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WAVELET TRANSFORM AND FUZZY REASONING FOR UNDERGROUND POWER CABLE FAULT DIAGNOSIS

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Abstract

Traditional fault diagnosis methods, such as Time-Domain Reflectometry and Frequency-Domain Reflectometry, often struggle to handle complex fault signals and have limitations in accuracy and real-time performance. This research aims to develop a more effective cable fault diagnosis model that combines wavelet transform and fuzzy reasoning to improve detection accuracy and real-time performance. The proposed model uses wavelet transform for multi-scale decomposition of fault signals, extracting high-frequency and low-frequency features, while the fuzzy reasoning system classifies and diagnoses the fault signals based on a preset rule base. Experimental results show that the model achieves high accuracy in identifying various fault types, including short circuit, grounding, open circuit, and partial discharge, with a short circuit fault accuracy of 94.5% and an average diagnosis time of 0.8 seconds. The model also demonstrates strong robustness under noise interference, maintaining over 90% classification accuracy even at a noise intensity of 20 dB. Compared to traditional methods, the model excels in handling complex faults and multiple signals while maintaining high noise resistance. Future research will focus on enhancing real-time performance, improving rule base design, and expanding the model's ability to handle multi-fault scenarios.

Keywords: cable fault diagnosis; wavelet transform; fuzzy reasoning; fault classification

List of Symbols/Acronyms

TDR - Time-Domain Reflectometry
FDR - Frequency-Domain Reflectometry
WT - Wavelet Transform
FIS - Fuzzy Inference System
SNR - Signal-to-Noise Ratio
SC - Short Circuit
GF - Ground Fault
OC - Open Circuit
PD - Partial Discharge
HFE - High-Frequency Energy
LFE - Low-Frequency Energy
$x(t)$ - Original signal
$\psi^*(t)$ - The complex conjugate of the mother wavelet function.
a - Scale factor
b - Translation factor
$W_\psi(a,b)$ - Wavelet transform of the signal at scale aaa and translation bbb
$c_{j,k}$ - Wavelet transform coefficients
$\psi_{j,k}(t)$ - Wavelet function at different scales and translations
$\hat{x}(t)$ - Denoised signal
d_k - Denoised wavelet coefficients
λ - Threshold parameter
$\mu_A(x)$ - Membership function of fuzzy set AAA
x - Input variable in fuzzy logic
c - Center of the membership function
σ - Spread of the membership function
y - Inference output in fuzzy logic
w_i - Rule weight in fuzzy inference
z_i - Output value of each fuzzy rule

1. INTRODUCTION

With the development of modern power systems, underground cables are increasingly used in urban power supply networks, and their safety and reliability are directly related to the stable operation of power systems. However, due to the deep burial of underground cables, the location of faults is often difficult to determine, greatly increasing the complexity of fault diagnosis. Traditional fault diagnosis methods such as TDR and FDR often have limitations in dealing with complex cable fault signals, as Laurie pointed out, including low accuracy and poor real-time performance [1]. Therefore, there is an urgent need to develop new fault diagnosis methods based on emerging technologies.

Researchers worldwide have conducted extensive studies on cable fault diagnosis

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techniques. In traditional methods, many scholars have employed time-domain and frequency-domain analysis to locate cable faults. However, the primary issue with these methods is their suboptimal performance when handling complex cable signals, particularly nonlinear and non-stationary fault signals. As pointed out by Feng and Kumar, traditional methods often fall short in terms of accuracy and efficiency, especially when dealing with such intricate and dynamic fault characteristics [2, 3].

In recent years, WT has been widely applied to cable fault diagnosis [4]. Yan et al. and Wang reviewed the use of WT in diagnosing rotating machinery faults, emphasizing its unique advantages in time-frequency analysis [5]. Similarly, Mo et al. and Wang proposed a modified WT method based on cyclic content ratio, significantly improving the accuracy of bearing fault diagnosis [6, 7]. In cable fault diagnosis, Zhang et al. and Xu introduced a precise cable defect location method based on FDR, which enhanced the accuracy of fault detection [8, 9].

In terms of fuzzy reasoning, Shao et al. and Zhang employed intuitionistic fuzzy sets and correlation matrices to propose a new power system fault diagnosis method, demonstrating its effectiveness in managing complex system faults [10, 11]. In addition, Guo et al. utilized case-based reasoning and fuzzy association rule mining techniques in transformer fault diagnosis, achieving promising results [12]. Liu et al. also reported excellent results in related fault diagnoses [13].

Domestically, Wu et al. conducted online monitoring of cable insulation by injecting chirp signals and proposed a diagnostic method based on resonance frequency analysis, significantly enhancing fault detection sensitivity [14]. Feng et al. introduced a decision support-based monitoring method for mine cable fault diagnosis and validated its effectiveness in the mining environment [15]. Huang et al. demonstrated the high efficiency of wavelet packet transform in signal processing and showed that WNN-based fault-tolerant diagnosis methods perform well in analog circuit fault diagnosis [16].

