Research on the Condition Monitoring of Transmission and Transformation Equipment Based on Improved Support Vector Machine in the Internet of Things

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Abstract. The realization of smart grid is based on the real-time command of important operation parameters of power transmission and transformation equipment. The Internet of things has powerful capabilities of information collection and interactive, which can be used as the support for the condition monitoring of transmission and transformation equipment in the smart grid environment. This paper takes the power grid equipment as the center, takes intelligent on-line monitoring of equipment as the direction, starting from the equipment condition assessment and fault types, carried out the research about of grid equipment real-time state monitoring and fault diagnosis under the environment of Internet of things. Paper mainly includes: constructing the status evaluation framework and real-time evaluation model of power grid equipment from the angle of the status value of on-line monitoring of IoT, using support vector machine (SVM) for power transmission and transformation equipment condition monitoring, choosing a suitable kernel function by comparing the linear kernel function, polynomial kernel function, the radial basis kernel function and multilayer perceptron kernel function of multiple parameters; by analyzing the traditional cross-validation method, this paper proposed the improved cross validation (K-CV) method, and we use Actual data of power grid field as the sample, finally obtain the fault classification result by constant parameter optimization. The experimental result shows that the support vector machine based on improved 10-CV cross-validation method in the Internet of things is able to monitor the condition of transmission and transformation equipment more rapidly and accurately.

Keywords: Internet of Things
Power transmission and transformation equipment
On-line monitoring · Support vector machines (SVM)

1 Preface

Content service net is the product of the information technology developing, its meaning is defined by the Ashton scholar at the Massachusetts institute of technology, they said the Internet of things is a network which uses A range of sensing devices such

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as RFID to realize the interconnection of objects and the Internet, this technology can realize objects' intelligent identification and real-time management [1]. The international telecommunication union launched a specific research report about the Internet of things in the early 20th century, the report makes a comprehensive description of the Internet of things, namely a network which can be applied to all items to realize the information interaction, Internet of things can also make a more effective application of wireless sensors, RFID radio frequency technology and other advanced technology.

At present, the Internet of things can be widely used in all sorts of objects. Through deploying different form of sensor devices at different positions, with the communication network specified in standard protocol, the Internet of things can realize the safe and reliable transfer of data, and also achieve objects like the uniformed services, collaborative processing, data association and real-time monitoring. The Internet of things makes many changes in technology from birth, from using the radio frequency identification technology to construct logistics network, to using the Internet technology, wireless sensor technology, nanotechnology, big data and cloud computing technology for data acquisition, data transmission and analysis, which implement the exchange of information between people and objects or objects and objects in wide-area scope. In fact, the basic network structure should include the perception layer, network layer and application layer according to the function implementation of the Internet of things platform, as shown in Fig. 1.

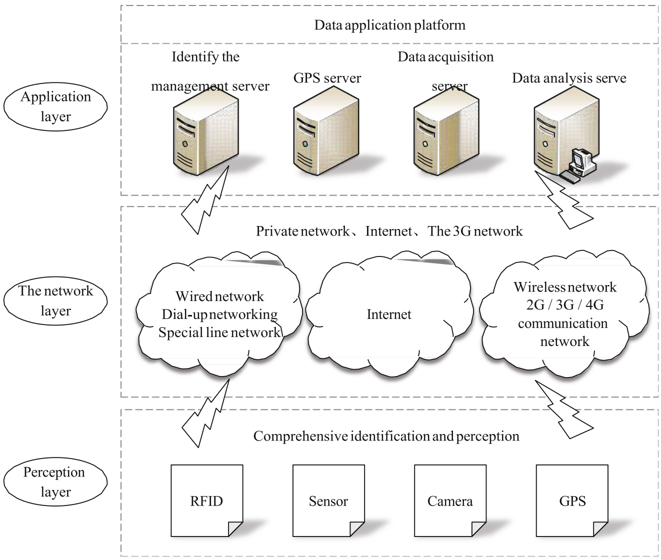

Fig. 1. Simple three-layer network structure diagram

The concept of IOTIPS (Internet Of Things In Power System) is apply the Internet of things platform too electric power system industry, which refers to using the sensors related to Internet of things to get monitoring information of power grid equipment, to transmit monitoring information of specific network, and process the information with certain means (Intelligent Methods, Data Mining, etc.), and finally realizes the intelligent data acquisition, fault diagnosis and maintenance decision support of power grid equipment. IOTIPS is applied in every link in smart grid, and also has been practicing and developing constantly, the application of Internet of things can not only promote the intelligent level of power system, but also realize the efficient management of the equipment operation, which promoting the combination of the informatization and the integration of power system.

