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GIS Discharge Pattern Recognition Based on LS-SVM

Renjie Song[1], Shuang Yang[2], Changyin Liu[3], Jun Li[4]

[1,2]College of Information Science and Engineering
Northeast Electric Power University
169 Changchun Road, Jilin City 132012, Jilin Province, China
1939811347@qq.com.cn, yangshuanglearn@163.com.cn

[3]Qitaihe Power Supply Company, State Grid Heilongjiang Electric Power Corporation,
Qitaihe City 154600, Heilongjiang Province, China

[4]Jiamusi Power Supply Company, State Grid Heilongjiang Electric Power Corporation,
Jiamusi City 154000, Heilongjiang Province, China

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Abstract. *In order to increase the accuracy of fault diagnosis, this paper proposes a multi-class least squared support vector machine method based on DCA, aiming to optimize the fault diagnosis model of GIS. On the basis of digging the fault information contained in the DCA, the hierarchical decision-making is added to solve the problem of discharge pattern classification. The improved grid search method is applied to get the optimal parameters by double search, so the general performance of the classifier can be improved compared to the traditional method of a small step. The example shows that this model can effectively find the optimal solution in the feature space of SF_6 decomposition products of GIS.*

Keywords: GIS; Fault diagnosis; DCA, LS-SVM, Grid search method.

1. **Introduction.** Gas Insulated Switcher, GIS in short, is widely used in electric power system owing to its stability and safety of the entire equipment [1, 2, 3]. However, on the operating condition of GIS in the global power system, the accidents occur frequently in recent years. According to the analysis of historical data, faults caused by insulation defects account for above 50 percent. Insulation fault diagnosis has been one of the key problems in academic circles and power enterprises.

The discharge fault diagnosis of GIS always uses the pulse current method [4], the ultrasonic method [5] and the ultra high frequency(UHF) method [6]. The first two methods are readily disturbed by the electromagnetic noise of the site. Although the anti-interface ability of the UHF is strong, it is difficult to analyze the discharge quantitatively and make an accurate judgment on the insulation defect type.

The pure SF_6 has stable chemical property. In recent years, a large number of studies have concluded that SF_6 molecules in the ionic bond would crack and generate low-fluoride such as SF_x $(x = 1, 2, 3, 4, 5)$ under the discharge. On one hand, these products reacting with trace moisture, oxygen and insulation material will generate new component gases, and result in the reduction of insulation [7]. On the other hand, some of the new component gases called characteristic components are closely connected to the internal fault diagnosis that causes the cracks. The formation and regular variation of these characteristic components build a method based on the decomposition component analysis (DCA), which can accomplish the status monitoring and fault diagnosis [8].

Many different principles based on the DCA fault pattern recognition are applied to the diagnosis of insulation defect types. Some scholars at home and abroad have applied Artificial Neural Network (ANN) [9] and Support Vector Machine (SVM) [7] to the discharge fault diagnosis. However, due to complexity and dispersion of DCA, the neural network is not difficult to be limited by the conditions, so it has several problems such as low speed of convergence, and it is easy to fall into local convergence. Although SVM theory proposed by Vapnik in 1995 can address the problems in ANN, it uses the non-linear constraint to solve optimal solution, which influences the training speed with high dimensional data. Least Squared Support Vector Machine originated from standard SVM proposed by Suykens JAK in recent years [10]. It transforms inequality constraints into equality constraints and has good accuracy for processing non-linear signals. It is commonly used in electric power system. In [11] LS-SVM is used to establish the classifier to identify the discharge insulation defect caused by the partial discharge, however, the discharge type related to the discharge capacity did not be discussed.

Therefore, this paper combines LS-SVM and DCA to recognize GIS discharge pattern types, and utilizes the hierarchical decision-making model and improved grid search method respectively to construct the optimal model. Compared with SMO method, back propagation neural network (BPNN) and standard SVM, the proposed method has higher diagnostic accuracy.

