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Intelligent Wireless Monitoring System for Circuit Breaker Fault Detection

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Abstract: This paper proposes an intelligent wireless monitoring system integrating grey wolf optimization and support vector machine for real-time fault detection in low-voltage circuit breakers. A wireless measurement network collects vibration signals from circuit breakers for feature extraction. An optimized support vector machine model using an improved grey wolf optimization algorithm is developed for fault diagnosis. Experiments demonstrated a 93.2% diagnosis accuracy for the model on single faults. The integrated monitoring system achieved 0.74 AUC, 0.35 *F*1 score, and 2.8 seconds response time, outperforming other systems. The wireless intelligent monitoring framework enabled efficient fault detection and maintenance for circuit breakers. However, limitations include small dataset size and lack of validation on real breakers. Further research on model optimization and testing on field data will be valuable. In conclusion, this paper proposed and validated an intelligent wireless monitoring system integrating grey wolf optimization and support vector machine for real-time low-voltage circuit breaker fault detection.

Keywords: circuit breaker; monitoring system; operating status; support vector machine; wireless measurement

1 INTRODUCTION

In recent years, as technology and society progress, the safety and reliability of power systems have increasingly attracted people's attention. As an important component of the power system, the operating status of low-voltage circuit breakers (LCB) is directly related to the normal operation of the power system and the safety of equipment [1]. The failure of LCB will lead to short circuits, overload, and other faults of the power system, bringing significant impact to the power system, and may cause equipment damage, power failure, and even fire and other serious consequences [2]. Therefore, if the diagnostic accuracy and real-time performance of the LCB are insufficient, the safety of the power system will be greatly limited. To accurately and timely diagnose the abnormal state of LCB, the research of low-voltage circuit breakers operating state (LCBOS) monitoring has important theoretical and practical value. However, the traditional LCBOS monitoring method has some limitations and shortcomings. First, traditional methods usually rely on manual inspection, which is not only time-consuming and laborious but also prone to errors or omissions due to human negligence or subjective judgment [3]. Secondly, the traditional method cannot monitor the running state of LCB in real time, and can only obtain information through regular inspection or periodic tests, and abnormal conditions cannot be found in time. In addition, data collection is also a problem. In traditional methods, data collection usually requires direct contact with circuit breakers or the use of specialized equipment, which increases the complexity and risk of operation and prevents long-term continuous monitoring. Finally, traditional methods fail to accurately and effectively extract useful information and conduct fault diagnosis analysis [4-5]. Therefore, the improvement of the traditional LCBOS monitoring method has become an urgent social need to be solved. To realize efficient and accurate low-voltage circuit breaker operation state LCBOS monitoring and fault diagnosis, reduce the labor cost of LCB diagnosis, and then promote the safe development of the power system. The study proposes to collect the LCB running state signal to realize the manual dependence of the traditional LCBOS monitoring method. Subsequently, the LCBOS monitoring model is constructed based on a Support Vector Machine (SVM) and Improved grey Wolf algorithm (IGWO) to realize real-time monitoring and remote management of LCB. Combining SVM, IGOW, and wireless measurement networks in LCBOS monitoring, the LCBOS monitoring method proposed by the study can fill the gap in the gap of this part and is innovative. The low-voltage circuit breaker operation status monitoring system based on a wireless measurement network has a wide range of research uses, which is suitable for power system operation and maintenance, industrial automation, building electrical systems, new energy and smart grid, and other fields. Remote control of LCBOD can improve the reliability, operation efficiency, and safety of the equipment, and promote the development and progress of related fields. Key innovations include: 1) realizing real-time collection of LCB operating state signal by using wireless measurement network; 2) improving the selection of SVM parameters with IGOW algorithm to realize the optimal performance of SVM; 3) the integration of wireless sensor and SVM to realize real-time LCB fault diagnosis. The contributions of the research include: 1) reducing the labor cost of real-time monitoring of LCBOS and improving its safety; 2) proposing an SVM based on IGOW to achieve the best performance optimization of SVM; 3) proposing a monitoring model of LCBOS with wireless measurement network and SVM to provide a new solution for the realization of LCBOS monitoring and fault prediction. Discuss the development status of the wireless measuring network and low-voltage circuit breaker, and construct the running state monitoring system of the low-voltage circuit breaker based on the wireless measurement network. In the third section, the optimization algorithm, fault diagnosis model, and performance of the state monitoring system. In Section 4, the conclusions and future research directions are discussed.

As wireless communication technology develops, wireless measurement technology has been widely applied in various fields in recent years. To avoid the problem of traditional rectal temperature measurement methods being limited by wired probes, Gosselin et al. proposed a wireless measurement technology-based absorbable temperature measurement telemetry pill. The effectiveness of this method was verified and it was found that the rectal error measured by this method did not exceed 0.2 degrees Celsius, which can reliably measure rectal temperature. Therefore, as a suppository, wireless absorbable temperature telemetry pills can be applied in practical applications [6]. To improve the effectiveness of cardiopulmonary resuscitation surgery, Ward et al. proposed using electromyography and inertial measurement units to construct a portable cardiopulmonary resuscitation surgery assistance support system. The effectiveness of the system was verified and it was found that the system performed well in surgical error classification detection, providing real-time feedback for on-site training and use of cardiopulmonary resuscitation surgery, thereby improving the effectiveness of the surgery [7]. To measure the performance indicators of wireless devices in a reverberation room, Xue et al. proposed using total radiation power to construct an economically effective testing and derivation method. By analyzing the distribution of total radiation power in the reverberation room, it was found that total radiation power was a random variable. The proposed testing method can reveal the uncertainty of total radiation power measurement more deeply than traditional methods [8]. To improve the universality of non-bedridden blood pressure monitoring cuff devices in the diagnosis and treatment of hypertension, Nachman et al. proposed using wireless testing networks to construct a new type of the optoelectronic wearable device and verify its effectiveness. It was found that this device significantly reduced the inconvenience it brought to patients compared to traditional methods, and the effectiveness of hypertension diagnosis was comparable to traditional methods [9].

As science and technology progress, society pays more attention to the power system. To ensure the consistency between the generated signals of the circuit breaker coil current model and the energy storage motor current model and the actual signals, Ji et al. proposed a network-based operating condition monitoring model and conducted empirical research on this model. It was found that it had a better monitoring performance than traditional models, ensuring the quality of extracted feature signals while avoiding the negative impact of large-scale data on classification results [10]. To explore the application effect of the gallium nitride-based three-mode intelligent solid-state circuit breakers in low-voltage configuration, Zhou et al. conducted empirical experiments on the pulse width modulation and current limiting states in the design concept of the circuit breaker. The study found that the circuit breaker had a 99.95% transmission efficiency, passive cooling response time of microseconds, and excellent performance, which can be used in practical applications [11]. To improve the application scale of low-voltage DC microgrids, Gaurav et al. proposed a circuit breaker protection scheme based on multiple threshold current values and verified its effectiveness. It was found that this scheme can respond to faults in a few milliseconds, and can effectively achieve circuit protection under heavy load transient and high fault resistance conditions, with better universality than traditional schemes [12]. To investigate the pre-start characteristics of double-break vacuum circuit breakers under the influence of the magnetic field, Geng et al. conducted empirical experiments to analyze the pre-start gap, voltage, electric field strength, impact current interruption, and contact surface erosion of the circuit breaker. The empirical experimental results showed that the pre-start gap dispersion was reduced by nearly 50% compared to traditional single-break vacuum circuit breakers, and it reduced the erosion caused by current on the contact surface [13].

