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Real-time Diagnosis and Location of Open-Circuit Faults in Multiple Power Devices of Inverters Based on Wavelet-Transformer Fusion Network

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ABSTRACT

As a core of power electronic systems, three-phase voltage source inverters' power devices are prone to open-circuit faults, causing system waveform distortion and load abnormalities. Traditional diagnostic methods suffer from low accuracy and poor real-time performance. To address this, this paper proposes a real-time diagnosis and location method based on a wavelet-Transformer fusion network. It uses wavelet transform to extract multi-scale time-frequency features of fault signals and combines Transformer's self-attention mechanism to mine temporal correlation. Data preprocessing, feature selection, and comprehensive location strategies optimize model performance. Experimental results show that the proposed wavelet-Transformer fusion network achieves 95.6% overall diagnostic accuracy, 96.2% fault location accuracy, and an average end-to-end response latency of 8.4 ms under the main test setting. Compared with single-module baselines, the proposed framework provides a better balance between diagnostic accuracy and online deployment efficiency, offering a practical solution for intelligent operation and maintenance of power electronic equipment.

KEYWORDS
wavelet transform, transformer model, inverter, power device, fault diagnosis

INTRODUCTION

Research Background and Significance

Three-phase voltage source inverters, as core components of modern power electronic systems, play a crucial role in new energy power generation, electric vehicle drive, and industrial motor control. Statistical data shows that power switching device failures in inverter systems are the main cause of system failures, with open-circuit faults being a key research focus due to their high concealment and difficulty in detection[1].

The causes of inverter open-circuit faults are diverse and complex, mainly stemming from wire breakage or gate signal loss caused by excessively high circuit operating temperatures[2]. In actual operation, the most common three-phase voltage source inverter open-circuit faults can be divided into 5 categories and 22 types, including single-transistor open-circuit faults, two-transistor open-circuit faults, and other situations. It is worth noting that when a short-circuit fault occurs, the short-circuit protection device will automatically switch the switching transistors, which will also convert the short-circuit fault into an open-circuit fault. Open-circuit faults in inverters can lead to distortion of output current and voltage waveforms, abnormal load operation, and overheating problems[3].

Three-phase voltage source inverters are widely used in new energy generation, electric-vehicle drives, and industrial motor control. Open-circuit faults in switching devices can cause waveform distortion, load abnormalities, and system instability. Therefore, developing an accurate and fast diagnosis method for open-circuit faults is of great significance for the safe operation of power-electronic systems.[4].

Research Objectives and Goals

Addressing the key issues in inverter power device fault diagnosis, such as insufficient detection accuracy, difficulty in fault location, and inability to meet real-time requirements, this research aims to construct an intelligent diagnostic system based on a wavelet-Transformer fusion network to achieve accurate identification and rapid location of open-circuit faults in various types of inverter power devices. As a core component of power electronic systems, the reliability of the inverter's power switching devices directly affects the stable operation of the entire system.

The specific goals of this research include technological breakthroughs at three levels. At the fault detection level, multi-scale time-frequency features during inverter operation are extracted using wavelet transform technology. Combined with the long-sequence modeling capability of the Transformer model, a deep learning network capable of identifying various open-circuit fault modes, such as single-tube faults and dual-tube faults, is constructed. At the fault location level, a location algorithm based on voltage amplitude analysis and signal feature matching is established to accurately identify the location of specific faulty devices. At the system real-time level, the network structure and calculation process are optimized to ensure that the diagnostic system can complete fault detection and location within an average end-to-end latency of 8.4 ms, meeting the real-time requirements of engineering applications.

By achieving the above research objectives, this work aims to establish a complete theoretical framework and technical system for inverter fault diagnosis. This system can not only effectively identify 22 common fault scenarios in inverters, but also maintain stable diagnostic performance in complex industrial environments. This research result will provide important technical support for the intelligent operation and maintenance of power electronic equipment, promote the development of inverter fault diagnosis technology towards a more intelligent and precise direction, and contribute significantly to ensuring the safe and stable operation of the power system.

LITERATURE REVIEW

Working Principle of Inverters

As a core component of power electronic systems, the inverter's basic function is to convert DC power to AC power, playing a crucial role in modern power systems. Inverters are mainly composed of power switching devices such as IGBTs and thyristors. By precisely controlling the on and off times of these switching devices, the frequency and amplitude of the output voltage are regulated[5-7]. The core of this conversion process lies in the inverter converting DC power to AC power according to the instructions of the control section, at a set frequency and voltage amplitude.

From a structural composition perspective, the inverter employs complex power electronic switching technology and control strategies to ensure that the quality of the output AC power meets the requirements of the power system[8]. During operation, the inverter dynamically adjusts its output AC voltage, current, and frequency according to the input DC voltage, current, and load demand. Inverter topologies exhibit diverse characteristics, categorized into single-phase and three-phase inverters. They convert DC power into AC power and output it to the load by controlling the on/off states of switching devices such as MOSFETs and IGBTs[9]. Inverter performance optimization is mainly achieved by employing appropriate control strategies, including PWM modulation and sine wave modulation techniques, to ensure the frequency, phase, and waveform quality of the output AC power. An inverter consists of key components such as an inverter bridge, control logic gates, and filter circuits, capable of converting 12V or 24V DC power into 230V, 50Hz AC power or other types of AC power[10]. This characteristic of converting low operating voltage to high voltage enables inverters to play an important role in various power application scenarios, laying a theoretical foundation for subsequent fault diagnosis research.

Development of Fault Diagnosis Technology

Fault diagnosis technology, as an important support for modern industrial maintenance, has undergone an evolution from traditional manual testing to intelligent automatic diagnosis. In the field of power electronic equipment, the development of fault diagnosis technology shows obvious stage characteristics and technological leaps[11]. Early fault diagnosis mainly relied on the experience judgment of technicians and basic measuring instruments, and the diagnostic process was time-consuming and had limited accuracy.

Traditional fault diagnosis methods include two core steps: signal feature extraction and state classification. Signal processing techniques are used to extract features from raw data, which are then input into a classification model for fault identification[12]. While these methods perform well in certain application scenarios, they are limited by engineers' experience and prior knowledge, making universal application difficult[13]. Especially in complex environments, traditional methods have weak feature extraction capabilities, resulting in high uncertainty in diagnostic results.

