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SINGLE-PHASE GROUNDING FAULT LINE SELECTION METHOD FOR SMALL CURRENT GROUNDING SYSTEM BASED ON VMD-PSO-SVM

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Abstract

The precision of fault line identification is crucial for the secure and reliable functioning of the power distribution system. This study presents a new method to identify single - phase fault location in a low - current power system, using a hybrid approach combining particle swarm optimization and variational mode decomposition. Besides linear models like logistic regression, Support Vector Machines (SVM) can be integrated into the predictive framework. First, the variational mode decomposition method is applied to the transient zero - sequence signal from the line in small current grounding systems after a fault, which solves the feature extraction problem in a dynamic, noisy power grid. Then, a fault - line identification method integrating particle swarm optimization and support vector machine neural networks is developed. After data processing and structuring, the model is trained and validated with a fault - specific dataset for optimal performance. A comprehensive simulation study validates the precision and speed of this approach in identifying fault lines. The model offers a rapid, precise, and efficient approach for selecting the line of small - current ground faults, which holds significant importance for the fault maintenance operations of the power system. In the future, more comprehensive feature extraction techniques and more efficient neural network systems can be employed to enhance the model.

Keywords: fault line selection; variational mode decomposition; particle swarm optimization; support vector machine; small current grounding system

List of Symbols/Acronyms

VMD – variational mode decomposition;
PSO – particle swarm optimization;
SVM – Support Vector Machines;
HGF – high-resistance ground faults;
CCV – PV– characteristic current variation;
CSO – cutting optimization algorithm;
RBF – radial basis function;
IMF – intrinsic mode functions;
MAE – Mean Absolute Error;
RMSE – Root Mean Square Error;
R^2 – Determination Coefficient;
$u_k(t)$ – the Kth IMF component;
∂_t – the partial derivative of the function with respect to time;
$\delta(t)$ – the unit impulse function;
ω – the weight vector,;
b – the bias;
ξ_i – the relaxation vector;
C – the penalty factor;
G – kernel paramete;
$A_k(t)$ – the amplitude at time t[V];
$\varphi_k(t)$ – the phase angle at time t[rad];
$\omega_k(t)$ – frequency[Hz];
λ – noise tolerance[dB];

1. INTRODUCTION

As a critical backbone of national progress, the power system serves as a vital component in driving economic growth and fostering social development, while simultaneously providing essential services to the populace's daily needs. The smooth functioning of contemporary life is fundamentally reliant on a stable and continuous supply of electrical energy. Repeated power outages in industrial infrastructure could disrupt the operations of enterprises that depend on uninterrupted electricity, thereby causing production halts impacting the stability of business operations and undermining their profitability. It could potentially disrupt the functioning of medical devices and cause malfunction in traffic signals, thereby endangering the safety and well-being of residents and their property. Regular power outages not only pose a threat to the stability of the State Grid's operations but also erode public confidence in

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its reliability, potentially triggering widespread dissatisfaction and a deepening crisis of trust.

The inherent variability in load types and the intricate network configuration of the power grid contribute to this phenomenon. Faults in the distribution network are a common issue, with single-phase grounding faults being the most prevalent type, representing 80% of all recorded incidents. In light of the critical importance of maintaining system integrity, prompt detection and resolution of potential issues are essential to prevent cascading failures and ensure operational stability. Therefore, it is imperative to implement a robust fault-monitoring mechanism that enables early identification and swift corrective action 1.Currently, several power supply management units within China still employ the practice of conducting isolated line power outages to detect if the grounding fault is resolved, thereby identifying the affected transmission lines 1. This refers to the commonly known "wire pulling technique" or "wire drawing process" 3. The traditional wire pulling technique, while commonly used in certain applications, is inherently inefficient and labor-intensive, frequently resulting in substantial financial expenditures due to its inefficiencies 4.

The primary categories of existing fault line selection strategies encompass two distinct approaches, which are both fundamentally different in their underlying principles and application methods 5. The active line selection process involves choosing the current working line from a set of available options. The process of actively choosing a line involves intentionally introducing a defined type of excitation signal, such as high-frequency currents, into the system to facilitate precise line selection. The voltage fluctuations, including but not limited to those from system failures, must be integrated into the power grid following a fault event. This process involves determining the fault line by analyzing the response characteristics of the line to the applied excitation signal. The core objective lies in actively altering the system's natural state following a fault to generate distinguishable, measurable behavioral patterns. The other method involves selecting lines passively, which entails the system automatically choosing the most suitable lines without requiring user input. The passive line selection approach refrains from directly altering the system's operational flow. However, it employs the static or dynamic behaviors of electrical parameters (such as zero-sequence current) to analyze and interpret system performance. During the occurrence of a fault, various transient voltage components, power flow directions, and other system-generated signals are generated within the electrical network. These transient responses, when analyzed, allow for the precise identification of the fault location by correlating them with known reference data from the system's operational parameters. This method is based on the inherent signal generated by a fault and is classified as a non-intrusive detection technique. Current research predominantly focuses on the analytical evaluation of phase selection strategies and line selection methodologies for high-resistance ground faults (HGF) within the distribution grid. In the initial analysis, the paper first examines the evolution of the zero-sequence voltage component's behavior under both normal and single-phase ground fault conditions, followed by a detailed investigation into its underlying response mechanisms 6. Next, by analyzing the distinctions in the core attributes of the characteristic current variation (CCV-PV) during the healthy and faulted phases of a power system. A novel fault active phase selection technique has been developed, which is grounded in the bus CCV-PV method. Furthermore, through a comparative analysis of the CCV-PV profiles between healthy and faulty feeders, a fault detection and active line selection strategy utilizing feeder CCV-PV data is developed. Nevertheless, this particular system relies on a specific type of current injection device to function effectively. A study introduced a novel fault line identification approach for resonant grounding systems, which integrates wavelet packet decomposition with the fifth harmonic analysis technique. The objective of this research is to enhance the precision and dependability of single-phase grounding fault detection methods, thereby ensuring more reliable identification of fault locations in power systems 7. The approach to identify fault lines involves first establishing and computing the specific attributes of each potential fault line. When all the characteristic frequency ranges across the different lines are identical, the corresponding fault identification values can be directly compared. When the characteristic frequency bands fail to align, the fifth harmonic method and wavelet analysis are integrated to dynamically identify fault lines. Nevertheless, the system's capacity to accommodate intricate feeder configurations is constrained.

