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Research Article

Abnormal Diagnosis Method of Self-Powered Power Supply System Based on Improved GWO-SVM

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In order to solve the problem of low abnormal diagnosis rate of self-powered power supply system, an improved grey wolf optimization-support vector machine (GWO-SVM) algorithm combined with maximal information coefficient (MIC) are proposed. First, the feature sets of 11 kinds of monitoring data are optimized and selected based on MIC for self-powered power supply system. By eliminating redundant variables and insensitive variables, feature variable sets with great influence on abnormal diagnosis are selected. Second, by upgrading the selection method of control parameter σ from linear to nonlinear, an improved GWO-SVM algorithm that can take into account both global and local search capabilities is proposed. Furthermore, the optimal feature set which has great influence on abnormal diagnosis is selected as the input of the proposed algorithm, and then the abnormal diagnosis method combining the improved GWO-SVM with MIC is constructed for self-powered power supply system. The specific algorithm flow and step are given. Finally, compared with other algorithm, the simulation experiments show that the GWO-SVM method has a higher accuracy and a higher recall rate for the abnormal diagnosis in the self-powered power supply system.

1. Introduction

The self-powered power supply system is the self-generating equipment that uses the vehicle chassis engine as the power source, drives the generator through the power take-off transmission device, and provides electrical energy to the electrical equipment without an external power source. Different from other on-board power supply systems, the self-powered power supply system has the advantages of safety, strong mobility, light weight, small size, freedom from external environmental influences, low installation requirements, and easy maintenance. In the modern battlefield, no matter how rapid the growth of mechanized and informatized weapons and equipment, they are inseparable from the strong support of military power stations, and self-powered power supply systems are the main source of electrical energy for weapon systems. If the self-powered power supply system is abnormal, faulty, damaged, invalid, etc., the entire weapon system may fall into a paralyzed state, which will seriously affect the military's combat effectiveness. Therefore, it is an unavoidable problem that some components of the self-powered power supply system have different degrees of abnormality [1, 2]. If effective measures are not taken in time, the weak ones will affect the training due to the lack of normal power supply for the weapon equipment system, and the serious ones will even endanger the lives of personnel. Therefore, the abnormal diagnosis for self-powered power supply system is very meaningful for weapons and equipment. At the same time, how to accurately diagnose abnormalities from a large amount of system operation data, as far as possible to detect and alert the accident in advance, to provide valuable information for subsequent condition-based

maintenance. The abovementioned study is a work with certain research significance and practical value [3].

To perform abnormal diagnosis of self-powered power supply system, data feature selection is an indispensable step [4], which can efficiently enhance the generalization capacity of the model and reduce overfitting [5]. The maximum information coefficient is adopted for feature selection based on the actual collected monitoring data. The original monitoring data always contains redundant information, which will conceal the true information contained in the data itself, and the redundant information may even interfere with the diagnosis results. Therefore, it is essential to obtain the hidden feature information from the original data. Data noise must be removed and redundant data must be reduced to reduce the impact on the diagnosis result [6]. This process is data dimensionality reduction. Data dimensionality reduction includes feature transformation and features choose two methods [7–9]. A binary version of the hybrid two-phase multiobjective FS approach is proposed based on particle swarm optimization (PSO) and grey wolf optimization (GWO) in [10]. The traditional typical data dimensionality reduction method mainly uses the principal ingredient analysis approach, which is to transform the characteristic space to obtain a new comprehensive feature to replace the original feature to realize the goal of data dimensionality decrease. This approach can efficiently decrease the dimensionality of many learning tasks, but there is an obvious disadvantage that it is difficult to interpret the features after dimensionality reduction. Even if a simple linear combination of the original features is performed, there will be a problem of poor interpretation performance of the model. The study uses the variable correlation measurement of the maximum information coefficient to perform feature selection and can better extract important features.

Relative to abnormal monitoring, abnormal diagnosis is a more accurate classification problem. Aiming at achieving the ideal abnormal diagnostic efficacy, the classification method is to establish a classification model with the label data set. Artificial intelligence-based methods are widely used in many abnormal diagnosis and classification methods, which use the historical data of the system under normal and various abnormal conditions to train through machine learning algorithms and then use it for abnormal diagnosis [11]. Among them, there is a classification method based on clustering, and its clustering effect is greatly affected by independent points, noise, and initial clustering centers [12, 13]; the rules are learned in the data set, and the rules will be changed with the change of the data set [14, 15]; the abnormal diagnosis method based on neural network has strong diagnostic ability, but the setting of the neural network model parameters has a greater influence on the outcomes, and there is no unified standard so far [16, 17]. The SVM shows the merits of short training time and great generalization ability and can be better used in abnormal diagnosis [18]. The SWM which is on basis of the learning principle of structural risk minimization criterion can overcome the defect of slow convergence rate. In the solution of classification problems, SVM's kernel function coefficients and penalty factor values will affect the accuracy of classification. If the kernel function coefficients and penalty factor values are too large or too small, the diagnostic error will become larger. At present, the coefficients of the support vector machine are mainly improved by intelligent improvement algorithms including grid search method, PSO, genetic algorithm (GA), whale algorithm, and GWO, but there is still a problem that the optimal penalty element and kernel function coefficients cannot be obtained accurately [19, 20].

For solving the abovementioned issues, first the features are selected based on MIC, and the GWO algorithm is modified by improving the control parameter σ. The location update method of GWO in conjunction is updated with Levi flight. Furthermore, the kernel function coefficients and penalty elements are optimized, and SVM parameters are obtained. The optimal solution to achieve the purpose of abnormally accurate diagnosis of the self-powered power supply system is given at last.

