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Neural Network Modeling of Distribution Transformer with Internal Winding Faults using Double Fourier Series

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ABSTRACT
An efficient transformer model is required to characterize the transformer internal faults for its condition assessment, which is experimentally very costly. This paper discusses the application of Neural Network (NN) techniques in the modeling of a distribution transformer with internal short-circuit winding faults. A transformer model can be viewed as a functional approximator constructing an input-output mapping between some specific variables and the terminal behaviors of the transformer. Neural network model takes fault specification and energized voltage as the inputs and the output voltage or terminal currents as the outputs. A major kind of neural network, i.e. back-propagation feed-forward network (BPFN), is used to model the faults in distribution transformers. The NN models are trained offline using training sets generated by a field based model, i.e. Double Fourier Series based field (DFSF) models. These models are implemented using MATLAB. The comparison between some simulation cases and corresponding experimental results shows that the well-trained neural networks can accurately simulate the terminal behavior of distribution transformers with internal short circuit faults.

Categories and Subject Descriptors
I.5.2 [**Pattern recognition**]: Design Methodology – *Classifier design and evaluation.*

General Terms
Algorithms, Performance, Design, Economics, Reliability.

Keywords
Neural Network, Distribution Transformer, Double Fourier Series, Field-based computation, Reactance Evaluation, Inter-turn or Earth Faults.

1 INTRODUCTION
Early detection and diagnosis of transformer internal faults are desirable for condition assessment, maintenance schedule, and improved operational efficiency of the transformer. Transformer fault diagnosis requires accurate modeling under fault conditions, particularly internal faults. Nearly 70% of transformer failures are caused by undetected turn-to-turn faults. These faults usually begin as undetected turn-to-turn faults in a coil, which progress to phase-to-phase or phase-to-ground short circuit faults. Because of costly repair, down time, and safety consideration, early detection of transformer internal faults is highly desirable. However, the implementations of the existing monitoring methods [1-4] tend to cost too much to be applied to distribution transformers. As a major basis, characterization of the terminal behaviors of the transformer in the normal operation and in faulty conditions must be done. Considering the safety of personnel, the damage that will occur in the transformer, the consuming time and related cost, a computer simulation model is indispensable in providing data for analysis. Various transformer models have been developed for different purposes in the past [5-6]. However, it is difficult to modify these models to represent a transformer with an internal fault because the distribution of the magnetic flux is fundamentally changed in that condition [7]. Reference [8] presented a linear model for power transformer with an internal short circuit fault. The algorithm is adapted by the authors in earlier work to apply to distribution transformers, but comparison results showed the models were not very accurate [9-10].

There are two main issues associated with the detection of these types of faults. The first issue is the modeling of transformers under fault conditions due to the lack of comprehensive field fault test databases. The second issue is the algorithm that addresses the difficulty in distinguishing between the degrees of the various faults. Modeling of transformers with internal faults is the first step in the design of the fault detection systems. With internal faults, transformer modeling is more complex because the field picture totally changes due to the fault which will affect the transformer model parameters. Finite elements (FEs) can be used to model the transformer under different internal faults. A 2D FEA model is developed for dynamic analysis of transformers with internal short circuit faults [11]. However, a main drawback with this approach is that one needs to fully repeat the analysis for each change in fault conditions. The simulation time for each fault scenario is very long. In an attempt to overcome this problem, a field based method namely Double Fourier Series based Field (DFSF) method is used to calculate the fault currents [12], This DFSF method is used generate the samples to train neural network (NN) models. These NN models are used to predict the terminal values of distribution transformers with internal short circuit winding faults.

In the work reported in this paper, a transformer model is viewed as a functional approximator constructing a mapping between some specific variables and the terminal behaviors of the transformer. Since neural networks have been proven to be capable of finding internal representations between given input/output data using available training data, they are suitable to implement the approximation task. In addition, a properly designed and trained neural network is capable of interpolating cases for which it is not trained. This is in contrast to the conventional approaches, where the analysis must be performed for each new faulty condition. In this paper back propagation feed for neural networks are applied to implement transformer internal short circuit fault models. The training set is taken from Double Fourier Series based Field (DFSF) models. The DFSF Model is implemented using MATLAB Software, a commercial software package. The comparison between some simulation cases and corresponding experimental results are also provided.

