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Detailed model Parameters Estimation of Transformer HV Winding Based on Neural Networks

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Abstract- This paper presents a new algorithm for the use of Artificial Neural Network (ANN) to estimate transient parameters of transformer HV winding model, known as detailed model, from frequency response measurements.The ANN with different structures has been discussed in this paper. It is shown that Multi-Layers perception network with Levenberg-Markuardt training algorithm has the best performance. The training and test pattern of this ANN are generated by the sampling of the frequency response of a 2-part detailed model. To reduce the amount of needed training data for ANN, sensitivity of frequency response of detailed model to its transient parameters has been used. The results show that the well-trained ANN can precisely estimate the transient parameters of detailed model.

Keywords- Parameter estimation, Transformer Detailed Model, ANN, FRA, Transient

I. INTRODUCTION

To study the fast and very fast transient phenomena in transformer HV winding, manufacturers provide computer programs which convert physical geometry and material characteristics into a lumped RLC network, known as detailed model [1] [2]. The parameters of this model are determined based on numerical field analysis method, analytical methods or charge simulation method. The ability of the detailed model to faithfully reproduce the transient characteristics of the transformer depends on accurate values of model parameters. In the design stage it is necessary to evaluate the designed transformer. The impulse voltage test is a known solution for this problem. An uneven voltage distribution along the winding can be anticipated using this test but this method is a destructive test [3] [4].

The transformer behavior can be characterized in the frequency domain by its frequency response too. The voltage and current can either be measured by frequency domain sweeps (Frequency Response Analysis, FRA) or by time domain measurements that are subjected to the Fourier transform. FRA, which is a nondestructive test, has been used to detect small displacements in transformer HV winding [5].

This nondestructive test and artificial neural network (ANN) have been used in this paper to estimate the winding transient parameters. After parameter estimation of transformer winding it is possible to compare the results with the design parameters. A deviation between these two sets of parameters indicates a design problem which is detected before applying a destructive impulse voltage on transformer winding.

The ability of ANN technique to map complex and highly non-linear input/output patterns provides an attractive solution to different transformers problems; e.g. transformer core characteristics prediction [6] transformer internal faults modeling [7]. Many papers have been published on the subject of transient parameters estimation, which are based on time [8, 9] and frequency [10, 11] domain measurements. This paper presents the application of ANN for estimation of transient parameters of transformer HV winding from frequency response measurement data.

II. TRANSFORMER HV WINDING DETAILED MODEL

A lumped linear model of a transformer winding described in [1] is used as a based model. The Coil-by-Coil representation of the winding in Fig.1 shows this network. The base element of the model is a double coil. Each of the two coil (double coil) are represented by a self inductance ($L_{i,i}$), a shunt resistance (R_i), a series capacitance (K_i), and a ground capacitance (Ce). The mutual inductance with the other double coils ($L_{i,j}$) are considered but not shown in Fig. 1. The Coil-by-Coil Model of the winding in Laplace domain can be presented as follows:

$$[I_{(s)}]=[Y_{(s)}].[U_{(s)}] \quad (1)$$

where,

$$[Y_{(s)}]_{n*n} = \frac{1}{s}\{[\Gamma]+s.[G]+s^2.[C]\} \quad (2)$$

with $[\Gamma]$, $[G]$ and $[C]$ as inverse nodal inductance, nodal conductance and nodal capacitance matrixes, respectively. $[I_{(s)}]$ and $[U_{(s)}]$ are nodal current and voltage vectors. Assuming an exciting source connected to node n, the only non zero element of $[I_{(s)}]$, is the element of the last row. Considering this point and solving for voltage vector of (1) we get:

$$\alpha_{j(s)} = \frac{1}{Z_{in(s)}} \cdot [Y_{(s)}]^{-1}_{j,n} \ for\ j=1,...,n \quad (3)$$

where for simplicity α_j stands for U_j/U_n and $Z_{in(s)}$ is the input impedance of the winding. This equation for $j=n$ represents $Z_{in(s)}$, the terminal model of the winding.

