

Status Assessment of Secondary Equipment in Substation Based on Fuzzy Comprehensive Support Vector Machine Method

Ma Bo*, Dong Haiying

¹School of Automation & Electrical Engineering, Lanzhou Jiao Tong University
Anning West Road, 730070 Lanzhou, China, +86-0931-4956106/4956028

²Lanzhou Electric Corporation
No.66, Minle Road, 730050, Lanzhou, China, +86-0931-2866951-8010

*Corresponding author, e-mail: ktm3000@163.com¹

Abstract

In this paper, a status assessment model based on fuzzy comprehensive support vector machine (FC-SVM) is proposed for the scientific basis in the maintenance of secondary equipment in substation is insufficient. Then, an effective utilization and information extraction of various assessment factors is achieved by using fuzzy comprehensive assessment method (FCA) and the secondary equipment status is assessed via SVM on the basis of the online alarm information and offline information. Experiment analysis is carried out on three different kernel functions and the radial basis function (RBF) is selected as the kernel function for the proposed model in the assess process of SVM. Experimental results show that the status assessment accuracy of secondary equipment is improved by using FC-SVM.

Keywords: substation secondary equipment, status assessment, FC-SVM, analytic hierarchy process, Kernel function

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1. Introduction

The safety and stability of the power grid directly affected the growth of the national economy. In the long term, the power business has been adopted regular inspection and inspection methods to secondary equipment maintenance. This maintenance way has the characteristics like inadequate or excessive maintenance, lack of pertinence, the maintenance cycle not corresponding in the law of equipment failure, resulting in the high maintenance cost and the poor reliability. Therefore, it is very necessary for secondary equipment to carry out status assessment based on real-time status.

Various comprehensive evaluation methods are studied by both foreign and domestic scholars. In [1] the state parameters assessment model of secondary equipment is constructed, in which, the weight of parameters is distributed by using an analytic hierarchy process. The status assessment model of secondary equipment based on fuzzy comprehensive evaluation is proposed in [2]. A status assessment model based on SVM is proposed to microcomputer protection device [3], and the result shows that this model is feasible. While in [4] introduces a power transformer status assessment model based on data mining and fuzzy theory. All these methods deepen the research of secondary equipment status assessment. However, there are still some limitations: 1) the microcomputer secondary equipment has the ability to upload a large number of self-inspection and alarm information, so these online and offline information should be analyzed and used effectively. 2) The fuzzy comprehensive evaluation is widely used in the status assessment, but the samples cannot be learned [5]. 3) If a large number of evaluation factors cannot be handled during the SVM analysis process, it will result in the higher dimension of samples, the complexity of model, and a slow of training speed [6].

In this paper, with considering the secondary equipment of the 750kV substation as research objects, analyzing the online alarms information and various defects in inspection report detailed, research the membership relation between the secondary equipment operating status and the assessment factors [7], learn the relevant technical standards of the State Grid Corporation, combined with the actual operation experience to make an assessment criteria for the secondary equipment of the special high-voltage substation, and establish the status

assessment model of secondary equipment based on fuzzy SVM. Compared with three kinds of the kernel function, the best performance of the kernel function can be obtained. Afterward, compared with the fuzzy comprehensive evaluation model, the performance of the new mode is verified [8].

2. The Evaluation Factors of Secondary Equipment

For the secondary equipment of 750kV substation, the researchers found that these devices are the microcomputer controlled automatic device, which generally has the functions like inspection diagnosis and uploaded self-inspection in the power system, CPU, storage, communication, and so on. The information reflects the operational status of the secondary equipment directly. Hence, the monitoring background of substation automation system will collect a lot of self-inspection information and alarm information of secondary equipment. In which the online alarm information are various and the different information has different influence on the status of secondary device. So the online information would be divided into two categories, type-1 and type-2 alarm information. When the type-1 alarm occurs, the related plug-ins and modules would be replaced timely, or the monitoring and protection functions will lose to primary equipment. When the type-2 alarm occurs, it would not pose a direct threat to the operation of secondary equipment temporarily and can be resolved to reset and re-download the software usually [9].

