Spotlight on Transformer Design

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IN TODAY'S COMPETITIVE MARKET ENVIRONMENT, THERE IS AN URGENT NEED for the transformer manufacturing industry to improve transformer efficiency and to reduce costs, since high-quality, low-cost products and processes have become the key to survival in the global economy. The aim of transformer design optimization is to completely calculate the dimensions of all the parts of the transformer based on prescribed specifications, using available materials economically to achieve lower cost, lower weight, reduced size, and better operating performance. In this article, we investigate the selection of the material of the transformer windings, which can be copper (Cu) or aluminum (Al). The variation in the cost of the winding materials has a direct impact on the optimum transformer design, since these materials are stock exchange commodities, and their prices can significantly fluctuate through time. Thus, in some transformer designs, it is more economical to use Cu windings instead of Al, and in others vice versa.

To achieve an optimum design of a transformer, an integrated artificial intelligence (AI) technique is proposed. Over the last few years, AI has seen increased usage in various fields such as industry, medicine, and finance. In our case, AI is used to reach an optimum transformer design solution for the winding material selection problem. To be more precise, we combine decision trees (DTs) and adaptive trained neural networks (ATNNs) with the aim of selecting the appropriate winding material (Cu or Al) to design an optimum distribution transformer (Figure 1). Both methodologies have emerged as important tools for classification (in our case, the classification problem has two possible classes: Cu or Al).

Importance of the Materials

The variation in the cost of the materials used in transformer manufacturing has a direct impact on the design of the technically and economically optimum transformer. The material of the transformer windings can be Cu or Al (Figure 2). Since Cu and Al are stock exchange commodities, their price can significantly change through time. In addition, both materials have different technical characteristics. To check which winding material results in a more economical solution, there is a need to optimize the transformer twice (once with Cu and once with Al windings) and afterwards to select the most economical design. The solution of the winding selection problem can be implemented using AI, since AI has been proven very efficient in solving problems in the transformer industry.

How to Optimize a Transformer Design

It is essential to find an optimum transformer that satisfies the technical specifications and the customer needs with the minimum manufacturing cost. Three-phase wound-core

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How Artificial Intelligence Uses Decision Trees and Adaptive Trained Neural Networks to Select Winding Material

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figure 1. A three-phase distribution transformer.

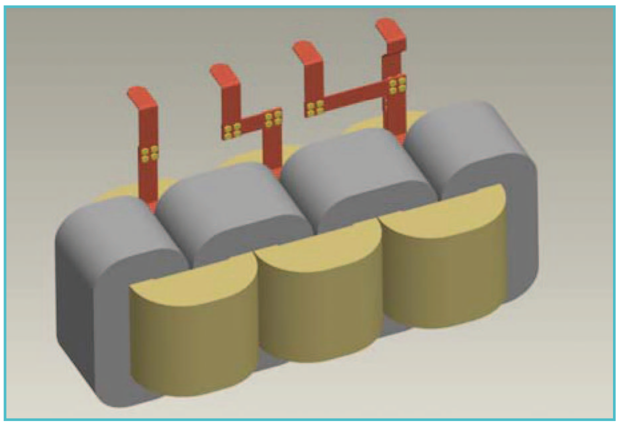

figure 2. Assembled active part of three-phase wound core distribution transformer. Windings are illustrated in beige color.

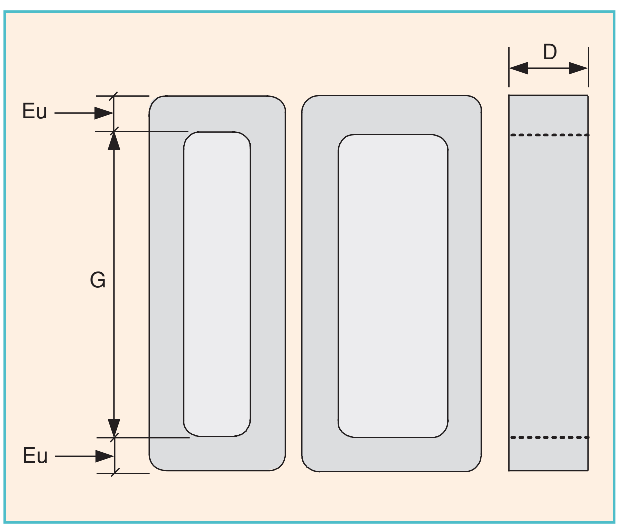

figure 3. Core constructional parameters (G: height of core window, D: width of core leg, Eu: thickness of core leg).

