IMPLEMENTATION OF A SOLUTION FOR FAULT DIAGNOSIS IN 3-PHASE TRANSFORMERS USING INTELLIGENT SIGNAL PROCESSING METHODS

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ABSTRACT

Power system is a complex system in both structure and operation. Any incident during the system operation affects the reliability of power supply, power quality and may cause great losses. The power transformers are key elements of a power system. Thus, the online identification of the transformers' status helps us to early diagnose the possible malfunctions, thereby will help to reduce economic losses and improve the reliability. This makes the online identification at great desire. This paper presents a method of supervising and detecting the faults in a distribution 22/0.4kV transformer based on electrical and vibration signals. The data samples are simulated using ANSYS software, the classical artificial neural network MLP is used as the classifier. The numerical results show the correctness of the proposed solutions.

Keyword: *Fault Detection, Transformer Model, Finite Elements Method, Mechanical Vibration, Neural Networks.*

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1. INTRODUCTION

There are now many solutions for transformer faults detections [2]–[4]. Most of the methods bases on the input and output electrical signals, among which some methods use the features in time-domain, some methods analyse the frequency response scan (FRA) [1]. Other methods use the partion discharge effect. This paper focuses on the use of mechanical signals to identify the state of the transformer. As the mechanical signals we use vibration signals measured on the shelter of the transformer and the force acted on the core by the coils of the transformer. The displacement and the vibration can be measured in practice by using accelerometers or other types of vibration sensors. Since the real data are hard to measure, we will design a finite elements model of the transformer and simulate them with the ANSYS software.

From the mechanical signals, a feature vector of 6 components will be generated and as the classifier, this paper will use the classical artificial neural network MLP (Multi Layer Perceptron).

2. THE FINITE ELEMENTS MODEL FOR A DISTRIBUTION TRANSFORMER IN ANSYS

In this paper, we have selected the popular distribution 400kVA 22-0.4kV Y-Y0 transformer to work with. The detail parameters of the transformer and its mechanical and electrical model in ANSYS were described in [5].

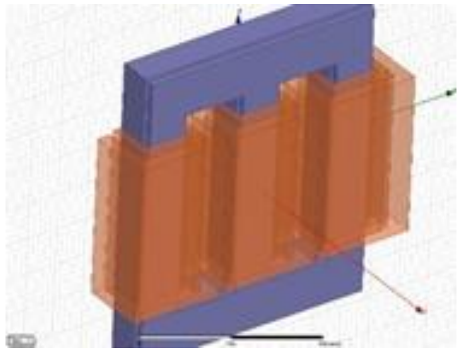


Fig. 1: The 400kVA 22/0.4kV distribution transformer model

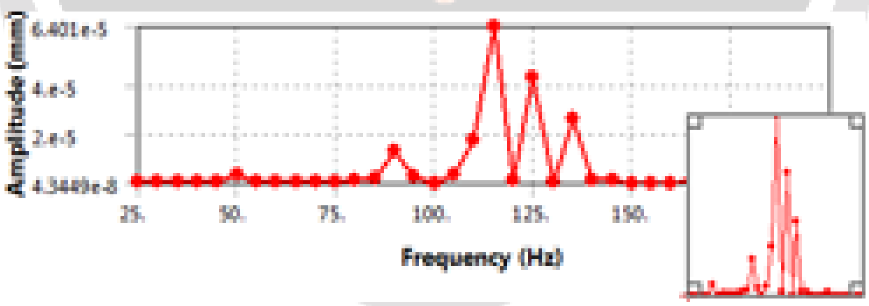
The designed model was used to simulated the transformer in 6 different states, 1 normal and 5 abnormal states:

1. Loosen up of one screw tidying the high voltage coil to the shelter,
2. Loosen up of high voltage coil around its core tower,
3. Shortage of two consecutive turns in high-voltage coil,
4. Shortage of 5% of turns in high voltage coil,
5. Shortage of 10% of turns in high voltage coil.

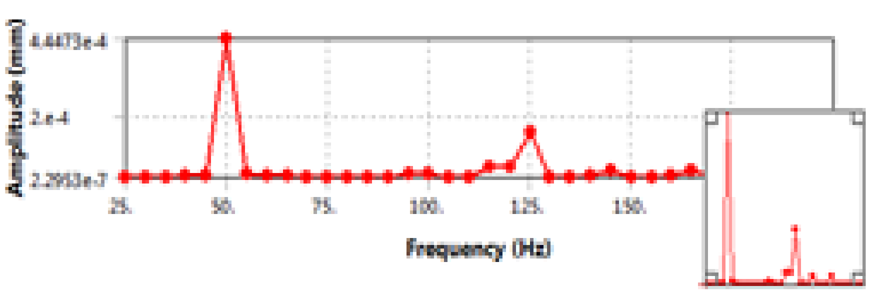
For each state, we simulate 3 cases of loads, which are 50%, 80% and 100% nominal. Totally, 18 sets of data were generated, each set contains:

- . The instantaneous values of the total force acted on the coils and the core of the transformer,
- The instantaneous values of all currents and voltages of input (primary side) and output (secondary side),
- The spectrum the the vibration (measured as the displacement of a selected point) of the transformer shelter on all 3 axes Ox, Oy and Oz.

