

# Electric Field Signal Recognition Method of DS Switching Operations Based on Wavelet Packet Analysis and PSO-HSVM

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**Abstract.** In order to monitor the state of Gas Insulated Substation (GIS), this paper established a fault simulation experimental platform for Disconnecting Switch (DS), and collected data through a 3D radiation electric field (E-field) measurement system. For extract the feature parameters, four-layer wavelet packet decomposition was performed on the data to obtain normalized energy, and the dimension of the eigenvector was reduced by principal component analysis (PCA) algorithm. Then, the model was trained with the hybrid kernel support vector machine (HSVM) algorithm, and the parameters was optimized with the particle swarm optimization(PSO) algorithm. The result shows that compared with the traditional SVM model, the method proposed in this paper improves the diagnosis accuracy of DS defect signals.

## 1. Introduction

As a key structure of GIS, DS can ensure the safety of high-voltage electrical equipment during maintenance and can isolate high voltage. DS is widely used and highly reliable, which has an important effect on the safe operation of GIS [1]. Therefore, in order to ensure the healthy operation of DS and GIS, it is necessary to conduct effective state monitoring of DS, so as to diagnose its possible faults.

Transient radiation field is generated during DS switching operation [2]. Reference [3-5] has obtained a series of methods for fault feature extraction and fault diagnosis of radiation field signals through field measurement and analysis. Reference [6] compares the energy in the characteristic frequency bands after a random circuit breaker operation with that of the typical radiation E-field obtained when GIS totally is in good condition, insulation faults of circuit breaker can be detected and the operating state of GIS could be evaluated. With the rapid development of artificial intelligence, it has become a new trend to acquire high-precision classification model through data training. Support vector machine (SVM) is a machine learning method based on structural risk minimization and statistical learning theory [7-9]. The diagnosis accuracy of SVM mainly depends on the selection of parameters [10]. There are many algorithms for parameters optimization, and the PSO algorithm has strong directivity, high convergence rate and high optimization accuracy, it has been widely used in the field of engineering optimization [11].

In this paper, wavelet packet analysis was used to process the data to obtain the feature parameters, and PCA algorithm was used to select the feature. In order to overcome the shortcomings of the traditional SVM, the hybrid kernel SVM was used to train data instead of single kernel SVM, and the PSO algorithm was used to optimize the parameters. The result shows that the method can be



effectively used for DS defect recognition.

## 2. Signal acquisition and feature extraction

### 2.1. Signal acquisition

In order to meet the research requirements of this paper, a DS fault simulation experimental platform was built. Figure.1 displays the equivalent circuit of experimental platform. Where  $C_1$  and  $C_2$  represent capacitive voltage dividers,  $U$  represents an external high voltage power supply.  $DS_1$  and  $DS_2$  are the disconnecting switches at both ends of the system. The research object in this paper is  $DS_2$ [5].

The implementation of the system is shown in Figure.2. The E-field signal is received by three vertical small antennas of three-dimensional E-field probe. The output electric signal is driven by the coupling circuit to realize the conversion of electro-optic signal, optical signal is transmitted to optical receiver through optical fiber to realize photoelectric conversion, the converted radiation field signal is finally received by an oscilloscope.

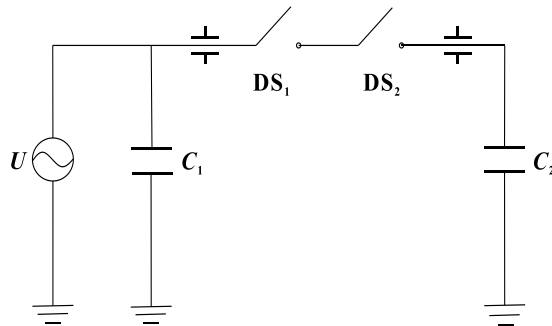


Figure 1. Equivalent circuit of the switching operation test system for the 110kV DS.

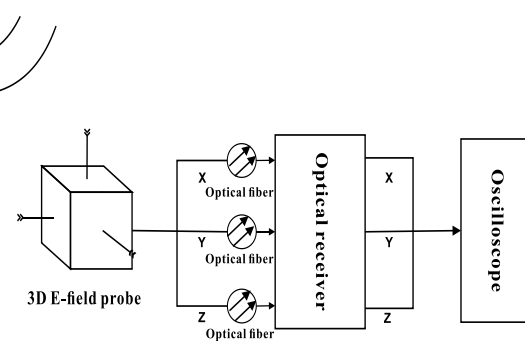


Figure 2. 3D E-field measurement system.

