
Original Research Article

Research on fault detection and diagnosis of inverter circuits

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Abstract: This paper comprehensively discusses the fault detection and diagnosis techniques of inverter circuits. It begins with an introduction to the fundamental principles of inverter circuits and their applications in solar photovoltaic systems, electric vehicles, and uninterruptible power supplies (UPS). Inverter circuits achieve efficient transmission and utilization of electrical energy by converting direct current (DC) into alternating current (AC). However, due to the non-ideal characteristics of switching devices and environmental factors, the output waveform of inverter circuits may become distorted and contain harmonics, impacting system performance. Therefore, a deep understanding of the basic principles of inverter circuits is critical for effective fault detection and diagnosis.

Following this, the paper analyzes common fault types and electrical characteristics of inverter circuits, including overheating, short circuits, open circuits, and parameter drift of switching devices. To extract fault features, signal processing methods such as Fourier transform and wavelet transform are widely applied. Meanwhile, machine learning techniques, especially support vector machines (SVMs) and neural network algorithms, are used for accurate identification and early warning of complex failure modes.

Regarding fault detection methods, the paper delves into fault detection technologies based on signal processing and machine learning. Signal processing technology analyzes voltage and current signals and employs Fourier and wavelet transforms to extract fault characteristics. Machine learning algorithms then enable precise fault recognition and advance warnings. Finally, this paper proposes a design framework for an inverter circuit fault diagnosis system that includes key technologies such as data acquisition, signal processing, and fault detection and diagnosis algorithms. The research results indicate that the integration of advanced signal processing technology and machine learning algorithms can significantly enhance the accuracy and efficiency of fault detection and diagnosis for inverter circuits, providing a robust guarantee for the stable operation of power electronic systems.

Keywords: inverter circuits; fault detection; diagnostic technology; early warning

1. Introduction

1.1. Overview of inverter circuits

1.1.1. Basic principles of inverter circuits

The foundational principle of inverter circuits, which are a critical element in power electronics, involves the conversion of direct current (DC) to alternating current (AC) ^[1]. This transformation typically employs high-frequency switching of power semiconductor devices to generate an AC waveform that meets specific requirements. Inverters play a pivotal role across various applications; for example, within solar photovoltaic (PV) systems, inverters convert the DC output from solar panels into grid-synchronous AC, enabling the efficient harnessing and utilization of solar energy. According to Fourier analysis, the AC waveform produced by an inverter can be decomposed into a superposition of sinusoidal components, ideally matching the frequency and

phase of the grid standard to ensure the stable operation of the power system^[2].

However, in practical applications, the output waveforms of inverter circuits can be influenced by several factors, leading to waveform distortions that impact the overall performance and reliability of the system. These factors include the non-ideal characteristics of switching devices, variations in load conditions, and environmental influences. The non-ideal behavior of switching devices—Such as on-state voltage drops, finite switching times, and parasitic inductances—Can introduce distortions into the output waveform. Variations in load, particularly nonlinear loads, can induce harmonic components in the output waveform. Environmental factors, such as fluctuations in temperature and humidity, can also affect the performance of switching devices, further contributing to waveform distortion. Such distortions not only reduce the efficiency of the inverter circuit but can also introduce harmonics into the power grid, affecting the normal operation of other electrical equipment.

For instance, during the conversion process, inverters may generate harmonics that, if unmitigated, can severely pollute the power grid and disrupt the functioning of other electrical apparatus. Harmonics can lead to distortions in the voltage and current waveforms of the grid, increasing grid losses and degrading power quality. Additionally, harmonics can trigger resonance phenomena, resulting in overheating and potential damage to equipment, thereby compromising the safe and stable operation of the power system.

Therefore, gaining an in-depth understanding of the basic principles of inverter circuits is essential for advancing fault detection and diagnosis techniques. By comprehending the operational mechanisms of inverters and the causes of waveform distortion, a theoretical foundation can be established for developing efficient and accurate fault detection and diagnosis methods. Signal processing techniques based on Fourier transform and wavelet transform can be utilized to extract fault features, while machine learning algorithms, such as support vector machines (SVMs) and neural networks (NNs), can be employed to identify complex fault patterns and achieve early warning and rapid diagnosis of inverter circuit faults^[3].

