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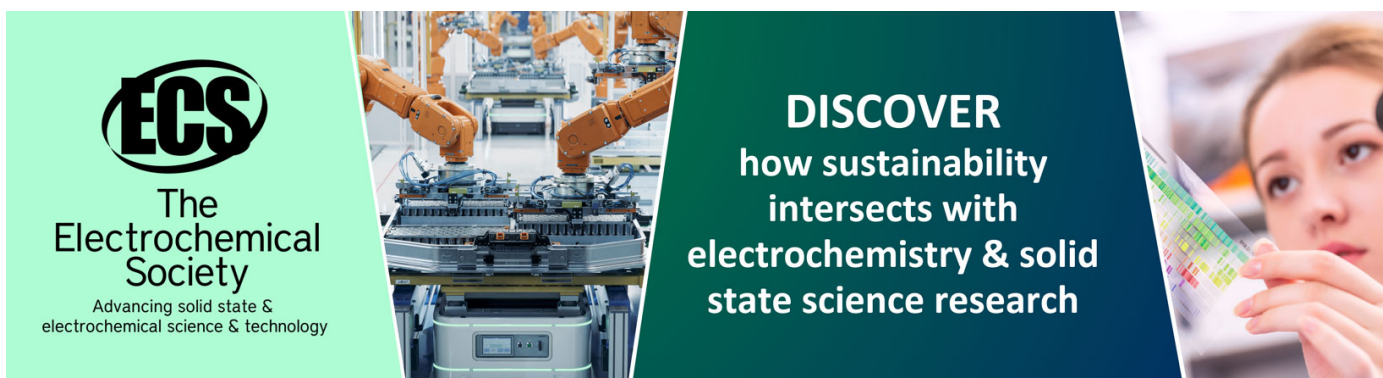
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Intelligent substation fault diagnosis based on optimization support vector machine

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Abstract. In view of the present intelligent substation fault diagnosis of complicated structure, sample data acquisition difficult, randomness of failure and other issues, build a kind of intelligent substation fault diagnosis based on the optimization of support vector machine (SVM) model, first of all, through the principal component analysis (pca) to simplify the fault source and key fault feature extraction, reduce the complexity of fault diagnosis. Then, based on the characteristics of the operation mode of the substation, the multi-classification SVM classifier is constructed and optimized by the imperial competition algorithm to find the optimal parameters. At last, the fault events of real substation are verified by experiments. The results show that the proposed fault diagnosis method can effectively solve the problem of less training samples and has a better diagnosis effect.

1. Introduction

The substation plays an important role in the power system. With the development of artificial intelligence, the intelligent substation has emerged in most countries[1]. When the power system fails, the intelligent substation often produces a large number of alarm signals. It is difficult for substation staff to accurately identify the fault type and location from these disorder signals within a short time[2]. The realization of intelligent substation fault diagnosis is the process of obtaining the final fault cause by fault characteristics caused by equipment. Therefore, it has important real meaning and economic value to study how to quickly and accurately diagnose the fault information and take corresponding effective measures to carry out the fault treatment. The fault diagnosis is an important means to ensure the safe operation of the power system. Rough set, fuzzy set[3], artificial neural network[4], and Petri net[5]. These algorithms have been widely used in various fields.

The expert system plays an important role in substation fault diagnosis and is one of the most mature technologies. Although this method has a high level of reasoning and proving ability. However, the diagnostic rules in the knowledge base are mainly written by experts with operational experience[6]. Therefore, when substation related equipment failure, the use of expert system results may produce a large error. Support vector machines (SVM) can solve the problems of high-dimensional data and nonlinear characteristics well because of its solid statistical theory foundation[7-8]. These characteristics coincide with the complex structure and limited samples of intelligent substation fault, so it is suitable for substation fault diagnosis. However, the performance of SVM mainly depends on its kernel function and its parameters[9]. Therefore, the selection of an appropriate



