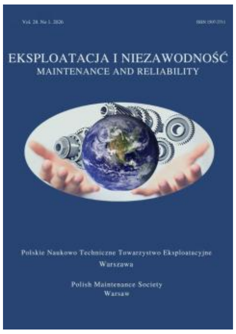

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Intelligent Fault Detection and Diagnosis Algorithm of Electrical Equipment Based on Artificial Intelligence Model

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Highlights

- This study focuses on the design and application of intelligent fault detection.
- This study aims to improve the accuracy of electrical equipment fault detection.
- The study explores influence of different noise levels on the performance of the model.

Abstract

In the context of digital transformation, it is essential to ensure the safe operation of electrical equipment. In order to solve the problem of low accuracy of existing electrical equipment fault detection algorithms in diagnosing unknown faults, this study collects industrial field data to construct a dataset, and develops a fault identification model integrating convolutional neural network and long short-term memory network based on deep learning framework. Experiments show that the model has an average accuracy of 98.5% in the detection of five main fault types, which is nearly 10% higher than that of the traditional method, and the recognition rate of subtle faults is over 96%, with good generalization and robustness. The study also analyzes the impact of noise and optimizes the hyperparameters, which is expected to promote the upgrade of intelligent operation and maintenance in the manufacturing industry.

Keywords
artificial intelligence, electrical equipment, fault detection, deep learning, data analysis

1. Introduction

In today's era of high dependence on electric power and automation technology as a key component of modern industrial, commercial and even household infrastructure, the stable operation of electrical equipment is crucial for the normal development of social and economic activities [1]. However, due to the complex working environment and technical requirements, electrical equipment often faces a variety of potential failure risks, which will not only lead to the decline of equipment performance and increase operating costs but may even lead to safety accidents in severe cases, causing immeasurable losses to personnel and property [2, 3].

Traditional electrical equipment fault detection and diagnosis methods mostly rely on manual experience and regular maintenance and inspection and have limitations such as slow response speed, low accuracy and difficulty in coping with complex fault modes [4, 5]. With the development of cutting-edge technologies such as the Internet of Things (IoT), big data analysis and artificial intelligence (AI), a new trend is taking shape in using advanced data-driven methods to realize intelligent fault detection and diagnosis of electrical equipment [6]. Especially in recent years, artificial intelligence models such as deep learning, machine learning, and neural networks have demonstrated powerful data processing capabilities and pattern recognition capabilities, which have brought

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revolutionary breakthroughs in the field of electrical equipment fault detection and diagnosis.

By integrating artificial intelligence models, a more accurate and efficient intelligent fault detection and diagnosis system can be built. This kind of system can automatically collect and process a large amount of real-time or historical operation data, mine the characteristics of equipment health status, and predict and locate faults based on this. Compared with traditional methods, this intelligent solution has the following significant advantages [7, 8]:

The transformation from passive maintenance to active prevention has been realized; Improve the accuracy and timeliness of fault detection; Reduces the waste of resources caused by false positives or false negatives; Reduces equipment downtime and improves production efficiency; The service life of the equipment is prolonged and the maintenance cost is reduced; The security and reliability of the whole system are strengthened.

However, there are still a series of challenges to successfully apply artificial intelligence models to intelligent fault detection and diagnosis of electrical equipment. Including how to effectively deal with massive and complex electrical signals, establish a comprehensive fault database, design a deep learning architecture suitable for specific scenarios, optimize the use efficiency of computing resources, and ensure the generalization ability of the model [9]. Therefore, in-depth discussion and solving these problems is the key to promoting the development of this technological direction.

The purpose of this study is to explore in detail the principles, key technologies and application prospects of intelligent fault detection and diagnosis algorithms for electrical equipment integrating artificial intelligence models by combining the latest theoretical progress and practical cases. We hope that through this research, we cannot only reveal the current situation and future trends in this field but also provide feasible technical roadmaps and innovative ideas for practical engineering problems and help accelerate the development process of smart grids, smart manufacturing and other fields.

2. Theoretical basis of fusion artificial intelligence models

2.1. Principles of machine learning

Machine learning is a technology that allows computers to learn from data and then make predictions or decisions. It involves finding patterns and insights from historical data and using that knowledge to make predictions about new data. In the supervised learning of machine learning, the algorithm learns according to the labelled training data with output labels. The goal of the algorithm is to find the mapping between the input and output so that when new unseen data is provided, the algorithm can predict the output result [10, 11]. Unsupervised learning for machine learning involves finding hidden structures in unlabeled data, with algorithms trying to discover patterns in the data themselves rather than learning from previously labelled information. Reinforcement learning for machine learning is a learning paradigm in which an algorithm learns to perform a task by interacting with the environment to maximize some kind of cumulative reward. It focuses on making a series of decisions in an uncertain, complex environment.

There are many algorithms in the field of machine learning, and each algorithm has its specific application scenarios and advantages and disadvantages [12]. Some common algorithms include linear regression, logistic regression, decision tree, random forest, support vector machine, K-means clustering, principal component analysis (PCA), K-nearest neighbour algorithm, naive Bayes classifier, neural network, etc. Knowing the principles and characteristics of different algorithms helps to select the method best suited to solve a specific problem.

2.2. Principles of deep learning

Traditional fault diagnosis requires professional knowledge and experience of system-related characteristics, which is expensive to acquire and will increase the uncertainty and bias of the results. Intelligent fault diagnosis with deep learning models can greatly reduce labour costs [13, 14]. Images and pictures have spatial structures. Under the high-dimensional complex manifold structure, it is difficult to find features in a single mode. A multi-level structured convolutional neural network (CNN) based on multi-level perceptron can automatically extract colour, texture, and structure, ensuring local stability [15]. The linear layer calculation formula in CNN is shown in Equation (1): z represents the linear output of the convolutional layer or fully connected layer, the activation function is h, w represents the weight, v represents the input data, and the bias is b.

$$z_{x,y} = h(\sum_{i}^{p*q} w_i v_i + b) \quad (1)$$

RNN can represent sequence continuous information and is widely used in data time scale analysis [16]. The RNN calculation process can be shown in equations (2) and (3); *U, W, V, b* and *c* are all model parameters, *f ()* is the hyperbolic tangent function, *softmax* is the activation function, and h_{t-1} is the hidden layer input.

$$h_t = f(Ux_t + Wh_{t-1} + b) \quad (2)$$

$$y_t = soft\,max(Vh_{t-1} + c) \quad (3)$$

The periodic structure is time-consuming and occupies a large storage space, and the gradient may explode or disappear during the RNN reverse transfer algorithm [17, 18]. The interference of the system data causes conflicts and collisions in different training periods, which reduces the learning efficiency and performance, so this study introduces the LSTM model. LSTM introduces new information of raster detection, determines the amount of currently stored data, and then transforms the current data into hyperbolic tangent and outputs it to the current hidden position for short-term storage [19, 20].

