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Prediction of iron losses of wound core distribution transformers based on artificial neural networks

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Abstract

This paper presents an artificial neural network (ANN) approach to predicting and classifying distribution transformer specific iron losses, i.e., losses per weight unit. The ANN is trained to learn the relationship of several parameters affecting iron losses. For this reason, the ANN learning and testing sets are formed using actual industrial measurements, obtained from previous completed transformer constructions. Data comprise grain oriented steel electrical characteristics, cores constructional parameters, quality control measurements of cores production line and transformers assembly line measurements. It is shown that an average absolute error of 2.32% has been achieved in the prediction of individual core specific iron losses and an error of 2.2% in case of transformer specific losses. This is compared with average errors of 5.7% and 4.0% in prediction of specific iron losses of individual core and transformer, respectively, obtained by the current practice applying the typical loss curve to the same data. © 1998 Elsevier Science B.V. All rights reserved.

Keywords: Wound core distribution transformers; Individual core specific iron losses; Transformer specific iron losses; Artificial neural networks; Specific iron losses prediction and classification

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1. Introduction

In an industrial environment, dealing with distribution transformer construction, accurate prediction of iron losses is an important task, since the latter constitute one of the main parameters of transformer quality. In addition, accurate estimation of transformer iron losses protects the manufacturer of paying loss penalties. Alternatively, the transformer is designed at a lower magnetic induction, resulting in increase of the transformer cost, since more magnetic material is required. In case of wound-core-type transformers, estimation of iron losses of individual cores is also desired, since iron losses of some individual cores may significantly diverge from the designed ones. In this case, corrective actions (e.g., re-annealing of cores) should take place, which are both time and money consuming.

Due to the above-mentioned reasons, both the individual core and the transformer specific iron losses need to be accurately estimated. However, satisfactory prediction of iron losses can be achieved only if various parameters, involved in the process, both qualitative and quantitative, are taken into consideration. Instead, in the current practice, the loss curve is used, i.e., only the influence of the rated magnetic induction on iron losses, for each specific type of magnetic material, is considered. This is dictated by the fact that there is no simple and analytical relationship expressing the effect of the aforementioned parameters on the transformer iron losses. In the industrial environment considered, several statistical measurements have shown that a maximum absolute relative error of approximately 20%, in relation to the specific iron losses obtained by the loss curve, is usually observed. Reduction of this error requires better prediction of transformer losses.

Artificial neural networks (ANNs) [1,5,14] with their highly non-linear capabilities and adaptive learning properties can be very useful in such applications since all the involved parameters affect the final product with a highly and complex non-linear way. ANNs have been successfully applied in power systems, such as load forecasting [11,13,16], and security assessment [15,18,21]. In this paper an artificial neural-network-based scheme is proposed for determining individual core and transformer specific iron losses. For this purpose, multilayer feedforward neural networks are used, trained with the variant backpropagation algorithm described in Section 3.

For ANN architecture, the choice of features variables (signals given to the neurons in the input layer) is of primary importance. A learning set (LS) is required in order to train the ANN. The LS consists of a large number of training samples, covering all possible transformer designs, in order to ensure its representativity. Each training sample is characterised by a vector of feature variables, called attributes. The performance and the reliability of ANN are evaluated with independent testing sets (TS) which have the same structure as the LS, i.e., they are generated in exactly the same way, but comprise different samples of transformer designs. A validation data set is also used to improve network generalisation.

This paper is organised as follows: basic terms of designing wound core distribution transformers are presented in Section 2, while a short description of the adopted ANN methodology is given in Section 3. The applications of neural networks to predicting and classifying of specific iron losses and the obtained results are described in Section 4. Conclusions are finally presented in Section 5.

2. Wound core distribution transformer iron losses

Three-phase transformers are divided into shell and core type; in first type, the magnetic circuit is a shell encircling the windings while in second type a core surrounded by the windings. Another transformer classification is based on the way of stacking laminations. Accordingly, two basic types of cores can be produced [2]; the stacked and wound cores. In stacked cores lamination layers are placed so that the gaps between lamination ends of one layer overlap with the lamination in the next layer (Fig. 1). On the other hand, in wound cores, laminations are wound into a core shape from cut strips (Figs. 2 and 3).

In the design considered, the magnetic circuit is of the shell type and the cores of wound type. The assembled active part is shown in Fig. 2.

