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Oil-immersed power transformer internal fault diagnosis research based on probabilistic neural network

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Abstract

Oil-immersed power transformer is one of the key devices in power system. And the reliability of power grid is guaranteed by its safe operation. Therefore, it is necessary to reduce transformer failures with precautionary measures. Nowadays, three-ratio method of dissolved gas analysis (DGA) is the most effective and convenient method in transformer fault diagnosis. However, when using three-ratio method as the judgment, it exists some disadvantages such as coding defects and threshold criterion defect. A new way for this problem is provided by artificial neural network ,which has the advantages such as parallel processing, self-adaptation self-study, association memory, non-linear mapping and other features. Oil-immersed transformer internal faults are predicted in this paper by using probabilistic neural network algorithm, which brings its ability of processing non-linear problem into full play. What's more, the DGA judgment process is optimized and convenient setting of parameters is achieved. The high accuracy of diagnosis is confirmed by simulation results in KNIME platform.

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Keywords: Probabilistic Neural Network(PNN); Dissolved Gases Analysis(DGA); fault diagnosis

1. Introduction

Transformer, which is most important and fundamental component in complex power system shall be responsible for power transmission and voltage converting. While the multi-protection outside and inside shield transformers, transformer failures still occur. Meanwhile, the frequency of accidents is quite high due to the design, manufacturing, technology, raw materials of defects, and natural disasters, etc. As a result, it is important to forecast and diagnose transformer faults in real time.

Dissolved gas analysis (DGA) is the most effective and convenient method in transformer fault diagnosis. And there are three improved methods based on DGA technology , including Two-ratio method (proposed by Dornenburg to distinguish heat and electricity) the Lagorejer judgment method and the Rogers method (four-ratio method).[1,2] But many questions in engineering practice are exposed, some of which are incomplete coding , absolute encoding boundaries and the failure of faults diagnosis. As a result of the existence of these problems, a variety of artificial

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intelligence technologies for power transformer fault diagnosis have been proposed by domestic and foreign scholars . For example,the sample is to be classified effectively with the combination of genetic algorithm and FCM[3] . The optimization parameters of genetic algorithm can be accurately found in a wide range by using SVM[4].

In the meantime, artificial intelligence algorithms such as expert system[5] , fuzzy theory[6], rough set theory[7], evidence theory[8] are applied to diagnosis of power transformer. Nevertheless ,because of the new fault produced by power transformer in the actual process the above methods can't be updated the training sample in real time. Probabilistic neural network (PNN), a diagnosis of network system with the abilities of strong fault tolerance and adaptive structure,to diagnose power transformers,has been adopted in this paper. By the way, the network without having to retraining when there is a new fault occurs.

2. Oil-immersed transformer fault diagnosis based on probabilistic neural network

2.1. Pose problem

The workflow was set up on the KNIME platform in order to effectively predict power transformer faults and the types of fault. The input sample data set D, which is expressed as $(v_1, v_2, , v_n; F)$ is a previous fault data set. v_i is the content of the characteristic gases in power transformers and $F$is the corresponding fault types. The input test data set X, which the types of fault and the accuracy of the prediction to be observed, only including the content of the gases and expressed as $(v_1, v_2, , v_n)$.

2.2. Data pre-processing

The normalization processing , which is the linear function transformation method , is used in this article to make the data fall into the range of [0, 1] and to avoid the unequally using of the input variable with different physical meaning and dimension. It can also elimination the influence of dimensional , make the data become scalar ,improve the accuracy of fault diagnosis and accelerate the convergence of training network.

The conversion formula is:

$$Y = \frac{(v - minvalue)}{(maxvalue - minvalue)} \tag{1}$$

Y is the normalized value , *Maxvalue* is the maximum sample data, *minvalue* is the minimum sample data.

2.3. Probabilistic neural network algorithm process

Probabilistic neural network is composed of of three layers: the input layer, the hidden layer, and the output layer. This neural network model has the following features: the topology ,connection weights and thresholds can be set immediately when training samples are attainable. Its training is concise and classification ability is strong.