In conclusion, although the research of wireless communication technology and circuit breakers is relatively mature, there are relatively few studies that apply wireless communication technology to build wireless measurement networks and combine machine learning technology for monitoring the running state of low-voltage circuit breakers. However, the research potential in this field is huge and promises to bring significant improvements in the operation and security of power systems. Currently, the monitoring of many LCBs still relies on manual inspection or wired sensors, which consume large human resources and time and limit the scope and flexibility of LCBOS detection [14]. In recent years, several studies have begun to apply data-driven methods to perform the fault diagnosis of circuit breakers [15]. By analyzing the current, voltage, and temperature of the breaker, the breaker status and fault can be identified. However, although the application of machine learning algorithms such as deep belief networks to LBC fault detection can improve the fault detection performance of LCB, the research of integrating them with wireless measurement networks to realize real-time monitoring of LB COS is still limited [16-17]. Therefore, the study proposes to combine wireless communication technology with machine learning technology to build a wireless measurement network with real-time monitoring wireless measurement network for the state monitoring of the low-voltage circuit breaker. Wireless sensor nodes can be deployed on different circuit breakers to transfer the data to the central control center through wireless communication technology, which can reduce the workload of manual inspection and laboratory testing. Machine learning algorithms can analyze and process sensor data in real time to identify potential failures and anomalies. By finding problems in time, corresponding measures can be taken to avoid greater problems caused by circuit breaker failure.

2 RESEARCH METHOD

To improve the performance of fault prediction and operation status monitoring for LCB, this study combines wireless detection networks and machine learning technology to design and implement an intelligent LCBOS monitoring system.

2.1 Basic Architecture of Circuit Breaker Operating State Monitoring System Based On Wireless Measurement

To solve the problem, the traditional LCBOS monitoring method has high labor costs and low convenience, and cannot meet the growing demand for real-time monitoring and diagnosis. Based on the wireless detection network and machine learning technology, the

LB COS monitoring system based on the wireless measurement network is built to improve the operation state monitoring effect of the low-voltage circuit breaker. The basic framework of the circuit-breaker running state monitoring system based on wireless measurement is shown in Fig. 1.

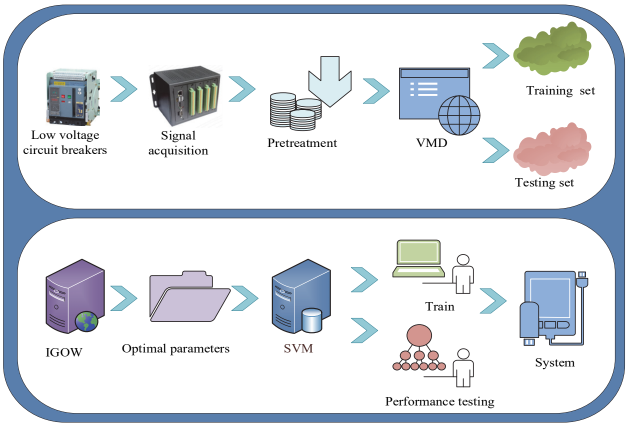


Figure 1 Basic framework of low-voltage circuit breaker operation status monitoring system based on wireless measurement network

As shown in Fig. 1, the study first uses the wireless measurement network to collect the working vibration signal data of the low-voltage circuit breaker. The acquisition object is the different components of the low-voltage circuit breaker, such as the motor, contact, connector, etc. These components will produce vibration signals of different frequencies and amplitudes during the working process, reflecting the working state and operating quality of the circuit breaker. The sensor selected in this study is the AD50S acceleration sensor of X & X Emerging Technology Company, using a simple, built-in charge amplifier circuit with a frequency response of 0.5 - 15000 Hz and measuring range of 10 - 1000 m/s^2. Subsequently, the collected data are preprocessed, including removing outliers, normalization, etc., to reduce the noise and bias of the data and improve the accuracy of the model. Removal of outliers can be done by statistical methods or threshold-based methods to exclude extreme data points that may negatively affect model training and prediction. Filling in missing values can be performed using interpolation methods or model-based methods to maintain data integrity. Normalization transforms the data into a uniform range to avoid the effect of differences between different features on the model. Through these preprocessing steps, the noise and bias of the data can be reduced, and the model accuracy and stability can be improved. The third step is feature extraction and data division, and extracting the effective features from the preprocessed data (Variational Mode Decomposition, VMD). VMD is an effective signal decomposition method to decompose signals into multiple local mode functions and extract features of different frequencies. Through the pre-processed data by VMD, various feature extraction methods, such as statistical features, frequency domain features, and time domain features, can be used to extract effective features. At the same time, the extracted feature data is divided into a training set and a test set. 70% of the data is used to train the model and 30% is used to test the accuracy of the model. In this way, the model is fully learned on the training set and validated on the test set, thus evaluating the generalization ability and accuracy of the model. In addition, IGOW is used to optimize the parameters of SVM model to find its parameter optimal solution to realize the best performance liberation of SVM. The selected parameters are mainly the penalty factor and the kernel function of the SVM. Subsequently, the study builds the SVM model based on the optimal parameters, and trains the SVM model using the training set. To evaluate the accuracy of the model, the study compares the data of the test set with a database of known anomalous states and evaluates the performance of the model by calculating such indicators as accuracy, recall, and $F1$ value. Finally, the study uses the test set and the router anomaly state database to test the trained model and evaluate the model's accuracy and performance by inputting the data of the test set into the trained model, the predicted results of the model for each sample. Then, the model predictions are compared to the true abnormal state to assess the model's accuracy and performance. The development environments used for the study are LabVIEW, ACCESS, and MATLAB. LabVIEW for data acquisition and preprocessing, ACCESS for the storage and management of the data.

2.2 Wireless Measurement Network Model Design for Low Voltage Circuit Breakers

The traditional monitoring methods for LCB often require manual inspection or the use of wired sensors, which is not only time-consuming and labor-intensive but also costly. In response to these issues, research proposes to integrate wireless sensor nodes in LCB to achieve real-time monitoring and collection of their vibration signal parameters. Common wireless transmission technologies include Wireless Fidelity (WIFI), Bluetooth, Non-fungible Certificate (NFC), and Zigbee technology. Given the high sampling frequency and large data transmission capacity of LBC signal data, the data transmission speed, transmission distance, and anti-interference performance of each wireless communication technology are selected. The data transmission rate of ZigBee technology is low, which cannot meet the signal data requirements of LBC. At the same time the maximum Bluetooth communication transmission distance is only 30 M and the signal transmission is unstable, easy to receive interference from the electromagnetic environment. NFC can only conduct close-range data transmission. The WIFI transmission method has stable signals, fast transmission speed, and a large network coverage area, making it suitable for the application of circuit breaker signal transmission. The WIFI high-speed protocol 802.11a is selected as the WLAN protocol, with a 5 GHz frequency band and a maximum rate of 54 Mbps. Therefore, the study constructs a wireless measurement network model based on WIFI transmission technology, and its basic architecture is shown in Fig. 2.