The production of wound core distribution transformer includes, at the first stage, the slitting of the raw material into bands of standard width. Then, the slit sheets are cut to pre-determined lengths and are wound on a circular mandrel. After that, a suitable press gives a rectangular shape to the circular core. However, the previously described process significantly deteriorates the core characteristics and especially its physical and electrical properties. To restore these properties, annealing follows at temperatures in a range of 760–860°C in a protective environment containing pure dry nitrogen mixed with hydrogen up to 2%.

The annealing cycle adopted is divided into four phases: starting and heating up phase (to avoid oxidation and to normally achieve the temperature of 825°C), soaking phase (to achieve homogeneous temperature distribution for all cores), slow cooling phase (to slowly cool the load for avoiding the development of internal stresses in the cores) and fast cooling phase (for reduction of the temperature to 380°C, so as to avoid oxidation of cores, when they are exposed to the natural environment).

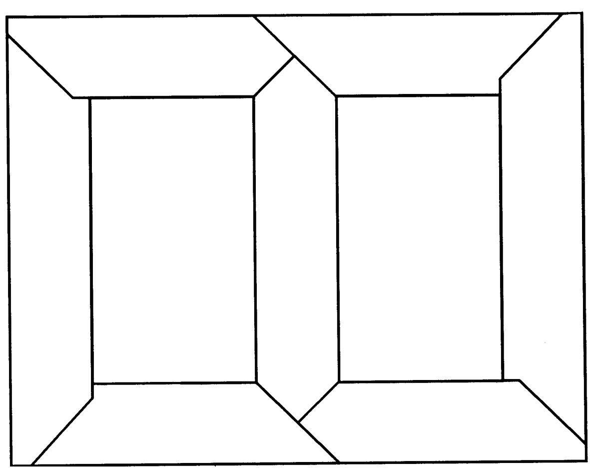

Fig. 1. Stacked core.

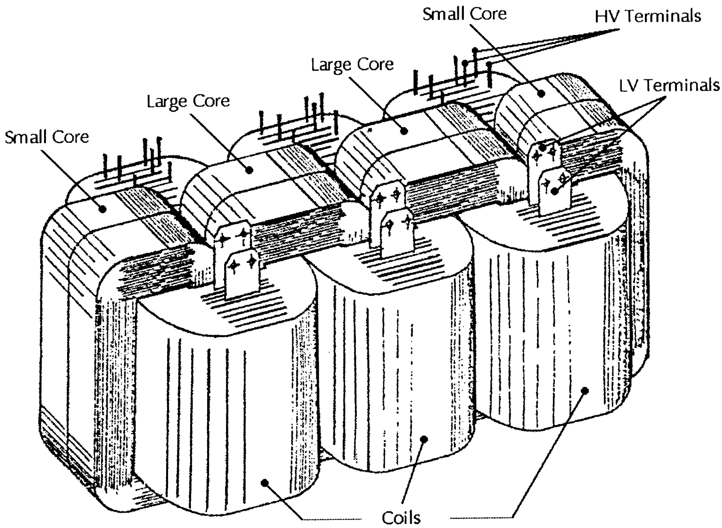

Fig. 2. Assembled active part of wound core distribution transformer.

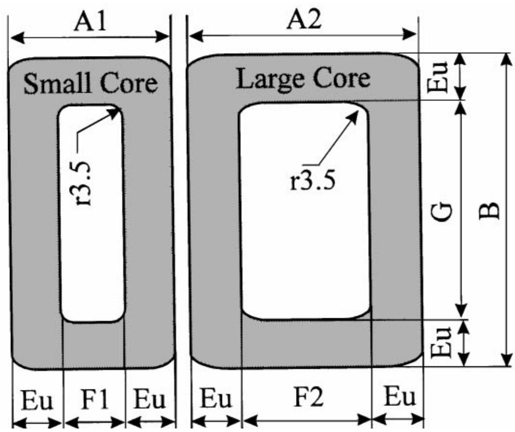

Fig. 3. Wound core constructional parameters.

In contrast to production of the stacked cores, wound cores present the following additional difficulties: (a) air gaps may diverge due to the tolerances of the machine performing the cutting and winding of sheets and due to difficulties in the processing of the magnetic material (slide), (b) the desirable dimensions of wound cores cannot accurately be obtained as in stacked cores, (c) core formation may deteriorate the magnetic material insulation and (d) homogeneous temperature distribution is hard to be obtained during the annealing procedure.

