

## Research Article

### A Fault Diagnosis Method for Food on-load Tap Changer Based on Probabilistic Neural Network

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**Abstract:** In this study, we present a fault diagnosis method based on Probabilistic Neural Network (PNN) to find the food on-Load Tap Changer (FFOLTC)s' faults. First the sample data was collected from the results of AC dynamic characteristic tests of (FFOLTC)s. Second features was extracted from the sample data and normalized. Then the parameters were set for the PNN and the samples were trained to get the diagnosis network. Finally we used the test data of FFOLTC to check the network for diagnosis. Experimental results show that the PNN method could detect the complex relationships, could be developed basis for the FFOLTC test data that can identify the fault types. The accuracy of the results is more than 70% in all cases and 100% in some cases. So the proposed method is fast, accurate, easy to modify and can be easily applied to practical application.

**Keywords:** Diagnosis method, food on-load tap changer, probabilistic neural network

## INTRODUCTION

Food on-Load Tap Changer (FFOLTC) is a switch device, which provides constant voltage for transformer when the load changes (Erbrink *et al.*, 2010a, 2010b; 2011). Its principle is that one winding tap of transformer is switch to another without interrupting the load current to change the turn number of the winding, namely the transformer voltage ratio, which can achieve the purpose of voltage regulation ultimately (Li *et al.*, 2012).

Nowadays, the FFOLTC has an important effect on the voltage quality in food power transmission industry. The transformers of capacity of 10 MVA and above are mounted (FFOLTC)s at present in the developed countries. And in China electric food power system and users more and more use the on-load voltage regulating transformer, in which FFOLTC is the most critical and expensive element.

According to the need of system load and system voltage, (FFOLTC)s are used to switch the winding taps without interrupting the load current. Because of the frequent operation and without arc device the taps will burn out easily causing bad contact and fever, which can ultimately cause transformer explosion. The fault number is a rising trend with the increase of (FFOLTC)s and the growth of operating time. So the fault diagnosis problem of FFOLTC should be paid more attention to Cichon *et al.* (2011). Off-line diagnosis of (FFOLTC)s during regular maintenance can detect maintenance errors and assess the condition

of FFOLTC parts not accessible for inspection. There are many methods using dynamic resistance measurements to diagnose (Erbrink *et al.*, 2011).

Artificial Neural Network (ANN) is a complex nonlinear system composed of a large number of simple processing elements widely connected. It is a self-adaptive pattern recognition technology, instead of the relevant mode of experience knowledge and discriminant functions. It automatically forms decision area required by its learning mechanism. In the perspective of mapping the task of neural network fault diagnosis is mapping from symptom to fault types. It needs regularly action characteristic test and fault diagnosis so as to make the FFOLTC work reliably and maintain correctly.

In this study, Probabilistic Neural Network (PNN) is used to FFOLTC fault diagnosis. The fault diagnosis method has been verified for FFOLTC by analyzing the parameters influence on the diagnosis results and establishing the relationship between training samples and parameter. We analyzed the influence of parameters on the diagnosis results and found a method to determine parameters.

## MATERIALS AND METHODS

### Probabilistic neural network:

**Neural network consists of three layers for fault diagnosis:** The input layer, the middle layer and the output layer. The input layer receives all kinds of fault information. The number of the units represents the