2. **The basic principle of LS-SVM.** Least squared support vector (LS-SVM) proposed by Suykens in 2002 is an extension and improvement of the standard Support Vector Machine (SVM). The method transforms the inequality constraints into equality constraints and solves the optimal solution through linear equations. Compared with the standard SVM, LS-SVM computes faster and more concisely, more suitable for solving large-scale data problems.

Considering the training samples, the LS-SVM classifier classified the training set by constructing an optimal hyperplane, and has good generalization. According to the principle of LS-SVM, it maps the nonlinear samples in the low-dimensional space into the high-dimensional space to be linearly separable through the kernel function, and then establishes the optimal hyperplane in the high-dimensional space.

According to the LS-SVM classifier, the optimal separating hyper plane can be gained by the following problem:

$$y(x_i) = \omega^{\mathrm{T}}\varphi(x_i) + b \tag{1}$$

Where ω is a weight vector, b is a bias term.

The optimal problem of LS-SVM can be translated into equality constraints. The objective function is shown as follows:

$$J(\omega, \xi) = \frac{1}{2}\omega^{\mathrm{T}}\omega + \frac{1}{2}C\sum_{i=1}^{l}\xi_i^2 \tag{2}$$

Subject to

$$y_i[\omega^{\mathrm{T}}\varphi(x_i) + b] = 1 - \xi \tag{3}$$

Among Eq. (2) and Eq. (3), ξ is an empirical error variable, and C is error penalty factor. The Lagrange function constructed by Eq. (1) and Eq. (2) is shown as follows:

$$L(\omega, b, \xi, \alpha) = J(\omega, \xi) - \sum_{i=1}^{l} \alpha_i y_i[\omega^{\mathrm{T}}\varphi(x_i) + b] - 1 + \xi_i \tag{4}$$

Where α is a Lagrangian multiplier.

The Karush-Kuhn-Tucker conditions for the problem are shown as follows:

$$\frac{\mathrm{d}L}{\mathrm{d}\omega} = 0 \Rightarrow \omega = \sum_{i=1}^{n} \alpha_i y_i \varphi(x_i) \tag{5}$$

$$\frac{\mathrm{d}L}{\mathrm{d}\xi} = 0 \Rightarrow \alpha_i = C\varphi(x_i) \tag{6}$$

$$\frac{\mathrm{d}L}{\mathrm{d}b} = 0 \Rightarrow \sum_{i=1}^{n} \alpha_i y_i = 0 \tag{7}$$

$$\frac{\mathrm{d}L}{\mathrm{d}\alpha_i} = 0 \Rightarrow y_i(\omega^T \varphi(x_i) + b) = 1 - \xi_i \tag{8}$$

Combined with Eq. (4), the optimal condition is shown as follows:

$$\begin{bmatrix} 0 & Q^T \\ Q & PP^T + C^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{9}$$

Where $P = [\varphi(x_1)^T y_1, ..., \varphi(x_i)^T y_i]$, $1 = [1, ..., 1]$, $Q = [y_1, ..., y_i]$, $\alpha = [\alpha_1, ..., \alpha_i]$.

The LS-SVM model is constructed as follows:

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{n} \alpha_i y_i k(x, x_i) + b) \tag{10}$$

Where k is a kernel function.

3. Grid Search Method.

3.1. basic concept.

A large number of studies have shown that radical basis kernel can make LS-SVM get better classification performance and promotion [12]. Therefore, The kernel function in the paper uses radical basis kernel, and the formula is shown as follows:

$$K(x, x_i) = \exp\frac{-(x_i - x)^2}{\frac{2}{2\sigma^2}} = \exp[-g(x_i - x)^2] \tag{11}$$

Where σ is a width parameter, g is the parameter of kernel, $g = \frac{1}{2\sigma^2}$.

In practice, two parameters of the LSSVM model using radial basis function need to be optimized, which are the error penalty factor(C) and the kernel parameter (g). The values of two parameters influence the performance of classifier. Selecting the kernel parameter subjectively contributes to the reduction of classifier performance. Therefore, the grid search method is adopted to optimize the model [13].