To construct a three-phase 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 (Fig. 2). The width $F2$ is in general twice $F1$. The core constructional parameters are shown in Fig. 3.

The theoretical iron losses, $W1$ ($W2$), of the small (large) individual core, are given by

$$W1 = WPK_1 * CTW1 \quad \text{for the small cores,} \tag{1}$$

$$W2 = WPK_1 * CTW2 \quad \text{for the large cores,} \tag{2}$$

where WPK_1 are the theoretical individual core specific iron losses at the rated magnetic induction (Fig. 4) and $CTW1$ ($CTW2$) is the theoretical weight of the small (large) core as defined in [4]. In the industrial environment considered, the maximum absolute relative error between theoretical and actual weight have been found to be approximately 1.5%.

Consequently, the theoretical total iron losses, $W1_{tot}$ (in Watt), of the four individual cores are given by the following equation:

$$W1_{tot} = 2 * (W1 + W2). \tag{3}$$

The theoretical iron losses of the three-phase transformer, $TFLosses$, are

$$TFLosses = WPK_3 * CTW, \tag{4}$$

where WPK_3 are the theoretical transformer specific iron losses at the rated magnetic induction, also obtained from Fig. 4 and CTW is the theoretical total weight of transformer.

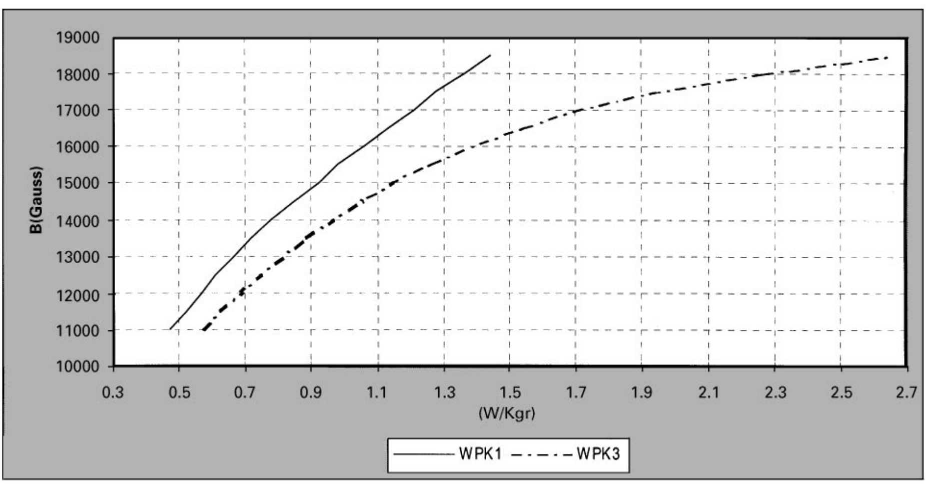

Fig. 4. Typical loss curve.

3. The neural network methodology

In case of predicting transformer iron losses, there is no simple relationship among the parameters involved in the process. Neural networks due to their highly non-linear capabilities and universal approximation properties can be very useful in such applications [5]. For this reason, they have become a topic of extensive research in recent years for applications in areas such as power systems, image processing, machine vision, medical imaging, face/object recognition or detection [3,7,13,18,21].

In this paper, multilayer feedforward neural networks are proposed as an effective tool for both predicting and classifying individual core and transformer specific iron losses. Various learning algorithms, such as variants of backpropogation [8] or the LVQ [5] are used to train the network based on a proper learning set comprising measurements during transformer production. The NNET package [12] has been used for this purpose. After the training procedure the network is able to learn (generalise) the input–output relationship and thus it can predict or classify iron losses to any input vector outside the training set.

However, good generalisation depends on the network structure. In particular, small size networks are not able to approximate complicated input–output relationships, since they are not sufficient neurons to implement all possible input–output relations. On the other hand, recent studies on learning versus network generalisation, including the VC dimension [20], indicate that an unnecessarily large network size heavily deteriorates the network performance outside the learning set. A variety of methods have been proposed in the literature for estimating the appropriate network size. Examples include pruning [17], constructive techniques [9], regularisation methods or modular and hierarchical networks [5]. In our approach we adopt a backpropogation variant [8] in a constructive framework [7] which begins with a small size network and subsequently adds neurons to improve the network performance. A validation data set has been also used during training to control learning with respect to generalisation ability of the network. Further improvement of the network performance to non-stationary data can be achieved by modifying the learning algorithm as described in [3].