2. Analysis of Abnormal Working Conditions of Self-Powered Power Supply System

The core modules of the self-power supply system are mainly cage-type asynchronous generator modules, generator control modules, and inverter modules. In the main three core modules of the self-powered power supply system, due to the long-term operation of the asynchronous generator in the electromagnetic and variable working environment, it is very prone to failure, and its common abnormal conditions are bearing condition, rotor broken strip working condition, air gap eccentric working condition, rotor unbalanced working status, and stator winding interturn short circuit condition. Under the help of "self-powered power supply system simulation platform" developed by our laboratory, in the early stage, the two types of gradient abnormal working conditions of the short circuit among the stator windings of the asynchronous motor and the broken rotor bar in the early stage of the self-powered power supply system are realized by modifying the main module simulation parameter. In the actual engineering, the two types of short circuit among the stator windings of the asynchronous motor and the broken rotor bar in the early stage occur more frequently. The electrical fault caused by the short circuit among the stator windings of the asynchronous motor accounts for 30% to 40%; in addition, the rotor break and the electrical fault caused by it account for 10%. Stator winding interturn short circuit and rotor break are the common progressive development of abnormal conditions, that is, the system parameters from the initial appearance of abnormal to abnormally obvious process. Therefore, abnormal diagnosis studies were carried out on anomalies caused by two types of gradient faults in the stator windings of asynchronous generators, namely, short circuits between turns and rotor breaks.

3. Abnormal Diagnosis Scheme of Self-Powered Power Supply System

This paper mainly studies the abnormal diagnosis of the short circuit among the stator windings and the broken rotor bar in the early stage of the asynchronous motor for the self-powered power supply system. For solving the above-mentioned issues, this paper puts forward an abnormal diagnosis approach on basis of the combination of the maximum information coefficient method (MIC) and the improved GWO-SVM, and the reasons for the improvement and combination of the abovementioned algorithms are because of the following reasons.

One is that the monitoring data collected in the self-powered power supply system have a strong or weak influence on the abnormal diagnosis effect of the system, and MIC can eliminate redundant characteristic data based on the correlation between the data.

Second, the SVM method is more sensitive to abnormal data than traditional methods, such as K-nearest neighbors and decision trees. The SVM has good generalization capabilities and is often used in abnormal diagnosis.

The third is that the GWO algorithm is a smart improvement algorithm, which shows the merits of quick convergence speed and great improvement ability. The improved GWO algorithm in this paper optimizes the SVM parameters and has outstanding performance in avoiding getting stuck at the local optimum and can possess a higher precision for abnormal diagnosing.

In summary, for the self-powered power supply system, an improved GWO-SVM abnormal diagnosis scheme combined with MIC is proposed, as shown in Figure 1.

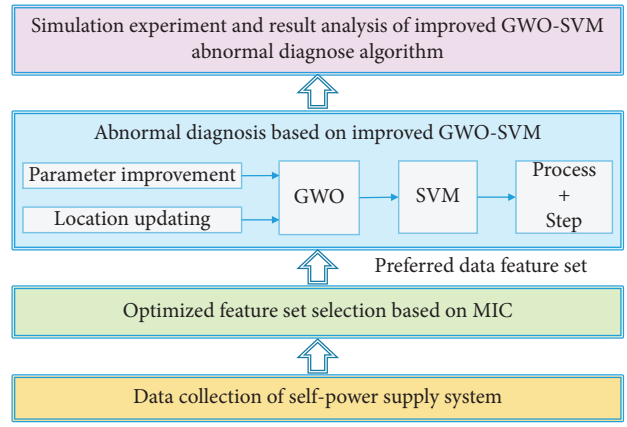

Figure 1: Abnormal diagnosis scheme of self-powered power supply system.

4. Feature Optimization Based on the Maximum Information Coefficient

When faced with tens of thousands of data variables, for a specific output result, some variables have important causal relationships with them that have not been revealed yet, some variables are redundant with each other, and some variables and output results are not relevant at all. Based on the MIC, the correlation of the early stage is calculated among the characteristic variables, the rotor broken bar, and the stator winding interturn short circuit. Furthermore, the rank of them will be given according to the relevant sensitivity scores. Finally, select the optimal feature subset that is more sensitive to anomalies in the monitored variables, that is, eliminate insensitive or even irrelevant data features with less impact. At the same time, eliminate redundant variables and select the most influential optimal characteristic set to improve the accuracy of the abnormal diagnosis method.

The core idea of the MIC is as follows: for the certain output and two variables, if there is a certain correlation between the two, then the grid $x \times y$ can be drawn continuously in the two-dimensional plane. The data points in the scatter diagram composed of two variables are divided, and the maximum mutual information in their state is obtained. Also, then the maximum mutual information obtained in different network grid states can be obtained. The information forms a characteristic matrix A, which is expressed as follows:

$$F = \begin{bmatrix} f_{22} f_{23} \cdots f_{2y}, \\ f_{32} f_{33} \cdots f_{3y}, \\ \vdots \ \vdots \ \cdots \ \vdots, \\ f_{x2} f_{x3} \cdots f_{xy}. \end{bmatrix}_{(x-1)\times(y-1)}. \quad (1)$$

Then, the matrix F is standardized to eliminate the influence of the number of grids, so that the maximum mutual information of the elements of matrix F can be compared with each other. After standardization, the element value of matrix F is between 0 and 1. Finally, the MIC is calculated. The calculation formula is

$$\mathrm{MIC}(X, Y) = \max_{x * y < B} \frac{I(X(G), Y(G))}{\log\min\{x, y\}}. \quad (2)$$

In equation (2), X, Y are the given two variables. $I(X(G), Y(G))$ is the mutual information. $\log\min\{x, y\}$ stands for normalization. B is the maximum number of grids. B is usually taken as $n^{0.6}$, and n is the amount of data. Furthermore, the MIC is applied to the abnormal diagnosis of the self-powered power supply system. The characteristics are sorted by calculating the MIC that represent the correlation of the characteristics, and the characteristics are eliminated according to the correlation from small to large. Finally, the optimal feature set is selected by comparing the accuracy of the algorithm.

