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Research on Electrical Equipment's Fault Diagnosis Based on the Improved Support Vector Machine and Fuzzy Clustering

Yuling Yan

Department of Electronic information and Control Engineering, Yibin vocational and technical college, Yibin 644004, China
yanyu_5318949@126.com

In this paper, the author research on electrical equipment's fault diagnosis based on the improved support vector machine and fuzzy clustering. Combining the support vector combined fuzzy sets and neural network to carry on the fault diagnosis is a most prosperous diagnosis method. This article put forward a sample processing method using fuzzy clustering and studied the application of fuzzy competition classification method in extracting contradiction samples, then advanced the diagnosis method of neural network based on fuzzy clustering, finally carried on the simulation research. The calculation results show that all the above-mentioned methods are quite practical. It is a better and prosperous way to combine neural network theory and fuzzy clustering to carry on insulation diagnosis. The experiment result shows the proposed method is effective.

1. Introduction

Nowadays, more and more accidents have to do with electrical accidents and many great electrical accidents have been happened related to electrical accidents. According to statistics, occurred frequently electrical accidents have caused serious economic loss and casualty. In China accident identification technology and method haven't developed fully. As to in-depth understanding the characteristics of electrical accidents and electrical energy propagation after electrical faults and accurate identification of electrical accident failures, it is beneficial to inquiry into the reasons for the accident in time, take effective actions to guard against the accident' spread and carry out prevention directed against the accidents. Unluckily, the studies mostly aim at the reasons of electrical accidents in China. There are few studies for the electrical accidents' characteristics and identification methods and electrical energy propagation's characteristics after electrical faults. Even if several related studies have appeared, there are many shortcomings. There are few studies for the electrical accidents' features and recognition methods deeply (Zou and Huang, 2015; Pan et al., 2009; Li et al., 2013)
To begin with, this paper makes a brief introduce of the low-voltage distribution system and grounding scheme, deeply analysis the features of electrical accidents' time and region. Meanwhile, we study the electrical energy propagation's characteristics after electrical faults. It is shown that electrical energy in fault circuits is redistributed and spread, then transmitted into heat and light, and lights insulator around equipment or flammables surrounding equipment, and ultimately causes an accident. Secondly, the paper presents a simulation of several common electrical failures in low-voltage distribution system, including short circuit fault, unbalanced three-phase fault when neutral point is disconnecting and open phase and gains the changes of voltage and electric current in electric transmission line when the above electrical failures are undergoing. Thirdly, in order to achieve visual effect, we use a simulation model to design the graphical user interface. Finally, we identify the patterns of the voltage and electric current when the above electrical faults are going on using the improved support vector machine and fuzzy clustering in Matlab (Sun et al., 2014).

2. Overview

The distinguished advantage of fuzzy diagnosis lies in that it needn't a creation of precise mathematic model as long as subordinate function, fuzzy relation and fuzzy rules are applied properly, then carry on fuzzy deduction, and we can realize the intellectualization of fuzzy diagnosis. But as for the complex diagnosis

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system, creating the right fizzy rules and subordinate functions is very difficult, and needs long time (Li, 2016). Because of the complexity of the electronic equipment faults, the mapping relation from time or frequency domain fundamental space to fault pattern space is strongly nonlinear. At the same time the shape of the subordinate function is extremely irregular. Only the shape of normal subordinate function can be used to process approximately, but to do so limits the precision and possibility of processing the input system with wider range, and makes the results of the nonlinear system diagnosis dissatisfactory. In order to solve these problems existing in fuzzy diagnosis, it is a better way to introduce neural network. As we all know, in the fault diagnosis of equipment exists a lot of indeterminacy. Studying the indeterminacy is the key to determine whether the diagnosis is right or not. Exiting fuzzy diagnosis methods usually use fuzzy relation matrices to transform the indeterminacy, however, introducing neural network to fuzzy diagnosis is using network structure to transform the indeterminacy. This is the nature of the fuzzy diagnosis methods based on neural network. This method has become the most prosperous one in electronic equipment fault diagnosis. Although many learners have carried on the research in this field, it is still in the probing phase regarding creating learning sample, input fashion and the convergence of the Teaming process. So, this article stressed the fuzzy processing methods of learning sample, and put forward the fuzzy diagnosis methods based on neural network, and carried on the simulation research (Sun et al., 2014; Kong et al., 2011; Ren et al., 2013; Huda et al., 2014).