At present, the maintenance companies use the regular maintenance mode each quarter and the inspection tour mode before major holidays. The regular inspection and inspection tour records a variety of defect, fault and process information of secondary equipment. It records the missing or manual operation information, family defect, anti-measures implemented, device defect and service life, etc. which has great reference value to the secondary equipment status. As the status assessment of the devices should not only focus on the online monitoring data, also combine with the fault and defect information of the regular inspection and inspection tour, the secondary equipment status can be assessed accurately.

3. The Fault Diagnosis Method Based on Rough Sets and Grey Relational Analysis

3.1. Fuzzy Support Vector Machine (SVM) model

The specific relationship between the inputs and outputs is not absolutely necessary in SVM application process. Through the study of samples it can reflect the complex mapping relation between input factors and the output results perfectly [5]. The feature of FCA is that it could deal with uncertain and fuzzy information. The target and idea using fuzzy SVM model for secondary equipment status assessment is that classify the secondary equipment status based on FCA and effective use of many evaluation factors. Model diagram is shown in Figure 1.

The input sample sets of fuzzy SVM model is: (x_i, y_j) , $i=1,2,\dots,n$; $j=1,2,\dots,5$. Among them, x_i is a vector which elements in the vector representing various evaluation factors, y_j refers to the equipment status. First, input sample is processed by FCA of the, the results as the SVM inputs. Then the SVM model is trained to get the mapping relationship between independent variables and the dependent variable. Finally, verify the correct rate of model through test sample. Fuzzy SVM model uses one-over-all classifier design approach, the state of the secondary equipment is divided into five levels: good, normal, attention, abnormal, severely abnormal.

The model evaluation criteria mainly from the State Grid Corporation internal department for secondary equipment overhaul maintenance work to develop relevant guidelines, as well as the production of secondary equipment manufacturers to provide technical specifications. And according to the experience of secondary equipment operation process combining foreign requirements of the evaluation related to computer equipment and evaluation requirements, the evaluation standards of model can be further improved.