5. The Abnormal Diagnosis Method of Self-Powered Power Supply System Based on Improved GWO-SVM

As an algorithm of machine learning, SVM shows unique merits in settling nonlinear, small sample, and high-dimensional pattern recognition issues, but the performance of SVM is largely affected by internal parameters. Using the traditional particle swarm algorithm, cuckoo search algorithm, and GA to optimize SVM parameters, the

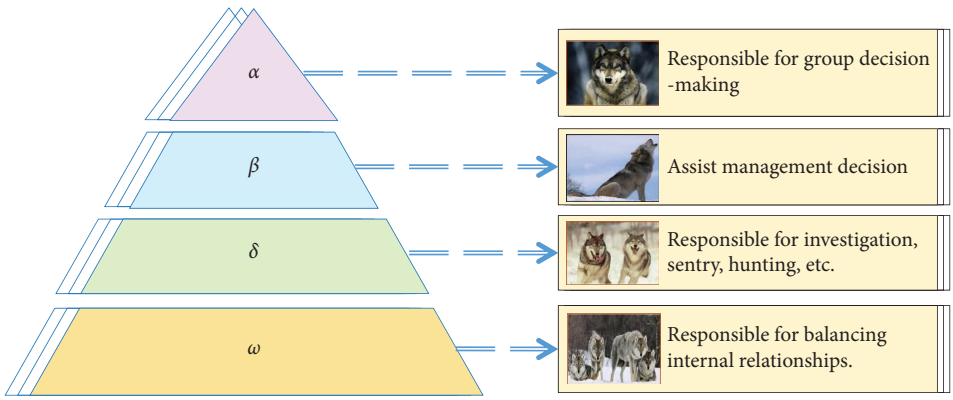

Figure 2: The hierarchical structural diagram of grey wolf populations.

improvement performance is limited. Since 2014, the authors in [20] proposed that the grey wolf algorithm is simple and efficient in finding the optimal solution. But it is not easy to take into account the global search and local search capabilities at the same time. An optimized grey wolf algorithm to enhance SVM parameters is proposed, and the effect of abnormal diagnosis is thereby improved.

5.1. Grey Wolf Optimization Algorithm. The GWO algorithm is a new algorithm proposed in recent years. This algorithm is derived from predation behavior and the social hierarchy of wolf populations [20]. Other related algorithms inspired by nature have their own limitations and shortcomings. The GA which exhibits immature convergence cannot guarantee global optimization and have low search efficiency in the later stage. Although the PSO algorithm is simple and easy to implement without too many parameters to adjust, it is difficult to select network weights and genetic operators. The differential evolution algorithm cannot achieve global optimal evolution and is prone to search stagnation. The annealing algorithm has slow convergence speed and complex parameter tuning. The ant colony algorithm has slow convergence speed and is prone to falling into local optimal. Compared with the naturally inspired algorithms mentioned above, the GWO algorithm has a simple structure, and requires fewer adjustment parameters. The GWO is easy to implement and has an adaptive convergence factor and information feedback mechanism, which can achieve a balance between local and global search. Therefore, it has superior performance in terms of problem solving accuracy and convergence speed. The hierarchical structural diagram is shown in Figure 2 for the grey wolf populations.

The predation behavior includes three parts: searching and tracking, encircling, and attacking prey. When the grey wolf is searching and tracking prey, the distance from the prey to the individual grey wolf is

$$\text{dis} = \left|D \times f_P(t) - f(t)\right|. \tag{3}$$

In equation (3), $f_P(t)$ means the position of the prey, $f(t)$ stands for the position information of the current iteration wolf ω, and D is the coefficient vector.

The formula of predation position updating is expressed as the following for grey wolf populations:

$$\begin{cases} f(t+1) = f_P(t) - C \times \text{dis}, \\ C = 2\sigma m_1 - \sigma, \\ \sigma = \dfrac{2-2t}{T}, \\ D = 2m_2. \end{cases} \tag{4}$$

In equation (4), C represents the coefficient vector and σ represents the distance control parameter, that is, the convergence factor. Each component of σ linearly reduces from 2 to 0 in iterative process. m_1 and m_2 are selected as random vectors, and the selecting range of them are between [0, 1]. T is selected as the maximum number of iterations.

The grey wolf tracking prey is described as follows:

$$\begin{cases} \text{dis}_\alpha = \left|D_1 \times f_\alpha(t) - f(t)\right|, \\ \text{dis}_\beta = \left|D_2 \times f_\beta(t) - f(t)\right|, \\ \text{dis}_\delta = \left|D_3 \times f_\delta(t) - f(t)\right|. \end{cases} \tag{5}$$

In equation (5), $f_\alpha(t), f_\beta(t), f_\delta(t)$ are the present positions of the wolf in α, β, δ, respectively. D_1, D_2, D_3 is the coefficient vector of the wolf in α, β, δ, respectively. $\text{dis}_\alpha, \text{dis}_\beta, \text{dis}_\delta$ are the distance from α, β, δ to other individuals, respectively, that is, the distance at which the current wolf tends to the 3 optimal solutions.