Despite significant advancements, some challenges persist. WT, as a time-frequency analysis tool, effectively handles non-stationary signals and has been widely applied in various signal processing fields [17]. Meanwhile, FR plays a crucial role in handling uncertain information and is essential for cable fault classification. Combining WT with FR not only facilitates the extraction of multi-scale features from cable fault signals but also enables intelligent fault diagnosis through fuzzy reasoning, presenting a new solution for accurate cable fault diagnosis. The integration of wavelet transform and fuzzy reasoning offers a potential approach to solving the aforementioned issues. Gubarevych et al. systematically reviewed the methods for diagnosing stator winding insulation in asynchronous motors and proposed new approaches, which provide valuable insights for cable fault diagnosis [18]. Therefore, the integration of WT and FR offers a potential solution to address the shortcomings of existing diagnostic methods and warrants further exploration.

Based on the current state of research both domestically and internationally, this paper aims to diagnose cable faults using the combination of WT and FR. WT is employed to decompose the multi-scale features of cable fault signals, and related features are extracted. A fuzzy logic-based fault classification system is designed to tackle the problem of fault type determination. By integrating WT and FR, a comprehensive diagnostic model is constructed and validated for its effectiveness in real-world cable fault diagnosis. The research results can provide technical support for the rapid location and repair of cable faults, reduce grid maintenance costs, and improve the operational efficiency of the power system. Therefore, the proposed diagnostic method has important practical application value for fault management and maintenance optimization in power systems.

The paper is organized as follows: the introduction outlines the research background, motivation, and key gaps. The theoretical foundation explains the principles of wavelet transform and fuzzy inference system. The methodology section details the design and implementation of the proposed model, followed by results and performance evaluation through simulations. Finally, the conclusion discusses challenges, future improvements, and practical implications. While laboratory results are promising, future work will focus on enhancing real-time performance, optimizing the rule base, and expanding diagnostic capabilities for multi-fault scenarios in real-world applications.

2. THEORETICAL FOUNDATION

2.1. Overview of Wavelet Transform Theory

2.1.1. Basic Concept of Wavelet Transform

The WT is a powerful mathematical tool for signal analysis that decomposes a signal into various frequency components, allowing the study of its characteristics over time. Yan et al. highlighted that WT effectively captures the time-frequency characteristics of fault signals through multi-scale decomposition [4]. The fundamental concept of WT involves generating a series of wavelet functions by translating and scaling a mother wavelet function. These wavelets can analyze the local characteristics of the signal at different scales, thereby detecting local anomalies in fault signals.

The WT is mathematically expressed as shown in equation (1).

$$W_{\psi}(a,b) = \int_{-\infty}^{\infty} x(t) \cdot \psi^{*}(\frac{t-b}{a})dt \qquad (1)$$

In this formula, $x(t)$ is the original signal, is the mother wavelet function, a is the scale factor, b is the translation factor, and $\psi^*(t)$ represents the complex conjugate of the mother WT. Mo et al. stated that this formula can decompose a signal into different frequency components and time windows, providing multidimensional information about cable fault signals [6].

2.1.2. Basic Concept of Wavelet Transform

The key to WT lies in the selection of the wavelet basis function. Different mother wavelets have different time-frequency resolutions, so selecting the appropriate wavelet basis function is crucial for different types of signal processing. Mo et al. pointed out that Haar wavelet and Daubechies wavelet are two commonly used wavelet basis functions, with the former being suitable for signals with sudden changes and the latter being more appropriate for the analysis of smooth signals [6]. By using these wavelet basis functions, cable fault signals can be effectively decomposed at multiple scales, extracting features at different frequencies.

MRA is a key feature of WT, enabling the analysis of both detailed and overall structures of a signal at varying scales. The fundamental process of MRA is expressed in formula (2).

$$x(t) = \sum_{j \in Z}\sum_{k \in Z} c_{j,k}, k\psi_{j,k}(t) \tag{2}$$

Among them, $c_{j,k}$ represents the WT coefficients, and $\psi_{j,k}(t)$ refers to the wavelet functions at different scales and translations. This process effectively separates different frequency components of the cable fault signals, providing a basis for precise fault location.

2.1.3. Application of Wavelet Transform in Signal Processing

The WT is widely applied in signal processing, particularly in fault signal feature extraction and noise reduction. Qin et al. noted that in cable fault diagnosis, WT can effectively detect abrupt changes and frequency variations in fault signals, which are often linked to physical damage in the cable [19]. By decomposing the signal using WT, the exact timing and frequency components of the fault can be identified, allowing for the determination of the fault type and severity.

The WT also provides significant advantages in noise reduction. Hsueh et al. proposed that actual cable fault signals are often accompanied by substantial noise, particularly in complex electromagnetic environments. Through wavelet threshold denoising techniques, noise can be effectively removed while preserving the useful information in the fault signal [20, 21]. This denoising technique commonly employs soft or hard thresholding, filtering the detail coefficients obtained from wavelet decomposition by setting a threshold, thereby achieving signal denoising. The formula is given by (3).

$$\hat{x}(t) = \sum_k d_k \cdot \psi_k(t), Where\ d_k = \begin{cases} x_k - \lambda, if x_k > \lambda \\ x_k + \lambda, if x_k < -\lambda \\ 0, otherwise \end{cases} \tag{3}$$

Among them, $\hat{x}(t)$ is the denoised signal, d_k represents the denoised wavelet coefficients, and λ is the threshold parameter. This method can significantly improve the SNR of cable fault signals.