In Fig. 2, the wireless measurement network model constructed in the study includes two functions: data collection and transmission. In data collection, research utilizes vibration sensors to collect signals from LCB, which can convert the vibration signals of the circuit breakers into electrical signals. The sensor sends the collected vibration data to the intelligent collection unit.

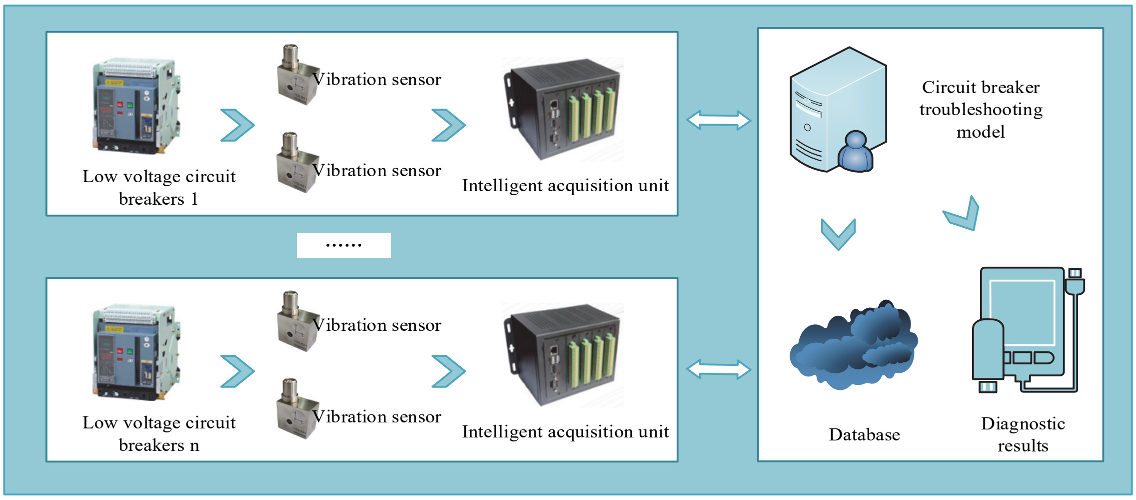


Figure 2 Wireless measurement network model using WIFI technology

The sensor selected for the research is the AD50S acceleration sensor of X & K Xinchen Technology Company, which is a simple, built-in charge amplification circuit with a frequency response of 0.5 - 15000 Hz and a measurement range of 10 - 1000 m/s^2. The intelligent acquisition unit uses a high-precision 14-digit module conversion unit to ensure the accuracy and clarity of the collected signal. However, due to the large number and scattered distribution of circuit breakers in the substation to conduct overall monitoring of circuit breakers in substations, a distributed intelligent acquisition unit is studied to collect signals from the operation status of each circuit breaker. After preprocessing operations such as filtering, these collected data are transmitted to the monitoring platform through WIFI wireless communication technology to build a status database of LCB. Subsequently, the study utilized an LCB status detection model to extract features and detect faults from the signals of LCB, ultimately achieving monitoring of the operation status and fault warning of LCB. To construct a database of abnormal states of circuit breakers, a study is conducted to summarize the common types and causes of faults in LCB using existing literature and practical experience [18-19]. The common types and causes of faults in LCB are shown below.

Table 1 Common fault types and causes of LCBs

Fault type	Reason	Fault type	Reason
Mechanical failure	The transmission mechanism connecting rod is loose and detached	Mechanical failure	Control circuit broken line
	False closing		Poor contact of the secondary loop
	Iron core travel is insufficient		The coil burns down or breaks off
	The operator card is astringent		Overpressure or underpressure
	The top bar resistance is abnormal		Coil aging
	The separation is not complete		The coil is stuck or stuck
	Iron core card astringent		Turn-to-turn short circuit; turn-to-turn fault
	The energy storage spring is stuck or falls off		Energy storage power supply or switch failure
	Shake handle fault		Energy storage motor overload or aging

2.3 SVM Detection Algorithm Based on IGWO Optimization

In practical applications, the data of LCB is nonlinear, so traditional classification fault diagnosis methods cannot be applied to circuit breaker diagnosis. SVM is used as a common machine learning algorithm for performing classification and regression analysis [20]. It can find a hyperplane in the high-dimensional space, and separate the different categories of samples as far as possible to realize the classification of samples. Therefore, SVM has powerful non-linear modelling and classification capabilities and has good practicability in fault diagnosis and running state detection of low-voltage circuit breakers [21-22]. However, the analytical performance of SVM is limited by the selection of key values such as penalty factors and kernel parameters, and its performance is usually difficult to maximize. GWO is an optimization algorithm based on the natural group behaviour, inspired by the cooperation and competition of the Gray Wolf in the predation behaviour. The algorithm was proposed by Mirjalili et al. in 2014 to optimize the problem by simulating the interaction behaviour between leaders and followers in the Gray Wolf population. It can realize the search for the optimal solution by simulating the elite population in the grey Wolf group. Due to its good global search ability and convergence performance, GOW has a certain application value in the field of optimization problems and fault diagnosis. Therefore, to ensure the SVM performance, this study proposes to improve the SVM algorithm using GWO to ensure the optimal selection of its parameters. Fig. 3 shows the SVM basic idea.

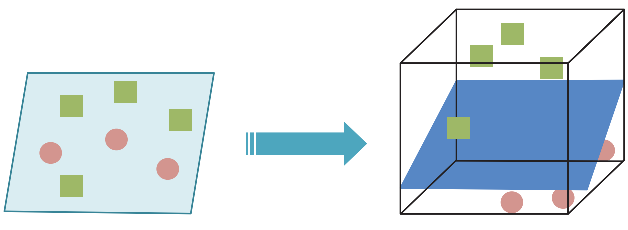


Figure 3 SVM basic idea

In Fig. 3, the SVM core idea is to analyze samples through hyperplanes in the feature space, and the calculation formula for the plane separation process is shown in Eq. (1).

$$f(x) = w\varphi(x) + \beta \tag{1}$$

In Eq. (1), w represents the spatial weight, which assigns different weights to samples from different regions in the feature space. φ() represents the mapping process. x represents the input sample vector. β represents a regression bias item, which represents the difference or bias between the model prediction values and the actual observed values. The calculation formula for the risk function is shown in Eq. (2).

$$R(w) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} l\left(f\left(x_i\right) - y_i\right) \tag{2}$$

In Eq. (2), C represents the penalty factor, whose value plays a decisive role in determining the values of the classification gap and risk function; y_i represents a mapping vector; $l()$ represents a high-dimensional mapping. The kernel function can map linear circuit breaker data in two-dimensional space to high-dimensional feature space, and its calculation formula is shown in Eq. (3).