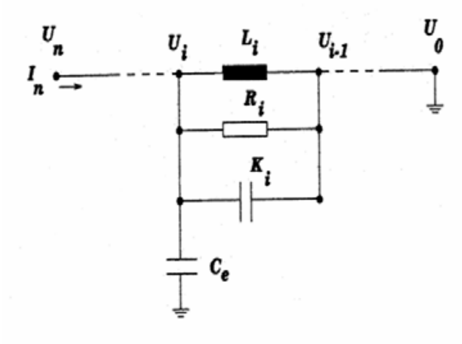

Fig. 1. detailed model

III. INPUT AND OUTPUT MATRIXES OF ANN

The ability of ANN to map input/output patterns provides an effective solution to transient parameter estimation of detailed model shown in Fig.1. In our case the outputs of ANN are the parameters of the detailed model and the inputs include the sampled data from frequency response of HV winding, i.e., input impedance of winding, $Z_{in}(f)$.

In order to cover the typical range of interest, the possible range of parameter variations must be considered. Table (1) presents this range for the detailed model.

Table 1. The range of parameters variations

Parameter	Min. value	Max. Value
K_i	0.1 nF	100 nF
Ce	0.001 nF	0.01 nF
L_i	0.1 mH	10 mH
R_i	1 kΩ	100 kΩ

Considering this wide range of variations, unlimited frequency responses (curves) can be generated by the simulation of the detailed model. It is important to have enough data to yield sufficient training and test sets to train and evaluate the performance of neural networks effectively, but to reduce the amount of needed training data the following points must be considered:

- $Z_{in}(f)$ is more sensitive to L_i , R_i and K_i .As a result the variation steps of these parameters must be small and for the rest of parameters it must be large
- The possible range of variations must be covered,

- The number of simulated frequency responses must be limited which reduces the size of the ANN,
- The training and test sets must be different and
- Physical and experimental results, such as $K_i >> Ce$ or $M_{ij} > M_{ik}$ if $|i-j|<|i-k|$ must be used, too.

The pattern space is essentially the domain which is defined by the sampling of data from $Z_{in}(f)$ curves. A full-length input vector can theoretically produce more selective frequency response characteristics, but a shorted (or reduced) input vector, which reduces the size of ANN, is practically required. This reduced input vector must include the following important data:

- Resonance frequencies,
- Bandwidth of each resonance,
- Minimums of $|Z_{in}(f)|$,
- $Z_{in}(f)$ at f_{min} and f_{max} and
- The information of the mid-points which is located between two neighboring maximum and minimum points.

For a detailed model with *n* nodes, *r* points must be selected from each $Z_{in}(f)$ curve. Considering the above mentioned points, *r* can be calculated with the following equation:

$$r = 6n + 1 \tag{4}$$

Each point of $Z_{in}(f)$ has the frequency (*f*) and amplitude (*Z*) information. As a result each pattern (*P*) has *2r* rows. The general form of *i*-th pattern, P_i, is as follows:

$$P_i = \begin{bmatrix} F_{1i} & F_{2i} & \dots & F_{ri} & Z_{1i} & Z_{2i} & \dots & Z_{ri} \end{bmatrix}^T_{\ i=1,\dots k} \tag{5}$$

Where *k* is the number of frequency responses (patterns) which is required for training. Now the input matrix of *P* can be defined as follows:

$$P = \begin{bmatrix} P_1 & P_2 & \dots\dots & P_K \end{bmatrix}_{R*K} \tag{6}$$

To present the output matrix, first of all the following parameters vectors must be defined for a detailed model with *n* nodes.

$$L^i = \begin{bmatrix} L_1^i & L_2^i & \dots & L_n^i \end{bmatrix}^T \tag{7}$$

$$K^i = \begin{bmatrix} K_1^i & K_2^i & \dots & K_n^i \end{bmatrix}^T \tag{8}$$

$$R^i = \begin{bmatrix} R_1^i & R_2^i & \dots & R_n^i \end{bmatrix}^T \tag{9}$$

$$Ce^i = \begin{bmatrix} Ce_1^i & Ce_2^i & \dots & Ce_n^i \end{bmatrix}^T \tag{10}$$

$$M^i = \begin{bmatrix} L_{12}^1 & L_{13}^i & \dots & L_{1n}^i & L_{23}^i & L_{24}^i & \dots & L_{2n}^i & \dots & L_{(n-1)n}^i \end{bmatrix}^T \tag{11}$$

The pattern P_i can be generated by using the parameters given in L^i, K^i, C_e^i, R^i and M^i.
Now the output matrix can expressed by the following equation:

$$T = \begin{bmatrix} L^1 & \dots & L^k \\ K^1 & \dots & K^k \\ R^1 & \dots & R^K \\ Ce^1 & \dots & Ce^k \\ M^1 & \dots & M^k \end{bmatrix} \tag{12}$$

To increase the speed of data processing, the following equation has used for normalizing the inputs before training of the ANN. Thus, the values of parameters for all the samples fall in the range of [-1, 1].

$$y_{Nor} = 2 \times \frac{y - y_{\min}}{y_{\max} - y_{\min}} - 1 \tag{13}$$

As a result instead of *P* and *T* now the matrixes $P_{normalized}$ and $T_{normalized}$ must be respectively used.