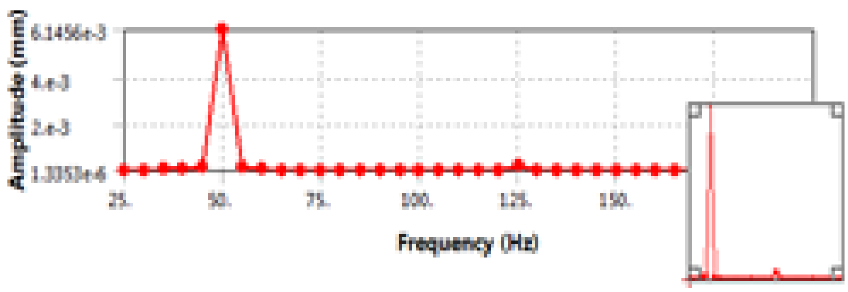
An example of the spectrum for axes Ox, Oy and Oz for the transformer in normal state and 50% load is shown in Fig. 2. As it can be seen, for this case, the peak point of the spectrum (maximum displacement) for the Ox direction is $6,4.10^{-5}mm$ at frequency 115Hz, for the Oy direction is $4,447.10^{-4}mm$ at frequency 50Hz, for the Oz direction is $6,146.10^{-3}mm$ also at the frequency 50Hz.



(a)



(b)



(c)

Fig. 2: The spectrum of Ox (a), Oy (b) and Oz (c) displacements of the transformer shelter

By the trial and errors method, we have tested various combination and came up with the following features extracted from the signals generated by ANSYS:

- From each spectrum of displacement on each of the 3 axises we extract the maximum value, or in other words: $x_1 = max\,(M_x(\omega))$; $x_2 = max\,(M_y(\omega))$; $x_3 = max\,(M_z(\omega))$;
- From the forces acted on the transformer core, we extract the maximum values of the force projections on axises: $x_4 = max\,(F_x(t))$; $x_5 = max\,(F_y(t))$; $x_5 = max\,(F_z(t))$;

As total, the feature vector for each case contains of 6 components listed above

3. ARTIFICIAL NEURAL NETWORK MLP AND APPLICATION INCLASSIFYING THE STATES OF THE TRANSFORMER ARTIFICIAL NEURAL NETWORK MLP

Based on the units of single neuron proposed by McCulloch - Pitts, the MLP (*MultiLayer Perceptron*) is a feedforward network with 1 *input layer*, 1 *output layer*, and a number of *hidden layers* [6]. The network with 1 hidden layer is the most popular in applications. In Fig. 3 an example of MLP network for the Ox direction is presented.

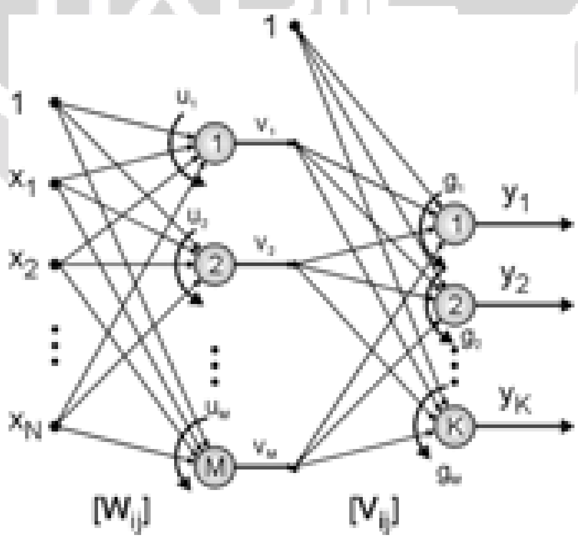


Fig. 3: An example of MLP with one hidden layer

3.1 The training process of MLP

The MLP as shown in Fig. 3 is used widely in nonlinear mapping problem.To determine an MLP, a learning data samples set is given. The set contains p pairs of input-output $\{x_i,\ d_i\}$ where $i=1,...,p,\ x_i \in R^N;\quad d_i \in R^K$. With this set, we need to estimate the parameters of MLP to minimize the error function

$$E = \frac{1}{2}\sum_{i=1}^{p}\left\| MLP(x_i) - d_i \right\|^2 \to \min$$

For a given dataset, the dimension of the input vectors sets the number of MLP inputs, the dimension of the output vectors sets the number of MLP output. If we use the MLP with 1 hidden layer then the number of hidden neurons should be chosen as smallest but still allow the satisfaction of training condition. The parameters left to be adapted are the weights connecting input layer and hidden layer and connecting hidden layer and output layer. We used the classical Levenberg - Marquadrt gradient algorithm for tuning those weights [6]

3.2 Application of MLP to classify the state of the transformer based on the mechanical signals

The output corresponding to the input is the code of the state, where: d = 1: the transformer is in the normal state, d = 2 : the transformer has one screw tidying the high voltage coil to the shelter, ..., d = 6: the transformer has 10% of turns in high-voltage coil shorted (in this paper, we simulate the shortage in phase B).