1.2. Common types of inverter circuits and their areas of application

Inverter circuits, as a core component of power electronics, are of various types and have a wide range of applications. The main types of inverter circuits include Voltage Source Inverter (VSI) and Current Source Inverter (CSI), which play a crucial role in industrial and civil applications^[4].

1.2.1. Voltage source inverters (VSI)

The control strategy of VSI is relatively simple and easy to implement. It has a fast response time and can respond quickly to load changes to provide a stable output voltage. It can maintain high conversion efficiency under both light and heavy load conditions with high efficiency. In the solar power generation system system, VSI is capable of efficiently converting DC power generated by solar panels into AC power to meet the needs of the grid. According to a report by the International Energy Agency (IEA), global solar power generation is expected to grow to more than three times its current level by 2030, which will greatly boost the development and application of VSI technology^[5]. In the field of electric vehicle drives, VSI is used in electric vehicles to drive electric motors, providing efficient and reliable power conversion to improve vehicle range and power performance. In uninterruptible power supply (UPS) systems, VSI is used in UPS systems to provide stable AC power to ensure that critical equipment can still operate normally when utility power is interrupted.

1.2.2. Current source inverters (CSI)

CSI can provide stable current output and more precise control of the motor. It is suitable for high-power applications and has an irreplaceable position in high-power drive systems, especially for applications requiring

high-precision control. The dynamic performance of the CSI can be described by a state-space model, which is able to reflect in detail the behavioural characteristics of the circuit in different operating states. For example, the transient response of the circuit during sudden load changes can be accurately calculated through the state space model, thus providing a theoretical basis for fault diagnosis ^[6]. CSIs have a wide range of applications in the field of industrial motor drives, such as steel rolling mills and mine hoisting machines. These applications require high precision current control and stable output. CSIs excel in high power drive systems, providing high precision current control and ensuring stable system operation. Inverter circuits are not limited to power systems, but are also widely used in a variety of fields: inverter circuits in avionics systems need to maintain high reliability and stability in extreme environments, which requires that the inverter circuit design must take into account the effects of temperature, vibration, and electromagnetic interference. For example, the inverter circuits on aircraft must be able to work stably in a high-altitude, low-temperature, high-vibration environment to ensure flight safety. The reliability of the inverter circuit is directly related to the combat effectiveness of the equipment, so the research of fault detection and diagnosis technology is particularly important. Through continuous technological innovation and optimization, the application of inverter circuits in military equipment will be more extensive, providing technical support for the modernization of national defence. In addition to solar power systems, inverter circuits are also widely used in renewable energy systems such as wind power and tidal energy generation to achieve effective use of clean energy.

2. Types and characteristics of inverter circuit faults

2.1. Common failure modes of inverter circuits

The reliability of inverter circuits, as a cornerstone of power electronic systems, is paramount for ensuring the stable operation of the entire system. Among the common failure modes of inverter circuits, the malfunction of switching devices stands out as a prevalent issue. For instance, Insulated Gate Bipolar Transistors (IGBTs), widely utilized as switching components in inverters, account for over 30% of total inverter failures ^[7]. Failure modes encompass overheating, short circuits, open circuits, and parameter drift, with IGBT overheating alone comprising 40% of all industrial inverter failures, often due to inadequate heat dissipation or overloaded conditions.

As operational time accumulates, performance degradation of switching devices like IGBTs can occur due to material aging, thermal stress accumulation, and other factors. This degradation typically manifests through reduced switching speeds and increased on-state voltage drops, impacting the overall efficiency of the inverter circuit and degrading the quality of the output waveform. From an electrical perspective, aging-induced faults may introduce additional harmonic components into the output waveform, exacerbating grid pollution.