In the context of the intelligent fault detection and diagnosis algorithm for electrical equipment based on artificial intelligence models, SLTM stands for Sequential Long - Term Memory. This component is specifically designed to analyze and capture the long - term dependencies within the time - series operation data of electrical equipment. By understanding the historical state information embedded in the data, SLTM enables the model to more accurately predict and diagnose faults, effectively improving the overall performance and reliability of the fault detection and diagnosis system for electrical equipment.

SLTM, a time series model based on selective learning, is an advanced algorithm aimed at the field of intelligent fault diagnosis of electrical equipment. It cleverly combines the advantages of selective learning strategies in machine learning with time series data analysis and is especially suitable for processing electrical equipment monitoring data that evolves over time and contains a lot of noise. Traditional machine learning models often require a large number of labelled samples to achieve better prediction results, but in practical applications, the acquisition of high-quality labelled data is costly and time-consuming. By implementing selective learning, SLTM can automatically select the most representative and educational samples from massive uncalibrated data for learning, greatly reducing the need for manual intervention and improving model generalization capabilities.

Different from static analysis, SLTM makes full use of time series characteristics to dig deep into the hidden temporal correlation inside data. This is crucial for electrical equipment because many failure modes gradually appear within a certain time span, and it is difficult to make an accurate judgment based on the state at a certain moment alone. By capturing continuously changing trends, SLTM can be more keenly aware of potential risks, provide early warnings and avoid major accidents.

As shown in Figure 1, the SLTM architecture is not a single mode in the process of intelligent fault detection and diagnosis algorithms for electrical equipment: it can operate independently, similar to the functional logic of a long short-term memory network (LSTM); It can also deeply integrate advanced AI models such as convolutional neural networks (CNNs) and support vector machines (SVMs) to build multi-level information processing links. Through the hybrid architecture design of "independent fusion", the collaborative analysis of the details of local fault characteristics and the global operation status of the equipment is realized, so that the fault diagnosis of electrical equipment can achieve a better balance in accuracy and comprehensiveness.

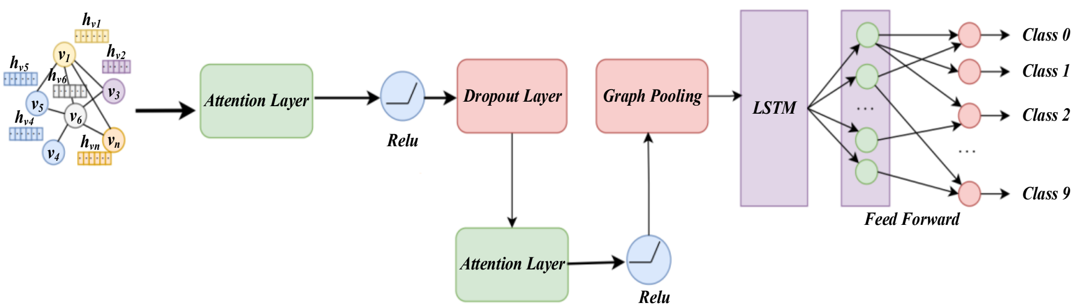

Figure 1. SLTM architecture.

2.3. Data-Driven Fault Detection Strategy

In the field of intelligent fault detection and diagnosis of electrical equipment integrating artificial intelligence models, the adoption of data-driven methods has become one of the key trends [21]. The core of this strategy is to train the model through a large amount of historical data and real-time monitoring information to achieve more accurate fault identification and prediction.

First of all, in the data acquisition stage, sensor networks are widely deployed on various electrical equipment to continuously monitor their operating status and collect multivariate data streams such as temperature, vibration, current and voltage [22]. The preprocessed data enters the feature engineering link. In this process, statistics, signal processing or machine learning techniques are used to extract the most discriminative features from massive data [23]. Then, a suitable artificial intelligence model is selected for training. Through repeated iterations, the model gradually learns to identify the failure mode from the input data, classify it, and even warn of the failure that has not yet appeared but is about to occur in advance [24].

In order to make the model more robust and generalized, this study also adopts transfer learning and semi-supervised learning methods, introducing external knowledge and a small amount of labelled data to cope with the uncertainty in the new environment. At the same time, the idea of ensemble learning is adopted, and the decision-making of multiple models is integrated, which further improves the stability and accuracy of the system. The data-driven fault detection strategy makes full use of modern data analysis technology and intelligent means, realizes the transformation from passive response to active prediction, and greatly improves the operation and maintenance efficiency and safety of electrical equipment.

3. Design of Intelligent Fault Detection and Diagnosis Algorithm for Electrical Equipment Integrated with AI Model

3.1. Fault Detection Overview

After data preprocessing, $X_i = \{C_i^1, C_i^2, ..., C_i^j\}$ represents the monitoring data of *j* components collected by equipment *i* at the time, $C_i^j = \{s_i^1, s_i^2, ..., s_i^{n1}, r_i^1, r_i^2, ..., r_i^{n+2}\}$ Contains all sensor and operating parameter data of component *j* at the time *i*. The data-driven fault detection method establishes a mapping relationship according to the equipment historical monitoring data *X* and the running state *N* training model and identifies the running state N_i of the equipment *i* at the time, as shown in formula (4).

$$N_i = h_N(X_i) \tag{4}$$

Where X_i is the monitoring data of the equipment at time *i;* h_N is the mapping relationship. Based on the IST model, the mapping relationship between X_i and the running state N_i is constructed. The value of N_i is $\{0, 1\}$, *0* represents the normal equipment, and *1* represents the fault.