IV. ANN BASED PARAMETER ESTIMATION

A. Training

The ANN must be trained for the parameter estimation of the detailed model. This training procedure must be repeated for each type of transformer winding (or *P* matrix) and the results (or *T* matrix) are valid only for that type of winding. As a case study and for reasons of presentation simplicity, a 2-part detailed model, shown in Fig.2, is studied in this paper.

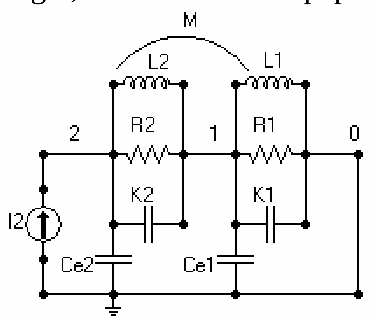

Fig. 2. 2-part detailed model

The input impedance amplitude of this 2-part detailed model is shown in the Fig.3 (solid curve). Considering the approach explained in part III of the paper, the sampled data from this curve have been selected. These points are shown in Fig. 3 by circles. The dashed curve in this figure presents on approximation for the original curve. In this case r is equal to 13, P has a dimension of $26*k$ and the output vector is given by the following equation:

$$T_1 = \begin{bmatrix} L_1^1 & L_2^1 & K_1^1 & K_2^1 & R_1^1 & R_2^1 & Ce_1^1 & Ce_2^1 & M_e^1 \end{bmatrix}_{9\times 1}^T \quad (14)$$

As it can be seen the dimension of the vector T_1 is $9*1$ and therefore the ANN should have 9 neurons in the last layer.

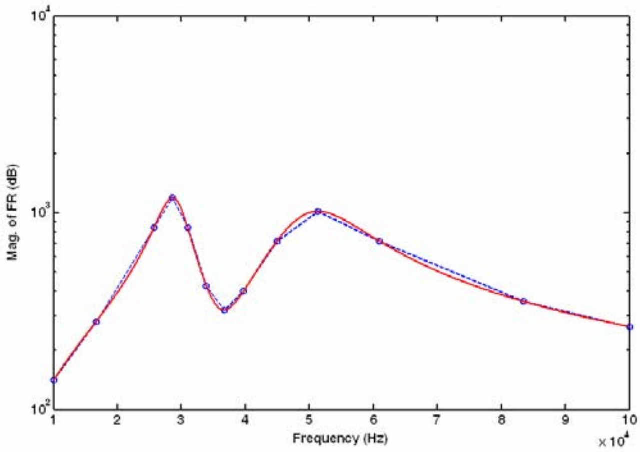

Fig. 3. frequency response of 2-part detailed model

B. ANN Structure

The MLP (Multi-Layer Perceptron) neural networks with the training algorithm of BP (Back Propagation) have been successfully used for classification, Recognition, internal representation, encoding, identification and control of systems. The results of researches verify the capability of this method in these fields [12]. Considering this point and the structure of the input data, BBP (Batching Back Propagation) algorithm has been used for training. The selection of the best ANN structure (with a minimum learning error) is open issues and has to consequently be determined by experimentation involving training and testing various MLP network configurations.

Table 2 presents the BP algorithms and their descriptions which have been considered in this paper.

Table 2. BP algorithms

Function	Description
GD (traingd)	Basic gradient descent. Slow response, Can be used in incremental mode training.
GDM (traingdm)	Gradient descent with momentum. Generally faster than GD. Can be used in incremental mode training.
CDA (traingda) GDX (traingdx)	Adaptive Learning rate (variable learning rate). Faster training than GD, but can only be used in batch mode training.
LM (trainlm)	Levenberg-Marquardt algorithm. Fastest training algorithm For networks of moderate size. Has memory reduction feature For use when the training set is Large.

