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The Condition Based Maintenance Evaluation Model on On-post Vacuum Circuit Breaker

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Abstract

The safe operation of power supply equipments is closely related to the security of electric network. The planned maintenance of existing power equipments o cannot meet the needs of development of power system. To solve the problems in maintenance for vacuum circuit breaker, this paper build the equipment condition and risk assessment index system and bring out the outdoor on-post vacuum circuit breaker condition based maintenance evaluation model which based on Rough Set and Support Vector Machine according to the real condition. To prove the high accuracy of this method, a research which about the data of 100 Box-type substation in the distributing network of one power supply company is conducted in this paper.

Key words:：Condition Based Maintenance；On-post Vacuum circuit Breaker；Evaluation model；Rough sets; Support Vector Machine；

1. Introduction

In recent years, on-post circuit breaker in the electric power equipments, as distributed protective equipment, has been widely applied in the transformation of distribution systems. Our out-door on-post circuit breakers mainly rely on vacuum circuit breaker which has ruled the on-post switch market. Functions of power users to the vacuum circuit breaker mainly embodies in overcurrent or short circuit protection. Therefore, when power users operate the vacuum circuit breaker, they should not only safeguard the operation of equipments but also concern other factors affecting equipment condition and risks.

This paper constructs the on-post circuit breaker condition and risk assessment index system and brings out the equipment condition and risk assessment model based on Rough Set Attributes Reduction and Support Vector Machine Classification. In this model, the Rough Set is used to fill up a deficiency of Support Vector Machine in cutting down the redundant information, while the Support Vector Machine

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can fill up a deficiency of the Rough Set in generalization ability. To prove the effectiveness of the method, an empirical research based on real data is adopted, indicating high classification accurate rate.

2. Equipment condition and risk evaluation index system

Constructing a set of scientific and improved evaluation index system is a significant premise of evaluating equipment condition and risk evaluation and the base of making comprehensive evaluation. On the characteristics of the on-post vacuum circuit breaker, this paper builds an index system (Table.1) consisting technical parameter, operation security, protective function and reliability through analyzing various affecting factors of the equipment condition and risk.

Table 1 Equipment condition and risk evaluation index system

First-grade indexes	Second-grade indexes
Technical parameter indexes	Switch in/on position indication P1
	Temperature of guide pole junction P2
	Temperature of scaffold's auxiliary equipments P3
	energy storage position indicator p4
	Seal design differenccesP5
	grounding resistance P6
Operation security indexes	Switch itself corrosion P7
	defection of Pole's number plate P8
	slope of Scaffold P9
	Crack of pole P10
	Accumulated short open circuit times P11
	Unsmooth stagnation of spring mechnismsP12
	Grounding connections P13
Protective function indexes	Out-taken isolation toolP14
	inrush current defense functionP15
	Voltage transformer installation methodP16
	Surge arrester installationP17
Reliability indexes	length of Operation P18
	Family defect P19
	Historical defect P20

3. Attribute reduction based on the rough set

Not all of the indexes selected are very important, in which some attributes are redundant. In condition of keeping attribute conditions unchanging, attribute reduction is removing the ones not related or not important. If $pos_c\left(D_j\right)=pos_{c-\{a\}}\left(D_j\right)\left(pos_c\left(D_j\right)\right)$ ($\forall a \in c$) is c Positive field of a and a is redundant, $c^{'}=c-\{a\}$ will be a reduction of c.

The condition attributes are interconnected in a decision system. Reduction can be considered as dependency and association of conclusion attributes to condition attributes set in a simple way without losing any information. The more significant the attributes are, the greater the influences of attributes are on the division of policy[1][2][3].

4. Principle and algorithm of Support vector machine

Support Vector Machine, based on forward network structure and setting up a hyperplane as decision camber, mainly make pros and cons more incline to the lateral edge of interval line. Error rate of test data on machine learning makes the sum of training error rate and Vapnik Chervonenkis dimension bound. In division mode, Support Vector Machine is zero for the previous value, and minimal for the second. It possesses excellent generalization ability on pattern classification. The basic thoughts can be shown by 2D case of figure 1. In figure 1, the two kinds of sample square, expressed by triangle and square, can be divided by hyper planes H. The distance, between H1 and H2, is called classification interval. The optimizing classification hyperplanes request both correct separation and biggest classification interval.[4]-[8]