2.3.1. Determining weights

According to the features of learning samples and the desired output, network connection weights of hidden units is acquired directly by probabilistic neural network.

weight matrix (Input layer to hidden layer) :

$$W_{ki}^{IH} = x_i(k), (i = 1, 2, \ldots.N) \tag{2}$$

$W^{IH} = [w_{ki}^{IH}]_(3N)$

$X(k) = [x_1(k), x_i(k), \ldots.x_N(k),]^T$

N is the Number of nodes in the hidden layer.

weight matrix (Hidden layer to output layer):

$$W_{kj}^{HO} = \begin{cases} 1, & k \in type1 \\ 0, & k \in type0 \end{cases} \tag{3}$$

$W^{HO} = [w_{kj}^{HO}]_(k9), (j = 1, 2 \ldots.9)$

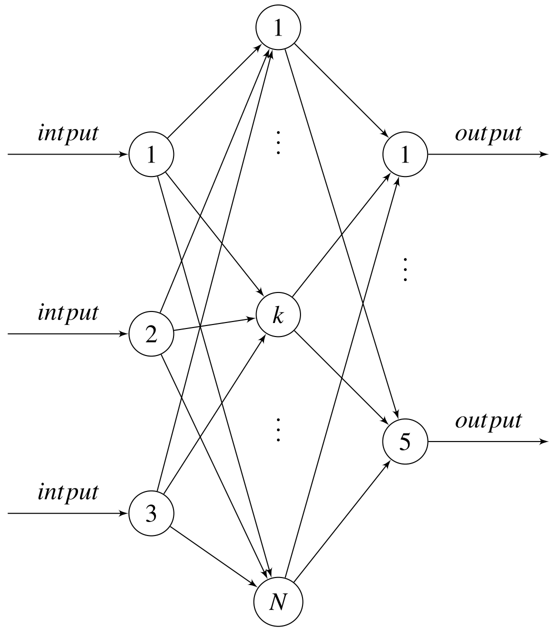

Fig. 1. Probabilistic neural network topological structure .

2.3.2. Probabilistic neural network diagnosis process

- Connection weights matrix of the network W^{IH}, W^{HO} and training sample set D are read ;
- Training sample set D is entered into the hidden layer and the output of the hidden layer is calculated;
  A nonlinear operator of hidden layer by gauss function as fellow :

$$f_k = exp(-net_k/\sigma^2) \tag{4}$$

σ is smoothing factor.

$$net_(k = \sum_{(i=1)}^{n} (x_i - w_{ki}^{IH}) \tag{5}$$

$$H_k = exp(\frac{-net_k}{2\sigma^2}) \tag{6}$$

smoothing factor $\sigma_1 = \sigma_2 = \ldots.\sigma_N = \sigma_0$.

- Probability sum O_j ,which belongs to the first category,with the value as output from hidden layer to output layer is calculated;

$$O_j = \sum_{(k=1)}^{k} (w_{kj}^{HO} H_k), k \in type1 \tag{7}$$

- Probability sum of hidden layer outputs and the final output probability P_j are calculated.

$$P_j = \frac{O_j}{\sum_{k=1}^{N} H_k} \tag{8}$$

2.3.3. computation

Failure prediction reasoning path of predicted data along the level of the network and the final output matching inference results. The output of failure data expressed as:$(v_1, v_2, , v_n; Z)$, v_i is property values ,Z is predicting fault type.

3. Simulation and analysis of Power transformer fault diagnosis based on PNN

Dissolved gas analysis (DGA) is one of the most effective and important methods in oil-immersed power transformer fault diagnosis. Among various diagnostic methods of DGA, the three-ratio method improved has the highest accuracy. The three-ratio of oil dissolved gas content are selected as input vectors of neural network. And the output vectors are the types of transformer faults.

3.1. The sample data set

A total of 500 sample data is got from the UCI machine learning repository , which contains seven attributes : $CH_4, C_2H_6, C_2H_4, C_2H_2, H_2, CO, CO_2$.

Table 1. Failure type and number:

Failure type	number
Low temperature overheat	54
hyperthermia and superheating	265
Low energy discharge	125
high energy discharging	24
Discharge and overheating	32

From this 500 sample data, 450 sample data are selected randomly for probabilistic neural network training, others are the test data for testing the accuracy of power transformer fault diagnosis which is based on probabilistic neural network.