4. Prediction and classification of specific iron losses with neural networks

In this section results from the application of ANNs for predicting and classifying individual core and transformer specific iron losses are presented. Prediction aims at estimating the actual specific iron losses, while classification at categorising the iron losses to one of, say p, available classes.

In the industry, it is usual to construct a transformer, whose cores have been produced under different conditions than the ones assumed by the design engineers, e.g., using magnetic material from different suppliers, same supplier but different specific losses of the magnetic material, different annealing conditions or quality of winding. In this case, the actual specific iron losses can significantly deviate from the theoretical ones. Consequently, the final product does not fulfil the guaranteed losses to the customers.

Moreover, in some cases it is sufficient to simply classify whether the final product is of acceptable quality. For example, transformers are constructed based on different sheets of magnetic material whose specific losses are varied within some limits. Furthermore, classification is also desired for determining what is the effect on iron losses of changing one or more parameters involved in the manufacturing process (e.g., annealing conditions). In all the aforementioned cases it is preferable to check if iron losses are within the limits defined by the international standards and if they are in accordance with the guaranteed to the customer iron losses, rather than predicting accurately their value.

The performance of the neural network structure in both applications is compared with that obtained by the current practice of using the typical loss curve.

4.1. Specific iron losses of individual cores

In case of individual cores, nine attributes have been selected and used as the input vector of the multilayer feedforward neural network. The selection of these attributes was based on extensive research and transformer designers' experience. These attributes correspond to parameters which actually affect the iron losses of the individual cores. In particular, the impact of the annealing cycle, the divergence of the actual core weight from the theoretical value, the size of core and the quality of core magnetic material are taken into consideration as elements of the network input vector. Six attributes have been investigated corresponding to the annealing process, depicted in Table 1. The other three attributes are the actual over theoretical core weight ratio (ATTR7), specific losses (W/Kg at 15 000 Gauss) of core magnetic material (ATTR8) as well as the size of core (e.g., small or large core) (ATTR9).

In order to take into account all the combinations of the six attributes with two values (Low and High), 32 experiments are required. However, all these combinations are time consuming and therefore reduction of the implemented experiments is achieved through the statistical design of experiments method (SDE). According to SDE [10,19] the parameters are varied at the same time in a systematic way, assuring the reliable and independent study of the impact and interaction of all the main parameters in the production procedure. This means that only some representative experiments can characterise the process and these are taken into account during the

Table 1
"Annealing" attributes

Symbol	Attribute name	Low value (*L*)	High value (*H*)
ATTR1	Annealing final temperature	825°C	855°C
ATTR2	Temperature rising time	3 h	4 h
ATTR3	Furnace opening temperature	250°C	350°C
ATTR4	Duration of constant temperature	2 h	3 h
ATTR5	Position of core in the furnace	Down	Up
ATTR6	Protective atmosphere	100% N_2	mixture of 98% N_2 and 2% H_2

Table 2
Conditions of the various annealing tests

	Annealing test Nb							
	1	2	3	4	5	6	7	8
ATTR1	L	H	H	L	L	H	H	L
ATTR2	L	L	H	H	H	H	L	L
ATTR3	L	H	H	L	H	L	L	H
ATTR4	L	L	H	H	L	L	H	H
ATTR5	H	L	H	L	H	L	H	L
ATTR6	H	H	H	H	L	L	L	L

network training phase. In our approach only eight experiments out of 32 were required. The parameters characterising each of the eight tests are shown in Table 2. It can be seen that, due to the symmetric property, the four experiments are carried out with low value of each attribute while the other four with high value.

All tests were done using the same 160 kVA transformer design and the same supplier of cores magnetic material. The magnetic steel was of grade M3, according to USA AISI, 1983, with thickness 0.23 mm. For every one of the eight tests, 96 (48 small and 48 large) cores were constructed. It should be noticed that all cores were annealed at the same furnace. 768 samples were collected for the creation of the learning and testing sets. The 3/4 (576) of them were used as learning set and the rest (192) as testing one. Moreover, 1/4 (144) of the samples of the learning set were used as validation set during learning to avoid over-training problems [5].

