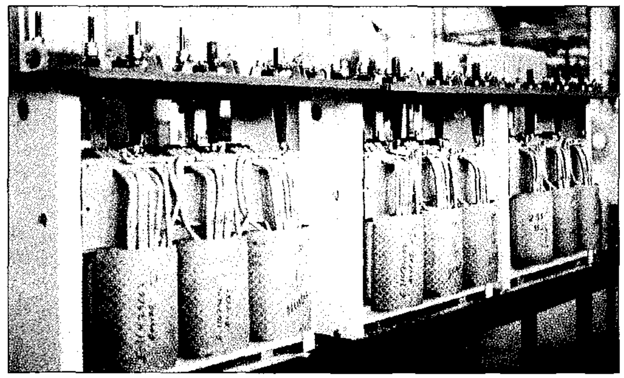
AI Helps Reduce Transformer Iron Losses

Paul Georgilakis,[1] Nikos Hatziargyriou,[2] Dimitrios Paparigas[1]

In today's competitive market environment, there is an urgent need for the transformer manufacturing industry to improve transformer efficiency and to reduce costs. High-quality, low-cost products and processes have become the key to survival. Transformer efficiency is improved by reducing load and no-load (iron) losses. Low costs for the transformer user include costs for the purchase of the transformer, installation, maintenance, and losses. Among the losses, iron losses are particularly important, considering the fact that the transformer is continuously energized, and, therefore, considerable energy is consumed in the core, while load losses occur only when the transformer is on load. Iron losses constitute one of the main parameters of transformer quality. Accurate prediction of transformer iron losses is an important task in transformer manufacturing, since it protects the manufacturer from paying loss penalties.

In this article, methods for iron loss reduction during manufacturing of wound-core distribution transformers are presented. More specifically, measurements taken at the first stages of core construction are effectively used, in order to minimize iron losses of transformer (final product). To optimally exploit the measurements (feedback), artificial intelligence methods are applied. It is shown that intelligent systems are able to learn and interpret several variations of the same conditions, thus helping in predicting iron losses with increased accuracy.



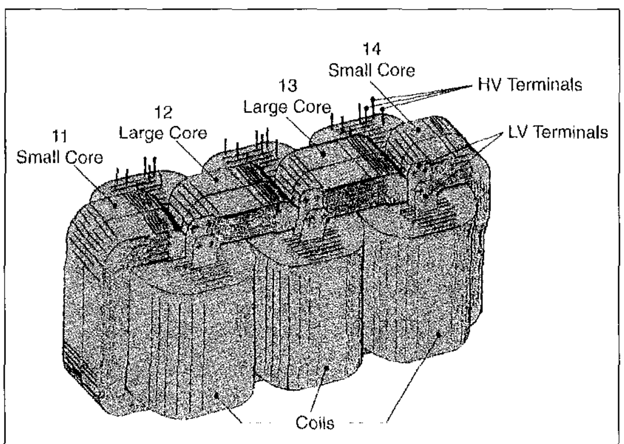


Figure 1. Assembled active part of wound core distribution transformer

Transformer Losses

Transformer losses are categorized as no-load losses (or iron losses) and load losses. Iron losses include losses due to no-load current, hysteresis losses and eddy current losses in core laminations, stray eddy current losses in core clamps and bolts, and losses in the dielectric circuit. Load losses include losses due to load currents, losses due to current supplying the losses, and eddy current losses in conductors due to leakage fields. In order to produce a high-efficiency transformer, all of these losses must be reduced to a minimum. This can be achieved in one or more of the following ways:

- Use lower loss core materials
- Decrease core flux density
- Decrease flux path length.

In general, these actions lead to increased load losses and costs. Alternatively, the designer can reduce the load losses by one or more of the following:

- Use lower loss conductor materials or winding methods
- Decrease current density
- Decrease current path length.

These steps however result in increased iron losses and costs. Steps that tend to decrease the iron losses tend to increase the load losses and vice versa. The decision on the best design is based on the loading and other specifications of each individual transformer application. In most cases, it is required that the transformer is designed with minimum iron losses.

