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UHF Detection of Partial Discharge on Typical Defects in GIS

Liqing DAI, Liqiang LIU, Changling LI,
Faculty of Electric Power Engineering, Inner Mongolia University of Technology,
Huhhot, 010080, China
E-mail: dailee@163.com

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Abstract: In order to study the ultra high frequency method applied for partial discharge detection in gas insulated switchgear, the typical defects including free particles, metal spikes, floating metals, insulator defects were designed and simulated in the gas insulated switchgear. The ultra high frequency method was applied for detect defects discharge signal, and extracted the statistical operators of the defect characteristics. Applied support vector machine for pattern recognition, and used particle swarm optimization and grid search to optimization support vector machine penalty parameter "c" and kernel function parameter "g". The results show that the ultra high frequency signal of different types of defects in the spectrum would show different characteristics in the ultra high frequency detection; two optimization methods of support vector machine are shown better robustness and generalization ability than the support vector machine in pattern recognition. *Copyright © 2013 IFSA.*

Keywords: Gas insulated switchgear (GIS), Partial discharge (PD), Ultra high frequency (UHF), Support vector machine (SVM), Particle swarm optimization (PSO), Grid search (GS).

1. Introduction

Gas insulated switchgear (GIS) started to be introduced in the 1970s in substation. Their high reliability, low maintenance and compact size have made them an attractive option in many circumstances. Although the reliability of GIS is high, the return of practical experience shows that some of the in-service failures are related to insulate defects [1, 2].

PD measurement techniques have been recognized as promising tools for monitoring GIS when assessing the dielectric performance of insulation and expected residual life of a GIS [3]. Among various PD detection methods, the ultra high frequency (UHF), which acquires electromagnetic waves in the UHF band (300 MHz ~ 3 GHz), has been widely studied and used for PD detection, and as a technique for diagnosing the insulation performance of a GIS [4].

Different types of PDs have different influences on power apparatus. For instance, damage caused by PD from free particles and insulator defects are more dangerous than that caused by PD from floating metals and metal spikes. Therefore, PD identification is of great importance for the healthy assessment of in-service power assets [5, 6]. Recently, Support Vector Machine (SVM) has been widely used for pattern recognition, because of its excellent Robustness and generalization ability. But there is not consistent conclusion in the selection of parameter "c" and kernel function parameter "g" in SVM [7-8].

In this paper, the different defects in the experimental GIS equipment were detected by the UHF method, and the characteristic operators were extracted from the detected Phase Resolved Partial

Discharge (PRPD) spectrum. Applications of support vector machine for pattern recognition, and used particle swarm and grid search to optimization support vector machine penalty parameter "c" and kernel function parameter "g".

2. Experimental Arrangement

In order to get the similar signals to the actual partial discharge signals, the typical experiment was designed to get various fault defects partial discharge data.

2.1. Partial Discharge Experiment Equipment

Experiment platform is by means of GIS experiment equipment of Hangzhou Electronics Institute high voltage laboratory, the model is the fault defect structure based on GIS partial discharge, Experiment GIS is shown in Fig.1. The GIS gas chamber is filled with SF_6 and maintained at a pressure of 0.3 MPa. The experimental chamber can add four kinds of defect, it can select the experimental defects by adjusted height of defects by the screw rod.

Fig. 1. Experimental GIS.

2.2. PD Measurement System

Detection system is composed of UHF sensor, UHF signal receiver, AD acquisition card and Computer operator interface etc, UHF sensor selected design plan of cavity backed spiral antenna, it has a relatively flat frequency response in the 300~2000 MHz frequency range, Voltage Standing Wave Ratio (VSWR) is less than 2. And UHF signal receiver is composed of pre-filter, low noise amplifier, mixer, IF filter, logarithmic detector, LO frequency source etc, the specific principles is shown as Fig. 2, ultimately selected word frequency band is for 400~1600 MHz.