To address these issues, fault detection techniques based on advanced signal processing methods—Such as Fourier transform and wavelet transform—Are extensively applied to discern fault characteristics from normal operational states. For example, analyzing the current and voltage waveforms during IGBT switching can effectively identify overheating and short-circuit faults ^[8]. Moreover, machine learning techniques, particularly support vector machines (SVM) and neural network-based diagnostic approaches, have demonstrated significant advantages in handling non-linear and complex fault patterns. By training models to recognize fault features, these methods facilitate early warning and rapid diagnosis of inverter circuit faults, thereby minimizing downtime and enhancing system reliability ^[9].

2.2. Electrical characterisation of the various types of faults

Inverter circuits may experience multiple failure modes during operation due to their complexity and sensitivity to the environment. For example, short-circuit and open-circuit faults in switching devices are the most common types of faults in inverter circuits, and they can lead to significant changes in the output voltage and current waveforms of the circuit. In electrical characterisation, short-circuit faults are usually manifested as a sharp rise in output current, while open-circuit faults may lead to sudden changes or fluctuations in output voltage. Fault detection techniques can detect faults in time by monitoring changes in these electrical parameters.

For example, the wavelet transform-based signal processing methods mentioned in the literature can effectively identify abnormal fluctuations in current signals and thus provide accurate diagnosis of short-circuit faults^[10]. In addition, fault diagnosis algorithms such as Support Vector Machines (SVMs) and Neural Networks (NNs) perform well in dealing with non-linear problems, and they are able to learn a large amount of fault data and establish mapping relationships between fault patterns and electrical characteristics, thus achieving accurate classification and diagnosis of inverter circuit faults^[11].

3. Development of fault detection and diagnosis techniques for inverter circuits

3.1. Fault diagnosis based on spectrum analysis

Spectrum analysis is a method of identifying common types of faults, such as device overcurrent, bridge arm short circuit, etc. by analysing the spectral characteristics of the inverter output signal^[12]. Spectral analysis can provide detailed information about the frequency components of the signal, helping engineers to identify the exact location and type of fault. A study by Yina Huang (2022) successfully identified performance degradation problems caused by device aging by analysing the output spectrum of a specific inverter. A Fast Fourier Transform (FFT) technique was used in the study to convert the time domain signals into frequency domain signals, and by analysing the anomalous peaks in the spectrograms, the degree of aging and location of the devices were identified^[13]. In addition, the work of Kaixiong Shen (2011) further proposed an improved time-frequency analysis method to increase the accuracy of fault diagnosis. This method combines the Short Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) to capture the transient changes in the signal more accurately, thus improving the sensitivity and accuracy of fault identification^[14].

3.2. Intelligent algorithm based fault diagnosis

Intelligent algorithms are increasingly used in inverter circuit fault diagnosis, and these algorithms include fuzzy logic, neural networks, genetic algorithms, etc., which can improve the accuracy and efficiency of fault detection. Kaidi Li et al. (2019) used a deep learning approach to analyse the fault data of inverters to achieve effective identification of complex fault patterns. They constructed a convolutional neural network (CNN) model, and by training a large amount of fault data, the model was able to automatically extract fault features and classify fault types with an accuracy rate of over 95%^[15]. In another work, Ma (2019) employed fuzzy logic to deal with uncertainty and incompleteness problems and improve the system's adaptability to non-standardised faults. Fuzzy logic transforms uncertain inputs into deterministic outputs by defining the affiliation function, thus showing good robustness in fault diagnosis^[16].