First the DFSF Model will be introduced in Section II and then the principles related to neural network techniques will be presented in Section III. The following section will discuss the implementation of the neural network models. The simulation results and comparison results between the simulation and the experimental will also be provided in this section. Finally conclusions will be given.

2 SIMULATION OF FAULTS USING DFSF MODEL

The continuous increase in demand of power has resulted in the addition of more generating capacity and interconnections in power systems. Both these factors have contributed to an increase in short circuit capacity of networks, making the short circuit duty of transformers more severe. Failure of transformers due to short circuits is a major concern of transformer users. When short circuit occurs at any point in a system the short circuit current is limited by the impedance of the system up to the point of fault. In many situations the impedances limiting the fault currents are largely reactive. Of course every conductor has its own resistance, but is of very much negligible when compared with the reactance, so it is neglected in the calculation of short circuit current by considering the inductive reactance. The error introduced by this assumption will not exceed 1%. The various fault types are studied: turn-to-earth fault on the primary side, turn-to-earth fault on the secondary side, turn-to-turn fault on the primary winding, and turn-to-turn fault on the secondary winding.

The m.m.f of the faulty portion of the winding is assumed as zero, and thus the leakage reactance of the transformer under various faulty conditions is evaluated using DFSF method, which is illustrated in [12]. This gives an accurate value of output for the irregular flux distributions, which equally works for the case faulty conditions, because magnetically both are having the same characteristics. It is easy to calculate the short circuit current from the leakage reactance of the transformer by following the steps shown in the flow chart in fig.1

The evaluation of internal fault currents is carried out for various cases and the results are used further to train the neural network, which is explained in detail in the next sections.

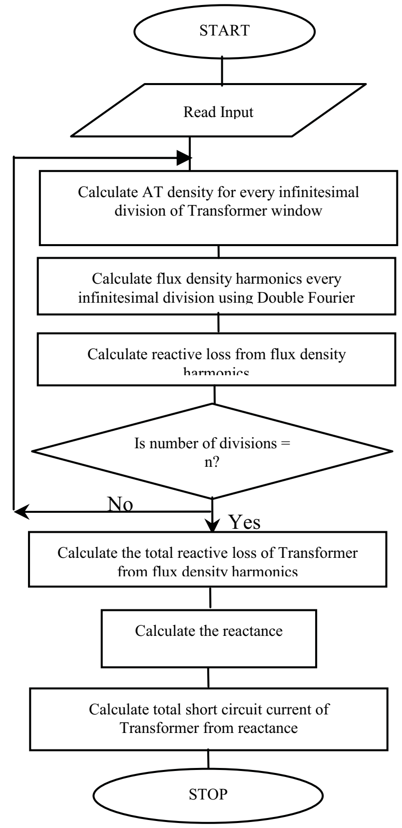

Fig 1: A generalized flow chart for inter turn / earth fault calculations

3 NEURAL NETWORK MODELING

A transformer model can be viewed as a black-box with a certain internal functional relationship between its inputs and input-output mapping between some specific variables and the terminal behaviors of the transformer. It is well-known that neural networks can establish an approximation model by fitting the relationship between given input/output data without requiring any fundamental physical theories using available training data. Neural networks are composed of simple elements operating in parallel. Thus once a neural network has been developed that generally models the transformer under many fault conditions, the neural network will simulate a new case very quickly. In addition, the employment of neural networks provides a solution with very good generalization properties. Because of these virtues, neural network techniques are adopted to model transformer internal short circuit faults. The universal approximation theory proves back-propagation multi-layer feed-forward network (BPFN) is sufficient to uniformly approximate any continuous function to any desired degree of accuracy if the layers have enough neurons [15]. However, in practice, determining the number of neurons is complex and not a science.

The typical model for a neuron in BPFN is shown in Fig.2. In mathematical terms, a neuron can be described using.

$$y_k = \varphi\left(\sum_{j=1}^{p} x_j w_{kj} - \theta_k\right)$$

where *x1, x2, ... xp* are the input signals, *wkl , wk2 ,...* wA, are the synaptic weights of neuron *k;* 9k is the threshold; (P(.) is the activation function; and yk is the output signal of the neuron. Generally, the sigmoid function is used as the activation function:

$$\varphi(v) = \frac{1}{1 + \exp(-av)}$$

where 'a' is slope.