distribution transformers are considered, whose magnetic circuit is of shell type. The optimum transformer is calculated with the help of a suitable computer program, which uses 134 input parameters to make the transformer design as parametric as possible. These 134 input parameters are split into the following eight types:

- *Description variables:* e.g., rated power, rated low and high voltage, frequency, material of low- and high-voltage coil, and low- and high-voltage connection.
- *Variables that rarely change:* e.g., core space factor, turns direction space factor, and specific weight of materials used.
- *Variables with default values:* e.g., low- and high-voltage taps, tolerance for no-load losses, load losses, and short-circuit voltage.
- *Cost variables:* e.g., cost per weight unit for low- and high-voltage conductor, magnetic steel, oil, insulating paper, duct strips, and corrugated panels.
- *Optional variables:* e.g., variables that can either be calculated by the program or defined by the user.
- *Various parameters:* e.g., type of low- and high-voltage conductor, number of low- and high-voltage ducts, low- and high-voltage maximum gradient, maximum ambient temperature, and maximum winding temperature.
- *Variables for conductor cross-section calculations:* low- and high-voltage conductor cross-sections can be defined by the user or can be calculated using current density or thermal short-circuit test.
- *Solution loop variables:* e.g., low voltage turns, width of core leg, height of core window, magnetic induction, low- and high-voltage cross-section area. Figure 3 shows the height of core window (G) and the width of the core leg (D) that are used as solution loop variables during the transformer optimization process. Note that the magnetic material properties (e.g., type, grade, thickness, and specific losses) are given as input data when defining the values of magnetic induction within the solution loop variables.

The computer program allows many variations in design variables. These variations permit the investigation of enough candidate solutions. For each one of the candidate solutions, it checks if all the specifications (limits) are satisfied, and if they are satisfied, the manufacturing cost is estimated and the solution is characterized as acceptable. On the other hand, the candidate solutions that violate the specification are characterized as nonacceptable solutions. Finally, among the acceptable solutions, the transformer with the minimum manufacturing cost is selected, which is the optimum transformer. It is important to note that some of these 134 input parameters have a very strong impact on the characteristics of the optimum transformer, such as the unit cost (in US$/kg) of the magnetic material and the type of the winding material (Cu or Al).

Impact of Key Parameters on the Designer's Decision Process

Table 1 shows how changing core and conductor design can reduce no-load and load losses but also affect the cost of the transformer when we try to further improve the optimum design.

The optimum design is implemented through the following steps:

1) Initially, the input variables are entered in the computer program. A lot of different values to the solution loop variables are given, so a lot of candidate solutions are considered.
2) The computer program calculates the candidate solutions that are acceptable and the candidate solutions that are rejected (they violate one or more of the constraints).
3) The acceptable solutions are sorted according to their manufacturing cost. The optimum transformer corresponds to the least-cost solution.

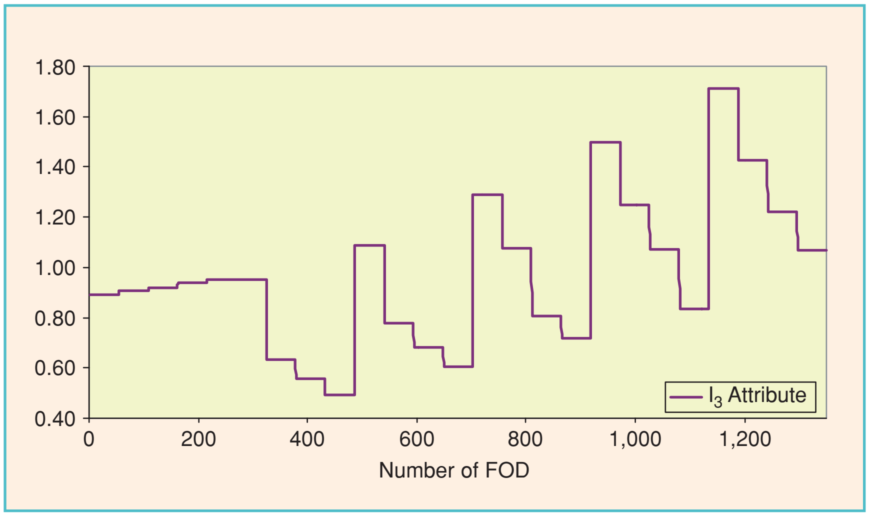

figure 4. Value of attribute I_3 for part of the knowledge base (1,350 FOD).