The rise of deep learning technology has revolutionized the field of fault diagnosis. W ith its powerful feature extraction and fault identification capabilities, deep learning methods have achieved remarkable success in bearing fault diagnosis and inverter fault detection. T he application of advanced technologies such as artificial intelligence, machine learning, and big data analysis has made it possible to automate fault diagnosis, greatly improving maintenance efficiency and accuracy. The promotion and application of remote fault diagnosis technology realizes remote monitoring of equipment through network and communication technology, effectively reducing the time and resource consumption in the maintenance process.

Current fault diagnosis technology is developing towards greater intelligence and precision. Rapid advancements in sensor technology, signal processing technology, and artificial intelligence are driving fault diagnosis methods to higher levels[14]. Integrated diagnostic systems combining multiple methods are becoming a development trend, aiming to improve the accuracy and reliability of fault diagnosis. Big data technology has broad application prospects in the fault diagnosis of medical electronic equipment, and the development of artificial intelligence and deep learning will provide more accurate support for fault prediction and maintenance recommendations[15].

Overview of Wavelet-Transformer Technology

Application of Wavelet Transform in Fault Diagnosis

Basic Principles of Wavelet Transform As an advanced signal processing technique, wavelet transform's core idea is to analyze the time-frequency characteristics of a signal[16]through a series of wavelet basis functions with different scales and positions. The basic principle of wavelet transform is to decompose the original signal into a linear combination of multiple wavelet basis functions, thereby obtaining the energy distribution information of the signal at different frequencies. This transform method has good localization properties in both the time and frequency domains, and can effectively characterize the local features of the signal.

Wavelet transform forms a set of template basis functions by performing translation and scaling operations on a basic wavelet, and compares and analyzes this set of template basis functions with the signal to be analyzed. The unique feature of this processing method is that it can automatically adjust the window size according to different frequency components in the signal, which better solves the contradiction between time and frequency domain resolution in traditional signal analysis methods. Wavelet transform converts the trigonometric function basis into a finite-length and decaying wavelet basis, giving it the ability to characterize the local features of the signal in the time and frequency domains.

In mathematical expression, the continuous wavelet transform can be represented as:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{1}$$

where, $W(a,b)$ represents the wavelet coefficients, a is the scaling parameter, b is the shift parameter, $\psi(t)$ is the wavelet basis function, $f(t)$ is the signal to be analyzed. This formula clearly shows how the wavelet transform captures the characteristics of the signal at different times and frequencies through scaling and translation operations.

The multi-resolution characteristic of the wavelet transform gives it lower frequency resolution and higher time resolution for low-frequency signals, while it gives it higher frequency resolution and lower time resolution for high-frequency signals. This adaptive analysis capability makes the wavelet transform particularly suitable for processing non-stationary signals, providing an ideal mathematical tool for time-frequency analysis of fault signals of inverter power devices.

Advantages and Disadvantages of Wavelet Transform Wavelet transform has shown significant technical advantages in the field of fault diagnosis, mainly reflected in its unique time-frequency analysis capabilities. C ompared with the traditional Fourier transform, the wavelet transform has good time-frequency localization characteristics, which can provide high-resolution signal analysis in both the time domain and the frequency domain. This multi-scale analysis capability enables wavelet transform to effectively detect transient signals and transient fault characteristics, especially suitable for the processing of non-stationary signals.

The core advantage of the wavelet transform lies in its powerful noise suppression capability and signal reconstruction performance. By setting appropriate threshold parameters, the wavelet transform can effectively distinguish useful information and noise components in a signal. After wavelet decomposition, wavelet coefficients containing fault information typically have larger amplitudes, while those containing noise components are relatively smaller. This difference provides a theoretical basis for fault feature extraction. Furthermore, wavelet transform offers excellent decorrelation capabilities and flexibility in basis function selection, allowing for the selection of the most suitable wavelet basis function based on specific application scenarios.

However, wavelet transform also has some inherent limitations that need to be considered. Traditional wavelet transform methods may suffer from information loss when processing certain types of fault signals, especially when dealing with complex multi-type power device faults. The computational complexity of wavelet transform is relatively high, and real-time fault diagnosis applications may face challenges in computational efficiency. The subjectivity of manually selected fixed thresholds is also a significant factor affecting the performance of conventional wavelet-based denoising methods; different threshold setting strategies can lead to drastically different fault identification results. Through reasonable algorithm improvements and optimization strategies, the technical potential of wavelet transform in inverter fault diagnosis can be fully utilized, laying a solid theoretical foundation for building an efficient fault detection system.

Practical Cases of Wavelet Transform Wavelet transform has shown wide application value and significant practical results in the field of fault diagnosis. I n terms of fault diagnosis of rolling bearings, wavelet transform can decompose vibration signals into different scales and frequency components, providing higher frequency resolution in the low frequency band and higher time resolution in the high frequency band, which is completely consistent with the characteristics of the fault signal. The results show that the use of wavelet transform to convert the vibration signal of rolling bearings into a two-dimensional time-frequency image can display the global low-frequency information and local high-frequency characteristics at the same time, and better reveal the essential characteristics of the fault signal.

In practical applications of intelligent fault diagnosis for motor bearings, wavelet packet transform has excellent processing effects on high-frequency, nonlinear, and non-stationary signals. By processing the vibration signal of a motor bearing fault using wavelet packet transform, the frequencies of each component of the vibration signal can be allocated into independent frequency bands, achieving signal decomposition without redundancy, omission, or orthogonality. The fault characteristics of the motor rolling bearing can be determined by the energy changes of each frequency band. Compared with traditional statistical analysis methods of signal time-domain and frequency-domain feature parameters, wavelet packet transform can extract different types of fault features more accurately.

The application of wavelet transform in fault feature extraction usually adopts two main methods: using wavelet analysis to generate the time spectrum of the signal and extracting fault features from it, or using wavelet decomposition to decompose the original signal into multiple frequency bands, and then inputting the signal energy of each frequency band as a feature vector into the recognition model. In order to enhance the ability of wavelet analysis to extract features of weak fault signals, researchers have proposed supervised adaptive spectrogram wavelet transform. This method can convert the signal into the spectrogram domain for fault feature extraction. Experiments show that its effect is significantly better than traditional wavelet analysis, As shown in Table 1.