During the period of power generation, using power Internet make a great improvement of the monitoring situation of equipment state. During the transmission phase, the Internet of things can realize the real-time monitoring of transmission equipment and lines, which ensures the safe equipment operation, and improve the efficiency and reliability of the equipment. In the stage of transformation, the Internet of things can accurately monitor the relevant parts of the substation and reduce the unnecessary loss of the equipment; In the stage of the power distribution, the Internet of things technology can monitor, diagnose and analyze the distribution network state, to ensure a safe and reliable operation of the distribution network, and enhance the level of power supply and reduce the risk of loss and maintenance equipment. The common application architecture for IOTIPS is shown in Fig. 2.

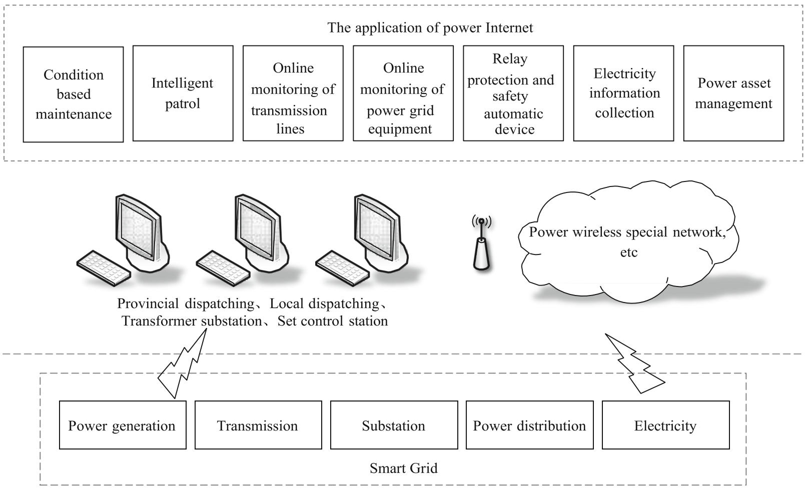

Fig. 2. Schematic diagram of network architecture of power Internet

2 State Monitoring and Maintenance Decision

There are two kinds of data collected by equipment condition monitoring which are online data and offline data. Real-time online data collection, relying on the Internet of things technology, is basis for equipment condition assessment, fault diagnosis and maintenance decision. State monitoring and timely key data acquisition can be done through some key technology in Internet of things, which can monitor the main equipment in power grid operation, such as power transformer, high voltage circuit breaker, transmission line. Such as the real-time data for transformers is transformer oil status and gas content, partial discharge and Operating Humidity; High voltage circuit breaker can use vibrating sensors to collect machinery vibration signal, combined with network transmission technology, the data can be uploaded to the server for processing. When there is abnormal vibration, warning can be sent; the online monitoring of transmission lines also has a certain development, which is constructing the correlation between the leakage current of the insulator surface and the degree of pollution, and estimate the operation state of the insulator by monitoring the leakage current of the device.

The maintenance decision of the power grid equipment's state is based on the condition monitoring and trend analysis of equipment, implementing condition-based maintenance requires timely monitoring of power grid equipment operation, and obtaining information such as the real-time running parameters [2]. In the Internet of things' environment, real-time monitoring can be used to detect the parameters of the relevant parameters of power grid equipment through intelligent sensing device, which can be used to acquire the status information of the component movement, vibration signal, loop current and real-time temperature of the equipment. By analyzing the data obtained from these sensors and the data of the off-line test, it can detect the running state and potential failure problems of the power grid equipment, so as to formulate a reasonable maintenance plan [3]. Based on the factors such as reliability, security and economy, introducing the expert decision-making system can guarantee these factors reach an acceptable level. In order to select the most suitable maintenance scheme for equipment maintenance, effectively reduce the loss and impact of blind routine maintenance to ensure timely and reliable power supply, improve the efficiency use of equipment and reduce maintenance risk.