It is possible that all the candidate solutions are rejected. Then the computer file of nonacceptable solutions must be studied, and the reasons of rejection must be understood. Generally, the following cases may appear:

- ✔ necessity to decrease or increase no-load losses
- ✔ necessity to decrease or increase load losses
- ✔ necessity to decrease or increase short-circuit voltage.

The no-load losses are decreased by one of the following methods (linked to solution loop variables):

- ✔ increasing the number of turns of the low-voltage coil
- ✔ decreasing the magnetic induction
- ✔ decreasing the height of core window.

The no-load losses are increased by one of the following methods (linked to solution loop variables):

- ✔ decreasing the number of turns of the low-voltage coil
- ✔ increasing the magnetic induction
- ✔ increasing the height of core window.

The load losses are decreased with the following ways (linked to solution loop variables):

- ✔ decreasing the number of turns of the low-voltage coil
- ✔ increasing the magnetic induction
- ✔ increasing the cross-section area of the high-voltage coil
- ✔ increasing the cross-section area of the low-voltage coil
- ✔ increasing the height of core window.

The short-circuit voltage is decreased as follows:

- ✔ decreasing the number of turns of the low-voltage coil
- ✔ increasing the height of core window.

Generally, the cost of transformer is decreased as follows:

- ✔ increasing the no-load losses
- ✔ increasing the load losses.

From the aforementioned, we derived that there is an interaction between the input and the output variables (manufacturing cost, designed no-load losses, load losses, and short-circuit voltage). For example, the no-load losses are decreased with the decrease of the magnetic induction (with the rest of the input parameters to be constant), but unfortunately the load losses are increased. The optimum solution is derived from selecting such values for the input variables so that the transformer satisfies the constraints with the minimum manufacturing cost. This selection is implemented

table 1. Loss reduction alternatives.

	No-Load Losses	Load Losses	Cost
To decrease no-load losses			
A) Use lower-loss core material	Lower	No change	Higher
B) Decrease flux density by			
1) Increasing core Cross Section Area (CSA)	Lower	Higher	Higher
2) Decreasing volts per turn	Lower	Higher	Higher
C) Decrease flux path length by decreasing conductor CSA	Lower	Higher	Lower
To decrease load losses			
A) Decrease current density by increasing conductor CSA	Higher	Lower	Higher
B) Decrease current path length by			
1) Decreasing core CSA	Higher	Lower	Lower
2) Increasing volts per turn	Higher	Lower	Lower

