Fault prediction of power system distribution equipment based on support vector machine

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Abstract

Aiming at the problem of low efficiency in the utilization and analysis of massive data in power system operation and maintenance, combined with the characteristics of operation and maintenance management of power distribution equipment, a fault prediction solution for power distribution equipment based on support vector machine algorithm is proposed. By learning the features of existing data, a predictive model is constructed, and early warning information is sent to the abnormal part of the newly acquired data to implement the fault pre-judgment function of the power distribution equipment.

Keywords

Power distribution; support vector machine; fault prediction.

1. Introduction

"Internet + Power" has promoted the deep integration of power industry and informationization, and has realized the innovation drive, intelligent transformation and green development of power grid by using the technologies of network, digitalization and Intelligentization. The future integration of the Internet and grid systems will be even closer.The rapid development of distributed power supply, energy storage device, intelligent electrical appliance, electric vehicle and so on, as well as the wide application of modern information technology such as cloud computing, big data and artificial intelligence, require continuous innovation of power grid technology, improve the efficiency of resource allocation, the adaptability of power access, the interactivity of electricity service, and the reliability of power supply quality[1].

The fault of distribution equipment is one of the reasons that affect the reliability of power supply quality. How to predict equipment fault quickly and accurately is the main problem to be considered in the safety prevention and control of power system. Nowadays, the power system is becoming more and more complex, the power network is becoming bigger and larger, and the expert system based on human-specified rules can not solve the problem of fault preview in large-scale operation and maintenance. Intelligent operation and maintenance does not depend on people for the specified rules, advocating that the machine learning algorithm automatically from the mass operation and maintenance data (including the event itself and the manual processing log of operation and maintenance personnel) in continuous learning[3], and constantly refine and summarize the rules.At its core is a machine-learning-based brain that directs monitoring systems to capture the data needed for brain decisions, make analysis, decisions, and direct automated scripts to execute brain decisions to achieve the overall goals of the operations system.

Machine learning is undoubtedly a hot topic in the field of data analysis, which has been used in the macroscopic prediction of power load and the evaluation of power system transient stability.

If the large amount of distribution room operation data and machine learning algorithm accumulated by operation and maintenance company are combined, the fault preview function of the operation and maintenance system to the distribution equipment can be realized.

2. Design ideas

The basic idea of solving the problem of fault preview of distribution equipment by using machine learning algorithm is to obtain the equipment characteristic quantity before and after the fault occurs respectively, to provide the data as training set to the machine learning algorithm, and to obtain the prediction model[4]. The model is then used to analyze the stable state of the device in real time and to make corresponding warnings. In this paper, the support vector machine of one of the common algorithms of machine learning is adopted, and the principle of SVM algorithm is to find a segmented hyperplane, which can classify the data correctly and have the greatest spacing. The basic model is the linear classifier that defines the maximum interval in the feature space.

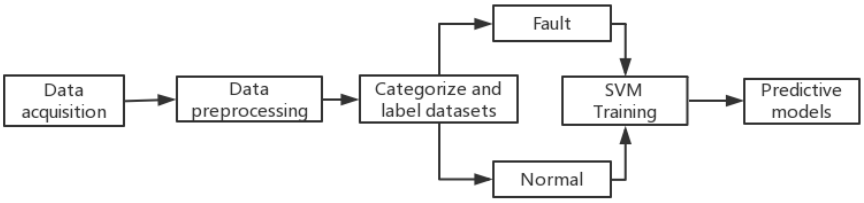

Fig. 1 The process of building a model

2.1 Standard SVM basic idea

Support Vector Machine is a statistical method based on the principle of structural risk minimization and the goal of constructing optimal hyperplane[5].