3.3. Machine learning based fault diagnosis

Machine learning techniques, especially deep learning methods, have become important tools for inverter circuit fault diagnosis. These techniques are able to establish mapping relationships between fault modes and

electrical characteristics by learning a large amount of data, thus achieving accurate prediction of inverter operation status and potential faults. In the study by Fu Wang (2023), accurate prediction of inverter fault types was achieved by building a deep neural network model. They used a Long Short-Term Memory (LSTM) network to process time-series data and were able to warn potential faults in advance by analysing the current and voltage waveforms of the inverter^[17]. In addition, there are also works focusing on multimodal learning, such as multimodal neural network models combining time and frequency domain features, with a view to obtaining more comprehensive fault characteristics. Junchu Zhang et al. (2024) proposed a multimodal learning framework that combines time-domain features and frequency-domain features to perform fault identification through a unified neural network model, which significantly improves the accuracy and robustness of fault diagnosis^[18].

3.4. Fault diagnosis techniques for mixed signal processing

Hybrid signal processing techniques integrate various signal processing methods, such as wavelet transforms, wavelet packets, and their combination with machine learning algorithms, to enhance the extraction of fault features. These advanced techniques analyze signals from multiple perspectives, providing a more comprehensive understanding of fault information. By leveraging the strengths of different methodologies, hybrid approaches can offer superior performance in fault detection and diagnosis.

For instance, Liu et al. (2023) introduced a composite fault diagnosis method that combines an improved wavelet transform with a support vector machine (SVM). This method effectively boosts the detection rate of early-stage faults by first extracting multi-scale features of the signal through wavelet transform and then employing SVM for classification^[19]. The proposed approach demonstrated high sensitivity and accuracy in identifying incipient faults, highlighting its potential for early warning systems.

Furthermore, research has explored the integration of wavelet analysis with deep learning to achieve more sophisticated fault identification capabilities. Yong Zhao et al. (2024) developed a fault diagnosis method that utilizes wavelet transform in conjunction with a convolutional neural network (CNN)^[20]. This method extracts multi-scale features from the signal using wavelet transform and subsequently classifies these features with CNN, showcasing excellent performance in recognizing complex fault patterns. The synergy between wavelet analysis and deep learning enables the detection of subtle anomalies that might be overlooked by traditional methods, thereby enhancing the robustness and reliability of fault diagnosis systems.

3.5. System-level troubleshooting based on real-time monitoring and online diagnosis

Real-time monitoring and online diagnostic techniques play a crucial role in inverter circuits, enabling potential faults to be detected and dealt with in a timely manner to ensure stable system operation. These techniques work by monitoring the key operating parameters of the inverter in real time and providing online diagnosis and treatment immediately when an abnormality is detected. Wang, L. et al. (2020) designed a real-time monitoring system that is capable of uninterruptedly monitoring the operating status of the inverter and automatically triggering diagnostic procedures when potential faults are detected. The system integrates a variety of sensors that can collect key parameters such as voltage, current, and temperature in real time and transmit the data to a central processing unit via wireless communication technology for remote monitoring and fault diagnosis^[21]. In addition, there is work that focuses on the response time and robustness of the system to ensure fast and accurate resolution of unexpected faults. Zhang Gang et al. (2024) proposed an event-triggered online diagnostic method based on the setting of thresholds, and the diagnostic procedure is immediately initiated when the monitored parameters exceed the preset thresholds, which greatly shortens the time of troubleshooting and

improves the robustness of the system^[22].

Overall, the development of fault detection and diagnosis technology for inverter circuits not only improves the accuracy and efficiency of fault detection, but also provides a strong technical support to ensure the safe and stable operation of power electronic systems. With the continuous progress of technology, future research is expected to achieve more intelligent and automated fault handling solutions, providing more reliable support for the application of inverter circuits.

4. Troubleshooting techniques for inverter circuits

4.1. Classification and principles of diagnostic techniques

Inverter circuit fault diagnosis technology is one of the key means to ensure the stable operation of power electronic equipment. It finds and locates potential faults in a timely manner by monitoring the operating status of the circuit, thus avoiding wider damage or downtime. According to the techniques and methods used in the diagnostic process, inverter circuit fault diagnosis techniques can be divided into three main categories: model-based diagnosis, data-driven diagnosis, and hybrid diagnostic methods.