2.2. Overview of Fuzzy Reasoning Theory

2.2.1. Basic Concept of Fuzzy Logic

Fuzzy logic is a mathematical method used to deal with uncertainty and vagueness by introducing the concept of membership degrees to represent the fuzziness of things. Unlike classical binary logic, fuzzy logic allows the value of a variable to continuously vary between 0 and 1, which better simulates the uncertainty present in the real world. In fuzzy logic, the membership function defines the degree to which an element belongs to a fuzzy set, its formula is given by (4).

$$\mu_A(x) = \frac{1}{1 + (\frac{x-c}{\sigma})^2} \tag{4}$$

Among them, x represents the input variable, c is the center of the membership function, and σ denotes the spread of the function. The core strength of fuzzy logic lies in its ability to manage uncertainty using fuzzy sets and rule-based reasoning, making it highly applicable in complex areas such as cable fault diagnosis.

2.2.2. Components of a Fuzzy Inference System

An FIS is composed of four main components: fuzzification, a fuzzy rule base, an inference engine, and defuzzification. These components work together to transform inputs into outputs:

(1) Fuzzification: Converts the precise input data into degrees of membership in fuzzy sets.
(2) Fuzzy Rule Base: Establishes relationships between input and output using "if-then" rules.
(3) Inference Engine: Uses the fuzzy rule base to perform fuzzy logic reasoning and generate fuzzy outputs.
(4) Defuzzification: Converts the fuzzy outputs into a clear decision or classification result.

Huo et al. emphasized that the fuzzy rule base within the inference engine is critical to the performance and diagnostic accuracy of the FIS, as the design of the rule base significantly impacts the system's effectiveness [22]. The inference process is mathematically expressed by formula (5).

$$y = \sum_{i=1}^{n} w_i \cdot z_i \tag{5}$$

Among them, w_i represents the rule weight, and z_i represents the output value of each rule.

2.2.3. Application of Fuzzy Reasoning in Uncertainty Problems

FIS can handle uncertainty in complex systems, making them valuable for cable fault diagnosis. Underground cables are subjected to various external factors during operation, resulting in significant uncertainty and noise in the signals, which increases the difficulty of fault diagnosis.Traditional deterministic methods typically require high input accuracy and perform poorly when dealing with fuzzy or uncertain signals. In contrast, FIS can process uncertain information, enabling accurate fault classification and decision-making even when the input data is incomplete or noisy.

Wang et al. proposed that FIS can map various fuzzy characteristics of cable fault signals into membership degrees through fuzzification, allowing fuzzy logic rules to classify these signals. In cases where multiple fault types coexist or signals overlap, the inference engine in FIS can effectively distinguish between different fault types, ensuring diagnostic accuracy [23]. This rule-based reasoning mechanism gives the system strong robustness, enabling it to handle overlapping fault types and produce reasonable outputs even when the signal input is unclear. Fuzzy inference systems can also be integrated with other intelligent algorithms, such as neural networks or genetic algorithms, to further enhance their ability to deal with uncertainty. Therefore, FIS has unique advantages in cable fault diagnosis, particularly in handling uncertainty problems. Their flexibility, robustness, and scalability make them suitable for complex cable fault environments, providing strong support for fault diagnosis.

2.3. Integration of Wavelet Transform and Fuzzy Reasoning in Cable Fault Diagnosis

2.3.1. Application of Wavelet Transform in Fault Feature Extraction

In cable fault diagnosis, WT effectively extracts key features from fault signals, particularly high-frequency transient signals. WT can decompose the cable fault signal into detail coefficients of different frequencies, helping identify local anomalies in the fault signal. Using multi-resolution analysis, WT separates frequency components at varying scales, enabling precise fault localization by identifying the position of the fault.

By comparing the different wavelet basis functions in Table 1, the most suitable wavelet basis function for the characteristics of cable fault signals can be selected to optimize the diagnostic process.

2.3.2. Application of Fuzzy Inference System in Fault Classification

The FIS effectively handles the fuzziness and uncertainty of signals in fault classification. After WT extracts the relevant features, the FIS classifies the fault types based on these features. Through the establishment of a reasonable fuzzy rule base, fuzzy inference can accurately determine the fault category even when faced with multiple fault characteristics. The inference rules can be expressed by formula (6).

$$IF\ x_1\ is\ A_1\ and\ x_2\ is\ A_2,\ y\ is\ B \tag{6}$$

Among them, A_1 , A_2 represents the fuzzy set of the input signal, and B represents the output fault category.

Table 1. The effect of wavelet basis functions in fault feature extraction

Wavelet basis function	Applicable range	Advantages	Disadvantages
Haar	Signals with sudden changes	Simple computation	Poor smoothness
Daubechies	General fault signals	Good smoothness	High computational complexity
Symlets	Symmetric signals	Strong signal recovery capability	High computational complexity

2.3.3. Advantages of Combining Wavelet Transform and Fuzzy Inference

The integration of WT and FIS significantly enhances the accuracy and real-time performance of cable fault diagnosis. WT is used to extract multi-scale features of fault signals, while the fuzzy inference system utilizes these features for intelligent fault classification. This combination not only handles complex non-stationary signals but also addresses uncertainty through fuzzy reasoning, resulting in highly accurate fault diagnosis.