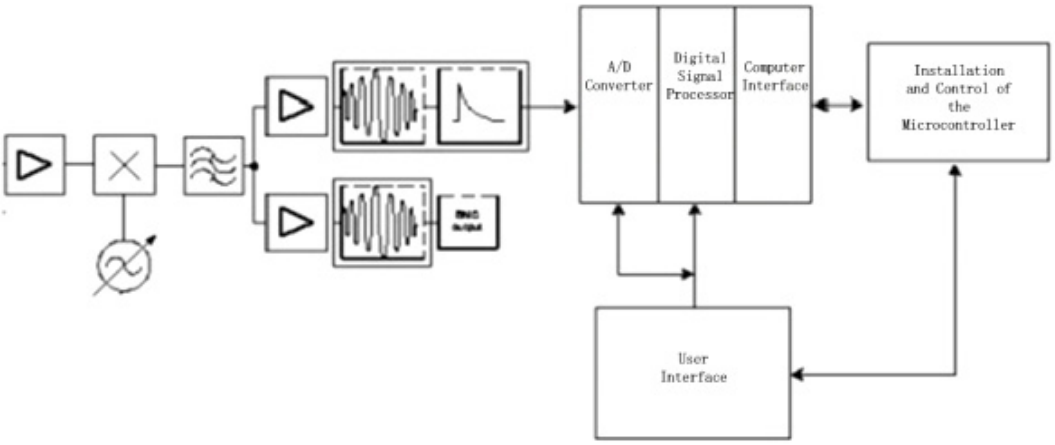


Fig. 2. UHF Detection System.

2.3. Typical Defect Model

This paper simulates six typical partial discharge models, including free metal particles, floating potential, bus metal spike, shell metal spike, insulator surface metal particles and insulator bubbles, whose structure is shown from Fig.3 to Fig 8.And in these figures, the left side is the defect model, the right side is the camera monitor picture. The six testing models are described as follows:

Type A: Free particle consists of five iron balls whose diameter is 0.3 cm and twenty five iron balls whose diameter is 0.5 cm, these balls were put into a hemispherical glass with 3 cm long and 2 cm diameter.

Type B: Floating potential consists of a round pie copper with 0.8 cm thickness and 4 cm diameter.

Type C: Bus metal spike consists of round pie with 0.8 cm thickness and 3 cm diameter, and cylinder with column 0.5 cm length and 1 cm diameter, and conical with cone 1 cm length and 1 cm diameter .

Type D: Shell metal spike consists of copper cone with cone 1.5cm length and 1cm bottom diameter.

Type E: Insulator surface metal particles consist of cylindrical PTFE with 2.5 cm diameter and 7 cm long, whose surface is stuck copper metal powder with glue.

Type F: Insulator bubbles consist of cylindrical epoxy resin with 4 cm diameter, 6 cm length, it was filled with many bubbles, at the bottom of which is a cylinder with 1cm long and 1 cm diameter.

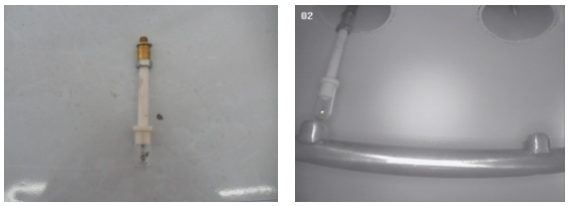


Fig. 3. Free Metal Particles Model.

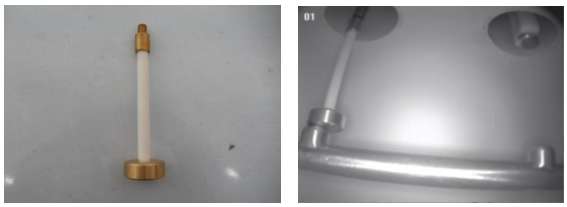


Fig. 4. Floating Potential Model.

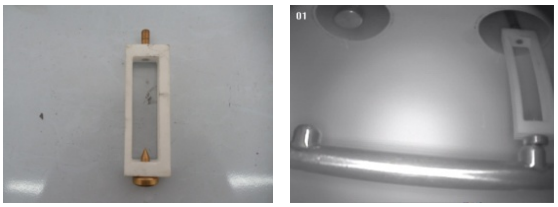


Fig. 5. Bus Metal Spike Model.