The basic principle of the grid search method is to let C and g divide the grid in a certain range and traverse all points in the grid. For each selected set of values, the method of cross validation is used to train in the classification, and finally the group that results in the highest classification accuracy is the optimal parameter. In the traditional method, the training step is always set to 0.1, which costs a quantity of time.

3.2. **improved grid search method.** From the Fig.1, C and g in a certain range could get higher accuracy. However, the accuracy of most areas is poor. If we look for the reasonable parameter thresholds firstly, then search precisely, It could cost less time. In order to improve LS-SVM training speed, firstly, use the large step to search roughly in a wide range, and then use the traditional small step to carry out the second precise search in the neighboring area to find out the optimal parameters. It is important to choose the most appropriate neighboring area in the second precise search. Because the improved interval search has a certain amount of experience, the paper takes a value by combining the values in multiple ranges for finding the best parameters of the highest accuracy.

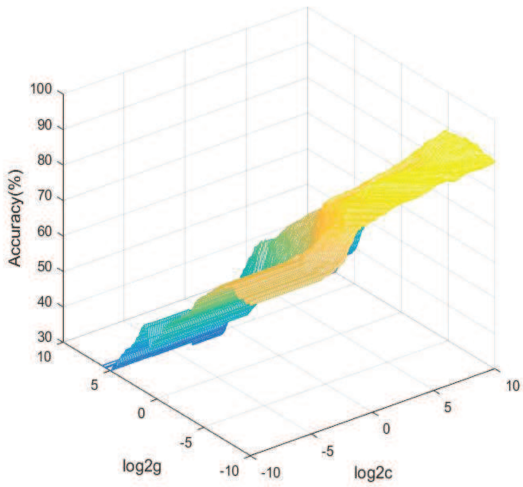


FIGURE 1. Original GS results

4. GIS Discharge Pattern Recognition Based on LS-SVM.

4.1. **fault classification based on DCA.** According to the DCA data collected from multiple GIS equipment, 350 sets of data are gotten after removing some incomplete and incorrect data. In the analysis of the characteristics of GIS discharge fault, DCA contains just limited fault information. The direct fault location to insulation fault is not comprehensive, and promotion is poor as well. So it is critical to design the reasonable classification model [14]. In the paper, faults from rough to detailed are divided into discharge faults involving insulation defects and discharge faults that characterize the severity of the discharge. The former is subdivided into four types of insulation faults, which are the discharge model of metal protrusions (N type), free metal particle (P type), insulator (M type) and air gap (G type). The latter is subdivided into discharge models of spark, arc and corona.

Because the two-level structure of the hierarchical model designed in this paper involves various kinds of faults, LS-SVM is a two-level classifier, so the classifier needs to be extended to multi-class. DAGSVM gets a new learning architecture proposed by Platt et al to combine multiple "1-v-1" classifiers. It avoids the traditional "1-v-r" method to classify with all samples, which cost much time [15]. In the training phase, DAGSVM needs to construct two-level classifiers, which is the same as "1-v-1". But in the classification phase, this method forms all the classifiers into a two-way directed acyclic graph, including $\frac{n(n-1)}{2}$ nodes and n leaves. DAG-SVM is simple and easy to implement. Only $n-1$ decision functions can be used to obtain the result. Compared with the "1-v-1" method, DAG-SVM can improve the test speed without misclassification and rejection. In addition, due to its special structure, it has a certain degree of fault tolerance, and the classification accuracy is higher than the general directed acyclic graph method. The hierarchical structure is shown in Fig.2.