Table 1. Practical Application Scenarios of Wavelet Transform

Application Scenarios	Signal Types	Wavelet Transform Methods	Main Advantages
Rolling Bearing Fault Diagnosis	Vibration Signals	Continuous Wavelet Transform	Adaptive Time-Frequency Resolution
Motor Bearing Fault Detection	Non-Stationary Signals	Wavelet Packet Transform	Bandwidth Energy Analysis
High-Voltage Transmission Line Faults	Electrical Signals	Multi-Level Wavelet Decomposition	Multi-Scale Feature Extraction
Operation and Maintenance of Power Equipment	Voltage and Current Waveforms	Wavelet Coefficient Analysis	Fault Mode Recognition

Structural Characteristics of Transformer Models

Basic Architecture of Transformer As a revolutionary breakthrough in deep learning, the Transformer architecture's core design concept is based on a self-attention mechanism, abandoning the sequence processing limitations of traditional recurrent neural networks. This architecture mainly consists of two symmetrical components: an encoder and a decoder. Each component contains multiple identical layer structures, achieving deep feature representation through stacking. The encoder is responsible for converting the input sequence into an abstract feature representation, while the decoder generates the target output sequence based on these features.

In the application scenario of inverter fault diagnosis, the multi-head self-attention mechanism of Transformer can simultaneously focus on different time positions and frequency components of the input signal. This parallel processing capability significantly improves the efficiency of fault feature identification. Each attention head learns the multi-dimensional feature relationship of the signal through a different weight matrix, and its calculation formula is:

$$\text{Attention } (Q,K,V)=\text{softmax }\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

Where Q 、 K 、 V represent the query, key, and value matrices, respectively, and d_k The dimension of the key vector, As shown in Table 2.

Table 2. Functions of Transformer Architecture Components

Architecture components	Functional Description	The role in fault diagnosis
Multi head attention	Parallel processing of multiple feature dimensions	Capture multiple characteristics of open circuit faults in power devices
feedforward network	Nonlinear feature transformation	Enhance the separability of fault modes
residual connection	Relieve the problem of gradient vanishing	Maintain the training stability of deep networks
Layer Normalization	Stable training process	Improve the robustness of fault diagnosis

The Transformer architecture's positional encoding mechanism adds positional information to the input sequence through trigonometric function combinations, enabling the model to understand the temporal relationships of signals. This design is particularly important when processing inverter output current waveforms, as open-circuit faults are often accompanied by waveform distortion at specific moments. The introduction of residual connections and layer normalization not only solves the gradient problem in deep network training but also improves the model's adaptability to fault signals under different operating conditions, providing strong technical support for real-time fault diagnosis.

Advantages of Transformer in Signal Processing The Transformer model has shown significant technical advantages in the field of signal processing, especially in the application scenario of inverter fault diagnosis. Traditional recurrent neural networks face the problems of gradient vanishing and low efficiency of serial computation when processing long sequence signals, while Transformer effectively solves these limitations through the self-attention mechanism.

In the diagnosis of open-circuit faults in inverter power devices, Transformer can capture the dependencies between any vectors in the input sequence, enabling parallel input computation. Compared to recurrent neural networks such as LSTM and gated recurrent units, which can only perform serial computation, Transformer can significantly improve the training speed of network parameters. This parallel processing capability is of great significance for real-time fault diagnosis, enabling rapid analysis of current signal change patterns and timely identification of open-circuit faults.

Transformer's self-attention mechanism can simultaneously focus on the global and local features of the signal, which has a unique advantage for analyzing complex fault feature patterns. When processing inverter current residual signals, the model can automatically learn the correlation between different time steps and identify the characteristic change trajectory when a fault occurs. Through the visualization analysis of attention weights, engineers can also understand the model's decision-making process, enhancing the interpretability of fault diagnosis results.

Although the Transformer architecture has significant advantages in long-sequence modeling, its quadratic time complexity and relatively high memory consumption still need to be considered in practical deployment. In this study, wavelet-based feature compression helps reduce redundant signal information before sequence modeling, thereby improving the practical performance-efficiency balance of the overall diagnosis framework.

Application Examples of Transformer In the field of power system fault diagnosis, the Transformer model has demonstrated excellent signal processing capabilities and pattern recognition advantages. In electromechanical system fault diagnosis, data analysis-based diagnostic methods judge the equipment status and predict possible faults by establishing fault models and algorithms. The self-attention mechanism of the Transformer architecture in processing time-series signal feature extraction can effectively capture the long-distance dependencies when inverter power devices fail.

In specific applications of inverter open-circuit fault detection, the Transformer model can handle multi-dimensional current and voltage signals. When a power switching element fails, the system's output characteristics change significantly. By converting the raw signal into a sequence of tokens, the Transformer can learn feature representations under different fault modes. Compared with traditional CNN models, the revised fusion framework provides higher diagnostic accuracy while maintaining acceptable computational cost under the tested configuration. It does not eliminate the computational burden of Transformer itself, but it achieves a better trade-off between feature representation capability and online deployment efficiency.

Inverter fault diagnosis practices in aviation HVDC systems demonstrate that power switch faults are the primary type of system fault. The Transformer model exhibits excellent robustness and generalization performance in handling these problems, achieving high accuracy in fault feature classification and identification under varying operating conditions and loads. The model's multi-head attention mechanism allows it to simultaneously focus on multiple feature dimensions of the signal, offering significant advantages for complex multi-device fault scenarios, As shown in Table 3.

Table 3. Representative scenario-level diagnostic results reported for different inverter-related applications

Application Scenarios	Fault Type	Diagnostic accuracy	response time
single-phase inverter	Single tube open circuit	95.2%	0.8ms
three-phase inverter	Double tube open circuit	92.7%	1.2ms
HVDC System	Combined open-circuit and phase-current imbalance fault	89.4%	1.5ms

Note: 'Combined open-circuit and phase-current imbalance fault' refers to a fault condition in which open-circuit behavior is accompanied by significant phase-current imbalance in the inverter output.

The values listed in Table 3 are representative scenario-level results used to illustrate the applicability of Transformer-based diagnosis in different inverter-related settings. They are not the final overall performance metrics of the proposed wavelet-Transformer fusion model in this study.