$$K(x_i, x_j) = \Phi \max(x_i) \cdot (x_j) \tag{3}$$

In Eq. (3), Φ represents a nonlinear mapping. $\Phi(x)$ can replace the original sample vector to solve the original feature space, and the calculation formula for this solution is shown in Eq. (4).

$$\begin{cases} \max L = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j x_i x_j \left(\Phi\left(x_i\right)\cdot\left(x_j\right)\right) \\ st.\begin{cases} \alpha_i \geq 0, i = 1, 2, \ldots, n \\ \sum_{i=1}^{n}\alpha_i y_i = 0 \end{cases} \end{cases} \tag{4}$$

In Eq. (4), α represents the constraint conditions, which are used to define and optimize the model. The calculation formula for the classification decision function is shown in Eq. (5).

$$y = \operatorname{sgn}\left(\left(w^* \cdot \Phi\left(x\right)\right) + b^*\right) = \operatorname{sgn}\left(\sum_{i=1}^{n}\alpha_i y_i K\left(x_i \cdot x\right) + b^*\right) \tag{5}$$

In Eq. (5), sgn() represents the decision function; w^* and β^* represent the spatial weights and regression bias items of the optimal hyperplane. From the above formula, it can be seen that the SVM analysis performance parameters are directly affected by the penalty factor and kernel function. The penalty factor controls the degree of penalty for misclassified samples. A smaller penalty factor causes the model to tolerate misclassification easier, potentially leading to underfitting, while a larger penalty factor causes the model to penalize misclassification more rigorously, potentially leading to overfitting. Another key parameter is the choice of the kernel function and the adjustment of the kernel parameters. The kernel functions are used to map the input data to a high-dimensional feature space to deal with non-linear problems. Different kernel functions have different complexities and nonlinear abilities. The commonly used kernel functions are linear, polynomial, and Gaussian.

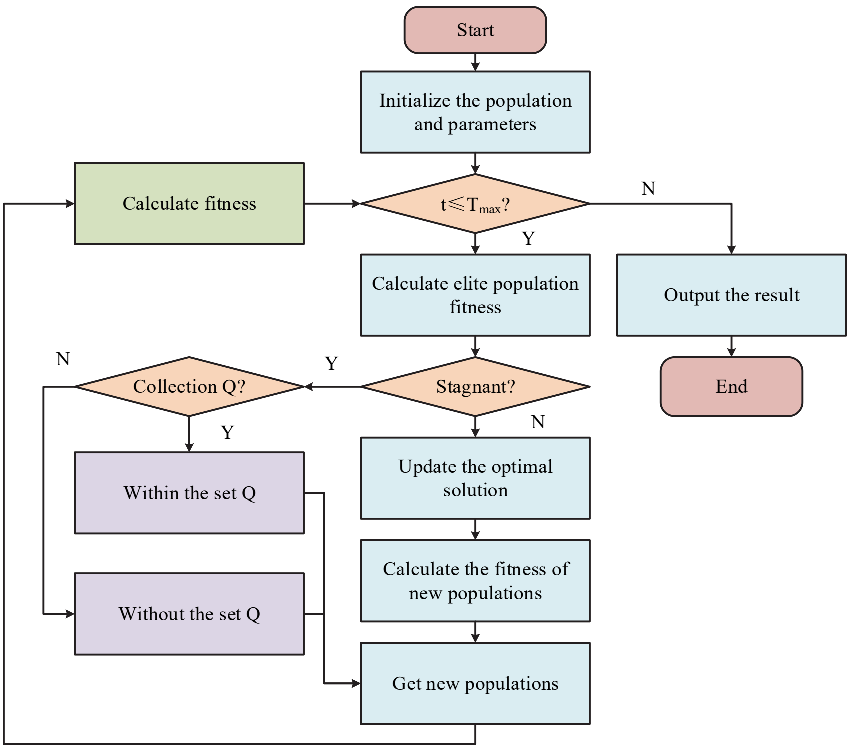


Figure 4 Basic flow of the GWO algorithm

Therefore, to ensure the optimal selection of parameter penalty factors and kernel functions in SVM, and improve the training speed of SVM, GWO is studied for optimization. However, when facing complex optimization problems, GWO often faces difficulties in parameter selection, decreased convergence speed, and local optimal solutions. To address these issues, research is being conducted to construct the IGWO using optimization algorithms such as quasi-reverse learning strategies. IGWO's basic process is shown in Fig. 4.

In Fig. 4, the study first utilizes a quasi-reverse learning strategy to ensure the diversity of the initial population, and the calculation formula for this process is shown in Eq. (6).

$$\begin{cases} \hat{z}_i^j = a_i^j + b_i^j - z_i^j, \mathbf{X}_i = \left(\hat{z}_i^1, \hat{z}_i^2, \ldots, \hat{z}_i^d \right) \\ z_i^j \in \left[a_i^j, b_i^j \right] \left(\mathrm{i}=1,2,\ldots d; j=1,2,\ldots d \right) \end{cases} \tag{6}$$

In Eq. (6), $\boldsymbol{X_i}$ represents the position of the gray wolf i. $\hat{z}_i^j$ represents the reverse solution of z_i^j; a_i^j represents the upper bound; b_i^j indicates the lower bound; d represents a dimension. Subsequently, research is conducted to randomly reverse solve the reverse and center points of the initial population of Gray wolves, thereby improving the algorithm's global search ability. The calculation formula for this process is shown in Eq. (7).

$$\hat{z}_i^j = \begin{cases} rand(avg_i^j, \hat{z}_i^j), \hat{z}_i^j \le avg_i^j \\ rand(\hat{z}_i^j, avg_i^j), \hat{z}_i^j > avg_i^j \\ avg_i^j = b_i^j - a_i^j / 2 \end{cases} \tag{7}$$

In addition, to select a better elite population, the study also uses fitness to screen for random solutions and quasi inverse solutions. The selection process is shown in Eq. (8).

$$fit\left(X\right) > fit\left(\overset{V}{X}\right) ? X, \overset{V}{X} \tag{8}$$

In Eq. (8), *fit*() represents the fitness function; X represents a random individual; $\overset{V}{X}$ represents a quasi-reverse learning random individual. Individuals with higher adaptability will be retained as elite individuals. To ensure a balance between the global search and local development functions of the algorithm, while meeting the nonlinear requirements of LCB data, a nonlinear convergence factor is introduced into the optimization algorithm in Eq. (9).

$$a = 2 - \frac{2}{e^2 - 1} \times \left(e^{e^{\frac{2r}{T_{\max}}}} - 1 \right) \tag{9}$$

In Eq. (9), $T_{\max}$ represents the maximum iteration; a represents the convergence factor, which can control the convergence rate and stability of the algorithm. Finally, to avoid local optima in the algorithm, a multi-elite search strategy is studied to optimize it. The study sets up a set Q to save the elite population. When no more optimal solution occurs during the algorithm iteration, an elite population is added to the set Q until the maximum population save value is reached. When the updated individual is in the set Q, its update calculation formula is shown in Eq. (10).

$$\begin{cases} \mathbf{X}^{t+1} = \mathbf{X}^t + |\chi| \cdot \left(\mathbf{X}_{best}^{t+1} - \mathbf{X}^t \right) + D \cdot \left(1 - t / t_{\max}\right) \cdot r_{rand}\left(t+1\right) \\ \chi \sim N(0,1), \mathbf{X}_{best} \in Q, \mathbf{X}_{best} \ne \mathbf{X} \end{cases} \tag{10}$$

In Eq. (10), t represents the number of iterations; D indicates the distance between wolves and prey; r represents the oscillation factor.

$$\begin{cases} \boldsymbol{X}^{t+1} = \boldsymbol{X}_{best} + \sigma \cdot \left(\boldsymbol{X}_{best}{}^t - \boldsymbol{X}^t \right) + l \cdot \boldsymbol{X}_{best}{}^t - l \cdot \boldsymbol{X}^t \\ \sigma \sim N(0,1), l \sim N(0,1), \boldsymbol{X}_{best} \in Q \end{cases} \tag{11}$$

In Eq. (11), l represents disturbance, which is used to introduce randomness during the search to improve the exploration power of the algorithm; σ is a standard normal distribution.

