An Evaluation Method of DC Magnetic bias Vibration for Transformer based on Prior Knowledge and Neural Network Modeling

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Abstract. At present, the number of fault samples is insufficient in the field of transformer fault diagnosis based on vibration, and the experimental data of existing research results mostly come from laboratory conditions, which is difficult to popularize in a large scale. Therefore, combining with the idea of fuzzy mathematics, this paper integrates the prior knowledge into the neural network, and extracts the function of characteristic quantity and fault probability from the trained neural network model by numerical test, which is the basis of fault diagnosis. Then, the effectiveness of this method is verified on the test sample set. The results can be used as a means to incorporate prior knowledge into intelligent algorithms, and help to study the relationship between different feature quantities. In general, this article provides a way of applying prior knowledge to vibration diagnosis algorithms, which has broad development prospects.

1. Introduction
Transformer is the key equipment in power system, so it is of great significance to monitor its condition. The current transformer monitoring methods include traditional oil chromatogram analysis, reactance test, micro water analysis, local detection, iron core grounding current, etc. [1]. Among them, oil chromatography analysis, local detection and iron core grounding current can realize on-line monitoring, but only fuzzy fault information can be obtained, which can not confirm the fault. Reactance test can accurately determine the fault type and fault, but the transformer is required. The vibration monitoring method is a new transformer monitoring method proposed in the 1990s, which has been developed for more than ten years, and tends to be mature. This method can realize on-line monitoring and has the advantages of practical accuracy [2]. At present, the bottleneck of this method lies in the further improvement of the accuracy, so that it can become a main monitoring hand. In the field of vibration monitoring, some existing research results are based on laboratory data, which is not beneficial to practical application. Therefore, how to achieve better diagnosis results under the limited amount of actual data, and in-depth analysis of the relationship between the characteristics of the transformer and fault, is a more important problem at present.

At present, in the aspect of transformer vibration diagnosis, the research on vibration mechanism is very sufficient, and the diagnosis methods mainly include threshold method and neural network method [2-10]. Among them, the threshold method is a method to determine whether the transformer is
fault by studying the vibration signal characteristics of the fault, defining a threshold or setting a judgment function to determine whether the transformer is in fault \cite{2-6}; the neural network rule is to input the vibration characteristic quantity of the transformer fault into the neural network, and achieve good classification accuracy through sample training \cite{7-10}. At present, most of the research on transformer fault is based on laboratory data and theory. For the complex actual situation, there is not enough practical method; for the problem of small sample, there is no good solution, these problems are the bottleneck of transformer vibration diagnosis method. For this reason, the academia has gradually put their attention on the coupling relationship of the characteristic variables, hoping to further reveal the vibration characteristics of the fault, so as to reduce the demand for data and improve the diagnostic accuracy.

This paper presents a method to analyze the coupling relationship of eigenvalues by using neural network. The prior knowledge is integrated into the neural network, and the trained neural network is tested numerically to obtain the coupling relationship between each characteristic quantity. Based on this, the fault probability of transformer is given, and the basis for further study on the coupling relationship of characteristic variables is provided.

2. Brief Introduction of Transformer Magnetic Bias Vibration Mechanism and Characteristic Selection

2.1. Vibration Mechanism

Transformer vibration generally includes body vibration, auxiliary equipment vibration and environmental factors vibration. Here, the body vibration refers to the vibration caused by the iron core and winding of the transformer. The vibration of auxiliary equipment includes the vibration of fan, oil pump and other auxiliary equipment, and the vibration of environmental factors is caused by the external environment. In this paper, the vibration data are processed in advance to filter out the irrelevant vibration.