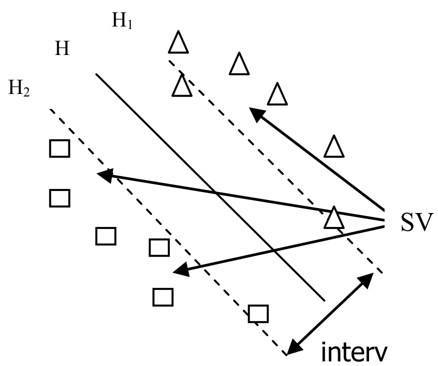

fig 1： the optimal classification face for linear Separability

For the Non-linear classification, the optimal classification hyperplanes can be gained in transformation space through inverting nonlinear transformation into a high linear dimensional. The inner product of kernel function $K(x_i, x_j)$, which meet the Mercer`s conditions, realizes linear classification of nonlinear transformation. Then the problem is looking for maximizing objective function

$$Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \qquad (1)$$

$\{\alpha_i\}_{i=1}^{n}$ is the Lagrange coefficient. Classification function can be gained by solving constraints

$$f(x) = \operatorname{sgn}\left\{\sum_{i=1}^{n} \alpha_i^* y_i K(x_i, x_j) + b^*\right\} \qquad (2)$$

That is Support vector machine
Radial base kernel function is chosen in this paper:

$$K(x, x_i) = \exp\left[-\frac{\|x - x_i\|^2}{2\sigma^2}\right] \qquad (3)$$

5. Empirical study

5.1. data collecting and processing

The data in this paper comes from 100 Box-type substation in the distributing network of one power supply company. With the purpose of making original inputting equipment data meet requirements of the model, the inputting vectors attain standardization and are suitable for the model through preprocessing. Main steps of revising the original data of 100 on-post vacuum circuit breaker are the following:

First, make a data collecting table, that is to collect original data of every on-post vacuum circuit breaker and those that are unable to collect information can't be evaluated, and hence delete 1 incomplete information sample (the serial number is 580 belonging to A-lister branch equipment of red-star street) with 99 samples left.

Next, process all the original data of equipment and make them positive vector according to the following formula:

$$x_i^j{}' = \frac{T - x_i^j}{T} \qquad (4)$$

In the above formula, $x_i^j{}'$ is the revise value, T is the total score, x_i^j is the deducted score. Take number Z732 vacuum circuit breaker belonging to Hua Lin district as an example, the positive vector information is obtained as is shown in table 2

Table 2 positive vector information of Z372 on-post vacuum circuit breaker

index	positive vector	index	positive vector	index	positive vector	index	positive vector
1	1	6	1	11	1	16	1
2	1	7	0.6	12	1	17	1
3	0.8	8	0.8	13	1	18	0.8
4	1	9	1	14	0.8	19	1
5	0.8	10	1	15	1	20	1

5.2. Attributes discretization

For better making study, we randomly take out 20 equipment data as the selected sample for this study. Take U as the scope, that is $U = \{1, 2, 3, \cdots 20\}$, which indicates a set of all the sample unit attributes with one attribute representing an index.

Discretization index can be achieved by applying FCM Cluster Algorithm, which is supported in the Matlab fuzzy logic tool box.

With the aid of Matlab, every attribute value in the above figure can be clustered and be divided into six categories according to the above scores. Give sample attributes 1, 2, 3, et al characteristic values respectively because there are only 3 score values in the object of study without 0.4 and 0.2.

5.3. Attributes reduction

Make reduction of index using Rosetta (Version 1.4.41) rough set Algorithmic Program and use characteristic value processed with the discrete way as the input data. The reduction of attributes algorithmic mainly consists of Genetic Algorithm and Dynamic Reduction Algorithm, and making reduction of index by combining the two algorithms using programs is effective than using one single algorithm. This paper adopts Johnson's Algorithm to make attribute reduction for the decisive data and the reduction set {switch in/on position indication, temperature of guide pole junction, temperature of scaffold's auxiliary equipments, grounding resistance, defection of Pole's number plate, slope of Scaffold, accumulated short open circuit times, Surge arrester installation}is acquired. Use the reduced attributes as the input of supporting vector machine, and make training and test.