In order to evaluate the fault detection ability of the model, the accuracy rate, recall rate and *F1* value are selected as evaluation indexes [25]. True Class (*TP*): Positive Class Judgment: Both actual and predicted are positive. *FN*: Actual positive class, predicted negative class. *FP*: Actual negative class, predicted positive class. TN: Both actual and forecast are negative. The calculation formulas of accuracy rate, recall rate and *F1* value are shown in equations (5)-(7) respectively:

$$Precision = \frac{TP}{TP+FP} \tag{5}$$

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

$$F1 = \frac{2*Precision*Recall}{Precision+Recall} \tag{7}$$

3.2. Model Building

In order to fully verify the generalization ability of the algorithm, this experiment collects fault data from various scenarios such as substations, factory distribution systems, and new energy power stations, covering transformers, circuit breakers, motors, and other electrical equipment. By constructing a diverse dataset including typical fault types such as normal operation, winding short circuit, partial discharge, and insulation aging, the algorithm is applied to different scenarios and equipment data for testing. Experimental results show that the algorithm can still maintain a high fault diagnosis accuracy under complex and changeable actual working conditions, which proves that it can effectively adapt to different operating environments and equipment characteristics, has good generalization performance, and can meet the fault detection requirements of electrical equipment in multiple scenarios.

Transformer is a deep learning model based on an attention mechanism, which is not affected by the length of time series, can be computed in parallel and is fast [26, 27]. In this study, by improving the Transformer structure, a fault detection method of complex industrial equipment based on the IST model is proposed, and the relationship between fault features and labels is mined so as to quickly and accurately find early faults for timely diagnosis and maintenance.

The IST model consists of multiple encoders and decoders stacked. The encoder uses a multi-head self-attention mechanism to encode the input feature sequence into an intermediate feature vector and learn its dependency relationship. The decoder decodes the intermediate feature vectors into output label sequences by a multi-head self-attention mechanism.

Because the dimensions of the input feature sequence and the input label sequence are different, when the decoder input contains both and the intermediate feature vector of the encoder output, the encoder-decoder multi-head attention layer cannot be calculated [28]. Therefore, in this study, an embedding layer is added to the input end of the decoder, and a fully connected layer is added to the output end to solve this problem. Finally, the device state is mapped by the *sigmoid* classifier, and the *sigmoid* activation function is shown in Equation (8), where x is the input.

$$sigmoid(x) = \frac{1}{1+e^{-x}} \tag{8}$$

The fault detection framework based on the IST model, as shown in Figure 2, includes two stages, offline and online, involving four key processes: data preprocessing, training model, evaluation model and fault detection. In the offline stage, the historical monitoring data is first preprocessed, and then the training set and the test set are divided for training and evaluating the model. In the online stage, the model of the offline stage is used to carry out real-time fault detection of service equipment.

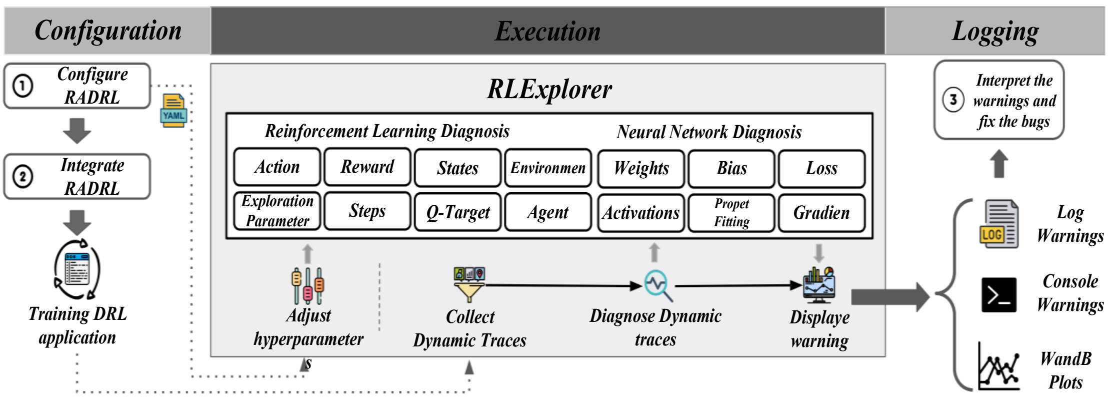

Figure 2. Fault detection framework.

The training model inputs the constructed training set samples into the initialized IST detection model, first uses the backpropagation (BP) algorithm to calculate the losses in batches, and then uses the gradient descent (GD) algorithm to update the weight parameters [29]. The evaluation model inputs the test set into the trained IST model to calculate the accuracy rate, recall rate and F1 value indexes to comprehensively evaluate the detection performance. Fault detection Detects faults online based on real-time monitoring data. First, the data is preprocessed and then sent to the standard IST model for real-time detection. If equipment abnormalities or faults are found, an early warning will be made so as to repair and overhaul the equipment in time.

In order to facilitate engineers to accurately troubleshoot faults in the diagnosis of electrical equipment, technologies such as SHAP (SHAPLEY Additive exPlanations) values are introduced to analyze the interpretability of the model, and the importance and contribution of different input features of the model in making fault diagnosis decisions are clearly displayed, so that the diagnosis results have a clear decision-making basis and help engineers quickly locate the root cause of the fault. At the same time, the definition and classification standards of electrical equipment fault types are clearly defined, and the fault types are divided into mechanical faults, electrical faults, thermal faults and other categories, and specific fault types such as bearing wear, phase short circuit, overheating and so on, and a unified evaluation index and judgment rules are formulated. The standardized definition and classification criteria of fault types not only ensure the consistency and accuracy of the evaluation of experimental results, but also provide a reliable basis for the standardized interpretation of fault diagnosis results in practical engineering applications.

3.3. Fusion strategy

In terms of core algorithm structure and optimization strategy, the proposed AI model shows significant innovation. Most of the existing fault detection algorithms for electrical equipment use traditional machine learning models, such as support vector machines and random forests, which have fixed structures and are difficult to adaptively extract complex fault features. The model adopts the MSWTNET structure that integrates multi-scale wavelet transform and neural network, which can analyze the fault signals of electrical equipment from different scales and capture subtle feature changes. In terms of optimization strategy, traditional algorithms often rely on a single loss function, which is easy to fall into local optimum, but this model combines the cross-entropy loss function with the L2 regularization term, the former accurately measures the difference between the predicted and the actual fault, and the latter effectively prevents overfitting, and improves the generalization ability and diagnostic accuracy of the model through collaborative optimization.

