V_{in} denotes the DC bus input voltage; T_s and ω_s correspond to the switching period and its angular frequency respectively; L is the matched filter inductance of each branch; D refers to the steady-state duty cycle of power switches; m stands for the harmonic order after

Fourier series expansion. θ_k is defined as the carrier phase-shift angle between each branch, satisfying $\theta_k = 2\pi k/n$.

Based on Kirchhoff's Current Law, the total system current is the sum of the currents of all normal branches. When an open-circuit fault occurs in a specific branch of the topology, the remaining total current of the system becomes

$$I_{sum}^F(t) = \sum_{\substack{k=0 \\ k \neq q}}^{n-1} i_{L_k}(t) \quad (2)$$

If the above time-domain features are mapped to the frequency domain for observation, the spectral response of the total current under the open-circuit fault state can be expressed as

$$I_{sum}^F(m) = I_h^{(1)}(m) \left| \sum_{k=0}^{n-1} e^{-jm\theta_k} - e^{-jm\theta_q} \right| \quad (3)$$

where I denotes the intrinsic amplitude of a single-phase branch at the m -th harmonic.

Further analysis of fault characteristics shows that the loss of one phase alters the original ripple state of the system, resulting in an increase in low-frequency harmonic energy. The amplitude distortion magnification ratio h_{ratio} of the dominant low-frequency harmonic ($m = 1$) in the faulty state relative to the equivalent switching frequency harmonic ($m = n$) in the normal state can be derived as

$$h_{ratio} = \frac{|I_{sum}^F(1)|}{|I_{sum}^F(n)|} = n \left| \frac{\sin(\pi D)}{\sin(n\pi D)} \right| \quad (4)$$

Herein, $\delta = 1$ when $k = q$, indicating an open-circuit fault occurs in the corresponding branch, while δ remains 0 under normal operating conditions of other branches. This unified expression not only covers two operating conditions of normal multi-phase interleaved operation and single-phase open-circuit fault, but also establishes a direct physical correlation between the time-domain current waveform and frequency-domain characteristics. Specifically, each cosine term in the formula corresponds to a harmonic component at a specific frequency, and their linear superposition directly forms the actually observed time-domain ripple of total current. From the frequency-domain perspective, the combination of amplitude magnitude and phase offset of each harmonic fundamentally determines the spectral distribution distortion law of the system under normal and faulty operating states.

The time-domain waveform is susceptible to load fluctuations. In practical operation, to achieve accurate fault warning and diagnosis, it is necessary to define clear criteria for distinguishing fault characteristics from normal operating modes. Fault waveforms share similarities with those under normal operating conditions in terms of time-domain features. Reliance solely on time-domain characteristics will lead to low classification accuracy for certain fault waveforms. The introduction of FFT enables the extraction of frequency-domain features to assist time-domain analysis.

Taking Measurement Point 1 as an example, Figure 3 presents the frequency-domain waveforms of two typical signals. There are distinct differences in spectral characteristics before and after the fault under steady-state operating conditions. The proportion of low-frequency components increases when a fault occurs. In fault classification, time-domain analysis alone yields limited performance. The combination of frequency-domain information and time-domain features can effectively improve the distinguishability of different fault patterns.

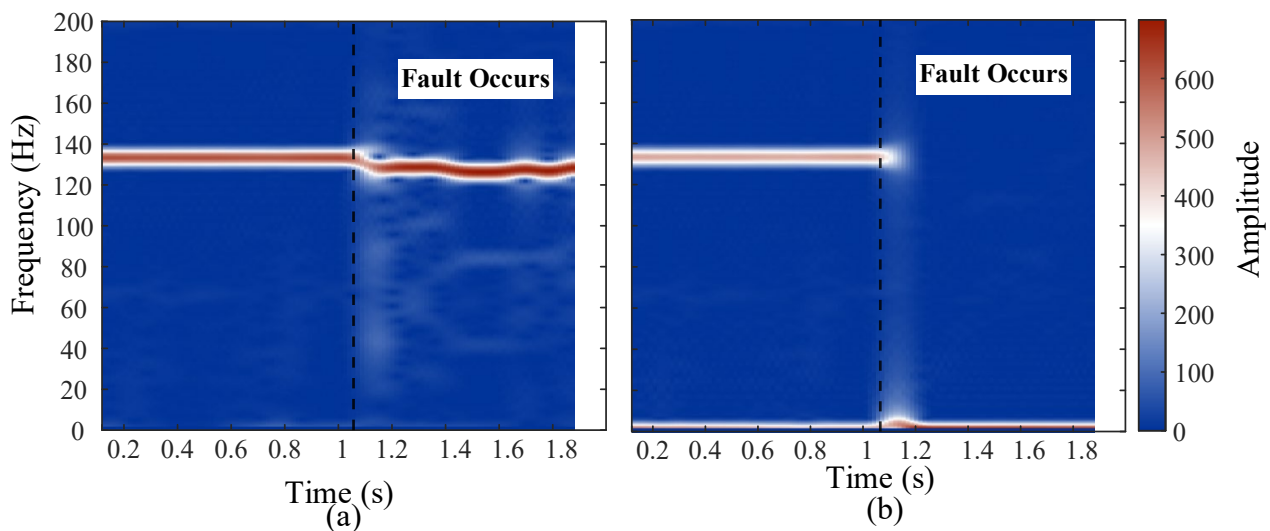


Figure 3. Fault frequency domain diagram. (a) Waveforms before and after Fault 3 at Measuring Point 1. (b) Waveforms before and after Fault 7 at Measuring Point 1.

Figure 3 illustrates the two-dimensional time–frequency evolution process of the system when switching from normal steady-state operation to different fault modes (Fault 3 and Fault 7). In the figure, the horizontal axis represents time and the vertical axis denotes frequency, while the color mapping characterizes the local amplitude of frequency-domain components, with dark blue indicating low-energy background noise and dark red representing high-energy concentration. Before the fault occurrence, both sets of time–frequency maps exhibit completely consistent steady-state characteristics. The system maintains a dominant frequency band with highly concentrated energy at a center frequency of approximately 135 Hz, and the surrounding frequency bands present a pure background, which indicates stable system operation without obvious harmonic pollution. Although both cases share a similar steady-state initial state, they follow distinct two-dimensional time–frequency evolution trajectories after the fault occurs. Mapping one-dimensional time-series signals into high-dimensional time–frequency images can effectively amplify the latent features under different fault types. It also verifies that the integration of frequency-domain information can significantly expand the feature boundaries among various fault modes, providing high-quality input data for high-precision classification by subsequent deep learning networks.

2.2. HIL Platform, Dataset Construction, and Signal Preprocessing

The hardware-in-the-loop experimental platform was established based on the RT-LAB real-time simulation system. The DC microgrid model was constructed and compiled on the host computer and then downloaded to the real-time simulator for real-time operation. The built-in I/O board of the simulator was connected to the external signal acquisition and conditioning board to collect the voltage and current signals required for fault diagnosis. During the HIL test, the simulated electrical signals were synchronously acquired and transmitted to the host computer for dataset construction, model training, and edge-side inference verification.