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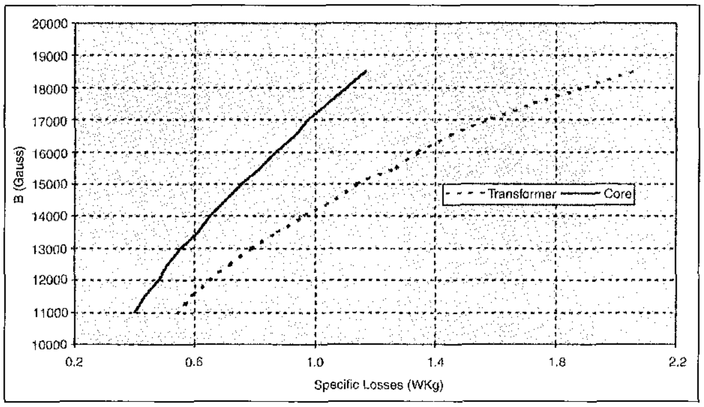

Figure 2. Typical loss curve

The losses specified by the customer are called *guaranteed* losses. The engineer designs the transformer in order to achieve iron and load losses as close as possible to the guaranteed ones. In addition, the losses must be within the tolerances defined by the international (ANSI, IEC, etc.) standards, in order to avoid paying loss penalties.

Losses that are calculated during the design phase are called *designed* losses, so, for each transformer studied, the designed iron losses and the designed load losses are calculated in advance.

At the end of transformer production, the transformer losses are measured. These losses are called *actual* losses. The bottom line is that the actual iron losses and the actual load losses should conform to customer requirements and international standards.

Calculating Iron Losses

Typically, iron losses depend upon the grade of steel, its thickness, current frequency, magnetic flux density, and weight. These factors are taken into account during the transformer design stage. A number of additional factors affect iron losses during manufacturing, such as the kind of lamination insulation, annealing, core construction, quality of assembly, etc. However, it is not possible to consider all these factors analytically, and, therefore, the calculations are based on graphs and tables obtained from past measurements on actual transformers. The basic data taken from these tables are updated by coefficients that account for the specific features of the magnetic core design and technology of core production.

Figure 1 shows the assembled active part of a wound core distribution transformer. It can be seen that two small individual cores (width of core window equal to F1) and two large individual cores (width of core window equal to F2) need to be assembled. In general, the width F2 is twice that of F1.

Indicative loss curves traditionally used to estimate iron losses of individual cores and of assembled transformers are shown in Figure 2. Using these loss curves, only the influence of the rated magnetic induction on iron losses for each specific magnetic material is considered.

Producing Wound Core Transformers

The production of wound core distribution transformers starts with slitting of the raw material into bands of standard width. Then, the slit sheets are cut to predetermined lengths and are wound on a circular mandrel. After that, a suitable press gives a rectangular shape to the circular core. This process significantly deteriorates the core 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 percent.

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 to avoid 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.

This procedure introduces the following additional difficulties in the production of wound cores, when compared to the production of the stacked cores: 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; desirable dimensions of wound cores cannot accurately be obtained as in stacked cores; core formation may deteriorate the magnetic material insulation; and homogeneous temperature distribution is hard to be obtained during the annealing procedure.

It should be noted that, during transformer construction, actual weights and losses of individual cores diverge from the theoretical ones. Although these deviations are within predictable statistical limits, they cause variations in the iron losses of assembled transformers.

The conventional technique used to reduce the variation in iron losses of assembled transformers is to premeasure and assign a grade (quality category) to each individual core and then combine higher and lower graded individual cores to achieve an average value for the entire transformer. This is referred to as *conventional grouping* process.

AI Approach to Minimize Losses

The first step in the application of artificial intelligence methods is to collect measurements during the first stages of core construction. When a satisfactory number of measurements has been collected, methods are applied in order to learn the information included in the databases. This training stage is executed offline, providing an iron loss prediction model.

The second stage of the method includes the online application of the iron loss prediction model in order to reduce the variation of iron losses of assembled transformers.

