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Fault diagnosis method of fire-proof oil system in thermal power plant based on real-time monitoring

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Abstract

INTRODUCTION: Fire-proof oil systems in thermal power plants are prone to pump wear, leakage, oil degradation, and valve jamming, threatening operational safety. Real-time fault diagnosis is required.
OBJECTIVES: To develop a real-time and accurate fault diagnosis method for fire-proof oil systems.
METHODS: A multi-sensor monitoring framework integrating pressure, flow, temperature, and oil-quality signals was established. A lightweight deep learning model based on multi-source feature fusion was constructed, with a confidence-driven decision mechanism to reduce the influence of low-quality samples. Experiments were conducted on an open hydraulic-system dataset under multiple operating conditions.
RESULTS: The proposed method achieved accuracies of 0.96–0.93 and AUC values of 0.98–0.97. Average diagnostic time was 3.17–3.58 ms, with alarm delays of 49.36–54.82 ms. The model outperformed MBDNN and TDANet in accuracy, efficiency, and robustness under noise.
CONCLUSION: The proposed framework enables reliable real-time fault diagnosis of fire-proof oil systems and supports intelligent operation and maintenance in thermal power plants.

Keywords: thermal power plant, fire-proof oil system, real-time monitoring, fault diagnosis, multi-source feature fusion

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1. Introduction

With the continuous development of China's power industry, large-capacity and high-parameter thermal power generating units occupy an important proportion in the power grid, and the safe and stable operation of the units is directly related to the reliability of the power grid and the safety of energy supply [1]. On one hand, in the complex auxiliary machinery and control system of thermal power unit, fire-proof oil system, as a key safety guarantee device, undertakes the hydraulic drive function of steam turbine regulation and protection mechanism [2,3]. On the other hand, participating in fire prevention and accident isolation in an emergency, whether its operation state is reliable or not directly affects the safety of the unit and the prevention and control ability of fire accidents [4]. Fire-proof oil system is usually in the working environment of high temperature, high pressure and strong coupling, and long-term operation is prone to many hidden troubles such as oil pump wear, valve jamming, pipeline leakage, filter blockage and oil quality deterioration [5,6]. Once this kind of fault develops into serious leakage or splash, it will easily lead to fire and even explosion accidents if it is superimposed on the high-temperature metal surface and electrical fire source. Even if it does not evolve into an accident, it may lead to slow response of the actuator and failure of protection actions, resulting in unplanned shutdown

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of the unit and economic losses [7,8]. Therefore, accurate and timely state perception and fault diagnosis of fire-proof oil system is an important link to improve the intrinsic safety level of thermal power units [9]. At the same time, the rapid development of Internet of Things (IoT), industrial big data and intelligent algorithms provides new technical conditions for building real-time monitoring and intelligent fault diagnosis methods for fire-proof oil systems [10,11]. However, the existing research focuses more on the main engine equipment, steam turbine vibration or lubricating oil system, and the systematic research on the fire-proof oil system, which is a key safety subsystem, is still insufficient, especially in the integrated method of "real-time monitoring-feature extraction-intelligent identification-online decision-making" and engineering implementation. There is still a lack of targeted and landing technical solutions [12,13].

Overall, existing research still has deficiencies in three aspects: First, insufficient fusion of multi-source monitoring information makes it difficult to fully characterize the complex state of the fire-resistant oil system. Second, the lack of explicit modeling for data quality issues limits the robustness of models in actual industrial environments. Third, the lack of effective characterization of the uncertainty of diagnostic results makes it difficult to meet the needs of online early warning and decision-making safety. Therefore, it is necessary to construct a fault diagnosis method framework integrating multi-source fusion, data quality control and uncertainty decision-making.

Therefore, this study conducts research on the real-time monitoring and intelligent fault diagnosis of the fire-resistant oil system in thermal power plants, and its main contributions can be summarized into the following three points:

(1) Aiming at the operating characteristics of high temperature, high pressure and strong coupling of the fire-resistant oil system, a real-time fault diagnosis framework integrating multi-source monitoring information such as pressure, flow, temperature and oil quality is constructed. This framework breaks through the limitations of traditional single-parameter or local signal analysis, and can characterize the state evolution characteristics of the fire-resistant oil system under complex operating conditions from multiple dimensions, providing more complete data support for the comprehensive identification of typical faults.

(2) To address the common problems in on-site monitoring data such as noise interference, outliers, missing values and time alignment deviations, a data quality evaluation and sample validity screening mechanism is designed. By performing quality scoring and low-quality sample suppression on multi-source monitoring windows, the reliability and consistency of input data are improved, thereby enhancing the robustness and stability of the fault diagnosis model in complex industrial environments.

(3) On the basis of the fault identification model, a confidence decision-making mechanism for online early warning scenarios is introduced, which jointly models the fault classification results and prediction confidence. It not only realizes the accurate distinction between normal states and multiple fault modes, but also provides risk prompts and decision compensation for low-confidence samples, thereby improving the interpretability, controllability and engineering application value of the diagnosis results.

2. Literature review

In recent years, with the rapid development of intelligent monitoring technology, industrial IoT and machine learning algorithm, the research on condition monitoring, fault diagnosis and predictive maintenance of power system and its key subsystems is gradually enriched. Existing studies have provided an important foundation for industrial equipment condition identification and intelligent operation and maintenance. However, research targeting the fire-resistant oil system of thermal power plants, a high-safety-level and strongly coupled operating object, remains relatively limited. To more clearly define the research orientation of this study, a literature review is conducted from three dimensions: condition monitoring technology of power equipment, fault diagnosis methods for oil-based systems, and the application of intelligent algorithms in industrial fault identification. A critical analysis is provided after reviewing each type of research.

(1) Condition monitoring technology of power equipment.

Condition monitoring technology is the basis of fault diagnosis, and its core lies in continuous acquisition, effective perception and feature recognition of equipment operating parameters [14,15]. In recent years, many scholars have carried out research on key parameters such as temperature, pressure and vibration, which laid an important foundation for subsequent intelligent diagnosis. Khamees and Altınkaya constructed a data acquisition system based on multi-source sensors from the point of view of the operation safety of generator sets, and synchronously monitored the main operation parameters [16]. The advantage of its research lied in improving the precision of data acquisition, but it relied too much on fixed measuring points, did not involve the complex coupling characteristics of oil systems, and had insufficient filtering mechanism for abnormal data. Such studies have primarily addressed the “perceptibility” of equipment operating conditions, providing a data foundation for subsequent fault identification. However, most of these studies focus on general equipment monitoring or the acquisition of a single type of physical quantity, and lack a systematic design for the collaborative perception of multi-source heterogeneous information including pressure, flow, temperature, oil quality and valve position in the fire-resistant oil system. Especially under operating conditions with coexisting high temperature, high pressure and dynamic disturbances, relying solely on fixed measuring points and conventional monitoring variables makes it difficult to fully characterize the evolution process of faults in the fire-resistant oil system. Therefore, how to construct a multi-parameter continuous online perception framework for the fire-resistant oil system has become an important entry point of this study.