The problem of a two-valued classification of a given training dataset with a hyperplane of a feature space is assumed, for a given sample point (x_i;y_i), i= 1,...,n;y∈{+1,-1}. x_i is a support vector and y_i is a category index, and the goal of learning is to construct a decision function that separates the two types of patterns as correctly as possible.The construction decision function can eventually be transformed into one typical second planning issues, that is, the minimum value of the formula (2) under the constraint conditions shown in formula (1).

$$y_i[(w \cdot x_i) - b] + \xi_i - 1 \geq 0, \xi_i \geq 0 \tag{1}$$

$$\varphi(w) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i, \text{ (i=1,2,...,n)} \tag{2}$$

In the formula: w is the vector of the classification surface weight coefficient, b is the classification domain value, the ξ_i is the deviation of the training sample about the separation surface, and $\varphi(w)$ is the objective function; C As a penalty factor, c>0.

By using the Lagrange multiplication method, the decision function can finally be obtained as

$$f(x) = sgn[\sum_{i=1}^{n} a_i y_i \cdot (x \cdot x_i) + b] \tag{3}$$

The a_i is a Lagrange multiplier in the formula.

For nonlinear situations, separate surfaces can be introduced, through nonlinear mapping $\varphi(w)$: Rd→f The input Space Rd to the high-dimensional inner product space F, then the optimal hyperplane is constructed, the classification is completed with a linear classifier, and according to the functional analysis theory, under the condition of meeting Mercer, this non- Linear mapping can be achieved by defining the appropriate kernel function, introducing the kernel function K (x_i,x), the formula (3) Decision function can be written as

$$f(x) = sgn[\sum_{i=1}^{n} a_i y_i K(x \cdot x_i) + b] \tag{4}$$

Formula (4) is the support vector machine, where the corresponding vector of a_i with a non-0 value supports the optimal classification surface and therefore becomes the support vector. In a nutshell, Support vector Machine is a linear classifier determined by support vector, which first transforms the input space into a high dimensional space through the nonlinear transformation defined by the kernel function[6], and then solves the optimal classification surface in this space.

2.2 Optimization mechanism

As a widely used modeling method in machine learning, the least squares support vector machine (LS-SVM) has the advantage of using small samples to realize accurate modeling. LS-SVM based on SVM theory, through the expansion and deformation of SVM model[7], the equation constraint is used to replace the inequality constraint in the traditional SVM, and the error squared and the loss function are set, which reduces the complexity of the operation, thus improving the speed and precision of the model operation, and the constraint condition is

$$y_i = \phi(x_i)\psi + b + \xi_i \quad \text{(i=1,2,...,l)} \tag{5}$$

In formula: ψ is the weight vector of $\phi(x_i)$; b is a constant; ξ_i is an error item; and the function of $\phi(x_i)$ is to map samples in nonlinear cases to high dimensional space.

The objective functions of the LS-SVM model are:

$$\min \; J(\Psi, \xi) = \frac{1}{2}\Psi^T\Psi + \gamma \sum_{i=1}^{L} \varepsilon_i^2 \tag{6}$$

In formula: γ is a regularization parameter.

$$\begin{pmatrix} 0 & I^T \\ 1 & ZZ^T \end{pmatrix}\begin{pmatrix} \beta \\ \alpha \end{pmatrix}=\begin{pmatrix} 0 \\ y \end{pmatrix} \tag{7}$$

In formula:y=[y_1,...,y_l]^T;b=[b_1,b_2,...,b_l]^T; α =[$\alpha_1, \alpha_2, \dots, \alpha_L$]^T.

By solving the Formula (7), the parameters of the regression equation can be obtained, that is,

$$f(x) = \sum_{i=1}^{L} \alpha_i K(x, x_i) + b \tag{8}$$

In formula: K is the kernel function matrix, $k_{ij} = \varphi(x_i)^T \varphi(x_j) = K(x_i, x_j), i, j = 1, \dots, l$; $\varphi(x_i)$ is the inner product of 2 sample points in the space after the expansion of the dimension.