4.1.1. Prediction problem

In the prediction problem, a multilayer feedforward neural network structure with one output has been used while the input neurons are equal to the number of attributes (9). The network output corresponds to the value of the specific iron losses. After training the ANN, its reliability is evaluated based on the *average absolute relative error* providing using data of the testing set

$$\text{Error} = \frac{1}{N} \sum_{\substack{\text{for all N} \\ \text{samples}}} \frac{\|\text{actual specific losses} - \text{predicted specific losses}\|}{\text{actual specific losses}} * 100\%. \quad (5)$$

Table 3 illustrates the network performance or equivalently the percentage of prediction error for several network structures. It is observed that a network size consisting of one hidden layer and small number of neurons is the most adequate. Instead, the use of many neurons leads to an increase of the prediction error due to the unnecessarily large network size.

Fig. 5 presents the fractile diagram or the *Q–Q* plot (quantile–quantile) [6] of the specific iron losses. 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° slope. It is

Table 3
Error (%) of individual core specific iron losses prediction

Nb	Neurons in hidden layer 1	Neurons in hidden layer 2	Error (%)
1	100	50	2.56
2	100	20	2.39
3	20	0	2.52
4	15	0	2.32

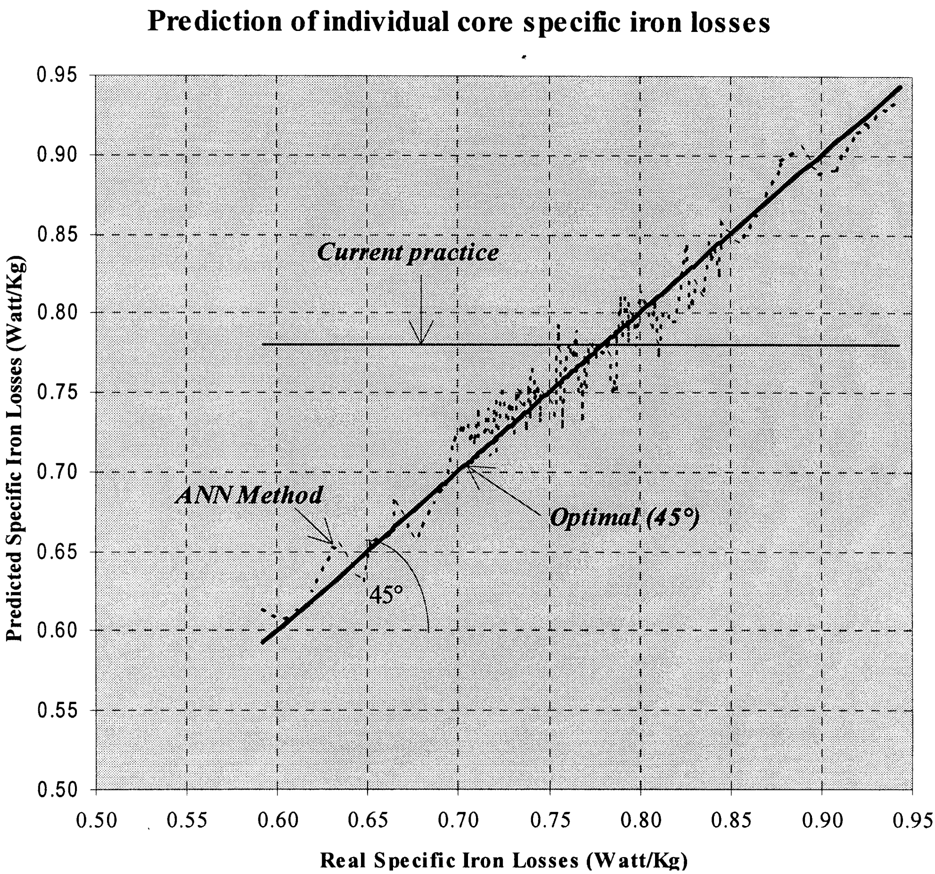

Fig. 5. Prediction of individual core specific iron losses using the typical loss curve (current practice) and the artificial neural network method.

observed that, the prediction of the individual core specific iron losses, based only on rated magnetic induction and ignoring all the other parameters, provides a constant (equal to 0.78 W/Kg) estimate for all samples belonging to the testing set. This occurs since only a unique loss curve is used for each type of magnetic material. Therefore, it significantly diverges from the line of 45°, providing an erroneous prediction especially at large or small actual W/Kg values in a range from 0.5925 to 0.9433 W/Kg. On the contrary, the proposed ANN method is able to accurately estimate the iron losses of individual cores for all the testing samples, due to the neural network learning capabilities. The maximum absolute relative error is 31.6% for the current practice, while the respective error in the ANN method is 5%. The average error is 5.7% for the current practice and 2.32% for the ANN method. It is observed that the proposed neural network architecture gives much better results as far as the mean absolute error and the worst case error, as indicated by the maximum relative error, are concerned.