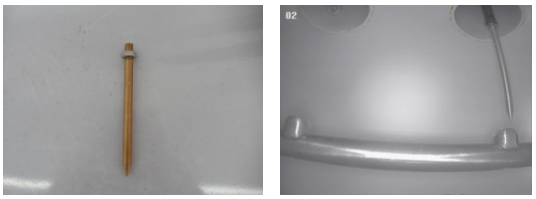


Fig. 6. Shell Metal Spike Model.

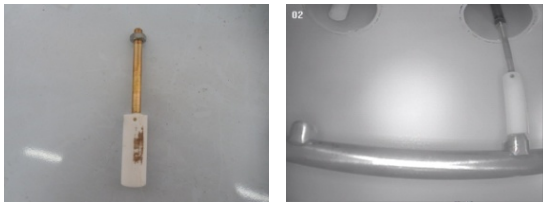


Fig. 7. Insulator Surface Metal Particles Model.

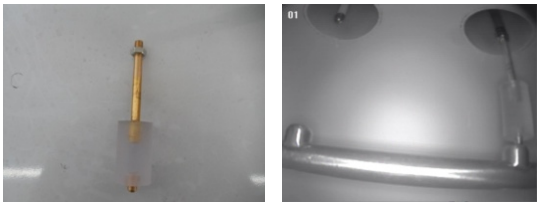


Fig. 8. Insulator Bubbles Model.

3. Experimental Result

The UHF signals from signal receiver is sent to the computer operator interface, 50 cycles in 1 second of the discharge are saved as a sample, 10 samples will be superposition of a spectrum of PRPD discharge information. Specific types of various defects PRPD spectrum and three dimensional spectrum and their characteristics are shown in Table 1.

4. Discharge Fingerprint Extraction

Extract of *n-φ, n-q, q-φ* fingerprint of discharge spectrum can get some useful statistical operator. Currently, the main statistical operator of partial discharge spectrum is as follows:

1) Skewness.

Skewness (S_k) is described as deflection of the shape compared with standard normal distribution.

$$S_k = \sum_{i=1}^{w} p_i(\varphi - \mu)^3 / \sigma^3 \tag{1}$$

The formula, W is the number of phase windows of half cycle, this paper take 2 for a phase window, so W is 90, φ_i is the phase of the i^{th} phase window, P_i, μ,σ is the probability, mean, standard deviation which occurred in phase window i when φ_i as a variable. Calculated formula (2), (3), (4) are as follows:

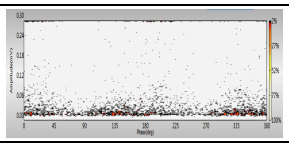
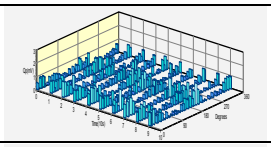
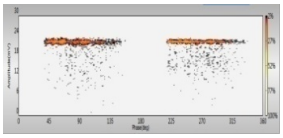
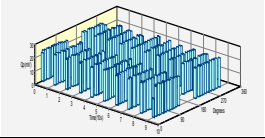
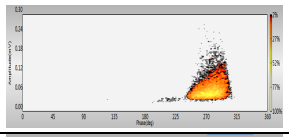
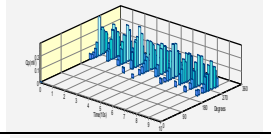
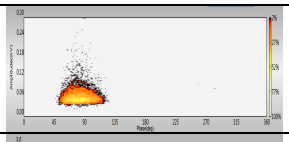
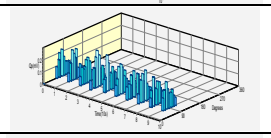
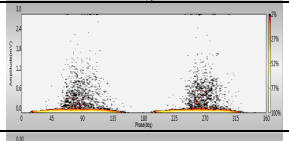
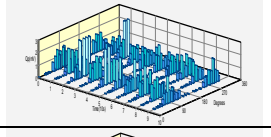
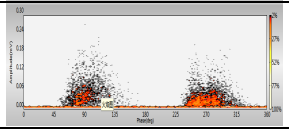
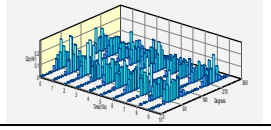
$$P_i = y_i / \sum_{i=1}^{w} y_i \tag{2}$$

