A Neural Network Framework for Predicting Transformer Core Losses

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Abstract: In this paper a neural network based framework is developed for predicting core losses of wound core distribution transformers at the early stages of transformer construction. The proposed framework is also used to improve the grouping process of the individual cores so as to reduce the variation in core loss of assembled transformer. Several neural network structures and the respective training sets have been stored in a database, corresponding to the various magnetic materials. Selection of the most appropriate network from the database is relied on the satisfaction of customers' requirements and several technical and economical criteria. In case that the network performance is not satisfactory, a small adaptation of the retrieved network weights is performed. A decision tree methodology has been adopted to select the most appropriate attributes used as input vectors to the neural networks. Significant improvement of core loss prediction is observed in comparison to the current practice.

Keywords: Wound Core Distribution Transformers, Iron Losses, Neural Networks, Adaptive Learning, Decision Trees.

I. INTRODUCTION

In an industrial environment, dealing with distribution transformer construction, accurate prediction of iron losses is an important task, since they constitute one of the main parameters of the transformer quality.

Furthermore, accurate prediction of transformer iron losses protects the manufacturer from paying loss penalties. In order to avoid this risk, and in view of the fact that iron losses cannot be accurately predicted in the current practice, one possible method is to design the transformer at a lower magnetic induction, resulting in an increase of the transformer cost since more magnetic material is required [1]. Satisfactory prediction of iron losses, however, can be achieved only if various parameters involved in the process, both qualitative and quantitative, are taken into consideration. Instead, in the current practice, only the loss curve is used, i.e., the influence of the rated magnetic induction on iron losses for each specific magnetic material. This is dictated by the fact that there is no analytical relationship expressing the effect of the other parameters on transformer iron losses.

For this reason, accurate prediction of iron losses has become a topic of extensive research in the field of transformer construction. In [2] the effects of a number of core production attributes on transformer core loss performance have been investigated. In [3] spatial distribution components and total core losses are calculated using a generic 2D finite difference method. Both papers have been concentrated on stacked transformer cores. In case of wound core type, the influence of magnetic material, constructional and core production parameters has been studied in [4] using Decision Trees for quality improvement of individual cores. Artificial Neural Networks are used for prediction of iron losses in [5] for both individual and transformer cores. In that work prediction of iron losses has been concentrated on a specific supplier, thickness and grade of magnetic material. In this paper the problem is treated in a more general way, i.e., several suppliers and various thickness and grade of magnetic material are taken into account. Furthermore, additional attributes have been investigated, compared to our work presented in [5], for increasing the prediction accuracy.

To achieve these goals the approach proposed in [5] has to be extended by using several neural networks and by storing the respective training sets in a database. Each of neural networks is suited to a different condition (environment), i.e., to a certain supplier, grade and thickness of magnetic material. Selection of the most appropriate network (or equivalently environment) is based on the satisfaction of customers' requirements and several technical and economical criteria [6].

Furthermore, in this approach selection of the most relevant attributes among the candidate ones, used as inputs to the networks, is performed based on the Decision Tree methodology, instead of the heuristic method used in [5].

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Additionally, an adaptively learning procedure has been investigated in this paper for efficiently improving the network performance during its operation. Experimental results indicating the good performance of the neural network scheme as far as core loss prediction is concerned are presented. Significant improvement of core loss prediction is observed in comparison to the current practice.

This paper is organized as follows: the current practice for predicting iron losses is presented in Section 2, and the proposed neural network framework is given in Section 3. Section 4 describes the selection of attributes, and Section 5 refers to the individual core grouping process. Section 6 presents the results of the extensive verification of the proposed method on actual commercial transformers produced in the considered industrial environment. Section 7 concludes the paper.

II. THE CURRENT PRACTICE FOR PREDICTING IRON LOSSES

In order to construct a three-phase wound core distribution transformer, two small individual cores (width of core window equal to F1) and two large individual cores (width of core window equal to F2) should be assembled (Figure 1). In general, the width F2 is twice F1.