4.1.2. Classification problem

In this framework the specific iron losses are divided into two classes. The first class, say Class 1, corresponds to iron losses less than 0.78 W/Kg (theoretical specific iron losses for the examined design), while the second class, say Class 2, corresponds to iron losses greater than or equal to this value. Thus, individual cores belonging to Class 1 are of better quality than the theoretical expected while cores belonging to Class 2 are of worse quality. Since we investigate individual cores and a transformer consists of four cores, the performance of each of them partially affects the transformer iron losses and thus partition of individual core losses into two classes is quite satisfactory.

Table 4 illustrates the proportion that both Classes 1 and 2 occupy in the learning and testing sets. It can be seen that Class 2 comprises almost twice the samples of Class 1 since in industry most of the cores present actual specific iron losses greater than the theoretical ones. In this experiment the network output consists of two neurons each of them corresponds to one of the two available classes. The input layer neurons are also nine since the same attributes are used as input elements, while the neurons of the one hidden layer are again 15, as in the previous prediction problem. After the neural network training its reliability is evaluated using the 192 samples of the testing set. In particular, it is found that 88% (59 out of 67) of the samples belonging to Class 1 have been correctly classified and 93% (116 out of 125) of samples belonging to Class 2. It is also observed that Class 2 presents higher classification success rate than Class 1 due to the fact that Class 2 contains more representatives than Class 1. The total classification success rate is 175/192 or 91%.

Table 4
Partition of the learning and testing set in two classes

	Learning set		Testing set	
Class	Measurement sets	Percentage (%)	Measurement sets	Percentage (%)
1	192	33.33	67	34.90
2	384	66.67	125	65.10
Total	576	100.00	192	100.00

4.2. Transformer specific iron losses

As in Section 4.1, several attributes have been used in order to predict or to classify the transformer specific iron losses of wound core distribution transformers. However, in this case different attributes have been selected, since at the transformer level geometrical characteristics are of primary importance and the individual core specific iron losses are known from measurements. The attributes fed to the neural network structure in case of the prediction/classification of transformer specific iron losses are shown in Table 5. The attributes ATTR5 through ATTR8 are core constructional parameters shown in Fig. 3.

The learning and testing sets consist of 2595 samples. 1945 of them are used as training data in the learning process of neural network, while the rest (650) as testing data. As validation set we have used the 1/4 of the samples of learning set. Each of the data comprises nine input variables (ATTR1 to ATTR9).

4.2.1. Prediction problem

As in individual cores, the network output in the prediction experiment consists of one neuron indicating the prediction of the transformer specific iron losses. Table 6 presents the percentage of the error prediction using different network sizes. It is observed that the proper size comprises a neural network with one hidden layer and a small number of neurons (20).

Table 5
Attributes for the problem of transformer total specific iron losses

Symbol	Attribute name
ATTR1	Ratio of actual over theoretical total iron losses of the four individual cores
ATTR2	Ratio of actual over theoretical total weight of the four individual cores
ATTR3	Magnetic material average specific losses of the four individual cores
ATTR4	Rated magnetic induction, B
ATTR5	Thickness of core leg, E_u
ATTR6	Width of core leg, D
ATTR7	Height of core window, G
ATTR8	Width of core window, $F1$
ATTR9	Transformer volts per turn

Table 6
Error (%) of transformer total iron losses prediction

Nb	Neurons in hidden layer 1	Neurons in hidden layer 2	Error (%)
1	100	50	2.31
2	100	20	2.24
3	20	0	2.20