(2) Fault diagnosis method of oil system.

Oil systems (such as lubricating oil system, hydraulic system and fire-proof oil system) have strong coupling characteristics of "pressure-flow-oil quality", and their faults are multi-source and early characteristics are not obvious, which makes fault diagnosis more difficult [17,18]. Recent research has made some progress in mechanism analysis and feature extraction. Chen et al. built an oil quality change model for lubricating oil system, and monitored the deterioration trend through multi-index fusion [19]. Although this method had advantages in oil-bearing faults, it failed to consider the comprehensive diagnosis problems of various faults such as abnormal pressure and pipeline leakage, and its application scope was limited. From existing achievements, studies on oil-fluid systems have begun to focus on the relationship between fault mechanisms and feature evolution, with certain accumulations particularly in oil degradation and wear state assessment. However, relevant studies often concentrate on single-type faults or single degradation processes, lacking a unified diagnosis framework for concurrent multi-fault scenarios under complex operating conditions. In addition, most research targets conventional hydraulic or lubrication systems, whereas fire-resistant oil systems fulfil the dual functions of fluid power transmission and safety protection, leading to more critical fault consequences and higher requirements for real-time performance, accuracy, and false alarm control. Therefore, conducting research on integrated multi-fault identification and real-time early warning for fire-resistant oil systems possesses significant theoretical significance and engineering value.

(3) Application of intelligent algorithm in industrial fault identification

With the development of Artificial Intelligence (AI), machine learning and deep learning methods have gradually become the hot research direction of industrial fault diagnosis, which can realize nonlinear feature mining and complex pattern recognition [20,21]. Hadroug et al. used support vector machine combined with pressure and vibration characteristics to classify mechanical equipment faults [22]. The results showed that its diagnostic performance was better than the traditional threshold method, but the model was sensitive to parameters and the feature engineering depended on manual design, so its applicability in large-scale real-time scenes was limited. Such studies indicate that intelligent algorithms can significantly improve the ability to identify complex fault patterns, serving as an important means to advance industrial fault diagnosis from experience-driven to data-driven. Nevertheless, existing research tends to focus more on classification accuracy itself, while paying insufficient attention to common industrial issues such as data noise, missing values, asynchronous time series, and uncertainty of boundary samples. In the fire-resistant oil system scenario, these problems directly affect the input quality and output reliability of the model, thereby restricting its online deployment performance. Accordingly, this study focuses on the fault identification model itself, and further introduces a data quality evaluation and confidence decision-making mechanism to enhance the robustness and engineering applicability of the model in complex industrial environments.

Through the arrangement of the above three dimensions, it shows that most of the current research focuses on the vibration of the main engine, lubricating oil system and hydraulic system, and there is a lack of systematic research on the key safety subsystem of fire-proof oil system. Moreover, the existing monitoring mostly relies on a single or small number of parameters (such as pressure and temperature), and makes insufficient use of multi-source information such as oil quality, flow rate and valve opening. Existing research still exhibits obvious deficiencies in data quality control and the reliability representation of diagnostic results, and a complete closed loop covering multi-source acquisition, feature fusion to decision-making security control has not yet been formed. To address these issues, this study comprehensively utilizes multi-dimensional parameters including pressure, temperature, flow rate and oil quality to realize continuous online perception of system states. Meanwhile, combined with time-domain, frequency-domain and multi-sensor fusion features, a fault identification model suitable for oil-fluid systems is designed. Moreover, data quality evaluation and confidence decision-making mechanisms are adopted to improve diagnostic accuracy, robustness and online application capability.

3. Research method

3.1. Analysis of fire-proof oil system and its fault characteristics

Fire-proof oil system in thermal power plant is an important part of speed regulation and protection device of steam turbine. Its main tasks include providing stable hydraulic power for actuator, quickly completing cut-off and interlocking actions under abnormal working conditions, and having fire prevention and isolation ability in emergency [23,24]. The system usually consists of oil tank and purification unit, oil pump and driving mechanism, filtering and cooling module, pressure stabilizing and overflow unit, pipeline and valve assembly, actuator and injection unit, monitoring and control unit, etc. Its operating environment is characterized by high temperature, high pressure, strong coupling and long continuous operation period.

Under normal operating conditions, the parameters (pressure, temperature, flow rate, oil level, oil quality, vibration, valve opening, etc.) of the fire-proof oil system show a relatively stable coupling mode. When mechanical wear, oil quality deterioration, pipeline leakage or valve jamming occur in the system, different monitoring parameters will show characteristic abnormal changes, which provide a basis for fault diagnosis and model construction, as shown in Table 1.

Table 1. Structure, key parameters and typical fault characteristics of fire-proof oil system

Subsystem/component	Key monitoring parameters	Normal operation characteristics	Typical failure mode	Brief introduction of fault mechanism	Monitoring characteristics (abnormal performance)	Potential risk
Oil pump and driving device	Pressure, flow rate, pump vibration and noise	Stable pressure, steady flow and low vibration.	Oil pump wear, cavitation and bearing damage	Long-term operation leads to impeller wear, cavitation at the suction port and bearing fatigue failure.	The outlet pressure drops slowly, the flow fluctuation increases, and the high-frequency vibration increases.	The oil supply capacity decreases, the actuator moves slowly, and the protection misoperation/refusal to operate.
Piping and joints	Pressure, oil level and flow rate	The pressure changes slightly with the load and the oil level is stable.	Micro-leakage and serious leakage	Pipeline corrosion, aging seal and loose joint lead to oil leakage.	Pressure drops slowly, oil level drops continuously, and oil supply is insufficient.	High fire risk and insufficient oil lead to system instability.
Filtration and cooling unit	Pressure difference before and after, oil temperature and flow rate	Small pressure difference, controllable oil temperature and normal flow.	The filter is blocked and the efficiency of the cooler is reduced.	Impurities blocking the filter element and scaling of the heat exchange tube will weaken the cooling capacity.	The pressure difference between front and back increases, the oil temperature is high and the fluctuation increases with the load.	The deterioration of oil quality is accelerated, and the system pressure adjustment is slow.
Pressure stabilizing and overflow unit	System pressure, valve position	Stable pressure and sensitive valve action.	The pressure stabilizing valve is jammed and the overflow fails.	Impurity sticking and spring fatigue lead to the decrease of voltage stabilizing ability.	The pressure cycle fluctuates, and the pressure set point cannot be maintained.	Actuator misoperation, pipeline fatigue damage
Actuator and cut-off valve	Valve position feedback signal, pressure and flow rate	The valve position is consistent with the instruction and the action is timely.	The valve is stuck and not in place.	Wear of valve core, oil pollution condensation and aging of sealing parts.	Incorrect valve position, lagging action and slow pressure/flow response.	The critical cut-off failed and the accident expanded.
Oil body (oil quality)	Acid value, moisture, granularity, oil temperature	Indicators are stable and slowly changing.	Deterioration of oil quality, excessive water content and particle pollution	High-temperature oxidation, external moisture intrusion, corrosion and	The trend of acid value rising, water content rising, particle size worsening and oil	Friction increases, component wear accelerates, and system reliability decreases.

				oxidation generate metal particles.	temperature rising is obvious.	
Monitoring and sensor unit	Pressure/temperature/flow signal, valve position signal	The signal is stable and consistent with the physical state.	Sensor drift, signal failure	Aging, interference and loose lines lead to inaccurate measurement.	Single point signal drift, mutation or inconsistent with other variables.	False alarm/omission, misleading control logic

Table 1 shows that it is difficult to judge the fault type with single parameter abnormality, and it is necessary to comprehensively analyze the pressure, flow rate, oil temperature, oil quality, vibration, valve position, etc., and most faults show trend deviation or weak fluctuation in the early stage, which is difficult to identify by simple threshold method.