3. Construction and application of predictive model

3.1 Establishment of Index factor system

Based on the fault prediction of distribution equipment, this paper analyzes the relationship between the running state of distribution equipment and the monitoring parameters, selects the index factors that affect the fault prediction, and makes an empirical analysis on the fault evaluation of distribution equipment. According to the traditional operation and maintenance system, the following parameters are finally determined as the equipment condition evaluation Index, which is mainly divided into four large aspects, namely, electrical parameter monitoring, temperature monitoring, distribution room environmental monitoring and equipment condition monitoring. As shown in table 1 below.

Table 1 Equipment Status Assessment metrics

Factor symbol	Factor name	Factor symbol	Factor name
C1	A Phase Current	C40	C phase harmonic voltage distortion rate
C2	B Phase Current	C41	Three-phase current unbalance degree
C3	C Phase Current	C42	Three-phase voltage imbalance
C4	A Phase Voltage	C43	Frequency deviation
C5	B Phase Voltage	C44	Ambient temperature
C6	C Phase Voltage	C45	Ambient humidity
C7	A Phase Load	C46	A phase Voltage deviation
C8	B Phase Load	C47	B phase Voltage deviation
C9	C Phase Load	C48	C Phase Voltage deviation
C10	A Phase Power Factor	C49	AB line Voltage Deviation

C11	B Phase Power Factor	C50	BC line Voltage Deviation
C12	C Phase Power Factor	C51	CA line Voltage Deviation
C13	A Phase Reactive Power	C52	Positive Phase Active power
C14	B Phase Reactive Power	C53	Positive Phase reactive POWER
C15	C Phase Reactive Power	C54	Reverse Phase Active Power
C16	0 Sequence Current	C55	Reverse-phase reactive power
C17	Total Active Power	C56	Total apparent power
C18	Total power factor	C57	A Phase Active Power
C19	Total reactive power	C58	B Phase Active Power
C20	Frequency	C59	C Phase Active Power
C21	AB line Voltage	C60	A Phase Reactive POWER
C22	BC line Voltage	C61	B Phase Reactive POWER
C23	CA line Voltage	C62	C Phase Reactive POWER
C24	A phase voltage Phase angle	C63	Phase A Cable Temperature
C25	B phase voltage Phase angle	C64	Phase B Cable Temperature
C26	C phase voltage Phase angle	C65	Phase C Cable Temperature
C27	A Phase Current Phase angle	C66	Switching capacity 1
C28	B Phase Current Phase angle	C67	Switching capacity 2
C29	C Phase Current Phase angle	C68	Switching capacity 3
C30	Load Rate	C69	Switching capacity 4
C31	Positive phase active Electrical degree	C70	Switching capacity 5
C32	Positive Phase reactive POWER degree	C71	Switching capacity 6
C33	Reverse Phase Active Electrical degree	C72	Switching capacity 7
C34	Reverse Phase Reactive POWER degree	C73	Switching capacity 8
C35	A phase harmonic current distortion rate	C74	Switching capacity 9
C36	A phase harmonic voltage distortion rate	C75	Switching capacity 10
C37	Harmonic current distortion rate of B phase	C76	Switching capacity 11

C38	Harmonic voltage Distortion rate of B phase	C77	Switching capacity 12
C39	C Phase Harmonic Current distortion rate	C78	Switching capacity 13

3.2 Sample Data processing

In order to reduce the influence of different dimensional factors on the model prediction, it is necessary to complete the data preprocessing[8], that is, to normalize the power distribution equipment data, and get the following formula (9). In the formula, x_i is the original value, x_i' is the normalized value, x_{max} refers to the maximum value of the adaptive factor, x_{min} corresponds to the minimum value.

$$X_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{9}$$

3.3 Predictive analysis Results

By using adaptive algorithm, the parameters of LS-SVM model can be optimized to obtain the optimal parameter. By substituting the optimal parameters into the test samples for prediction, it can be found that the predicted values are in good agreement with the actual observed values, and the maximum prediction error does not exceed 2. 65%, with an average error of 1. 7%, the predicted results can therefore be considered valid. In order to determine the generalization ability of the model, the LS-SVM model and the conventional support vector machine need to be compared, and two algorithms are used to establish the power load forecasting model, and the prediction results are compared.