Figure 4 presents the functional structure of the RT-LAB-based fault diagnosis platform and edge deployment architecture. The platform consists of two parts: simulation operation and data acquisition, and edge computing deployment. In the simulation and data acquisition part, the DC microgrid and converter fault model are executed on the RT-LAB real-time simulator, and the voltage/current waveforms are observed through the SCOPE interface. The generated signals are transmitted to the signal acquisition card

and the control implementation board for data collection and control verification. In the edge computing part, the acquired data are processed on the PC for model training and testing, and the trained EPFCN model is deployed on the Raspberry Pi 4B for edge-side fault diagnosis. The arrows in the figure indicate the data transmission path from RT-LAB to the acquisition module, PC, and edge computing device. To reproduce the dynamic operating conditions of a DC microgrid, the output power of the photovoltaic port and the interactive power of the EV port were randomly varied within 0–100% of the rated capacity in each simulation case. The dataset covered one normal state and nine fault states, totaling ten operating states. For each state, 700 simulation cases were conducted under different operating parameters. Therefore, 7000 complete multi-channel diagnostic samples were generated in total.

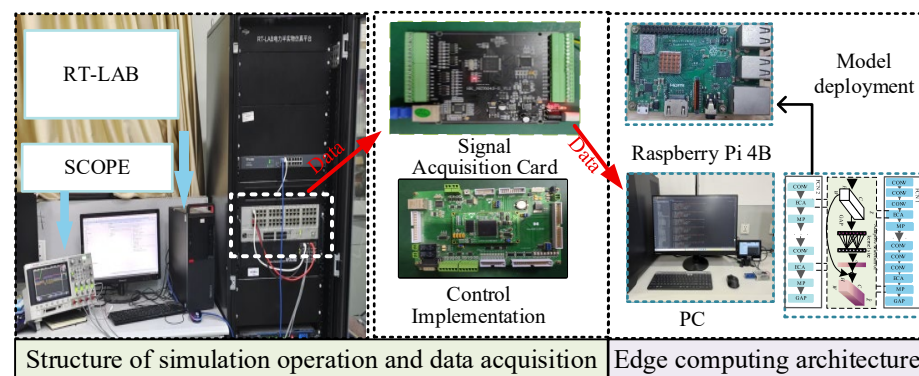


Figure 4. Functional diagram of the RT-LAB-based fault diagnosis platform and edge deployment architecture.

In each simulation case, six measurement channels were collected synchronously and combined into one multi-channel diagnostic sample. The input size of each sample was 2000×6 , where 2000 represents the number of sampling points and 6 represents the number of measurement channels. The sampling frequency was 1 kHz, so each diagnostic sample corresponded to an approximately 2 s signal window. Therefore, the dataset contained 42,000 channel-wise signal records in total, calculated as $10 \text{ states} \times 700 \text{ cases} \times 6 \text{ channels}$, while the model-level input was the complete six-channel signal matrix from the same simulation case.

After all complete multi-channel samples were constructed, the dataset was randomly divided into training, validation, and test sets at a ratio of 80%/10%/10%. The complete six-channel signal matrix from each simulation case was used as the minimum division unit, and all synchronized channels belonging to the same case were assigned to the same subset. For the frequency-domain branch, FFT was applied to each channel of the normalized time-domain signal to obtain the corresponding frequency-domain amplitude sequence. The original time-domain signal and the FFT-domain sequence were then used as the two inputs of the proposed EPFCN.

For the FFT branch, each measured channel was transformed from the time domain to the frequency domain using a 2000-point FFT. The sampling frequency was 1 kHz, and each diagnostic sample contained 2000 sampling points, corresponding to a 2 s signal window under the diagnostic data sampling frequency of 1 kHz. Therefore, the length of one FFT window was 2 s, and the frequency resolution was $(\Delta f = f_s/N = 1000/2000 = 0.5 \text{ Hz})$. No overlapping sliding window was used, and the overlap ratio was 0%. No additional

tapering window was applied, which is equivalent to using a rectangular window. For each signal $x[n]$, the FFT was calculated as

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-j2\pi kn/N}, \quad k = 0, 1, \dots, N-1 \quad (5)$$

The magnitude spectrum was normalized by the FFT length:

$$A[k] = \left| \frac{X[k]}{N} \right| \quad (6)$$

The normalized magnitude spectrum was used as the frequency-domain input of the FFT branch.

With the diagnostic data sampling frequency of 1 kHz, the corresponding Nyquist frequency is 500 Hz. The FFT-domain input was constructed within the 0–500 Hz diagnostic band. The frequency-domain comparison of representative normal and faulty samples shows that the fault-induced variations are mainly reflected in spectral energy redistribution, ripple-envelope modulation, and low- to mid-frequency harmonic changes within this band. Therefore, the selected diagnostic sampling setting provides the frequency-domain information used by the EPFCN for fault classification.

The warning interval in the implemented diagnosis setting is determined by the diagnostic window length. Since each diagnostic sample contains 2000 sampling points and the sampling frequency is 1 kHz, one diagnostic decision corresponds to an approximately 2 s signal window from fault-related signal acquisition to diagnosis output.

2.3. Proposed EPFCN Architecture and Training Strategy

To clarify the structural difference between the proposed EPFCN and existing CNN/FCN-based diagnostic architectures, a comparison is shown in Figure 5. Single-domain CNN/FCN models usually use either time-domain waveforms or frequency-domain features as the input, which may lose complementary fault information. General time–frequency CNN/FCN models introduce both time-domain and frequency-domain information, but these features are often stacked at the input side or processed through a common feature extraction path. In contrast, the proposed EPFCN adopts two independent branches. The time-domain branch extracts transient waveform distortion and dynamic response features, while the FFT-domain branch extracts spectral variation and harmonic-related features. The two types of features are fused only after branch-specific feature extraction. In addition, ECA modules are embedded in the convolutional feature extraction process to enhance channel-sensitive fault responses. Therefore, the proposed EPFCN differs from existing CNN/FCN-based structures by combining branch-separated time–frequency feature extraction, ECA-based channel enhancement, and a lightweight Conv1D-based implementation.

The proposed EPFCN is designed as a time–frequency dual-branch diagnostic network, as shown in Figure 6. The network contains a time-domain branch and an FFT-domain branch. The time-domain branch takes the normalized raw signal as input, with an input size of 2000×6 , corresponding to 2000 sampling points and six measurement channels. This branch consists of six Conv1D layers, and the numbers of filters are set to 16, 16, 32, 32, 64, and 64, respectively. The FFT-domain branch takes the corresponding frequency-domain sequence as input, also with an input size of 2000×6 . This branch consists of three Conv1D layers, with the numbers of filters set to 16, 32, and 64, respectively.