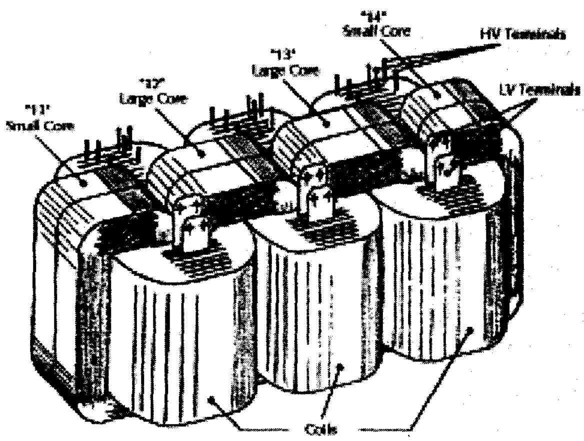

Fig. 1. Assembled active part of wound core distribution transformer.

As it is observed from Figure 1 the four cores are arranged in space as (from left to right): a small core, followed by a large, followed by another large and finally followed by a small one. In our industrial environment, we denote as "11" and "12" the left small and large core respectively, while as "13" and "14" the other two cores. Thus, the core arrangement from left to right will be "11"-"12"-"13"-"14" as it is depicted in Figure 1.

The theoretical iron losses, say $DSFL_i$, of the *i-th* individual core are given by:

$$DSFL_i = DWPK_i * DKg_i \ , \ i = "11",...,"14" \tag{1}$$

where $DWPK_i$ are the theoretical specific iron losses of individual core at the rated magnetic induction obtained from Figure 2 and DKg_i is the core theoretical weight as defined in [4]. It should be noticed that the specific iron losses are defined as losses per weight unit.

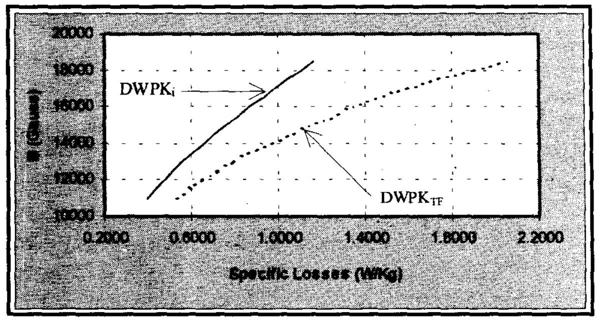

Fig. 2. Typical loss curve.

Consequently, the theoretical total iron losses, say $DSFL_{TF}$, of the four individual cores are:

$$DSFL_{TF} = DSFL_{"11"} + DSFL_{"12"} + DSFL_{"13"} + DSFL_{"14"} \tag{2}$$

Furthermore, the theoretical iron losses, say $DNLL_{TF}$, of the assembled three-phase transformer are provided by:

$$DNLL_{TF} = DWPK_{TF} * DKg_{TF} \tag{3}$$

where $DWPK_{TF}$ denotes the theoretical transformer specific iron losses at the rated magnetic induction, also obtained from Figure 2, and DKg_{TF} the theoretical total weight of transformer evaluated as follows:

$$DKg_{TF} = DKg_{"11"} + DKg_{"12"} + DKg_{"13"} + DKg_{"14"} \tag{4}$$

It should be noticed that during transformer construction actual weights and losses of individual cores diverge from the theoretical ones. In order to produce acceptable transformers, given the iron losses of individual cores, a suitable grouping algorithm is applied.

Particularly, assuming that we have L small cores and L large cores and L is an even number, then $L/2$ transformers can be assembled. Each transformer has four positions where cores can be put. As we have stated the two outer positions are occupied from small cores while the other two middle positions are occupied by large cores (Figure 1). Each small core can be put to any of the two positions and to any of the $L/2$ transformers. The same assumption exists for each large core. From all possible combinations of grouping $L/2$ transformers, only one combination, providing the optimum core loss performance, should be selected.

Core	s1	s2	s3	s4	L1	L2	L3	L4
Losses (W)	65.2	65.4	64.3	65.1	74.2	73.9	74.7	74.2

Table 1: Actual Iron Losses of Individual Cores.

In the current practice, selection is based on the minimization of the deviation of actual total iron losses of individual cores (parameter $ASFL_{TF}$, defined in Appendix A) from the theoretical ones (parameter $DSFL_{TF}$, defined in (2)). To clearly illustrate the aforementioned procedure an example is presented in the following. Let us assume that 4 small cores (s1, s2, s3, s4) and 4 large cores (L1, L2, L3, L4) are going to be assembled producing two transformers (T/Fs). Table 1 presents the actual iron losses for each individual core.