The experimental platform simulates three DS defect states, including internal tip defect state, internal particle defect state and external flashover defect state. Under different voltage levels (20-100kV), this paper measured the radiation E-field signals under four states, and finally obtained a series of experimental data. 50% of the data were selected as training set and 50% of the data as test set. The normal signal label is 0, the internal tip defect signal label is 1, the internal particle defect signal label is 2, and the external flashover signal label is 3. Table 1 shows the detailed partitioning of the data set.

Table 1. Different types of radiation E-field samples distribution.

Type	Training set	Test set
0	23	45
1	41	33
2	55	36
3	36	41
Total	155	155

### 2.2. Features extraction

This paper mainly studies the maximum pulse waveform of the radiation E-field, and performs wavelet packet analysis to extract the characteristic parameters for the training of the SVM. The Figure.3 shows the maximum pulse( $P$ ) waveform of the radiation E-field of the closing operation under normal state of DS. The  $P$  exhibits a high-frequency damped oscillation pulse characteristic with a maximum amplitude of 4.62 kV/m and a duration of about 3 $\mu$ s. The wavelet packet transform is

performed on the  $P$  pulse, and the wavelet packet transform is a linear transform, which satisfies the energy conservation principle (1).

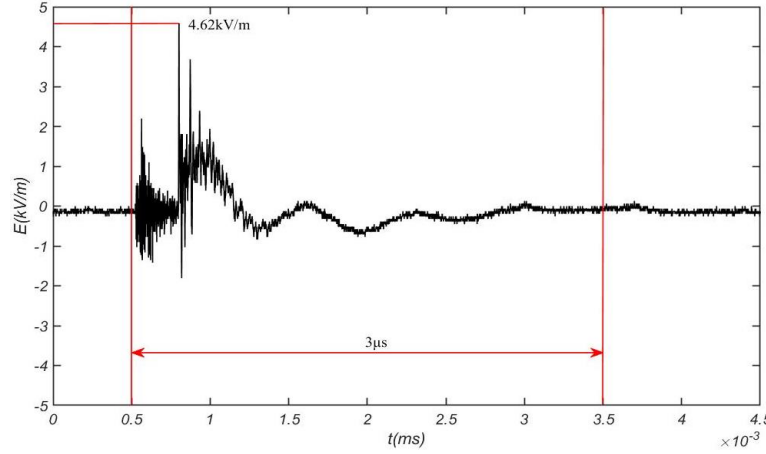


Figure 3. The detailed waveform of  $P$ .

$$\int_{-\infty}^{+\infty} |f(t)|^2 dt = \sum_j \sum_k |c_{j,k}|^2 \quad (1)$$

In (1),  $f(t)$  represents the original data signal, and  $c_{j,k}$  is wavelet packet decomposition coefficient[13-15]. The bior5.5 wavelet base is used, and the decomposition scale is  $J = 4$ . In order to satisfy the tight support in time-frequency domain, the order of wavelet transform is  $N_{wt}=3$ . Through wavelet packet decomposition, data can be decomposed into 16 bands. All nodes in Layer 4 are reconstructed, and the reconstructed signal is represented by  $S_{4j}$ . The energy of each band of wavelet packet can be obtained as shown in (2).

$$E_{4j} = \int |S_{4j}|^2 dt = \sum_{k=1}^{N_l} |x_{jk}|^2 \quad (2)$$

Table 2. Four-layer wavelet packet normalization decomposition energy results.

Node	Energy	Node	Energy
(4,0)	0.3164	(4,8)	0.0178
(4,1)	0.0674	(4,9)	0.0308
(4,2)	0.0414	(4,10)	0.0514
(4,3)	0.0745	(4,11)	0.0404
(4,4)	0.0271	(4,12)	0.0311
(4,5)	0.0313	(4,13)	0.0386
(4,6)	0.0482	(4,14)	0.0730
(4,7)	0.0495	(4,15)	0.0610

From (2), where  $x_{jk}$  is the amplitude of the discrete value of the signal, and  $N_l$  represents signal length of the radiation field, and finally the wavelet packet energy  $E_{4j}$  of each frequency band can be obtained. Finally, the normalized energy of wavelet packet of 16 frequency bands are obtained through (3).

$$E_{norm}(j) = \frac{E_{4j}}{\sum_{j=1}^{16} E_{4j}} \quad (3)$$

Table 2 shows the normalized energy results of the four-layer wavelet packet, the energy ratio in the first frequency band is much higher than other frequency bands, and energy ratio in other frequency bands are relatively small, and there are no much difference. Let the eigenvector be  $E$ ,  $E=[E_0, E_1, \dots, E_{15}]$ , where  $E_i$  represents the energy of the  $i$ -th frequency band. In order to extract the part of the feature vector that best represents the signal feature, PCA algorithm is used to extract the independent principal component in the feature vector to reduce the dimension of the feature vector. The following is the process of PCA dimension reduction.