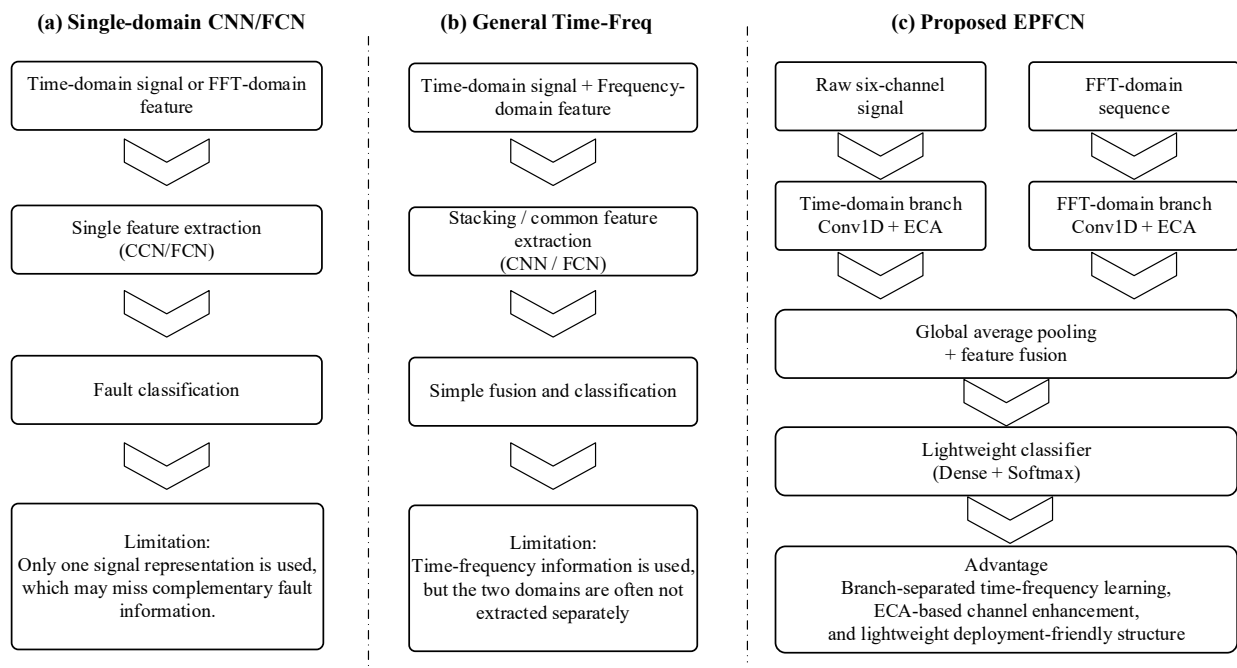


Figure 5. Schematic comparison of single-domain CNN/FCN, general time–frequency CNN/FCN, and the proposed EPFCN.

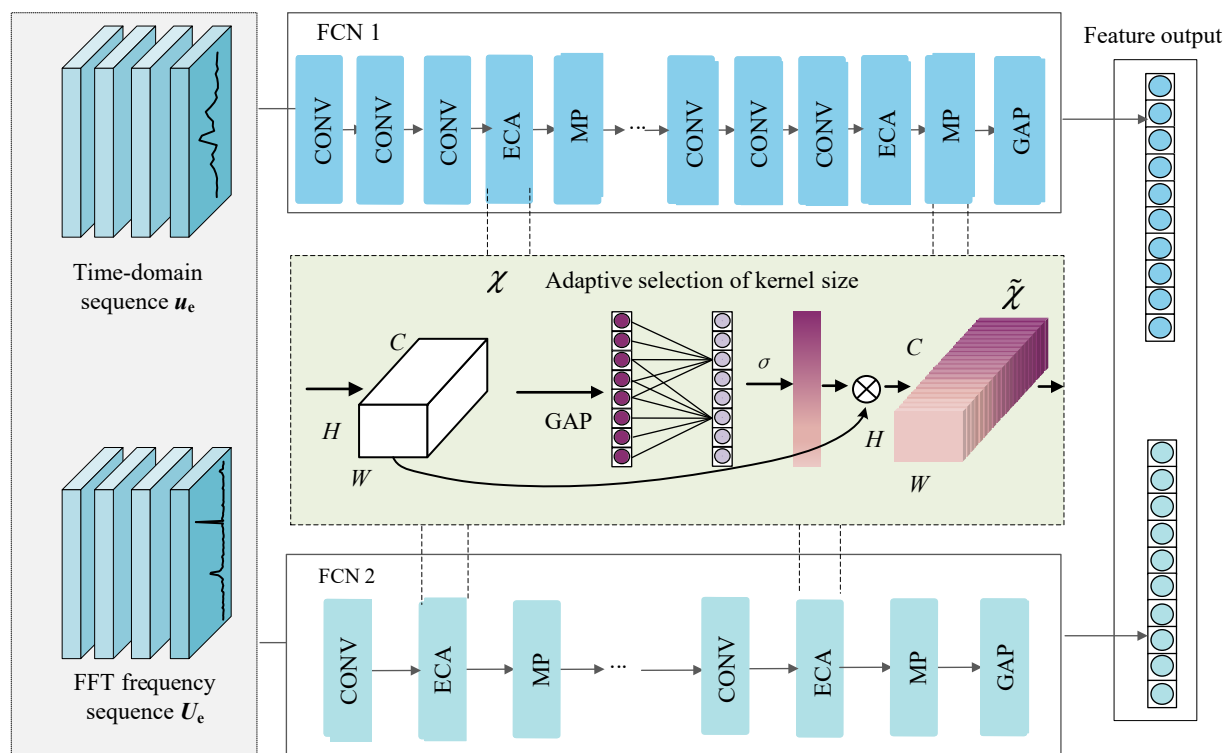


Figure 6. Proposed network architecture.

For all Conv1D layers in the proposed EPFCN, the convolution kernel size is set to 3, the stride is set to 1, and the padding mode is set to valid. The ReLU function is used as the nonlinear activation function. ECA modules are embedded in the convolutional feature extraction process to enhance fault-sensitive channel responses, and the ECA kernel size is set to 3. After branch-specific feature extraction, global average pooling is applied to compress the feature maps of both branches. The time-domain and FFT-domain features are then fused by concatenation. The fused feature vector is further processed by batch

normalization and a dense layer with 128 neurons and ReLU activation. Finally, a dense layer with 10 neurons and Softmax activation is used to output the ten-class diagnosis result.

As shown in Figure 6, the input of the dual-branch feature fusion network consists of both time-domain and frequency-domain sequences. Let x_t denote the time-domain sequence of the original sampled signal, and x_f represent its corresponding frequency-domain amplitude sequence extracted via the FFT. The constructed dual-domain input feature set can be expressed as

$$\begin{aligned} \mathbf{x}_t &= [x_t(1), x_t(2), \dots, x_t(L)]^T \\ \mathbf{x}_f &= [x_f(1), x_f(2), \dots, x_f(L/2)]^T \end{aligned} \quad (7)$$

where L denotes the data length of the sampled sequence.

During the feature extraction phase, the 1D convolutional kernel of the l -th layer performs a sliding cross-correlation operation on the output feature map of the $(l-1)$ -th layer to extract local temporal and spectral dependencies. The discrete mathematical expression for the convolutional output of the c -th channel, $y_c^{(l)}$ is given by

$$y_c^{(l)}(j) = f\left(\sum_{i=1}^K \mathbf{w}_c^{(l)}(i) * \mathbf{x}^{(l-1)}(j+i-1) + \mathbf{b}_c^{(l)}\right) \quad (8)$$

where K represents the physical size of the sliding convolutional kernel; $\mathbf{w}_c^{(l)}$ and $\mathbf{b}_c^{(l)}$ denote the trainable weight matrix and bias vector for the corresponding channel in the l -th layer, respectively; and $*$ is the convolution operator. To accelerate network convergence and effectively mitigate the vanishing gradient problem, the rectified linear unit is adopted as the nonlinear activation function $f(\cdot)$:

$$f(x) = \max(0, x) \quad (9)$$

To enhance the representation capability of critical state features, an ECA mechanism is embedded after the convolution operation. The channel descriptor generation and feature reweighting process of the ECA module is shown in Figure 7.

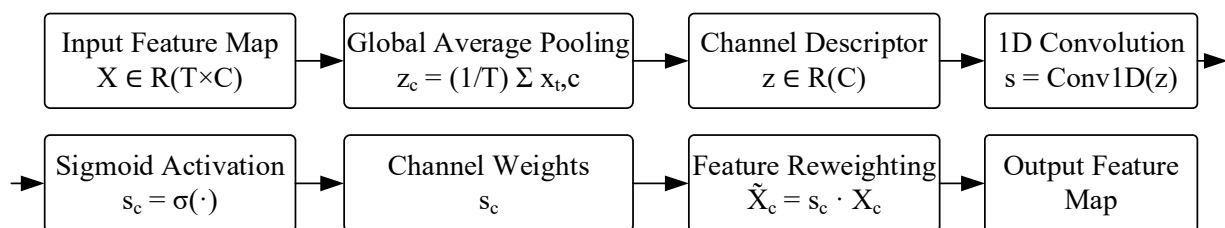


Figure 7. Channel descriptor generation and feature reweighting process.