The step length and direction of individual ω of the wolf pack that towards α, β, δ can be expressed as follows:

$$\begin{cases} f_1(t) = f_\alpha(t) - C_1 \times \text{dis}_\alpha, \\ f_2(t) = f_\beta(t) - C_2 \times \text{dis}_\beta, \\ f_3(t) = f_\delta(t) - C_3 \times \text{dis}_\delta. \end{cases} \tag{6}$$

Furthermore, the position of wolf ω is updated as follows:

$$f(t+1) = \frac{\left(f_1(t) + f_2(t) + f_3(t)\right)}{3}. \tag{7}$$

According to the position of α, β, δ wolf, the positional relationship between the prey and the grey wolf individual ω can be judged.

5.2. Improving the GWO Algorithm. In the general GWO algorithm, it can be seen from equations (4)–(6) that the parameter σ determines the change of the control coefficient C which can coordinate the global and local search capability of the GWO algorithm. The value of σ in equation (4) reduces linearly from 2 to 0 in the iterative process.

It can be seen from the literature [20] that when $|C| > 1$, in order to seek better prey, the encirclement will be expanded by the wolf populations, corresponding to the global search capability. The strong global search capability can maintain the grey wolf population's diversity, and it can prevent the GWO algorithm from plugging into the local maximum; when $|C| < 1$, the grey wolf population will shrink the encirclement to complete the final attack on the prey. At the same time, it can reflect the better local search capability, and the algorithm with strong local search capability, and the algorithm with strong local search capability can ensure the accurate search and can enhance the convergence rate. Therefore, the selecting value of C has a relationship with the global and local search capability for the GWO.

However, the change of the control parameter C depends on σ. When σ selects a linear decreasing strategy, the actual optimization search process cannot be fully reflected. Also, it is not easy to take into account the global search and local search capabilities simultaneously. In a word, it is important to improve the control parameter σ and propose a new nonlinear method for updating the control parameters, which can be expressed as follows:

$$\sigma = 2 \cdot \sqrt{1 - \left(\frac{t}{T}\right)^2}. \tag{8}$$

It can be seen from equation (8) that the nonlinear strategy changes slowly in the early phase of the search, and its representative algorithm has a great global exploration capability; in the later stage of the search, σ changes quickly, and its representative algorithm will have good local search capability. The control parameter σ expressed in equation (8) is simpler and easier to implement than the parameter selection method in [21]. The convergence factor σ will show a nonlinear dynamic change law with the growth of evolutionary iterations number, and it can provide a compromise between global and local search capabilities.

Figure 3 shows the change trend of the control parameter σ before and after the enhancement.

5.3. Location Update Method of GWO Algorithm. The general GWO algorithm is still prone to fall into a local extreme prematurely when solving complex optimization problems, that is, premature convergence occurs [22]. For solving the above issues, it is necessary to use Levi flight for updating the position of the grey wolf populations [23]. Levi's flight is a random walk, which is a good search strategy. It performs

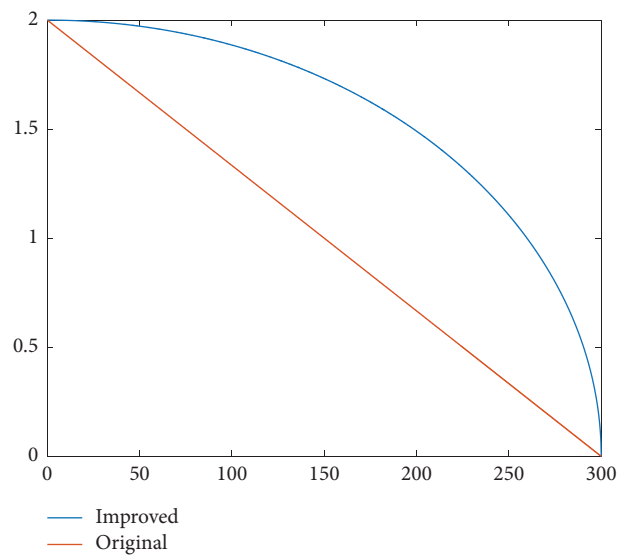

Figure 3: The change trend of the control parameter σ.

a global search for α grey wolves in the group, which can expand the search scope of the algorithm and can avoid the problem of falling into local optimality prematurely. The updating method of its location can be shown as follows:

$$L(t+1) = f_\alpha + f_{\text{alpha}} \oplus f_{\text{Levy}}(\lambda). \tag{9}$$

In equation (9), f_{alpha} is 0.01. The random search path is selected as follows:

$$f_{\text{Levy}}(\lambda) = \frac{v}{|u|^{1/\lambda}} \cdot [f(t) - f_m(t)] \cdot f_{\text{random}}. \tag{10}$$

In equation (10), $f_{\text{Levy}}(\lambda)$ is a random search path. The value of λ is 1.5. $f_m(t)$ is the position of α, β, δ wolf in the present iteration. f_{random} is a random number in the interval [0, 1]. u, v both correspond to normal distribution:

$$\begin{aligned} u &\sim N(0,1), \\ v &\sim N\left(0, S^2\right), \\ S &= \left[\frac{\Gamma(1+\lambda) + \sin(\pi \cdot \lambda/2)}{\Gamma(1+\lambda/2) \cdot \lambda \cdot 2^{(\lambda-1)/2}}\right]^{1/\lambda}. \end{aligned} \tag{11}$$