The formula, y_i indicates the discharge rate n or discharge capacity q.

$$\mu = \sum_{i=1}^{w} p_i \phi_i \tag{3}$$

$$\sigma = \sqrt{\sum_{i=1}^{w} p_i(\phi_i - \mu)^2} \tag{4}$$

Table 1. Character of six types of defect PD sources.

Defects typical	PRPD spectrum	3-D spectrum	PD characteristics
Free Metal Particles			The discharge phase information is not obvious, and the entire discharge can happen in any phase.
Floating Metal			Both half waves have discharge, and the phase information is remarkable, and most of the discharge in a stationary amplitude.
Bus Metal Spike			Only the negative half wave has discharge, and phase information is remarkable, and shaped like a conical.
Shell Metal Spike			Only the positive half wave has the discharge, and phase information is remarkable, and shaped like a conical.
Insulator Surface Metal Particles			Both half waves have discharge, discharge divide into two tiers, the upper phase information is remarkable, and the lower is not.
Insulator Bubbles			Both half waves have discharge, the lower discharge occurred in the whole phase, the upper phase information is remarkable.

2) Kurtosis.

Kurtosis (K_u) represents the spectrum precipitous differences compared with standard normal distribution. K_u is shown in formula (5).

$$K_u = \frac{\sum_{i=1}^{w}(\varphi_i - \mu)^4 \bullet p_i}{\sigma^4} - 3 \tag{5}$$

The meaning of each variable in the formula is the same as with the skewness.

3) Cross correlation coefficient.

Cross correlation coefficient describes that it will be obvious differences in the distribution of positive and negative half cycle of the PD system discharge conditions in the asymmetric electrode, the formula is as follows:

$$CC = \frac{\sum_{i=1}^{w} q_i^+ q_i^- - (\sum_{i=1}^{w} q_i^+ \sum_{i=1}^{w} q_i^-)/w}{\sqrt{[\sum_{i=1}^{w}(q_i^+)^2 - (\sum_{i=1}^{w} q_i^+)^2/w][\sum_{i=1}^{w}(q_i^-)^2 - (\sum_{i=1}^{w} q_i^-)^2/w]}} \tag{6}$$

In the formula, q_i is the average discharge capacity in the phase window i of spectrum, the superscript "+/–" corresponds to the positive and negative half-cycle in the q-φ spectrum.

4) Discharge capacity factor.

The discharge capacity factor is the reaction of difference of positive and negative half-cycle of spectrum, formula as follows:

$$Q = \frac{\sum_{i=1}^{w} n_i^- q_i^-}{\sum_{i=1}^{w} n_i^-} \Big/ \frac{\sum_{i=1}^{w} n_i^+ q_i^+}{\sum_{i=1}^{w} n_i^+} \tag{7}$$

In the formula, n_i is discharge times when discharge capacity factor is q_i in the discharge cycles.

5) Modified cross correlation coefficient.

The cross correlation coefficient CC and discharge factor Q combined together would constitute a new characteristic quantity – modified cross correlation coefficient, the formula as follows:

$$Mcc = CC \bullet Q \tag{8}$$

Although the operators has the Mcc, it does not means the CC and Q lost sense, because in some discharge pattern $CC<1$, $Q>1$, CC and Q have different trends, discharge pattern CC and Q still have discrimination.