As artificial intelligence advances, the approaches centered around neural networks have become increasingly prevalent. Vector-based systems and various advanced computational methods have gained significant traction in the selection of fault lines, offering both high precision and reliable performance across diverse applications 8. A study presented a novel approach for identifying grounding faults in small current systems, which employed wavelet packet decomposition and fuzzy neural networks to achieve accurate fault line detection 9. This approach employs a wavelet-based fuzzy neural network model, which is trained using zero-sequence current data collected post-grounding, to accurately determine the location of the grounding conductor. However, the model's effectiveness is significantly influenced by the quantity of training data used during its development. However, the collected samples must encompass a broad range of potential operational situations, yet the actual power system's operational contexts could be significantly more intricate. A study introduced a novel fault detection strategy for distribution networks, which was implemented using the cross-cutting optimization algorithm (CSO) to enhance the performance of a radial basis function (RBF) neural network. This method is employed to enhance the precision of fault detection and isolation for single-phase ground faults in low-current grounding systems, as detailed in reference 10. Nevertheless, the implementation of this model for fault line identification presents several challenges, notably the requirement for extensive training periods and an increased risk of converging toward suboptimal local minima 11.

Nevertheless, the aforementioned method exhibits an excessive degree of simplicity in its design and implementation. Owing to this simplicity, it becomes highly vulnerable to diverse environmental factors, such as temperature variations, humidity fluctuations, electromagnetic interference, or other external conditions that can substantially impact its performance. Moreover, under fault circumstances, such as system malfunctions, hardware glitches, or unforeseen operational scenarios, this method tends to encounter even greater challenges. Additionally, the method demonstrates a relatively feeble ability to withstand interference from both internal and external sources, rendering it unreliable when confronted with any form of noise or disruptions. Due to these limitations, its practical application is severely constrained, as real - world environments are frequently unpredictable and complex, necessitating far more robust solutions than what this method can provide. Therefore, despite its conceptual simplicity, the method's lack of resilience renders it inappropriate for numerous practical situations where precision and reliability are of utmost importance.

To enhance the efficiency and precision of fault line identification in the low-current grounding system of a distribution network, this study introduces a novel approach to identify the grounding fault line in a small current system, leveraging Variation Mode Decomposition (VMD) combined with Particle Swarm Optimization (PSO) and Support Vector Machine (SVM) for enhanced accuracy 12. It significantly decreases the volume of training data required for model development, thereby minimizing computational demands. However, this method not only achieves high classification accuracy when working with small datasets but also effectively prevents the risk of getting trapped in local optima during optimization processes 13. The parameter dependency issue is effectively addressed through the application of the Particle Swarm Optimization (PSO) algorithm. The lightweight training of Support Vector Machines (SVM) with robustness against noise is employed to effectively navigate the challenges posed by high levels of interference and dynamic conditions in power systems 14. Ultimately, this approach culminates in a dual success in both engineering feasibility and technical performance, specifically by reducing computational demands while minimizing the impact of sample variability, as well as enhancing precision and reliability 15. This approach employs the Variational Mode Decomposition (VMD) technique to analyze and break down the zero-sequence current signals across each power line 16. The decomposed signal is then fed into the PSO-SVM model to facilitate both training and validation processes, ultimately enabling the system to complete the fault line identification task as outlined in reference 17.

The novelty of this approach resides in its profound integration of Variational Mode Decomposition (VMD), Particle Swarm Optimization (PSO), and Support Vector Machine (SVM), thereby constructing a comprehensive solution for feature extraction, parameter optimization, and classification recognition. VMD strengthens the robustness of feature extraction, whereas PSO averts SVM from being ensnared in local optima, which in turn enhances the model's adaptability to dynamic fault scenarios. Moreover, the lightweight training of SVM curtails the requirements for computational resources, and the global optimization ability of PSO expedites the model's convergence, attaining a equilibrium between rapidity and accuracy in fault path selection **Błąd! Nie można odnaleźć źródła odwołania.Błąd! Nie można odnaleźć źródła odwołania.**.