3. ANALYSIS OF THE CURRENT STATUS OF CABLE FAULT DIAGNOSIS

3.1. Types and Characteristics of Cable Faults

Cable faults are common issues in power systems, particularly in underground cables where the complex installation environment and maintenance challenges make fault detection and diagnosis especially important. To effectively classify and locate faults, it is crucial to understand the types of faults and the characteristics of their signals.

3.1.1. Main Types of Cable Faults

The common types of underground cable faults can be categorized as follows, as shown in Table 2.

Table 2. Common fault types of underground cables

Fault type	Characteristics	Signal properties
SC	High current surge	Instantaneous high-frequency signals
GF	Conductor breakage	Slow signal changes
OC	Conductor-to-ground contact	Low-frequency components
PD	Insulation breakdown	Weak signals, sporadic discharge

From Table 2, it is evident that SC faults occur when the conductive parts of the cable come into contact with the ground or adjacent conductors. This results in a sudden surge in current, producing strong fault signals that typically manifest as transient high-frequency components. OC faults, on the other hand, are caused by a break in the cable conductor, preventing current flow. These faults usually lead to gradual signal changes without significant current fluctuations, making them harder to detect. GF occurs when the cable conductor directly contacts the ground, forming a ground current. These faults are characterized by distinct low-frequency components, often accompanied by increased cable temperature and current fluctuations. PD faults are caused by small arc discharges due to defects in the cable's internal insulation layer. This type of fault is often difficult to detect in its early stages, as the signal is relatively weak, but prolonged accumulation can lead to more severe faults.

3.1.2. Characteristics of Cable Fault Signals

Each type of cable fault generates distinct signal characteristics, and these signal features exhibit clear differences in both the time domain and frequency domain. The characteristics are illustrated in Fig. 1.

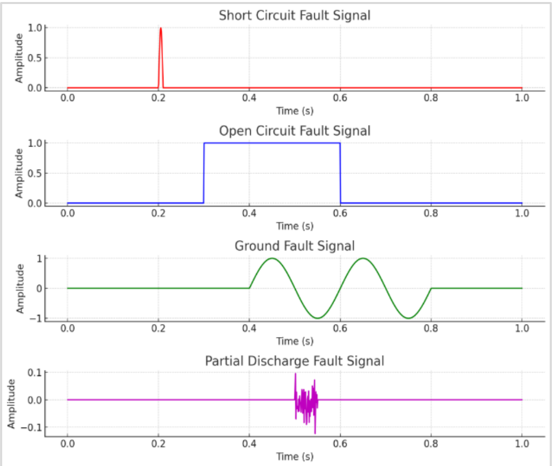

Fig. 1. Time domain waveform of cable fault signal

Fig. 1 illustrates the typical time-domain waveforms of various cable faults. These waveforms display distinct differences in pulses, frequency, and amplitude under different fault conditions, providing a foundation for accurately identifying fault types.

(1) SC: Triggered by a sudden surge in current, the waveform of an SC contains prominent spikes, manifesting as transient high-frequency pulses in the time domain.

(2) OC: The waveform of an OC is relatively smooth, lacking significant high-frequency components.

GF: GF signals exhibit sustained low-frequency oscillations, reflecting the stable flow of ground current.

PD: The waveform of a PD typically consists of irregular small pulses caused by minor arc discharges within the cable's insulation layer.

These distinct waveform characteristics are critical for accurately diagnosing and categorizing cable faults. Table 3 summarizes these signal characteristics, highlighting the different analysis methods required for diagnosis. For instance, detecting high-frequency pulse signals is key for SC, while for PD, the detection system must exhibit high sensitivity to capture weak discharge signals. Extracting these signal features not only aids in identifying fault types but also helps in fault localization, providing crucial information for repairs. By analyzing these fault signals and integrating WT and FIS, cable faults can be more precisely identified, and fault classification and localization can be effectively achieved based on the signal characteristics.

Table 3. Summary of characteristics of cable fault signals

Fault type	Time domain characteristics	Frequency domain characteristics
SC	Sharp peaks	High-frequency components
GF	Gradual changes	Low-frequency, smooth signal
OC	Continuous low-frequency oscillation	Strong low-frequency components
PD	Small, irregular pulses	Sporadic high-frequency components

3.2. Traditional Cable Fault Diagnosis Methods

3.2.1. Time-Domain Analysis Method

The time-domain analysis method primarily diagnoses faults by analyzing the variation of cable fault signals over time. One of the most commonly used time-domain methods is TDR. The basic principle of TDR is to inject a pulse signal into the cable and monitor the arrival time and amplitude of the reflected wave to determine the location and type of fault. TDR is highly effective in precisely locating common faults such as SC and OC and is particularly suitable for medium- to short-distance cable fault detection.

The typical workflow of TDR is as follows:

(1) Inject a known pulse signal into the cable.

(2) Detect the signal traveling along the cable and identify the reflected wave after the fault occurs.