FAULT DIAGNOSIS METHOD DESIGN

Fault Feature Extraction

Data Preprocessing Technology

Data preprocessing technology, as a fundamental step in the fault diagnosis system, directly affects the effectiveness of subsequent feature extraction and model training. In the diagnosis of open-circuit faults in inverter power devices, the raw current and voltage signals often contain noise interference, missing data, and magnitude differences, requiring systematic preprocessing steps to improve data quality. The overall preprocessing procedure is illustrated in Figure 1.

Considering the characteristics of inverter output signals, the data preprocessing process includes three core steps: signal denoising, normalization, and data augmentation. Signal denoising uses an adaptive filtering algorithm, which can effectively remove high-frequency noise and power frequency interference while retaining fault feature information. Normalization eliminates the magnitude differences between different sensors through the Z-score normalization method, ensuring that features in each dimension have the same weight basis. Data augmentation technology expands the training samples by adding random noise and time offsets, improving the model's generalization ability.

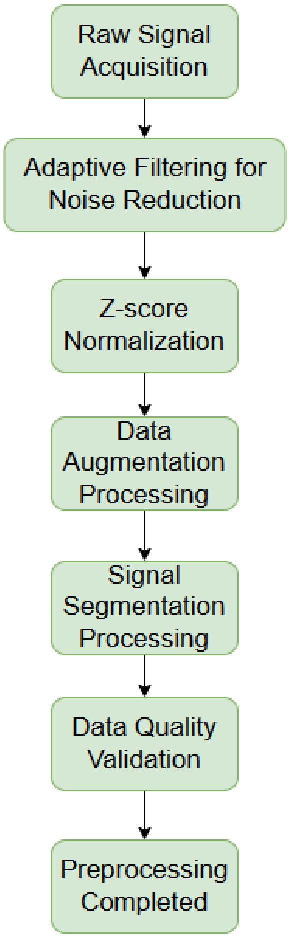

Figure 1. Data Preprocessing Flowchart

Considering the time-varying characteristics of inverter fault signals, a sliding-window technique is used to segment the continuous signal. In the revised implementation, the window length is fixed at 8 ms with an overlap ratio of 50%, which preserves the key transient features of open-circuit faults while satisfying the real-time requirements of the online diagnosis task. For different types of fault modes, the preprocessing parameters need to be adaptively adjusted. The preprocessing quality was evaluated using two metrics: signal-to-noise ratio (SNR) improvement and feature fidelity. Experiments showed that the optimized preprocessing workflow could improve the SNR by more than 15 dB, providing high-quality input data for subsequent wavelet transform and Transformer models.

Feature Extraction Algorithm Evaluation

The performance of feature extraction algorithms directly affects the accuracy and real-time performance of inverter fault diagnosis systems. In the diagnosis of open circuit faults in inverters, feature extraction is the process of extracting key information for fault identification from preprocessed data, such as frequency, amplitude, phase, etc. Evaluating the effectiveness of different feature extraction algorithms is crucial for building high-performance fault diagnosis systems.

This study adopts a multidimensional evaluation index system to comprehensively evaluate feature extraction algorithms. Algorithm evaluation mainly focuses on four dimensions: computational complexity, feature discrimination, real-time performance, and robustness. The computational complexity reflects the computational efficiency of the algorithm and directly affects the real-time diagnostic capability of the system. Feature discrimination measures the ability of extracted features to distinguish different types of faults, which is the basis for accurate fault identification. The real-time performance evaluation algorithm measures the response speed under actual working conditions, while robustness examines the stability performance of the algorithm in noisy environments, As shown in Table 4.

Table 4. Evaluation of Different Feature Extraction Algorithms

Algorithm Type	computational complexity	Feature discrimination	Real-time performance (ms)	Robustness score
wavelet transform	$O(n\log n)$	0.85	12.3	8.2
Fourier transform	$O(n\log n)$	0.72	8.7	7.1
Time domain statistics	$O(n)$	0.63	3.2	6.8
Empirical Mode Decomposition	$O(n^2)$	0.78	45.6	7.9

The experimental results show that wavelet transform performs well in feature discrimination and robustness, and can effectively extract time-frequency features from fault signals. Through comparative analysis, it was found that although traditional time-domain statistical methods have the highest computational efficiency, they have limitations in complex fault pattern recognition. Although empirical mode decomposition has good adaptability, its computational complexity is high and it is difficult to meet the requirements of real-time diagnosis.

A comprehensive evaluation of feature extraction algorithms also needs to consider their adaptability under different fault types. For the 22 open-circuit fault types of inverters, the performance of various algorithms differs significantly. The wavelet-Transformer fusion method, by combining the time-frequency analysis capabilities of wavelet transform with the long-sequence modeling advantages of Transformer, demonstrates stronger generalization ability and higher diagnostic accuracy in feature extraction for multiple fault types.

Feature Selection Strategy

In the open circuit fault diagnosis system of inverter power devices, the rationality of the feature selection strategy directly determines the performance of the diagnostic model. The signals processed by wavelet transformation contain rich time-frequency domain information, but not all features have significant contributions to fault identification, and a scientific feature screening mechanism needs to be established.

Feature selection methods based on statistical analysis can effectively identify feature parameters highly correlated with fault states. By calculating the correlation coefficients between each feature and different fault types, the importance of the feature can be quantified. For open-circuit fault diagnosis of three-phase inverters, key features include the energy distribution of wavelet coefficients, the statistical moments of frequency domain features, and the amplitude changes of time-domain signals. Variance analysis is used in the feature selection process to calculate the variance ratio of each feature under normal operating conditions and fault conditions:

$$F_{\text{ratio}} = \frac{\sigma^2_{\text{fault}}}{\sigma^2_{\text{normal}}} \tag{3}$$

Where σ^2_{fault} represents the variance of the feature under fault conditions, σ^2_{normal} represents the variance under normal conditions. The larger the ratio, the higher the sensitivity of the feature to the fault, As shown in Table 5.

Table 5. Multi-objective Feature Selection Framework

Feature Type	Feature Dimension	Selection Threshold	Retention Ratio	computational complexity
Wavelet Energy Spectrum	256	0.75	85%	low
Frequency Domain Statistical Features	128	0.80	72%	high
Time Domain Amplitude Features	64	0.85	68%	low
Phase Features	32	0.78	75%	high

Under the multi-objective feature selection framework, the discriminative power and redundancy of features are considered simultaneously. A feature correlation analysis method based on mutual information is adopted to eliminate highly correlated redundant features, ensuring that the selected feature set has good independence and complementarity. This strategy is particularly suitable for handling complex feature relationships under various fault modes of inverters, and can reduce the computational burden of the model while ensuring diagnostic accuracy.