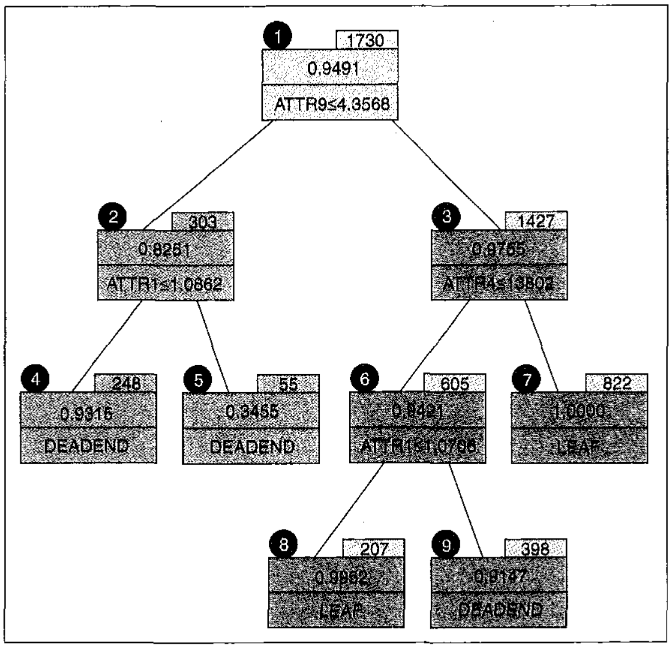

Figure 3. DT developed using the nine-attribute set

Table 1. Environments selected			
Parameter	Environment 1	Environment 2	Environment 3
Supplier	SUP_A	SUP_B	SUP_A
Steel grade	M3	M4	Hi-B
Thickness (mm)	0.23	0.27	0.23

The test sets have the same structure as the learning sets, i.e., they are created in exactly the same way, but comprise different (independent) measurement sets. For example, the learning and test sets for environment 1 consist of 2,240 samples. Each of the measurement sets comprises the nine attributes of Table 2, and 1,730 measurement sets were used as the learning set, and the rest as test set.

Classifying Losses Using Decision Trees

Classification of specific iron losses into two classes (acceptable or unacceptable) is achieved using decision trees. The criterion for classifying transformer iron losses as unacceptable is based on the comparison of the actual iron losses to the designed iron losses.

In Figure 3, a characteristic decision tree (DT) is illustrated, developed with a confidence level of 0.999. Its success rate, tested with the independent test set, is 96 percent.

Except for the root node (or top node), every node of a decision tree is the successor of its parent node. Each of the nonterminal nodes (or test nodes) has two successor nodes. Nodes that have no successor nodes are called *terminal nodes.* In order to detect if a node is terminal, i.e., sufficiently class pure, the classification entropy of the node with a minimum preset value H_{min} is compared. If it is lower than H_{min}, then the node is sufficiently class-pure, and it is not further split. Such nodes are labeled LEAF. Otherwise, a suitable test is sought to divide the node by applying the optimal splitting rule. The optimal splitting rule decides what is the best attribute and its threshold value, so that the additional information gained through that test is maximized. The best attribute and its threshold value are obtained by sequential testing of all attributes and candidate thresholds and comparing their information gain. In the case that no test can be found with a statistically significant information gain, the node is declared a DEADEND, and it is not split.

The notation used for the DT nodes is explained in Figure 4. The acceptability index of a node is defined as the ratio of the acceptable MS in the subset E_n of node n to the total number of MS in E_n. For example, among the

Table 2. Attributes for the prediction of transformer specific iron losses	
Symbol	**Attribute**
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, Eu
ATTR6	Width of core leg, D
ATTR7	Height of core window, G
ATTR8	Width of core window, F1
ATTR9	Transformer volts per turn

Creating Learning and Test Sets

For the creation of the learning sets, measurements collected during the initial stages of transformer manufacturing are grouped according to the supplier, grade, and thickness of magnetic material. Each different supplier, grade, and thickness of magnetic material is categorized as a different subset, called *environment* in the sequel. In the application presented, three different environments are considered, each defined in Table 1. For example, environment 1 is characterized by magnetic material of grade M3 according to ANSI 1983, thickness of 0.23 mm, while the supplier of material was Supplier A.

The databases are composed of sets of actual industrial measurements and each measurement set (MS) is composed of a collection of input/output pairs. The input pairs or *attributes* are the parameters affecting transformer iron losses. Attributes have been selected based on extensive research and transformer designers' experience. They include grain oriented steel electrical characteristics, core constructional parameters, and quality control measurements of core production line. The list of nine attributes initially selected is shown in Table 2. The output pairs comprise the actual specific iron losses.

1,730 MS of node 1, the 1,642 MS (94.91 percent, i.e., acceptability index of 0.9741) are acceptable, while the remaining 88 are unacceptable.

The terminal nodes correspond to a class label (acceptable or unacceptable) that can be used to classify any measurement set as either belonging to the learning set or a completely new one. The class of a terminal node is assigned, using its acceptability index. For example, if the acceptability index of a terminal node of the DT is 0.9, then the MS falling to this node have a 90 percent probability of being acceptable.