3.2. Design of real-time monitoring platform and data acquisition framework

To realize continuous perception and quick response to the running state of fire-proof oil system in thermal power plant, this study constructs a real-time monitoring and data acquisition framework of "field acquisition-data preprocessing-time alignment and windowing-multi-source feature fusion-data quality evaluation". Figure 1 is a system frame diagram.

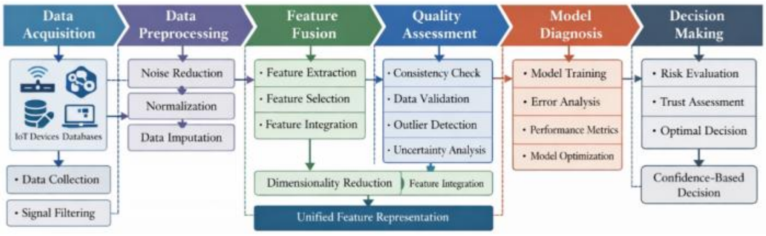


Figure 1. System Framework Diagram

In the field layer, various sensors such as pressure, temperature, flow, oil level, oil quality and vibration are arranged. The discrete measurement value obtained by the ith sensor at the kth sampling time can be abstracted as the superposition model of real signal and noise:

$$x_i(k) = s_i(t_k) + n_i(k) \quad (1)$$

x_i is the actual sampling value, t is the time, n_i is the noise term, and s_i is the real value [25,26]. To reduce the influence of high-frequency noise and random fluctuation on the diagnosis results, this study carries out first-order recursive smoothing filtering on the original signal at the edge calculation or real-time database side. The smoothed signal $\tilde{x}_i(k)$ of the measurement sequence of each sensor is expressed as:

$$\tilde{x}_i(k) = \alpha x_i(k) + (1-\alpha)\tilde{x}_i(k-1) \quad (2)$$

α is the smoothing coefficient. To eliminate the differences in dimensions and orders of different physical quantities and facilitate the subsequent feature fusion and model training, it is necessary to standardize the smoothed signal [27]. The normalized form based on the statistical characteristics of historical normal working conditions is adopted:

$$\hat{x}_i(k) = \frac{\tilde{x}_i(k)-\mu_i}{\sigma_i} \quad (3)$$

$\hat{x}_i(k)$ is a standardized dimensionless signal. μ_i and σ_i are the average and standard deviation of sensors under historical normal working conditions. In practical engineering, different sensors may have problems such as sampling delay, time stamp deviation or lost sampling. To ensure the consistency of multi-source data in time dimension, this study adopts linear interpolation to align time:

$$\bar{x}_i(t) = \hat{x}_i(t_j) + \frac{t-t_j}{t_{j+1}-t_j}\left[\hat{x}_i(t_{j+1}) - \hat{x}_i(t_j)\right] \quad (4)$$

$\bar{x}_i(t)$ is an interpolated signal. $\hat{x}_i(t_j)$ and $\hat{x}_i(t_{j+1})$ are standardized signals at two adjacent sampling moments. t_j and t_{j+1} are two sampling timestamps before and after t. After time alignment, to capture the dynamic characteristics of system evolution with time, a sliding time window is adopted. Taking a window with length L as an example, in the kth window, the multi-source alignment signals can be organized as:

$$\mathrm{X}(k) = \begin{bmatrix} \bar{x}_1(k) & \bar{x}_1(k-1) & \cdots & \bar{x}_1(k-L+1) \\ \bar{x}_2(k) & \bar{x}_2(k-1) & \cdots & \bar{x}_2(k-L+1) \\ \vdots & \vdots & \ddots & \vdots \\ \bar{x}_N(k) & \bar{x}_N(k-1) & \cdots & \bar{x}_N(k-L+1) \end{bmatrix} \quad (5)$$

In the equation, $\mathrm{X}(k)$ is a multi-source monitoring data matrix, and N represents different sensors. Based on sliding window, multi-source and multi-time raw data should be mapped to feature space to effectively distinguish different fault modes. In this study, the monitoring feature vector is constructed by means of "feature mapping+linear fusion":

$$\mathrm{z}(k) = \mathrm{W}\phi(\mathrm{X}(k)) \quad (6)$$

$\mathrm{z}(k)$ is the fusion feature vector, ϕ is the feature mapping operator, and W is the feature fusion weight matrix. In actual engineering operation, the monitoring data may be affected by sensor failure, communication abnormality or field interference, which directly affects the reliability of diagnosis results. Therefore, this study designs a data quality evaluation index in the data acquisition framework to measure the validity of samples in each time window. Let the data quality index of the kth window be $Q(k)$, which is defined as:

$$Q(k) = 1 - (w_m M(k) + w_o O(k) + w_d D(k)) \tag{7}$$

M is the proportion index of missing data, O is the proportion index of abnormal value, D is the proportion index of abnormal timestamp or alignment failure. w_m, w_o and w_d are the corresponding weights.

3.3. Construction of fault diagnosis model

In this study, a multi-class probability classification model based on deep feature mapping is adopted to redefine loss function, parameter updating strategy and diagnosis decision rules, and confidence evaluation is introduced to realize early warning marking of low confidence samples. The goal of the diagnosis model is to learn a mapping function f_θ whose parameter set is θ, and map the input features into various posterior probability estimates

$$\hat{\mathrm{p}}(k) = f_\theta(\mathrm{z}(k)) \tag{8}$$

$\hat{\mathrm{p}}(k)$ is the probability vector of each category. To ensure that the output is a legal probability distribution, this study uses the softmax normalization function at the output layer to constrain the probability of each category

$$\hat{p}_c(k) = \frac{\exp(o_c(k))}{\sum_{j=0}^{C-1}\exp(o_j(k))}, c = 0,1,\ldots,C-1 \tag{9}$$