The vibration of transformer body includes the vibration caused by iron core and winding. The vibration of the iron core is mainly caused by the magnetostrictive force of the iron core, and is also affected by the electromagnetic force of the iron core; the vibration of the winding is mainly affected by the electromagnetic force.

\begin{align}
    m_w \ddot{x}_w(t) + f_w\left[\dot{x}_w(t), x_w(t), t\right] &= f_{emw}(t) \\
    m_c \ddot{x}_c(t) + f_c\left[\dot{x}_c(t), x_c(t), t\right] &= f_{emc}(t) + f_{ms}(t)
\end{align}

Where $x_{w}$ and $x_{c}$ are the displacements of the winding and core particles respectively; $f_{w}$ and $f_{c}$ are the internal forces produced by the winding material and the core respectively; $f_{emw}$ are the electromagnetic forces acting on the winding particles; $f_{ms}$ and $f_{emw}$ are the magnetostrictive force and electromagnetic force on the core respectively.

DC bias has the greatest influence on the core vibration. When the transformer has DC bias, the transformer excitation will be saturated, and a DC component will be superimposed on the AC magnetic flux of the normal transformer. Under the action of magnetostriction, the core vibration of the transformer will be affected.

According to some existing research results \cite{11}, DC bias will lead to three obvious characteristics of transformer vibration:

- The amplitude and waveform of two half cycles in one power frequency period of transformer oil tank vibration signal are quite different;
- Power frequency component can be used to measure the degree of transformer magnetic bias to a certain extent;
- The high frequency component of transformer vibration increases sharply and the signal complexity increases.

Among them, the first feature is the main feature, and the other two features can be used as auxiliary criteria.
2.2. Vibration Characteristic Quantity

According to the related characteristics of DC magnetic bias vibration, we can sum up three characteristic quantities, namely the ratio of odd to even harmonic amplitude value, the fundamental frequency of 50Hz and the frequency complexity. Among them, the ratio of odd to even harmonic amplitude is the main characteristic of DC magnetic bias, and can reflect the severity of DC magnetic bias to a certain extent; the frequency complexity changes obviously when other types of faults occur, but it can still be used as one of the evaluation indexes of DC magnetic bias vibration. The formulas for calculating the ratio of amplitude value and frequency complexity of odd and even harmonics are shown in equations (3) and (4),

$$\lambda_{oe} = \frac{\sum p_{2f}^2}{\sum p_{2f-1}^2}$$  \hspace{1cm} (3)

$$FC = |\sum_{f=100}^{2000} p_f \log_2 |p_f| |$$  \hspace{1cm} (4)

Among them, $\lambda_{oe}$ is the ratio of even and odd subharmonic amplitudes, $FC$ is the frequency complexity, $p_f$ is the amplitude of the main frequency component in 100-2000Hz.

When the three parameters increase significantly, it can be considered that the higher the probability and the more serious the DC bias occurs. According to this characteristic, we can use S-type function to express the relationship, as shown in equation (5),

$$S(x) = \frac{1}{1 + e^{-\alpha(x + \beta)}}$$  \hspace{1cm} (5)

The S-type function is shown in the figure.

**Figure 1.** The graph of S-type function.

According to experience, when the characteristic value of DC magnetic bias of transformer is at a low value, it will fluctuate in a small range, but it does not belong to the fault situation, and the fluctuation may come from other faults or load changes; when the characteristic value increases significantly, the fault probability will rise sharply. The function characteristics of S-type function are consistent with the vibration characteristics of DC magnetic bias, which can well reflect the fault situation.

3. Neural Network Model and S-type Function

3.1. Neural Network Model Structure

Three characteristic quantities correspond to three S-type functions, each of which contains two undetermined parameters. In this paper, neural network is used to optimize the two parameters. The structure of the neural network is shown in the figure. The neural network is composed of six layers, which are input layer, S-type function layer, three hidden layer and output layer. Each hidden layer has six neurons.
After the training, the neural network does not directly modify the S-type function, but also needs to "black box test" to determine the parameters of the S-type function.

### 3.2. Parameter Determination of S-type Function

In order to use the trained output function of the transformer as a good output function, that is to say, we only need to express the trained output function as a good one. Therefore, we need to determine at least two points to determine the parameters of the S-type function.