- Let the correlation matrix be  $X$  satisfy  $x_{i,j}=x_{j,i}$  and  $x_{i,i}=1$ , then:

$$X = \frac{1}{n} (E^*)' E = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,j} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,j} \\ \vdots & \vdots & \vdots & \vdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,j} \end{bmatrix} \quad (4)$$

- Calculate the eigenvalues of  $X$  and order from largest to smallest:

$$\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \cdots \lambda_j \geq 0 \quad (5)$$

The corresponding eigenvector can be expressed as  $L_1, L_2, \dots, L_j$ , and arrange them in descending order of eigenvalues.

- Calculate the variance contribution rate  $\alpha_j$ :

$$\alpha_j = \lambda_j / \sum_{k=1}^j \lambda_k \quad (6)$$

$\alpha_j$  is sorted in descending order, and then the cumulative variance contribution rate is calculated. When the contribution rate is greater than 90%, only the first to the  $h$ -th principal components are retained, and it is considered that enough key feature information has been included in it. If the principal component is taken out and set as the transformation matrix  $P$ , the final eigenvector  $E'$  can be expressed as:

$$E' = E \times P \quad (7)$$

### 3. Construction of DS defect diagnosis model based on PSO-HSVM algorithm

#### 3.1. Hybrid support vector machine (HSVM) algorithm

SVM is a classification method based on statistical learning theory. In linear SVM, assuming that the training set is  $\{(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_n, y_n)\}$ , where  $x_i \in \mathbb{R}^n$  and  $y_i \in \{-1, 1\}$ , if all samples can be linearly partitioned by a hyperplane, the hyperplane is called the optimal hyperplane when the distance to the hyperplane is maximum. The optimal hyperplane satisfies (8).

$$y_i(w \cdot x_i) + b \geq 1 \quad i = 1, 2, 3, \dots, n \quad (8)$$

$$\phi(w) = \|w\|^2 / 2 \quad (9)$$

In (8), Where  $w$  is the weight matrix and  $b$  is the classification threshold. The classification interval is  $2/\|w\|$ , and the problem of finding the optimal hyperplane becomes to find the minimum value of the (9) on the basis of satisfying (8). This is a convex quadratic programming problem, using the Lagrange multiplier method to get its dual problem, we can finally get (10).

Non-linear SVM can map input vector  $x$  into a high-dimensional space by non-linear mapping to construct the optimal hyperplane. Kernel function can avoid complex computation in high-dimensional space, where the kernel function  $K$  satisfies (11).

$$\max_{\alpha} \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j x_i x_j \quad (10)$$

$$S.t \sum_{i=1}^n \alpha_i y_i = 0, \alpha_i \geq 0, i = 0, 1, 2 \dots n$$

$$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j) \quad (11)$$

By introducing (11) into (10), the final model is

$$f(x) = \sum_{i=1}^n \alpha_i y_i K(x_i, x) + b. \quad (12)$$

After training, only unknown samples need to be brought into the model to get their categories. Selecting different kernel functions will produce different SVM, and the choice of kernel functions will greatly affect the prediction ability of SVM. The strong learning ability and weak generalization ability of the local kernel function, and the global kernel function has strong generalization ability and weak learning ability. If two kernel functions are superimposed linearly, the single defect of kernel function learning performance can be solved. Polynomial kernel function is typical global kernel function and RBF kernel function is typical local kernel function. In this paper, two kernel functions are combined linearly to construct hybrid kernel functions.

The Polynomial kernel function and the RBF kernel function are (13) and (14).

$$K_{poly} = (x \cdot x_i + 1)^d \quad (13)$$

$$K_{rbf} = \exp(-(x - x_i)^2 / 2\sigma^2) \quad (14)$$

Linear combination of two kernel functions can be obtained as

$$K_{mix} = \varepsilon \cdot K_{poly} + (1 - \varepsilon) \cdot K_{rbf}. \quad (15)$$

Where  $\varepsilon$  is the weight coefficient,  $\varepsilon \in [0, 1]$ , and the effect size of each kernel function is controlled by the adjusting  $\varepsilon$ . According to the algorithm improvement, HSVM can be gained.