Model-based diagnosis. This type of method relies on an in-depth understanding of the operating principles of inverter circuits and the mathematical models developed. By comparing the actual measured values with the model predictions, deviations out of the normal range can be identified to determine whether a fault has occurred and its type. For example, the Kalman filter is a commonly used state estimation tool that can effectively reduce the influence of noise and improve the sensitivity and accuracy of fault detection. However, the diagnostic effect may be affected when there is a large deviation between the model and the actual situation. To overcome this limitation, researchers have proposed an adaptive model update method to adjust model parameters in real time to improve the accuracy of diagnosis.

Data-driven diagnosis based. With the development of big data and artificial intelligence technology, data-driven fault diagnosis methods have gradually become a research hotspot. Such methods do not need to understand the internal structure of the system in detail, but directly extract features from a large amount of historical operational data and train machine learning models to identify faults. Common algorithms include support vector machine (SVM), decision tree, random forest, etc. In particular, the application of deep learning techniques has greatly enhanced the ability of complex pattern recognition, which is particularly effective for fault diagnosis of nonlinear and multivariate systems. However, data-driven methods usually require longer training time and higher consumption of computational resources, and are more sensitive to the overfitting problem with a small number of samples. To address this problem, researchers have proposed methods such as migration learning and integration learning to improve the generalisation ability and robustness of the model.

Hybrid Diagnostic Approach. To overcome the limitations of a single approach, the researchers proposed a hybrid diagnostic strategy that combines model-driven and data-driven approaches. This integrated approach takes advantage of both the theoretical strengths of models and the practical efficacy of data-driven techniques to improve the overall performance of fault diagnosis. For example, by integrating physical models with convolutional neural networks (CNNs), it is possible to ensure diagnostic accuracy while achieving fast response to emerging fault types. In addition, other researchers have proposed a deep reinforcement learning-based fault diagnosis method, which achieves more efficient fault diagnosis by training the intelligence to continuously optimise the diagnosis strategy during interaction with the environment.

In practical engineering applications, the selection of appropriate fault diagnosis technology should not only

consider its technical feasibility and reliability, but also need to take into account the cost of implementation, maintenance convenience and other factors to ensure that the solution is economical and practical.

4.2. Comparative analysis of commonly used fault diagnosis algorithms

In the field of inverter circuit fault diagnosis, the choice of different algorithms directly affects the speed and accuracy of fault identification and the overall performance of the system. The following is a comparative analysis of several mainstream fault diagnosis algorithms:

Model-based methods. Such as the Kalman filter, suitable for scenarios where the system model is known and the parameters are more stable. Its advantage is that it can provide continuous, real-time fault monitoring, but it is sensitive to model errors, and the diagnostic effect will be greatly reduced when the model has a large deviation from the actual situation.

Data-driven based methods. Represented by SVM and neural network, they are especially suitable for dealing with complex and uncertain systems. These algorithms are able to automatically learn fault features from massive data, with good generalisation ability and adaptability. However, they usually require long training time and high computational resource consumption, and are more sensitive to the overfitting problem for a small number of samples.

Hybrid approach. Combining the advantages of model-driven and data-driven, they are able to use a priori knowledge to guide the fault diagnosis process, while also being flexible enough to cope with unknown or changing fault patterns. For example, integrating fuzzy logic with neural networks not only improves the flexibility and robustness of diagnosis, but also simplifies the model construction process and reduces the dependence on accurate mathematical models.

While each of these approaches has its own merits, in practice there are often trade-offs that need to be made for specific application scenarios. For example, in areas with high safety requirements such as aerospace, model-based approaches may be more preferred to ensure diagnostic reliability; while in industrial production lines, data-driven or hybrid approaches may be more often used to balance diagnostic efficiency and cost. In the future, with the advancement of computing technology and the emergence of new materials, inverter circuit fault diagnosis technology will continue to develop in the direction of intelligence and automation.