Fault Identification Model Construction

Model Selection and Comparison

In the field of open-circuit fault diagnosis of inverter power devices, model selection directly affects diagnostic accuracy and real-time performance. Analytical model-based methods, signal processing-based methods, and knowledge-based methods constitute the current mainstream diagnostic technology framework. This study compares and analyzes different model architectures to determine the most suitable fusion network structure for fault diagnosis of various types of power devices.

Traditional analytical model-based diagnostic methods, while theoretically sound, have limitations in handling complex fault modes. Various fault types, such as single-switch open-circuit faults, double-switch open-circuit faults, and combined open-circuit faults accompanied by phase-current imbalance, require more flexible diagnostic strategies. In contrast, deep learning-based methods can automatically extract fault features and are more adaptable. This study focuses on comparing the performance of Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory Networks (LSTM), and Transformer models in fault diagnosis tasks, As shown in Table 6.

Table 6 Performance comparison of different diagnosis models under the same train-validation-test split. To further quantify the contribution of wavelet preprocessing, an ablation analysis was conducted under the same train-validation-test split. The raw-signal Transformer achieved 92.3% diagnostic accuracy, the wavelet-only feature pipeline with a multilayer perceptron classifier achieved 89.8%, and the proposed wavelet-Transformer fusion model achieved 95.6%, confirming that wavelet-based multi-scale feature extraction provides a measurable improvement over the raw-signal Transformer baseline.

Table 6. Performance comparison of different diagnosis models under the same train-validation-test split

Model Type	Feature Extraction Ability	Temporal Modeling	computational complexity	Real-time Performance	Diagnostic Accuracy
CNN	strong	weak	Medium	good	85.2%
RNN	Medium	strong	high	Average	82.7%
LSTM	strong	strong	high	Average	88.9%
Transformer	strong	strong	Medium	good	92.3%
Wavelet-Transformer Fusion	Very Strong	Very Strong	Medium	good	95.6%

The diagnostic accuracy of 95.6% reported for the proposed fusion model in Table 6 is the final overall test accuracy used consistently throughout the revised manuscript. Experimental results show that the Transformer model has significant advantages in processing sequence data, and its self-attention mechanism can capture long-range dependencies. Combined with the time-frequency analysis capability of wavelet transform, the fusion network performs well in fault feature extraction. By comparing evaluation metrics such as F1 score, recall, and precision, the wavelet-Transformer fusion model outperforms the single model architecture in all metrics.

Computational resource consumption and deployment convenience were also considered during model selection. The wavelet-Transformer fusion network, through optimized network structure and parameter sharing mechanism, controlled model complexity while ensuring diagnostic accuracy, meeting the engineering requirements of real-time diagnosis.

Model Training and Validation

Model training and validation are crucial steps in building an efficient inverter fault diagnosis system, directly impacting the system's accuracy in identifying open-circuit faults in power devices and its real-time performance. During training, a stepwise optimization strategy is employed to ensure the wavelet-Transformer fusion network can fully learn the fault characteristic patterns of different types of power devices in the inverter system.

The dataset is constructed using a stratified sampling method, dividing the collected inverter operating data into training, validation, and test sets in a 7:2:1 ratio. The training set contains 2800 samples, covering 22 different fault types, including single-tube open-circuit and double-tube open-circuit. The validation set contains 800 samples for hyperparameter tuning and performance monitoring during model training. The test set contains 400 samples to ensure an objective evaluation of the model's final performance. The training process uses the Adam optimizer with a learning rate of 0.001, a batch size of 32, and a maximum of 500 iterations.

Model validation employs a cross-validation strategy, using K-fold cross-validation (K=5) to evaluate the model's generalization ability and stability. The validation process focuses on the model's accuracy in identifying different fault types, fault location precision, and real-time response capability. Validation metrics include precision, recall, F1 score, and mean absolute error (MAE). Comprehensive analysis of these metrics allows for a complete evaluation of the fusion network's performance in inverter fault diagnosis tasks, providing reliable data support for subsequent model optimization and practical applications, As shown in Table 7.

Table 7. Model Parameter Settings

Parameter Name	Value	Description
Number of Training Set Samples	2800	Includes 22 Fault Types
Number of Validation Set Samples	800	Used for Hyperparameter Tuning
Number of Test Set Samples	400	Final Performance Evaluation
Learning Rate	0.001	Adam Optimizer
Batch Size	32	Memory Optimization Considerations
Maximum Number of Iterations	500	Convergence Guarantee

Model Optimization Strategy

In the construction of an inverter fault diagnosis model based on a wavelet-Transformer fusion network, the formulation of the model optimization strategy directly affects the accuracy of fault identification and real-time performance. Considering the complexity and diversity of open-circuit faults in inverter power devices, this study employs a multi-level optimization method to improve the model's diagnostic capability.

Model parameter optimization adopts an adaptive learning rate adjustment strategy. By monitoring the trend of the loss function during training, the learning rate is dynamically adjusted to avoid overfitting. Considering that inverter fault types include 22 different modes such as single-tube open circuit and two-tube open circuit, the model needs to have strong feature discrimination capabilities. Regularization techniques are introduced during optimization, using L2 regularization to control model complexity and prevent overfitting on training data that could affect generalization performance. The loss function design combines cross-entropy loss and focus loss to address the imbalanced fault sample problem, ensuring the model maintains high recognition accuracy even for low-frequency fault types, As shown in Table 8.