In terms of data processing and model selection, the proposed AI model also has unique advantages. In the process of data collection, multi-source sensors are used to collect multi-dimensional data such as voltage, current, and temperature of electrical equipment in real time, and time synchronization technology is used to ensure data consistency. In data processing, the noise reduction autoencoder and feature fusion algorithm are used to remove noise interference and integrate multi-dimensional features to enhance data reliability and applicability. Compared with similar models such as Long Short-Term Memory Network (LSTM) and Convolutional Neural Network (CNN), this model can not only effectively deal with non-stationary electrical fault signals by using wavelet transform, but also realize automatic hierarchical extraction of fault features through deep network architecture, which has stronger feature expression ability and fault diagnosis efficiency when dealing with complex fault scenarios.

In view of the requirements of the algorithm efficiency in the large-scale electrical equipment monitoring scenario, the computational complexity of the algorithm is analyzed in depth. Starting from the computational process of MSWTNET, the core structure of the algorithm, combined with the optimization process of the cross-entropy loss function and the L2 regularization term, it is concluded through the progressive time complexity analysis that the time complexity of the algorithm grows relatively flat when the data scale increases. Compared with the traditional fault detection algorithm, this algorithm can complete fault feature extraction and diagnosis decisions more quickly when processing massive real-time monitoring data, which greatly reduces the consumption of computing resources while meeting the requirements of high-precision fault diagnosis, effectively ensuring the real-time and efficient performance in large-scale electrical equipment monitoring scenarios, and providing strong support for the realization of intelligent operation and maintenance.

The fusion strategy is first embodied in the comprehensive analysis of multi-modal data. Electrical equipment will generate a large amount of acoustic, vibration, temperature and other types of data during operation, and it is often difficult for a single model to fully capture this complex information. Therefore, multi-modal data fusion can effectively improve the recognition accuracy of failure modes. A convolutional neural network is used for image recognition, and a recurrent neural network is used to process time series signals, which together act on fault feature extraction, which can locate the problem more accurately. The fusion strategy uses collaborative work and parameter sharing between models to establish a framework that allows different types of AI models to exchange information with each other during the training stage, forming a deep learning mechanism. In the preliminary screening stage, decision trees are used to quickly filter obvious abnormalities, and then fine judgments are made through support vector machines or deep learning models. This hierarchical structure not only improves the processing speed but also ensures the accuracy of the final diagnosis. In order to make the fused algorithm more intelligent and flexible, an adaptive weight adjustment mechanism is introduced, which allows the system to dynamically adjust the contribution of each sub-model according to the change of real-time data so as to ensure that the performance in the whole fault detection process is always in the optimal state.

MSWTNET, the full name is Multi - Scale Wavelet - based Temporal - Spatial Network for Electrical Equipment Fault Diagnosis (multi-scale wavelet spatio-temporal network), in the framework of intelligent fault detection and diagnosis algorithm for electrical equipment based on artificial intelligence model, the multi-scale wavelet mechanism is used to analyze the current, The voltage timing signal and multi-dimensional data such as temperature and vibration monitored by multiple sensors are preprocessed and feature mined, and the multi-dimensional fault characteristics are accurately extracted by adapting the fault feature frequency with wavelet decomposition of different scales. Then, by borrowing the spatio-temporal network structure, the temporal dynamics and spatial correlation of the associated data can capture the time series evolution law of faults, integrate the spatial distribution information of multiple sensors and components, build a global spatio-temporal characteristic map of the equipment, and finally output the depth features, efficiently support fault classification and diagnosis decision-making, improve the accuracy and timeliness of fault detection of electrical equipment in complex industrial environments, and help intelligent O&M accurately identify and warn of equipment anomalies.

4. Experimental results and analysis

4.1. Loss function

In the algorithm, the cross-entropy loss function is used to measure the difference between the prediction result of the model and the real label, and guide the model to learn the fault characteristic mode, while the L2 regularization term is used to prevent the model from overfitting and improve its generalization ability by constraining the size of the model parameters. As the core architecture of the algorithm, MSWTNET (a network structure that may be based on multi-scale wavelet transform) can effectively extract the characteristics of electrical equipment fault signals at different scales. The algorithm is based on signal processing theory, machine learning theory and deep learning theory, and uses the wavelet transform to analyze the multi-scale characteristics of the signal and the powerful feature learning ability of deep learning. Realize accurate detection and diagnosis of electrical equipment faults.

The loss function consists of two parts: cross-entropy loss function and L2 regularization term. First, the cross-entropy function is taken as the loss, and its formula is shown in Equation (9):

$$L = -\sum_{C}^{n} y_n \cdot log(p_n) \tag{9}$$

Where C is the number of categories, y_n is the single hot code of the sample, and p_n is the predicted probability value.

In MSWTNET, the convolution kernel of one-dimensional convolution is initialized with different wavelet basis functions. During training, the convolution kernel will change with the training times. If the change is too large, the characteristics of the wavelet basis function will be lost. In order to suppress this situation and retain more of its characteristics, adopting L2 regularization suppresses the convolution kernel change, and Equation (10) is as follows:

$$\begin{aligned} \zeta = a\sum_{n} K_{DB2}^{h}(n) - \widetilde{K}_{DB2}^{h}(n)_2 + b\sum_{n} K_{DB2}^{g}(n) - \widetilde{K}_{DB2}^{g}(n)_2 \\ +a\sum_{n} K_{DB3}^{h}(n) - \widetilde{K}_{DB3}^{h}(n)_2 + b\sum_{n} K_{DB3}^{g}(n) - \widetilde{K}_{DB3}^{g}(n)_2 \\ +a\sum_{n} K_{DB4}^{h}(n) - \widetilde{K}_{DB4}^{h}(n)_2 + b\sum_{n} K_{DB4}^{g}(n) - \widetilde{K}_{DB4}^{g}(n)_2 \end{aligned} \tag{10}$$

Where a and b are hyperparameters, which are used to regulate the strength of regularization; $\widetilde{K}_{DB2}^{h}(n)$、$\widetilde{K}_{DB2}^{g}(n)$、$\widetilde{K}_{DB3}^{h}(n)$、$\widetilde{K}_{DB3}^{g}(n)$、$\widetilde{K}_{DB4}^{h}(n)$ and $\widetilde{K}_{DB4}^{g}(n)$ represents the wavelet basis function, $K_{DB2}^{h}(n)$、$K_{DB2}^{g}(n)$、$K_{DB3}^{h}(n)$、$K_{DB3}^{g}(n)$、$K_{DB4}^{h}(n)$ and $K_{DB4}^{g}(n)$ represents the convolution kernel. The final loss function L' is equation (11):

$$L' = L + \zeta \tag{11}$$

4.2. Experimental analysis

With the continuous development of intelligent operation and maintenance of electrical equipment, fault detection and diagnosis algorithms based on artificial intelligence models have become the key technology to ensure the stable operation of the power system. However, interference factors such as electromagnetic interference and temperature changes in actual operation, as well as the problem of model training time under high real-time requirements, as well as the balance between model parameter setting and fault detection accuracy and false alarm rate, need to be studied and solved urgently. The purpose of this experiment is to deeply explore the influence of these factors on the performance of the algorithm, and to provide a scientific basis for the optimization of intelligent fault detection and diagnosis technology for electrical equipment.