2. VMD-PSO-SVM MODEL

2.1. VMD Algorithm

In the context of VMD's analysis, the original signal is decomposed into a set of sub-signals, each characterized by a unique frequency component 20. The objective is to identify the center frequency and bandwidth of the sub-signal by employing a systematic process of iterative refinement. Unlike traditional recursive signal decomposition methods, this approach relies entirely on non-repetitive algorithmic processes to analyze and break down signals. It demonstrates remarkable versatility in handling the breakdown of intricate signals and efficiently addresses the challenges posed by modal aliasing. The endpoint effect and genetic mutations within conventional signal decomposition techniques often lead to suboptimal results, as these methods typically fail to account for dynamic shifts in data patterns or incorporate non-linear transformations that can introduce systematic errors. The Variational Mode Decomposition method employs a variational framework to derive a decomposition function that is optimized under the constraints imposed by the input signal. The algorithm efficiently computes the optimal solution of the model by performing a systematic search strategy at regular intervals, which ensures that the most effective outcome is consistently selected. Ultimately, this process ensures that the preset modal decomposition parameter K is selected to break down the signal into distinct frequency components 21. The sequential process of the Variational Mode Decomposition algorithm is outlined below:

The VMD (Variational Mode Decomposition) approach fundamentally diverges from the conventional recursive decomposition method. The process involves breaking down the original signal into K distinct intrinsic mode functions (IMFs) through the application of a constrained variational model. During each successive iteration, the central frequency and spectral width of the K intrinsic mode functions (IMFs) are dynamically adjusted in real time to reduce the overall sum of their respective bandwidths. In this process, the cumulative effect of the K Independent Component Analysis (K-IMFs) components is utilized to regenerate the original input signal. Each intrinsic mode functions (IMF) entity can be represented through an FM-AM signal configuration, as detailed in the provided equation.

$$u_k(t)=A_k(t)\cos(\varphi_k(t)) \tag{1}$$

Among them, $u_k(t)$ is the Kth IMF component; $A_k(t)$ is the amplitude at time t $u_k(t)$; $\varphi_k(t)$ is the phase angle at time t . $u_k(t)$ expression obtained $\omega_k(t)$ by taking the derivative with respect to time is:

$$\omega_k(t)=\frac{d\varphi_k(t)}{dt},\varphi_k(t)\geq 0 \tag{2}$$

VMD, a technique that employs a tailored variational framework, utilizes the estimation of individual IMF frequency bands' bandwidths to develop a structured model for analyzing time series data. The process is outlined in the following manner:

Perform Hilbert transform on the modal function to further obtain its:

(1) The analytical signal and the single-sided spectrum represent distinct yet related mathematical representations, each serving a unique purpose in signal processing.

$$\left[\delta(t)+\frac{j}{\pi t}\right]*u_k(t) \tag{3}$$

(2) The spectrum of each eigenmode function is modulated to the corresponding

To enhance the baseband signal, an exponential component can be incorporated into its mathematical formulation.

$$\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t} \tag{4}$$

(3) The optimization problem derived through the application of Winner filtering, Hilbert transform, and heterodyne demodulation.

To address the challenge of managing multiple finite bandwidth components with distinct center frequencies, heterodyne demodulation is employed to minimize the total bandwidth estimates across all modes. The derived variational equation that arises under the imposed constraints is presented in the subsequent mathematical expression.

$$\begin{cases} \& \left\{\sum_{k=1}^{K} \left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} \\ \&\text{s.t.} \sum_{k=1}^{K} u_k(t)=x(t) \quad \&\& \end{cases} \tag{5}$$

Among them, ∂_t is the partial derivative of the function with respect to time; $\delta(t)$ is the unit impulse function; and * is the convolution operator.

Given that the variational problem under consideration is governed by equality constraints and presents significant challenges in resolution, to convert the constrained optimization problem into an unconstrained form, the penalty factor and Lagrange multiplier are incorporated into the mathematical formulation. This transformation allows the original constraint to be effectively integrated within the variational framework without requiring explicit handling of the constraints. The enhanced Lagrangian function can be described as follows:

$$\begin{aligned} L(\{u_k\},\{\omega_k\},\lambda)\&=\alpha\sum_{k=1}^{K} \left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2 \\ \&+\|x(t)-\textstyle\sum_{k=1}^{K} u_k(t)\|_2^2+\langle\lambda(t),x(t)-\sum_{k=1}^{K} u_k(t)\rangle \end{aligned} \tag{6}$$

By applying a sequence of systematic refinements and iterative modifications, the critical equilibrium point in the extended Lagrangian formulation is identified. The alternating direction method for multiplication is applied to address the above variational problem, which involves optimizing a function under certain constraints.

The cyclical refinement method operates in this structured manner:

$$\begin{aligned} u_k^{n+1}\&=\arg\min_{u_k\in X}\sum_{k=1}^{K} \left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2 \\ \&+\left\|x(t)-\textstyle\sum_i u_i(t)+\frac{\lambda(t)}{2}\right\|_2^2 \end{aligned} \tag{7}$$

The equidistant method is applied to transform the time-frequency domain into a corresponding frequency representation, which is mathematically represented by the following equation.

$$\begin{aligned} \hat{u}_k^{n+1}\&=\arg\min\{\alpha\|j(\omega-\omega_k)\|\|[(1+\text{sgn}(\omega))]\hat{u}_k(\omega)\|_2^2 \\ \&+\left\|\hat{x}(\omega)-\textstyle\sum_i \hat{u}_i(\omega)+\frac{\hat{\lambda}(\omega)}{2}\right\|_2^2 \end{aligned} \tag{8}$$