2.4 LCB Operation Status Monitoring System Construction Based on Wireless Measurement Network Model

After completing the construction of the IGOW-SVM detection algorithm, a LCB fault detection model is studied and combined with a wireless measurement network model to construct a LCBOS monitoring system using wireless measurement network model. The implementation process of the IGOW-SVM based LCB fault detection model is shown in Fig. 5.

As shown in Fig. 5, the study first initializes the parameter penalty factor C and kernel function g in SVM and uses them as inputs for the grey wolf position in the IGOW algorithm. The second step is to initialize the population, spatial dimension, maximum number of iterations, and wolf pack position in the IGWO algorithm, calculate the fitness of all (C, g), and select elite wolf packs based on the size of fitness. Subsequently, research is conducted to determine whether the algorithm has stalled and updated the population based on the updated status of the adaptive set Q. After obtaining the updated location of the grey wolf population, the fitness value of the new population is calculated again. If a higher fitness value occurs, the optimal solution is updated; if it is lower than or equal to the current fitness value, the optimal solution remains unchanged until the maximum iteration is reached.

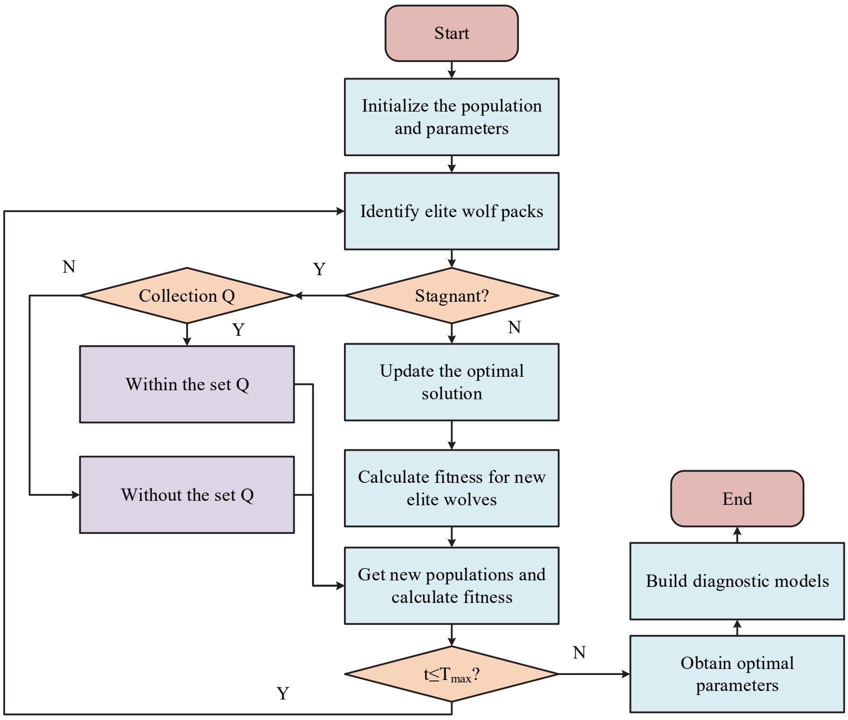


Figure 5 Implementation process based on IGOW-SVM LCB fault detection model

Finally, based on the selected optimal parameters (C, g), an LCB fault detection model is constructed and its performance is evaluated. After completing the construction of the LCB fault detection model, the model is combined with the LCB wireless measurement network model to construct an LCBOS monitoring system based on the wireless measurement network.

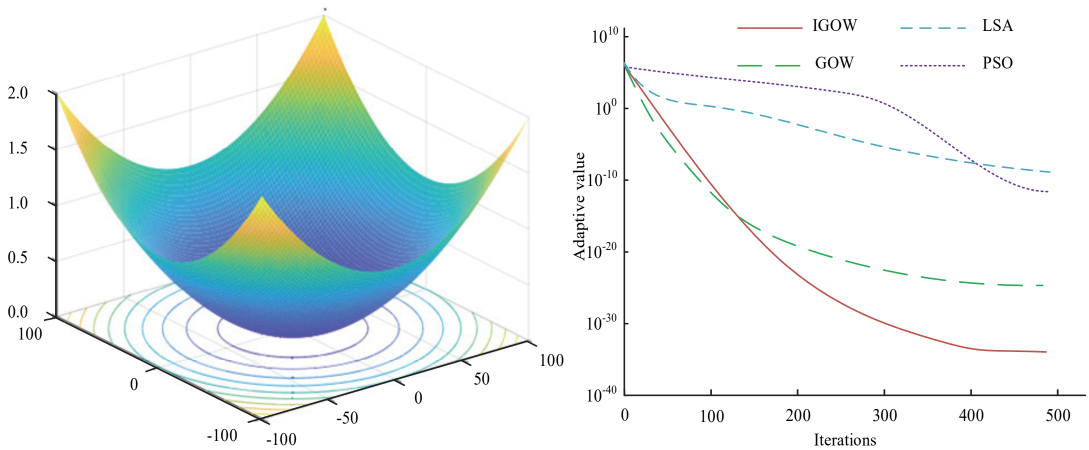
3 LOW VOLTAGE CIRCUIT BREAKER OPERATION STATUS MONITORING SYSTEM EMPIRICAL ANALYSIS

To verify the IGOW effectiveness, the fault diagnosis model using the IGOW SVM algorithm, and LCBOS monitoring model based on the wireless measurement network proposed in the study, performance comparison experiments and empirical analysis were conducted on them.

3.1 IGOW Algorithm Parameter Optimization Performance Experimental Verification

3.1.1 Convergent Performance Test of the IPSO-FPN Algorithm on the Unimodal Function

To explore the effectiveness of the IGOW algorithm constructed in the research, the benchmark function Sphere was used to test its parameter optimization performance. The Sphere function was a 30-dimensional unimodal testing function. The comparative optimization algorithms selected for the study were the GOW algorithm, Lightning Search Algorithm (LSA), and Particle Swarm Optimization (PSO) algorithm. To maintain the validity of the experiment, the population size N of such algorithm was set to 30, the corresponding maximum number of iterations was set to 500, and the dimension d was set to 30. All the parameters of each algorithm were set according to the parameters of the standard algorithm.