5.4. Support Vector Machines. The major concept of the SVM algorithm is as follows: first, select the mapping function $\Psi(\tilde{x}_i)$ to match with the n-dimensional sample vector $(\tilde{x}_i, \tilde{y}_i)(i = 1, 2, \ldots, l)$, which can shine the original space upon the Gaussian feature space. Second, set up the optimal linear decision function in this Gaussian feature space and convert the classification work into an optimization work. Finally, in order to reduce the complexity of the operation, the dot product operation for the feature space is replaced by the kernel function for the original space cleverly.

$$\left\{ \min \frac{1}{2} \cdot \|r\|^2 + \overline{C} \sum_{i=1}^{l} \varsigma_i, s.t. \tilde{y}_i \left[\left(\Psi \left(\tilde{x}_i \right) \cdot r + b \right) \right] + \varsigma_i = 1. \right. \tag{12}$$

In equation (12), r is the weight vector. $\Psi(\tilde{x}_i)$ is the mapping function. ς_i means a relaxation variable. $\overline{C}$ is the penalty factor. $\tilde{x}_i$ is the input data, and $\tilde{y}_i$ is a category tag.

Using Lagrange's equation to solve equation (8), the optimization problem can be expressed as follows:

$$\left\{ \max \sum_{i=1}^{l} \overline{c}_i - \frac{1}{2} \sum_{i,j=1}^{l} \overline{c}_i \tilde{y}_i \tilde{y}_j K\left(\tilde{x}_i, \tilde{x}_j\right) \overline{c}_j, s.t. \sum_{i=1}^{l} \overline{c}_i \tilde{y}_i = 0. \right. \tag{13}$$

Select the kernel function of SVM as follows:

$$\overline{K}\left(\tilde{x}, \tilde{x}_i\right) = e^{-\|\tilde{x} - \tilde{x}_i\|^2 / \gamma^2}. \tag{14}$$

The values of $\overline{C}$ and γ in equations (13) and (14) influence the classification role of SVM. The former plays the role of balancing the maximization of the classification interval and the minimization of misclassification samples. The latter determines whether the low-dimensional samples can be effectively shined upon the high-dimensional space for achieving linear separability.

5.5. The Abnormal Diagnosis Process and Steps of Self-Powered Power Supply System Based on Improved GWO-SVM Algorithm. Through the combination and improvement of the abovementioned algorithm, taking the self-powered power supply system as the research object and considering two types abnormalities of stator winding interturn short circuit and rotor broken bar, the steps for diagnosing the two types of abnormalities in the early stage are as follows:

Step 1: collect state monitoring characteristic data from the self-powered power supply system.

Step 2: based on the maximum information coefficient (MIC), select the optimal feature set of the data.

Step 3: perform numerical initialization, including: grey wolf population, position $(\overline{C}, \gamma)$ of individual grey wolves, and objective function values.

Step 4: for the grey wolf population, update its position information, furthermore update the predation position information of the wolf populations according to equation (4) and Levi's flying formula.

Step 5: calculate the fitness of the wolf pack after updating the position. If the fitness value of the new individual is more suitable than the old individual, modify the new generation individual, and replace the original position with the new individual position. On the contrary, keeping the old individual, the original fitness value remains unchanged.

Step 6: calculate the parameters C, D obtained by each iteration, and then update the parameters C, D and update the grey wolf individual position information $(\overline{C}, \gamma)$.

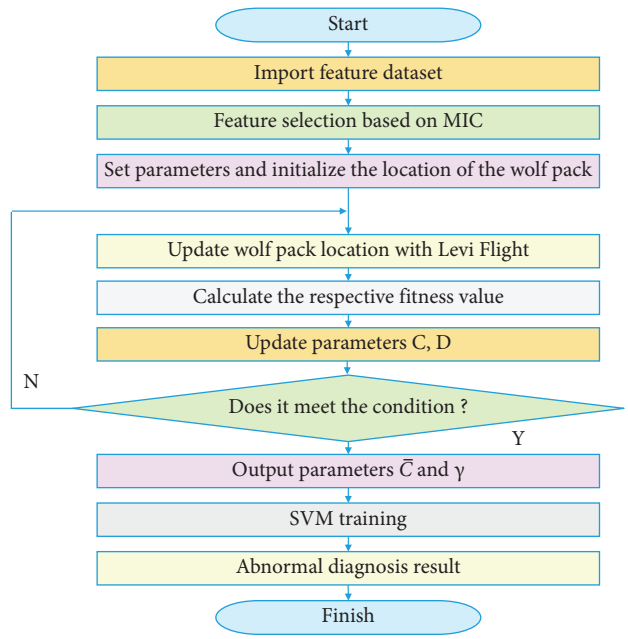

Figure 4: Abnormal diagnosis flow chart based on improved GWO-SVM.

Step 7: if the iteration termination condition is reached, the value of output $\overline{C}$ and γ will enter Step 8, otherwise it will return to Step 4.

Step 8: based on the optimal parameters $\overline{C}$ and γ, build the SVM modeling, and diagnose the test set, and give abnormal diagnosis results.

Based on the improved GWO-SVM algorithm, the abnormal diagnosis flowchart is shown in Figure 4.

The computational complexity of our algorithm is reduced by balancing global and local search. The time complexity of the algorithm mainly refers to the time that is spent on abnormal diagnosis for the self-powered power supply system. In the improved GWO-SVM, the time complexity of the algorithm is equal to $O(T * \mathrm{Fn} * \mathrm{Wp} * \mathrm{An} * \sigma)$. T is selected as the maximum number of iterations. Fn represents the number of features which is filtered out through the maximum information coefficient (MIC). Wp represents the total number of wolves. An represents the number of objectives. σ represents the distance control parameter.