Convert the above formula into an integral form for non-negative frequency interval

$$\begin{aligned} \hat{u}_k^{n+1}(\omega)=\arg\min\{\textstyle\int_0^\infty 4\alpha(\omega-\omega_k)^2|\hat{u}_k(\omega)|^2 \\ +2\left|\hat{x}(\omega)-\textstyle\sum_i \hat{u}_i(\omega)+\frac{\hat{\lambda}(\omega)}{2}\right|_2^2 \end{aligned} \tag{9}$$

Just like the adjustment of the center frequency, the process of recalibrating the central frequency involves a systematic procedure.

$$\omega_k^{n+1}=\arg\min\left\{\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} \tag{10}$$

Convert the given signal from its time-based representation into a frequency analysis and derive its corresponding spectral representation.

$$\omega_k^{n+1}=\arg\min\{\textstyle\int_0^\infty (\omega-\omega_k)^2|\hat{u}_k(\omega)|^2 d\omega\} \tag{11}$$

Through the derivation of the optimal solution from the preceding mathematical expression, we arrive at a revised version of the update equation.

$$\omega_k^{n+1}=\frac{\int_0^\infty \omega|\hat{u}_k(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_k(\omega)|^2 d\omega} \tag{12}$$

The given equation illustrates the rate at which the IMF power spectrum fluctuates over time. This equivalence can be further explained by the fact that it corresponds to the frequency obtained through a least squares linear regression analysis of the IMF's instantaneous phase, which is a critical component in analyzing the periodicity within the signal.

The formula used to implement the change is described below:

$$\lambda^{n+1}=\lambda^n+\lambda\left(x-\sum_k u_k^{n+1}\right) \quad (13)$$

To determine the appropriate value for λ, which represents the noise tolerance threshold, it is essential to consider the permissible deviation in signal quality that the system can tolerate under varying environmental conditions.

VMD iterative solution. Set the initial values of the parameters of the VMD algorithm to 0, update the values of parameters u_k, ω_k, according to step (2) λ, and determine whether the following iteration termination conditions are met:

$$\frac{\sum_K \left\|\hat{u}_K^{n+1}-\hat{u}_K^n\right\|^2}{\sum_K \left\|\hat{u}_K^n\right\|^2}<\varepsilon \quad (14)$$

Among these options, there exists a specific value ε that satisfies the condition of being greater than zero.

When the prerequisites are satisfied, the process halts and the resulting IMF elements are presented. If the current process does not yield a valid result, then the previously outlined steps must be revisited and executed again to proceed with the decomposition.

2.2. Fault Line Selection Model Based on PSO-SVM

2.2.1. SVM Principle

Support Vector Machine (SVM) employs a hyperplane in a high-dimensional feature space to separate data points by maximizing the margin between the support vectors of the training dataset. However, the essential computations are executed within a lower-dimensional framework. The plane satisfies the following constraints:

$$\begin{cases} \min\limits_{\omega,b,\xi} \frac{1}{2}\|\omega\|^2+C\sum_{i=1}^n \xi_i \\ s.t. y_i(\omega^T x_i+b)\geq 1-\xi_i, \xi_i\geq 0 \quad i=1,2,...,n \end{cases} \quad (15)$$

Where: $\omega$is the weight vector, b is the bias, $\xi_i$is the relaxation vector, and C is the penalty factor.

The construction of a hyperplane involves solving the constrained quadratic optimization problem presented earlier, which effectively defines the boundary that separates different classes in a high-dimensional space. The result derived from solving the problem is a mathematical model that represents the decision function.

$$y(x)=\text{sgn}\left[\sum_{i=1}^n \alpha_i y_i(x,x_i)+b\right] \quad (16)$$

2.2.2. SVM Parameter Optimization Based on PSO

In the context of Support Vector Machines (SVMs), two fundamental parameters—namely, the penalty factor C and the kernel paramete g —play a pivotal role in determining the classification accuracy and overall performance of the model. Within the Particle Swarm Optimization (PSO) framework, each individual is defined by a pair of parameters, specifically (C, g). In this context, the values of the constants C and g are directly tied to the coordinates of the particle within the solution space. The Particle Swarm Optimization (PSO) algorithm continuously refines the current best individual position within the population and identifies the global optimal position by evaluating the fitness of each particle. In the following steps, the particle dynamically recalibrates both its velocity and spatial coordinates through a process that involves repeatedly analyzing these two critical positions 22. With each cycle of the algorithm, the particles' positions shift toward regions where the fitness function yields higher scores. Upon the completion of the iterative optimization procedure, the position of the particle that yields the highest fitness score is selected for output, thereby representing the most effective solution identified through this process 23.

The Particle Swarm Optimization (PSO) algorithm is utilized to conduct a global optimization of the kernel function parameter g and the penalty factor C, thereby obtaining a globally optimal solution. This method addresses the limitations of manual parameter selection, including randomness and low efficiency, consequently enhancing the prediction accuracy of the model 24. The modeling process of the PSO - Support Vector Machine (SVM) prediction model is presented in Fig. 1.

2.3. Line Selection Process Based on VMD-PSO-SVM

In light of the models developed through the integration of VMD and PSO-SVM, a fault line identification strategy was established that leverages a hybrid approach combining these two techniques 25. This approach integrates the time-frequency domain properties of the Variational Mode Decomposition (VMD) with the optimal solution derived from the Particle Swarm Optimization-Sequential Minimal Optimization (PSO-SVM) algorithm's autonomous evaluation of data, thereby enabling the identification of fault lines and achieving precise fault line selection (as shown in Fig. 2

The precise sequence of actions can be outlined as follows:

Construct a single-phase grounding fault simulation model for the distribution network, and gather the zero-sequence current data from each individual line. To ensure accurate analysis, we will employ a sampling rate of 20 Hz to capture the waveforms of the one subsequent cycles following the fault event. This approach allows for precise signal acquisition and provides the necessary data points for further processing.