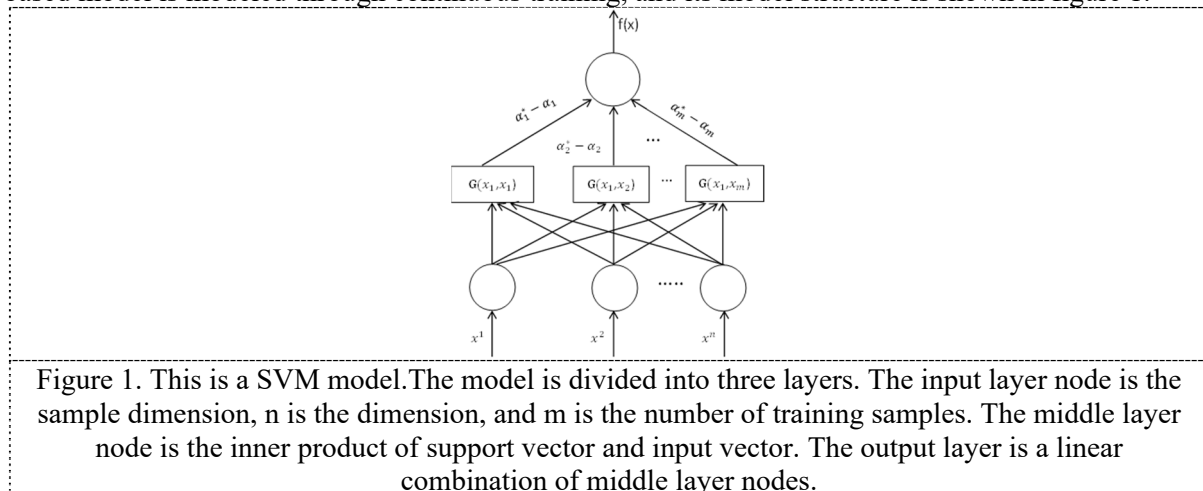
optimization algorithm to optimize kernel function parameters is particularly important for substation fault diagnosis. Among them, the imperial competition algorithm (ICA) is an optimization algorithm that relies on the imperialist colonial competition mechanism and obtains the best parameters through the colonial expansion among empires[10]. Compared with other optimization algorithms, the advantages of this algorithm are mainly reflected in the short operation time and strong optimization effect. Principal component analysis (PCA) is an unsupervised method for dimensionality reduction of high-dimensional data, which maximizes the variance of the original data by preserving several important components in the dimensionality reduction process[11]. There are several influencing factors in substation fault problems. Each fault type and cause corresponds to a fault parameter, and the parameters are correlated and overlapped. To solve substation fault problems, key data should be extracted from these parameters.

To sum up, this paper proposes an intelligent substation fault diagnosis method based on optimization parameter support vector machine (SVM). The method first uses PCA to analyze the influencing factors, so as to achieve data dimensionality reduction. Then, the selected sample data is trained by SVM, and the parameters are optimized by imperial competition algorithm. The test results are satisfactory.

2. Support vector machine model based on the optimization of imperial competitive algorithm

2.1 The SVM model and nonlinear transformation

The core goal of SVM is to find an optimal classification hyperplane for classification of linear separable problems through continuous training, which is a typical dichotomy problem. The svm-based model is modeled through continuous training, and its model structure is shown in figure 1.



However, in the practical application, most of the problems are nonlinear and cannot be solved by linear separability[12]. Intelligent substation fault diagnosis is a linear indivisible problem, which needs to be transformed into a linear indivisible problem by nonlinear transformation.

The nonlinear transformation of SVM can be expressed in the following optimization form.

$$\min \Phi(\omega, \xi) = \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^l \xi_i \quad (1)$$

$$s.t. \begin{cases} y_i [\omega^T \varphi(x_i) + b] \geq 1 - \xi_i \\ \xi_i \geq 0, i = 1, 2, \dots, l \end{cases} \quad (2)$$

On the type ξ_i is the relaxation variable. The parameter C is the penalty factor.

Optimization by Lagrange function.

$$L(\omega, b, \xi, a, \beta) = \Phi(\omega, \xi) - \sum_{i=1}^l a_i \{y_i [\omega^T \varphi(x_i) + b] - 1 + \xi_i\} - \sum_{i=1}^l \beta_i \xi_i \quad (3)$$

Thus, the objective function can be obtained as.

$$f(x) = \text{sign} \left[\sum_{i=1}^l a_i y_i K(x, x_i) + b \right] \quad (4)$$

2.2 ICA parameter optimization

Like other optimization algorithms, ICA starts with a certain number of randomly generated initial solutions in the search space. Each initial solution is called a country and the degree to which these countries are evaluated by optimizing the objective function. Some of the best countries were called imperialist countries, and the rest were called colonies and randomly assigned to imperialist countries. An imperialist country and its colonies formed an imperial group. When colonies were allocated to imperialist countries, the number of colonies each imperialist country was in direct proportion to its excellence. If a colony moves to an imperialist country and its new position is superior to that of the imperialist country, the positions of that colony and the imperialist country need to be swapped. The various imperial groups would compete for colonies to strengthen their own forces. The process is as follows.