1) When the characteristic quantity $X$ is greater than a certain value, no matter how the other two characteristic values are taken, the neural network will judge that it is in fault state, and the characteristic quantity $X$ is recorded as $X_H$. We can see that there are,

$$\lim_{X \to X_H} S(X) = \frac{1}{1 + e^{-\alpha(X+\beta)}} = 1$$

(6)

Taking $\varepsilon$ as the minimum, the above formula can be expressed as,

$$\frac{1}{1 + e^{\alpha(X+\beta)}} = 1 - \varepsilon$$

(7)

After finishing, we can get,

$$\alpha = \frac{\ln \frac{1-\varepsilon}{\varepsilon}}{X_H - \beta}$$

(8)

In the concrete calculation, we can take $X$ as 0.01 and $(\alpha, \beta) \in [(\alpha_1, \beta_1), (\alpha_2, \beta_2), (\alpha_3, \beta_3)]$ as the parameters in membership function of $p_{f50}, \lambda_{pe}$ and $FC$. $X_H$ represents the input characteristic variable.

2) For the characteristic quantity $X$, when we determine the other two eigenvalues, we can find a point $X_M$ on membership function curve. The output of the trained model is changed from 0 to 1. It can be considered that the corresponding failure probability in the membership function curve is $1/2$,

$$S(X_M) = \frac{1}{1 + e^{-\alpha(X_M+\beta)}} = \frac{1}{2}$$

(9)

After finishing, we can get,

$$\beta = -X_M$$

(10)

The precondition of finding $X_M$ is to determine the other two eigenvalues, namely

$$\beta = -X_M = f(X_1, X_2)$$

(11)

Where, $X_1, X_2$ is two characteristic quantities except $X$; the $f(X_1, X_2)$ can be tested by the value of the existing network to fit the curve of $X_M$.

After the $f(X_1, X_2)$ is determined, we can construct the membership function of three characteristic quantities, namely the fault probability curve.

### 4. Experiment and Verification

The experimental data we use the DC bias data provided by Hunan Electric Power Research Institute.
The data was recorded on December 17, 2015. When recording, the transformer had obvious DC bias. At the same time, we also have the vibration data of the transformer during normal operation. Taking the two kinds of data as the analysis object, the effectiveness of the method proposed in this paper is verified.

4.1. Neural Network Training
First of all, we initialize the neural network, set up three hidden layers, each layer has six neurons, and the activation function uses SIGMOD function. The DC bias data is divided into 3000 samples and 1000 normal data. After mixing and labeling, 70% of the samples are used as the training set and 30% as the test set. The training set is input into the set neural network for training, and the accuracy of the trained model is verified in the test set. The training process and results are shown in Fig. 3 and Fig. 4.

![Figure 3. Neural network training process chart.](image)

![Figure 4. Graph of the result of neural network training.](image)

The result of neural network training shows that the classification accuracy of the graph on the test set reaches 96.7%. For simple sample classification, BP neural network has good effect and fast calculation speed.

4.2. Neural Network Training Parameter Determination of S-type Function
According to formula (α) and formula (β), we test the trained neural network and determine \( X_H \) and \( X_M \). After three characteristic inputs are determined, we can determine the unique set of α and β parameters. In theory, the method used in this paper should have three membership functions. After determining all the parameters, the DC bias probability dominated by three characteristic variables can be given at one time. However, considering that the ratio of the amplitude of odd and even harmonics is the vibration characteristic quantity which mainly reflects the characteristics of transformer when DC bias occurs, so it is selected as the dominant diagnostic value, so a membership function is considered.

In order to characterize the calculation results conveniently, the frequency complexity and the amplitude of 50Hz frequency component are set as variables to study the β parameter of membership function, i.e. \( X_M \). The calculation results are shown in the figure.