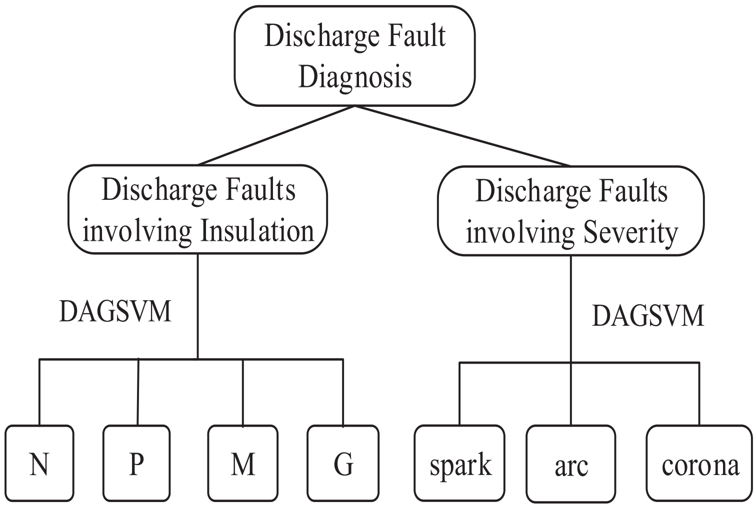


FIGURE 2. Discharge Fault Diagnosis Model

4.2. **selections of fault characteristics.** In the field of discharge fault pattern recognition, effective parameters need to be extracted to train the classifier. However, it is necessary to normalize the features in the extraction process of discharge characteristics considering the complexity of gas decomposition products and the large differences between the products. In order to get small, representative variables instead of the large and redundant variables, how to choose representative variables, has become the key of fault pattern recognition. In order to select the SF_6 decomposition component products that could reflect fault characteristics and are most suitable for SVM input, the paper combines with [16, 17]and analyzes the characteristics of various products by step-by-step discriminant analysis. In the analysis, the relative content of each king of gas is taken as the input of the model, and the rationality of the analysis is determined according to the mean equality test of the relative content of each gas, and the rationality is determined by the significance level of each index in the test. The results are presented in TABLE.1.

It can be seen from the table that the significance level of each gas is zero, which indicates that the classification of faults in this paper can be discriminated by the following five types of gas. Therefore, the input of the LS-SVM model is the relative contents of the following five kinds of gas, SO_2F_2, SOF_2, SO_2, CO_2 and CF_4.

TABLE 1. Results of Analysis of Relative Concentrations of DCA Step by Step

SF_6 decomposed composition products	Wilks lambda (λ)	Significance level α
SO_2F_2	0.139	0.000
SOF_2	0.226	0.000
SO_2	0.284	0.000
CO_2	0.303	0.000
CF_4	0.192	0.000

4.3. **steps of the classification model.** According to DCA data of GIS, LS-SVM classification model is applied for data processing and analysis to identify discharge faults. The steps of GIS fault diagnosis model are take as follows:

(1) Due to the two-level discharge fault model designed, therefore, the total fault type output vector is defined as 0 and 1, the second hierarchical decision output is defined as $[1, 0, 0]$, $[1, 0, 1]$, $[1, 1, 0]$, $[1, 1, 1]$ and $[0, 0, 1]$, $[0, 1, 0]$, $[0, 1, 1]$.

(2) Use improved grid search method to search the optimal kernel function parameter and penalty factor.

(3) Combined with the optimal penalty factor and kernel function parameter, LS-SVM based on fault diagnosis model is constructed by training samples. The second layer of hierarchical decision-making is based on the SVMDAG multi-classification method, which needs to construct 5 and 4 classifiers respectively.

(4) Use the test samples to test the constructed discharge fault diagnosis model and evaluate the classification performance of the model. The flow chart is shown in Fig.3.