(3) Calculate the fault distance based on the time delay of the reflected wave.

Although the time-domain analysis method allows quick diagnosis of cable faults, its sensitivity to complex fault types is relatively low. It struggles to differentiate overlapping signals in the presence of multiple fault sources. Moreover, TDR is highly sensitive to high-frequency noise and can be easily affected by external interference, which may reduce the accuracy of the diagnostic results.

3.2.2. Frequency-Domain Analysis Method

The frequency-domain analysis method diagnoses cable faults by analyzing changes in the frequency domain of fault signals. The most widely used frequency-domain method is FDR. The basic principle of FDR is to inject a series of sine waves with different frequencies into the cable and monitor the frequency response of the reflected waves to identify faults. FDR has higher accuracy in identifying multiple fault types, especially for long-distance cable fault detection.

The key difference between FDR and TDR is that FDR analyzes cable characteristics using frequency signals, making it more suitable for handling fault signals with complex frequency components. The specific workflow of FDR is as follows:

(1) Inject signals with different frequencies into the cable.
(2) Detect changes in the frequency response, particularly in amplitude and phase.
(3) Identify fault location and type through discontinuities in the frequency domain.

3.3. Limitations of Current Cable Fault Diagnosis Technologies

Despite significant advancements in cable fault diagnosis technologies, several limitations persist. First, in terms of diagnostic accuracy, traditional methods like TDR and FDR perform poorly when dealing with complex signals. TDR relies on reflected signals, and when the signal attenuation is high or subject to noise interference, the localization accuracy decreases significantly. While FDR is more sensitive to high-frequency signals, it is less accurate when dealing with low-frequency fault signals. Additionally, intelligent diagnostic methods offer certain advantages in handling complex fault signals but depend heavily on large amounts of training data. Misdiagnosis may occur when data is insufficient.

Another major limitation is diagnostic speed. The signal propagation and reflection processes in both TDR and FDR introduce delays, leading to poor real-time performance, particularly in long-distance cable scenarios. Furthermore, when multiple faults coexist or signals overlap, both methods struggle to effectively differentiate between fault sources, further limiting their diagnostic efficiency.

Based on the information in Table 4, current cable fault diagnosis technologies require significant advancements in both diagnostic accuracy and real-time performance. In particular, the development of robust algorithms is essential to effectively manage complex, multi-fault signals, ensuring precise fault identification and localization in challenging scenarios.

Table 4. Limitations of cable fault diagnosis technologies

Diagnosis method	Insufficient accuracy	Slow diagnosis speed	Limited complex fault handling
TDR	Signal attenuation, noise interference	Long propagation time, poor real-time response	Difficult to distinguish multiple faults, noise-sensitive
FDR	Poor accuracy for low-frequency signals	High computational complexity, slow response	Weak fault signals difficult to detect, severe signal attenuation
Intelligent Diagnosis Methods	Relies on large training data, accuracy drops with insufficient data	Long training and inference time, slower real-time diagnosis	Poor generalization, struggles with new or complex faults

4. CABLE FAULT DIAGNOSIS BASED ON WAVELET TRANSFORM AND FUZZY INFERENCE

4.1. Model Design Framework

4.1.1. Wavelet Transform Feature Extraction Module

The primary function of the WT feature extraction module is to decompose cable fault signals and extract their time-frequency characteristics. WT can effectively handle the non-stationary components in cable fault signals and capture the local details of the fault signals through multi-scale analysis.

The specific steps of feature extraction include:

Step 1: Decompose the fault signal using WT to obtain coefficients at different scales.
Step 2: Select an appropriate wavelet basis function to ensure that useful fault features are extracted.
Step 3: Identify the key information of the fault signal based on the energy characteristics of different frequency bands.

After feature extraction, common fault types exhibit significant differences across different scales. This multi-scale analysis enables clearer detection of the characteristic information when faults occur. Table 5 demonstrates the effectiveness of different wavelet basis functions in fault feature extraction.

By utilizing WT, features such as sudden spikes in SC faults or subtle variations in PD signals can be extracted with high accuracy. These extracted features provide a robust foundation for subsequent classification and diagnosis processes.

4.1.2. Fuzzy Inference Fault Classification Module

The FIS fault classification module is designed for intelligent classification of the features extracted by WT. This module relies on a fuzzy logic system to fuzzify the input feature signals and infer and determine the fault type through a pre-set fuzzy rule base.

Table 5. The effectiveness of different wavelet basis functions in fault feature extraction

Wavelet basis function	Performance in fault signal analysis	SuiTab fault types
Haar	Good at detecting abrupt changes	Short circuit faults
Daubechies	Provides smooth signal representation	General fault detection
Symlets	Symmetrical, good for reconstruction	Ground and open circuit faults

The FIS operates through the following steps:

Step 1: Fuzzification: The input feature signals are converted into membership degrees and represented using fuzzy sets.

Step 2: Fuzzy Rule Base: "If-Then" rules are set based on the feature signals, with the rule base containing the characteristics of various faults and corresponding classifications.

Step 3: Inference: Fuzzy logic is used to infer the fault type by processing the signals through the fuzzy rule base.