3 Improved Support Vector Machine Status Monitoring

3.1 Support Vector Machine

Support Vector Machine (SVM) is a universal learning algorithm for realizing structural risk minimization principle, which is suitable for classification of small sample data [4]. The core idea is to transform nonlinear problems in low dimensional space into high dimensional linear problems through kernel functions, the kernel function is the key to the nonlinear transformation in SVM. SVM is a binary classifier, and it is necessary to construct multivariate classifier for fault diagnosis for multiple fault types.

According to the principle of SVM and the characteristics of the power transmission and transformation equipment condition monitoring, taking the most common hexafluoride high voltage circuit breaker as an example. The support vector machine condition monitoring method is proposed, and the system structure is shown in Fig. 3:

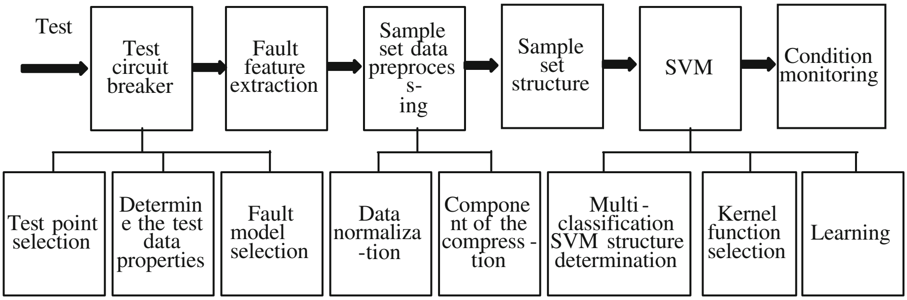

Fig. 3. The fault diagnosis structure of high voltage circuit breaker based on SVM

3.2 Sample Data Pretreatment

3.2.1 K-Means Clustering Algorithm Initialization

K-means clustering algorithm is an unsupervised machine learning algorithm, its essence is to group the data that people don't know beforehand, make the data in the same group as similar as possible and the data in different groups as different as possible, its purpose is to reveal the true status of the distribution of data [5]. K-means clustering algorithm is based on random clustering center, whose parameter K is the sampling frequency. Generally speaking, K takes 3–10 [6], and the overall square error criterion has converged. In this paper, the original data is preprocessed by this algorithm, and some data deviation is greatly removed, so it is not easy to have high dimensional partitioning in support vector machine operation.

Based on the data of actual case, the samples for the 4D of four types of data, normal and fault code expressed with N, P_1, P_2, P_3 respectively (As described in Sect. 4.1), the K-means clustering algorithm is used for data initialization, as shown in Fig. 4.

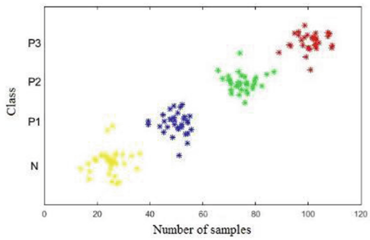

Fig. 4. K-means clustering algorithm preclassification

3.2.2 Sample Normalization

Based on the support vector machine theory, the focus of the high voltage circuit breaker status monitoring is how to convert the collected sample data into data suitable for support vector machine processing. When the sample value fluctuates a lot, it applies to all equally small data in the data group, which avoids difficult problems like the big data occupies the dominant position and calculation in support vector machine training, In the literature [7], why the scale transformation is elaborated, the ultimate goal is to use unified standard conversion to the same range of [0, 1] or [1, + 1], so the scale transform is also called the normalized and standardized [8]. The data is transformed to [a, b], as shown in Eq. 1:

$$\bar{x}_i = a + (b \quad a) \times \frac{x_i \quad x_{\min}}{x_{\max} \quad x_{\min}} \tag{1}$$

x_i is the sample data, x_{min} is the smallest data of sample concentration value, and x_{max} is the largest data of the sample concentration value.