According to the current practice the deviation of the actual total iron losses, denoted as *Div*, should be minimized: That is,

$$Div = \sum_{i=1}^{2} \left(Target - ASFL_{TF,i} \right)^2 \tag{5}$$

where *Target* is calculated from Table 1 as follows:

$$Target = \frac{\sum_{k \in V} A_k}{2} = 278.5\,W \tag{6}$$

and $ASFL_{TF,i}$ are the actual total iron losses of the four individual cores of the *i-th* transformer. In (6), A_k is the actual iron losses of the *k-th* individual core, where *k* belongs to the set $V = \{s1, s2, s3, s4, L1, L2, L3, L4\}$.

Among various possible arrangements of cores, three of them are presented in Table 2 along with the respective value of parameter *Div*. The #1 arrangement corresponds to the maximum value of *Div*, the #2 to an intermediate value and the #3 to the minimum value of *Div*. The #3 arrangement has been selected since it corresponds to the minimum deviation.

Arrangement	1st T/F	2nd T/F	*Div*
#1	s1-L3-L4-s2	s3-L1-L2-s4	2.00
#2	s1-L1-L4-s2	s3-L2-L3-s4	0.50
#3	s1-L1-L3-s3	s2-L2-L4-s4	0.02

Table 2: Parameter *Div* for 3 Different Arrangements.

III. THE PROPOSED NEURAL NETWORK FRAMEWORK

A novel neural network architecture is proposed in this paper for predicting transformer specific iron losses at the early stages of transformer construction. Figure 3 presents the overall procedure of the proposed structure consisting of two main modules; a neural network database and an adaptation mechanism.

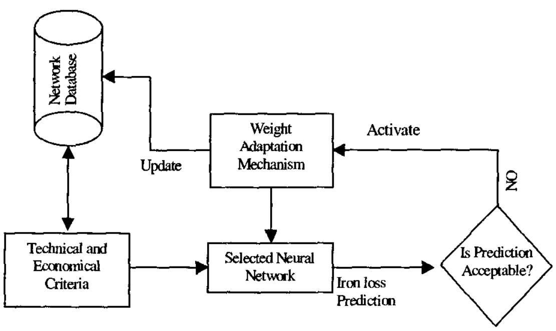

Fig. 3. The proposed neural network scheme for predicting transformer iron losses.

The goal of the first module is to discriminate the effect of a different environment to the specific iron losses while the second module aims at slightly modifying the network weights, in case that the average absolute relative error is beyond an accepted limit. The iron loss prediction, provided by the proposed neural network framework, is next used for developing an innovative individual core grouping algorithm described in Section 5. In the following we describe the implementation of each module as well as the network design and structure used.

A. Network Design and Structure

In the following, the term environment refers to a given supplier, thickness and grade of the magnetic material. Since each supplier follows a specific technology of producing the magnetic material and each grade and/or thickness of magnetic material has its own technical characteristics, different neural network structures are required for a specific environment.

Extensive experiments show that the network performance is unacceptable, if samples of all environments were used as training set. Almost similar results have been observed even if the parameters of the environment (i.e., the supplier, grade and thickness of the magnetic material) are used as neural network input vectors.

Hence, let us denote as N_i, i=1,2,..,M the neural network corresponding to the *i-th* environment with its respective structure and training set denoted as R_i and S_i respectively. A multilayer feedforward network structure has been adopted in this paper, trained using the backpropagation variant algorithm [7]. The learning set consists of measurements obtained by data acquisition systems of high accuracy during the transformer construction process. To appropriately select the input vectors of each network, a Decision Tree methodology has been adopted as it is described in the following. Such a selection leads to fast convergence of the neural network training as well as to better network performance to data outside the training set (good generalization). A validation set has been used during training to control the generalization ability of the network. Furthermore, the appropriate structure of the network is provided using a constructive technique, which begins with a small sized network and subsequently adds neurons to improve the network performance [8].