Step 4: Defuzzification: The fuzzy output is converted into a specific fault category, providing a clear diagnostic result.

This process enables the FIS to handle complex and uncertain fault signals effectively, leveraging fuzzy rules to intelligently classify faults and accurately determine fault types and locations.

In summary, the cable fault diagnosis model, which integrates WT and FIS, functions through two collaborative components: feature extraction and intelligent reasoning. This approach improves fault detection accuracy and efficiency, making it particularly suitable for handling complex and multi-type cable fault signals.

4.2. Model Construction and Implementation

4.2.1. Selection and Optimization of Wavelet Transform Parameters

The selection of the wavelet basis function must be optimized based on the characteristics of the signal, as different wavelet basis functions yield varying performances for different types of fault signals. Additionally, the decomposition level of WT should be carefully determined according to the frequency characteristics of the signal. Excessive decomposition levels may lead to increased computational complexity, while too few levels may result in the loss of critical fault signal information. Therefore, the choice of wavelet function is a critical factor in optimizing the model. Table 6 outlines the wavelet functions selected for this study, along with their respective advantages and disadvantages.

By optimizing the wavelet function and setting an appropriate number of decomposition levels, the model ensures that key features of the fault signal are effectively captured while maintaining computational efficiency.

Table 6. Selection and optimization of wavelet basis function parameters

Wavelet basis function	Suitable fault types	Advantages	Disadvantages
Haar	Sudden changes (short circuit)	Simple computation	Poor smoothness
Daubechies	General fault detection	Good at multi-resolution analysis	Higher computational complexity
Symlets	Complex signal reconstruction	Symmetric, good for detailed analysis	High complexity

4.2.2. Design of the Fuzzy Inference Rule Base

The core of the FIS lies in the design of its rule base. By constructing a well-defined "If-Then" rule base, the system classifies faults based on the features extracted through WT. Each rule is built upon the fuzzified characteristics of the input signal and is represented using membership functions. The membership degree determines the extent to which the input signal belongs to various fuzzy sets.

The principles for designing the fuzzy inference rule base include simplicity of the rules and full coverage of the fault categories.

The rule base in this study is designed according to different fault characteristics such as signal frequency, energy distribution, and abrupt changes. Using fuzzy sets and the rule base, these characteristics are classified to determine the fault type.

(1) Input Variables and Fuzzy Sets:

The input variables for the FIS are derived from the features extracted by WT, which include HFE, LFE, and the signal variation rate. Each input variable is assigned to corresponding fuzzy sets, represented by membership functions. Table 7 presents the input variables and their associated fuzzy sets.

Table 7. Input variables and their related fuzzy sets

Input variable	Fuzzy sets
HFE	Low, medium, high
LFE	Low, medium, high
Signal variation rate	Slow, moderate, fast

(2) Rule Base Design

Based on the previously mentioned input variables, a set of rules has been established in the rule base to infer fault types. These rules leverage the fuzzy sets of HFE, LFE, and signal variation rate to classify different types of cable faults. The FIS utilizes these rules to analyze the input features and make accurate decisions regarding the fault type.

Based on the rules outlined in Table 8, the classification of fault types follows logical reasoning: If HFE is high and the signal variation rate is fast, the fault is likely a SC. If LFE is high and the signal variation rate is slow, the fault is likely a GF. If HFE is low and LFE is high, the fault is classified as an OC. If both HFE and LFE are moderate, and the signal variation rate is also moderate, the fault is identified as a PD. These rules guide the FIS in reasoning over the input fuzzified signals, producing a fuzzy output that indicates the fault type.

Table 8. Fuzzy inference rule base design

Input conditions	Output condition
If high-frequency energy is high and signal change rate is fast	SC
If low-frequency energy is high and signal change rate is slow	GF
If high-frequency energy is low and low-frequency energy is high	OC
If both high-frequency energy and low-frequency energy are medium and signal change rate is moderate	PD

(3) Defuzzification:

The fuzzy output generated by the inference process is subsequently processed through defuzzification. This step converts the fuzzy output into a precise fault category, ultimately delivering specific diagnostic results, such as SC, GF, OC, or PD. Defuzzification ensures that the final output is actionable and provides clear fault classification for further analysis or repair.

4.2.3. Model Operation Process and Algorithm Description

In the cable fault diagnosis model based on WT and FIS, the operation process and algorithm description involve five primary steps, from signal acquisition to the final fault diagnosis output. Each step encompasses algorithmic operations that transform cable fault signals into accurate diagnostic results. The detailed workflow is as follows:

Step 1: Signal Acquisition

Real-time fault signals are collected from underground cables using sensors. These signals typically contain noise and interference across multiple frequency bands, necessitating preprocessing and feature extraction in subsequent steps.

Step 2: WT Feature Extraction

After preprocessing, WT is applied to decompose the signal, enabling simultaneous analysis in the time and frequency domains. The specific algorithm involves:

Selecting an appropriate wavelet basis function based on signal characteristics.

Performing multi-scale decomposition to extract coefficients across different frequency bands.

Extracting key features from the decomposed signal, including HFE, LFE, and signal variation rate.