3.3 Selection of Kernel Function and Its Parameters

The function of the kernel is to map the input space to the characteristic space of high dimensional [9], which means using different kernel functions can get different high-dimensional feature space, the kernel function parameter changes influenced the distribution of the sample data in the complexity of high dimensional feature space, thus, the generalization ability of the optimal classification hyperplane obtained in the feature space is affected.

Select the characteristic parameter of linear kernel function, polynomial kernel function, the radial basis function (RBF) and multi-layer perceptron kernel function (MLP), and a one-to-one method is used to train multi-classification support vector machines, The number and classification of support vectors for different kernel parameters are compared, and the training time and test time are compared respectively. The results are shown in Tables 1, 2, 3 and 4.

Table 1. Polynomial kernel function SVM diagnosis results (C = 10)

Nuclear parameter γ	The number of SV	Proportion of SV	Training time (s)	The test of time (s)	Classification accuracy
2	613	33.17%	2.73	0.52	91.31%
4	397	21.47%	3.06	0.43	93.25%
6	459	24.87%	4.25	0.49	87.38%

Table 2. SVM diagnosis result of gaussian kernel function (C = 10)

Nuclear parameter γ	The number of SV	Proportion of SV	Training time (s)	The test of time (s)	Classification accuracy
0.5	833	46.27%	2.85	0.48	80.13%
1	765	43.27%	1.73	0.82	93.37%
2	750	41.65%	2.11	0.38	89.32%

Table 3. Radial basis kernel function SVM diagnosis result (C = 10)

Nuclear parameter γ	The number of SV	Proportion of SV	Training time (s)	The test of time (s)	Classification accuracy
0.5	823	47.17%	2.56	0.99	96.53%
1	765	42.47%	3.45	1.21	97.85%
2	751	41.67%	1.30	0.81	92.34%

Table 4. The diagnostic result of SVM for multi-layer perceptron kernel function (C = 10)

Nuclear parameter ρ and b	The number of SV	Proportion of SV	Training time (s)	The test of time (s)	Classification accuracy
0.1, −1	1126	65.3%	5.78	1.98	84.78%
0.1, −1.5	1401	77.6%	5.26	1.23	93.21%
0.1, −2	1327	73.12%	4.98	2.03	84.36%

The experimental results (Tables 1 and 4) shows that the support vector machines with radial basis and polynomial kernel function are better than those of the other two kernel functions. Among them, the number of support vector machines with multinomial kernel is the least, and the multi-layer perceptron kernel has the most support vector, the longest training and testing time, and the shortest training time of gaussian kernel.

3.4 Improved K-CV Cross Validation Method

With regard to optimization of SVM parameters, there is no universally acknowledged best method in the world, and many of them are Cross Validation (CV) method. CV method is used to examine the effects of machine learning, its essence is to divide the sample data into training sets and validation sets, and with the training set to train a classifier and using validation set to test the classification accuracy of the model, and also test the performance of classifiers [10]. In most literatures, [11] the CV method is the original data were randomly divided into training set and validation set two groups, the first adopts the training set training classifier, and then using a validation set to test model, the classification accuracy is used as the criterion. This Method is called Hold-Out Method, the advantages of this method is obvious: random and simple classification, running fast, but essentially speaking, Hold-Out Method is not a cross-validation method, because this method does not meet the ideas of the cross, simply random grouping, therefore, the classification accuracy of the final verification set lacks relative independence, leading to the result is not convincing. This paper proposes a modified Hold-Out Method (K-CV Method) based on Hold-Out Method, Divide the original data into K groups evenly, Make a validation set of each subset data respectively, The rest of the k − 1 subset data is used as a training set, it will get K models, as shown in Fig. 5, the arithmetic mean of classification accuracy of K model was adopted, namely, $\frac{1}{C_K^{K-1}}\sum_{I=1}^{K} P_i$ as the K-CV Method under the performance of the classifier. K is generally greater than or equal to 2 (Only Take 2, When the Data Volume of the Original Data Collection is Very Small), during the actual operation, K is usually from 3, and in this paper K is 10. K-CV method abandoned the traditional random grouping method, it overcomes the difficulties of the classification accuracy of verification set is related to the original data grouping largely, which ensure the classification accuracy of the objective independence.