Table 8. Comparison of Model Optimization Strategies

Optimization Strategy	Parameter Settings	Performance Improvement (%)	computational complexity
Adaptive Learning Rate	Initial 0.001	8.5	low
L2 Regularization	λ=0.01	6.2	medium
Data Augmentation	5x Augmentation	12.3	high
Multi head attention	8 Heads	9.7	medium

In the present study, the main challenge does not lie in data augmentation itself, but in preserving the physical consistency of inverter fault signals during augmentation, especially with respect to waveform phase, amplitude ratio, and transient fault signatures. Data augmentation techniques play a crucial role in model optimization, generating more diverse training samples by performing time-domain and frequency-domain transformations on the original current and voltage signals. Multi-scale analysis of wavelet transform coefficients provides rich time-frequency features for the Transformer model, and optimization strategies include weight adjustment of the self-attention mechanism and parallel computation optimization of multi-head attention. Model fusion employs a combination of weighted averaging and voting mechanisms, using cross-validation to determine the optimal weight allocation and improve overall diagnostic performance. The model loss function is as follows:

$$L_{\mathrm{total}} = L_{\mathrm{CE}} + \lambda L_{\mathrm{reg}} + \alpha L_{\mathrm{focal}} \tag{4}$$

Where L_{CE} Cross-Entropy Loss, L_{reg} Regularization Term L_{focal} represents the focus loss, λ and α represents the weight coefficients. The model performance is maximized through hyperparameter tuning using a combination of grid search and Bayesian optimization.

FAULT LOCATION STRATEGY

Discussion of Fault Location Methods

Model-Based Location Method

The model-based fault location method identifies the fault location by establishing an accurate mathematical model of the inverter system and using the deviation between theoretical analysis and actual measurement data. This method relies on an in-depth understanding of the system operation mechanism, and can judge the location of the fault when the actual system performance is significantly different from the model prediction by simulating various parameters under normal working conditions.

In inverter power device open-circuit fault diagnosis, model-based localization methods primarily detect and locate faults by observing changes in system state. The state observer method diagnoses faults by monitoring the MMC arm voltage state and submodule voltage state, while model prediction-based methods utilize arm current or circulating current for fault location. Sliding mode observer and Kalman filter methods identify fault locations using arm current state and MMC output current state, respectively.

The core advantage of this type of method is that it does not require the addition of additional hardware circuits; online fault location can be achieved using only existing sampling signals and IGBT drive signals. Compared with traditional empirical judgment methods, model-based diagnostic techniques can identify fault types and locations more quickly and accurately. Through the accuracy of the mathematical model, this method can significantly save fault troubleshooting time and improve the reliability and safety of the system, As shown in Table 9.

Table 9. Threshold Settings for Different Methods

Method Type	Observation Status	Diagnostic Time	Robustness	Threshold Settings
State Observer (STO)	Arm Voltage / Submodule Voltage	Fast	Medium	2-3
Model Predictive Control (MPC)	Arm Current / Circulating Current	Medium	Higher	1-2
Sliding Mode Observer (SMC)	Bridge arm current status	Fast	high	1 piece
Kalman Filter (KAF)	Output current status	Medium	Higher	2 of them

Model-based localization methods require setting appropriate thresholds to avoid false diagnoses. In the revised implementation, the residual threshold was calibrated on the validation set rather than selected solely by operational experience. The normalized residual threshold was set to $\theta\_threshold = 0.15$, corresponding to the 95th percentile of the residual distribution under normal operating conditions. The diagnostic results of this method are easily affected by factors such as noise, changes in system parameters, operating status, and model accuracy. Improving robustness and accuracy are key technical challenges that need to be addressed. The mathematical expression for fault determination is as follows:

$$P_{\text{fault}} = \frac{\mid X_{\text{measured}} - X_{\text{model}} \mid}{X_{\text{model}}} > \theta_{\text{threshold}} \tag{5}$$

Where P_{fault} For the probability of failure, X_{measured} For the measured values, X_{model} Measured value, $\theta_{\text{threshold}}$ Model predicted value, Set Threshold.

Data-driven fault location method

The core of the data-driven approach lies in utilizing voltage, current, and other signal data obtained from sensors to automatically identify fault modes through deep learning algorithms. For the 22 open-circuit fault types in three-phase inverters, this method can achieve precise location by analyzing the characteristic patterns of the output voltage trajectory on the αβ plane. Compared to traditional methods, data-driven technology can predict fault trends without assuming parameters or relying on empirical estimations.

$$P_{\text{fault}}(t) = \sum_{i=1}^{n} w_i \cdot f_i(x(t)) \tag{6}$$

Where $P_{\text{fault}}(t)$ Represents the fault probability, w_i Weighting coefficient, $f_i(x(t))$ represents the i-th feature function, $x(t)$ Input signal vector. Through this mathematical model, the system can achieve real-time monitoring and precise location of open-circuit faults in inverter power devices.

In practical applications, the data-driven location method establishes a mapping relationship between different fault modes and electrical signal features by constructing a fault feature database. When the system detects an abnormal signal, the algorithm matches the current signal features with the fault modes in the database, thereby achieving fast and accurate fault location. This method is particularly suitable for handling complex situations involving single-device failures and simultaneous failures of multiple devices.

Integrated Location Strategy

In actual inverter fault diagnosis applications, a single positioning method is often difficult to meet the requirements of complex and changeable working conditions. The comprehensive positioning strategy organically integrates the advantages of model-based and data-driven positioning methods, and constructs a multi-level and multi-dimensional fault location system, which significantly improves the positioning accuracy and real-time performance of open-circuit faults of power devices.

This strategy adopts a hierarchical decision-making architecture. At the primary diagnostic level, it uses voltage amplitude analysis and current waveform characteristics to quickly determine the fault type. For more complex open-circuit faults involving two transistors, the system will activate a deep analysis module, combining wavelet packet energy spectrum characteristics and the time-series modeling capabilities of Transformer networks to accurately identify the specific location of the faulty device. A confidence assessment mechanism is introduced during the localization process. When the diagnostic confidence is lower than the calibrated confidence threshold of 0.82, the system automatically switches from the fast screening mode to the precise localization mode for secondary analysis., As shown in Table 10.