The suggested structure of ANN for the parameter estimation of the 2-part detailed model has been shown in Fig. 4. This structure has had minimum learning errors among different configurations and has following features:

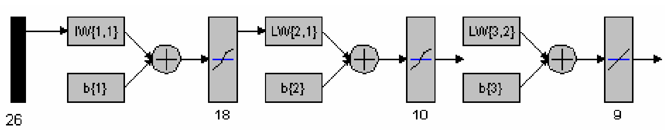

Fig.4. suggested ANN structure

- It has 3 layers,
- Exciting function of inner layer is a tansig (tangent sigmoid) type,
- The last layer type is purelin (linear) and
- The first layer has 18 neurons and the inner and the last layers have 10 and 9 neurons, respectively.

Fig. 5 shows the learning process of the suggested ANN using LM algorithm.

As it can be seen, after 4250 epochs there are no changes in training error and the final error is about 2.5 percent, which shows an acceptable performance.

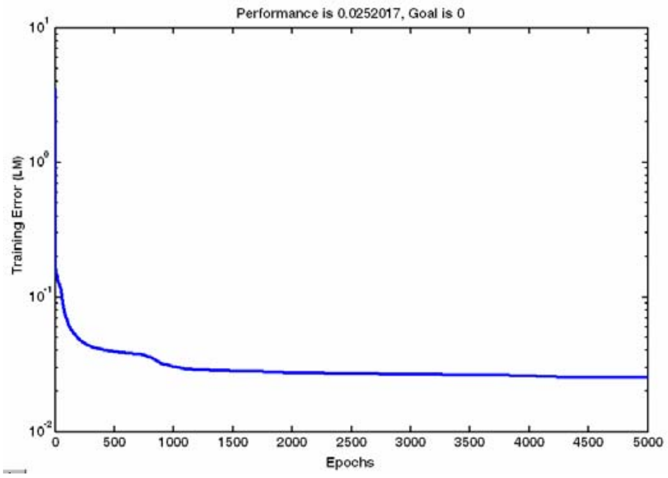

Fig. 5. learning process; LM algorithm.

The performances of BP algorithms have been compared based on the training errors. The comparison results are listed in Table 3. It is obvious that the selection of LM training function is the best selection.

Table 3. comparison of BP algorithms

Training function	Epoch	Training Error %
LM	5000	2.5
GDX	5000	16.6
GDA	5000	16.3
GDM	5000	20.8
	50000	16.8
	200000	14.8
GD	5000	23.6
	300000	14.5

C. Testing

Two sets of test parameters are listed in Table 4. These parameters have been used to generate 2 frequency responses for 2-part detailed model.

The suggested ANN has been tested by these curves to evaluate the performance and ability of the parameter estimation algorithm. The results of parameters estimation are listed in the same table too. The comparison of tested and estimated parameters verifies the effectiveness of the proposed ANN.

Table 4. Input and estimated parameters

No.	Parameter	Test data	Estimated parameters	Error %
1	L1(H)	7e-3	7.175e-3	2.5
2	L2(H)	10e-3	9.68e-3	3.2
3	K1(F)	30e-9	28.98e-9	3.4
4	K2(F)	70e-9	71.96e-9	2.8
5	R1(ohm)	30e3	29.19e3	2.7
6	R2(ohm)	50e3	49.20e3	1.6
7	Ce1(F)	4e-12	3.796e-12	5.1
8	Ce2(F)	4e-12	4.184e-12	4.6
9	M(H)	3e-5	2.93e-5	2.3
1	L1(H)	3e-3	2.937e-3	2.1
2	L2(H)	5e-3	5.175e-3	3.5
3	K1(F)	20e-9	20.62e-9	3.1
4	K2(F)	50e-9	51.10e-9	2.2
5	R1(ohm)	20e3	20.46e3	2.3
6	R2(ohm)	30e3	30.63e3	2.1
7	Ce1(F)	6e-12	5.706e-12	4.9
8	Ce2(F)	7e-12	7.392e-12	5.6
9	M(H)	6e-5	6.15e-5	2.5

V. CONCLUSION

A new algorithm for the use of ANN to estimate the transient parameters of transformer HV winding from frequency response measurements has been presented in this paper. The frequency response method is a non-destructive measuring method. Therefore after parameter estimation it is possible to compare the results with design parameters and a deviation between these two sets of parameters indicates a design problem which is detected before applying a destructive impulse voltage on transformer winding.

This idea can be used for the transformers installed in substations, too. The estimated parameters and as built/design parameters can be different because of mechanical displacements in transformer windings.

As a case study a 2-part detailed model has been studied in this paper. From the comparison of the tested and estimated results, it is concluded that the proposed NN using LM training algorithm can provide an accurate estimation for the transient parameters of transformer HV winding.

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