B. Network Weight Adaptation

The application of the above *M* neural networks to the industrial environment considered has shown that, in some cases, there is a need to improve their performance, since slight changes of the considered conditions may occur. For this reason, a small modification of the respective network weights is performed. This modification is based on the creation of a new training set, say, $S_c = \{(\mathbf{x}_1, d_1), \cdots, (\mathbf{x}_m, d_m)\}$ which is formed using additional measurements of the current conditions, with subscript *m* denoting the number of elements of S_c. In the previous definition, $\mathbf{x}_i$ is the *i-th* training input vector and d_i

the respective desired output. Let us also denote by $S_b = \{(\mathbf{x}'_1, d'_1), \cdots, (\mathbf{x}'_l, d'_l)\}$ the training set which exists in the network database and by l the number of its training samples. The $\mathbf{x}'_i$ and d'_i are the i-*th* training element and the respective desired output for the set S_b. If we also denote by $\mathbf{w}_b$ the network weights before the adaptation and by $\mathbf{w}_a$ those obtained after it, then these new weights are estimated by minimizing the following error:

$$E = E_c + \eta E_b \tag{7}$$

where E_c, given by:

$$E_c = \frac{1}{2}\sum_{i=1}^{m} \left\| z_a(\mathbf{x}_i) - d_i \right\|_2 \tag{8}$$

expresses the error over the data of set S_c and E_b is the error over the data of the S_b:

$$E_b = \frac{1}{2}\sum_{i=1}^{l} \left\| z_a(\mathbf{x}'_i) - d'_i \right\|_2 \tag{9}$$

In (8), (9) z_a denotes the network output when the new weights are used that is the transformer specific iron losses after the small weight adaptation and $\|\cdot\|_2$ denotes the L_2 (Euclidean) norm. In (7), η is a weighting factor that controls the significance of the two terms. A value around 0.7 is found to be satisfactory.

Assuming a slight change of the environment, the weights before and after the adaptation are related as:

$$\mathbf{w}_a = \mathbf{w}_b + \Delta\mathbf{w} \tag{10}$$

where $\Delta\mathbf{w}$ is a small quantity compared to $\mathbf{w}_b$ and $\mathbf{w}_a$.

To stress the importance of current training data in (7), one can replace (8) by the constraint that the actual network outputs are equal to the desired ones, that is:

$$z_a(\mathbf{x}_i) = d_i \quad \text{for all data in } S_c \tag{11}$$

It can be proved in [9] that solution of (11) with respect to the weight increments can be decomposed to the following system of linear equations:

$$\mathbf{c} = \mathbf{A} \cdot \Delta\mathbf{w} \tag{12}$$

where vector $\mathbf{c}$ and matrix $\mathbf{A}$ can be expressed as a function of the previous network weights. In particular, the vector $\mathbf{c}$ corresponds to the difference between the network output before and after the adaptation for all data in set S_c. The dimension of vector $\mathbf{c}$ is in general smaller than the number of unknown weights $\Delta\mathbf{w}$, since generally a small number m of additional training data is chosen. We should mention that m refers to the new training set, i.e., the additional samples. Uniqueness is imposed by an additional requirement which is due to the term E_b in (7). In particular, (9) is solved with the requirement of minimum degradation of the previous network behavior and can lead to:

$$E_s = \frac{1}{2}(\Delta\mathbf{w})^T \cdot \mathbf{K}^T \cdot \mathbf{K} \cdot \Delta\mathbf{w} \tag{13}$$

where the elements of matrix $\mathbf{K}$ are expressed in terms of the previous network weights $\mathbf{w}_b$ and the training data in S_b [10]. Thus, the problem results in minimization of (13) subject to constraints imposed by (12).

The error function defined by (13) is convex since it is of squared form and the constraints in (12) are linear equalities. Thus, a global minimum exists. A variety of methods can be used to estimate the weight increments based on minimization of (13) subject to (12). In this paper we adopt the gradient projection method [11]. The philosophy of this technique is, starting from a feasible point, to move in a direction which decreases (13) and simultaneously satisfies the constraints (12).