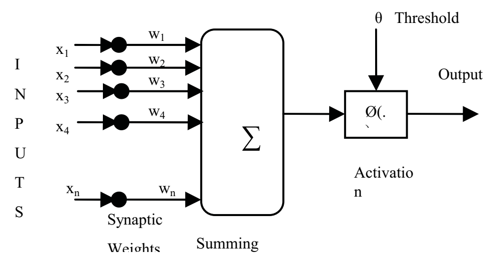

Fig. 2 A typical neural network model

The error back-propagation process consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an activate pattern is applied to the input neurons of the network, and its effect propagates through the network, layer by layer. Finally a set of outputs is produced as the actual response of the network. The actual response of the network is subtracted from a desired response to produce an error signal. This error signal is then propagated backward through the network, against the direction of synaptic connections. The synaptic weights are adjusted so as to make the actual response of the network move closer to the desired response.

4 IMPLEMENTATION AND RESULTS

The development of a neural network model of short circuit faults in Distribution Transformer is as follows.

4.1 Data

The data set for training is generated from DFSF model. Tests are performed on a simulated model, which is built using MATLAB. The transformer parameters taken are as follows:

- The rated voltage ratio is 7200 V/ 240 V.
- Normal impedance: 1.75%; normal reactance: 1.62%.
- Turns ratio is 780/26; two coils on the secondary winding are connected in series; each sub-winding has 13 turns.
- Taps at different turn positions on both the primary and secondary winding make it possible to stage internal faults at various locations within the transformer.

Turn-to-earth and turn-to-turn faults at different position along the primary winding and the secondary winding were simulated. Considering that in the actual daily operation, the transformer may be operated at various voltage levels, from 90% to 110% of the rated voltage, eight different source voltage levels were used to energize the transformer for each fault scenario. As a result, the data set is composed of 112 secondary fault cases and 384 primary fault cases. 90% of the primary fault cases and 90% of the secondary fault cases were selected randomly to make up the training set and 10% to make up the testing set.

4.2 Pre-processing of data

Generally, the majority of the effort in neural network development goes into collecting data examples and pre-processing them appropriately. In general, better performance is yielded when the input values are between 0 and 1, or some specified interval. Therefore, the following steps were adopted for normalizing the raw data before using it in the neural network model to generate input values between 0 and 1.

(1) Divide the primary and secondary voltages and currents by the individual base values and change the actual values into per unit values;

(2) Divide the number of the turns by the total number of the turns of the corresponding windings and change the actual values into percentage values.

(3) Normalize the data across all the channels between the maximum and minimum values selected from the given set. Formula used is .

$$\textit{NormalizedValue} = \frac{\textit{Actual Value - Min Value}}{\textit{Max Value - Min Value}}$$

4.3 Implementation of neural networks in MATLAB

For each simple neural network three-layer back-propagation neural network is implemented using MATLAB Neural Network Toolbox [13]. In the implementation of a BPFN, determination of the optimal number of hidden neurons is a crucial issue. If it is too small, the network cannot possess sufficient information, and thus yields inaccurate approximating results. On the other hand, if it is too large, the training process will be very long. In our application, a standard tool in statistics, known as cross-validation, is adopted to choose a good model structure for the training data set [14]. The activation functions for the hidden layer neurons were sigmoid functions and for the output layer were the pure linear functions.

4.4 Results and Discussion

After the parameters for the networks were determined, the neural network is trained and tested. After the training and testing, the secondary and primary fault modules in NN Model were used to simulate the fault scenarios in the field experiments. Since the experiments were performed on different days and time, the supply voltage is slightly different for each experiment. In the corresponding simulation, the source voltage is changed to match the supply voltage in the experiment. For the same fault scenario, which is repeated on the different days, the average percentage errors between BPFN simulation and field tests were calculated and listed in Table 1.

Table 1. Comparison results using BPFN

Case	V2	Il	12
PG 15	3.54%	9.12%	3.76%
PG 55	3.14%	1.13%	3.88%
SG 2	2.45%	2.26%	5.73%
P772-780	2.02%	9.26%	2.19%
P752 -772	5.32%	1.46%	5.74%
P337-364	1.64%	0.25%	1.86%
P364 -392	3.67%	0.92%	3.92%
S19-20	0.64%	8.87%	5.76%
S16-17	0.71%	9.93%	8.25%
S10-13	2.26%	9.90%	7.98%

In the table, P or S represents the fault is on the primary winding or on the secondary winding. The letter G represents the ground. Thus PG_15 represents a turn-to-earth case where the 15^{th} turn on the primary winding is connected to earth and P337-364 represents a turn-to-turn case where the 337^{th} and the 364^{th} turns on the primary winding are connected together. From the table, we can see that percentage errors between the simulation results and the experimental results in all cases are less than 10%.