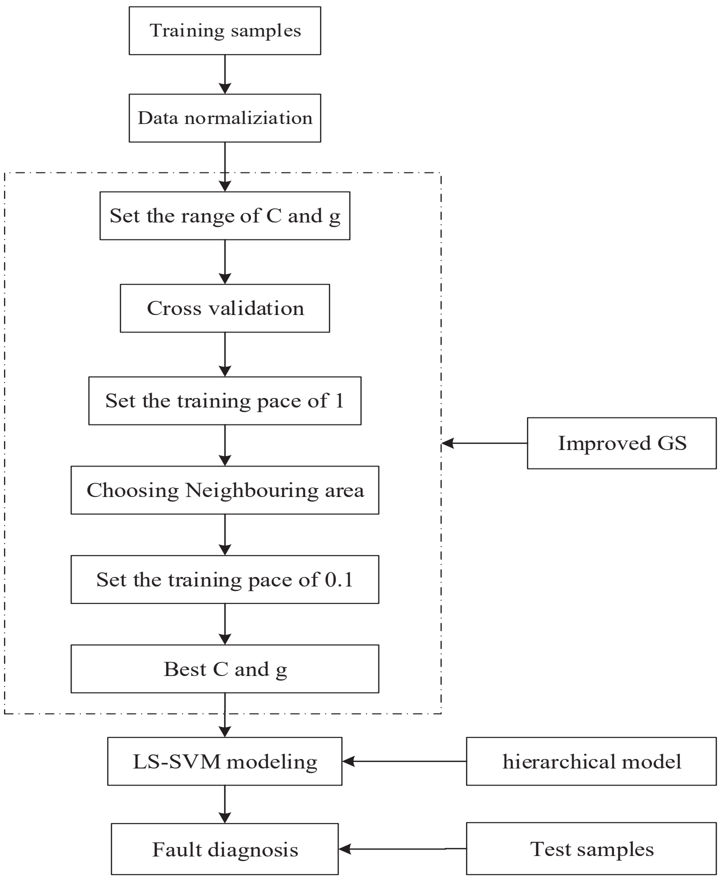


FIGURE 3. Flow Chart of Discharge Fault Diagnosis Procedure

5. **Case analysis and comparison.**

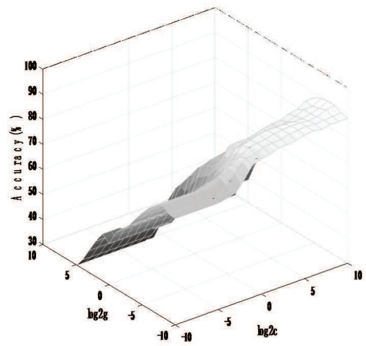
5.1. **case analysis.** After normalizing the fault samples, set 350 samples as the training set and randomly select 35 samples of each discharge fault as the test set. Fault sample statistics are shown in Table.2.

The paper sets the range of the initial grid search (c, g) to $[2^{-8}, 2^{8}]$. Since the first step is to make a rough range selection, the purpose is to determine the approximate position of the parameters with the step 1. The optimal parameters which achieve the highest classification accuracy is obtained, c=32, g=0.0039, and then the range and the step are redefined in the vicinity of c and g, where $c = [2^3, 2^6]$, $g = [2^{-6}, 2]$. The optimal parameters achieved are c=14.92, g=0.0051. The improved results are shown in Figure 4.

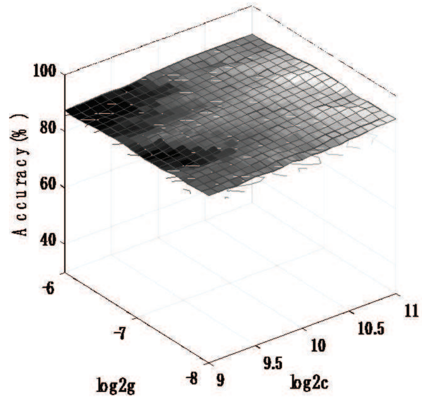
The Fig.5 and the Table.3 show the fault diagnosis results of training samples. Depending on the Fig.5, there is simply one diagnostic mistake in the overall 350 samples. In the Table.3, the accurate rates of several diagnostic types, such as N, P, arc and corona, are above 90%. Total accuracy has reached 92.44%, which verifies the effectiveness of this method in GIS discharge fault diagnosis.