### 3.2. Particle Swarm Optimization (PSO) algorithm to Optimize HSVM Parameters

When using SVM for model training, the parameters need to be determined, which is directly related to the quality of the final model. This paper adopts PSO to optimize the parameters of HSVM.

In the PSO algorithm,  $N$  particles form a group in an  $M$ -dimensional search space. where  $V_i = (v_{i,1}, v_{i,2}, \dots, v_{i,M})$ ,  $V_i$  represents the speed of the  $i$ -th particle,  $S_i = (s_{i,1}, s_{i,2}, \dots, s_{i,M})$ ,  $S_i$  is the position of the  $i$ -th particle. The optimal position of the  $i$ -th particle up to now is the individual extremum, which is denoted as  $p_i = (p_{i,1}, p_{i,2}, \dots, p_{i,M})$ . The optimal position for the entire particle swarm is called the global extremum and is expressed as  $p_g = (p_{g,1}, p_{g,2}, \dots, p_{g,M})$ . Particles can be updated for velocity and position based on the following formula:

$$v_{i,M}^{(t+1)} = W^{(t)} v_{i,M}^{(t)} + c_1 r_1 (p_{i,M}^{(t)} - s_{i,M}^{(t)}) + c_2 r_2 (p_{g,M}^{(t)} - s_{i,M}^{(t)}) \quad (16)$$

$$s_{i,M}^{(t+1)} = s_{i,M}^{(t)} + v_{i,M}^{(t)} \quad (17)$$

Among them,  $i=1, 2, \dots, N$ ,  $W$  is inertia weight,  $m$  is spatial dimension,  $c_1$  and  $c_2$  are learning factors or acceleration constants, the value range is  $[0, 2]$ ,  $r_1$  and  $r_2$  are two random data distributed as  $[0, 1]$ , and  $t$  is the number of iterations[16].

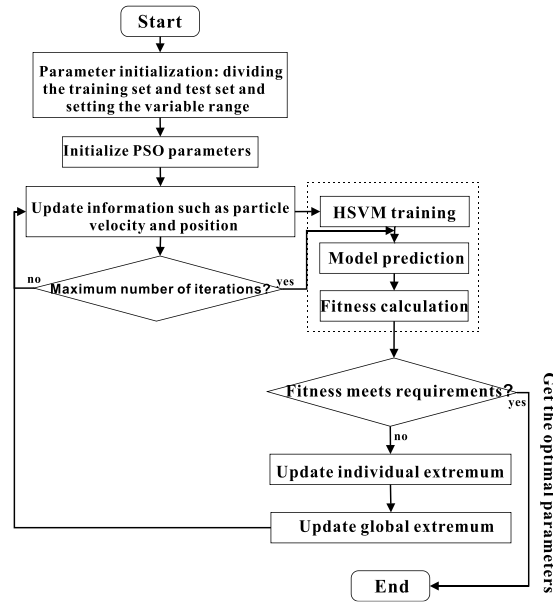


Figure 4. Flowchart of PSO algorithm.

Figure.4 is the flowchart of the optimization parameters of the PSO algorithm. Firstly, the parameters are initialized, then the particle position and speed are updated, and the fitness calculation is carried out by iteration to update various parameters. Finally, the optimal parameters are obtained.

#### 4. Forecast results and analysis

Based on the above analysis, the model training was carried out by using the software Matlab2016a and the SVM toolbox-Libsvm, and the algorithm was improved to some degree.

Firstly, the maximum pulse of radiation E-field is extracted for wavelet packet analysis, and the eigenvector  $E$  composed of four layers of wavelet packet normalized energy is obtained. The eigenvector  $E'$  for model training is obtained by principal component analysis of  $E$ .

Secondly, the training set was trained and the PSO was used to optimize the model parameters. The PSO algorithm needs parameters initialization, the particle spatial dimension was set to 4, the population number was 50, the iteration number was  $T=200$  times, and the learning factors  $c_1$  and  $c_2$  were 1.0 and 1.4. The search range for  $\lambda$  was  $[0.1, 100]$ ,  $d$  was  $[1, 15]$ ,  $\sigma$  was  $[0.1, 10]$ , and  $\varepsilon$  was  $[0, 1]$ . Then, data training was carried out by six-fold cross-validation, and the average of the cross-validation accuracy was taken as the classification accuracy of the HSVM. In order to evaluate the performance of the HSVM after parameters optimization, the fitness function was set to the average accuracy of k-fold cross-validation.

$$F = \frac{1}{k} \sum_{l=1}^k \left( \frac{P_{Tl}}{P_l} \times 100\% \right) \quad (18)$$