4. Experimental simulation and analysis

The introduction of kernel function avoids the "dimension disaster" and greatly reduces the computation amount. The dimension n of the input space has no effect on the kernel function matrix, so the kernel function method can effectively handle the high dimensional input[9].

According to the existing research conclusions, combined with the characteristics of power data, the project selected linear nuclei and Gaussian nuclei respectively, in general, the Gaussian kernel effect is better than linear nuclei, but the Gaussian core in time will consume more.

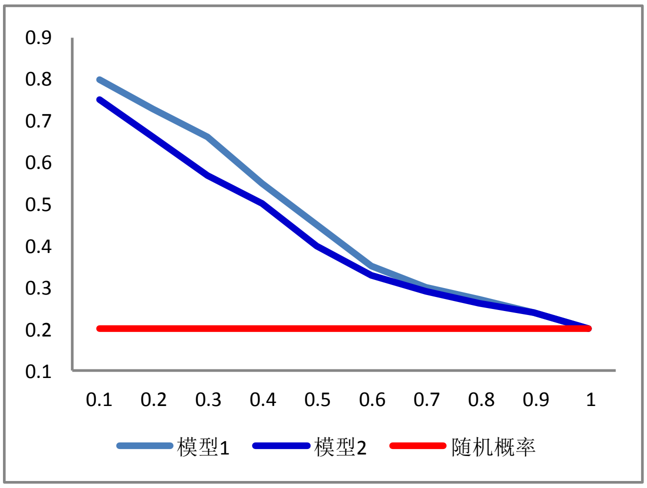

Fig.2 Firefly algorithm flo

Response rate refers to the percentage of an interval or cumulative interval observation object in which a positive observer accounts for the total number of observed objects in that area or the cumulative interval. Therefore, the greater the response rate, the higher the prediction accuracy of the interval model in this area or cumulative. For example, in the first 10% of the model, model 1 yields 1 class samples and 80%, and Model 2 is 73%. As shown in Figure 2, model 1 uses LS-SVM better than Model 2 using general support vector machines.

In each interval segment, the cumulative value of the 1 class is calculated as the percentage of the overall 1 class as the capture rate. The measure is the proportion of objects that catch 1 categories in a cumulative interval. As shown in Figure 3, model 1 uses LS-SVM better than Model 2 using general support vector machines.

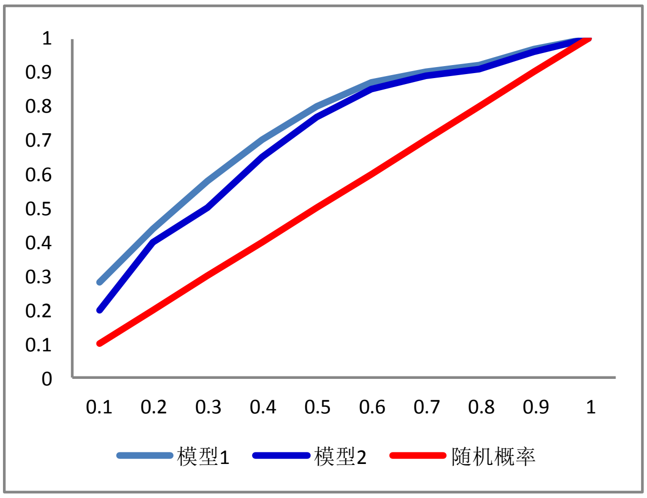

Fig. 3 Firefly algorithm flo

5. Conclusion

According to the influencing factors of fault formation of distribution equipment, and referring to the experience of operation and maintenance in the past, this paper analyzes the relationship between the running state of distribution equipment and the monitoring parameters from the fault prediction of distribution equipment, and finally selects the index factors that affect the fault prediction. The health state evaluation model of distribution equipment is obtained by using LS-SVM algorithm training. The test results show that the predictive model constructed by the LS-SVM algorithm is working normally and the output results are in line with expectations.

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