5.6. Evaluation Index. The essence of abnormal diagnosis is still a classification problem. For this type of problem, false positives and underreports are usually used to reflect the true situation of the classification, and the accuracy and recall rate as evaluation indicators can be used to measure the classification results.

(1) Accuracy:

$$p = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN} + \mathrm{TN}} \times 100\%. \tag{15}$$

(2) Recall rate:

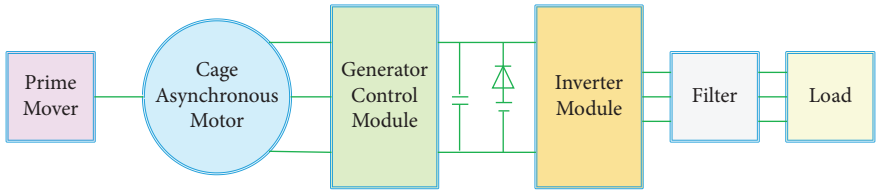

Figure 5: Self-powered power supply system.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\%. \quad (16)$$

In equations (15) and (16), TP means the normal number of matching correct, FP refers to the number of misreporting, TN is the number which stands for abnormal matching correctly, and FN is the number which stands for false negative.

6. Simulation Analysis

A 8 kW military self-powered power supply system is taken as the simulation object. It mainly includes cage, asynchronous generator, generator, control module, and inverter module. Its model is shown in Figure 5.

6.1. Data Acquisition. At present, due to the insufficient accumulation of data on abnormal faults in the self-power supply system, the abnormal working conditions of the short circuit between turns and rotor break strips of the stator winding are simulated in the simulation platform for the self-power supply system. The operating state monitoring data were collected for the abovementioned two types of abnormalities, of which the main monitoring data is shown in Table 1.

The collected status monitoring data is shown in Table 2.

6.2. Data Set Division. The state monitoring data are collected from the built simulation platform, and the related preprocessing is performed. The sorted 6000 sets of data are firstly used for MIC feature selection to eliminate redundancy, and finally the feature selection subset is used as the diagnosing data group, which is decomposed into H1 (training set) and H2 (test set). Among them, 4800 sets of data for H1 are used for training SVM classifier, and the remaining data are used as H2 for verifying the training effect test. Table 3 shows the distribution results.

In Table 2, F1 represents normal data. F2 and F3, respectively, represent the two states of insignificant and obvious abnormal short circuit between turns of the stator winding. F4 and F5, respectively, represent the two states of insignificant and obvious abnormality of broken rotor bars.

6.3. Result Analysis of Feature Optimization Based on MIC. Based on the 11 kinds of state monitoring characteristic data collected in Section 6.1, the MIC representing the correlation is calculated according to Section 4 and sorted according to the size of the MIC. Table 4 shows the sorting results.

Table 1: Correspondence between feature no. and feature name.

Feature no.	Name of feature
1	Rotating speed
2	Bus voltage
3	The output voltage
4	Output current
5	Active power
6	Frequency
7	Power factor
8	THD
9	Steady-state voltage regulation
10	Asynchronous motor torque
11	Asynchronous motor stator current

In response to the complexity and diversity of data collected by the self-powered power supply system, the relationship between each performance indicator and abnormal states was independently measured. Using classification inspection and chi-square test in statistical testing, we can compare the degree of deviation between the actual value and the theoretical value, such as the size of the chi-square value. Also, 11 kinds of collecting state monitoring feature data are sorted. The relevant results are shown in Table 5.

From Table 5, it can be seen that the order of chi-square values is the steady-state voltage adjustment rate, bus voltage, active power, frequency, asynchronous motor stator current, and asynchronous motor torque. The diagnosis results of the improved GWO-SVM algorithm based on the abovementioned features are 95.2% and 93.9%, respectively. By comparison, it was found that the optimal feature subset selected by MIC has a higher accuracy in abnormal diagnosis.

In order to select the optimal feature set for abnormal diagnosis of the self-powered power supply system, the less correlated features and redundant features are sequentially eliminated. The precision rate is used as the assessment index, which can reflect the pros and cons of the selected feature subset, and Table 6 shows the outcomes.

As can be seen from Table 4, the MIC is sorted from largest to smallest as torque, bus voltage, steady-state voltage regulation, and active power. In order to determine the optimal set of input features from Table 4, it can be seen that as more and more redundant or insensitive variables are excluded, when the first 6 feature variables are excluded, the accuracy rate reaches a peak, that is, 95.2%. Compared with the elimination of 5 variables and 7 variables, in the case of retaining 5 characteristic variables, it can not only retain the valid characteristics of the data but also reduce redundant

Table 2: 11 kinds of status monitoring data (partial only).