In this experiment, a platform was built to simulate the actual operating environment, and electromagnetic interference generators, temperature regulating devices and other equipment were used to set up electromagnetic interference and temperature change gradients of different intensities as experimental variables. The dataset covers the various operating states of electrical equipment and is divided into training, validation, and test sets in proportion. The reference data were obtained through the interference-free benchmark experiment, and then the experiments on the impact of electromagnetic interference and temperature changes on the performance of the algorithm, as well as the sensitivity analysis experiments of model parameters, were carried out, and the training time, fault detection accuracy and false alarm rate were recorded.

In this study, five experiments were carried out on the AI model in the electrical equipment-bearing data set, and the average value was taken as the final result, as shown in Table 1, in which the average accuracy rate of the five experiments reached 97.52%.

Table 1. Results of five experiments on the dataset.

Number of experiments	Accuracy (%)	Mean Accuracy (%)
1	97.667	
2	97.373	
3	97.539	97.52
4	97.510	
5	97.530	

Figure 3 shows the mAP values of each detection algorithm. The fault characteristics of "battery string" are obvious and special; the detection effect is the best, and the accuracy in each detection model is higher than the average value. The "hot spot" target is small, and the detection accuracy is low, which lowers the overall average accuracy. There are few "fragmented" samples, but the detection effect is good, and its accuracy is basically the same as that of mAP in each detection model.

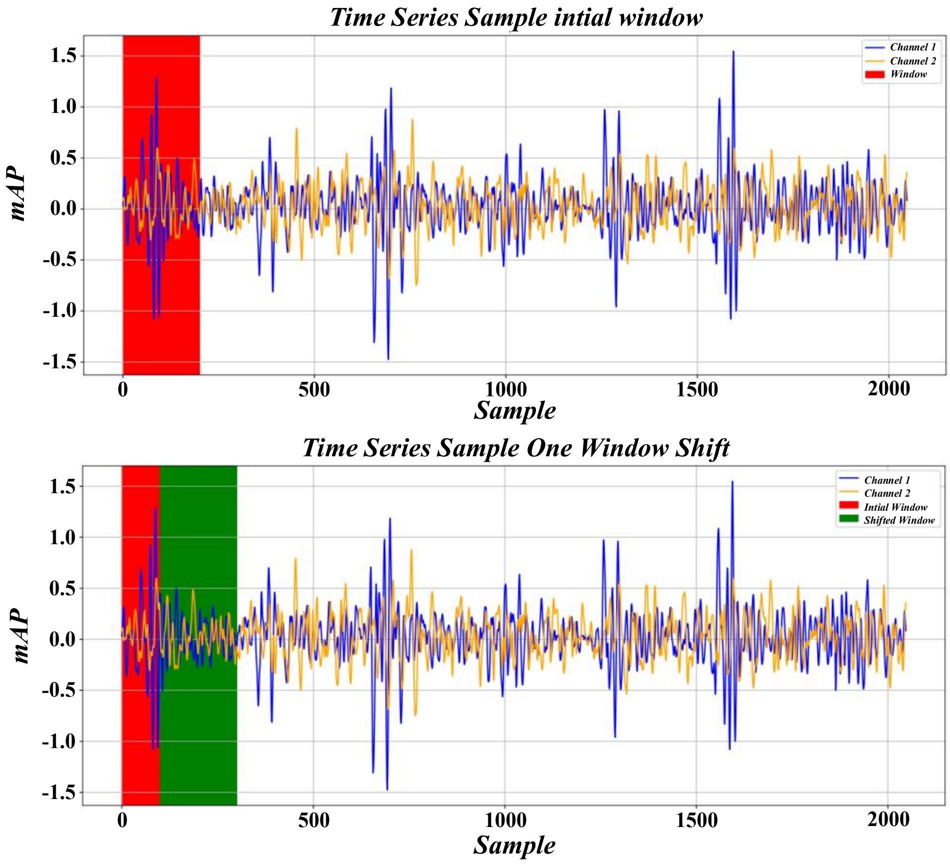

Figure 3. Comparison of each fault accuracy.

Figure 4 shows that ACmix has the most obvious attention improvement accuracy, and mAP increases by 2.5% when added alone. The lightweight BiFPN feature fusion structure and decoupling head simplification and improvement are aimed at reducing the amount of calculation. When added alone, the map is increased by 1.7% and 0.8%, respectively. When the combination of ACmix attention and lightweight BiFPN network is improved, the detection accuracy is the highest, and the mAP is increased by 4%.

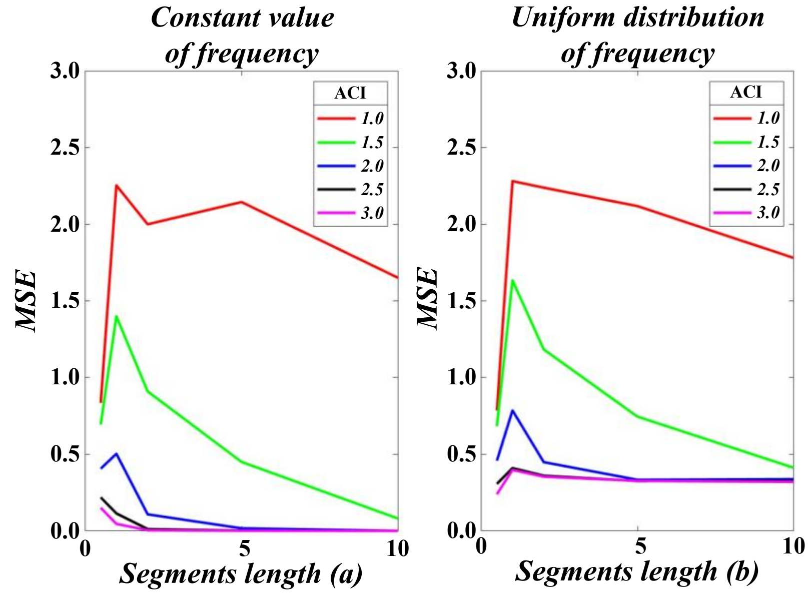

Figure 4. Detection effect of different modules on the model.