The DT of Figure 3 consists of four test and five terminal nodes and has automatically selected only three attributes among the nine candidates. These attributes in decreasing order of significance are ATTR9, ATTR1, and ATTR4. ATTR9 corresponds to transformer volts per turn, ATTR1 is the ratio of actual over theoretical total iron losses of the four individual cores, and ATTR4 represents the rated magnetic induction. The selection of these attributes is reasonable and expected, since they are all related to the transformer iron losses.

Each terminal node produces one decision rule, on the basis of its acceptability index. For example, from terminal node 7, the following rule is derived: *if ATTR9≤4.3568 and ATTR4>13802, then transformer-specific iron losses are of acceptable quality.* Consequently, based on the decision tree of Figure 3, rules useful for the design (parameters ATTR4 and ATTR9) and also for the core production (parameter ATTR1) can be derived.

It is desirable to construct transformers leading to nodes 7, 8, and 4, if it is technically and economically feasible. These nodes have acceptability indexes greater than 93 percent.

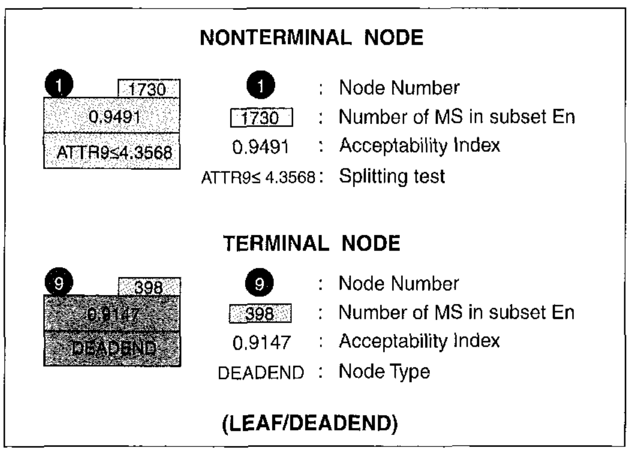

Figure 4. Notation of the DT nodes

The measurement sets following the rule ATTR9≤4.3568 and ATTR1>1.0862 lead to node 5 and are characterized as unacceptable. In order to avoid this, ATTR1 must be reduced during transformer construction. The method is to reduce the actual total single-phase iron losses of individual cores by removing from the transformer cores set one or more cores with high single-phase iron losses and adding cores with lower ones.

The measurement sets following the rule ATTR9>4.3568 and ATTR4>13802 lead to node 7 and are characterized as acceptable. This is equivalent to increasing the volts per turn (ATTR9) and also increasing the rated magnetic induction (ATTR4). Design engineers determine both these parameters. In fact, the rated magnetic induction offers enough flexibility, therefore, it is desirable to design transformers leading to this node, if it is technically and economically feasible.

Predicting Losses Using Neural Networks

There is no simple relationship among the parameters involved in the production process that expresses analytically the transformer iron losses. Artificial neural networks have the ability to automatically learn relationships between inputs and outputs independently of the size and complexity of the problem. Neural networks have, therefore, been applied to iron loss prediction.

Extensive experiments have shown, however, that the performance of the neural networks is unacceptable if samples of all environments were used as a training set. Similar results have been observed even if the parameters of the environment (i.e., the supplier, grade, and thickness of the magnetic material) were used as neural network input vectors. Hence, the training set is divided into subsets, each corresponding to a specific environment. This approach has provided very satisfactory results.

A multilayer feed-forward neural network structure with one input layer, one hidden layer, and a single output neuron was found to provide satisfactory results. The input neurons correspond to eight attributes selected by applying decision trees. These attributes include the rated magnetic induction as well as the magnetic material average specific losses of the four individual cores at 15,000 Gauss and at 17,000 Gauss. Moreover, attributes such as the ratio of actual over theoretical total weight of the four individual cores and the ratio of actual over theoretical total iron losses of the four individual cores are also selected. The remaining three attributes are formed by the combination of other measurements. The number of neurons of the hidden layer was selected so that the performance of the network can be generalized for each given environment. For example, for environment 1, one hidden layer of five neurons was found completely adequate. The activation function for all neurons is the sigmoid function.