IV. ATTRIBUTE SELECTION

To appropriately select the input vectors of the network structure, a large set of candidate attributes is formed based on extensive research and transformer designers' experience. These attributes correspond to parameters, which actually affect the transformer iron losses. The task of deciding which of the candidate attributes should be selected as input vectors is an arduous task. For this reason, a Decision Tree (DT) methodology [12,13] is used to indicate the most characteristic ones. This methodology aims at reducing the dimensionality of the input space by dismissing attributes, which do not carry useful information to predict the output [13]. The DT technique provides not only attribute selection, but also attribute ranking in the sense that it assigns an information quantity to each attribute [12].

Given a transformer acceptability criterion (i.e., type and threshold value), a DT is built to classify samples and to automatically identify attributes relevant for classification, with respect to this particular criterion.

Two different acceptability criteria are used for the classification of iron losses. According to the first criterion one transformer is acceptable, if its actual specific iron losses are not greater than *Lim1%* of the theoretical specific iron losses (given by the loss curve). According to the second one transformer is acceptable, if its actual specific iron losses are in the range ± *Lim2%* of the theoretical losses. Parameters *Lim1%* and *Lim2%* (i.e., threshold values of the transformer acceptability criteria) are defined by the transformer designer in accordance with customer requirements. The above acceptability criteria correspond to alternative customer requirements. It should be mentioned that for both acceptability criteria comparison is based on specific iron losses in order to correspond to the current practice of designing wound core distribution transformers, as described in Section 2.

Several DTs were built for various scenarios: two different suppliers of magnetic material, three different grades of magnetic material, two acceptability criteria, 10 different values for parameters *Lim1%* and *Lim2%* and 48 different candidate attribute lists. According to these scenarios, approximately 6300 DTs were constructed, corresponding to various environments and alternative customer requirements. The DTs were evaluated on the basis of independent test sets. In our investigation only DTs with high acceptability success rates (more than 90%) are taken into consideration.

Several candidate attributes have initially been considered in order to classify transformer specific iron losses. Using the DT based algorithm, only 8 attributes are automatically selected. These attributes are presented in Table 3. The quantitative improvements achieved through the attribute selection process are described in Section 6.

No.	Attributes
#1	Rated magnetic induction
#2	$(WPK_{"11",mat,a}+WPK_{"12",mat,a}+WPK_{"13",mat,a}+WPK_{"14",mat,a})/4$
#3	$(WPK_{"11",mat,b}+WPK_{"12",mat,b}+WPK_{"13",mat,b}+WPK_{"14",mat,b})/4$
#4	AKg_{TF}/DKg_{TF}
#5	$ASFL_{TF}/DSFL_{TF}$
#6	$(AWPK_{"11"}+AWPK_{"12"})/(DWPK_{"11"}+DWPK_{"12"})$
#7	$(AWPK_{"12"}+AWPK_{"13"})/(DWPK_{"12"}+DWPK_{"13"})$
#8	$(AWPK_{"13"}+AWPK_{"14"})/(DWPK_{"13"}+DWPK_{"14"})$

Table 3: Selected Attributes for Transformer Iron Loss Problem.

The above 8 attributes are calculated using the equations and definitions of Section 2 and Appendix A. In our approach the prediction of transformer iron losses is applied at the early stages of transformer's construction, given the individual cores. This means that the quality of magnetic material (parameters $WPK_{i,mat,a}$ and $WPK_{i,mat,b}$ defined in Appendix A), the actual weight and the actual losses of individual cores are known from measurements.

The selection of attributes presented in Table 3 is reasonable and expected. More specifically, #1 attribute is the rated magnetic induction, which is also used in order to calculate iron losses at the design phase by using the loss curve. Attributes #2 and #3 express the average specific losses (W/Kg at 15000 Gauss, and 17000 Gauss, respectively) of magnetic material of the four individual cores used for transformer construction. Attribute #4 is the ratio of actual over theoretical weight of the four individual cores. Attribute #5 is equal to the ratio of actual over theoretical iron losses of the four individual cores. The significance of the attribute #5 is that the iron losses of the three-phase transformer depend on the iron losses of its individual cores. In the industrial environment considered it is observed that the arrangement of cores influences the assembled transformer core losses. Let us consider the data for an actual transformer construction presented in Table 4. Table 5 presents two different arrangements of cores in order to construct the transformer together with the values of attributes #6, #7, and #8. Parameter *AAD* appearing in Table 5 denotes the average absolute divergence of these three attributes from their ideal value, (i.e., from 1.0). It is shown that *AAD* for the second arrangement is smaller. In general, the second arrangement leads to smaller iron losses. That is the reason the selection of attributes #6, #7, and #8 is important to appear in the input vector of the neural network.