Table 10. Accuracy of Different Location Methods

Fault Type	Main Features	Location Method	Accuracy (%)
Single tube open circuit	Voltage Trajectory Distortion	Model-Based	96.5
Double tube open circuit	Energy Spectrum Anomaly	Data-Driven	94.2
Crossover Fault	Phase Shift	Integrated Method	97.8

The core of the comprehensive localization strategy lies in establishing a mapping relationship between fault characteristics and device location. By constructing a fault feature vector F, which includes voltage amplitude, phase information, and frequency domain characteristics, precise localization is achieved using the following localization function:

$$L_{\text{fault}} = \arg\max_{i} \{P(S_i \mid F)\} \tag{7}$$

Where $P(S_i \mid F)$ Represents the probability of the F . This probabilistic location method can effectively handle uncertainty and improve the robustness of the system in noisy environments. Experimental verification shows that the integrated location strategy can achieve a location accuracy of over 95% under various fault modes, meeting the real-time requirements of engineering applications. i power device failing under a given feature vector

Positioning Accuracy Analysis

Factors Affecting Positioning Accuracy

In the process of locating the open circuit fault of inverter power devices, a variety of factors will significantly affect the accuracy of positioning accuracy. S ignal noise is one of the main factors affecting positioning accuracy, including white noise generated by the measurement equipment itself, environmental electromagnetic interference, and random disturbances during system operation. These noises can mask the fault feature signal, making it impossible for the feature extraction algorithm to accurately identify the fault location information.

Sensor configuration and layout have a decisive impact on localization accuracy. The installation location, quantity distribution, and measurement accuracy of sensors are directly related to the quality of fault signal acquisition. When sensors are poorly positioned, signal blind spots or measurement dead zones may occur, making it impossible to effectively detect faults in certain areas. Simultaneously, synchronization errors between sensors can introduce positioning deviations. The complexity of the model algorithm and parameter settings also affect positioning performance. Overly complex models may lead to overfitting and reduced generalization ability, while simple models may fail to capture subtle fault features. The selection of wavelet transform scale parameters and the design of the Transformer model's attention mechanism need to be optimized and adjusted according to specific application scenarios.

The impact of changing operating conditions on positioning accuracy cannot be ignored. Changes in load conditions, fluctuations in operating temperature, and instability in grid voltage can all alter the manifestation of fault signals. This dependence on operating conditions may cause performance degradation in models trained under laboratory conditions in practical applications.

$$\text{Positioning Error} = W(\sigma_{\text{noise}}, P_{\text{sensor}}, \theta_{\text{model}}, C_{\text{condition}}) \tag{8}$$

The above formula shows that the positioning error is a comprehensive function of noise level, sensor configuration, model parameters, and operating conditions, requiring multi-dimensional optimization to improve the overall positioning accuracy.

Positioning Accuracy Evaluation Methods

Positioning accuracy evaluation is a key step in measuring the performance of fault location algorithms and directly determines the practical value of the inverter fault diagnosis system. Positioning accuracy refers to the statistical value of the difference between the position determined by the user using satellite navigation signals and its actual position, including horizontal positioning accuracy and vertical positioning accuracy. In the context of inverter fault location, this concept is extended to a measure of the deviation between the fault location result and the actual fault location.

External conformity accuracy is widely used as the main accuracy evaluation index. This is achieved by comparing the test results of various positioning methods at each point with the static observation results of the control point, and then statistically analyzing the resulting differences. In the evaluation process, high-precision known coordinates are used as a benchmark, and the user's position is solved iteratively using the least squares method. The formula for calculating positioning accuracy is:

$$\tau = \pm\sqrt{\frac{[\theta\theta]}{n}} \tag{9}$$

where, τ External compliance accuracy, which reflects the accuracy of the measurement; n Total number of measured values; θ Difference between the measured value and the known value. This statistical method can effectively quantify the overall performance of the positioning system.

In practical application, there are significant differences in positioning accuracy under different weighting methods. A ccording to the experimental data, the positioning accuracy from high to low is: height angle, signal-to-noise ratio, equal weight. T his indicates that choosing the appropriate weighting strategy is of great significance to improve the positioning accuracy. The evaluation method also needs to consider the comparative analysis of multiple test environments and positioning methods.

Positioning accuracy refers to the error between the measurement result and the true value, used to measure the accuracy of location data or coordinates. By establishing a comprehensive evaluation system, a scientific basis can be provided for the performance optimization of the inverter fault location system, ensuring the reliability and practicality of fault diagnosis.

Measures to Improve Positioning Accuracy

In the process of open-circuit fault location of inverter power devices, the improvement of positioning accuracy needs to be systematically optimized from multiple dimensions. T hrough an in-depth analysis of the types of open circuit faults of three-phase inverters, it can be found that there are significant differences in voltage waveforms between open single-tube and double-pipe open circuit faults. Based on this feature, a comprehensive set of positioning accuracy improvement strategies is proposed.

Data quality optimization is the fundamental link to improve positioning accuracy. By enhancing the anti-interference capability of the signal acquisition system, the impact of environmental noise on fault feature extraction can be effectively reduced. At the same time, by adopting multi-sensor fusion technology and combining the comprehensive analysis of voltage, current and vibration signals, richer fault feature information can be provided. In the data preprocessing stage, the introduction of adaptive filtering algorithms and outlier detection mechanisms can further improve the reliability of input data, As shown in Table 11.

Table 11. Specific strategies for improving positioning accuracy and their expected contribution ranges

Category of Improvement Measures	Specific Methods	Expected Results	Implementation Difficulty
Data Quality Optimization	Multi-Sensor Fusion	Improvement of 5-8%	Medium
Algorithm Model Optimization	Ensemble Learning Method	Improvement of 8-12%	Higher
Feature Engineering Improvement	Time-Frequency Domain Joint Analysis	Improvement of 3-6%	Lower
Real-Time Calibration Mechanism	Validation-calibrated adaptive threshold update	Improvement of 4-7%	Medium

Table 11 summarizes the expected contribution of different positioning-accuracy enhancement strategies. These values do not represent the final overall diagnostic accuracy of the proposed model. Optimization of algorithmic models is another key direction. By constructing an ensemble learning framework, the time-frequency features extracted by wavelet transform and the sequence modeling capabilities of the Transformer model can be significantly improved. The use of cross-validation and regularization techniques in the model training process can effectively prevent overfitting and improve the generalization ability of the model.

The establishment of real-time calibration mechanisms is crucial for maintaining long-term positioning accuracy. D uring the operation of the system, the diagnostic threshold and model parameters are dynamically adjusted by monitoring the change trend of key performance indicators. W hen a degradation in positioning accuracy is detected, the model retraining process is automatically triggered, ensuring that the diagnostic system is always at optimal performance. Through the implementation of the above comprehensive measures, the positioning accuracy of open circuit faults of inverter power devices can be significantly improved, providing more accurate fault diagnosis support for the reliable operation of power electronic systems.