Constituted by these parameters, PD pattern recognition statistical operators is:

$$V=(S_{kq+}, K_{kq+}, S_{kq-}, K_{kq-}, S_{kn+}, K_{kn+}, S_{kn-}, K_{kn-}, CC, Q, M_{CC}) \tag{9}$$

5. Pattern Classification

5.1 Data Normalization

This paper is normalized in the range -1 to 1, namely coordinate distribution of the statistics, formula is as follows:

$$Y = \frac{(Y\max - Y\min) * (X - X\min)}{(X\max - X\min)} + Y\min \quad (10)$$

5.2. Support Vector Machine

Support vector machine (SVM) is proposed a small sample statistical theory [9] by Vapnik et al, it can solve the problem of artificial neural network over learning, less learning, and easy to fall into local minima. SVM learning theory is actually in the process to find the optimal classification surface:

$$w \bullet \phi(x) + b = 0 \quad (11)$$

Decision function is:

$$y(x) = sign[w \bullet \phi(x) + b] \quad (12)$$

In this paper, pattern recognition of statistical operators which has been extracted by using the National Taiwan University Lin Chih-Jen et al. has developed a library for Support Vector Machines (LIBSVM) which based on sequential minimal optimization algorithm [10]. A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one "target value"(i.e. the class labels) and several "attributes" (i.e. the features or observed variables). The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes. Given a training set of instance-label pairs (x_i, y_i), i=1,…,l where $x_i \in R$ and $y \in \{-1,1\}^l$, the support vector machines (SVM) require the solution of the following optimization problem:

$$\min_{w,b,\xi} \ \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \quad (13)$$

$$y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0. \quad (14)$$

Decision function is:

$$\operatorname{sgn}(w^T \phi(x) + b) = \operatorname{sgn}(\sum_{i=1}^{l} y_i a_i K(x_i, x) + b) \quad (15)$$

Training vector x_i is mapped into a high dimensional space by the function Φ, SVM in high dimensional space to find an optimal linear separating plane, C>0 is a penalty parameter of error term, great C come great penalty for misclassification, and:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \quad (16)$$

is called kernel function, which includes linear, polynomial, radial basis function, sigmoid. This paper chose radial basis function (RBF):

$$K(x_i, x_j) = \phi(x_i)\phi(x_j) = \exp(-g\|x_i - x_j\|^2) \quad g>0 \quad (17)$$

Parameters -g (gamma) is the same as the common Gaussian kernel $1/2\sigma^2$, the default value is the reciprocal of attribute, decision function is:

$$y(x) = sign[\sum_{x_i \in SV} a_i y_i K(x_i, x) + b] \quad (18)$$

Threshold function b is:

$$b = \frac{1}{N_{NSV}} \sum_{x_i \in SV} (y_i - \sum_{x_j \in SV} a_j y_j K(x_j, x_i) \quad (19)$$

The penalty parameter C is set to 2, Kernel function parameter g is set to 0.02, others parameters are default values. Total recognition accuracy is 84.5238%, and recognition of each group as shown in Table 2.

As the Table 2 showed, there is a high recognition accuracy in each defect, except the bus metal spike, the bus metal spike recognition accuracy is only 35.71 %, the wrong part of classification placed in insulator particles. This implies that the operator of bus metal spike is similar as insulator particles. In order to make sure the accuracy of classification of all defects, it necessary to make recognition further.

Since SVM does not support multi-classification drawing, this paper only draws two insulator defects which shown in Fig. 9, the "+" of class 1 are insulators bubbles and the "*" of class 2 are insulator surface metal particles. Circled by the blue are support vectors, the green line "0" is the two types of classification optimal plane, the defects from line -1 to line 1 are the support vectors, the left side of line "0" should be "+" of class 1, so the "*" in the left side of line "0" are the wrong classification and vice versa. The two types of recognition accuracy is 96.4286 %, regression mean square error is 1.21858.

In classification problems, penalty parameter C controls the misclassified samples severity of the punishment and its size affects the accuracy of the system. Kernel function parameter g controls the ability to the kernel function identify, and its size

affects the generalization ability of the entire system. Therefore, these two parameters have a great influence on the support vector machine identification ability. This paper applies particle swarm optimization method and grid search method for finding the optimal C and g.

Table 2. SVM classification result.