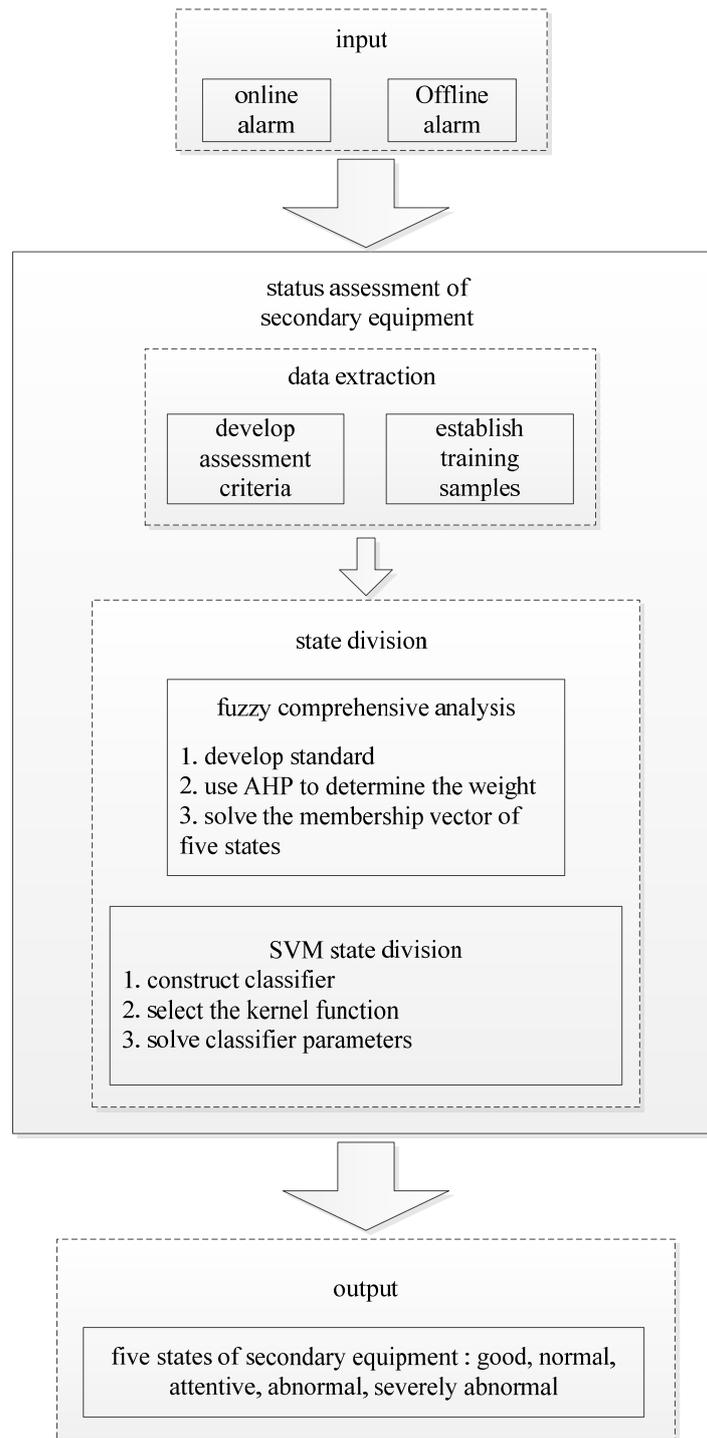


Figure 1. Model of fuzzy support vector machine

3.2. Fuzzy Comprehensive Evaluation

A. Information Extraction Based on the Fuzzy Analysis

The steps of FCA are: develop grading policy, setting up the assembly of evaluation factors, to establish the evaluation sets, to determine the weight, to establish the fuzzy matrix and fuzzy synthetic computing [10]. Alarm information and defect information themselves would not be directly used for analysis. Various factors need to be converted to digital quantity from status quantity by the principle of grading, and then bring them into model to analyze.

$$N_i = 100 - A_i n_i \quad i \in \{1, 2, \dots, 8\} \quad (1)$$

where N_i is the score of first item i evaluation factors, A_i is the evaluation factors corresponding penalty parameters and n_i represent the number of alarm occurs and defect types. Eight factors are selected as evaluation factors to constitute the evaluation factor set U , they are the I type alarms, II type alarms, refused to move, maloperation, family defects, anti-measures implemented, device defects and service life, that is:

$$U = \{u_1, u_2, \dots, u_8\}$$

Evaluation set V is constituted by five states of secondary equipment state evaluation results, that is:

$$V = \{v_1, v_2, v_3, v_4, v_5\}$$

The quantitative relationship between the evaluation factors and evaluation results are described by membership function. Fuzzy relationship matrix can be constructed by means of membership function. The SVM model uses normal distribution function as a membership function:

$$\left\{ \begin{array}{l} M_{better} = e^{-k(n_i-90)^2} \\ M_{normal} = e^{-k(n_i-80)^2} \\ M_{notice} = e^{-k(n_i-70)^2} \\ M_{abnormal} = e^{-k(n_i-60)^2} \\ M_{severely\ abnormal} = e^{-k(n_i-50)^2} \end{array} \right. \quad (2)$$

In the formula (2), k is the adjustment parameter. Fuzzy relation matrix R is constructed according to equation (2).

$$R = \begin{bmatrix} r_{11} & \cdots & r_{15} \\ \vdots & \ddots & \vdots \\ r_{81} & \cdots & r_{85} \end{bmatrix}$$

There r_{ij} denotes the membership degree of evaluation factors u_i to status evaluation results. Fuzzy synthesis operation is shown in formula (3), where b_j is equal to the supremum operation of weight vector W and Fuzzy relation matrix R .

$$B = W \circ R = (w_1, w_2, \dots, w_8) \circ (r_{ij})_{8 \times 5} = (b_1, b_2, \dots, b_5) \quad (3)$$

$$b_j = \bigvee_{i=1}^8 (w_i \wedge r_{ij})$$

The result of fuzzy synthetic operation is a five elements vector. The size of each element indicates the degree of belonging to each state, the vector B and y_i constituting the input samples of SVM.