Figures 5 and 6 present the Quantile - Quantile (Q-Q) plots of the specific iron losses, for the environment 1, using the typical loss curve and the proposed neural network method, respectively. According to the Q-Q plot method, the data of real specific iron losses is plotted versus the predicted ones. Perfect prediction lies on a line of 45° slope. It is observed that the neural network method provides more accurate results than

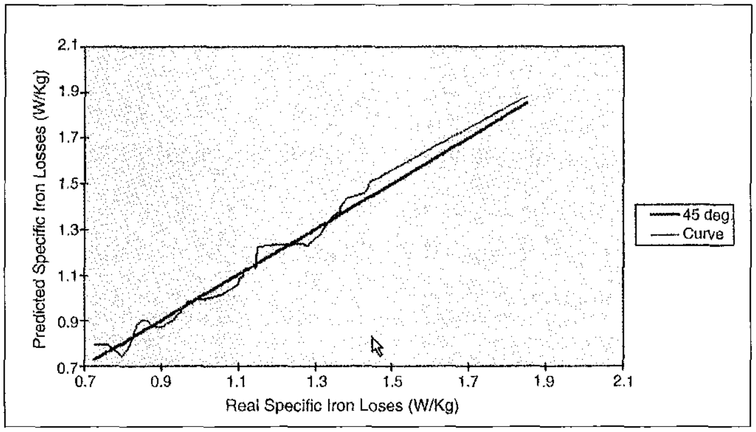

Figure 5. Prediction of transformer specific iron losses for environment 1 using the typical loss curve (current practice)

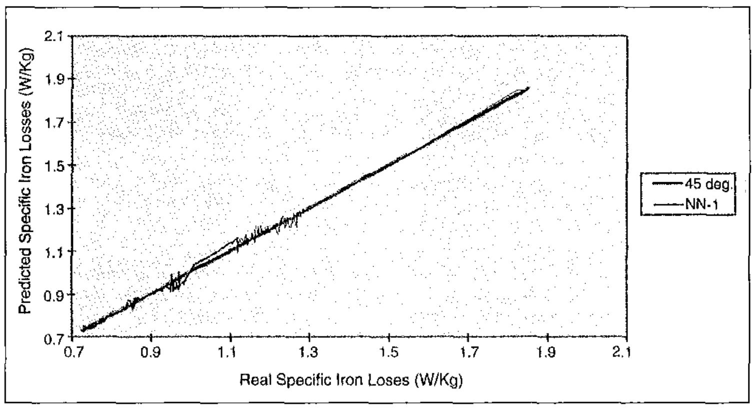

Figure 6. Prediction of transformer specific iron losses for environment 1 using the proposed neural network method

the typical loss curve. This is due to the learning capabilities of the neural network approach as well as due to the fact that more parameters (attributes) are taken into consideration.

Table 3 presents the average absolute relative error (AARE) on test set for the three environments considered, following the current practice (loss curve) and the proposed method (neural network). In all cases, the neural network method provides an improved accuracy by more than 45 percent.

Transformer Assembly Using Genetic Algorithms

The information that the neural networks have learned is exploited online in order to reduce the variation of iron losses of assembled transformers. More specifically, iron losses predicted by the neural networks are used to improve the grouping process. Assuming that an even number of L small cores and L large cores are available, then $L/2$ transformers can be assembled. Each transformer has four positions where cores can be placed. The two outer positions are occupied by small cores, while the other two middle positions 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 applies to each large core. From all possible combinations of grouping $L/2$ transformers, only one combination provides the optimum iron loss performance.

The effectiveness of neural networks when applied to the above selection process is strongly reduced, as the number of individual cores increases. For example, for $L=6$, the combinations of grouping the $L/2$ transformers are 1,800, while for $L=48$ the combinations are approximately $4*10^{13}$. For this reason, a genetic algorithm approach is adopted for this task. This procedure significantly improves the grouping process in relation to the conventional method.

According to the genetic algorithm based grouping process, the possible arrangements of the $L/2$ transformers (sets of arrangements) are represented as chromosomes whose genetic material consists of core numbers (indexes). An initial population of chromosomes is generated by selecting randomly $L/2$ sets of core numbers (arrangements). The total loss function is defined as the sum of the iron losses of the $L/2$ transformers, predicted by the neural network, while the fitness function is the inverse of the total loss function. The aim of the genetic algorithm is to minimize the total

Table 3. AARE (%) on test set, for the environments selected, using the current practice and the proposed neural network method