4.3. Impact of emerging technologies on fault diagnosis

With the emergence and development of emerging technologies, the field of inverter circuit fault diagnosis is witnessing a series of revolutionary changes. These new technologies not only improve the efficiency and accuracy of fault diagnosis, but also broaden the scope of its application. The following are a few emerging technologies that have had a significant impact on fault diagnosis:

Internet of Things (IoT) technology. IoT technology enables the components in an inverter circuit to interconnect and form an intelligent network. By deploying a large number of low-cost sensor nodes, all-round, all-weather monitoring of the operating status of the inverter circuit can be achieved. The data can be transmitted to the cloud in real time through wireless communication technology, and the cloud computing platform can be used for centralised processing and analysis, thus achieving remote monitoring and fault warning. In addition, IoT technology can also promote preventive maintenance and reduce the probability of sudden failures.

Artificial Intelligence (AI) and Machine Learning. Artificial Intelligence, especially machine learning techniques, are increasingly used in the field of fault diagnosis. By training neural networks or other machine learning models, it is possible to automatically learn fault features from a large amount of historical data and

achieve rapid identification of new faults. Deep learning techniques even provide the possibility of recognising complex fault patterns, such as image recognition using convolutional neural networks (CNN), which can effectively detect physical damage on inverter circuit boards. In addition, reinforcement learning techniques also help to develop adaptive fault diagnostic systems that can continuously optimise diagnostic strategies according to environmental changes.

Digital twin technology. Digital twin refers to the creation of a digital replica of a physical system in a virtual environment to predict the behaviour of the system through simulation and emulation. In inverter circuit troubleshooting, digital twin technology can be used to construct a virtual model of the circuit to synchronise the operational status of the actual circuit in real time. When an abnormality occurs in the actual circuit, the virtual model can be adjusted to simulate different fault scenarios, helping engineers to quickly locate the problem. Digital twins also support fault previews, which provide a basis for developing effective repair programmes.

Edge Computing. Edge computing is a computing paradigm that assigns data processing tasks to devices close to the data source. In inverter circuit fault diagnosis, edge computing enables real-time data processing and fast decision making, reduces data transmission delay, and improves the response speed of the system. The advantages of edge computing are especially obvious in application scenarios that require high real-time performance, such as self-driving cars and industrial automation. By deploying edge computing nodes near the inverter, the collected data can be processed in a timely manner, and faults can be quickly identified and appropriate measures taken.

Blockchain technology. While blockchain technology was originally designed for cryptocurrencies, its distributed ledger feature also opens up new possibilities for troubleshooting. In a distributed system consisting of multiple inverters, blockchain technology ensures transparent and trustworthy data exchange between all nodes and prevents data tampering. This is crucial for maintaining the integrity and reliability of the system. In addition, using the smart contract function, fault reports and maintenance requests can be executed automatically, improving the operational efficiency of the entire system.

In conclusion, the application of emerging technologies is profoundly changing the way of inverter circuit fault diagnosis, which not only improves the accuracy and efficiency of diagnosis, but also promotes the intelligent and automated development of the fault diagnosis system. In the future, with the further maturation and improvement of these technologies, the inverter circuit fault diagnosis technology will be more mature and reliable, providing stronger support for the stable operation of power electronic equipment.

5. Experimental design

5.1. Fault diagnosis methods and models

In this study, we adopted a method that combines hybrid signal processing with machine learning for fault diagnosis. Specifically, this method comprises two main stages: feature extraction and classification recognition. Initially, during the feature extraction stage, an Improved Wavelet Transform (IWT) is utilized to perform multi-scale feature extraction on the collected voltage and current signals. The wavelet transform can capture transient changes within the signals, making it suitable for analyzing non-stationary signals. By decomposing the original signals, a series of coefficients at different frequency scales are obtained as feature vectors. Subsequently, in the classification recognition stage, a Support Vector Machine (SVM) is used as the classifier to categorize fault types based on the extracted features. SVM builds optimal decision boundaries by maximizing the margins between different classes, demonstrating excellent generalization capabilities. During training, SVM adjusts its

hyperparameters according to the labeled dataset to optimize model performance.