- Initialize the empire by randomly selecting points on the function.
- Transfer the colonies to the relevant imperialist countries (assimilation).
- If there is a colony in the empire that costs less than imperialism, swap colonial and imperialist positions.
- Calculate the total cost of all empires (related to imperialism and the power of its colonies).
- Choose the weakest colony from the weakest empire and give it to the one most likely to have it (imperialist competition).
- Destroy weak empires.
- If there is only one empire, stop the algorithm, if not go to step 2.

A large number of experimental results show that the classification effect of SVM is better when the gaussian radial basis kernel function is used[13]. Therefore, this paper selects the gaussian radial basis kernel function, which has the ability to deal with nonlinear data.

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0 \quad (5)$$

Where, γ called the key parameters of the model. In the training process of SVM, the punishment factor C and kernel function γ have a great influence on the generalization performance of the whole model, so it is necessary to adjust these two parameters to improve the generalization performance of SVM. In order to apply ICA to parameter selection, the country cost function is set as the optimization objective function. Two important parameters (C and γ) of the target function need to be set in advance. The smaller the value of the objective function (the target value), the better the classification accuracy. All in all, the optimal value of the objective function is the same as the cost of the best country in ICA. When all the countries are unified into the most powerful empire, the total cost of the empire will be the smallest value in ICA, and the objective function will be the smallest value at the same time.

3. Key fault feature recognition based on PCA

PCA is a technique that can represent most of the information of the original variables by transforming multiple variables into a few principal components through dimensionality reduction. First failure data standardization, to compute a vector is called the first principal component, on behalf of the most important element in the fault, and its eigenvalue and eigenvector, the covariance matrix and principal component contribution rate, and the second principal component and principal component 1 orthogonal, represents the most explicit in the residual fault features of direction, so on. The entire process is shown in figure 2.

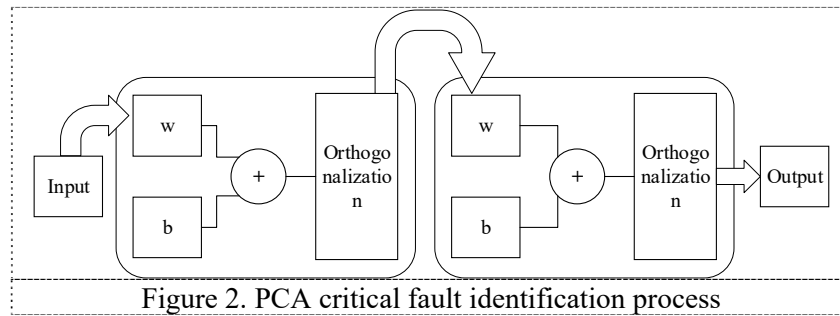


Figure 2. PCA critical fault identification process

When PCA is applied to fault diagnosis, the following steps are generally followed.

● Suppose that M is a fault data set with X characteristics and Y data in the data set. Therefore, the K th principal component vector is:

$$P_k = (p_{1k}, p_{2k}, \dots, p_{Xk})^T \quad (k = 1, 2, \dots, Y) \quad (6)$$

● The entries of the principal component matrix are:

$$t_{ij} = \sum_{k=1}^X p_{kj} x_{ik} \quad (i = 1, 2, \dots, Y; j = 1, 2, \dots, X) \quad (7)$$

● The contribution rate of principal component vector to the overall fault information is:

$$\mu_j = \frac{\lambda_j}{\sum_{i=1}^X \lambda_i} \quad (8)$$

The fault information of the third generation intelligent substation equipment is used as the data source, and the circuit breaker status and other warning signals are mainly included through the data screening and sampling. For all fault samples of fault feature group PCA principal component analysis, in turn, calculate all the cumulative contribution rate of the principal component, the results are shown in table 1, seven principal components before the cumulative contribution rate has reached 93.5280%, so according to the last leave the amount of data that should be reached the requirements of more than 90%, can choose before six or seven features as a best fault.

Table 1. Principal component analysis results

PCA number	Value	Contribute(%)	Cumulative(%)
1	3.9318	18.7227	18.7227
2	3.8024	18.1068	36.8295
3	3.3877	16.1319	52.9614
4	3.3463	15.9346	68.8960
5	3.2360	15.4097	84.3057
6	1.5658	7.45630	91.7620
7	0.3709	1.7660	93.5280
8	0.3161	1.5052	95.0332

According to the fault information processing and screening of the third generation smart substation equipment, the fault type table is obtained, as shown in table 2. And the fault property sheet, see table 3.