Core Name	c1	c2	c3	c4
Core Size	Small	Large	Large	Small
AKg_i (Kg)	87.3	98.7	98.5	88
$ASFL_i$ (W)	65.8	74	72.3	65.1
$AWPK_i$ (W/Kg)	0.754	0.750	0.734	0.740
$DWPK_i$ (W/Kg)	0.741	0.741	0.741	0.741

Table 4: Core Data from a Transformer Construction.

	Attribute			
Arrangement	#6	#7	#8	AAD
c1-c2-c3-c4	1.0145	1.0012	0.9945	0.007072
c4-c2-c3-c1	1.0051	1.0012	1.0039	0.003376

Table 5: Attributes #6, #7, and #8 for two Core Arrangements.

V. INDIVIDUAL CORE GROUPING PROCESS

In this paper we enhance the current grouping process presented in Section 2 by proposing a new algorithm which exploits the advantages of the neural network framework proposed in Section 3. Assuming that we have *L* small cores and *L* large cores as in Section 2, then *L*/2 transformers can be assembled. In this case, the algorithm comprises the following steps:

1. For each of the different combinations, calculate the neural network inputs (8 attributes of Table 3) for each one of the *L*/2 transformers. Using the respective neural network weights and thresholds, calculate the network output (i.e., the specific iron losses of transformer) for each of the *L*/2 transformers and for all combinations.
2. For each of the different combinations and for each of the *L*/2 transformers, calculate the actual iron losses by multiplying the neural network output (specific iron losses) with the respective actual weight of transformer.
3. From all combinations, select the one providing the minimum absolute relative error in relation to the guaranteed to the customer iron losses. However, in case that the number of combinations is too large, only a randomly selected small subset of them is used to find a relative minimum value.
4. For the combination selected in 3, check if there are any transformers, which are not acceptable according to transformer acceptability criterion considered. If it occurs, then the respective cores should not be grouped, awaiting (if possible) other cores of better quality and of the same production batch.

The proposed algorithm is used to improve the grouping process of the individual cores so that no unusable cores are left at the end of a particular production batch and also to reduce the variation in core loss of assembled transformer.

VI. APPLICATION OF THE PROPOSED METHOD TO TRANSFORMER MANUFACTURING INDUSTRY

In this section results from the application of the proposed neural network architecture to transformer specific iron loss prediction are presented. In particular, three different environments are considered, each defined in Table 6. For example, the #1 environment is characterized by magnetic steel of grade M3, according to USA AISI 1983, thickness 0.23 mm, while the supplier of material was SUP_A (Supplier A).

	Environment		
	#1	#2	#3
Supplier	SUP_A	SUP_B	SUP_A
Steel grade	M3	M4	Hi-B
Thickness (mm)	0.23	0.27	0.23

Table 6: Environments Selected.

For the environment considered, the knowledge base consists of 2240 actual industrial measurement sets (samples). 1680 of them are used as training data in the learning process of neural network, while the rest (560) as test set (TS). As validation set, we have used the 1/4 of the samples of the learning set.

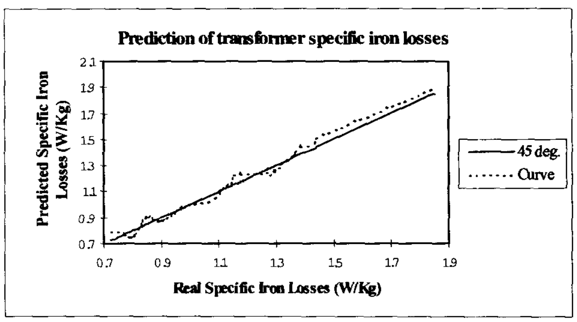

Fig. 4. Prediction of Transformer Specific Iron Losses Using the Typical Loss Curve for the #1 Environment.

A multilayer feedforward neural network structure with one output has been found to provide accurate results. The input neurons of the network are equal to the number of attributes (8) of Table 3 while the network output corresponds to the value of the specific iron losses. Using the algorithm of Section 3, the size of the hidden layer was selected so that it provides the best test results for the given environment. In particular, for the #1 environment, one hidden layer consisting of a small number of neurons (5 neurons) is found to be completely adequate. The activation functions of all neurons are the sigmoid function.