B. Analytic Hierarchy Process to Determine Weight

In the process of fuzzy analysis, the determination of weight should reduce the subjective factors influence to a large extent. Analytic hierarchy process (AHP) is a decision-making method of qualitative analysis and quantitative analysis that decomposes elements which always relevant to the decision into objectives, principles, programs, and other hierarchy. AHP can effectively reduce the influence of subjective factors to the weights [11, 12]. Specific steps as follow, to establish a program attribute decision table firstly. Table 1 gives the judgment

of the importance degree compared between two factors [13]. Judgment matrix F can be constructed according to previous judgment.

$$F = \begin{bmatrix} a_{11} & \cdots & a_{16} \\ \vdots & \ddots & \vdots \\ a_{61} & \cdots & a_{66} \end{bmatrix}$$

Consistency check:

$$C.I. = \frac{\lambda_{\max} - n}{n-1}, \quad C.R. = \frac{C.I.}{R.I.}$$

In the formula, λ_{\max} is the maximum eigenvalue of judgment matrix, n is the order of matrix. When the formula $C.I. < 0.1$ is reasonable, judgment matrix is acceptable. After consistency check, if the consistency of judgment matrix is acceptable, characteristic vector can be obtained through solving judgment matrix. Then get the weight vector by means of normalizing.

$$W = \{w_1, w_2, w_3, w_4, w_5, w_6, w_7, w_8\}$$

Table 1. Judgment of importance degree on secondary equipment evaluation factors

scale	equally important	minutely important	slightly important	more important	obviously important	very important	highly important	more strongly important	extremely important
$e^{0/5} - e^{8/5}$	1	1.211	1.492	1.822	2.266	2.718	3.320	4.055	4.953

3.3. SVM Status Assessment

A. Theory of SVM

SVM is based on VC dimension which from statistical theory and structural risk minimization inductive principle. Through find optimum compromise between the model complexity and learning ability according to the limited sample information in order to obtain the best generalization ability. SVM has been proposed since 1990s, widely used in the field of pattern recognition. In recent years, SVM has breakthroughs to solve the non-linear, disaster of dimensionality problems, over-fitting problems and local minimization problem has made breakthroughs [3, 5, 14]. In the model of fuzzy SVM, the results of FCA and the status of the corresponding secondary equipment constitute the support vector machine input samples (b_i, y_j) . There b_i is the results of fuzzy comprehensive analysis, y_j is the status of the secondary equipment.

SVM is proposed from optimal separate hyper-plane which in linearly separable situation. There is a hyper-plane $w^T x_i + b = 0$ for a linearly separable sample set. By Judging $g(x_i) = w^T x_i + b$ is positive or negative judgment to mark out which category of sample set the point x_i belong to. When the undivided linear sample point is in the sample, slack variables ζ_i ($\zeta_i \geq 0, i = 1, 2, \dots, n$) can be introduced. Not every sample point has a slack variable, ζ_i only for outliers in the sample. At this point hyper-plane $w^T x_i + b = 0$ must meet the status:

$$y_i(w^T x_i + b) \geq 1 - \zeta_i$$

When $\zeta_i < 1$ is satisfied, the sample point can still be correctly classified. When $\zeta_i \geq 1$ is satisfied, the sample point could not be classified correctly by hyper-plane. At this point introducing the following functions:

$$\varphi(w, \zeta) = \frac{1}{2} w^T w + C \sum_{i=1}^n \zeta_i$$

In the formula, C is the penalty factor which means the trade-off between good generalization ability and minimal training error. At this point SVM can be achieved through quadratic programming:

$$\begin{cases} \max \sum_{i=1}^n a_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n a_i a_j y_i y_j (x_i^T x_j) \\ \text{s.t. } a_i \geq 0, i = 1, \dots, n \\ \sum_{i=1}^n a_i y_i = 0 \end{cases} \quad (4)$$

In the formula, a_i is the Lagrange multiplier, b is the threshold, $K(x_i \cdot x)$ is the kernel function [5]. All functions which satisfy Mercer's status can be used as the kernel function. At present, there are not specific selection criteria on how to choice the kernel function form. Through analysis the three commonly used kernel function, and comparing the experimental results verify that evaluation model based on radial basis function radial kernel reach to the highest accuracy rate. Commonly used kernel functions are: polynomial kernel function, RBF, sigmoid kernel function.

B. Classifier Construction

Linear classifier is usually focused on two classification problems. However, in practical engineering application which is always facing with multi-classification. In solving multi-classification problem, there are mainly two ways as follow. One way is multi-class problem can be broken into multiple two-type problems. By means of multiple two-type classifiers to achieve multi-class classification. Another way is to design the multi-class classifier directly. In the two methods, there is a large and complex computation on design of multi-class classifier structure directly that less use of in actual project. The model uses the "one-over-all" classifier design method. Classification idea of the method is shown in Figure 2. State 1 could be got as a class, the rest of the four states as another class. So that four classifiers are designed to be used for five kinds of state division [6, 14, 15, 16].