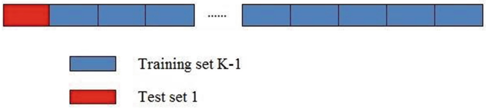

Fig. 5. K-CV cross validation method

Table 5 using the 10-cv to match the difference between the different nuclear function and the sorting time. The best effect is adopted when using RBF kernel function, and when using the polynomial kernel function is basically lost the significance of identification, its error rate is much bigger, it shows that under the kernel mapping, the different categories of parametric mixed together, became highly inseparable. Gaussian kernel function and multi-layer perceptron kernel function are not suitable for sulfur hexafluoride high voltage circuit breaker fault classification, integrated all the above factors, the RBF kernel function is chosen as the kernel function.

Table 5. Comparison of different kernel function under 10-CV method

Kernel function	Recognition rate (%)	Classification of time (s)
Polynomial kernel function	77.48	10.32
Gaussian kernel function (d = 3)	91.7	13.57
Radial basis kernel function (C = 10)	97.56	13.6
Multi-layer perceptron kernel function	91.23	21.65

Penalty parameters C and γ are two important parameters of RBF kernel function, the impact on the accuracy of the SVM diagnosis is big, too large value or too small value of C, will make the generalization ability of the system become poor, γ reflects the characteristics of the training data, it also has great influence on the generalization ability of the system.

4 Status Monitoring Cases

4.1 Test Data Set Description and Data Visualization

In this paper, we use the data from the LW25-252/T4000-50 circuit breaker which is installed in the third set of the west Shijiazhuang substation of Hebei electric power company EHV transmission and substation branch and produced by Xi'an High voltage switch Co Ltd. Fault types are as follows: base screw loosening, shock absorbers with extra impacting and motion parts falling off (Fault Codes Are P_1, P_2, And P_3 Respectively Express). Each fault type detects the breaker contact stroke, the breaker vibration signal, the breaker action coil current, and the main loop current 4 attributes respectively (Dimensions Are Represented by x_1, x_2, x_3, x_4). The data collector collects 120 points per phase at the rate of 25 kHz when the circuit breaker is simulated, and the data is transmitted to the PC via the rs-232-C bus to be preprocessed, and the signal is soft threshold denoising respectively. The data are shown in Table 6.

Table 6. High voltage circuit breaker characteristics sample data

Fault type	x_1	x_2	x_3	x_4
N	175.9	163.15	1.955	14.6
	177.1	178.9	2.38	8.64
	183.1	173.6	2.7783	13.5
	……	……	……	……
P_1	192.2	156.55	2.635	12.2
	205.6	159.32	2.3375	12.4
	192.7	155.4	2.448	16.8
	……	……	……	……
P_2	190.4	134.3	1.325	7.2
	181.8	124	1.265	6.1
	185.2	136.4	2.0825	4.3
	……	……	……	……
P_3	190.4	145.7	1.377	14.2
	204.5	137.94	1.172	7.7
	178.2	148.8	1.5215	11.3
	……	……	……	……

In order to provide an overview of the data statistics feature, data visualization operation is performed for data after preprocessing, and its data "boxplot" is shown in Fig. 6, the 120 groups of data are divided into the training set and the test set according to the 10-cv cross test model of the previous text subsequently, and the results are shown in Fig. 7.