Classification / Original data	Free Metal Particles	Floating Metal	Bus Metal Spike	Shell Metal Spike	Insulator particles	Insulator Bubbles
Free Metal Particles	92.86 %	0	0	0	0	7.14 %
Floating Metal	0	100 %	0	0	0	0
Bus Metal Spike	0	0	35.71 %	0	64.29 %	0
Shell Metal Spike	0	0	0	100 %	0	0
Insulator particles	0	0	0	0	100 %	0
Insulator Bubbles	0	0	14.29 %	0	7.14 %	78.57 %

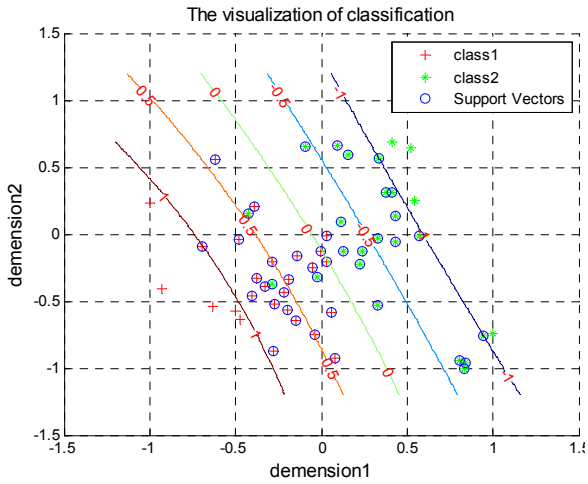


Fig. 9. Support vector figure.

5.3. Particle Swarm Optimization Support Vector Machine

Particle swarm optimization (PSO) was proposed by Eberhart and Kennedy, and its essence is to simulate processes of flying birds. Assuming there are m particles flying in a certain speed in space, in order to determine whether the current flying status is in the best position according to flying experience, these particles can dynamically adjust their flying status according to their own position vector $x_i=(x_{i1},x_{i2},\ldots,x_{id})$ and Flying vector $v_i=(v_{i1},v_{i2},\ldots,v_{id})$ and Companions flying experience [11].

The adjustment process of the algorithm, record current optimum position of individual particles, called individual extreme *pbest*, and record the best individual extreme *gbest* of all particles in the whole group

$$v_{id}^{k+1} = wv \times v_{id}^{k} + c_1 rand(\bullet) \times (pbest - x_{id}^{k}) + c_2 \times rand(\bullet) \times (gbest - x_{id}^{k}) \quad (20)$$

$$x_{id}^{k+1} = x_{id}^{k} + wp \times v_{id}^{k+1} \quad (21)$$

PSO specific optimization as follows:

Step 1: Initialization of the C and g of SVM, meanwhile, initialized the PSO particle velocity vector v to (0, 1) random number. Definition PSO iterations N_{max}=100, the initial population size is 20, inertia weight wv and wp is 1, the variation range of C and g to [0.1, 100], the ability of local search parameters of C1 is 1.5, the ability of global search parameters of C2 is 1.7, Cross validation number is 5.

Step 2: Take the training samples which have initialize into the network, according to the following formula to evaluate the fitness of the particle

$$j = \frac{1}{N}\sum_{d=1}^{N}(h(x)^d - h(x))^2 \quad (22)$$

In the formula, $h(x)$ from the SVM classification function $y(x) = sgn\{h(x)\}$. In the PSO iteration, if the current particle fitness is better than particle fitness of the previous generation, then let the current particle value equal to *pbest*. In the whole population, if some other particles fitness is better than the optimal value of the current particle, then let the value equal *gbest*.

Step 3: Take the *pbest* and *gbest* which have updated into formula (20), (21), then it will produce a new generation of the particle's position and velocity vector.

Step 4: After the current study, if the current number of iterations has reached the preset maximum number or minimum target error, then accords the formula (17) to output final value, or turn to step 1.

Step 5: Finally, test samples input the trained SVM, according to the output to determine the type of defect.