![Figure 5. Graph of calculation result of parameter β.](image)

It can be seen from the calculation results that when the frequency complexity and the amplitude of 50Hz frequency component increase gradually, \( X_M \) is gradually reduced. From the physical sense, when the frequency complexity and the amplitude of 50Hz frequency component increase gradually, the smaller the ratio of odd to even harmonic amplitude required for transformer "judging" DC bias is,
which is in line with the vibration law of transformer. At the same time, it can be seen from the diagram that the closeness between DC bias and frequency complexity is greater than that between DC bias and the amplitude of 50 Hz frequency component. It is generally considered that the amplitude of 50 Hz frequency component can only be used as the auxiliary judgment of DC bias, and its importance is lower than that of frequency complexity. From these information, the calculation results compound expectations and prove that the method is correct.

After determining the parameters of $\alpha$ and $\beta$, we can draw the corresponding S-type curve. Because the curve is uniquely determined by three characteristic quantities, the drawing results of several groups of typical values are given here, as shown in the figure,

![Graph of S-type function curve of typical parameter values.](image)

Figure 6. Graph of S-type function curve of typical parameter values.

In addition, this article gives the calculation results of the ratio of the odd and even harmonic amplitudes of the DC bias vibration data and the normal vibration data, as shown in the figure below.

![The ratio of the amplitude of the odd and even harmonics of the actual DC bias data based on time series.](image)

Figure 7. The ratio of the amplitude of the odd and even harmonics of the actual DC bias data based on time series.

![The ratio of the amplitude of the odd and even harmonics of the actual normal data based on time series.](image)

Figure 8. The ratio of the amplitude of the odd and even harmonics of the actual normal data based on time series.

In these data, the frequency complexity and fundamental frequency amplitude are stable at about 1.4 and 0.9, respectively. It can be seen from the above three figures that the extracted S function is not distorted. In actual use, after we have determined the three characteristic quantities, we can use a similar "look-up table" method to obtain the diagnosis results, which ensures the diagnosis speed and accuracy. But in fact, I think the greatest significance of this method is that the relationship between different feature quantities can be studied through the parameters of the S function, and the existing intelligent algorithms can be improved based on this method. At the same time, this is also conducive to our analysis of the coupling relationship between the characteristic quantities, which is a research point that has gradually received attention in the field of transformer vibration, which further strengthens the importance of this method.

5. Conclusion

In this paper, a neural network-based diagnosis method for DC magnetic bias of transformer is proposed. The S-type function is set to represent the variation trend of the characteristic quantity with the degree of DC magnetic bias, and the parameters of the function are determined by neural network training and subsequent numerical tests. According to the final calculation results, the probability of DC magnetic bias of current transformer can be given after the input characteristic quantity is given, which also contains the information of current transformer DC magnetic bias severity.
The experimental results prove the effectiveness of this method. In essence, the effectiveness of the method is based on the previous studies on the mechanism of DC magnetic bias vibration of transformers. This paper may not use a very advanced algorithm, the lack of data mining, but this idea can make full use of the previous research experience, can be used for other fault diagnosis, in the field of vibration based transformer fault diagnosis on the problem of scarce samples. At the same time, the method in this paper can be used for off-line calculation, and the calculation results can be used for on-line diagnosis. With the operation of transformer, that is, the expansion of transformer vibration database, the accuracy of this method can be further improved.

In addition, the method in this article is essentially a method of obtaining understandable knowledge from a neural network. With the help of the neural network, we can use the method in this article to determine the coupling relationship of the three characteristic quantities of the transformer DC bias vibration research. This kind of thinking can be applied to fuzzy decision-making systems as a link between expert knowledge and intelligent algorithms. This is also the author's follow-up research work. At the same time, this coupling relationship in this paper is another research hotspot in the field of transformer vibration diagnosis, and it has gradually received attention. Combining physical experiments with numerical testing methods similar to the method in this article is our follow-up work.

Acknowledgments
This work is supported by the Science and Technology Project of State Grid Corporation of China under Grant No. 520201190090.

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