	Environment		
	1	2	3
Current practice	2.9	3.1	3.3
Proposed method	1.5	1.7	1.8

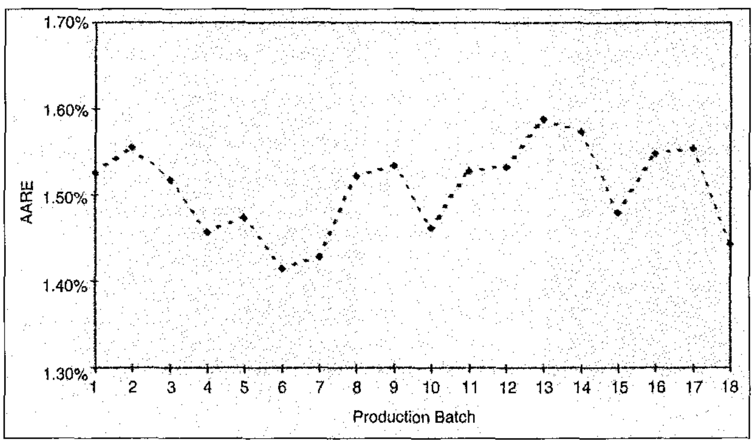

Figure 7. Average absolute relative error in prediction of transformer iron losses for environment 1 for various production batches using the proposed genetic algorithm based grouping process

loss function or to maximize the fitness. Following a proportionate scheme for parent selection, a set of new chromosomes (offspring) is produced by mating the parent chromosomes and applying uniform crossover and mutation operations.

Figure 7 illustrates the average absolute relative error in prediction of transformer iron losses, for the environment 1, for 18 production batches, using the proposed genetic algorithm based grouping process. It is observed that the proposed grouping process provides an AARE smaller than 1.60 percent for all of the production batches. This is compared with an AARE of 3.15 percent in prediction of transformer iron losses, which usually observed by the conventional grouping process.

Description of Software Used

Figure 8 shows a typical screen of the toolbox used for the creation of the learning sets, the prediction of iron losses using decision trees and neural networks, and the application of genetic algorithms. The appropriate reports and statistics are provided in graphical or tabular form. For example, Figure 8 shows statistics about the production batch 1160-047, namely, 50 transformers, 160 kVA, 20/.4 kV, 50 Hz. For the specific production batch, the average losses predicted by the proposed artificial intelligence technique are 313.27 W, while the average actual losses are 314.07 W.

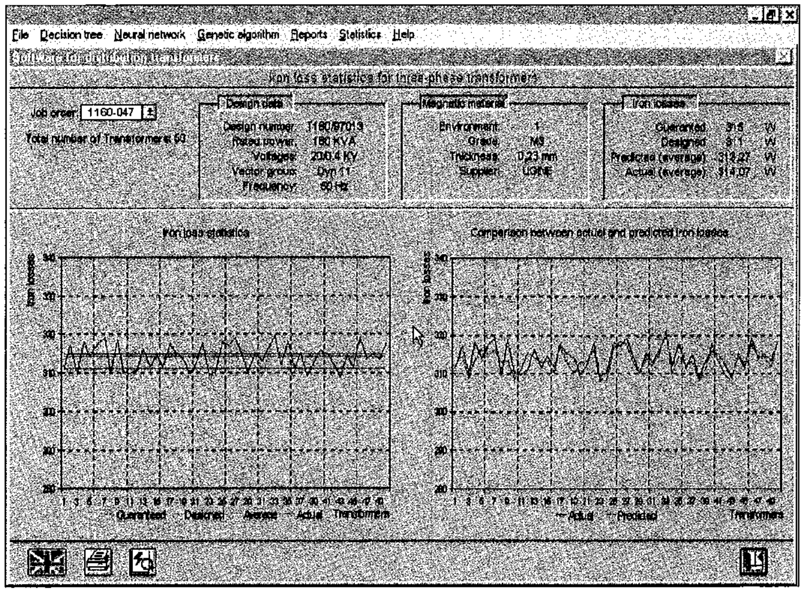

Figure 8. Toolbox used for the creation of learning sets, prediction of iron losses using decision trees and neural networks, and the application of genetic algorithms

This toolbox is currently used by different types of users: transformer designers, staff in core production, and those responsible for quality control. Each user has different needs and access rights. For example, the staff in core production collects measurements of individual cores and applies the genetic algorithm based grouping process, while the transformer designer collects information about a specific production batch (job order) and previews or prints reports and statistics. The toolbox is very flexible, and all it needs for maintenance is to periodically add new measurements and retrain the neural networks. The toolbox has proved useful for the evaluation of the adopted techniques in transformer manufacturing.

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For Further Reading

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Biographies

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