$\hat{p}_c(k)$ is the prediction probability, $c = 0,1,\ldots,C-1$ is different types of faults, $o_c(k)$ is the original output of faults, and exp is an exponential function. To consider expression ability and engineering realizability, this study adopts feed-forward neural network with relatively simple structure as the basic form of fault diagnosis model. The network includes a nonlinear hidden layer and an output layer. For the kth sample, the hidden layer is expressed as

$$\mathrm{h}(k) = \sigma(\mathrm{W}_1\mathrm{z}(k) + \mathrm{b}_1) \tag{10}$$

$\mathrm{h}(k)$ is the output vector of the hidden layer, W_1 is the weight matrix of the hidden layer, b_1 is the bias vector, and σ is the nonlinear activation function. Based on the hidden layer, the output layer gives logit representation for each category

$$\mathrm{o}(k) = \mathrm{W}_2\mathrm{h}(k) + \mathrm{b}_2 \tag{11}$$

$\mathrm{o}(k)$ is the logit vector of the output layer, W_2 is the weight matrix of the output layer, and b_2 is the offset vector of the output layer. To train the diagnosis model, it is necessary to define the loss function to measure the difference between the prediction probability and the real label

$$\mathcal{L}(\theta) = -\frac{1}{B}\sum_{k=1}^{B}\sum_{c=0}^{C-1} y_c(k)\log\hat{p}_c(k) + \lambda \parallel \theta \parallel_2^2 \tag{12}$$

$\mathcal{L}(\theta)$ is the total loss function value, B is the batch size, $y_c(k)$ is the real label, λ is the regularization coefficient, and the parameters are iteratively updated by using random gradient descent or its improved algorithm. Taking the most basic random gradient descent as an example, the update can be expressed as

$$\theta^{(t+1)} = \theta^{(t)} - \eta\nabla_\theta\mathcal{L}(\theta^{(t)}) \tag{13}$$

η is the learning rate and $\nabla_\theta\mathcal{L}$ is the gradient vector of parameters. After the model is trained and deployed on the real-time monitoring platform, the final diagnosis result should be given according to the prediction probability vector. In this study, the maximum posterior probability criterion is used to determine the category

$$\hat{y}(k) = \arg\max_{c\in\{0,\ldots,C-1\}}\hat{p}_c(k) \tag{14}$$

$\hat{y}(k)$ is a diagnostic output. However, in actual operation, some samples may be in the early stage of fault or in the boundary region of working conditions, and the maximum probability value of model output is not high. To avoid directly giving deterministic diagnosis to samples with low confidence, this study defines the anomaly measure under fault confidence compensation

$$S(k) = 1 - \max_{c\in\{0,\ldots,C-1\}}\hat{p}_c(k) \tag{15}$$

$S(k)$ is the anomaly measure, and $\max_{c\in\{0,\ldots,C-1\}}$ is the confidence of the model to the most likely category. In this way, the diagnosis model can not only automatically give the category judgment, but also give the risk warning to the boundary samples, thus improving the overall security and interpretability of the system.

From a theoretical perspective, fault diagnosis of fire-resistant oil systems is not a simple standard classification problem, but a complex recognition process affected by both data uncertainty and decision uncertainty. On the one hand, industrial on-site monitoring data are often characterized by noise interference, missing samples, asynchronous timestamps, and local outliers, meaning input samples do not always satisfy the ideal assumptions of identical distribution, high quality, and strong consistency. If all collected data are directly fed into the diagnostic model with equal weights, low-quality samples will distort the inter-class boundaries in the feature space, weaken the model's ability to represent real fault patterns, and further degrade its generalization performance under complex operating conditions. Therefore, this study introduces a data quality evaluation mechanism. Its theoretical motivation is to explicitly incorporate data reliability into the modeling process. By quantifying sample quality, unreliable inputs are suppressed or eliminated, thereby reducing the negative impact of data noise on parameter learning and decision boundaries, and improving the consistency and robustness of model training and online inference. On the other hand, different fault types in fire-resistant oil systems often exhibit strong similarity in the early stage, and condition switching, load fluctuations, and high-temperature disturbances may lead to local overlap between normal and fault samples in the feature space. In such cases, even if the model outputs a certain category, it does not mean the judgment is sufficiently reliable. If only the maximum posterior probability is used to directly give rigid classification results, high-risk misjudgments are likely to occur on boundary samples, transitional samples, and weak fault samples. Accordingly, this study further introduces a confidence mechanism. Its theoretical motivation is to distinguish classification results from result reliability, enabling the diagnostic model to determine which class the sample belongs to and indicate how credible the judgment is. This design essentially incorporates uncertainty representation into the fault diagnosis process, which helps improve the model's risk perception ability for boundary samples and provides a more reasonable basis for alarm grading, manual review, and subsequent operation and maintenance decisions.

Furthermore, the data quality evaluation and confidence mechanism act on the input and output ends of the diagnosis chain respectively. The former addresses the issue of "whether the input is credible", while the latter addresses "whether the output is reliable". Together, they form a closed-loop diagnosis framework for complex industrial scenarios: input noise propagation is reduced through data quality evaluation, and output risk diffusion is controlled via the confidence mechanism. This enables the fault diagnosis method to expand from the traditional single classification paradigm to a comprehensive framework that considers data reliability, model discrimination, and decision-making safety. This also serves as an important theoretical basis that distinguishes the proposed method from general engineering-oriented models.

4. Experimental design

In this study, the published dataset of "condition monitoring of hydraulic systems" is selected as the verification data of the fault diagnosis method of fire-proof oil system. The dataset is collected by a complex hydraulic test bench under various working conditions. The test bench consists of a working loop and a cooling-filtering loop, which relate to each other through an oil tank, and the system is synchronously measured by multiple sensors in a repeated 60s constant load period. The dataset contains 2205 running cycle samples, and each cycle corresponds to a complete load running process, which belongs to typical multivariable time series data. The dataset is downloaded through https://archive.ics.uci.edu/dataset/447/condition+monitoring+of+hydraulic+systems. Although the public hydraulic system condition monitoring dataset adopted in this study is not directly derived from the fire-resistant oil system of thermal power plants, it can still serve as a reasonable data foundation for verifying the effectiveness of the proposed method. This is because public hydraulic systems share a high consistency with fire-resistant oil systems in terms of physical mechanisms. First, both belong to typical hydraulic power transmission systems, and their operational processes can be summarized as a closed-loop chain of "oil pump pressure supply—pipeline transmission—valve regulation—actuator response—oil return circulation". The system conditions are jointly affected by pressure, flow rate, temperature, oil quality and component health status. Second, the faults involved in the dataset, such as decreased cooler efficiency, degraded valve performance, internal leakage and accumulator pressure changes, are similar to problems in fire-resistant oil systems including filter blockage, valve sticking, pipeline leakage, abnormal oil pressure and oil performance deterioration in terms of fault propagation mechanisms and monitoring signal manifestations. All of them cause characteristic changes such as pressure fluctuation, flow imbalance, abnormal temperature rise and delayed system response. Third, from the perspective of monitoring variables, the pressure, flow rate, temperature, vibration and efficiency-related parameters in the dataset are highly consistent with the actual measurable key variables of fire-resistant oil systems. Since the proposed method mainly constructs models focusing on fault characterization, quality differences and diagnostic discrimination mechanisms in multi-source monitoring signals, the experimental results obtained based on this dataset can effectively support the applicability and effectiveness of the proposed method in the fault diagnosis scenarios of fire-resistant oil systems.