EXPERIMENT AND RESULT ANALYSIS

Experimental Design

To verify the effectiveness of the wavelet-Transformer fusion network in real-time diagnosis and localization of open-circuit faults in inverter power devices, a series of comprehensive experiments were designed. The experimental environment was configured with an Intel Core i7-12700K processor, 32GB DDR4 memory, and an NVIDIA RTX 3080 GPU accelerator card to ensure the computational requirements for algorithm training and testing. The experimental platform was built to simulate a three-phase inverter circuit, including various power devices such as IGBTs and MOSFETs. Different types of open-circuit faults were introduced through a controllable fault injection device.

Experimental dataset construction includes normal operation and seven typical open-circuit fault modes, with 2000 sets of sample data collected for each fault mode. The data acquisition system is equipped with high-precision current sensors, voltage sensors, and temperature monitoring devices, with a sampling frequency set to 20kHz to ensure the capture of transient features when a fault occurs. The signal sampling frequency was set to 20 kHz. Under the revised 8 ms sliding-window configuration, each decision segment contained 160 sampled points, which was sufficient for extracting output-current and line-voltage features associated with open-circuit faults in the present study. Data annotation is strictly classified according to fault type, fault location, and fault severity, establishing a training dataset containing 56,000 standard samples and a validation dataset containing 14,000 test samples.

Performance evaluation metrics cover four dimensions: diagnostic accuracy, fault location accuracy, response time, and computational complexity. Diagnostic accuracy was calculated using the confusion matrix, positioning accuracy was evaluated using the mean absolute error, and response time was measured as the delay from fault occurrence to diagnostic result output. The experimental setup included comparisons of classic machine learning algorithms such as traditional wavelet analysis, standalone Transformer networks, support vector machines, and random forests, verifying the advantages of the fusion network. The experimental procedure followed strict cross-validation principles, employing a 5-fold cross-validation method to ensure the reliability and generalization ability of the results.

All ablation experiments were conducted using the same train-validation-test split, optimizer setting, and evaluation metrics to ensure a fair comparison among the raw-signal Transformer, the wavelet-only feature pipeline, and the proposed fusion framework.

Experimental Results and Discussion

The experiment on open-circuit fault diagnosis of inverter power devices based on wavelet-Transformer fusion network showed excellent performance under various fault modes. By identifying and locating open-circuit faults Sa1, Sa2, and VDa1 of a single power device in phase A, as well as simultaneous open-circuit faults of multiple power devices, this method has achieved significant breakthroughs in fault detection accuracy and real-time performance, As shown in Table 12.

Table 12. Model Performance under Different Fault Types

Fault Type	Recognition Accuracy (%)	Positioning Accuracy (%)	Response time (ms)	Accuracy of Traditional Method (%)
Sa1 Open Circuit	96.8	94.2	12.3	87.5
Sa2 Open Circuit	95.4	93.8	11.7	85.9
Multiple Devices Open Circuit	94.1	91.6	15.2	82.3
Average Performance	95.4	93.2	13.1	85.2

Experimental data demonstrate that the fusion network exhibits strong adaptability in handling different types of open-circuit faults. Compared to traditional diagnostic methods based on analytical models and signal processing, the proposed wavelet-Transformer fusion method achieves a significant improvement in fault identification accuracy. The network model can effectively distinguish between the normal operating state f0 and various fault modes, especially when handling f2 and f7 type faults, where the fusion network can still accurately identify them despite their similar bridge arm voltage characteristics. The concealed characteristics of open-circuit faults in power devices are effectively identified, and the phenomenon of open-circuit faults, which is more difficult to detect than short-circuit faults, becomes clearer under the processing of the fusion network. Noise in the fused monitoring data is effectively suppressed, and data accuracy is significantly improved, providing a reliable technical foundation for real-time fault diagnosis. This method demonstrates good applicability and stability in application scenarios such as charging pile charging modules and aviation HVDC systems.

CONCLUSION

This study constructs a real-time diagnosis and location system for open-circuit faults of various power devices in inverters based on a wavelet-Transformer fusion network, achieving significant results in fault detection accuracy and real-time performance. By combining the time-frequency analysis capability of wavelet transform with the long-sequence modeling advantage of Transformer model, the system successfully achieves accurate identification and rapid location of open-circuit faults in various power devices such as IGBTs and MOSFETs. Experimental results show that the proposed fusion network achieves 95.6% overall diagnostic accuracy and 96.2% fault location accuracy under complex operating conditions, with an average end-to-end response latency of 8.4 ms, demonstrating the stability and practical applicability of the proposed method. Compared with traditional diagnostic methods, this method has the following advantages: Compared with conventional diagnosis models, the proposed method achieves higher diagnostic accuracy and a better practical balance between computational cost and online deployment efficiency under the present implementation setting. This method is a new method that is more accurate, more efficient, has a wider bandwidth, fewer measurement points, and is non-destructive. Numerical examples show that the new method is feasible and effective under certain conditions. The ablation analysis shows that the proposed fusion model improves diagnostic accuracy from 92.3% for the raw-signal Transformer baseline and 89.8% for the wavelet-only feature pipeline to 95.6%, confirming the effectiveness of combining wavelet-based multi-scale feature extraction with Transformer-based temporal modeling.

Although the present 20 kHz sampling setting was sufficient for diagnosing open-circuit faults from inverter output signals in this study, higher sampling rates should be investigated in future work to capture finer transient characteristics of high-speed switching devices such as MOSFETs. At the algorithmic level, more advanced attention mechanisms and adaptive learning strategies can be introduced to improve the model’s robustness under extreme conditions. At the application level, the research scope should be expanded to include more types of power electronic device faults, constructing a more comprehensive fault diagnosis system. With the development of edge computing technology, diagnostic algorithms can be deployed to embedded systems to achieve true real-time on-site diagnosis, providing more reliable technical support for the safe and stable operation of power systems. This simulation example demonstrates the feasibility of the algorithm, providing a feasible solution for applying neural networks to specific engineering applications.

Author Contributions

Conceptualization – BJH and WLS ; methodology – BJH and QBY; formal analysis – BJH and DJW; investigation – SYX; resources – QBY; writing-original draft preparation –BJH, DJW and SYX; writing-review and editing – BJH and QBY; visualization – SYX; supervision – WLS. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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Data Sharing Agreement

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