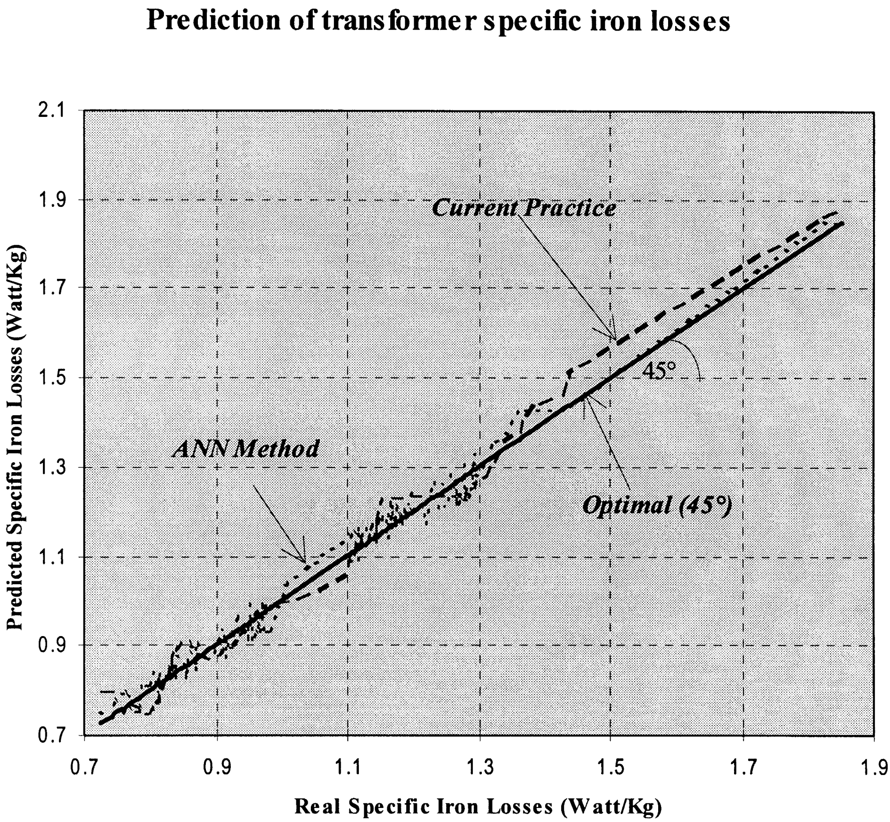

Fig. 6. Prediction of transformer specific iron losses using the typical loss curve (current practice) and the artificial neural network method.

Fig. 6 presents the *Q–Q* plot for the transformer specific iron losses. The case of current practice has been estimated according to the typical loss curve. Instead of the individual core experiment of Section 4.1 where only one 160 kVA transformer design is used, in the transformer prediction problem several designs and thus rated magnetic inductions are used. In the same plot, the prediction results of the neural network proposed scheme is shown. It is observed that, on average, the neural network prediction gives more accurate results in the sense that they are closest to the optimal line of 45° slope. In particular, the current method shows a maximum absolute relative error of 19.2% and average 4.0% while the proposed ANN method errors of 4.9% and 2.2%, respectively. It is observed, as in case of individual cores, that ANN performs better than the conventional method in both average and worst case error.

4.2.2. Classification problem

As in individual core, classification of transformer specific iron losses into two classes is considered. The neural network architecture is the same as in prediction problem case apart from the network output where two neurons are used, one indicating Class 1 and the other Class 2. One transformer is considered that it belongs to Class 1 if its actual specific iron losses are less than its theoretical expected ones (calculated by the loss curve), otherwise it belongs to Class 2. Based on the results of the classification experiment of the testing set a success rate of 91% (198 out of 218 samples) for Class 1 and 93% (402 out of 432) for Class 2 is observed. The total classification success rate is 92.3%.

5. Conclusions

In this paper, artificial neural networks are applied for the prediction and classification of individual core and also of transformer specific iron losses. The basic steps in the application of the method, like the generation of the learning and testing sets, the selection of candidate attributes and the derivation of the appropriate ANN structures are presented. The average absolute relative error for the prediction of individual core specific iron losses is 2.32%, while the average absolute relative error for the prediction of transformer specific iron losses is 2.2%. If two classes are used, the total classification success rate is 91% for the individual core and 92% for the transformer. It is shown that with the LS and TS used and for the selected candidate attribute sets, the ANN method is very suitable for prediction and classification of individual core and also of transformer specific iron losses.

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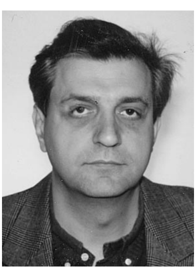

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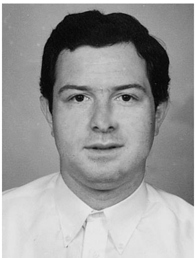

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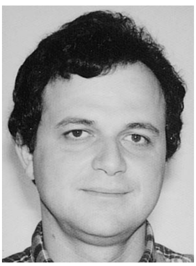

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