Table 2. Fault type table

Number	Fault type
D1	The circuit breaker explodes in the quench chamber
D2	Protection action circuit breaker disconnection
D3	Circuit breaker jump
D4	Control circuit break
D5	Low SF6 gas pressure
D6	Operating mechanism with pressure closure closure
D7	Abnormal oil level of oil circuit breaker

Table 3. Fault attribute list

Number	Fault properties
K1	Circuit breaker location division
K2	Circuit breaker current is zero
K3	Circuit breaker power is zero
K4	Circuit breaker position alignment
K5	Circuit breaker jump
K6	Control circuit break
K7	Low SF6 gas pressure alarm
K8	Low pressure lock signal
K9	Low oil pressure alarm of operating mechanism

4. Intelligent substation fault diagnosis model

4.1 Establishment of fault diagnosis model

The fault classification problem of smart substation belongs to nonlinear classification problem, and the standard SVM is not enough to meet the fault problem of substation, so the multi-classification transformation is needed to improve. In the problem of fault classification, compared with other classification methods, the binary tree-based multi-classification method has the advantages of short training time, no undivided region, and minimum classifier. Therefore, this paper studies the binary tree-based multi-classification support vector machine.

According to the dimension reduction and screening of PCA, five faults of substation were selected. That is, the circuit breaker trip, the main protection action, control circuit break, abnormal oil level of circuit breaker, low SF6 gas pressure. There is no inevitable causal connection between faults, and breaker trip is divided into breaker division and breaker jump, and the main protection action is divided into protection action circuit breaker disconnection and location circuit breaker location combination, so this paper based on the layered binary tree substation fault diagnosis, the classification diagram is shown in figure 3.

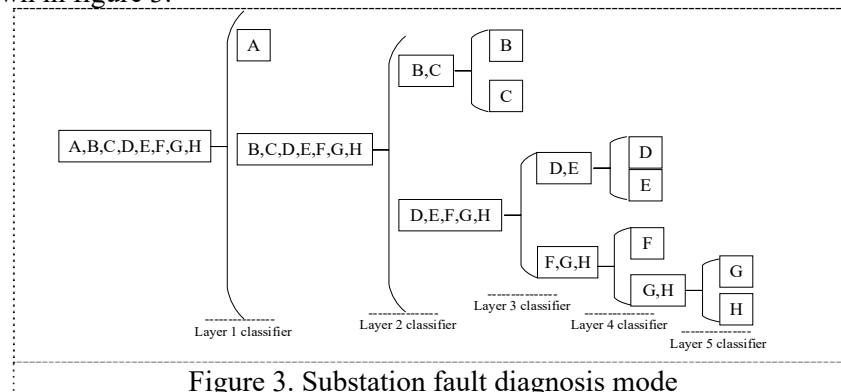


Figure 3. Substation fault diagnosis mode

Among them, A: Normal. B: Circuit breaker location division. C: Circuit breaker jump. D: Protection action circuit breaker disconnection. E: Circuit breaker position alignment. F: Control circuit break. G: Abnormal oil level of oil circuit breaker. H: Low SF6 gas pressure.

- The normal samples in the training samples were marked as 1 and the fault samples were marked as -1. The radial basis kernel function was used to optimize the ICA parameters at the same time to generate a layer classifier.

- Fault samples were selected, in which the breaker trip fault was marked as 1 and the remaining fault was marked as -1. ICA parameter optimization was conducted by using radial basis kernel function at the same time to generate a two-layer classifier.