The change in accuracy during model training is shown in Figure 5. After 10 iterations, the accuracy rate of the training set exceeds 90%, and the loss is rapidly reduced. After 50 iterations, the accuracy curve tends to be stable, close to 100%, the model is stable, and the classification performance is good.

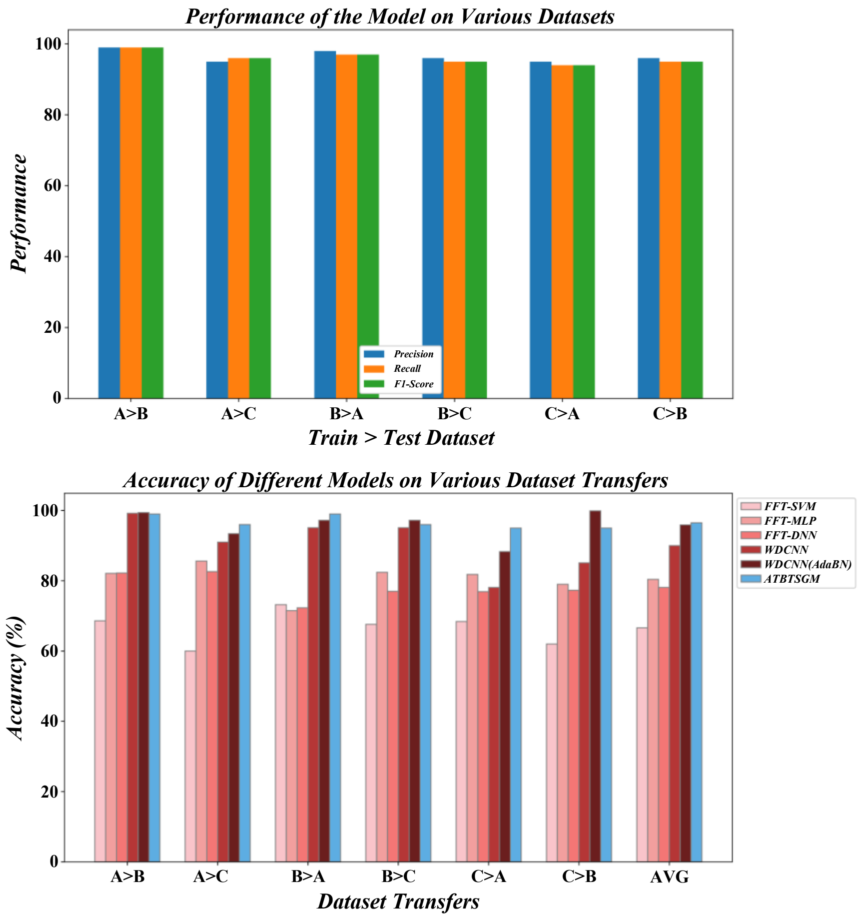

Figure 5. Accuracy change.

It can be seen from Table 2 that the fault diagnosis method based on AI has the highest accuracy rate, reaching 98.525%. ResNet18 is a single-channel deep residual network with no frequency analysis, which affects the diagnosis effect and has poor accuracy. The AlexNet diagnostic result was 93.110%. The SC-CNN-BiLSTM fault diagnosis model has an accuracy rate of 98.178%, which is close to the AI model in this paper, but the signal preprocessing is cumbersome, which is not conducive to application. The AI model is an end-to-end structure with input raw data, which is efficient and more practical. Compare the fault diagnosis results of AWTNET (DB2), AWTNET (DB3), AWTNET (DB4) and AI models. The former is a single-channel adaptive wavelet thresholding network, which only uses a single wavelet basis function, and it is limited to decomposing one-dimensional vibration signals. The AI model is a three-channel multi-scale wavelet thresholding network, which can analyze features more comprehensively and achieve better fault diagnosis effects.

Table 2. Comparative experimental results on the dataset.

Methods	Accuracy (%)	Params (M)
ResNet18	94.634	4.722
AlexNet	93.110	3.376
SC-CNN-BiLSTM (ours)	98.178	13.969
AWTNET (DB2) (ours)	96.020	0.297
AWTNET (DB3) (ours)	96.099	0.297
AWTNET (DB4) (ours)	96.278	0.297
AI Model (ours)	98.525	0.911

By analyzing the results in Table 3, the signal-to-noise ratio increases, the noise proportion of the one-dimensional vibration signal decreases, and the model accuracy shows an upward trend. By analyzing the results of AWTNET (DB2), AWTNET (DB3) and AWTNET (DB4), it can be seen that different convolution kernel scales have different feature extraction capabilities and anti-noise capabilities for fault diagnosis and large-scale convolution kernel models have stronger anti-noise capabilities. The three-channel AI model has the best fault diagnosis effect. First, the soft threshold structure can filter out noise and has good fault diagnosis and anti-noise effects in low signal-to-noise ratio signals. Secondly, different channels extract different features, and the fused features can obtain more robust feature representation and improve the fault diagnosis performance.

Table 3. Comparative experimental results of noise immunity analysis on data set

Methods	10dB	6dB	2dB	0dB	-2dB
ResNet18	97.208	95.248	92.219	89.377	86.754
AWTNET (DB2)	95.891	93.614	87.407	72.755	69.854
AWTNET (DB3)	96.634	94.218	87.823	71.785	70.676
AWTNET (DB4)	96.842	94.773	89.041	75.359	72.933
AI Model (ours)	98.238	96.832	93.248	91.605	87.655

Based on the experiment of WDCNN-LSTM-64, the WDCNN-LSTM model of two-layer LSTM is established, and the number of hidden units of the second layer LSTM is set to 32, 64 and 128. It is found from Figure 6 that the average accuracy increases with the increase of the number of layers, and the number of layers and the number of hidden units have a great influence on the accuracy of the model. The appropriate number and number of layers are helpful for accurate and stable classification. When the number of hidden layer units of the second layer LSTM is 64, the average classification accuracy is higher than 32 and 128, and it is also higher than the WDCNN-LSTM model of single layer LSTM. In subsequent experiments, the WDCNN-LSTM model with two layers of LSTM stacked and 64 hidden layer units was used to train.