For the output feature map of the l -th convolutional layer, it can be expressed as

$$\mathbf{F}^{(l)} = [f_1^{(l)}, f_2^{(l)}, \dots, f_{C_l}^{(l)}] \in \mathbb{R}^{T_l \times C_l} \quad (10)$$

where T_l denotes the temporal length of the feature map and C_l denotes the number of channels. Global average pooling is first applied along the temporal dimension to obtain the channel descriptor:

$$z_c^{(l)} = \frac{1}{T_l} \sum_{t=1}^{T_l} F_c^{(l)}(t), \quad c = 1, 2, \dots, C_l \quad (11)$$

The channel descriptor is written as

$$\mathbf{z}^{(l)} = [z_1^{(l)}, z_2^{(l)}, \dots, z_{C_l}^{(l)}] \in \mathbb{R}^{C_l} \quad (12)$$

The adaptive kernel selection mechanism of ECA determines the local cross-channel interaction range according to the channel number C_l . The kernel size is calculated as

$$k_l = \psi(C_l) = \left\lceil \frac{\log_2(C_l) + b}{\gamma} \right\rceil_{\text{odd}} \quad (13)$$

where γ and b are mapping parameters, and $\lceil \cdot \rceil_{\text{odd}}$ denotes the nearest odd integer operation. In this study, $\gamma = 2$ and $b = 1$ are adopted. The odd kernel size enables the 1D convolution to model a symmetric local neighborhood around each channel. The implemented odd-integer adjustment is expressed as

$$t_l = \left\lfloor \frac{\log_2(C_l) + b}{\gamma} \right\rfloor \quad (14)$$

$$k_l = \begin{cases} t_l & \text{odd} \\ t_l + 1 & \text{even} \end{cases} \quad (15)$$

In the proposed EPFCN, the main channel dimensions of the convolutional feature maps are 16, 32, and 64. According to the above adaptive rule, the corresponding ECA kernel size is $k_l = 3$. Therefore, the ECA kernel size used in this study is determined by the channel-dimension mapping rather than by an arbitrary manual setting.

After the adaptive kernel size is obtained, a one-dimensional convolution is performed on the channel descriptor to capture local cross-channel interaction:

$$s_c^{(l)} = \sum_{r=-\frac{k_l-1}{2}}^{\frac{k_l-1}{2}} q_r^{(l)} z_{c+r}^{(l)} \quad (16)$$

where $q_r^{(l)}$ denotes the trainable coefficient of the 1D convolution kernel. The channel attention weight is then generated by the Sigmoid activation function:

$$\alpha_c^{(l)} = \sigma(s_c^{(l)}) \quad (17)$$

Finally, the original feature map is recalibrated by channel-wise multiplication:

$$\hat{F}_c^{(l)}(t) = \alpha_c^{(l)} F_c^{(l)}(t) \quad (18)$$

Through this process, the ECA module adaptively selects the channel-interaction range according to the feature-channel dimension and assigns different weights to different fault-sensitive channels without dimensionality reduction. This mechanism enhances the voltage/current channels that contain stronger fault responses while maintaining the lightweight structure of the proposed EPFCN.

By extracting the peak activation values within the local receptive field, this pooling mechanism further endows the network with translation invariance to minor signal shifts.

Both sub-modules of the EPFCN conclude with a global average pooling layer. This operation calculates the global average of the output feature maps for each convolutional kernel, extracting representative features that serve as spatial feature representations in the time and frequency domains, respectively. These representations are subsequently

utilized for the ensuing fault classification task. The EPFCN architecture facilitates the comprehensive capture of distinct feature expressions of fault signals across both time and frequency dimensions. The model concatenates the output features from both channels in a fully connected layer, constructing an integrated deep learning model. This fusion enhances the overall representational capacity and improves classification performance.

Following feature fusion, the model applies batch normalization to the fused features. These normalized features are then fed into a dense layer for feature mapping. Ultimately, the Softmax activation function is employed to achieve the non-linear classification output for multi-class faults, completing the entire fault recognition task.

Based on the foregoing analysis, this paper proposes a fault warning and diagnosis method for DC microgrids based on a time–frequency dual-branch fully convolutional network. The overall procedure of the method is mainly divided into three stages: dataset construction, model training, and optimal model deployment, as illustrated in Figure 8.

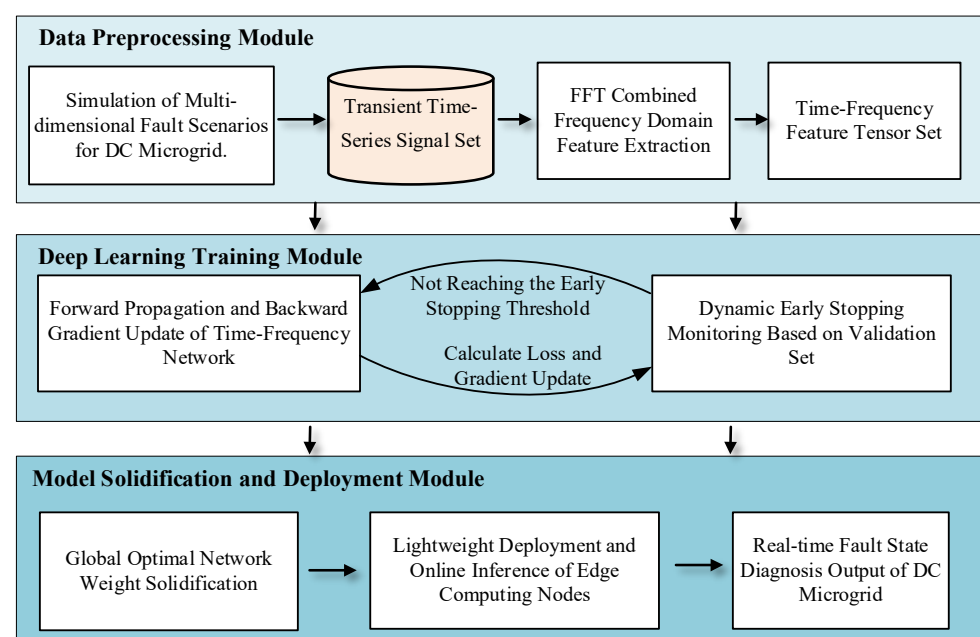


Figure 8. Flowchart of fault diagnosis and early warning for DC microgrid system.

The overall diagnostic workflow consists of three stages: data preparation, model training, and edge-side deployment. In the data preparation stage, the synchronized multi-channel signals collected from the HIL platform are normalized and transformed into time-domain and FFT-domain inputs. In the model training stage, the proposed EPFCN is trained using the constructed training and validation sets, and the optimal model is selected according to the validation performance. In the deployment stage, the trained model is used for online fault warning and diagnosis on the edge computing platform.