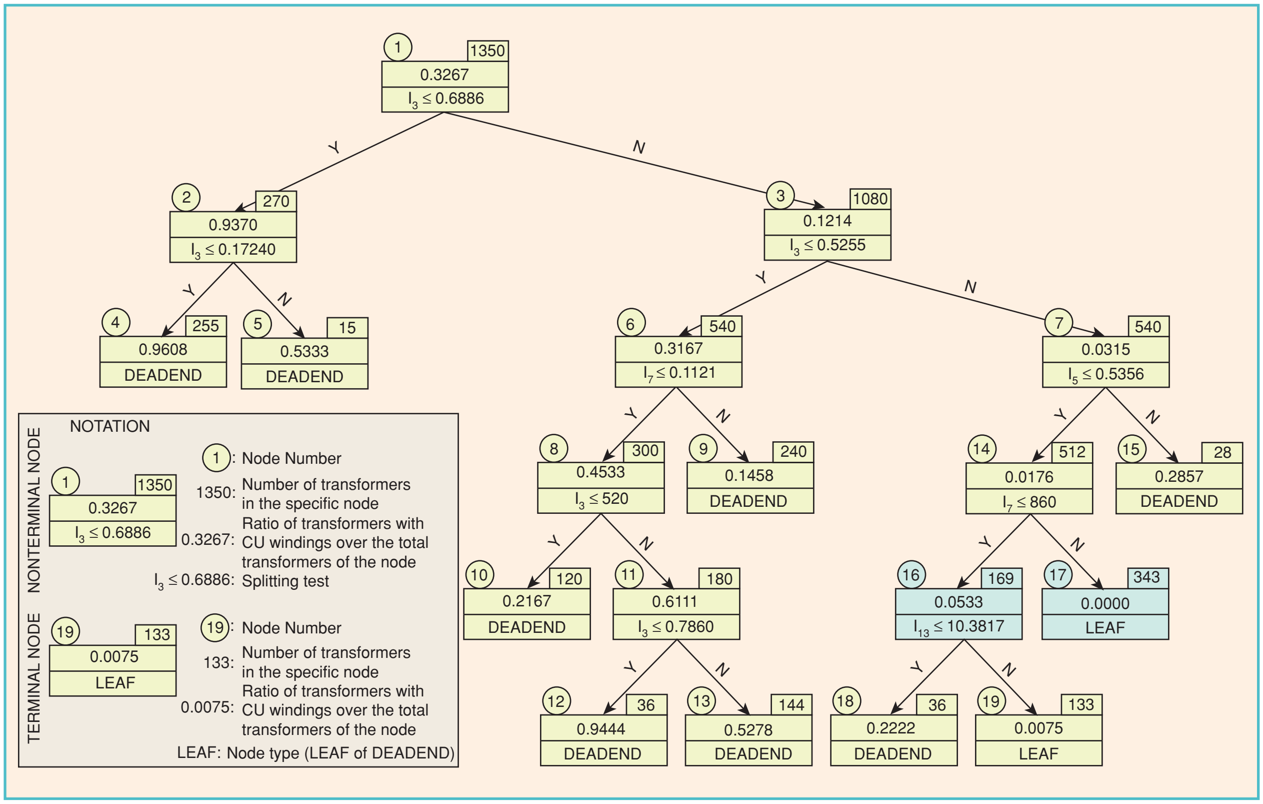

figure 5. DT for selection of winding material in distribution transformers.

through many tries (many different values for the input parameters) and is executed with the help of a suitable computer program.

Creation of the Knowledge Base

One of the most crucial steps in AI methodologies is undoubtedly the creation of the knowledge base, which is composed of the learning, validation (in the case of the ATNN), and test set. To generate these sets, six transformer power ratings (250, 400, 630, 800, 1,000, and 1,600 kVA) are considered. For each transformer, nine categories of losses are taken into account, namely AA′, AB′, AC′, BA′, BB′, BC′, CA′, CB′, CC′, according to CENELEC. For example, a 250 KVA transformer with AC' category of losses has 3,250 W of load losses and 425 W of no-load losses. Seven different unit costs (in US$/kg) are considered for the Cu and the Al winding. Based on the above, $6 \cdot 9 \cdot 7 = 378$ transformer design optimizations with Cu winding (Cu designs) and 378 transformer design optimizations with Al winding (Al designs) are realized. For each of them, either the Cu design or the Al design is the final optimum design, (FOD) i.e., the one having the least cost. In total, $6 \cdot 9 \cdot 7^2 = 2,646$ FODs are collected and stored into databases or other knowledge base. The knowledge base is composed of sets of FODs, and each of them is composed of a collection of input/output pairs. The input pairs or attributes are the parameters affecting the selection of winding material. Thirteen attributes are selected based on extensive research

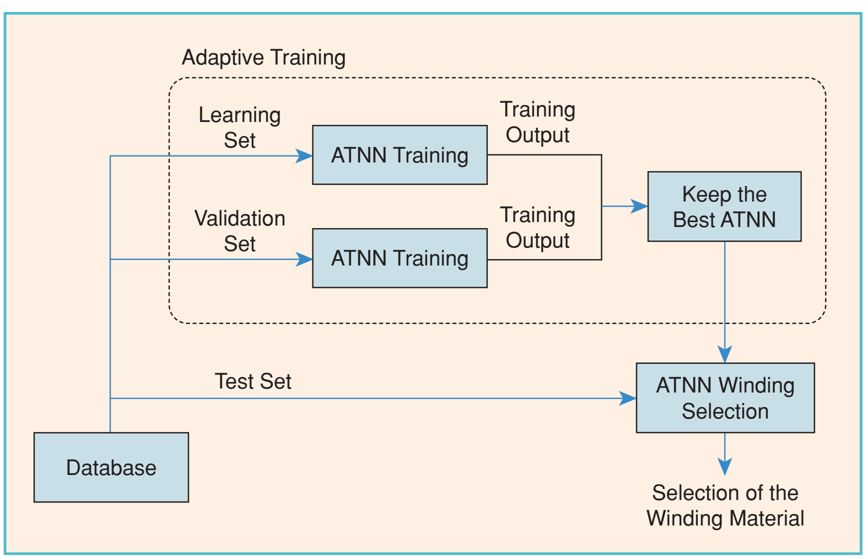

figure 6. Adaptive training mechanism for winding material selection.

and transformer design experience, as shown in Table 2. The output pairs comprise the type of winding (Cu or Al) that corresponds to each FOD. Figure 4 presents the values of the attribute I_3 for 1,350 FODs of the knowledge base. It is important to mention that to obtain each FOD, approximately two hours are required for a transformer designer who is familiar with the use of the transformer design software considered.