Considering that fault signals are prone to interference from noise during actual fault occurrence, to validate the superiority of the proposed method, the acquired fault signals were augmented with Gaussian white noise.

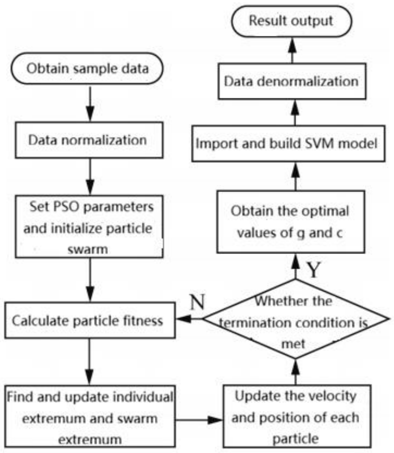

Fig. 1. PSO-SVM prediction model modelling process

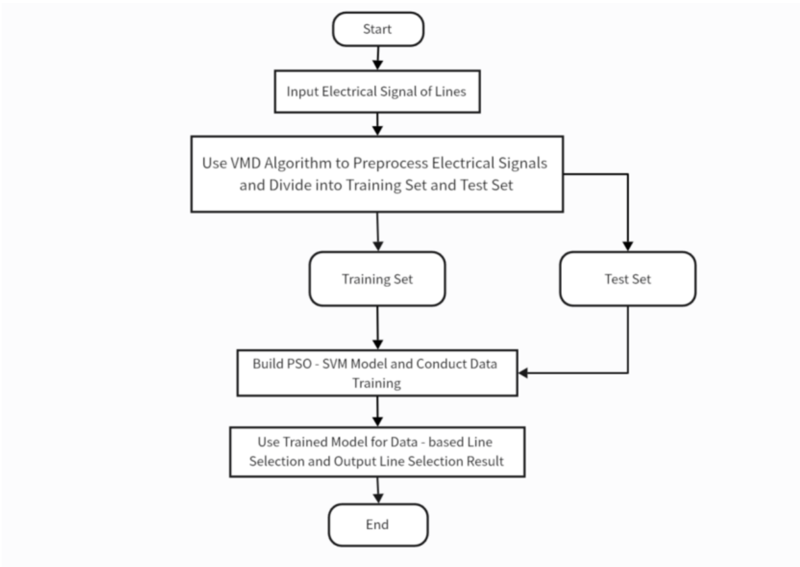

Fig. 2. VMD-PSO-SVM line selection flow chart

VMD is used to decompose the zero-sequence current signals of each line. The zero - sequence current signals of each line are subjected to variational mode decomposition (VMD), and the data features of each line are concatenated into a vector in accordance with the ascending order of the feeder numbers.

A PSO - SVM fault path selection model is established, and the feature vector processed by VMD is employed as the input to train the model, thereby achieving the recognition and classification of the fault feature vector.

Use the training model to perform fault line selection and verify the accuracy of fault line selection.

2.4. Model Accuracy Evaluation Index

This study employs three metrics to evaluate predictive model accuracy: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Determination Coefficient (R^2). MAE, a linear metric, assigns equal weighted scores to all data variations. RMSE calculates the average of squared deviations between predicted and actual values, quantifying the degree of variation. Both MAE and RMSE values decrease with improved model precision. R^2, also termed goodness of fit, measures the correlation between predicted and actual values as a ratio of squared deviations, with values ranging from 0 to 1. A higher R^2 indicates better predictive performance. The specific formula is:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_{pre}-x_{true}| \tag{17}$$

$$RMSE = \sqrt{\frac{1}{N}(x_{pre}-x_{tru})^2} \tag{18}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_{true}-x_{pre})^2}{\sum_{i=1}^{N}(x_{true}-\overline{x}_{true})^2} \tag{19}$$

Where: N is the total number of test samples; x_{pre} is the predicted value of the data; x_{true} is the true value of the data; $\overline{x}_{true}$ is the mean of the true values.

3. SIMULATION ANALYSIS

3.1. Simulation Model

The research paper constructs a computational framework for simulating a single-phase grounding fault within the distribution network's grounding system, as illustrated in Fig. 3.