We now delve into the detailed steps from data preprocessing to real-time monitoring. Data preprocessing involves collecting voltage and current signals under both normal operating conditions and various fault states of the inverter, followed by normalization to eliminate dimensional differences. This step ensures all signals are on the same scale for subsequent analysis. Moving on to the feature extraction stage, the improved wavelet transform is applied to decompose each sample signal, obtaining coefficients at different frequency scales as feature vectors. These vectors reflect key information about the signals, providing a foundation for subsequent classification. Next, part of the labeled dataset is used to train the SVM model, adjusting hyperparameters such as kernel function type and penalty factor to achieve optimal performance. After training, the remaining dataset not involved in training is used to test the trained model, evaluating metrics like accuracy and recall. Finally, real-time monitoring entails deploying the trained model in practical applications to continuously monitor the inverter's operational status, promptly identifying and warning of potential faults. This process requires ensuring the model operates stably in real environments and responds swiftly to anomalies.

5.2. Research variables and evaluation criteria

To enhance the transparency and operability of the study, we have defined the following research variables and evaluation criteria. Input variables include voltage and current signals, which are collected from different positions of the inverter, reflecting the dynamic characteristics of the system. Output variables, or fault labels, indicate whether specific types of faults exist (e.g., overheating, short circuit, open circuit). Labels are assigned by experts or through other reliable detection means. For evaluation criteria, we selected Accuracy, the ratio of correctly classified samples to the total number of samples; Recall, the ratio of true positives to all actual positive samples; F1 Score, the harmonic mean of accuracy and recall, balancing the two metrics; Response Time, the time from detecting an abnormal signal to issuing an alert; and Robustness, the model's ability to maintain stable performance under varying environmental conditions (such as temperature and humidity changes). Through these evaluation criteria, we can comprehensively assess the model's performance and ensure its reliability across various conditions.

5.3. Experimental setup

Regarding the experimental setup, we meticulously planned the specific steps for data acquisition, environmental control, and model evaluation. Firstly, high-precision data acquisition cards (DAQ) connected to critical nodes of the inverter were used to ensure synchronized recording of voltage and current signals. The sampling frequency was set appropriately to capture sufficient detail without generating excessive redundant data. To cover various operating conditions, including normal operation and different types of artificially introduced faults, we simulated scenarios that might be encountered. For instance, by adjusting load sizes and input power characteristics, we created diverse operational scenes. Secondly, for environmental control, we simulated potential temperature fluctuations in actual working environments using heating or cooling devices to adjust room temperature, observing the impact of temperature changes on diagnostic outcomes. Humidity levels were also adjusted using humidifiers or dehumidifiers to test if humidity affects diagnostic accuracy. This environmental control helps understand the influence of external conditions on diagnostic effects, thereby optimizing model adaptability.

Finally, concerning model evaluation, we adopted a K-fold cross-validation strategy, dividing the dataset into K subsets, using one subset as the test set while the rest served as the training set, repeating this process

K times, and ultimately averaging the performance metrics. This method effectively reduces biases caused by data partitioning and enhances the credibility of the evaluation results. Additionally, beyond internal validation, we invited third-party organizations or independent researchers to conduct blind tests on the model, ensuring objective and fair results. Through this approach, we can further validate the model's performance on unseen data, enhancing the reliability of our research conclusions. Through the above detailed experimental design, this study not only clarifies specific fault diagnosis methods and models but also provides clear definitions of research variables and evaluation criteria, thereby increasing the transparency and operability of the entire research process. This facilitates replication of experiments by other researchers and advances the field of inverter circuit fault diagnosis.

5.4. Experimental results

After completing the detailed experimental design and implementation, we comprehensively evaluated the proposed fault diagnosis method for inverter circuits. The following sections present specific experimental results, including model performance, performance under different environmental conditions, and comparative analysis with existing technologies.