The experiment of this study is completed in the following software and hardware environments, and the relevant configurations are as follows:

(1) The processor model is Intel Core i7-12700F, with a main frequency of 2.10 GHz and a 12-core structure;

(2) The graphics computing unit is NVIDIA GeForce RTX 3060, and the memory capacity is 12 GB;

(3) The memory capacity is 32 GB DDR 4;

(4) The storage device is 1 TB NVMe SSD;

(5) The operating system is Windows 1164-bit;

(6) The deep learning framework is PyTorch 2.1;

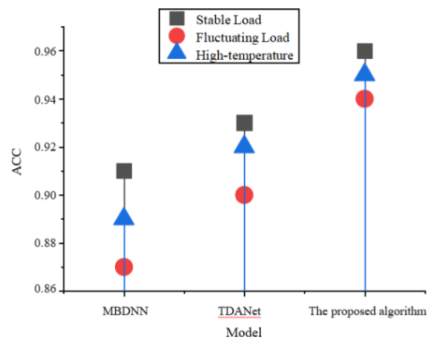
(7) Python 3.10, NumPy 1.26, Pandas 2.1, SciPy 1.11 and other tools are used for data processing and feature extraction.

To ensure the stable convergence of the optimized fault diagnosis model in the training process and obtain high recognition performance in the multi-source feature space, the key parameters are systematically set, the input feature dimension is set to 128. The activation function is ReLU. The loss function is cross-entropy loss, and L2 regularization with a coefficient of 0.001 is added. The optimization algorithm is Adam. The initial learning rate is set to 0.001. At the same time, the learning rate attenuation strategy is used to set the training batch size to 64, the maximum training rounds to 120. The sliding window length to 60, corresponding to the time series structure of one running cycle per minute in the dataset. The window step size is 1, which is used to ensure the continuity of time series samples. Multi-Branch Deep Neural Network (MBDNN) and Temporal-aware Dual-Attention Network (TDANet) are chosen as the contrast models in the experiment.

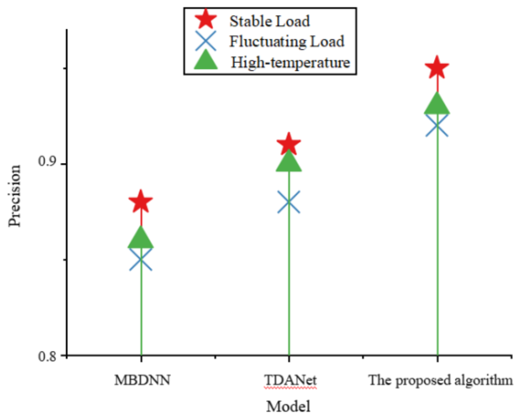
5. Analysis and comparison of experimental results

5.1. Fault identification analysis

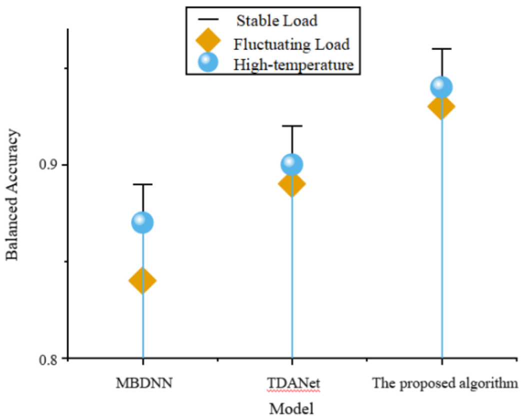
To verify the recognition ability of the proposed fault diagnosis method under different working conditions, the evaluation indexes include the overall classification accuracy dimension, separability and stability dimension, and the results of the overall classification accuracy dimension are shown in Figure 2.



(a) ACC(Accuracy)