3. Improved support vector machine and fuzzy clustering method

The support vector combined fuzzy sets and neural network to carry on the fault diagnosis is a most prosperous diagnosis method. When the BP network is applied to the fuzzy diagnosis, the inputs of the network are the subordinate degree value after the transition of the diagnosis parameters. By the fuzzy mapping relation that has been trained by the network we can get the output subordinate degree values of the fault reason that show the possibility of certain fault's occurrence. Article (Pan et al., 2009) carried on the research of the application of support vector combined fuzzy sets, expert system and neural network in the analysis and diagnosis of the dissolved gas in transformer oil and then advanced an insulation diagnosis method combining support vector combined fuzzy sets and neural network. From the analysis above, we can see that when the BP network is applied to diagnosis, it has extremely high demands for the range, density, consistency and uniformity which is distributed in the space by the sample data, otherwise, it will directly affect the adaptively and precision of diagnosis model. This section processes the sample using methods based on support vector combined fuzzy sets; it is also a respect of combining support vector combined fuzzy sets and neural network to carry on diagnosis (Janssens et al., 2015).

$$\overline{x_i} = \frac{x_i - b_i}{a_i - b_i} \tag{1}$$

Experimental data to determine, we can also experience the value of the formula (2) the decision.

$$n = \log_2 m \tag{2}$$

Hidden node output is calculated as follows:

$$h_j = f\left(\sum_{i=1}^{m} w_{ij} x_i - \theta_j\right) \tag{3}$$

In this posture, 'n' is the number of subset of the sample, m is the one of center sample subset; 'u' is the 'i' one of its element of the sample space. The purpose of the cluster is to minimize this function and classify the following algorithm. (1) Standardizing of data. In order to dispel the influence of the difference of every indexes of sample different from order of magnitude, we should deal with the normalization to every index value, obtained value is:
The output of the output node is calculated as follows:

$$f\left(\sum_{i=1}^{m} w_{ij} x_i - \theta_j\right) = f\left(f\left(\theta_j\right)\right) \tag{4}$$

Where in θ is an output node threshold.
Put Equation (3) into Equation (4), then we can get the S-type function:

$$f\left(\sum_{i=1}^{m} w_{ij} x_i - \theta_j\right) = f\left(f\left(\theta_j\right)\right) \tag{5}$$

In the structure of GA algorithm, we can get the optimization equation as the following equation (6):

$$h_j = \exp\left(-\frac{\left\| X - C_j \right\|}{2b_j^2}\right), \quad j = 1, 2, ..., m \tag{6}$$

The output of the network is given as:

$$y_m(k) = wh = w_1 h_1 + w_2 h_2 + ... + w_m h_m \tag{7}$$

Assuming the ideal output is y (k), the performance index function is:

$$E(k) = \frac{1}{2}\left(y(k) - y_m(k)\right)^2 \tag{8}$$

The equation of basic function is as equation (9) as follows:

$$\partial_j (C_{ijkl} \partial_k u_l + e_{kij} \partial_k \varphi) - \rho \ddot{u}_i = 0 \tag{9}$$

Under the linear relationship, basic equation is shown in equation (2):

$$\partial_j (e_{ijkl} \partial_k u_l - \eta_{kij} \partial_k \varphi) = 0 \tag{10}$$

The linear differential equation can be expressed into the following simplified forms:

$$L(\nabla, \omega) f(x, \omega) = 0 \,, \; L(\nabla, \omega) = T(\nabla) + \omega^2 \rho \mathrm{J} \tag{11}$$

In which,

$$T(\nabla) = \begin{Vmatrix} T_{ik}(\nabla) & t_i(\nabla) \\ t_k^T(\nabla) & -\tau(\nabla) \end{Vmatrix}, \; \mathrm{J} = \begin{Vmatrix} \delta_{ik} & 0 \\ 0 & 0 \end{Vmatrix}, \; f(x, \omega) = \begin{Vmatrix} u_k(x, \omega) \\ \varphi(x, \omega) \end{Vmatrix} \tag{12}$$

$$T_{ik}(\nabla) = \partial_j C_{ijkl} \partial_l \,, \; t_i(\nabla) = \partial_j e_{ijk} \partial_k \,, \; \tau(\nabla) = \partial_i \eta_{ik} \partial_k$$

Consider an infinite situation, we have the equation (5) in the following:

$$L^0 = \begin{Vmatrix} C^0_{ijkl} & e^0_{kij} \\ e^{0T}_{ikl} & -\eta^0_{ik} \end{Vmatrix} \tag{13}$$

Consider the propagation, instead the equation (13) with the following form:

$$C(\mathrm{x}) = C^0 + C^1(\mathrm{x}) \,, \; e(\mathrm{x}) = e^0 + e^1(\mathrm{x}) \,, \; \eta(\mathrm{x}) = \eta^0 + \eta^1(\mathrm{x}) \,, \; \rho(\mathrm{x}) = \rho_0 + \rho_1(\mathrm{x}) \tag{14}$$