(a) Sphere function 3D stereogram

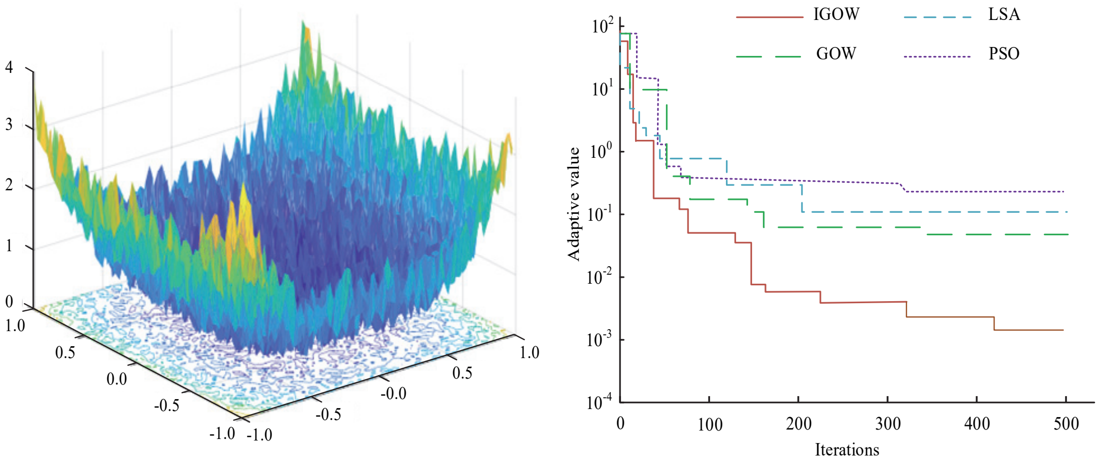
(b) Convergence curves in the search process of each optimization algorithm

Figure 6 The optimal convergence curve of each optimization algorithm in the sphere benchmark function

The experimental environment was on Windows 10 and MATLAB platforms. This observation indicated that the IGOW algorithm had high advantages in solving the problem of the Sphere benchmark function. The IGOW algorithm converged to the global optimal solution faster by improving the optimization strategy or parameter adjustment. Compared with other comparison algorithms, the IGOW algorithm can find the optimal solution faster with the same number of iterations, which indicates its higher search ability and optimization effect. The convergence curves of each optimization algorithm in the Sphere benchmark function are shown in Fig. 6. Fig. 6a and Fig. 6b show the three-dimensional images of the Sphere reference function and the optimization convergence curves of each algorithm, respectively. As shown in Fig. 6, the IGOW algorithm entered a convergence state when the number of iterations was 400, and its convergence performance was much higher than other comparative algorithms. Moreover, the IGOW algorithm also exhibited better parameter optimization ability, indicating that the IGOW algorithm proposed in the study had good application value in improving the SVM convergence speed.

3.1.2 Test Experiment of Multimodal Function Convergence Performance of IGOW Algorithm

The convergence performance of the IGOW algorithm was constructed for the exploration study of the multimodal function. The benchmark function was Quartic. The Quartic function is a multimodal test function in 30 dimensions. The comparative optimization algorithms selected for the study were GOW, LSA, and PSO. To maintain the validity of the experiment, the population size N of such algorithm was set to 30, the corresponding maximum number of iterations was set to 500, and the dimension d to 30. All the parameters of each algorithm itself were set according to the parameters of the standard algorithm. The experimental environment was the Windows 10 and MATLAB platforms. The convergence curves of each optimization algorithm in the Quartic benchmark function are shown in Fig. 6.



(a) Quartic function 3D stereogram (b) Convergence curves in the search process of each optimization algorithm

Figure 7 The optimal convergence curve of each optimization algorithm in the Quartic benchmark function

Fig. 7a and Fig. 7b show the three-dimensional images of the Quartic reference function and the optimization convergence curves of each algorithm, respectively. As shown in Fig. 7, LSA, PSO, and GOW algorithms fell into local optima at 200, 310, and 350 iterations, respectively, while IGWO did not fall into local optima at 500 iterations, and IGOW's optimization accuracy was higher than other comparative algorithms. The above results indicated that IGOW had good application value in terms of parameter optimization accuracy.

3.2 IGOW-SVM Fault Detection Model-based Empirical Experiment

3.2.1 Performance Test of a Single Failure Type for IGOW-SVM

To verify the diagnostic performance of the IGOW-SVM-based fault detection model proposed in the study, a single fault type of fault diagnosis performance verification experiments were conducted using the constructed router abnormal state database. Performance comparison testing was performed on a fault diagnosis model based on GOW-SVM, PSO-SVM, and LSA-GOW algorithms. The performance evaluation indicators were average diagnostic accuracy and standard deviation. The dataset used was a test set constructed from the data collected from the LCB wireless measurement network model. The experimental environment was on the Windows 10 and MATLAB platforms, with a computation count of 20. The diagnostic accuracy of each diagnostic model for a single fault type is shown in Fig. 8.

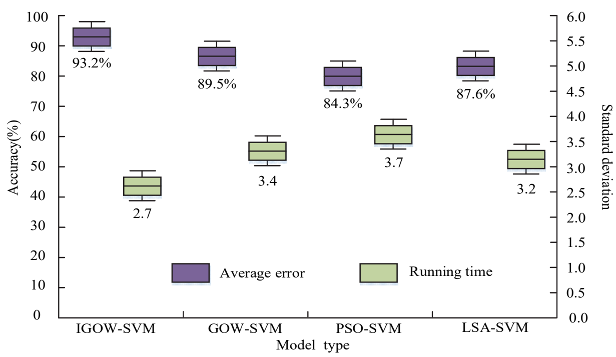


Figure 8 Comparison of the diagnosis accuracy of a single fault type of each model

In Fig. 8, the IGOW-SVM fault diagnosis model proposed in the study had a much higher diagnostic accuracy performance in a single fault compared to other comparative models, with a diagnostic accuracy of 93.2%, which was 2.8% higher than the GOW-SVM model. In addition, the diagnostic accuracy of the IGOW-SVM fault diagnosis model was also higher than other comparative models, with a diagnostic standard deviation of 2.7, which was 0.7 lower than the GOW-SVM model. The IGOW-SVM fault diagnosis model proposed in the study can better diagnose a single fault. The advantage of the IGOW-SVM fault diagnosis model may come from its improvement and optimization of feature selection, feature weight calculation, and classifier construction, which indicates its higher accuracy in single fault diagnosis. The results of this study are consistent with the literature [10], which has better accuracy than traditional fault diagnosis methods and has practical application value.

3.2.2 IGOW-SVM Multiple Fault Type Performance Detection Experiment

To verify the diagnostic performance of the fault detection model based on the IGOW-SVM algorithm, the database was used. Among them, multiple fault types were normal (category 1), false closing (type 2), closing bolt loosening (type 3), closing bolt loosening (type 4), and energy storage spring tightness (type 5). The fault diagnostic model based on GOW-SVM, PSO-SVM, and LSA-GOW algorithm was used. The performance evaluation index is the fault classification and diagnosis accuracy. The data set used is a test set constructed from the data collected in the wireless measurement network model of the low-voltage circuit breaker. The experimental environment was Windows 10 and MATLAB platform, and the operation number was 20. The diagnostic accuracy of various diagnostic models for various types of faults is shown in Fig. 9.