Obtained parameters by the PSO-SVM: *bestc*=3.1809, *bestg*=1.3169, recognition accuracy is 98.7179 %, Fig. 10 is PSO fitness curve, red line is the best fitness, blue line is the average fitness, the average fitness does not have a upward trend, it has been in the low shock.

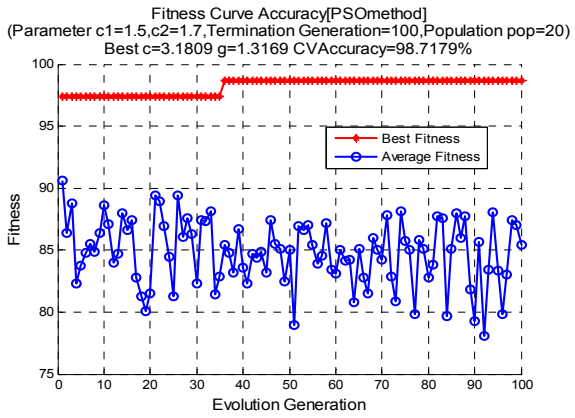


Fig. 10. PSO optimized fitness curve.

5.4. Grid Research Optimization Support Vector Machine

Grid search (GS) optimization SVM is the C and g are take M and N, for $M \times N$ (C, g) combination, training different SVM respectively, and then estimate the learning accuracy, the learning precision highest accuracy combination as the optimal parameter in the $M \times N$ (C,g) combination. Grid search is based on a given step search all combinations of parameters within a rectangle, Specific process is as follows:

Step 1: Set the range of the C and g of grid search and the corresponding search step, Set C and g in the range of (2^{-10}, 2^{10}), step size is 0.5, so the C and g construct a two dimensional grid on the coordinate system,

Step 2: Select a parameter (C, g) in the coordinate system of the structure of C and g, using the SVM for training the training samples. Then predict the test sample, record forecast accuracy.

Step 3: Repeat step 2 until all of the parameters training again in the two dimensional grid.

Step 4: Finally, the values of each group (C, g) correspond prediction accuracy shown with contours, thus determine the best value of (C, g).

Obtained parameters by the GS-SVM: *bestc*=1, *bestg*=0.7071, recognition accuracy is 97.4359 %, Fig. 11 is a contour map of the grid search, the grid can be seen that the position of the highest recognition rate inside the middle of the right side contour line "97", Fig. 12 is a 3D view of the contour lines.

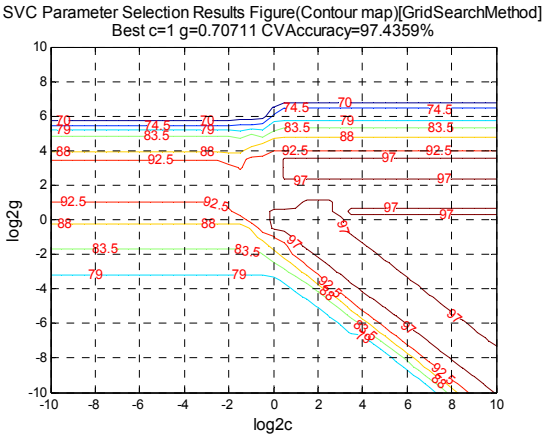


Fig. 11. Contour map.

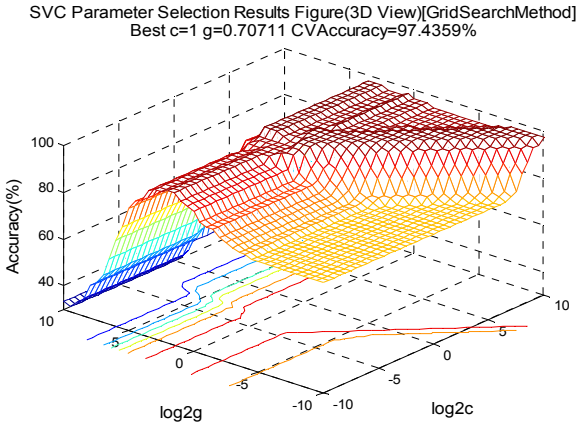


Fig. 12. 3D view.