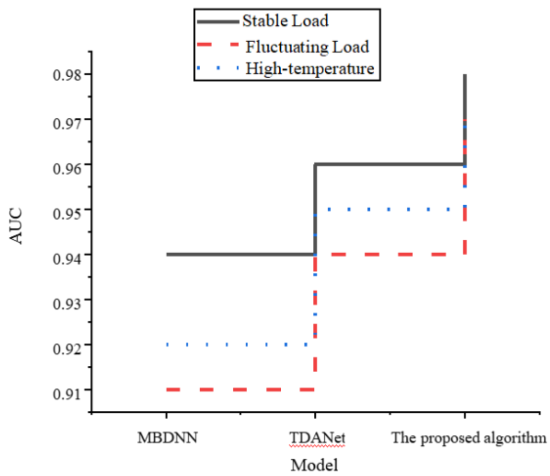
(b) Precision



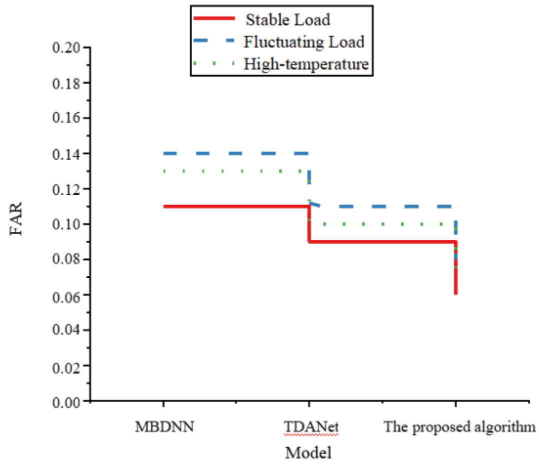
(c) Balanced Accuracy

Figure 2. Classification accuracy dimension

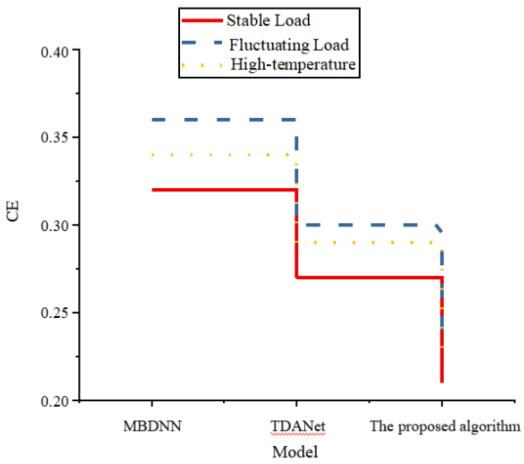
The results of Figure 2 show that the ACC of the proposed optimized model is kept at a high level under three working conditions, and the ACC is 0.96 under stable load, 0.94 under load fluctuation and 0.95 under high temperature stress, which is obviously superior to the comparative model. Under the stable load condition, the ACC of MBDNN is 0.91 and TDANet is 0.93. In contrast, the proposed optimized model can distinguish normal and various fault states at a higher accuracy level under the same load condition. In terms of Precision index, the accuracy rates of the proposed optimized are 0.95, 0.92 and 0.93 under the conditions of stable load, load fluctuation and high temperature stress, respectively, which shows that there are few false alarms when fault judgment is given, and most of the samples predicted as faults are real faults. In contrast, the Precision of TDANet is 0.90 under high temperature stress condition, which shows that the proposed optimized model can still maintain higher reliability of fault judgment under complex thermal stress scenarios. The balance accuracy further reflects the comprehensive recognition level of the model in the case of unbalanced categories. The experimental results show that the Balanced Accuracy of the proposed optimized is 0.96, 0.93 and 0.94 under stable load, load fluctuation and high temperature stress conditions, respectively, compared with the performance of MBDNN which is only 0.84 under load fluctuation conditions. It shows that the proposed optimized model also has good identification ability on a few types of fault samples, effectively alleviating the bias problem caused by category imbalance. The results of separability and stability dimensions are shown in Figure 3.



(a) AUC (Area Under Curve)



(b) FAR (False Alarm Rate)



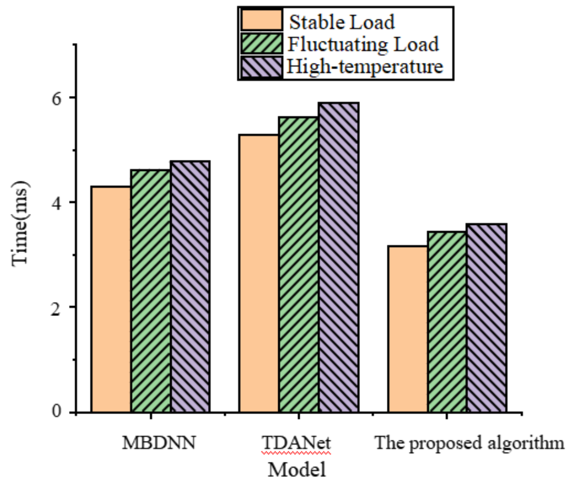
(c) CE (Confusion Entropy)

Figure 3. Separability & stability dimension

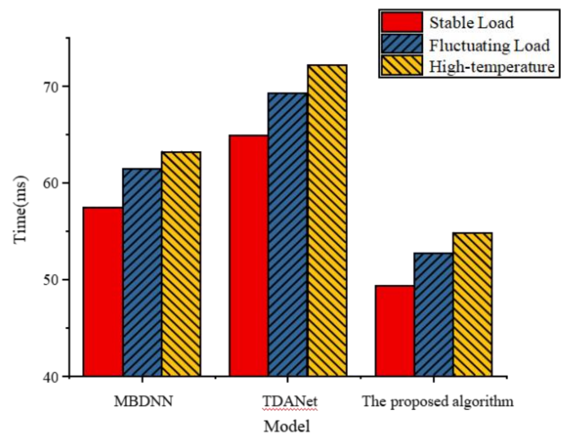
From the results of Figure 3, the AUC of the proposed optimized model is 0.98, 0.97 and 0.97 respectively under three working conditions, and the AUC is close to 1, which indicates that it can maintain a high true rate and a low false positive rate under different thresholds, and has a stronger ability to distinguish faults from normal states. From the FAR point of view, the FAR of the proposed optimized model is 0.06, 0.08 and 0.07 under the conditions of stable load, load fluctuation and high temperature stress, respectively, which is lower than that of the comparative model. Under the stable load condition, the FAR of TDANet is 0.09, while the FAR of MBDNN is 0.14 under the load fluctuation condition, which shows that in some scenarios, the comparison model misjudges the normal working condition as a fault. The proposed optimized model can effectively suppress the false alarm under different working conditions, which is more friendly to practical engineering application. CE index is used to measure the degree of overall confusion, and the lower the value, the less likely the model will be confused between different fault categories. The experimental results show that the CE of the proposed optimized model is 0.21, 0.24 and 0.23 under stable load, load fluctuation and high temperature stress conditions, respectively. Compared with the performance of MBDNN with CE of 0.36 under load fluctuation conditions, the degree of confusion is obviously reduced. This shows that the proposed optimized model can keep a clear category boundary and reduce the misclassification between different faults under complex working conditions where multiple fault types exist at the same time.

5.2. Analysis of real-time and stability

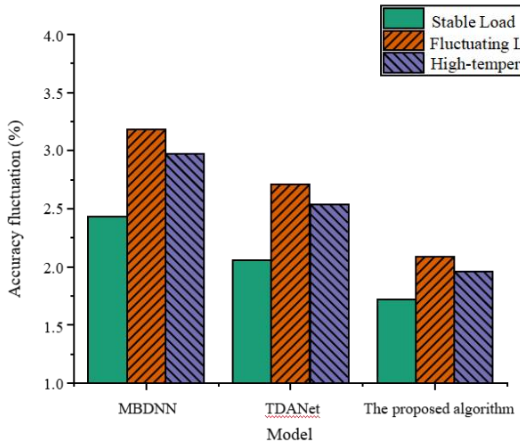
To evaluate the applicability of fault diagnosis method in engineering online deployment scenario, this section compares and analyzes the performance of the model under different working conditions from two aspects: real-time performance and long-term operation stability, and the results are shown in Figure 4.



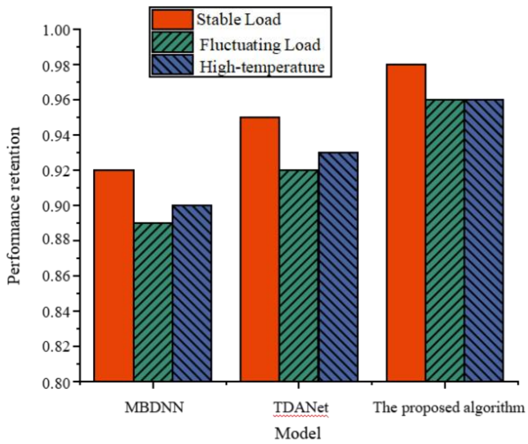
(a) Average diagnosis time per sample



(b) End to end alarm delay



(c) Long term accuracy fluctuation



(d) Performance retention rate under noise interference

Figure 4. Real time and stability analysis

The results in Figure 4 show that the average diagnosis time of single sample of the proposed optimized model is significantly lower than that of the comparative model under three working conditions. Under the stable load condition, the average diagnosis time of the optimized model is 3.17ms, while that of MBDNN and TDANet is 4.31ms and 5.28ms, respectively. Under load fluctuation and high temperature stress conditions, the T_inf of the proposed optimized model is 3.43ms and 3.58ms respectively, which shows that the inference time of the model can still be kept at a low level with the increase of data volume and working condition complexity. This shows that by simplifying the network structure and combining the multi-source feature fusion strategy, this method can ensure the recognition accuracy and consider the reasoning efficiency. In terms of end-to-end alarm delay, the end-to-end alarm delay of the proposed optimized MBDNN is 49.36ms, 52.71ms and 54.82ms under stable load, load fluctuation and high temperature stress conditions, respectively. Compared with the delay of 63.21ms under high temperature conditions and the delay of 69.27ms under load fluctuation conditions, the overall response time is shorter. Considering that the actual fire oil system is sensitive to the fault warning time, this result shows that the proposed method is more suitable to be deployed in online monitoring scenarios with high real-time requirements.