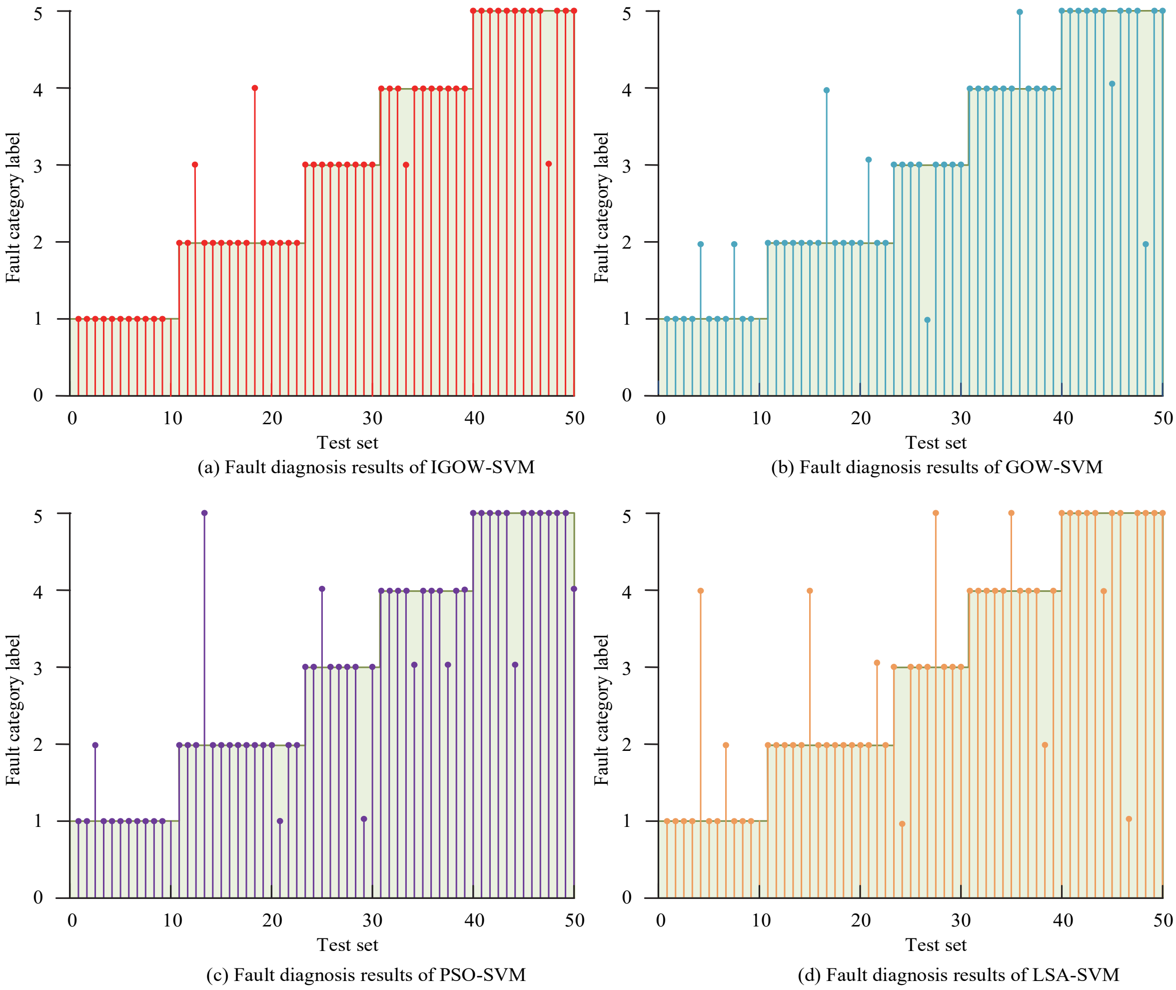


Figure 9 Comparison of the diagnostic accuracy results of various types of faults in each diagnostic model

Fig. 9a shows the multi-category fault diagnosis results of the IGOW-SVM fault diagnosis model. IGOW-SVM correctly diagnosed all normal types, misdiagnosed 2 cases of false closing, and misdiagnosed 1 case of loose closing bolts and stuck energy storage springs. The IGOW-SVM fault diagnosis model showed 4 diagnostic errors in 50 samples, with a diagnostic effect of 92%. Fig. 9b shows the multi-category fault diagnosis results of GOW-SVM. The GOW-SVM fault diagnosis model made 8 diagnostic errors in 50 samples, with a diagnostic effect of 84%. Fig. 9c shows the multi-category fault diagnosis results of PSO-SVM. The GOW-SVM fault diagnosis model made 9 diagnostic errors in 50 samples, with a diagnostic effect of 82%. Fig. 9d shows the multi-category fault diagnosis results of LSA-SVM. The GOW-SVM fault diagnosis model made 10 diagnostic errors in 50 samples, with a diagnostic effect of 80%. The IGOW-SVM fault diagnosis model had better classification accuracy in multiple types of fault diagnosis and had practical application value. This is because the IGOW-SVM algorithm combines an improved genetic optimization algorithm and an SVM classifier to better find the optimal classification boundary. In addition, the IGOW-SVM algorithm can also optimize the parameters and further improve the classification performance. The results are consistent with Jiao et al, where the fault diagnosis method has the advantages of being fast, accurate, economical, and efficient and can identify more detailed fault information [23]. The results are also consistent with Shen et al., which can improve the fault diagnosis efficiency of transformers and realize the rapid response of fault signals [24].

3.3 Low Voltage Circuit Breaker Operation Status Monitoring System Empirical Analysis

To verify the performance of the LCBOS monitoring system, a performance comparison test was conducted. The comparison model was a LCBOS monitoring system based on GOW-SVM, PSO-SVM, and SVM. The performance evaluation indicators included the receiver operating characteristic curve, $F1$ value, error, and fault response time of the subject. The dataset used was a test set constructed from the data collected from the LCB wireless measurement network model [25]. The experimental environment was on Windows 10 and MATLAB platforms. The ROC curves and $F1$ values of each monitoring system are shown in Fig. 10.