In the model training stage, as shown in Table 1, the Adam optimizer is adopted, with the learning rate set to 0.001 and the batch size set to 128. The loss function is categorical cross-entropy, and the maximum number of training epochs is set to 50. To reduce overfitting, early stopping is used by monitoring the validation accuracy, with the patience set to 5 epochs. In addition, ReduceLROnPlateau is used to adjust the learning rate during training. The reduction factor is set to 0.1, the patience is set to 3 epochs, and the minimum change threshold is set to 1×10^{-5} . The dataset is divided into training, validation, and test sets with a ratio of 80%/10%/10%, and the random seed is fixed at 42 to improve the reproducibility of the experimental results.

Table 1. Main configuration and computational complexity of the proposed EPFCN.

Item	Setting/Value
Time-domain input	2000 × 6
FFT-domain input	2000 × 6
Time-domain branch	Conv1D filters: 16, 16, 32, 32, 64, 64
FFT-domain branch	Conv1D filters: 16, 32, 64
Kernel size/stride/padding	3/1/valid
Activation function	ReLU
Attention module	ECA, kernel size = 3
Feature fusion	Global average pooling + concatenation
Optimizer/learning rate	Adam/0.001
Batch size	128
Train/validation/test split	80%/10%/10%
Total/trainable parameters	50,732/50,476
FLOPs/MACs	129,530,876/64,765,438
Average inference time/throughput	2.993 ms/sample/334.09 samples/s

The complete EPFCN contains 50,732 parameters, including 50,476 trainable parameters and 256 non-trainable parameters. Under float32 precision, the approximate parameter memory is 0.1935 MB. The computational complexity is 129,530,876 FLOPs, corresponding to 64,765,438 MACs. In the model complexity test, the average single-sample inference time is 2.993 ms/sample, and the corresponding throughput is 334.09 samples/s.

The last stage is optimal model deployment. The trained optimal model is lightweighted and deployed on an edge computing platform. In practical operation, the edge device can directly receive real-time sensing data of the DC microgrid for online inference, thereby realizing rapid early warning and accurate classification of system faults.

In summary, targeting the DC microgrid system shown in Figure 1, this paper proposes a time–frequency dual-stream feature fusion fault warning and diagnosis method based on an EPFCN. Compared with existing studies, the proposed strategy exhibits prominent advantages in the following three respects:

- (1) Feature extraction capability and algorithm robustness. Traditional fault identification relies heavily on manual feature engineering, and single-domain features (either time-domain or frequency-domain) tend to fail under complex operating conditions. The proposed EPFCN architecture can adaptively extract and fuse deep time–frequency dual-dimensional features of signals in an end-to-end manner, reducing the dependence on manually designed features. It effectively improves the classification accuracy and robustness of the system under nonlinear disturbances.
- (2) Hardware cost and engineering implement ability. At the data acquisition terminal, the proposed method fully utilizes the inherent basic voltage and current sensors of the underlying control system of the DC microgrid, without the need to add additional dedicated high-frequency monitoring hardware. Meanwhile, the algorithm only requires a sampling frequency of 1 kHz, and the preprocessing procedure merely involves basic FFT transformation. The characteristics of low sampling rate and low computational overhead greatly reduce the communication and computing pressure of underlying hardware, which well meets the lightweight deployment requirements of edge devices in practical industrial scenarios.
- (3) Topology generalization and system portability. Although this paper takes a specific interleaved parallel topology as the verification object, the underlying diagnosis logic based on time–frequency feature mapping is not strongly coupled with a particular circuit configuration. When applied to other types of DC hybrid energy systems or new power electronic equipment, the method can be rapidly migrated only by

flexibly adjusting the corresponding measurement point mapping and state labels, demonstrating potential portability to related converter systems.

3. Results and Discussion

3.1. Diagnostic Performance and Model Comparison

To evaluate the diagnostic performance of the proposed EPFCN, the trained model was tested on the independent test set constructed in Section 2.2. Mainstream deep learning architectures, including conventional CNN, Transformer, 1D-CNN, DNN, and LSTM, were selected as baseline models for comparative experiments. In addition, KNN, RF, and SVM were included as traditional machine-learning baselines. All models were evaluated using the same class labels and the same training, validation, and test split.

During the model training phase, all comparative networks are configured with the same early-stopping monitoring mechanism, and the maximum training epoch is uniformly set to 50. By synchronously tracking the accuracy variation curves of the training set and validation set, the fitting state and generalization capability of each model are comprehensively evaluated. Figure 9 presents the dynamic training convergence curves of all models. The results indicate that all models effectively activate the early stopping mechanism and achieve premature convergence before reaching the preset maximum training epochs.

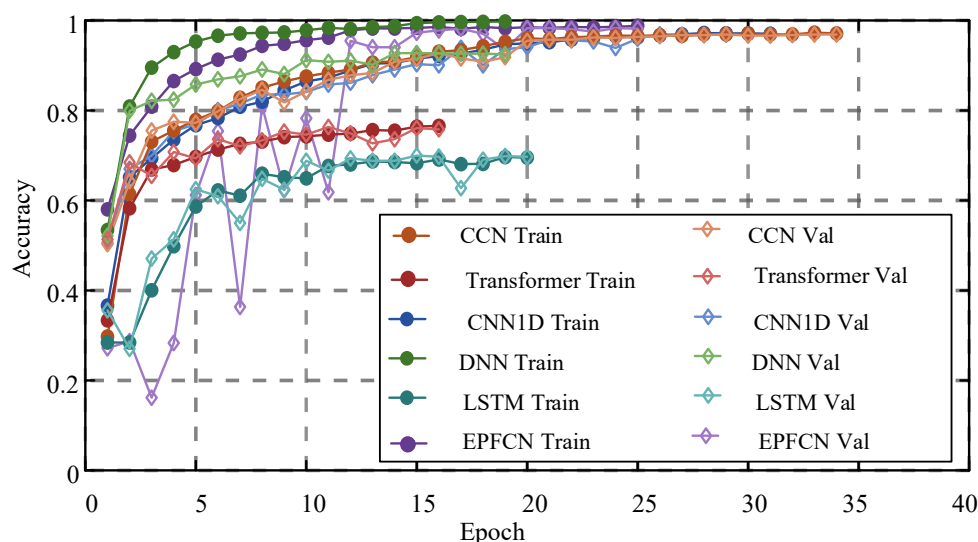


Figure 9. Training process of each model.

The analysis of the training convergence trajectories in Figure 9 reveals that although the DNN achieves a high training accuracy of 99.5%, its validation accuracy is only 92.4%, indicating a severe overfitting tendency. The Transformer converges rapidly and stabilizes within 16 epochs. However, under the current long-sequence input form and data scale, its attention-based representation does not extract the local fault-sensitive waveform and spectral features as effectively as the convolution-based models. The 2D CNN and 1D-CNN achieve comparable diagnostic performance, yet they incur relatively high time costs for network iteration and optimization. In contrast, the proposed model achieves stable convergence at the 24th epoch with a high accuracy of 98.8%. Balancing rapid convergence and high generalization accuracy, it delivers remarkably superior comprehensive diagnostic performance compared with the aforementioned baseline networks.

To quantitatively evaluate model performance more comprehensively, Table 2 summarizes the comprehensive evaluation metrics of the above deep learning models and several traditional machine learning algorithms. The comparison results show that conventional

shallow algorithms possess certain advantages in inference speed but lack representation capability when handling high-dimensional and nonlinear transient fault features of microgrids, resulting in poor overall recognition accuracy.

Table 2. Performance comparison of various models.