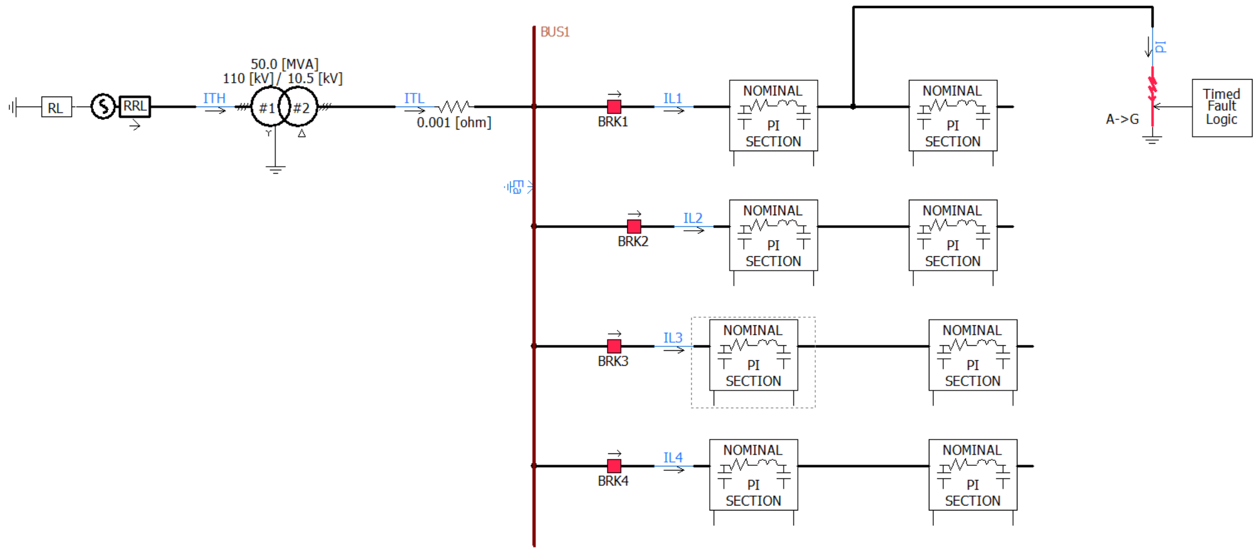

Fig. 3. Power transmission line simulation model

The power grid system consists of four overhead transmission lines, each measuring 20 km, 18 km, 16 km, and 14 km in length, respectively.

3.2. Selection of Fault Data Set

In order to precisely simulate a diverse range of practical ground fault situations, an extensive data set containing 240 meticulously selected test samples was carefully developed and compiled. To enhance the comprehensive fault model, we introduced a series of systematic modifications to the circuit parameters, which not only broadened its scope but also provided a more accurate depiction of various fault scenarios. Each line in the model was meticulously crafted to contain around 60 unique fault indicators, which collectively contribute to a comprehensive and granular representation of potential system failures. To make the simulation more lifelike, it is essential to incorporate advanced features that amplify its immersive qualities. The exact location of the fault and the specific distance at which it was implemented differed significantly across various lines. The design of this approach was intended to precisely replicate the intricate and varied ground fault scenarios that are common in real-world operational settings. As a result, the application of these findings becomes more practical and relevant in real-world scenarios, thereby increasing their utility and usability (see Fig. 4).

This figure depicts a meticulous and all - encompassing comparison of the intrinsic mode functions (IMF) generated subsequent to the application of the variational mode decomposition (VMD) method to the zero - sequence current signal.

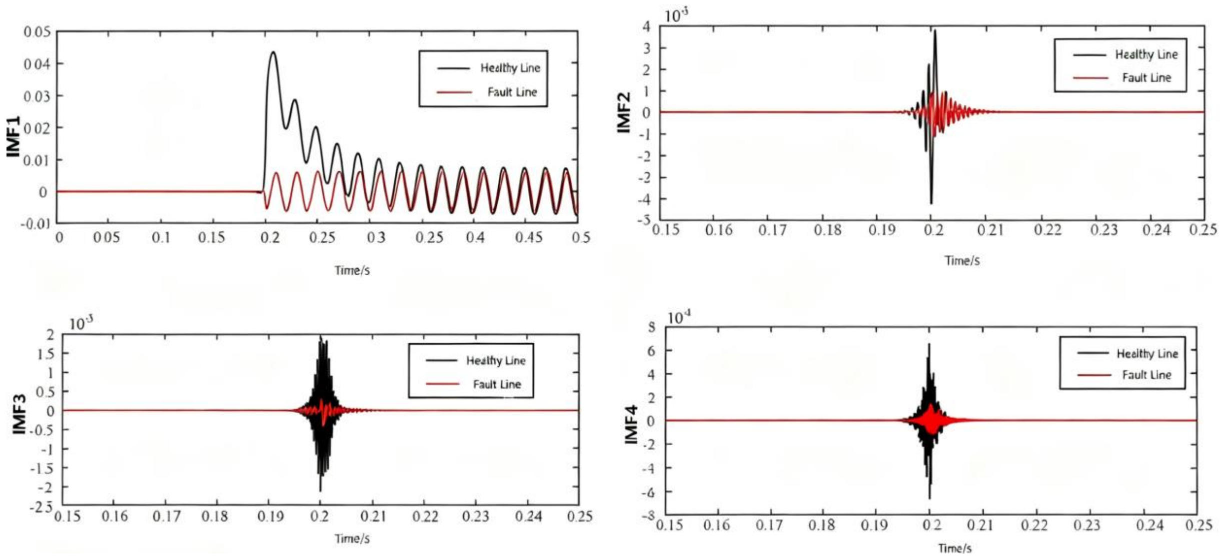

Fig. 4. IMF zero sequence current component diagram

The analysis not only offers a profound perspective but also clearly illustrates how the inherent property disparities between the fault line and the normal line are substantially influenced by the varying components of the IMF. In fact, upon a detailed examination of the structure of each IMF section, some intriguing phenomena can be observed. For example, within an approximate 0.2 - second brief period, a significant dynamic response is detected in the fault line. This dynamic response is characterized by both transient oscillations and abrupt shifts in energy distribution, which are highly distinctive and worthy of attention.

The irregularities detected in the data collected from the fault line can be ascribed to the existence of latent fault patterns. These patterns, however, are not fully manifested at present and necessitate further exploration for complete comprehension. In sharp contrast, the behavior of the zero - sequence current during normal operation is remarkably stable and uniform. During this normal operation, minimal deviations are noted, highlighting the distinct difference between normal and fault conditions.