From the point of view of stability, the standard deviation of accuracy fluctuation under continuous 4-hour online operation can reflect the output stability of the model in the long-term operation. The experimental results show that the long-term running accuracy fluctuation of the optimized MBDNN in this study is 1.72%, 2.09% and 1.96% under the conditions of stable load, load fluctuation and high temperature stress, respectively, which is obviously lower than the fluctuation level of 3.18% under the condition of load fluctuation and better than the performance of 2.54% under the condition of high temperature. This shows that the diagnostic performance of this method has little change during long-term operation, and it is not easy to have performance "drift", which is conducive to maintaining the consistency of diagnostic results. In the aspect of noise robustness, the performance retention rate under noise interference further reflects the model's resistance to sensor noise and environmental disturbance. The performance retention rates of the proposed optimized MBDNN are 0.98, 0.96 and 0.96 under the noise interference under three working conditions, which are obviously higher than the retention rate of 0.89 under the load fluctuation condition and 0.93 under the high temperature condition. It shows that the recognition accuracy of this method decreases slightly after the sensor signal is superimposed with a certain proportion of Gaussian noise, and it has better adaptability to the condition monitoring of fire-proof oil system in high noise environment.

5.3. Ablation experiment

To further analyze the contribution of each key module of the optimized model to the overall diagnostic performance, this section designs an ablation experiment, which eliminates the multi-source feature fusion module, data quality evaluation module and confidence decision mechanism in the model respectively, and compared it with the complete model. The following four model configurations are set in the ablation experiment:

(1) Full model: A complete optimization model of this study (including three modules);

(2) w/o Multi-source fusion: Remove the multi-source feature fusion module and only keep the main channel (pressure-related features);

(3) w/o Data quality module: Remove the data quality evaluation module and treat all samples equally;

(4) w/o Confidence mechanism: The confidence decision mechanism is removed, and the diagnosis result is given directly according to the maximum probability category.

The experimental results are shown in Table 2:

Table 2. Results of ablation experiment

Metric & Condition	Full model	w/o Multi-source fusion	w/o Data quality module	w/o Confidence mechanism
ACC (Stable Load)	0.96	0.92	0.94	0.93
ACC (Fluctuating Load)	0.94	0.89	0.91	0.92
ACC (High-temperature)	0.93	0.88	0.89	0.91
AUC (Stable Load)	0.98	0.96	0.97	0.97
AUC (Fluctuating Load)	0.97	0.93	0.94	0.96
AUC (High-temperature)	0.97	0.92	0.93	0.94
FAR (Stable Load)	0.07	0.12	0.09	0.08
FAR (Fluctuating Load)	0.09	0.14	0.11	0.11
FAR (High-temperature)	0.08	0.13	0.12	0.09

From Table 2, the complete model achieves the best results under three operating conditions and three evaluation metrics, indicating that the proposed three key modules are not simply superimposed, but form complementary and synergistic effects in the fault identification process. Further comparison of each ablation configuration reveals that different modules contribute significantly differently to model performance. First, the multi-source feature fusion module has the most significant impact on overall diagnostic performance. After removing this module, the ACC of the model under the three operating conditions drops to 0.92, 0.89 and 0.88 respectively, showing the largest decrease compared with the complete model. Meanwhile, the AUC also decreases to 0.96, 0.93 and 0.92 respectively, with more pronounced degradation especially under load fluctuation and high-temperature stress conditions. The corresponding FAR rises to 0.12, 0.14 and 0.13 respectively, indicating a significant increase in false alarms. This shows that the multi-source feature fusion module is the core source of performance improvement in the proposed model. The main reason is that faults in the fire-resistant oil system are not characterized by a single physical quantity in isolation, but are usually accompanied by coupled changes in multiple parameters such as pressure, flow rate, temperature and oil quality. Without multi-source fusion, the model can only rely on local or single-channel information, leading to insufficient representation of complex fault patterns. In particular, it is more likely to misclassify normal fluctuations as faults when subjected to large operating disturbances.

The data quality evaluation module plays an important supporting role in model robustness and stability. After removing this module, the ACC decreases to 0.94, 0.91 and 0.89 under the three operating conditions respectively. Although the reduction is smaller than that caused by removing the multi-source feature fusion module, it is still relatively significant under high-temperature stress and load fluctuation conditions. The AUC drops to 0.97, 0.94 and 0.93 respectively, indicating that the model’s ability to distinguish the boundary between faulty and normal states is weakened. At the same time, the FAR increases to 0.09, 0.11 and 0.12 respectively, showing that low-quality samples significantly raise the risk of false alarms. In particular, sensor noise, sampling deviations and local outliers occur more frequently under high-temperature and fluctuating conditions. Without a quality screening mechanism, such unreliable data directly participate in model training or inference, thus disturbing the decision boundary and impairing model stability. Therefore, the main contribution of the data quality evaluation module lies not merely in improving pure classification accuracy, but more crucially in enhancing the anti-interference capability of the model in complex industrial environments.

The confidence decision-making mechanism plays a more targeted role in boundary sample processing and false alarm suppression. After removing this mechanism, the ACC values are 0.93, 0.92 and 0.91 respectively, and the AUC values are 0.97, 0.96 and 0.94 respectively. Although the overall performance decreases, the decline is smaller compared with the previous two modules. However, in terms of the FAR index, it rises to 0.08, 0.11 and 0.09 under the three working conditions respectively, indicating that the confidence mechanism has a more direct effect on false alarm control. This shows that the confidence mechanism is not the most critical in improving the "average recognition ability" of the model, but can effectively reduce overly rigid erroneous judgments when dealing with boundary samples, weak fault samples and uncertain samples, thereby enhancing the reliability of online early warning results and decision-making safety. Especially in practical engineering scenarios, such a mechanism helps to convert low-confidence results into risk prompts or manual review signals, rather than directly outputting high-risk fault alarms.

Overall, the three types of modules differ significantly in their functional emphases within the model. The multi-source feature fusion module mainly determines the basic recognition capability and multi-fault discrimination ability of the model, serving as the dominant factor for performance improvement. The data quality evaluation module primarily enhances the model’s robustness under complex operating conditions and noisy environments, constituting an important support for ensuring stable model operation. The confidence decision-making mechanism mainly acts on the output layer, playing a critical role in false alarm suppression and risk control of boundary samples. The synergistic effect of the three modules enables the complete model to achieve higher recognition accuracy, lower false alarm rate, and better operating condition adaptability in the aforementioned experiments.