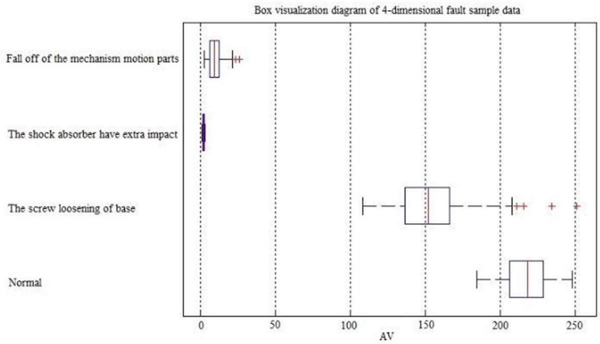

Fig. 6. 4-dimensional failure sample box diagram

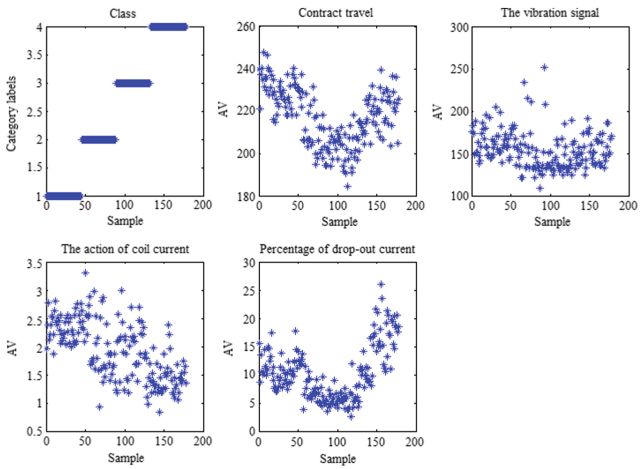

Fig. 7. Fractal dimension visualization diagram of fault samples

4.2 Parameter Optimization Based on RBF Kernel Function 10-CV Cross Validation Method

The original data was divided into 10 groups (Mean Points) to form the 10-cv cross validation method for parameter optimization. It usually uses a grid optimization algorithm or Particle Swarm Optimization (PSO—Particle Swarm Optimization) algorithm, although grid optimization can be used to find the highest classification accuracy in CV, which is the global optimal solution, But sometimes it takes a lot of time to find the best parameter C and γ, if you have a higher number of categories or in a larger range; the particle swarm optimization algorithm uses heuristic algorithm to avoid all the parameter points in the grid. And it is similar with genetic algorithm, which is a kind of based on iterative optimization algorithm, the system is initialized to a group of random solutions, It doesn't have the CV cross-thinking that the genetic algorithm uses. It's the particle that's searching for the optimal particle in the solution space. In view of this problem, in this paper, we use the gradual approximation method to optimize the parameters. First, we roughly search the suitable value of C and γ in a large range, so that the variation of values of C and γ are all 2^{-10}, 2^{-9}, …, 2^{10} and the simulation results are shown in Fig. 8:

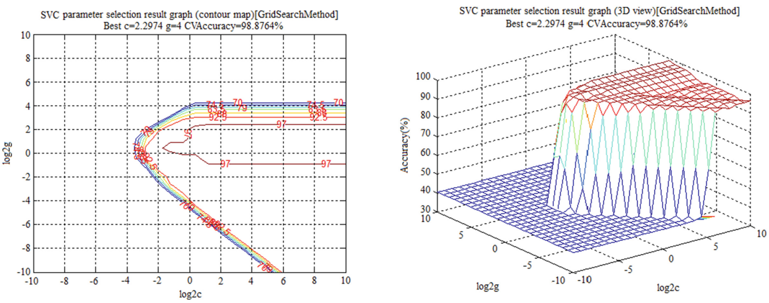

Fig. 8. Parameter optimization result graph (rough optimization)

In Fig. 8, The x axis is the value of the log base 2 of C, The Y-axis is the value γ of the log base 2, The contour line represents the accuracy of the 10-cv method corresponding to the corresponding C and γ value. As can be seen from the graph, the range of C can be narrowed down to 2^{-2}–2^{4}, and the range of γ can be reduced to 2^{-2}–2^{4}, so that the selection of parameters can be further refined based on the rough parameter selection above.

Change the value of C to: 2^{-2}, $2^{-1.5}$, …, 2^{4}, change the value of γ to 2^{-4}, $2^{-3.5}$, …, 2^{4}, and the change interval of the final parameter selection result graph is set to 0.9, so that the change of accuracy can be seen more clearly.