3.2. simulation workflow setting

KNIME ,a data mining software,is used for simulation experiment and the simulation of fault diagnosis is realized by constructing workflows.
The implementation steps as fellow:

- 500 oil-immersed transformer fault data for database are read;
- With the normalization processing ,this data are divided into sample data and test data randomly;
- Probabilistic neural network learning is used to learn of the data, and the fault prediction model for failure prediction is to be establish;
- the predict result and the existing result are compared, and the accuracy of prediction is calculated.

3.3. simulation results analysis

With different algorithms,the sample data are learn and used to predict fault. simulation results as shown in Table 2.

From the above calculation results, the fault diagnosis accuracy based on probabilistic neural network is 80%. It is higher than accuracy rate that based on other intelligent algorithms. As a result , satisfactory results on the accuracy of oil-immersed power transformer internal fault diagnosis are achieved by using probabilistic neural network.

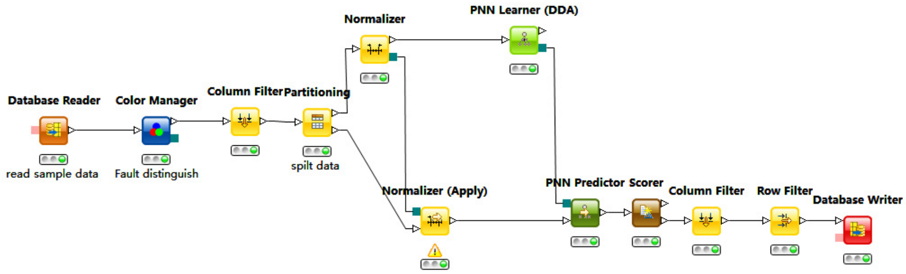

Fig. 2. Fault diagnosis workflow.

Table 2.

Algorithm	Accuracy prediction
Probabilistic Neural Network	0.8
BP-neural network	0.771
fuzzy algorithm	0.686
decision-making tree	0.605
bayesian algorithm	0.541

4. conclusion

A new method based on probabilistic neural network to establish workflow about oil-immersed power transformer internal fault diagnosis is introduced in this paper. With the ability of learning knowledge from the examples and convenient parameter settings, neural network with good fault-tolerance and adaptivity is obtained . The network, which has simple processing and rapid convergence, don't need training. Its corresponding weighting is the distribution of sample. The transformer fault sample library , which would change with the increase of transformer faults, should to be established. And with the full using of the strong ability of PNNs sample complementing, the practical application of diagnostic accuracy is increased.

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References

1. State Economic and Trade Commission. *DL/T7222000 Guide to the analysis and the diagnosis of gases dissolved in transformer oil* .Beijing :China Electric Power Press;2001.
2. Xiong Hao,Sun Caixin,Chen Weigen,etal.Aritifical immune network classification algorithm for fault diagnosis of power transformer. *Automation of Electric Power Systems*2006:30(6):57-60.
3. Tian Zhiguang,Zhang Huifen. Based on genetic clustering algorithm analysis of gases dissolved in transformer oil power transformer fault diagnosis. *Electric Power Automation Equipment* 2008;28(2):15-19.
4. Xiao Yancai,Chen Xiuhai,Zhu Hengjun. Genetic support vector machine in the application of the power transformer fault diagnosis . *Journal of Shanghai Jiaotong University* 2007;41(11):1878-1882.
5. Li Xionggang . Fault diagnosis expert system in the application of the power system .*Guangdong Electric Power* 1999;12(2):39-41.
6. Islam S M,Wu T,Ledw lch G. A novel fuzzy logic approach to transformer fault diagnosis. *IEEE Transaction on Dielectrics and Electrical Insulation*2000, 7(2):177-186.
7. Huang Wei,Zhao Yangbang, Chen Qiaosheng. Wang Junkai.Transformer Fault Diagnosis based on Improved Genetic Algorithm and Rough Set . *2015 the national smart grid client energy management academic annual meeting.*Shanghai;2015.p.296-299.
8. K. Spurgeon,W.H. Tang,Q.H. Wu etal.Dissolved Gas Analysis Using Evidential Reasoning.*IEE proceedings.A.Science, measurement & technology*2005,152(3):110-117.