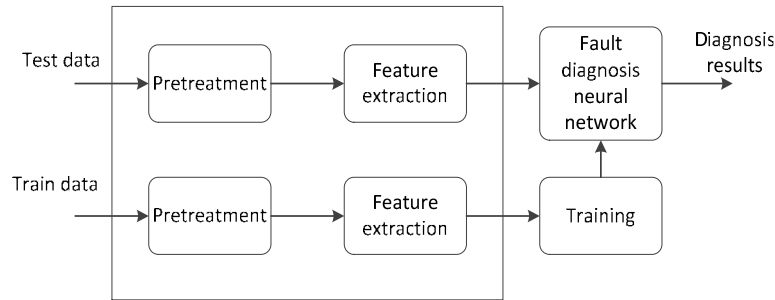


Fig. 1: Process of neural network fault diagnosis system

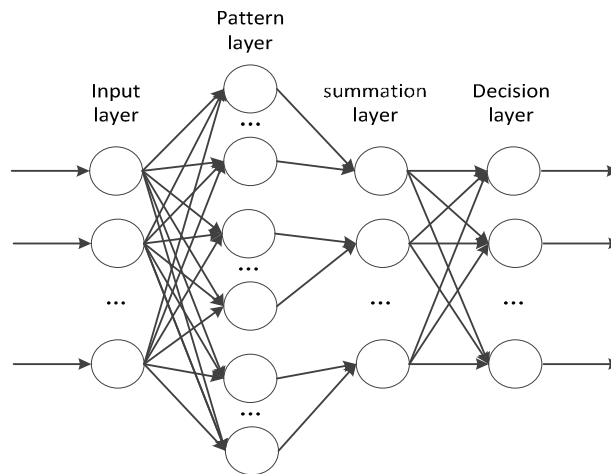


Fig. 2: PNN structure

number of feature parameters. The middle layer is also called the hidden layer. The fault information, which obtained from the input layer, is trained and handled in this layer. It is connected with the input layer and output layer through the weight coefficient. Each kind of sample input of the fault corresponds to a specific output fault state. The middle layer can be one layer, also can use multilayer. The output layer is used to output fault type concretely. When the network is well trained, the network can quickly give the diagnosis results for the state information of each new input.

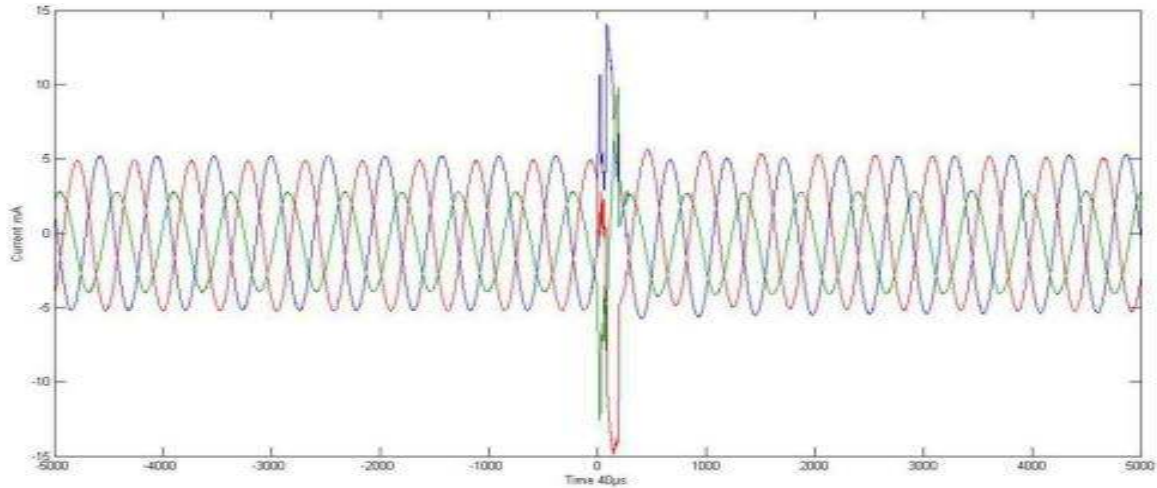
Process of neural network fault diagnosis system is shown in Fig. 1. The diagnostic process is divided into two steps: In the first step we train the samples to get the diagnosis network; in the second step test data of FFOLTC is inputted to the current diagnosis network for diagnosis. Preprocessing and feature extraction before learning and diagnosis is to provide the appropriate training samples and diagnosis input.

PNN was first proposed by Specht (1990) and Rivas *et al.* (2010). It is a branch of radial basis function network and is a kind of feed forward network. It is a simple structural, simple trained and widely used artificial neural network. The network structure is shown in Fig. 2. It is a supervised network classifier, which is a parallel algorithm developed from Bias

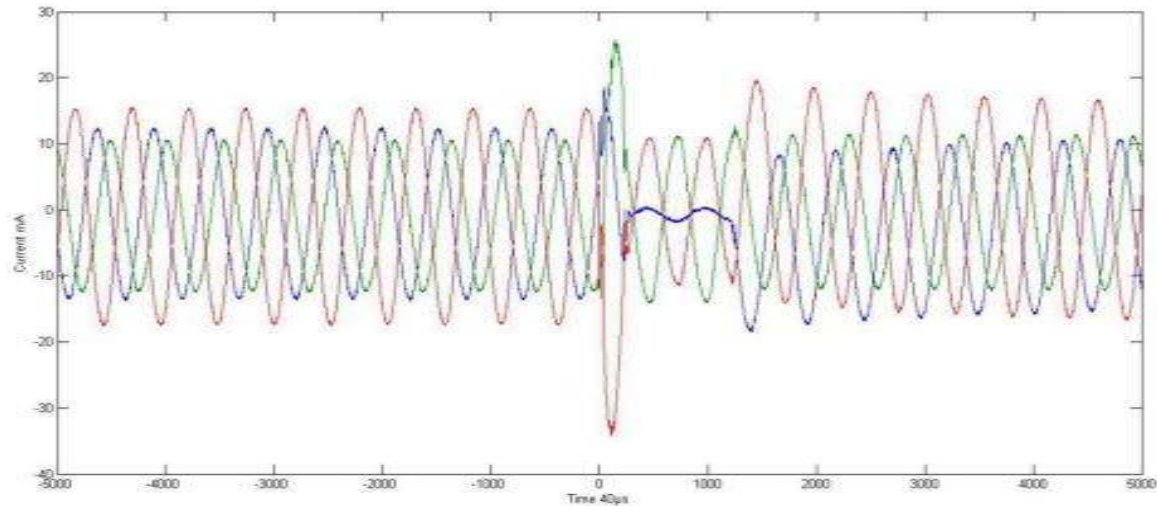
decision theory. PNN is formed by Bayes classification rules and use the Parzen window function to estimate the conditional probability density. PNN has a strong ability of nonlinear classification (Specht, 1990). The essence of fault diagnosis based on PNN is to map fault sample space to a fault in the pattern space, so as to form diagnosis network system of a strong ability of fault tolerant and self-adaptation. PNN is widely applied to radar target recognition and analyzing the fault diagnosis and the condition of equipment, which has made has made application results satisfactory (Jin *et al.*, 2005).