Model	Training Epochs	Training Accuracy	Test Accuracy
KNN	/	0.910	0.853
RF	/	1	0.932
SVM	/	0.685	0.691
1D-CNN	31	0.972	0.967
CNN	34	0.968	0.966
DNN	19	0.995	0.924
LSTM	20	0.691	0.690
Transformer	16	0.755	0.736
NO-ECA	21	0.991	0.974
RAW_only	24	0.963	0.952
FFT_only	37	0.915	0.868
EPFCN	24	0.988	0.984

Furthermore, to rigorously demonstrate the independent contribution of each core submodule in the proposed architecture, three groups of ablation experiments are reported in this paper. In the ablation settings listed in Table 2: “NO-ECA” denotes the degraded network structure with the efficient channel attention module removed; “RAW-only” and “FFT-only” represent single-branch baseline models driven exclusively by truncated time-domain features or frequency-domain features, namely utilizing only one-dimensional raw time-series data or one-dimensional FFT frequency-domain sequences individually.

Ablation experimental results indicate that the complete dual-branch model proposed in this work achieves the optimal level in terms of test set accuracy and model generalization, which supports the necessity of the time–frequency feature fusion mechanism.

Specifically, the RAW-only model (time-domain branch only) maintains relatively stable training performance but yields the lowest test accuracy, demonstrating that feature representation based solely on the time-domain dimension has an evident upper limit. By contrast, the FFT-only model (frequency-domain branch only) exhibits significant overfitting. This confirms that relying merely on high-frequency features easily traps the network into local optima, and global time-domain temporal information is indispensable for joint constraint.

In addition, although the NO-ECA variant without the attention mechanism achieves an extremely high fitting degree on the training set, its performance on the test set declines obviously. This contrast directly proves the crucial role of the ECA channel attention mechanism in suppressing invalid redundant features and improving network generalization capability. Overall, the dual-domain feature fusion structure and the ECA module complement each other, jointly endowing the model with high recognition accuracy and strong robustness.

3.2. Robustness, Feature Visualization, and Edge Deployment Results

In practical electrical engineering deployment scenarios, DC microgrid systems operate year-round under complex electromagnetic interference conditions. Signals collected by underlying sensors are inevitably contaminated by various background noises. To fully evaluate the noise immunity and robustness of the proposed model under harsh operating environments, Gaussian white noise with different signal-to-noise ratios (SNR) is artificially injected into the original test dataset for stress testing.

Figure 10 presents the diagnostic confusion matrices of the model under different noise intensities. Experimental results show that the model still maintains a high recognition accuracy of 96.0% under mild noise at 50 dB. When the background noise further increases and the SNR deteriorates to 40 dB, the diagnostic accuracy only fluctuates slightly and remains at 94.4%. Even under the extreme strong interference condition of 30 dB, the proposed model still achieves stable recognition accuracy of 89.1%, demonstrating excellent anti-interference feature extraction ability and fault-tolerant diagnostic performance.

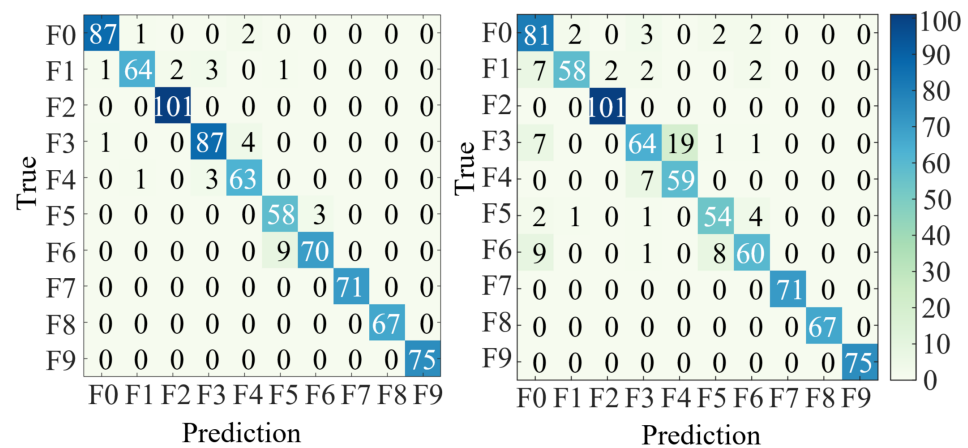


Figure 10. Noise data validation set confusion matrix.

To further verify the reliability of the algorithm, sample sets with different noise intensities are fed into each baseline model for comparative experiments. Three key evaluation indicators, namely Accuracy, Precision, and F1-score, are adopted to comprehensively assess the classification performance, prediction precision, and robustness of each model under noise interference.

The detailed experimental results are summarized in Table 3. In terms of performance trends, although all comparative models degrade to varying degrees as the signal-to-noise ratio (SNR) decreases, the proposed model maintains a leading position across all evaluation metrics. Especially under the extreme strong noise condition of 30 dB, the presented model still achieves an accuracy of 0.8915 and an F1-score of 0.8908, remarkably outperforming other network architectures and demonstrating outstanding anti-interference capability and generalization superiority.

Table 3. The performance metrics of each model on test sets with various SNR.

SNR (dB)	Model	Evaluation Index		
		Accuracy	Precision	F1-Score
50	1D-CNN	0.8307	0.8527	0.8242
	DNN	0.8475	0.8549	0.8436
	CNN	0.8734	0.8829	0.8590
	EPFCN	0.9599	0.9609	0.9600
40	1D-CNN	0.7842	0.8240	0.7747
	DNN	0.7623	0.7767	0.7568
	CNN	0.9069	0.9217	0.9064
	EPFCN	0.9444	0.9450	0.9444
30	1D-CNN	0.7325	0.8277	0.7065
	DNN	0.6925	0.7237	0.6819
	CNN	0.8010	0.8394	0.7742
	EPFCN	0.8915	0.8955	0.8908

In comparison, traditional DNN and 1D-CNN suffer from severe performance degradation under low SNR conditions, with a sharp drop in classification performance. Although CNN exhibits moderate robustness and even shows abnormal fluctuations at 40 dB noise with better results than at 50 dB—possibly because noise within specific frequency bands acts as an auxiliary data enhancement effect—it still has a noticeable gap with the proposed model in overall recognition accuracy and operational stability. The comparative results fully validate the engineering practicability and technical superiority of the proposed model in complex electromagnetic environments.

To intuitively demonstrate the hierarchical evolution of fault features and the enhancement of clustering capability of the EPFCN model, the t-SNE dimensionality reduction algorithm is introduced to visualize the feature extraction performance at different stages of the model, with the results illustrated in Figure 11.

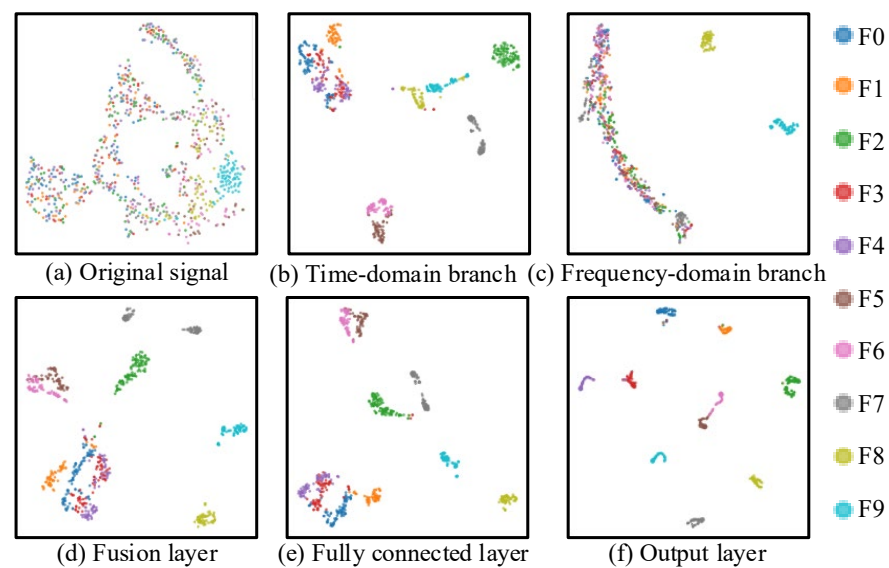


Figure 11. Visualization of feature clustering at different layers of EPFCN based on t-SNE.