Through a comprehensive and painstaking examination of the unique behavioral patterns exhibited by the fault line, it is feasible to accurately distinguish and characterize the specific fault markers. This process of identification and characterization is of critical importance for effective fault detection and management. The implementation of this extraction procedure plays a vital role as it functions as an indispensable auxiliary tool. This tool offers valuable assistance in the line selection during the analysis of small current grounding faults in power systems.

The provision of this assistance significantly enhances the accuracy and reliability of the fault identification and location processes. By improving these processes, we can guarantee a more reliable and efficient operation of power systems, ultimately resulting in superior performance and reduced downtime. Therefore, the utilization of the VMD method and the subsequent analysis of IMFs are of great significance in the domain of power system fault analysis and management, which in turn ensures the robustness and operational efficiency of the power grid.

3.3. Model Training and Testing

The gathered information is subjected to a rigorous analytical process utilizing the advanced technique of Variational Mode Decomposition (VMD). A highly advanced method meticulously crafted to break down complex datasets into fundamental components, enabling the identification and extraction of specific fault-related data sets. The systematic extraction procedure employed here guarantees that all fault-related data is precisely located and then systematically categorized into distinct types, which in turn allows for precise labeling of each fault category within the data set. After completing this thorough labeling process, the data is meticulously partitioned into two separate groups: one designated for training and another reserved for testing. The data set used as the initial training basis for the PSO-SVM model is essential in both starting the training process and executing it through iterative cycles of optimization. During this phase of the training process, meticulous attention is paid to execution, utilizing the PSO-SVM hybrid model's inherent strengths to refine the model's parameters and significantly improve its predictive accuracy.

After the extensive and meticulous training program has been fully executed, following the completion of the training phase, the test data set is systematically integrated into the model to conduct a thorough assessment and validate the model's performance under real-world conditions. The validation process is fundamental to evaluating the model's capacity to correctly categorize and pinpoint fault types in practical scenarios. The outcomes of the verification process are presented in a concise manner within the confusion matrix, which serves as an effective visual tool to illustrate the test set's performance. The detailed analysis of the model's fault line selection process demonstrates that its accuracy in identifying the correct fault lines is remarkable, reaching a high level of 94.0171%. The exceptional precision achieved in this study not only underscores the effectiveness and robustness of the approach introduced in this paper but also strongly validates its practical utility and dependability. This result underscores the system's remarkable proficiency in pinpointing fault lines with high precision, thereby affirming that this approach outperforms conventional techniques when applied to real-world scenarios.

Upon a meticulous and comprehensive analysis of the confusion matrix graph, which was carefully constructed using the test dataset (as shown in Fig. 5), the results clearly and unequivocally indicate that the model's overall performance, as evaluated by the comprehensive performance metric, exceeds the significant threshold of 94.0171%. This remarkable outcome is specifically measured by the overall macro - accuracy, a crucial indicator reflecting the model's balanced performance across all classes. Such a significant achievement not only highlights but also serves as a strong testament to the model's profound efficacy. This efficacy is effectively demonstrated through the seamless integration of advanced and sophisticated techniques, such as the Particle Swarm Optimization (PSO) algorithm combined with Support Vector Machines (SVM).

This remarkable level of precision, attained through these state - of - the - art methodologies, showcases the model's exceptional ability to perform with near - perfect consistency across a wide range of essential tasks. Consequently, owing to its high reliability and consistent accuracy, this method is particularly well - suited for reliable and precise categorization in critical, high - stakes scenarios where errors can have substantial consequences.

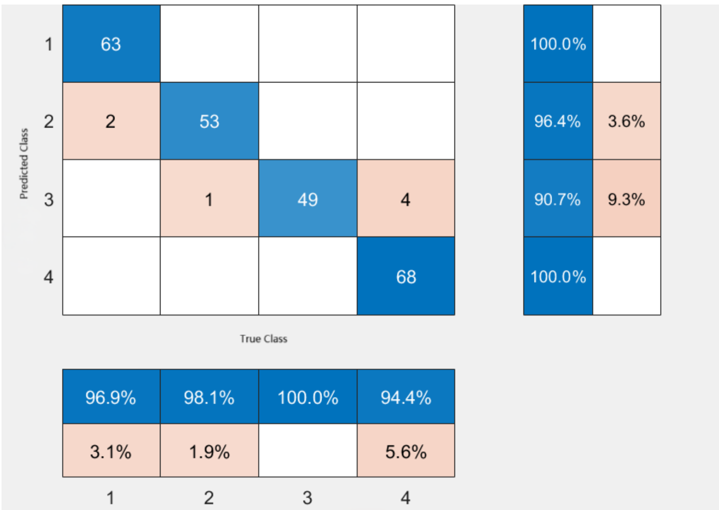

Fig. 5. PSO-SVM model test set confusion matrix

Therefore, it emerges as a robust, reliable, and optimal option for such demanding applications.