You can see that under the 10-cv method, the optimal parameter is C = 1.41421, γ = 1. As shown in Fig. 9.

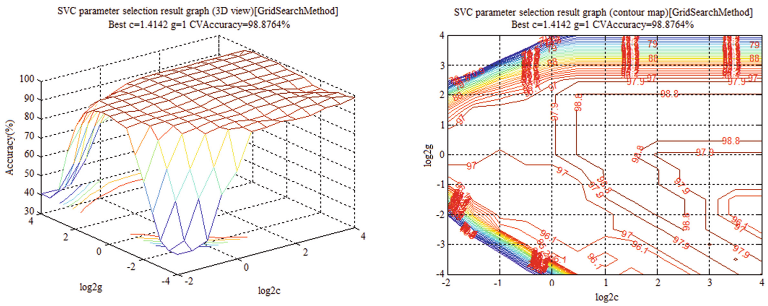

Fig. 9. Parametric optimization result graph (fine tuning)

4.3 Performance Evaluation and Analysis of Results

Receiver Operating Characteristic (ROC) is a visual evaluation of the performance of the classifier, which gives the competition relation between TPR and FPR of the classifier in the form of curve [12]. The horizontal axis in the ROC curve represents the false positive rate of FPR and the vertical axis represents real rate of TPR, and establish the two-dimensional plane rectangular coordinate system that at the origin, TPR = FPR = 0 [13]. Starting at the origin, if a sample is a positive sample of the correct classification, that is, a real data sample, TPR increases. In the ROC curve, move up and draw a point. In the ROC curve, move to the right and draw a point. If the classifier classifies a negative sample as positive, the false positive sample appears, then FPR increases. In the ROC curve, move to the right and draw a point. As the sample expands, so does the number of categories and negatives.

Figure 10 shows the ROC curve diagram of the test data set. In this data set, empirical parameters, rough parameter searching, and fine parameters are used respectively to correspond to three serrated curves of blue, green and red respectively, namely ROC curve. The diagonals in the graph are the ROC curves of random guesses. In general, If the curve is closer to the point (0, 1), the curve of TPR is higher, its classification performance the better. It can be seen that the classification performance is excellent as the parameters are optimized.

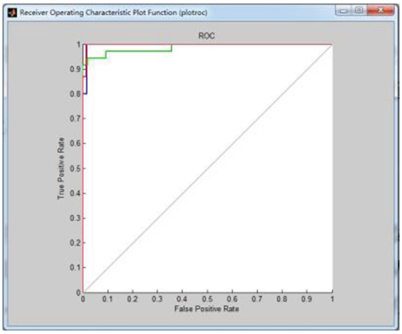

Fig. 10. The ROC curve quantifies schematic diagram (Color figure online)

After the parameters are optimized, and the SVM condition monitoring can be carried out on the field data. The results of the test set, as shown in Fig. 11, test classification accuracy to 98.8764%. As we can see from Fig. 11, although the classification effect is excellent, there are still outliers. This is associated with the selection of penalty parameter, although the classification accuracy is not 100%, but the purpose of parameter optimization is to find the best generalization properties, through a large number of field data validation, this method has good classification features, can be used in power transmission and transformation equipment condition monitoring.