Decision Trees

The DT methodology is a nonparametric technique able to produce classifiers to reduce information for new and unobserved cases. The attractiveness of DTs is that they solve a problem by creating IF-THEN rules, which are readily comprehended by humans. The DT is structured upside down, built on the basis of the learning set. The learning set comprises a number of preclassified states defined by a list of potential attributes. Except for the root node (or top node), every node of a DT 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. To detect if a node is terminal, i.e., sufficiently class pure, the classification entropy of the node is compared with a minimum preset value H_{min}. If it is lower than H_{min}, then the node is sufficiently class pure and it is not further split. Such nodes are labeled LEAVES. Otherwise, a suitable test is sought to divide the node by applying the optimal splitting rule. In the case that no test can be found with statistically significant information gain, the node is declared a DEADEND and it is not split.

In our case, the usage of the DT method helps us to select the most important attributes among 13 potential attributes (Table 2) to successfully select the winding material in distribution transformers. The learning set is composed of 1,350 sets of FODs, and the test set has 1,296 independent sets of FODs. Figure 5 illustrates the DT for the selection of the winding material, which is automatically constructed by using the learning set of 1,350 FODs with the 13 attributes (Table 2). Each terminal node of the DT (Figure 5) produces one decision rule, on the basis of its Cu index,

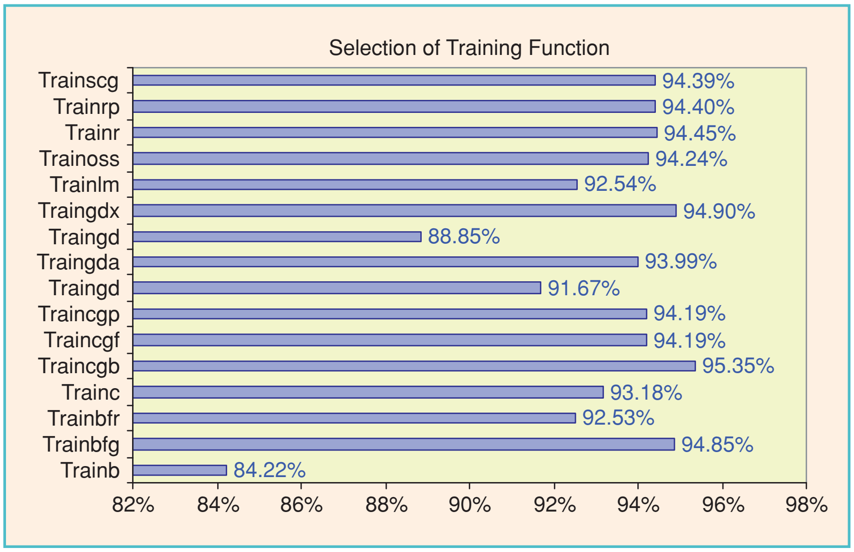

figure 7. Classification success rate on test set using 16 different training functions of MATLAB Neural Network Toolbox.

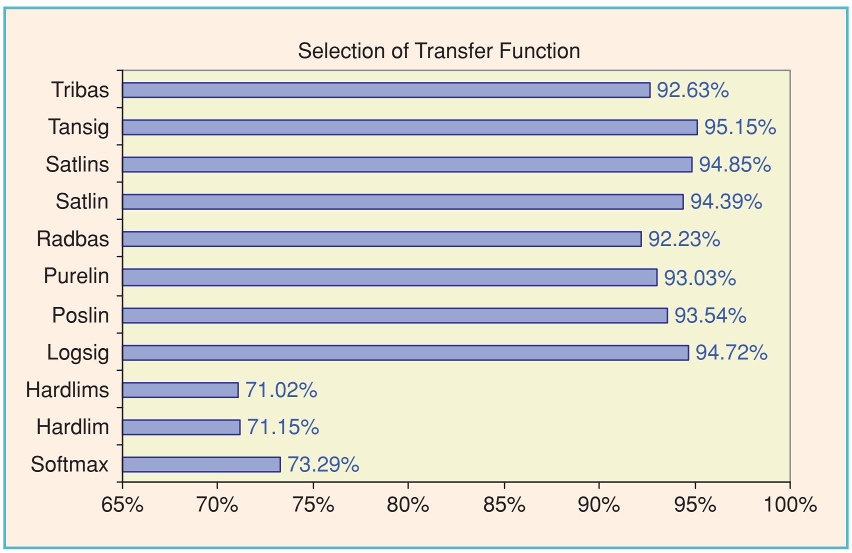

figure 8. Classification success rate on test set using 11 different transfer functions of MATLAB Neural Network Toolbox.

table 2. Thirteen attributes have been selected based on extensive research and transformer design experience.