The number of hidden neurons is selected also with the trial and error method. We started from a small number of hidden neurons (network with only 1 hidden neuron) and generated randomly 20 networks with that number of hidden neurons. All the networks were trained with the data sets, the network with the lowest testing error will be selected. If the best error was still too high, we increased the hidden neuron number by 1 and repeated the process. Simulations had shown that we needed about 2 to 3 hidden neurons to achieved satisfactory results.

The training and testing processes were performed using our scripts written in Matlab with the help of the Neural Network Toolbox.

4. NUMERICAL RESULTS

With the 18 cases listed in previous sections, the training results are as follow. The MLP with only one hidden neuron achieved the results are shown in Fig. 4a, where the destination values are marked with ‘*’, the output from MLP are marked with ‘o’, the errors are marked by the line. As it can be seen, a number of cases still have big errors, especially the cases of type 5 and 6.

The MLP with two hidden neurons achieved the results showed in Fig. 4b, which are better than previous case but still too simple to handle the data sets. The case number 4 of type 2 was wrongly recognized as type 3, the case number 17 of type 6 was wrongly recognized as type 5.

With 3 hidden neurons, the results are presented in Fig. 5, which showed that all the samples were correctly recognized, the errors were much less than the threshold 0.5 between the samples.

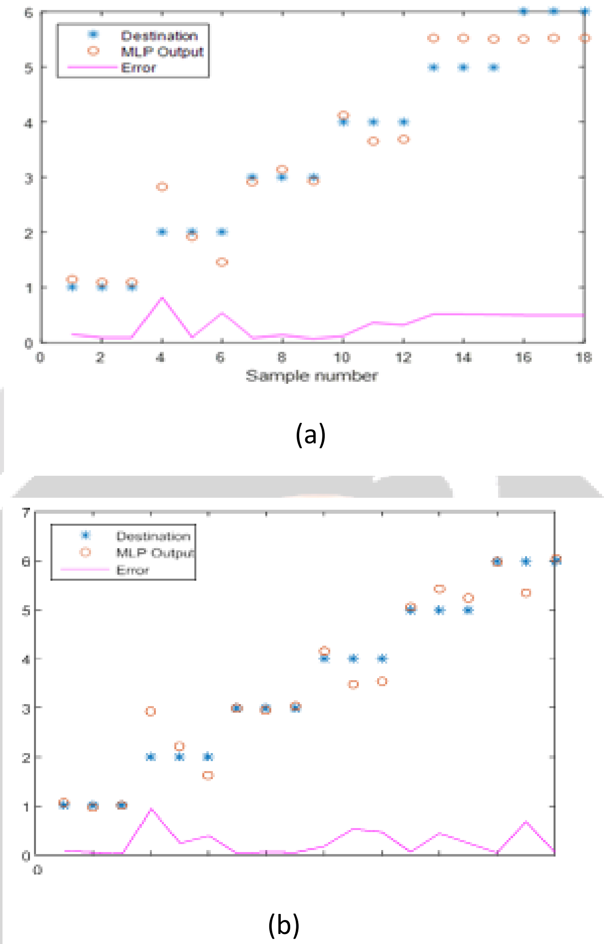


Fig. 4: Results of learning the samples using network with one (a) and two hidden neurons (b)

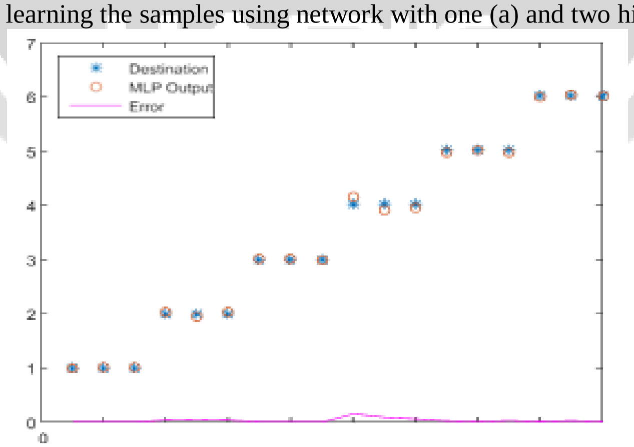


Fig. 5. Results of learning the samples using network with 3 hidden neurons

5. CONCLUSIONS

The paper presented a method to recognize the state of the transformer using the mechanical vibration and forces of the transformer itself. The normal states and 5 types of abnormal states were considered. The data were simulated from an ANSYS model of distribution transformer (3 phase, 400kVA, 22/0.4kV) and the finite elements methods. From the mechanical vibrations and forces achieved from simulations, a vector of 6 features was extracted for each case and put into a trained MLP neural networks. With 1 hidden layer with 3 neurons, the MLP was able to learned all the cases generated in our experiments.

The proposed method can be further extended by adding more learning data sets to increase the reliability of the results and implemented in instrumentation devices, where the vibration can be measured using accelerometers.

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