Step 3: Fuzzification

Features extracted via WT are input into the FIS for processing. The fuzzification process includes:

Membership function selection: Converting the feature values into fuzzy sets using predefined membership functions.

Assigning HFE, LFE, and signal variation rate to their corresponding fuzzy sets.

Fuzzify the feature data by converting precise values into fuzzy membership degrees.

Step 4: Fuzzy Reasoning

The FIS classifies the fuzzified signal features using predefined rules in the fuzzy rule base. The reasoning process involves:

Matching the fuzzy inputs with rules in the rule base.

Use the fuzzy inference engine to reason through the matched rules and get a fuzzy output.

Step 5: Defuzzification

The output of the fuzzy reasoning system is fuzzy, so the defuzzification step converts the fuzzy output into a clear fault classification result. The commonly used defuzzification method is the centroid method, as described by formula (7).

$$y = \frac{\int x \cdot \mu(x) dx}{\int \mu(x) dx} \tag{7}$$

Defuzzification transforms the fuzzy inference results into precise fault classifications.

Step 6: Fault Diagnosis Output

The defuzzified results provide the final fault type output. Based on these results, the system identifies the specific type of cable fault (SC, GF, OC, or PD) and offers corresponding fault locations and suggested remedial measures.

The complete process, integrating WT for signal processing and FIS for fault classification, allows for efficient diagnosis of complex fault signals. The system enhances diagnostic accuracy and real-time performance, particularly in cases of multiple fault types.

4.3. Model Validation and Performance Evaluation

To validate the effectiveness and performance of the cable fault diagnosis model based on WT and fuzzy inference, a simulation analysis was conducted using an experimental dataset. The model's performance was compared to traditional fault diagnosis methods in terms of accuracy, diagnostic speed, and the ability to handle complex faults.

4.3.1. Experimental Dataset Overview

The experimental dataset was used to evaluate the model's performance. The dataset contains real and simulated signals from different cable fault scenarios, including:

High-frequency transient signals during cable short circuits.

Low-frequency signals when the cable wire is broken.

Low-frequency, stable fluctuation signals generated when the conductor comes into contact with the ground.

PD signals in the cable insulation are characterized by irregular high-frequency pulses, often indicative of minor arc discharges within the insulation material. These signals are subtle and sporadic, requiring precise detection methods.

After collecting the fault signals, WT was applied for decomposition to extract features such as HFE, LFE, and signal variation rate. These extracted features served as the input for subsequent fuzzy inference and fault classification processes, ensuring an accurate diagnosis of fault types.

The dataset scale is shown in Table 9.

Table 9. Dataset size

Metric	Value
Sampling frequency	1000 Hz
Number of short circuit samples	2000
Number of ground fault samples	2000
Number of open circuit samples	2000
Number of partial discharge samples	2000
Signal duration per sample	2 seconds

4.3.2. Simulation Results Analysis

The simulation results evaluate the performance of the proposed model, highlighting its accuracy and classification efficiency when applied to different fault types. The combination of WT and FIS demonstrates significant improvements in fault identification and classification. The key simulation outcomes are summarized in Table 10.

Table 10. Simulation results summary

Fault type	Accuracy (%)	Diagnosis speed (seconds)	Noise resistance accuracy (at 20 dB, %)
SC	94.5	0.8	92.0
GF	92.8	0.8	90.5
OC	91.2	0.8	90.1
PD	89.6	0.8	91.0

4.3.3. Simulation Results Analysis Translation

According to Table 10, the model achieves an accuracy of 94.5% for short-circuit faults, 92.8% for ground faults, 91.2% for open-circuit faults, and 89.6% for partial discharge faults. These high accuracy rates can be attributed to the WT's ability to effectively extract both high-frequency and low-frequency signal features, while the FIS handles the uncertainties within these features, enabling efficient classification. The model's average diagnosis time for each fault classification is 0.8 seconds, making it highly suitable for rapid fault location. The combination of WT's multi-scale analysis and the FIS's efficient classification mechanism allows the model to maintain a quick response time, even under complex signal conditions. Furthermore, the model demonstrates strong robustness against noise interference. When the noise intensity reaches 20 dB, the classification accuracy for short-circuit faults remains at 92.0%, for ground faults at 90.5%, for open-circuit faults at 90.1%, and for partial discharge faults at 91.0%, all maintaining high levels of performance.

The simulation results highlight that the proposed model excels in accuracy, real-time performance, and noise resistance, making it well-suited for practical applications in real-world cable fault diagnosis scenarios.

4.3.4. Comparison with Traditional Methods

To assess the advantages of the proposed model, this study compares the WT and FIS-based fault diagnosis method with traditional TDR and FDR techniques. The comparison criteria include diagnostic accuracy, diagnostic speed, and the ability to handle complex faults.

According to Table 11, the proposed model outperforms traditional methods in all key indicators. Thanks to the multi-scale feature extraction capabilities of WT and the efficient classification of FIS, the diagnostic accuracy of the model is significantly higher than that of TDR and FDR methods. The average diagnosis time of 0.8 seconds is notably faster than the traditional methods, providing a clear advantage in real-time fault detection. In terms of handling complex faults, the FIS can process complex and uncertain fault signals, giving the model enhanced diagnostic capabilities, especially when multiple fault signals are present. The experimental results further demonstrate that the model exhibits strong noise resistance, whereas traditional methods suffer a significant decline in diagnostic accuracy under noise interference.