In the specific domain of power system management, where accuracy and reliability are of utmost importance, the process requires not only the strategic selection of fault lines to ensure proper system functionality but also the precise determination of equipment operational conditions at all times. The model's inherent capacity to dynamically adapt to a multitude of diverse scenarios enables it to achieve more than mere operational improvements. It plays a vital role in enhancing overall operational efficiency while safeguarding the structural integrity and safety of complex electrical systems, ensuring their security and full functionality under various conditions. Thus, the model represents a transformative advancement in both performance and application within the field of power systems

Upon conducting a comprehensive and meticulous examination of the model's output visualization, as clearly illustrated in Fig. 6, we are able to discern that the predictive accuracy has attained an exceptionally outstanding level. To be more precise, this accuracy has surpassed the impressive threshold of 94.0171% in precision. The truly remarkable accuracy that this model exhibits in its predictions serves to emphasize its robust and highly dependable ability to forecast outcomes in an effective manner. Furthermore, when we delve deeper into the model's forecasts, it becomes evident that there is a powerful and strong correlation between these predictions and the real-world outcomes. This is because the majority of the predicted results turn out to be extremely close to the actual true values that are observed in reality.

The model's results, which have been obtained through rigorous testing and analysis, serve to demonstrate a high degree of reliability and accuracy. This fact is made abundantly clear through the model's consistent and unwavering application across a wide array of diverse data sets. Moreover, the precision with which it generates outcomes is truly commendable and noteworthy. The existence of this strong correlation between the model's outputs and the real - world results plays a crucial role in highlighting its exceptional and extraordinary ability to predict future events with a great deal of precision. As a result, this serves to confirm and solidify the model's remarkable capacity for anticipating trends and outcomes in a highly accurate and reliable fashion, thereby instilling a great deal of confidence in its predictive capabilities.

The PSO - SVM and VMD - PSO - SVM models adopt identical PSO parameters, featuring a population size of 10 and a maximum iteration number of 50. The PSO - SVM model attains the optimal fitness after 37 iterations, whereas the VMD -PSO-SVM model accomplishes this within merely 6 iterations. This indicates that the VMD-PSO-SVM model reduces the iteration number by 83.8% in comparison with the PSO-SVM model, substantially decreasing the required iterations.

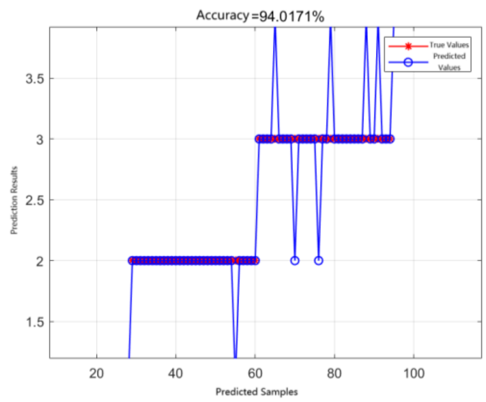

Fig. 6. Visualization of model prediction results

Table 1. Accuracy evaluation results of prediction models

STATE PREDICTION METHOD	MAE	RMSE	R^2
PSO-SVM	0.14	0.18	0.94
VMD-PSO-SVM	0.06	0.08	0.98

As shown in Table 1, the VMD-PSO-SVM model demonstrates superior predictive accuracy for compressor acceleration compared to the PSO-SVM model. The average absolute error and root mean square error are reduced by 57% and 55% respectively, with the R^2coefficient of determination approaching 1.

4. CONCLUSIONS

This study introduces a fault line identification technique for distribution networks, which is developed using the combination of Variational Mode Decomposition (VMD), Particle Swarm Optimization (PSO), and Support Vector Machine (SVM). This conclusion is substantiated through the analysis of a single-phase grounding fault simulation within the distribution network's framework. The following insights are derived from the analysis: The IMF matrix derived from zero-sequence current signals processed through the VMD algorithm is enriched with detailed fault characteristics offering high-quality, reliable, and optimized data to support the effective operation of the neural network training model. The developed PSO-SVM training framework enables the model to independently determine the global optimum without requiring external optimization methods, thereby significantly accelerating computation and simultaneously preventing the premature convergence to suboptimal local minima.

In conventional distribution networks, the actual accuracy rate of small - current ground fault line selection typically falls within the range of 60% to 85%, which serves as the prevailing industry measurement criterion. This performance is predominantly determined by three crucial factors: line selection principles, on - site operating conditions, and the distribution network architecture. The proposed line selection model attains an accuracy rate surpassing 94%, exhibiting both high precision and rapid response capabilities, which holds substantial innovative significance. Although the presented method showcases wide applicability, certain specialized line selection techniques currently achieve 100% accuracy in specific scenarios. The proposed method has not yet achieved absolute precision in fault line identification. Future enhancements may encompass optimizing the VMD algorithm to extract electrical signals more comprehensively and efficiently for a wider array of fault scenarios, as well as refining the VMD-PSO algorithm to improve line selection accuracy.

The combination of VMD, PSO, and SVM is a novel approach that merges the techniques of variational mode decomposition, particle swarm optimization, and support vector machine. This study has successfully proven its practical utility across various domains, notably in fault detection and analysis. In theory, it may facilitate the development of algorithmic integration innovations (e.g., through synergistic integration with deep learning platforms) and advance foundational research by refining the physical interpretation of parameters and enhancing the error analysis framework. In truth, it must transcend its current domain by integrating into energy sectors, transportation systems, healthcare applications, and other emerging fields. At the same time, we aim to refine the engineering landing trajectory (integrated into the online monitoring system and developed a visual interactive interface). By integrating cutting-edge theoretical advancements with real-world implementation, this method has emerged as a pivotal technical instrument capable of tackling intricate nonlinear challenges, thereby unlocking substantial potential for broader applications.

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