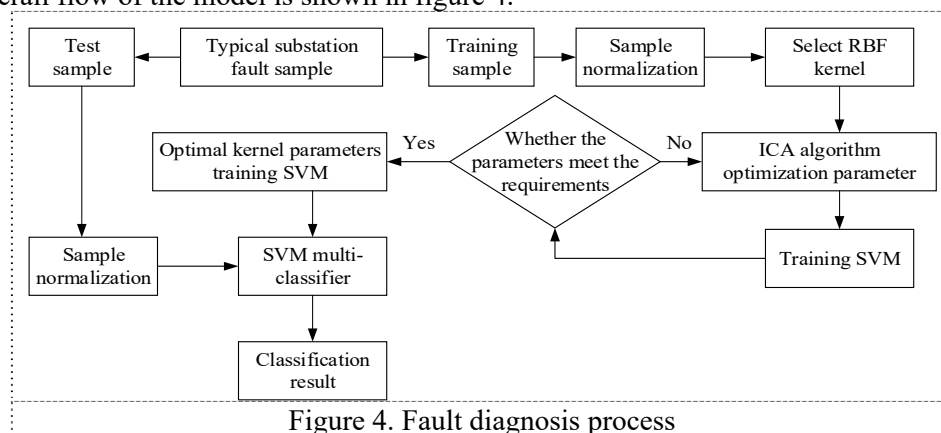
- The circuit breaker trip fault samples were selected, in which the breaker division fault was marked as 1 and the breaker steal trip fault was marked as -1. The first three-layer classifier was generated by using the radial basis kernel function to optimize the ICA parameters at the same time.
- The remaining fault samples were selected, in which the main protection action fault was marked as 1 and the remaining fault was marked as -1. The radial basis kernel function was used to optimize the ICA parameters at the same time, and the second three-layer classifier was generated.
- The fault samples of the main protection action were selected, in which the disconnection fault of the protective action circuit breaker was marked as 1 and the position matching fault of the circuit breaker was marked as -1. The first four-layer classifier was generated by using the radial basis kernel function to optimize the ICA parameters at the same time.
- The remaining fault samples were selected, in which the control loop fault breaking was marked as 1 and the rest as -1. The radial basis kernel function was used to optimize the ICA parameters at the same time to generate a second four-layer classifier.
- The remaining fault samples were selected. The abnormal oil level fault of the circuit breaker was marked as 1, and the fault of SF6 with low gas pressure was marked as -1. The radial basis kernel function was used to optimize the ICA parameters at the same time to generate a five-layer classifier.

4.2 Fault diagnosis procedure

In order to accurately diagnose substation faults, it is necessary to train the proposed multi-classification support vector machine (SVM) model many times. Through the screening and extraction of fault information of the third generation smart substation equipment, the extracted data are divided into training set and test set, and the data is normalized at the same time. Select the gaussian radial basis kernel function, and use the imperial competition algorithm to optimize the selection of the kernel function, generate the optimal classifier, the overall operation steps are as follows.

- PCA was used for linear transformation of the initial sample set, and the principal component was selected by the cumulative contribution rate after transformation. A new set of samples is obtained by reducing the dimension of the sample set after linear transformation with the selected principal component.
- The optimal objective function is formed by using the new sample set and the nonlinear multi-classification support vector machine with unknown parameters.
- ICA was used to find the optimal solution of the optimal objective function, and the optimal parameters of SVM for fault classification of smart substation were determined.
- The test samples were input into the support vector machine model to calculate the predicted values.

The overall flow of the model is shown in figure 4.



5. Instance analysis

The fault data of the third generation intelligent substation equipment is used for classification test. Through the selection and integration of data, 160 groups of 8 representative data were selected in

this paper, including 120 training samples and 40 test samples. The distribution of various sample data is shown in table 4.

Table 4. Failure data

Substation status	Training set	Test set
Normal	21	8
Circuit breaker location division	18	6
Circuit breaker jump	13	5
Protection action circuit breaker disconnection	17	7
Circuit breaker position alignment	16	3
Control circuit break	14	5
Abnormal oil level of oil circuit breaker	12	4
Low SF6 gas pressure	9	2

Because there is a large difference between different fault sample attributes of substation, in order to improve the overall generalization performance and classification accuracy of the model, it is necessary to unify the input samples for normalization, so that all data are within the range of $[0,1]$, to improve the generalization performance of support vector machines. The parameters are set as: the dimension of the optimization function is set as 2, the folding number of cross validation is set as 10, the number of countries is fixed as 20, the initial number of empires is set as 6, the evolution rate is set as 0.3, the assimilation coefficient is set as 2, and the assimilation coefficient Angle is set as 0.5, The parameters C and γ vary in two fixed ranges $[10^{-1}, 10^2]$ and $[10^{-2}, 10^2]$.

After the iteration and optimization of ICA, the average cost value and the minimum cost value in each iteration generation are calculated, thus the optimized parameters can be determined as $C = 145.26, \gamma = 0.8341$.