Then we have equation (15) to (18):

$$C^1 = C - C^0 \,, \; e^1 = e - e^0 \,, \; \eta^1 = \eta - \eta^0 \,, \; \rho_1 = \rho - \rho_0 \tag{15}$$

The containing inclusions can be simplified into the following integral equation set:

$$f(x, \omega) = f^0(x, \omega) + \int_V \mathcal{S}(x - x')(\mathrm{L}^1 F(\mathrm{y}') + \rho_1 \omega^2 \mathbf{g}(R) \mathrm{T}_1 f(\mathrm{y}')] S(\mathrm{y}') \mathrm{dy}' \tag{16}$$

In view of the following relationship

$$\frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-ik_3 x_3'} dx_3' = \delta(k_3) \tag{17}$$

Equation (8) can be converted into the following form:

$$f(y, \omega) = f^0(y, \omega) + \int_s S(y - y', \omega) \mathrm{L}^1 F(\mathrm{y}', \omega) \mathrm{dy}' + \rho_1 \omega^2 \int_s \mathbf{g}(y - y', \omega) \mathrm{J} f(\mathrm{y}', \omega) \mathrm{dy}' \tag{18}$$

In which, S is cylinder cross section, y=(x_1, x_2), and

$$\mathbf{g}(y-y',\omega)=\frac{1}{(2\pi)^2}\int_0^\infty \bar{k}d\bar{k}\int_0^{2\pi}\mathbf{g}(\bar{k},\omega)\exp(-i\mathrm{k}\cdot(\mathrm{y}-\mathrm{y}'))d\phi \quad \bar{k}=(k_1,k_2) \tag{19}$$

Suppose k_3=0, $g(\bar{k},\omega)$ can be obtained from Equation (17)
For such kind of material, general form of equation (10) is expressed as following equation (20):

$$G_{ik}(\bar{k},\omega)=\frac{1}{\rho_0\omega^2}[\frac{\beta^2}{\bar{k}^2-\beta^2}\theta_{ik}+\bar{k}_i\bar{k}_k\left(\frac{1}{\bar{k}^2-\alpha^2}-\frac{1}{\bar{k}^2-\beta^2}\right)+m_im_k\frac{\beta_\perp^2}{\bar{k}^2-\beta_\perp^2}] \tag{20}$$

Competed and revised many times like this, finally the seed steadied in the center of each of subset through competition, each sample is only one stature collection, thus divide the sample space into K subsets.
To different subsets, we should adopt the forward propagation algorithm to pool design and make the whole network (including its structure and algorithm), and separately adopt the corresponding sample data to train the network got a set of networks made up by K networks finally. Putting the measure samples into the network will get the results of K neural networks separately.
For measure sample, we can't decide whether it belongs to an accurate subset; we can just confirm that to how great a degree it belongs to a certain classification, then average the results of each sample and obtain the final result finally.

4. Experiment research

In order to verify the fuzzy diagnosis method based on neural network put forward by this article. Still take the data of dissolved gas in transformer oil as the analysis and simulation object of insulation diagnosis. The following is the concrete steps:
(1) Training and diagnosis of neural network
Figure 1 shows the convergence comparison before and after data sample cluster processing, the network ratio is R. This figure indicates that the learning convergence velocity of the standard sample after cluster processing increases largely, practical diagnosis results show that using standard sample after cluster processing to diagnose can meet the demand of diagnosis, and accurately diagnose. Figure 2 shows the support vector machine process. Figure 3 to figure 4 shows the experiment result.

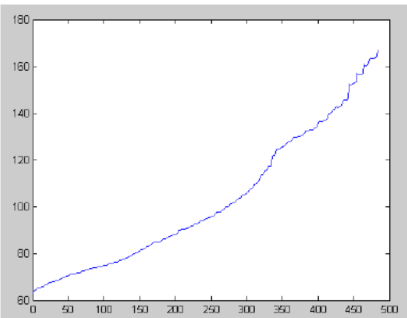

Figure 1: The convergence comparison after data cluster and support vector sets processing

(2) Create the initial sample
Allowing for the influence of such factors as the one, volume and operating environment of the transformer, according to the document at hand, we collected thirty transformer chromatogram test records and corresponding fault results which are produced by different manufacture factories and operating under different voltage levels and in different zones, in order to facilitate comparison, take 13 sets in article as experimental analysis sample, in addition, draw 7 sets from 30 sets randomly, they together form the initial data sample ,then adopt the fuzzy processing method advanced in the former section to analyze the initial sample. Here still adopt the method in article (Pan et al., 2009) to quantitatively process the test data ,then get the initial sample data. At present, when intelligently diagnosing and analyzing the dissolved gas in transformer oil, mostly adopt the gas content and total hydrocarbon value of CO, HZ, CH4, CZH2, CZH4, CZH6, as the input parameter, to diagnose and analyze.
According the synthetic consideration and comparison, take the total hydrocarbon value Total and the ratios in total hydrocarbon value of CZHZ, HZ CH4 and CZHZ as the parameter. Fault outputs are divided into general super-heating, serious super-heating, partial discharge, spark discharge and electric arc discharge.