## RESULTS AND DISCUSSION

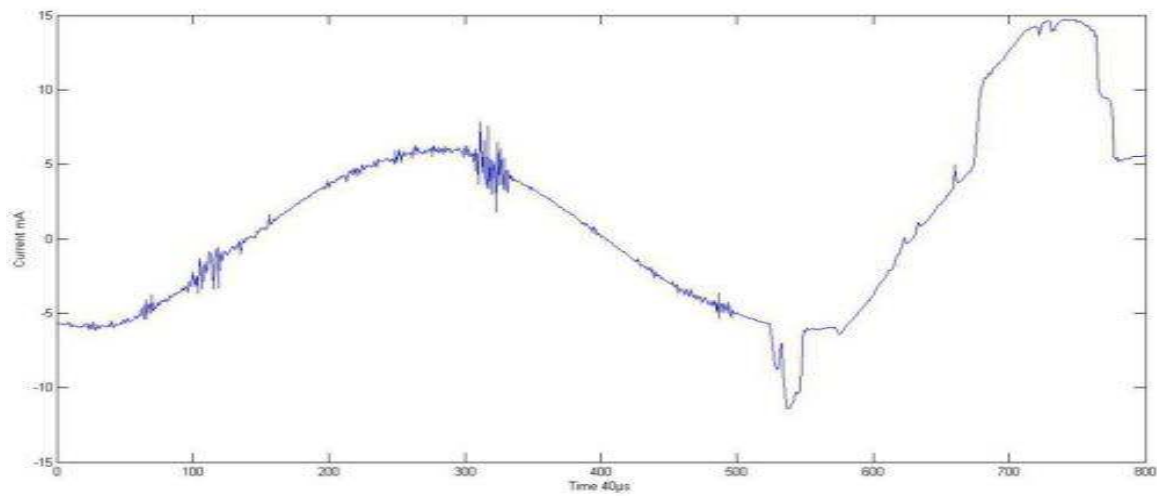
**The fault diagnosis experiment:** We use PNN method for fault diagnosis. Input samples are the data from AC dynamic characteristic test of (FFOLTC)s as shown in Fig. 3. Figure 3a is the normal case. Transition resistors are broken and taps contact poorly as shown in Fig. 3b and c separately. And then we got the features which are mean values, variances, derivative mean values and effective values. Initial feature data is normalized for training the network. Characteristic information of the input will be extracted to training network in the Matlab simulation. In the fault diagnosis system based on PNN, the influence of the accuracy rate of diagnosis is mainly



(a) Normal



(b) Broken transition resistors



(c) Poor contacted taps

Fig. 3: AC dynamic characteristic test of FFO LTC

the number of training samples and the spread value ( $\sigma$ ).

### CONCLUSION

In this study a fault diagnosis method based on PNN has been proposed for the (FFOLTC)s. We used the AC dynamic characteristic test data of (FFOLTC)s to diagnose. The experiments were respectively conducted on two influencing factors. The results confirmed that the PNN has the excellent ability of fault diagnosis. The simulation results have shown that the fault diagnosis accuracy increases with the increase of the number of training samples and increases with the decrease of spread value. PNN fault diagnosis system not only can meet the requirement of the safe and stable operation of FFOLTC and rapid troubleshooting, but also can reduce the labor intensity of technical personnel. However, the data what we used is not enough and the (FFOLTC)s' faults are very complex. There are still some other faults like spring aging and oscillation fault. In addition the (FFOLTC)s have complex structure and a high requirement of the operation. So we need to get more different kinds of fault data for further experiments to accomplish the fault diagnosis FFOLTC better.

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