No.	Rotating speed (r/s)	Bus voltage (V)	Output voltage (V)	Output current (A)	.....	Motor torque (N.m)	Motor stator electricity (A)
1	1980	685.0068	−0.855	16.2744	.....	−244.434	36.9714
2	1980	684.3561	−0.099	15.8872	.....	−240.698	37.4933
3	1980	684.7090	−0.074	15.8808	.....	−255.999	38.8008
4	1980	684.0253	−0.190	14.5645	.....	−239.161	33.7339
5	1980	684.0912	−1.035	18.1810	.....	−256.617	31.4926
6	1980	685.1518	−1.443	18.7798	.....	−215.894	20.9100
7	1980	683.8664	−1.821	20.3229	.....	−247.113	14.7941
8	1980	684.5162	−1.995	21.0897	.....	−228.342	5.7263
9	1980	684.0418	−0.164	19.9714	.....	−233.776	−5.3448
10	1980	684.2435	−2.196	18.3911	.....	−225.920	−13.6254
11	1980	684.8770	−2.018	21.1814	.....	−224.663	−21.4042
12	1980	683.2416	−2.186	21.7971	.....	−253.943	−30.6752
13	1980	685.1324	−2.244	22.2383	.....	−225.329	−30.7187
14	1980	683.8144	−2.541	25.3328	.....	−226.179	−34.7413
15	1980	683.0902	−0.548	24.2664	.....	−239.926	−38.8580
16	1980	685.0239	−0.821	22.4578	.....	−214.745	−34.7356
17	1980	683.7534	−2.622	25.5672	.....	−237.677	−35.7043
18	1980	684.5137	−2.684	26.2124	.....	−215.148	−28.2521
19	1980	683.7911	−2.546	24.6783	.....	−238.547	−23.4537
20	1980	684.5722	−2.700	26.4197	.....	−221.263	−13.9911
21	1980	683.7808	−1.143	26.5490	.....	−223.302	−4.6643
22	1980	684.7539	−1.308	23.6783	.....	−229.362	1.9127
23	1980	684.0512	−2.810	26.9005	.....	−228.594	11.1370
24	1980	684.1748	−2.763	26.5425	.....	−239.320	20.1172
25	1980	684.7045	−2.441	23.1981	.....	−215.281	23.8226
26	1980	683.6309	−2.467	23.7104	.....	−259.076	34.2500
27	1980	685.0180	−1.555	25.2376	.....	−215.378	31.7056
28	1980	683.4649	−1.609	21.5452	.....	−243.058	38.7012
30	.....	.....	.....	.....	.....	.....	.....
Average	1979	676.74	−1.67	22.03	.....	−233.53	65.4
Standard deviation	0.30	12.58	0.95	4.17	.....	13.54	27.92

Table 3: Assignment of H1 and H2.

Parameters	Training set H1	Test set H2	Total
F1	960	240	1200
F2	960	240	1200
F3	960	240	1200
F4	960	240	1200
F5	960	240	1200
Total	4800	1200	6000

Table 4: Correlation ranking of feature selection based on MIC.

Initial order	1	2	3	4	5	6	7	8	9	10	11
MIC sorting	11	2	9	10	4	8	6	7	3	1	5

Table 5: Feature selection and sorting based on chi-square test.

Initial order	1	2	3	4	5	6	7	8	9	10	11
Chi-square value sorting	11	2	9	5	3	4	8	7	1	6	5

Table 6: Number of feature elimination and abnormal diagnosis results.

The initial sequence number of the eliminating variable	The correlation number of the eliminating variable	The accuracy rate of abnormal diagnosis (%)
None	None	91.8
1	11	92.2
1, 4	11, 10	92.2
1, 4, 3	11, 10, 9	92.5
1, 4, 3, 6	11, 10, 9, 8	93.4
1, 4, 3, 6, 8	11, 10, 9, 8, 7	94.3
1, 4, 3, 6, 8, 7	11, 10, 9, 8, 7, 6	95.2
1, 4, 3, 6, 8, 7, 11	11, 10, 9, 8, 7, 6, 5	93.8

variables and insensitive variables, ensuring the accuracy of abnormal diagnosis of the self-power supply system. By comparing the original dataset with the selected feature subset, the results show that the selected optimal feature subset can effectively replace the original data feature set for abnormal diagnosis and achieve the purpose of feature selection.

In order to select the optimal feature set for abnormal diagnosis of self-powered power supply systems for training PSO-SVM, GA-SVM, and GWO-SVM, features with low correlation and redundant features were sequentially removed to determine the feature names in the optimal feature set. The results were compared with the improved GWO-SVM, as shown in Table 7.

From Table 7, it can be seen that the optimal feature subset of the improved GWO-SVM is bus voltage, active power, steady-state voltage regulation, asynchronous motor torque, and asynchronous motor stator current. The optimal feature subset of GWO-SVM is bus voltage, active power, steady-state voltage regulation, asynchronous motor torque, and asynchronous motor stator current; The optimal feature subset of GA-SVM is bus voltage, active power, power factor, THD, steady-state voltage regulation, asynchronous motor torque, and asynchronous motor stator current; the optimal feature subset of PSO-SVM is bus voltage, active power, power factor, steady-state voltage regulation, asynchronous motor torque, and asynchronous motor stator current. The accuracy rates of abnormal diagnosis are 95.2%, 93%, 94%, and 94.6%, respectively.

Table 7: The sequence number of excluded variables and diagnostic accuracy.

Algorithms	The initial sequence number of excluded variables	The abnormal diagnostic accuracy (%)
Improved GWO-SVM	1, 4, 3, 6, 8, 7	95.2
GWO-SVM	1, 4, 3, 6, 8, 7	93
GA-SVM	1, 4, 3, 6	94
PSO-SVM	1, 4, 3, 6, 8	94.6

In summary, the top 5 feature variables in this paper are selected as the optimal feature subset, namely, bus voltage, active power, steady-state voltage regulation, asynchronous motor torque, and asynchronous motor stator current.

6.4. Simulation Results Analysis of Improved GWO-SVM Algorithm. The abnormal diagnosis steps of the self-powered power supply system are given in Section 5.5. First, on the basis of completing the collection of 11 kinds of state monitoring data, the 11 kinds of monitoring data are selected by the MIC method, and then the optimized GWO improvement algorithm is adopted for analyzing the SVM optimize the coefficients $\overline{C}$ and γ. The grey wolf population size in the GWO algorithm is selected as 30. We select 300 as the iterations number. The independent variable dimension is 2, that is, the two parameters are optimized. The optimization ranges of $\overline{C}$ and γ are, respectively, [0.1, 100] and [0.01, 1000]. For SVM, the Gaussian radial basis function (RBF) with nonlinear mapping capability is chosen as the kernel function, and then some related value of parameters are 98.174 and 2.972, respectively, after optimization.