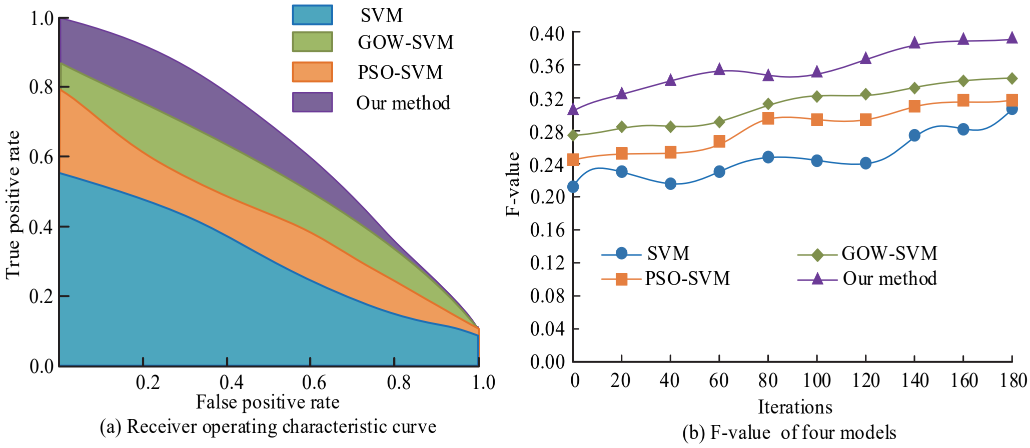


Figure 10 Comparison of the ROC curves and $F1$ values of each monitoring system

Fig. 10a shows the ROC curves of each circuit breaker operation monitoring system. The offline area of the ROC curve of the proposed monitoring system based on a wireless measurement network was 0.74, which was larger than the offline area of other systems, indicating that its operation status monitoring effect was better. Fig. 10a shows the $F1$ values of each circuit breaker operation monitoring system. The $F1$ value of the proposed wireless measurement network-based circuit breaker operation status monitoring system was 0.35, which was higher than the $F1$ value of other systems, indicating that it had better performance in monitoring the LCB operation status. Overall, the results showed that the performance of the system using wireless measurement networks was better than other models. The accuracy and fault response time of each monitoring system are shown in Fig. 11.

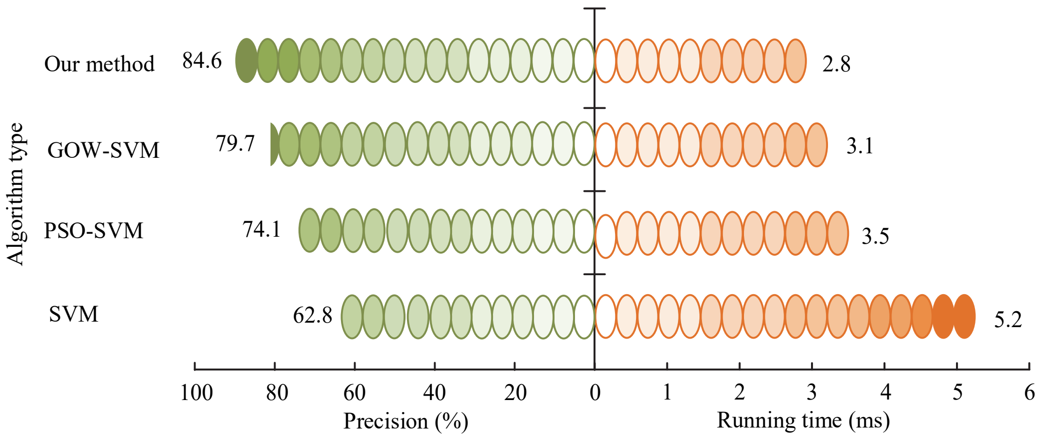


Figure 11 Accuracy and operation time of each monitoring system

In Fig. 11, the proposed wireless measurement network-based circuit breaker operation status monitoring system had an accuracy of up to 84.6%, significantly superior to other comparative models. In addition, the fault response time of this model was 2.8 seconds, which was significantly lower than other comparative models [26]. The circuit breaker operation status monitoring system based on wireless measurement networks had higher accuracy and lower fault response time compared to other systems [27]. This system had high reliability and efficiency in monitoring and predicting circuit breaker faults.

4 CONCLUSION

To improve the reliability and safety of the power system, reduce the probability of failure, reduce the downtime of the power system, and improve production efficiency, the LB COS state monitoring research is proposed. In response to the high workload of manual inspection and laboratory testing of LCB, a wireless measurement network was proposed using WIFI wireless communication technology to collect circuit breaker signals and extract their features. In addition, the study also optimized the GOW algorithm and utilized the IGOW-SVM algorithm to construct a circuit breaker fault diagnosis model. This study fused wireless measurement networks and circuit breaker fault diagnosis models to construct an LCBOS monitoring system using wireless measurement networks. Because the fault diagnosis and classification performance of SVM is closely related to its penalty factor and kernel function, its parameter optimization is very important. Therefore, the unimodal function and multimodal function are used to test the optimization algorithm and IGOW algorithm. The optimization performance of the constructed IGOW algorithm was tested, and the results showed that the algorithm can avoid entering local optimization problems, and IGOW's optimization performance was also higher than other comparative algorithms. The results showed that the improved grey Wolf algorithm had good search accuracy and optimization speed, which was used to optimize SVM parameters and improve the diagnostic performance of SVM. Performance verification tests were conducted on the constructed IGOW-SVM fault diagnosis model, and it was found that the model had a diagnostic accuracy of 93.2% in a single fault and a diagnostic effect of 92% in multi-category faults, which was better than other diagnostic models. The results showed that the SVM model improved by IGOW had high fault diagnosis accuracy, which was effectively used in the field of fault diagnosis to provide more accurate guidance and support for fault handling. Finally, the performance verification of the operational status monitoring system was conducted, and the area below the ROC curve of the system was 0.74, with an $F1$ value of 0.35, which was better than other systems in terms of performance. The fault response time of this system was 2.8 seconds, significantly lower than other comparative models. The results showed that the performance of the low-voltage circuit breaker monitoring model was optimal, which not only improved the reliability and safety of the low-voltage circuit breaker but also reduced the maintenance cost and improved the work efficiency. The results of this study demonstrated the importance and application value of low-voltage circuit breaker operation status monitoring system based on wireless measurement network, and provided an effective solution for fault diagnosis and monitoring of power equipment, and helped to improve the reliability, safety and operation efficiency of power system. In conclusion, the main contributions of the research are as follows: 1) Build a wireless measurement network by using WIFI wireless communication technology to collect low-voltage circuit breaker signals and extract features, which can reduce the workload of manual inspection and laboratory test, and improve the efficiency of data collection.2) Optimize the GOW algorithm, and use the IGOW-SVM algorithm to construct the circuit breaker fault diagnosis model. Optimizing the algorithm and combining the machine learning method can improve the accuracy and efficiency of fault diagnosis.3) Integrate the wireless measurement network with the circuit breaker fault diagnosis model to build a low-voltage circuit breaker operation status monitoring system based on the wireless measurement network. The system can monitor the running state of the circuit breaker in real time, and provide accurate fault diagnosis results to improve the reliability and safety of the low-voltage circuit breaker. However, the study also has some limitations, such as the non-linear convergence factor in the IGOW algorithm is only highly correlated with the number of iterations, and it does not reflect the fitness. At the same time, the study only carries out fault diagnosis and monitoring for low-voltage circuit breaker and further research is needed for other types of power equipment. In addition, the deployment of the system requires a large cost input, including the purchase and installation of wireless communication equipment and sensors, which may be less practical for some areas with limited resources. Future research directions are to explore a new fitness-related nonlinear convergence factor, and it will need more field testing and validation to verify the feasibility and effectiveness of the system in practical application.

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