In (18),  $P_{Tl}$  is the number of correct classification of the  $l$ -th verification set, and  $P_l$  is the number of samples in the verification set. Finally, the PSO-HSVM model was obtained by the iterative parameters optimization of the PSO algorithm. Figure.5 is convergence curves of fitness, where the mean fitness is the average fitness value of all particles in each iteration. The best fitness curve is the maximum fitness value of all particles in the particle group in each iteration. As in Figure.5, the fitness curve converges rapidly in the first 60 iterations. With the increase of the number of iterations, the best fitness of PSO gradually becomes stable, and the convergence level gradually becomes consistent. Finally, the optimization of the parameters is achieved. Final model accuracy is 92.90%, and the optimal parameters are  $\lambda=66.72$ ,  $d=4$ ,  $\sigma=5.32$  and  $\varepsilon=0.41$ .

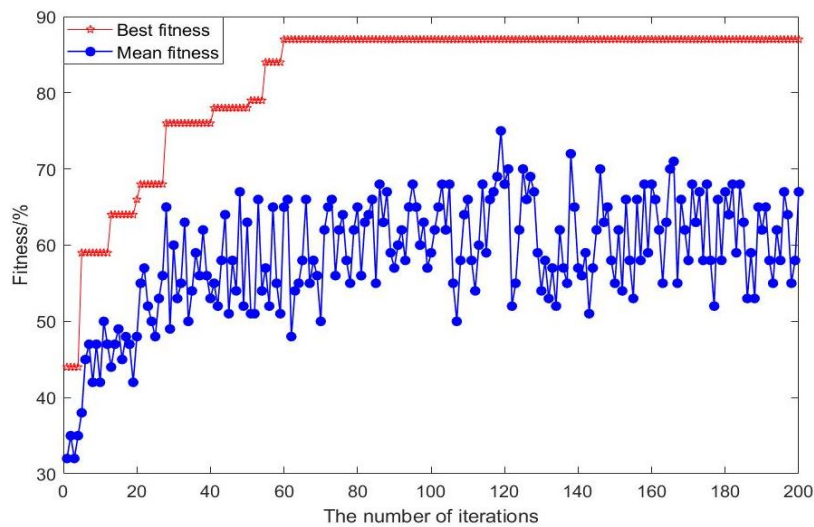


Figure 5. Convergence curves of fitness.

Table3. Test set identification result evaluation report.

Type	Precision	Recall	F1-score	Actual results	Predicted results
0	0.91	0.91	0.91	45	41
1	0.87	0.85	0.86	33	28
2	0.97	0.94	0.96	36	34
3	0.95	1.00	0.98	41	41

Table 3 is test set identification result evaluation report. It can be seen from table 3 that the model can fully recognize the external flashover signal, while the recognition effect for the internal tip signal is the worst, with five recognition errors. The precision of four defect type signals are more than 85%, and the precision of internal tip signals is the lowest, mainly because of the high sample error rate predicted as internal tip signals. It can be seen from the comprehensive index f1-score of precision and recall that the identification of signals from good to bad is the identification of external flashover signals, internal particle signals, normal signals, and internal tip signals.

Table 4. Comparison of multiple model recognition results.

Type	PSO-PSVM	PSO-RSVM	PSO-HSVM	KNN
0	0.89	0.91	0.91	0.87
1	0.85	0.82	0.85	0.79
2	0.92	0.92	0.94	0.83
3	0.95	0.98	1.00	0.88
Overall	0.90	0.91	0.93	0.85

Meanwhile, three models are respectively compared to verify the advantages of PSO-HSVM based on the same training set and test set. Three models including Polynomial kernel function SVM based on PSO (PSO-PSVM) and RBF kernel function SVM based on PSO (PSO-RSVM) and K-NearestNeighbor (KNN) algorithm, get the results as shown in table 4. As in table 4, compared with PSO-PSVM, PSO-RSVM and KNN, the overall accuracy and the accuracy for each type of PSO-HSVM are relatively high, which indicates that the PSO-HSVM proposed in this paper can effectively improve the recognition accuracy of defect signals.

## 5. Conclusions

In this paper, the radiation E-field of DS switching operations was taken as the research object, the normalized energy of four layers wavelet packet was extracted, and the feature vector was obtained by PCA dimension reduction. PSO-HSVM algorithm was used for data training. After several parameter optimization iterations, the PSO-HSVM model with an accuracy of 92.90%. Through the evaluation of the model, PSO-HSVM can effectively diagnose the defects of DS with high accuracy.

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