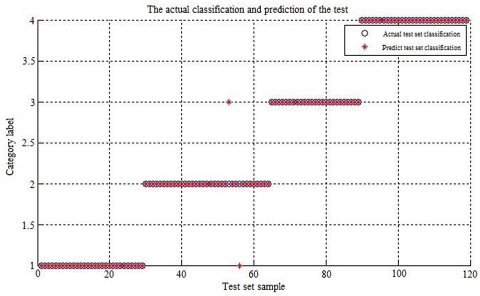

Fig. 11. Test set classification result graph

5 Conclusion

This article first expounds the relevant technology of the Internet of things, by analyzing the Internet of things monitoring technology and equipment condition monitoring, the relationship between construction of electric power of the Internet of things network architecture, which leads to the power grid equipment condition assessment and maintenance decision and the meaning of research and analysis. Then on the basis of support vector machine (SVM) theory, through the calculation of actual data to compare various kernel function classification accuracy, based on the analysis of traditional Method Hold-Out Method on the basis of in-depth study, put forward the modified 10-CV cross validation Method of optimization of support vector machine (SVM) classification Method, abandoned the traditional random grouping Method, the original data to overcome the classification accuracy with the original data of validation set grouping of excessive related this defect. Parameters of support vector machine (SVM) is put forward at the same time step by step optimization method, this method overcomes the grid optimization time consuming and the idea of particle swarm optimization algorithm optimization without crossing faults, can greatly accelerate the rate of parameter optimization, especially when dealing with high dimensional or large amount of data, and then to the subjects operating curve and classification accuracy as the criterion, has obtained the good diagnosis effect. Analysis results show that the proposed feature extraction method can effectively extract the fault signal characteristic, compared with the traditional methods, based on the radial basis kernel function is modified 10-CV cross validation method of support vector function is more rapid, accurate judgment high voltage circuit breaker mechanical fault type, and has good generalization.

Finally test validation tests, LW25-252/T4000-50 type sulfur hexafluoride high voltage circuit breaker condition monitoring, for example, in a normal state and base screw loosening, shock absorber, the mechanism motion parts have extra impact loss under three kinds of fault circuit breaker contact trip, breaker vibration signals, the main loop of the circuit breaker action coil current, current four properties of 120 groups of signals as the input sample set. The model parameters of support vector machine were optimized by using the improved 10-cv cross validation method, and the test results were obtained by using the operation curve and classification accuracy of the subject.

Test results meet the requirements of power transmission and transformation equipment condition monitoring design, test results coincide with theoretical analysis, compared with the traditional methods, based on improved support vector function is more rapid, accurate judgment power transmission and transformation equipment failure type, meet the power grid equipment under Internet real-time condition monitoring and fault diagnosis of demand.

References

1. Wu, C., Cheng, L., Tian, Z., et al.: Online monitoring system of substation based on the Internet of Things. New Technol. Electr. Electr. Power **32**(4), 110–114 (2015)
2. Yang, J., Fang, B., Zhai, L., et al.: Research on the security model of general control system for the Internet of Things. J. Commun. **33**(11), 49–56 (2014)
3. Huang, X., Zhang, Y., Zhu, Y., et al.: Research on transmission and transformation equipment monitoring system based on the Internet of Things. Power Syst. Prot. Control **41** (9), 137–141 (2016)
4. Li, L., Zhang, Z.: The application of support vector machine in mechanical fault diagnosis. Comput. Eng. Appl. **38**(19), 19–21 (2016)
5. Wang, S., San, Y.: A review of the training algorithms of support vector machines. J. Intell. Syst. (06) (2015)
6. Wu, J., Yang, S., Liu, C.: A short-term load forecasting method for support vector machines based on genetic algorithm optimization. J. Central South Univ. (Nat. Sci. Ed.) (01) (2007)
7. Wang, X., Wang, X., Wu, Y.: Rapid diagnosis and new knowledge acquisition methods in the fault diagnosis expert system of high voltage circuit breakers. J. China Electr. Eng. **27**(3), 96–99 (2016)
8. Gammermann, A.: Support vector machine learning algorithm and transduction. Comput. Stat. **15**(1), 31–39 (2016)
9. Lei, G., Wu, H.: Applying a novel decision rule to the sphere-structured support vector machines algorithm. Neural Comput. Appl. **18**(7), 675 (2013)
10. Wang, K., Cai, W., Deng, Y., et al.: Online monitoring system application and management platform of power transmission lines. High Volt. Technol. **38**(5), 1274–1280 (2014)
11. Han, M., Ding, J.: Improvement and implementation of BP algorithm based on cross-validation. Comput. Eng. Des. (14) (2011)
12. Zhang, D., Hu, J., Cui, T., et al.: Application of RF identification technology of sensor to the status information of electrical equipment in substations. High Volt. Technol. **39**(11), 2623–2630 (2015)
13. Li, X., Gong, Q., Qiao, H.: Application of the Internet of Things in power system. Power Syst. Prot. Control **38**(22), 232–236 (2015)