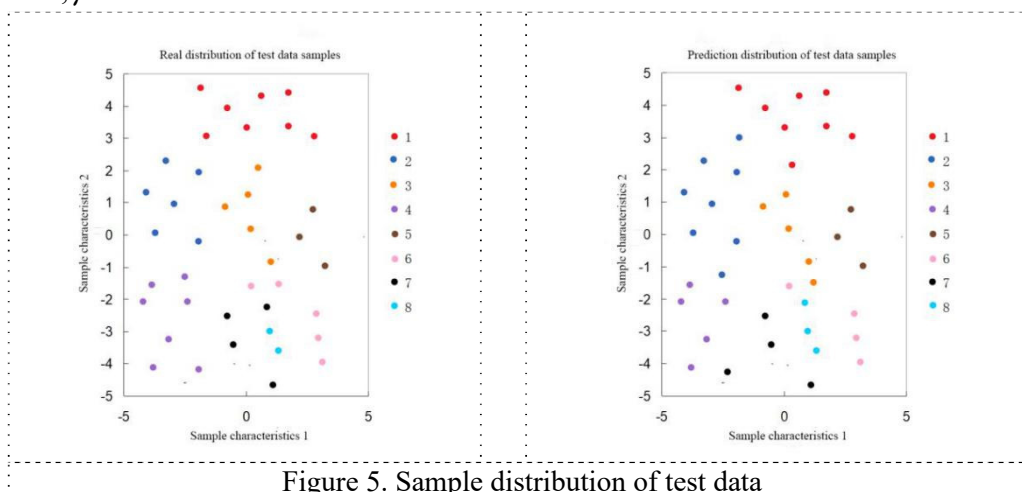


Figure 5. Sample distribution of test data

Figure 5 is a true distribution of the sample test data and prediction map (figure 1 corresponding normal data, the corresponding circuit breaker points 2 and 3 corresponding circuit breaker steal jump, 4 corresponding protection circuit breaker from points, five corresponding circuit breaker steal closed, 6 corresponding control circuit break line, 7 corresponding circuit breaker oil level anomalies, eight corresponding SF6 gas pressure low). From figure 5, it can be seen that only 6 test samples of 40 test data groups failed in fault diagnosis. The fault accuracy of the test data sample is 85%, which indicates that the method in this paper can effectively diagnose substation faults. Each fault characteristics of the corresponding precision rate and recall rate are shown in table 5, the precision rate and recall rate can further show that the precision and accuracy of the model, from table 5 shows that protection of break circuit breaker points, control circuit, the circuit breaker of oil level abnormal precision to 1, shows that the proposed model is more suitable for the protection of break circuit breaker points, control circuit, the circuit breaker oil level three kinds of fault diagnosis.

Table 5. Accuracy and completeness

Fault category	Accuracy	Completeness
Normal	0.875	0.875
Circuit breaker location division	0.750	1.000
Circuit breaker jump	0.800	0.800
Protection action circuit breaker disconnection	1.000	0.714
Circuit breaker position alignment	0.750	0.750
Control circuit break	1.000	0.800
Abnormal oil level of oil circuit breaker	1.000	1.000
Low SF6 gas pressure	0.670	0.670

In order to prove the effectiveness of this method, the BP neural network method, which is common in substation fault diagnosis, is compared with the support vector machine (SVM) method in this paper.

Table 6. Comparison of fault diagnosis methods

Fault diagnosis method	Classification accuracy(%)	Classification of time(s)
Multiple classification support vector machines	85.0%	9.8s
BP neural network	82.5%	4.2s

Display data from table 6 shows that using multiple classification support vector machine (SVM) classification is far higher than that of BP neural network classification with the time, but the BP neural network classification accuracy of 82.5%, lower than many classification support vector machine (SVM) classification accuracy, the accuracy of classification accuracy rate can show a model, how classification support vector machine in solving small sample, multi-dimensional number has a good effect.

6. Conclusion

An intelligent substation fault diagnosis method based on optimal parameter support vector machine (SVM) is presented. The principal component analysis (PCA) was used to extract the key characteristic values, which effectively reduced the repeated variables and reduced the complexity of the data. The failure data sets after dimensionality reduction were trained in the model, and the parameters were optimized by the imperial competition algorithm. The test results show that:

- The dimensionality reduction with PCA can significantly reduce the complexity of calculation without having a great impact on data recognition.
- ICA can be used to optimize the parameters, so as to improve the overall accuracy of the model.
- SVM has a good effect for small sample and multi-class fault identification, but the substation fault diagnosis model proposed in this paper has a high time complexity and requires more time for classification, so it still needs to be improved.

Acknowledgments

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