At the initial data input stage, the feature distribution of raw sampled signals is highly scattered with all categories intertwined with each other. Such chaotic distribution indicates that unprocessed signals cannot provide clear classification boundaries and are incapable of precise identification directly. As the signals are fed into the dual-branch network, the feature clustering effect gradually emerges. By extracting fault attributes from different dimensions, the time-domain and frequency-domain branches enable preliminary aggregation of homogeneous features toward their cluster centers. At the feature fusion layer, deep integration of time–frequency dual-domain information further widens the distance between heterogeneous features, remarkably improving the discriminability of the feature space. Eventually, at the fully connected layer, the feature clusters of ten fault categories achieve nearly complete linear separation. This evolutionary process from disorder to order intuitively verifies that the model possesses outstanding feature mining and data classification capabilities, and successfully accomplishes the identification of complex operating states of the energy router.

Figure 12 presents the system dynamic response waveforms captured via the hardware experimental platform, covering comparative sequences under normal operating conditions and typical fault states. Channels 1, 2 and 3 correspond to the DC bus voltage, PV output voltage, and battery-side current, respectively; Channels 4, 5 and 6 monitor the DC port voltage, DC port current, and battery terminal voltage in real time in sequence.

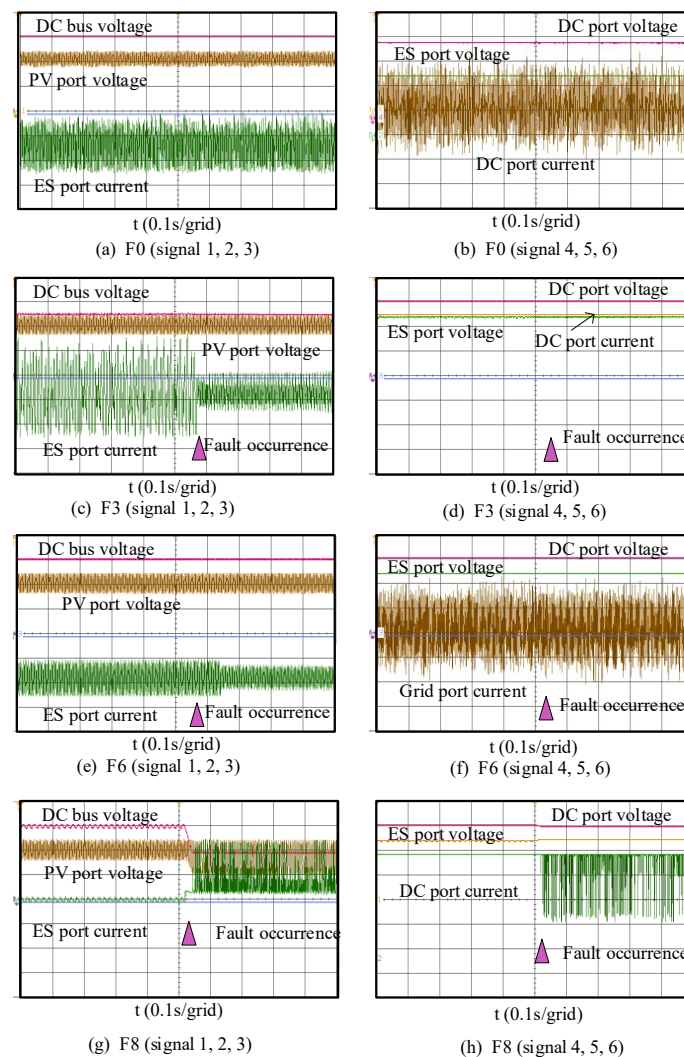


Figure 12. Fault waveform diagram of experiment.

Through synchronous resampling of the output signals from the RT-LAB simulator, the transient waveforms at the moment of fault occurrence and the subsequent dynamic process are accurately acquired. The red arrows in the figure mark the exact time when the fault is triggered. Experimental results show that under different load conditions and fault mechanisms, the electrical characteristics of each branch exhibit distinct differential response rules, which provides sufficient data support for subsequent feature extraction and operating.

To verify the real-time performance and online application capability of the model, fault data streams from the test set are injected into the edge computing platform in real time for online diagnosis.

For the test sequence containing 780 samples, the total time consumed by the platform to complete all recognition tasks is 14.608 s, yielding an average inference time of only 18.7 ms per sample, which fully satisfies the timeliness requirement for rapid fault response in power electronic systems.

During the recognition process, ten fault states are input in random sequences. Figure 13 illustrates the recognition accuracy distribution of each fault category on the edge computing platform. Experimental results show that the platform maintains an average diagnostic accuracy of 97.6% even under resource-constrained conditions. Its performance is highly consistent with the calculation results obtained on high-performance servers,

further demonstrating the efficiency and high confidence of the proposed algorithm when deployed on embedded edge devices.

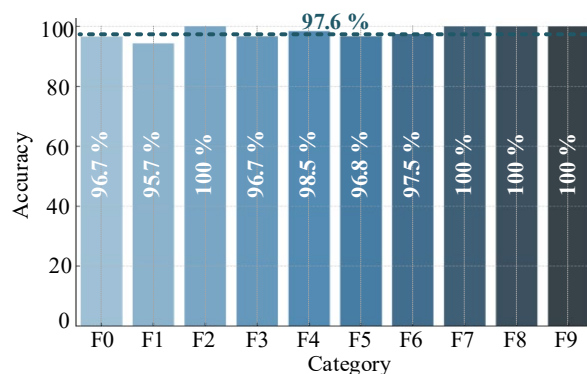


Figure 13. Diagnostic accuracy distribution of various fault categories on edge computing platform.

To further analyze the prediction reliability of different models under noise interference, this paper introduces a quantitative evaluation method based on the statistical characteristics of Softmax output distribution. This method adopts Softmax entropy to characterize the dispersion degree, i.e., uncertainty, of the model prediction probability distribution, and takes the maximum Softmax probability as the confidence indicator of model diagnosis results. By calculating the mean and standard deviation of the statistical metrics for all test samples, the prediction stability and output confidence of each diagnostic model in complex noisy environments can be objectively and quantitatively evaluated.

As shown in Figure 14, each subplot presents the statistical histograms of the model prediction entropy and confidence. The red and blue dashed lines represent the mean and standard deviation of the indicators respectively, providing an intuitive quantitative basis for evaluating the stability and consistency of diagnostic results.