5.5. Comparison of Two Optimization Methods

At present, for SVM optimization method, the international community has no consistent conclusion. For this paper, comparison of two optimization methods is shown in Table 3. The GS with a shorter running time, and the PSO with a higher accuracy, so the PSO optimization has better robustness and generalization ability than GS optimization.

Table 3. Comparison of two optimization methods.

Method	Run time	Bestc	Bestg	Accuracy
PSO	8.205s	3.1809	1.3169	98.72 %
GS	6.939s	1	0.7071	97.44 %

6. Conclusion

In this paper, according to the GIS application of UHF method of typical defects of partial discharge, conclusions are drawn as follows:

1) UHF method detected spectrum shows different characteristics on different typical defects in GIS.

2) According to different defect of discharge fingerprint extraction, different characteristics will produce different statistical operator, it can be applied to support vector machines for pattern recognition.

3) Two optimization methods of support vector machine were applied for GIS partial discharge pattern recognition, to solve the problem of parameter selection of support vector machine. Two optimization methods of SVM are showing better robustness and generalization ability than the SVM, and the PSO method has a higher recognition rate than GS method.

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References

[1]. Ju Tang, Qian Zhou, Ming Tang, Yanbin Xie, Study on mathematical model for VHF partial discharge of typical insulated defects in GIS, *IEEE Transactions on Dielectrics and Electrical Insulation*, Vol. 14, Issue 1, 2007, pp. 30-38.

[2]. S. Okabe, S. Kaneko, M. Yoshimura, H. Muto, C. Nishida, M. Kamei, Partial discharge diagnosis method using electromagnetic wave mode transformation in gas insulated switchgear, *IEEE Transactions on Dielectrics and Electrical Insulation*, Vol. 14, Issue 3, 2007, pp. 702-709.

[3]. T. Hoshino, S. Maruyama, T. Sakakibara, S. Ohtsuka, M. Hikita, G. Ueta, S. Okabe, Sensitivity of uhf coupler and loop electrode with UHF method and their comparison for detecting partial discharge in GIS, in *Proceedings of the International Conference on Condition Monitoring and Diagnosis (CMD'08)*, 2008, pp. 348-351.

[4]. Tianhui Li, Mingzhe Rong, Chen Zheng, Xiaohua Wang, Development simulation and experiment study on UHF partial discharge sensor in GIS, *IEEE Transactions on Dielectrics and Electrical Insulation,* Vol. 19, Issue 4, 2012, pp. 1421-1430.

[5]. Wensheng Gao, Dengwei Ding, Weidong Liu, Research on the typical partial discharge using the UHF detection method for GIS, *IEEE Transactions on Power Delivery*, Vol. 26, Issue 4, 2011, pp. 2621-2629.

[6]. R. M. Sharkawy, R. S. Mangoubi, T. Abdel-Galil, M. M. A. Salama, R. Bartnikas, SVM classification of contaminating particles in liquid dielectrics using higher order statistics of electrical and acoustic PD measurements, *IEEE Transactions on Dielectrics and Electrical Insulation*, Vol. 14, Issue 3, 2007, pp. 669-678.

[7]. Zaoqi Bian, Xuegong Zhang, Pattern recognition, *Tsinghua University*, 2000.

[8]. L. Hao, P. L. Lewin, Partial discharge source discrimination using a support vector machine, *IEEE Transactions on Dielectrics and Electrical Insulation*, Vol. 17, Issue 1, 2010, pp. 189-197.

[9]. V. Vapnik, The nature of statistical learning theory, *Springer-Verlag*, 1999.

[10]. C. C. Chang, C. J. Lin, LIBSVM: a library for support vector machines, *ACM Transactions on Intelligent Systems and Technology*, Vol. 2, No. 273SI, 2011.

[11]. S. W. Lin, K. C. Ying, S. C. Chen, Z. J. Lee, Particle swarm optimization for parameter determination and feature selection of support vector machines, *Expert Systems with Applications*, Vol. 35, No. 4, 2008, pp. 1817-1824.

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