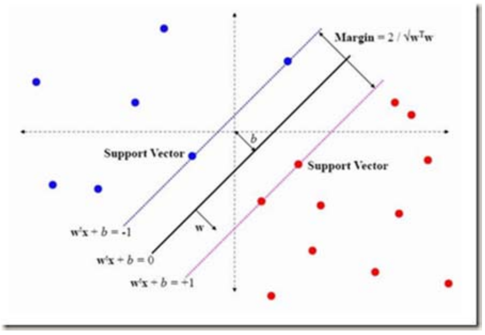

Figure 2: The support vector machine process

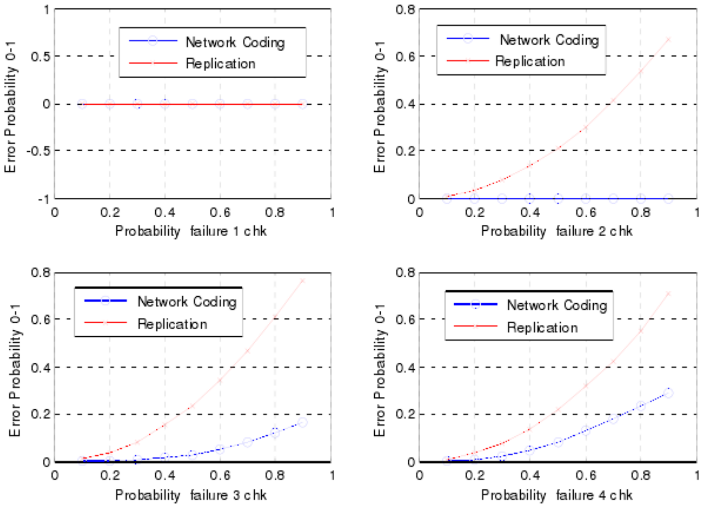

Figure 3: Error rate of the system

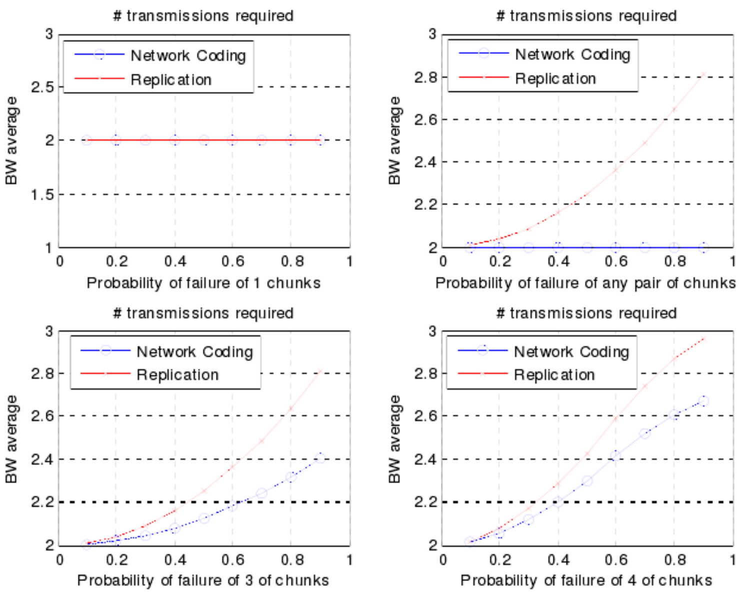

Figure 4: Experiment result

(3) Create standard sample
After creating the normal samples. According to the results of fuzzy cluster, choose the normal sample, the standard samples are twelve sorts, and then the standard sample can carry on the learning and training of neural network.

5. Conclusion

This paper studied the support vector and fuzzy sets of samples optimization processing and put forward the diagnosis method of neural network based on fuzzy clustering. Some useful conclusions can be drawn as follows: (1) It is a better and prosperous way to combine neural network theory and fuzzy clustering to carry on insulation diagnosis. (2) When using neural network to carry on insulation diagnosis, it is important that processing method based on fuzzy clustering can well analyses the problems of single sample, sparse sample and contradiction sample existing in samples, removing contradiction sample can distinctly improve the accuracy of neural network diagnosis.

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