The *Average Absolute Relative Error* (AARE), used to evaluate the network performance, is defined as:

$$AARE = \frac{1}{N} \sum_{\substack{\text{for all } N \\ \text{samples}}} \frac{|\text{actual losses - predicted losses}|}{\text{actual losses}} * 100\% \qquad (14)$$

Figures 4 and 5 present the fractile diagrams or the Q-Q plots (Quantile-Quantile plots) [14] of the specific iron losses, using the typical loss curve and the proposed neural network method, respectively for the #1 environment. According to this method the data of real specific iron losses are plotted versus the predicted ones. Perfect prediction lies on a line of 45^0 slope.

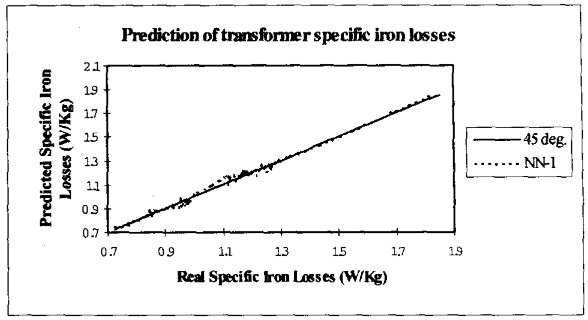

Fig. 5. Prediction of Transformer Specific Iron Losses Using the ANN method for the #1 Environment.

	Current Practice	Neural Network
AARE (%) on TS	2.9	1.5
Minimum Error (%)	-6.1	-4.5
Maximum Error (%)	9.9	4.8

a) #1 Environment

	Current Practice	Neural Network
AARE (%) on TS	3.1	1.7
Minimum Error (%)	-7.1	-4.9
Maximum Error (%)	10.6	5.5

b) #2 Environment

	Current Practice	Neural Network
AARE (%) on TS	3.3	1.8
Minimum Error (%)	-7.4	-5.1
Maximum Error (%)	10.8	5.8

c) #3 Environment

Table 7: Comparison of Current Practice and Neural Network for Predicting Transformer Specific Iron Losses.

It is observed that, on average, the neural network based prediction gives more accurate results in the sense that they are close to the optimal line of 45^0 slope. In particular, the current method (loss curve) shows a maximum absolute relative error of 9.9%, while the respective error in the ANN method is 4.8%. On the other hand, the average error is 2.9% for the current practice, and 1.5% for the neural network method. It is observed that the proposed neural network architecture performs better than the conventional method in both average and worst case (maximum) error.

It should be mentioned that this average error (i.e., 1.5%) is significantly smaller than that (i.e., 2.2%), provided by the neural network architecture, which has been presented in our earlier work [5]. This is due to the fact that additional attributes have been taken into account in this paper as well as a DT methodology has been adopted to select the appropriate network inputs. Consequently, the proposed neural network architecture provides an improved accuracy by more than 31% in relation to the method presented in [5] and an improved accuracy by more than 48% in relation to the current practice (loss curve).

Similar results are also presented for the # 2 and #3 environments in Table 7. In particular, in #3 the average error obtained by the current practice is equal to 3.3% while the error estimated by the neural network structure is equal to 1.8%. Moreover, there is a smaller fluctuation if the absolute error is predicted based on the network structure.

Despite the good performance of the network scheme in predicting iron losses, there are some cases after the completion of the transformer construction, where the prediction error is not acceptable. It should be mentioned that the error is calculated based on the difference between the predicted value, provided by the network output, and the actual value of the specific iron losses, which is available at the completion of the construction. In these cases the neural network is adaptively trained, i.e., the adaptation mechanism is activated and a small perturbation of the network weights is performed for improving the prediction accuracy of future samples.

In the experiments considered, we suppose that an AARE 10% above the average is the upper tolerated limit. That is, for the #1 environment where the average error for the initial test set (TS) is equal to 1.5% (Table 7a), the accepting limit (upper limit, UL) is 1.65%.