TABLE 2. Statistic of GIS fault diagnosis samples

Type 0	Training Samples	Test Samples	Type 1	Training Samples	Test Samples
N	50	5	Spark	50	5
P	50	5	Arc	50	5
M	50	5	Corona	50	5
G	50	5			
total	200	20	total	150	15



(a) pace 1



(b) pace 0.1

FIGURE 4. Parameters of Improved GS Results

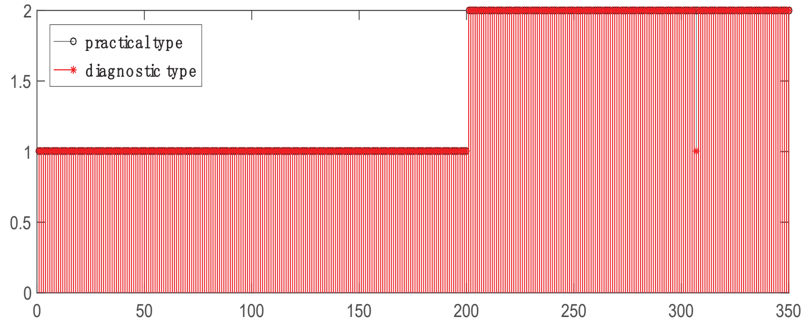


FIGURE 5. Results of first-layer fault diagnosis

Table 3. Results of second-layer fault diagnosis

Types	Training samples	Correct judgment	Accuracy/%	Overall accuracy/%
N	50	48	96	
P	50	50	100	
M	50	44	88	92.44
G	50	42	84	
Spark	50	40	80	
Arc	50	48	96	
Corona	50	45	90	

5.2. **case comparison.** In order to verify the superiority of the improved grid search method based on the same samples, the traditional grid search, genetic algorithm (GA) and particle swarm optimization (PSO) were used to optimize the parameters of the vector machine model respectively. In this article, the search step of traditional grid search method is set to 0.1. PSO sets the maximum of evolution to 200, the maximum of population to 20, and the number of cross-validation is 3. In addition to that, c1=1.5, c2=1.7, w1=0.9, w2=1. The maximum of GA is set to 200, the maximum of population is 20, and the cross-validation is the number of 5. The kernel functions used in the above algorithms are set to radial basis function, and all of them are iteratively optimized under the LS-SVM hierarchical model. Table 2 shows the classification accuracy and training results of different methods for parameter optimization model.

It can be seen from Table 2 that the parameters obtained by GA can achieve higher accuracy, but the training takes a long time. Compared with the traditional GS and PSO methods, the improved GS gets higher classification accuracy, faster model training speed, and is more suitable for the discharge fault diagnosis.

In order to verify the validity and practicability of the model presented in the paper, Table 3 lists the comparison between LS-SVM and standard fault diagnostic methods such as SVM, SMO and BPNN. For BPNN, the network structure of 5123 is adopted. The number of training times is 1000, the learning rate is 0.05, the hidden layer function is "transig", and the output layer function is "purelin". The standard SVM and SMO algorithms are still trained using the improved grid search method. According to the results in Table 3, the accuracy of BPNN model is only 70%. The reason is that the neural network method often requires a large amount of samples to obtain high accuracy. The accuracy of the standard SVM and SMO is 90.45% and 89.54% respectively, which shows that these two algorithms can construct an ideal diagnostic model. However, compared with the proposed LS-SVM, the accuracy is relatively lower.

Table 4. Different Methods of Fault Diagnosis Results

Set	GS-LSSVM	GS-SVM	GS-SMO	BPNN
Training Samples/%	92.44	90.4	89.54	70
Testing Samples/%	93.45	88.9	84	68

6. **Conclusions.** (1) In this paper, LS-SVM is applied to GIS discharge pattern recognition. The mathematical model based on DCA is constructed by hierarchical decision and DAG multi-classification algorithm. According to the relationship among DCA samples in the feature space, the effect is clearly obvious.

(2) The paper uses the improved grid search method to obtain the optimal parameters of LS-SVM. Compared with the traditional algorithm, this method has faster training speed and improves the generalization performance of vector machines.

(3) The examples in this paper show that the proposed multi-class hierarchical decision model based on improved grid search and LS-SVM has superior classification performance, and it is feasible to apply it to discharge fault diagnosis or GIS maintenance strategy.

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