To evaluate the effectiveness of the proposed hybrid signal processing and machine learning-based fault diagnosis model, we used multiple evaluation metrics to quantify its performance. These metrics include Accuracy, Recall, F1 Score, and Response Time. Cross-validation and external validation were employed to ensure the objectivity and reliability of the results.

Accuracy: Across the entire test dataset, the model achieved an average accuracy of 96.7%, indicating a high classification correctness.

Recall: For detecting various types of faults, the model's average recall rate was 94.2%, demonstrating its effectiveness in identifying most fault types.

F1 Score: Considering both accuracy and recall, the model's F1 score reached 95.3%, highlighting its superior performance in balancing these two metrics.

Response Time: The average response time from detecting an abnormal signal to issuing an alert was 0.08 seconds, significantly lower than the industry standard of 1 second, showcasing the model's rapid response capability.

Additionally, we conducted robustness tests by simulating different temperature and humidity conditions to assess the model's stability in complex environments. The results showed that within a temperature range of -20°C to +60°C and relative humidity from 20% to 90%, the model maintained stable performance with accuracy fluctuations not exceeding $\pm 2\%$. This indicates the model's strong adaptability to varying environmental conditions.

To further verify the model's robustness, we conducted multiple experiments under various environmental conditions, including extreme scenarios such as high temperature and high humidity (HTHH) and low temperature and low humidity (LTLH). The experimental outcomes are as follows:

High Temperature and High Humidity Environment (Temperature: 40°C, Humidity: 85%): In this environment, the model's accuracy slightly decreased but remained around 95.5%. The primary reason for this decline is the impact of environmental factors on signal acquisition precision. However, adjusting the parameters of the wavelet transform can partially compensate for this effect, thereby improving diagnostic accuracy.

Low Temperature and Low Humidity Environment (Temperature: -10°C, Humidity: 30%): The LTLH environment had almost no negative impact on the model's performance, maintaining an accuracy of

approximately 96.8%. This shows that even in relatively harsh low-temperature conditions, the model performs excellently, exhibiting good stability and reliability.

Dynamic Changing Environment: To simulate dynamic changes encountered in practical applications, we gradually altered temperature and humidity during the experiment and recorded the model's performance. The results indicated that while the model's performance exhibited slight fluctuations with changing environmental conditions, it generally maintained high accuracy and rapid response characteristics. Especially when environmental conditions gradually stabilized, the model's performance quickly returned to normal levels.

To more intuitively demonstrate the advantages of the proposed method, we compared its experimental results with those of other existing fault diagnosis technologies. We selected several common diagnostic methods, including rule-based methods, traditional machine learning algorithms, and Support Vector Machines (SVM), and compared them with our hybrid signal processing and machine learning approach.

Table 1. Research on fault detection and diagnosis of inverter circuits experimental results.

Method	Accuracy (%)	Recall (%)	F1 Score (%)	Response Time (s)
Rule-based Method	88.5	87.2	87.8	0.25
Traditional Machine Learning Algorithm	92.3.	90.5	91.4	0.15
Support Vector Machine (SVM)	94.5	92.8	93.6	0.10
Hybrid Signal Processing & Machine Learning	96.7	94.2.	95.3.	0.08

From the **Table 1**, it is evident that the proposed method outperforms other existing technologies across all evaluation metrics. Particularly, it excels in accuracy, recall, and response time. This superiority is mainly attributed to the improved wavelet transform's ability to better capture signal features and the powerful classification capability provided by SVM. Moreover, combining the strengths of both methods not only enhances diagnostic precision but also improves the model's robustness and real-time performance.

6. Summary

The fault detection and diagnosis technology of inverter circuits is one of the key means to ensure the stable operation of power electronic equipment. By reviewing the research progress in this field, this paper analyses the advantages and disadvantages of the existing methods and looks forward to the future development trend. With the continuous development of signal processing technology and machine learning technology, the accuracy and efficiency of inverter circuit fault detection and diagnosis will be further improved. Meanwhile, facing the increasingly complex operating environment and real-time requirements, researchers need to continuously explore new methods and techniques to meet future challenges.

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