5 CONCLUSTION

This paper presented a Neural Network Model to predict the terminal performance of a distribution transformer with an internal short circuit fault, quickly and accurately. Modeling a transformer with internal short circuit faults is viewed as approximating an input-output mapping between certain transformer parameters or fault information and the output voltage and terminal currents of the transformer.

From the comparison of results from computer simulation and field tests, we can conclude that the neural network can provide an accurate approximation for input/output mapping functions between transformer fault parameters and the output voltage and terminal currents if the training set is large enough. At the same time, a complex transformer fault modeling problem can be separated into several sub-models which each can be quickly implemented by a simple neural network. In the future, more complex fault information will be included in the neural network model. Using the neural network model presented in this paper, large number of internal short circuit fault winding fault cases will be created and a sufficient database of internal short circuit fault will be generated. Based on the analysis of the data in this database, a suitable intelligent fault detection technique will be developed using some artificial intelligent tools, such as expert systems or neural networks.

6 REFERENCES

[1] C.E. Lin, J. M. Ling, and C.L. Huang, "Expert system for transformer fault diagnosis using dissolved gas analysis", IEEE Trans. on Power Delivery,vol.8, no.1,Jan.1993, pp. 231-238.

[2] W.Yue,H.Zhuxiao,and Z. JiaXiang, "Expediting cellulose insulation aging evaluation and life prediction thorough degree of polymerization measurements", Properties and Applications of Dielectric Materials, 1988, pp. 328-331.

[3] A. Noro, K. Nakamura, T. Watanabe and T. Morita, "Acoustic-based real-time partial discharge location in model transformer",Proceedings ICSPAT'94., pp. 1077-1082.

[4] J. Bak-Jensen, B. Bak-Jensen, and S.D. Mikkelsen, "Detection offaults and aging phenomena in transformers by transferfunctions", IEEE Transactions on Power Delivery, vol. 10 no. 1, Jan. 1995, pp. 308-314.

[5] D.J. Greene, "Nonlinear modeling of transformers", IEEE Transactions on Industry Applications, Vol. 24, No. 3, May/June, 1988, pp.434-438.

[6] A. Morched, L. Marti, J. Ottenvangers, "A high frequency transformers model for the EMTP", IEEE Transactions on Power Delivery, Vol.. 8, No. 3, July 1993, pp.1615-1626.

[7] E. Billig, "Electrical and mechanical effects of internal faults in transformers", E.R.A. report. Ref. Q/T103, 1944.

[8] P. Bastard, P. Bertrand, M. Meunier, "A transformer model for winding fault studies ", IEEE Trans. on Power Delivery, vol..9, no.2, 1994, pp. 690-699.

[9] H. Wang, K. L. Butler, "Modeling transformer with internal winding faults by calculating leakage factors", Proceeding of the 31"North American Power Symposium, Oct. 1999, San Luis Obispo, CA., pp176-182.

[10] H. Wang, P. Palmer-Buckle, K. L. Butler, "Transformer Models for Detection of Incipient Internal Winding Faults", Proceedings of the 30 North American Power Symposium, Oct., 1998, Cleveland, Ohio. pp. 90-98.

[11] H. Wang, K.L. Butler, "Finite element analysis of internal winding faults in distribution transformers", IEEE Trans. on Power Delivery, January 2001, PE-016PRD.

[12] A. Srinivasula Reddy, Dr M. Vijaykumar, "Evaluation of Transformer faults using Double Fourier Series – A fastest method for field computation", Publications of Journal of Theoretical and Applied Information Technology, Vol. 4 No. 1, pp 1-6, February, 2008

[13] MATLAB Version 7.0, Mathwork Corporation.

[14] S. Haykin, *Neural Networks - A Comprehensive Foundation,* Macmillan College Publishing Company, New York, 1994.

[15] S. Haykin, *Neural Networks - A Comprehensive Foundation,*Macmillan College Publishing Company, New York, 1994.