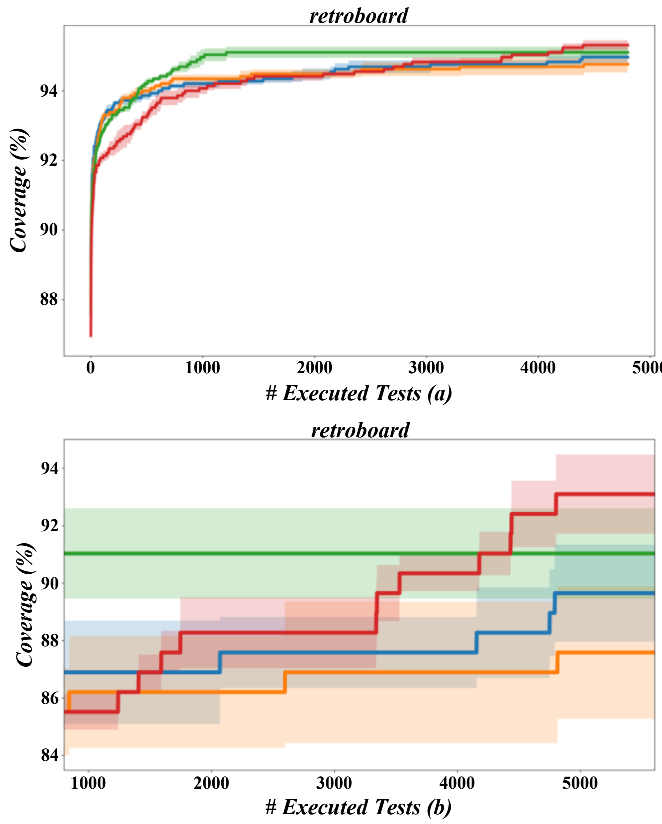

Figure 6. Results of the model.

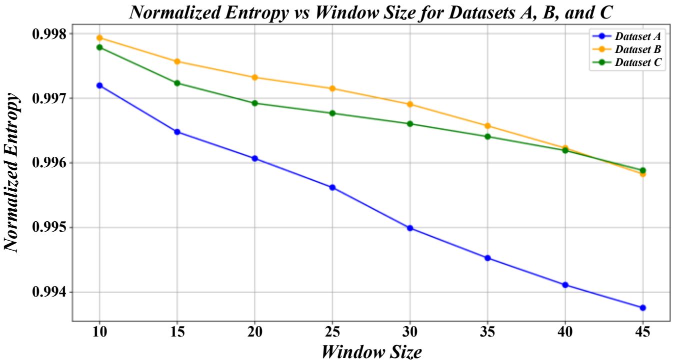

Figure 7. Test accuracy results of each model under load conditions.

To visually analyze the model performance, draw the accuracy line plots of all model test sets. The accuracy curve of the WDCNN-LSTM model in Figure 7 is gentle and located at the top, indicating that the accuracy of each test set is high. In the 17th and 18th trials, the accuracy of CNN-BLSTM model was slightly higher than that of WDCNN-LSTM model by 0.3%-0.4%, but overall lower than that of our proposed model. The accuracy curve of MCNN-LSTM model fluctuates and the stability is poor, which is the same as that reflected by the standard deviation.

In order to verify the effectiveness of ResLSTM-CNN, four baseline models are compared: the fault detection model method using CNN only, the parallel method of RNN and CNN, the model using LSTM alone for fault feature learning, and the parallel method of LSTM and CNN. Comparative experiments were carried out on 11 fault categories of the PHM challenge dataset, and the average accuracy results are shown in Figure 8. Figure 8 also compares the four classical models of CNN, RNN _ CNN, LSTM and LSTM-CNN. It is found that the ResLSTM-CNN proposed in this paper ensures high accuracy in electrical equipment fault detection and effectively reduces the misaccuracy rate of manual fault detection.