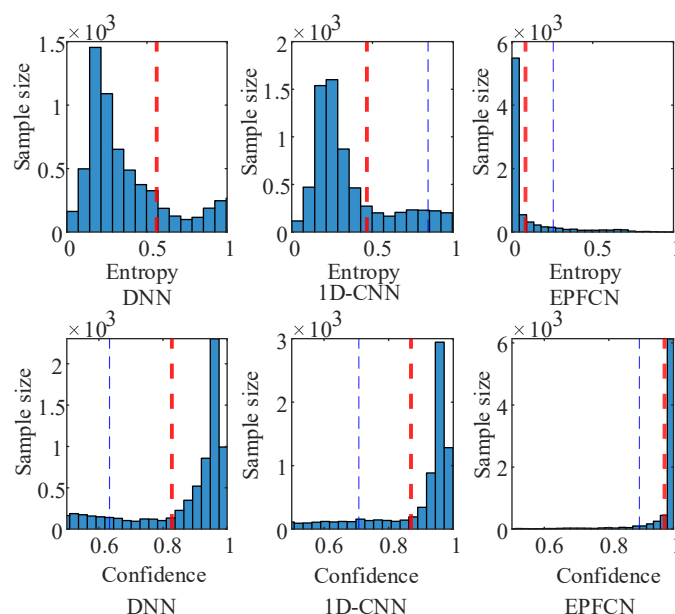


Figure 14. Statistical distribution of predictive uncertainty and confidence for different diagnostic models.

In terms of entropy distribution characteristics, the sample distributions of DNN and 1D-CNN are relatively scattered, covering almost the entire range from 0 to 1, indicating significant fluctuations in their prediction results. In contrast, the entropy values of EPFCN

are highly concentrated in the low interval of 0 to 0.3. Regarding the confidence distribution, the prediction probabilities of DNN and 1D-CNN are mainly concentrated between 0.6 and 0.8, while EPFCN exhibits a distinct right-skewed distribution, densely clustered in the high-value range of 0.8 to 1.0. These statistical features strongly verify that the EPFCN model possesses lower uncertainty and higher decision confidence in fault diagnosis, fully reflecting its reliability advantages in complex classification tasks.

3.3. Discussion on Limitations and Generalization

The validation in this study is focused on open-circuit faults of multi-phase interleaved parallel converters. This fault category provides a representative scenario for evaluating the proposed time–frequency diagnostic framework, because the loss of a conducting path directly affects current sharing, ripple distribution, transient waveform distortion, and spectral components. For other failure mechanisms, such as short-circuit faults, sensor failures, capacitor degradation, intermittent faults, and gate-driver malfunctions, the diagnostic applicability of the proposed framework depends on whether their fault-induced responses can be effectively reflected in the measured voltage/current channels and their time–frequency representations. Therefore, the extension of the method to broader fault categories requires corresponding fault-mode modeling, labeled data construction, and experimental validation under the target fault conditions.

The diagnosis results in this study were obtained under the specified voltage-current double closed-loop PI control condition. Under this control setting, the proposed model learns hardware-fault-related responses from multi-channel voltage/current signals and their FFT-domain representations. Abnormal operating conditions caused by controller-parameter mismatch or transient control instability may introduce oscillatory responses with different temporal and spectral characteristics. Reliable discrimination between hardware faults and control-induced abnormal states requires these control-related operating conditions to be included as additional labels or abnormal-state classes during dataset construction and model training.

The scalability of the proposed framework can be described from the input representation and feature extraction mechanism. The measured converter signals are organized as a multivariate time-series matrix:

$$\mathbf{X} \in \mathbb{R}^{T \times C} \quad (19)$$

where T is the temporal length of each sample and C is the number of measured electrical channels. When the number of interleaved phases increases, the input-channel dimension C can be adjusted according to the available voltage and current measurements, while the time-domain and FFT-domain branches of the EPFCN can be retained. The temporal convolution operation for multi-channel feature extraction can be expressed as

$$y_j(t) = \sigma \left(\sum_{c=1}^C \sum_{r=0}^{K-1} w_{j,c,r} x_c(t+r) + b_j \right) \quad (20)$$

where $x_c(t)$ denotes the c -th input channel, K is the convolution kernel size, $w_{j,c,r}$ is the convolution weight, b_j is the bias term, and σ is the activation function. For an interleaved converter with M phases, the normal phase current can be expressed as

$$i_k(t) = \frac{I_{\text{out}}}{M} + \tilde{i}_k(t), \quad k = 1, 2, \dots, M \quad (21)$$

where I_{out} is the total output current and $\tilde{i}_k(t)$ denotes the ripple component of the k -th phase. Under fault conditions, the current distribution changes and the phase current can be written as

$$i_k^f(t) = \frac{I_{\text{out}}}{M} + \tilde{i}_k(t) + \Delta i_k(t) \quad (22)$$

where $\Delta i_k(t)$ represents the fault-induced deviation. As the number of phases increases, the diagnostic feature may become less prominent in a single channel, while the correlation among multiple phase-related channels becomes more important. The FFT-domain branch further extracts the spectral representation of each channel:

$$X_c(f) = \left| \sum_{n=0}^{N-1} x_c[n] e^{-j2\pi f n/N} \right| \quad (23)$$

where $x_c[n]$ is the sampled signal of the c -th channel and N is the FFT length. Therefore, the proposed framework can be extended to converters with a larger number of interleaved phases by adjusting the input-channel dimension, redefining the measurement-channel mapping, and reconstructing the corresponding labeled dataset under the target phase number. The basic time-domain branch, FFT-domain branch, feature fusion strategy, and ECA-based channel enhancement mechanism can remain consistent during this extension.

The proposed EPFCN provides a time–frequency dual-branch diagnostic framework that can be reconfigured for other power electronic systems with measurable voltage and current fault responses. The model input can be represented as a multivariate time-series matrix:

$$\mathbf{X} \in \mathbb{R}^{T \times C} \quad (24)$$

where T denotes the temporal length of each sample, and C denotes the number of measured electrical channels. In this study, the trained model was evaluated using the investigated multi-phase interleaved parallel converter topology. For other converter topologies, the circuit structure, measured variables, dominant fault mechanisms, and fault-induced dynamic responses may differ. Therefore, topology-specific measurement-channel selection, fault-label definition, dataset construction, and model training are required before applying the framework to a different converter system.

4. Conclusions

This paper proposed a time–frequency dual-branch EPFCN-based method for fault warning and diagnosis of multi-phase interleaved parallel converters in DC microgrids. The proposed model uses synchronized multi-channel voltage/current signals and their FFT-domain representations as dual inputs. The time-domain branch extracts transient waveform distortion and dynamic response features, while the FFT-domain branch captures spectral redistribution and harmonic-related information. The ECA module further enhances fault-sensitive channel responses while maintaining a lightweight Conv1D-based structure. Based on the RT-LAB hardware-in-the-loop platform, a diagnostic dataset covering one normal state and nine fault states was constructed for model training and verification.

The experimental results demonstrate the effectiveness of the proposed method. The EPFCN achieved a test accuracy of 98.4%, outperforming traditional machine-learning models and mainstream deep-learning baselines. Ablation experiments confirmed the contribution of the time–frequency dual-branch structure and the ECA module. Under Gaussian noise interference, the proposed model maintained accuracies of 95.99%, 94.44%, and 89.15% at SNR levels of 50 dB, 40 dB, and 30 dB, respectively. Feature visualization based on t-SNE showed that the proposed model improves the separability of different fault categories through hierarchical feature extraction and fusion. Edge-side deployment on Raspberry Pi 4B achieved an average diagnostic accuracy of 97.6% and an average inference time of 18.7 ms per sample, indicating the feasibility of lightweight online diagnosis.

The present validation is based on RT-LAB hardware-in-the-loop data and focuses on open-circuit faults under the adopted voltage-current double closed-loop PI control strategy. Additional validation using real converter fault data, broader fault categories, different numbers of interleaved phases, and different control strategies is still required to further assess the cross-condition and cross-topology generalization capability of the proposed framework under practical hardware noise, parasitic effects, and non-ideal transient conditions.

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