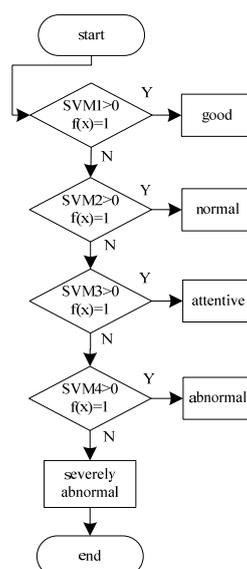


Figure 2. One-over-all principle diagram of the classifier

4. Result Analysis of Comparative Experiment

Sample data in this paper comes from the two 750kV UHV which subordinate Gansu provincial Power Company. In the SVM classification process, the sample points which are more close to the optimal separate hyper-plane, the greater significance for solving the classification function. In this paper, alarm information of secondary equipment can be collected online from substation automation system. Through viewing maintenance reports and defect reports to collect various defects information on secondary equipment, viewing commissioning documentation to get equipment operating life. Combined with secondary equipment evaluation criteria and maintenance staff experience consist a total of seventy groups of samples, including forty training sample set and validation samples of 30 groups. Some samples data are shown in Table 2.

Table 2. Part of the sample data

samples	type-1 alarm	type-2 alarm	missing operation	Mal operation	family defect	anti-measures implemented	device defect	service life
1	0	0	0	0	0	1	2	3
2	0	0	0	0	1	1	1	2
3	0	1	0	0	0	0	0	3
4	0	1	0	0	1	0	1	2
5	1	0	0	0	1	1	1	2
6	0	1	0	0	1	1	3	4
7	1	1	0	0	1	0	2	3
8	1	1	0	0	0	0	3	4
9	0	1	0	1	0	0	2	5
10	1	0	1	0	0	0	2	5

In the same status to experiment with three different kinds of kernel functions, parts of the results are shown in Table 3. Parameters of the support vector machine model are as follows. $C=0.45$, $\xi=0.0015$. In the RBF kernel function $\delta^2=4$, polynomial kernel function $d=4.5$, sigmoid kernel function $V=1/6$, $C=-1$.

Table 3. Kernel function part performance experiment results

samples	polynomial kernel function	RBF kernel function	sigmoid kernel function	true state
1	good	good	good	good
2	good	good	normal	good
3	normal	normal	normal	normal
4	attentive	normal	normal	normal
5	attentive	attentive	attentive	attentive
6	attentive	attentive	attentive	attentive
7	abnormal	abnormal	abnormal	abnormal
8	severely abnormal	abnormal	abnormal	abnormal
9	severely abnormal	severely abnormal	severely abnormal	severely abnormal
10	severely abnormal	severely abnormal	severely abnormal	severely abnormal

Comparative tests under the same status between fuzzy comprehensive evaluation model and fuzzy support vector machine comparison, partial results are shown in Table 4. The final results of the assessment can be determined by fuzzy comprehensive evaluation model through the maximum membership degree principle. The correct assessment rate of FC-SVM model is higher than fuzzy comprehensive evaluation model can be seen from the tables. Experimental results show that FC-SVM accuracy to 97.5%.

Table 4. Part of FC – SVM and fuzzy comprehensive evaluation contrast experiment results

samples	FC-SVM	Fuzzy Comprehensive Evaluation	true state
1	good	good	good
2	good	good	good
3	normal	good	normal
4	normal	normal	normal
5	attentive	attentive	attentive
6	attentive	attentive	attentive
7	abnormal	attentive	abnormal
8	abnormal	abnormal	abnormal
9	severely abnormal	abnormal	severely abnormal
10	severely abnormal	severely abnormal	severely abnormal

5. Conclusion

The result shows that the fuzzy SVM model which combines the FCA with the support vector machine in this paper, has a high accuracy and a good stability in small samples. Compared with FCA, this model improves the accuracy of assessment under the same status. The FC-SVM model overcomes the shortcomings of judgment lapse caused by the maximum membership degree effectively, and amends the error of assessment results caused by subjective factors. Therefore, the performance of the FC-SVM model constructed the RBF kernel function is best.

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