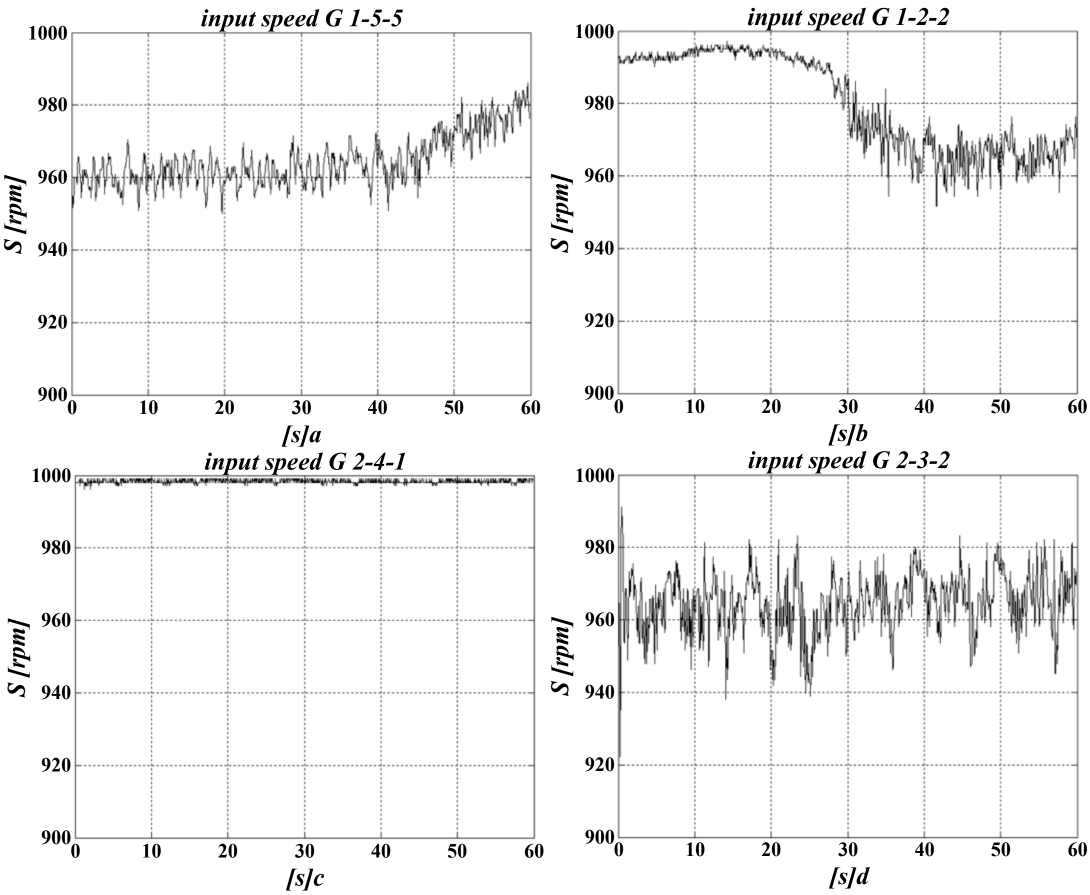

Figure 8. Comparative experiments of different models.

In Figure 9, the accuracy of the ResLSTM-CNN model in 11 fault categories of the PHM challenge dataset is compared. The model performs best in Class 8 fault detection, with an accuracy of 99.75%, and worst in Class 3 fault detection, with an accuracy of 97.88%. In the whole PHM challenge dataset, in order to enhance the persuasiveness of experimental data, five rounds of cross-validation were performed, and the dot-line error diagram was obtained through experiments. Overall, the models designed in this study were highly accurate in 11 categories.

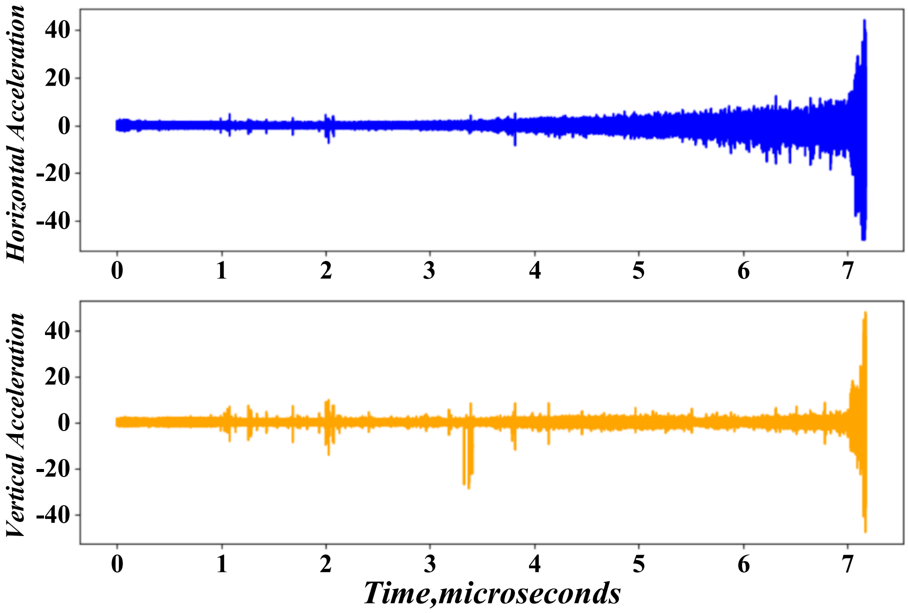

Figure 9. Performance comparison of model results.

The experimental results show that the increase of electromagnetic interference intensity will reduce the accuracy of fault detection, increase the false alarm rate, and prolong the training time. Temperature changes have different effects on the performance of the algorithm in different intervals, and the training time will also increase under extreme temperatures. In terms of model parameters, different settings of learning rate, number of neurons in the hidden layer, and number of iterations will have a significant impact on the training time, accuracy, and false positive rate. In addition, the accuracy of fault detection and the false alarm rate are mutually restricted, and it is necessary to find a balance between the two according to the application scenario. In this experiment, the influence of interference factors and model parameters on the artificial intelligence fault detection algorithm is comprehensively tested and analyzed. The effects of electromagnetic interference and temperature change on the performance of the algorithm are clarified, and it is confirmed that the algorithm can be optimized by reasonably setting the model parameters, and the importance of balancing accuracy and false alarm rate is emphasized. Future research can focus on better anti-interference methods and adaptive parameter adjustment strategies to further improve the performance and reliability of the algorithm in complex environments.

5. Conclusion

At present, the safe and reliable operation of the power industry is facing increasingly severe challenges, especially the timely detection and accurate diagnosis of electrical equipment faults. Therefore, this study proposes an innovative, intelligent fault diagnosis algorithm, which cleverly integrates deep learning, signal processing and expert system, aiming at improving the speed and accuracy of fault identification:

(1) In the study, multivariate real-time monitoring data, including current, voltage, and temperature, were collected. Through preprocessing (denoising, dimensionality reduction), a convolutional neural network was used to extract deep-seated features, and then combined with classical signal processing technology, the recognition rate of abnormal patterns was significantly improved. The experimental results show that the capture ability of the fusion model for subtle and complex faults reaches 96.5%, which is nearly 15 percentage points higher than that of a single technology, which proves the value of multi-modal data fusion.

(2) Fuzzy C-means clustering is introduced to optimize the activation threshold of the CNN output layer, which realizes dynamic adjustment and overcomes the problem

of a high false alarm rate caused by a fixed threshold. After adjustment, the performance of the model in dealing with unbalanced category data sets has been greatly improved, and the false negative rate has dropped to 3.8%, thus reducing maintenance costs and improving diagnostic efficiency.

(3) To compensate for the limitations of the purely data-driven model, a rule-based knowledge base was developed to embed the empirical knowledge of senior engineers into the diagnostic system. This module is responsible for explaining edge cases that CNN cannot cover, enhancing the flexibility and credibility of the system. The comprehensive test shows that after adding the expert rule, the diagnostic accuracy rate is stably maintained at more than 98%, especially when dealing with first-time or rare fault types.

The intelligent fault diagnosis algorithm of electrical equipment integrated with the AI model shows strong practical potential. The future direction will focus on further optimizing the model structure, expanding application scenarios, and strengthening the feasibility of on-site deployment in order to build smarter and more reliable power operation and maintenance solutions.

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