5.4. Classification evaluation of SVM

Based on classification requirements of Support vector machine, equipments of No.21-100 are chosen as training samples for Support vector machine, and No.1-20 as test samples of evaluation. According to the requirements of equipment condition based maintenance of State grid companies, we set the evaluation standard for the on-post vacuum circuit breaker as follows: {normal, notice, abnormal, serious}. Training set includes 59 normal samples and 11 notice samples and 4 abnormal samples and 5 serious samples, while test set includes 18 normal samples and 1 notice samples and 1 abnormal sample and 0 serious samples.

Fast classification machine structure, as is shown in figure 2, is designed with two support vector machines according to the requirements of classification numbers.

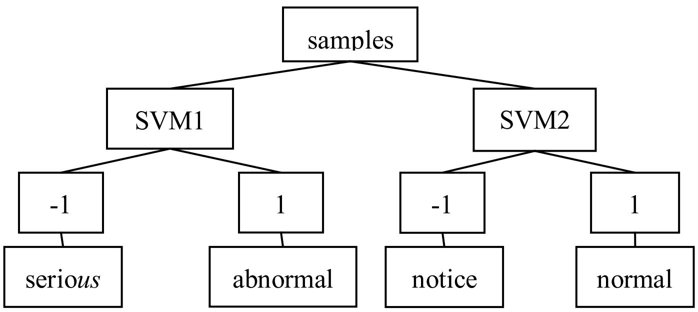

Fig 2: structure chart of fast classification machine

Training processes are as follows: SVM1 and SVM2 are parallel-structured support vector units; Samples are classified by parallel structures, and table 3 shows the classification rules.

Table 3 Reduction index

index	normal	notice	abnormal	serious
1	1	0.8	0.6	—
2	1	1	0.6	—
3	0.8	0.6	0.8	—
6	1	1	0.6	—
8	1	0.8	0.6	—
9	1	0.6	0.8	—
11	0.8	0.8	0.6	—
17	1	0.8	0.6	—
result	1—1	1—-1	-1—1	-1—-1

Radial basis function maps the data to high dimension characteristics space non-linearly, thus it takes effective action on feature variables and classification variables when they are non-linear. Parameters of RBF are less, which lead to simplifying the complexity of model choice. Due to less differences of RBF, we choose it as kernel function of SVM, in which δ is the width of RBF function and the optimal value is 0.607776.

The process of using SVM algorithm software is as follows: input test set to SVM1 by predesigned order {18 normal samples,1 notice sample,1 abnormal sample,0 serious sample }, then output is:

{+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,-1}

Input test set to SVM2 by predesigned order, and the output is

{+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,+1,-1,+1}。

Evaluation results {18 normal samples,1 notice sample,1 abnormal sample,0 serious sample}is gained by corresponding two groups of output results to classification rules shown in table 4.

In addition, the method of making classifications by SVM classifier through using the same training samples as are used in making index reduction by rough set can be evaluated by comparison. The evaluation result is shown in table 4

Table 4 Classification results contrast

Class	RS－SVM	SVM	tradition
excellent	90%	85%	70%
good	5%	10%	25%
qualified	5%	5%	5%
precision	1	0．88	0.8

It proves that SVM has good classification effect in equipment state and risk assessment. What`s more, it is found that training speed of this software for training samples is fast. Using less samples to Predict unknown samples explains that the method has much stronger actual application prospect.

6. Conclusion

It is can be seen from the experimental results that faults of on-post circuit breaker caused by switch on-off position indication, temperature of guide pole junction, temperature of scaffold's auxiliary equipments, grounding resistance, defection of Pole's number plate, slope of Scaffold, accumulated short-circuit breaking operations times, and Surge arrester installation are the most common. Corresponding overhaul countermeasures are introduced in this paper through evaluation studies so that the overhaul procedures of on-post circuit breakers are optimized enabling equipments well maintained timely, which is of important significance to secure operation of power supply enterprise.

The experimental results show that applying the model of Rough Set and Support Vector Machine to condition based maintenance evaluation of on-post circuit breaker solves dimensional problems by building non-liner mapping relations based on limited training samples. This algorithm is simple and possesses high accuracy and it can meet the needs of practical use. It provides an efficient tool for the equipment condition and risk evaluation and it is a used reference for accurate comprehensive evaluation with less data samples.

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