Table 11. Comparison of methods

Method	Diagnosis accuracy	Diagnosis speed	Complex fault handling	Noise resistance
Proposed method	91.0%	0.8 seconds	High	High
TDR	85.5%	1.5 seconds	Low	Low
FDR	87.2%	1.3 seconds	Medium	Medium

Through this comparative analysis, it is evident that the proposed WT and FIS-based cable fault diagnosis model provides significant improvements in all aspects of fault detection performance, particularly in diagnostic accuracy, speed, and robustness to noise.

5. CHALLENGES IN CABLE FAULT DIAGNOSIS BASED ON WAVELET TRANSFORM AND FUZZY INFERENCE

5.1. Limitations in Data Collection and Processing

In cable fault diagnosis, the quality and accuracy of data collection directly affect the diagnostic effectiveness of the model. However, in complex cable environments, signal collection is often susceptible to noise interference, such as electromagnetic interference and environmental noise, which can obscure or distort fault signals. Additionally, for long-distance cables or cables buried deep underground, the sensitivity of the collection equipment may be limited, affecting the accuracy of signal collection. Therefore, obtaining high-quality fault signals in complex external environments remains a significant challenge in data collection.

5.2. Complexity in Fuzzy Inference System Rule Design

The FIS relies on a rule base for fault classification, and the process of designing the rule base is often highly complex. Each fault type rule needs to be defined based on a large amount of experimental data, especially when dealing with multiple fault types and complex fault signals. The design and maintenance of the rule base can become challenging. Moreover, as the number and complexity of fuzzy rules increase with more fault types, the inference process may slow down, and rule conflicts may arise in practical applications. Therefore, simplifying and optimizing the design of the rule base is a challenge for fuzzy inference systems.

5.3. Real-time and Computational Efficiency Issues

Although the WT and FIS-based model offers high diagnostic accuracy, there are still challenges concerning real-time performance and computational efficiency. The multi-scale analysis performed by the WT requires frequent signal decomposition and reconstruction, which increases computational complexity, especially when dealing with long-duration or high-frequency sampled signals. This can lead to extended processing times. Additionally, the fuzzy inference system, when processing a large number of fuzzy rules, can also experience extended inference times, particularly when the rule base is extensive. Therefore, improving the computational efficiency of the model to meet real-time fault diagnosis requirements remains a key issue.

5.4. Model Optimization

5.4.1. Wavelet Transform Parameter Optimization Strategy

To address the issues of diagnostic accuracy, real-time performance, and computational efficiency, further optimization of the model is necessary. The performance of WT is highly dependent on the selection of the wavelet basis function and the number of decomposition layers. Optimizing the selection of wavelet basis functions can improve the precision of feature extraction. Automated selection of wavelet basis functions or using adaptive wavelet transform techniques can better adapt to different types of fault signals. Determining the appropriate number of decomposition layers can reduce computational load and improve processing speed without compromising the quality of feature extraction.

5.4.2. Intelligent Improvement of the Fuzzy Inference System

To reduce the complexity of rule base design, intelligent fuzzy rule generation methods can be introduced. By using machine learning algorithms to automatically generate the fuzzy rule base, the need for human intervention can be significantly reduced, enhancing the system's adaptability. Genetic algorithms or neural networks can optimize fuzzy rules, dynamically generating and updating the rules based on historical data, reducing rule conflicts, and improving the efficiency of the inference process.

6. CONCLUSION AND OUTLOOK

This study presents an efficient cable fault diagnosis model based on WT and FIS, achieving intelligent classification and rapid fault diagnosis. Using WT, the model extracts HFE and LFE features, while FIS addresses the limitations of traditional methods in handling complex and uncertain signals. Experimental results show the model achieves 94.5% accuracy for SC faults and an average diagnosis speed of 0.8 seconds. Compared to traditional TDR and FDR, with slower speeds of 1.5 and 1.3 seconds and lower accuracy, the proposed method performs significantly better in accuracy, speed, and handling complex fault scenarios.

The proposed method also shows high noise resistance and robustness under multi-fault conditions, outperforming TDR (low noise resistance and weak fault handling) and FDR (medium performance). These results highlight the advantages of integrating WT and FIS for precise and efficient cable fault diagnosis.

Despite these promising results, challenges remain. The next steps of this study will focus on expanding the model's diagnostic capability in multi-fault and dynamic environments, improving real-time performance, and enhancing signal collection accuracy, especially under severe noise conditions.

Future work will also explore integrating advanced algorithms, such as machine learning or deep learning, to optimize the rule base and enable adaptive diagnostics. Additionally, efforts will be directed toward validating the model in large-scale engineering applications and exploring its scalability for more complex power systems. This study provides a solid foundation for further research and engineering advancements in cable fault diagnosis.

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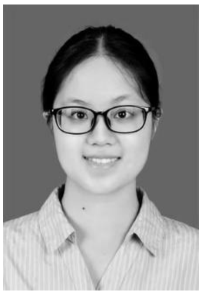

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