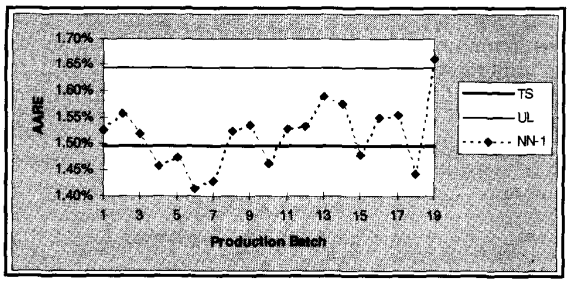

Fig. 6. Prediction Error for Various Production Batches for the #1 Environment.

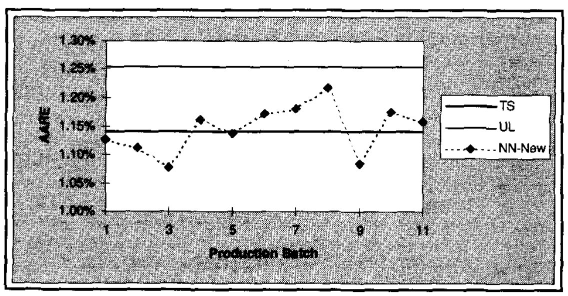

Fig. 7. Prediction Error for Various Production Batches After Adaptation of Weights for the #1 Environment.

Figure 6 illustrates the AARE for 19 batches during the transformer construction. It is observed that at the 19th batch, the AARE extends the defined threshold and a small adaptation of the network weights is activated. After the weight adaptation, the AARE on the TS is 1.14% and the new upper limit is set to 1.25% (i.e., 10% above the AARE). Figure 7 depicts the results obtained after the weight adaptation of the following 11 batches. In all cases, AARE was within the tolerated interval.

VII. CONCLUSIONS

In this paper, a novel neural network framework has been applied for predicting core losses at the transformer production phase. In particular, two main modules have been included in the network structure: A neural network database and an adaptation mechanism. The goal of the first module is to provide satisfactory results in any case of the environment considered, i.e., to a given supplier, thickness and grade of magnetic material. The second module slightly modifies the network weights when the average absolute relative error is above an accepted limit. This approach significantly improves the network performance, especially when the environment considered has undergone some small changes.

Attributes have been selected as input vectors for the network structure based on decision trees. The most significant attributes are chosen out of a large set of candidate ones formed by extensive research and using the transformer designers' experience. Finally, based on the good performance of the neural network structure, a new individual core grouping algorithm has been proposed. This algorithm selects, among the various possible combinations of grouping cores, the one providing the minimal deviation of predicting iron losses from the guaranteed to the customer losses.

Application of the proposed neural network framework to transformer manufacturing industry has verified the accurate prediction of iron losses in all the examined environments. Moreover, reduction of the transformer losses, given the individual core losses, is achieved.

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X. APPENDIX A

After the production and quality control of individual cores the following parameters are known from measurements:

$WPK_{i,mat,a}$: Specific iron losses of magnetic material of the *i-th* core, *i*:="11", ...,"14". This value (in W/Kg at 15000 Gauss) expresses the quality of magnetic material used for core construction.

$WPK_{i,mat,b}$: Specific iron losses (in W/Kg at 17000 Gauss) of magnetic material of the *i-th* core, *i*:="11", ...,"14".

AKg_i : Actual weight of the *i-th* core, *i*:="11", ..., "14"

$ASFL_i$: Actual iron losses of the *i-th* core, *i*:="11",...,"14"

Based on the previous mentioned measurements the following quantities can be evaluated.

The actual total iron losses, say $ASFL_{TF}$, of the four individual cores are:

$$ASFL_{TF} = ASFL_{"11"} + ASFL_{"12"} + ASFL_{"13"} + ASFL_{"14"} \quad \text{(A1)}$$

The actual total weight, say AKg_{TF}, of the four individual cores are:

$$AKg_{TF} = AKg_{"11"} + AKg_{"12"} + AKg_{"13"} + AKg_{"14"} \quad \text{(A2)}$$

The actual specific iron losses of the of the *i-th* individual core are, say $AWPK_i$, are given by:

$$AWPK_i = \frac{ASFL_i}{Akg_i}, i:="11",...,"14" \quad \text{(A3)}$$

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