The simulation experiment is carried out for the self-powered power supply system, and Table 8 shows the simulation outcomes.

According to Table 5, the accuracy rates of F1, F2, F3, F4, and F5 in 1200 groups test data are, respectively, 94.5%, 88.8%, 99.2%, 93.3%, and 100%. The recall rates are 89.72%, 90.25%, 100%, 96.14%, and 100%. In turn, it can be calculated that the average rate of abnormal diagnosis accuracy and recall rate is 95.16% and 95.22%, respectively.

Compared with unimproved GWO-SVM classification algorithm, the improved GWO-SVM algorithm shows good performance. Table 9 shows the comparison outcomes.

Table 8: Diagnosis results of the improved GWO-SVM

		Actual classification					Accuracy (%)
		F1	F2	F3	F4	F5	
Abnormal classification	F1	227	11	0	2	0	94.5
	F2	20	213	0	7	0	88.8
Classification	F3	0	2	238	0	0	99.2
	F4	6	10	0	224	0	93.3
Classification	F5	0	0	0	0	240	100
Recall rate		89.72%	90.25%	100%	96.14%	100%	

Table 9: Detection results of improved methods before and after.

Classifiers	Accuracy (%)	Recall rate (%)
GWO-SVM	93.00	93.12
Improved GWO-SVM	95.16	95.22

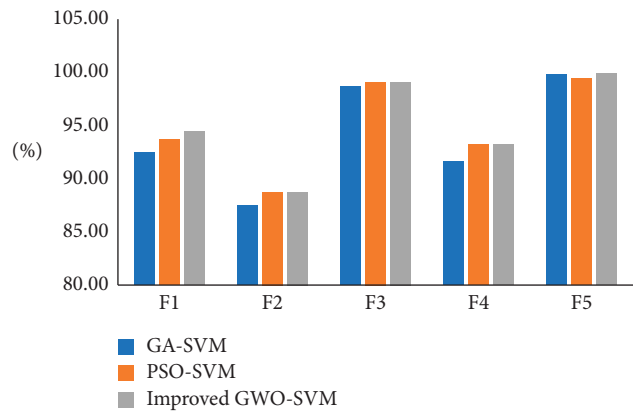

Figure 6: The comparative display of results accuracy of 3 optimization algorithms.

Table 10: The comparative display of results accuracy of 3 optimization algorithms.

Classifiers	Improved GWO-SVM (%)	GA-SVM (%)	PSO-SVM (%)
F1	94.50	92.50	93.75
F2	88.80	87.50	88.80
F3	99.20	98.75	99.20
F4	93.30	91.70	93.30
F5	100.00	99.95	99.50
Average accuracy	95.16	93.99	94.46

From Table 6, it can be drawn the conclusion that the accuracy and recall rate of the improved GWO-SVM have been significantly improved compared with the unimproved GWO-SVM, which are 2.16% and 2.1%, respectively. The control parameter σ in the GWO algorithm is improved and the position information updating method of Levi flight is added, which takes into account both the global and the local search capability, thereby improving the diagnostic accuracy of GWO algorithm.

For verifying the superiority of the algorithm put forward herein, the PSO algorithm and the GA algorithm are used to optimize the SVM, which are used as comparisons, and then the algorithm performance is judged by the accuracy of anomalous classification. Figure 6 and Table 10 show the experimental outcomes.

From the comparison of Figure 6 and Table 10, the qualitative and quantitative analysis shows that the diagnostic accuracy of the improved GWO-SVM is 1.17% and 0.7% higher than that of GA-SVM and PSO-SVM, respectively, which expresses that the abnormal diagnostic performance shown in the abnormal diagnosis process of the self-power supply system is significantly better than that of the other two algorithms.

The improved GWO-SVM is compared with other classification algorithms DT, LR, RF, k-NN, SVM, and RBF under the optimal feature subset, which is shown in Table 11:

Table 11: The accuracy of abnormal diagnosis using different algorithms under the optimal feature subset.

Algorithms	Accuracy of abnormal diagnosis (%)
Improved GWO-SVM	95.2
DT	85
LR	90.4
RF	89.3
k-NN	86.8
SVM	91.7
RBF	93.3

From Table 11, it can be seen that compared with other classification algorithms DT, LR, RF, k-NN, SVM, and RBF, the improved GWO-SVM still has significant advantages.

7. Conclusion

An improved GWO-SVM abnormal diagnosis algorithm combined with MIC is proposed in this paper. After a series of simulation tests and result analysis, the following conclusions are drawn.

First, the optimal feature set obtained from the MIC solves the problem of redundancy in the monitoring data of the self-powered power supply system, and eliminates redundant variables, insensitive and irrelevant variables, which can effectively improve the accuracy of abnormal diagnosis.

Second, based on improving the control parameters and improving the updated position of the grey wolf population with Levy flight, this algorithm can cooperate between the global and local search capacity. Furthermore, the improved GWO-SVM algorithm's performance is shown that the relevant abnormal data can be accurately diagnosed based on the monitoring data of self-powered power supply system.

Finally, by comparing with GA-SVM and PSO-SVM algorithms, it is shown that the diagnostic precision of the improved GWO-SVM is better than that of GA-SVM and PSO-SVM.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

This paper was developed based on a conference abstract which was published in CPCID2022, and the related link is https://www.cpcid.cn/lunwen/21-7223.pdf.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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