Therefore, it shows that the performance advantage of the proposed optimized model does not rely on any single module, but achieves an overall improvement from input reliability and feature discriminability to output security through the hierarchical design of "multi-source fusion – quality control-confidence decision-making". This further verifies the rationality and necessity of the proposed method in the fault diagnosis scenario of fire-resistant oil systems.

6. Discussion

The comprehensive experimental results show that the fault diagnosis method of fire-proof oil system constructed in this study shows high recognition accuracy and good separability under different working conditions, while maintaining low FAR and good real-time performance. This shows that the idea of multi-source feature fusion based on real-time monitoring can effectively mine the coupling relationship between pressure, flow, temperature, oil quality and other parameters. It is more suitable to describe the complex and multi-fault operation characteristics of fire-proof oil system than the model that only relies on single signal or single channel feature. From the engineering application point of view, the inference time of single sample and the end-to-end alarm delay are controlled in a small range, which shows that the proposed method can basically meet the needs of online monitoring and rapid early warning on the premise of ensuring the diagnostic performance. The long-term operation fluctuation is small and the performance retention rate is high under noise interference, which shows that the model is robust to sensor noise, working condition disturbance and data quality fluctuation, and is conducive to long-term stable operation in actual power plants. The ablation experiment further shows that multi-source feature fusion, data quality evaluation and confidence decision mechanism have complementary effects on performance improvement. The former significantly enhances the discrimination between fault categories, while the latter two play a key role in restraining the interference of low-quality data and controlling the risk of boundary samples, which together support the overall performance improvement. This also suggests that it is not enough to improve the classification accuracy for high-safety objects such as fire-proof oil systems, but also to pay attention to the reliability of data and the controllability of diagnosis results.

Compared with existing methods, the proposed fault diagnosis method exhibits obvious comprehensive advantages in three dimensions: accuracy, real-time performance, and reliability. In terms of accuracy, although MBDNN can extract features of different channels through a multi-branch structure, its ability to characterize complex fault boundaries under multi-operating-condition disturbances remains limited. TDANet improves the recognition ability of dynamic features by means of temporal modeling and attention mechanisms, but still suffers from certain performance fluctuations under high-temperature stress and load fluctuation scenarios. In contrast, the proposed method integrates multi-source information including pressure, flow, temperature, and oil quality, enabling a more comprehensive characterization of the fault evolution process of the fire-resistant oil system. Consequently, it achieves a stable leading advantage in metrics such as ACC and AUC, and shows stronger fault pattern discrimination ability especially under complex operating conditions and class-imbalanced conditions. In terms of real-time performance, despite their satisfactory feature representation capability, MBDNN and TDANet have relatively complex model structures, resulting in higher inference overhead and end-to-end alarm delay. Particularly in online deployment, they are more easily constrained by computing resources and response time limits. The proposed method balances feature effectiveness and structural lightweightness in model design. Through front-end data preprocessing, multi-source fusion feature compression, and a relatively concise diagnostic network architecture, it achieves shorter single-sample inference time and overall alarm delay, demonstrating that the method is effective under laboratory conditions and better meets the rapid response requirements of online monitoring scenarios in actual thermal power units. In terms of reliability, most existing studies focus primarily on classification accuracy itself, with insufficient consideration given to industrial on-site data noise, sampling anomalies, and uncertainty of boundary samples. MBDNN exhibits a relatively high false alarm rate under load fluctuation conditions, indicating that its distinction between normal fluctuations and fault disturbances is not robust enough. Although TDANet performs well in temporal modeling in some scenarios, its stability is compromised under long-term operation and strong noise interference. The proposed method further introduces a data quality evaluation module and a confidence decision-making mechanism, which suppress the interference of low-quality samples on the model decision boundary at the input end and provide risk prompts and decision compensation for low-confidence samples at the output end, thus achieving superior performance in metrics such as FAR, CE, and performance retention rate under noise interference. This indicates that the advantage of the proposed method lies in "whether faults can be identified" and more importantly in "whether faults can be identified continuously, stably, and reliably in complex industrial environments". From the perspective of engineering applicability, although the proposed method is validated based on a public hydraulic system dataset, its core modeling target is not a specific device structure but the universal "pressure-flow-temperature-oil quality" coupling mechanism and fault evolution laws in fluid power systems. Therefore, the method has favorable migration potential for fire-resistant oil systems in thermal power plants. Especially in typical scenarios such as abnormal oil pump pressure supply, sluggish valve actuation, pipeline leakage, reduced cooling efficiency, and oil performance degradation, the fault modes in the public dataset share strong mechanistic similarity with those in fire-resistant oil systems, so the conclusions drawn in this study can reflect its engineering application value at the methodological level. Nevertheless, it should be acknowledged that the fire-resistant oil system in thermal power plants differs from general hydraulic test benches in terms of medium characteristics, equipment layout, interlock logic, and operating boundary conditions. Therefore, subsequent retraining and parameter calibration based on actual unit monitoring data are still required to further improve the model's applicability in real power plant scenarios.

7. Conclusions

This study focuses on the fire-resistant oil system of thermal power plants and develops an integrated fault diagnosis method featuring "real-time monitoring-multi-source feature fusion-intelligent diagnosis-confidence decision-making". By modeling the structure and fault mechanism of the fire-resistant oil system, a multi-sensor real-time acquisition and data quality evaluation framework is designed, and a lightweight deep diagnosis model is constructed based on fused features. Experimental results show that the proposed method achieves favorable comprehensive performance in fault identification accuracy, false alarm control, real-time performance and stability, verifying its feasibility for real-time online diagnosis. Although certain research progress has been made, this study still has the following limitations. First, the experimental data are mainly derived from a public hydraulic system dataset, resulting in a relatively single data source. Despite its strong similarity with the fire-resistant oil system of thermal power plants in terms of fluid power transmission mechanisms, differences still exist in equipment layout, operation boundaries and interlock logic. Second, the current experimental verification is mainly based on public data and typical operating condition divisions, and long-term online operation verification in real power plant scenarios remains insufficient. In particular, its adaptability to extreme conditions, compound faults and on-site noise disturbances needs further examination. Third, although the constructed diagnosis model achieves satisfactory performance in recognition accuracy, its internal decision-making process is dominated by data-driven mapping, with limited explicit interpretability of key fault features. Thus, the model interpretability needs to be enhanced. Future research will combine real operating data from thermal power units to conduct on-site adaptive calibration of model parameters and thresholds. Multi-source heterogeneous data (e.g., acoustic signals and image information) will be further incorporated to improve the characterization ability for complex fault patterns. In addition, explainable artificial intelligence and predictive maintenance strategies will be introduced to expand the research scope from fault diagnosis to fault early warning and maintenance decision support.

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