Symbol	Attribute Name	Symbol	Attribute Name
I_1	CU unit cost ($/kg)	I_8	Guaranteed load losses (W)
I_2	AL unit cost ($/kg)	I_9	I_7/I_8
I_3	I_1/I_2	I_{10}	Rated power (kVA)
I_4	Magnetic material unit cost ($/kg)	I_{11}	Guaranteed short-circuit voltage (%)
I_5	I_4/I_1	I_{12}	I_7/I_{10}
I_6	I_4/I_2	I_{13}	I_8/I_{10}
I_7	Guaranteed no-load losses (W)		

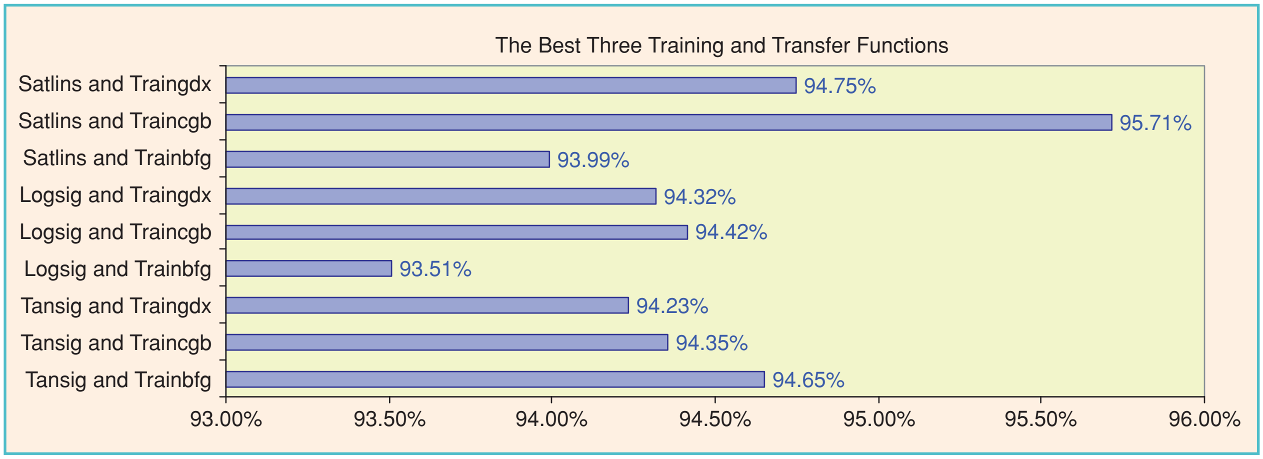

figure 9. The combination of the best three training and transfer functions.

i.e., the ratio of Cu designs over the FOD of that node. For example, from terminal node 17 of the DT of Figure 5, the following decision rule is derived: If $I_3 > 0.6886$ and $I_5 > 0.5255$ and $I_5 \leq 0.5356$ and $I_7 > 860$, then choose Al, since the Cu index of node 17 is 0.0.

It is also important to note that, among the 13 attributes, the DT method automatically selects the six most important ones (attributes I_3, I_4, I_5, I_7, I_8, and I_{13}) that are appearing in the various test nodes of the DT of Figure 5. The selection of the above six attributes is reasonable and expected, since they are all related to the selection of the winding material (Cu or Al) in distribution transformers. Thus, taking for granted the values of the six above-mentioned attributes, the DT of Figure 5 estimates the appropriate material (Cu or Al) from which the distribution transformer has to be designed.

The DT of Figure 5 achieves a total classification success rate of 90.92% on the test set, which makes the DT method very suitable for the selection of the winding material in distribution transformers.

Adaptive Trained Neural Networks

The artificial neural network methodology is a computer information processing system that is capable of sufficiently representing any nonlinear function. Techniques based on artificial neural networks are especially effective in the solving of high-complexity problems for which a traditional mathematical model is difficult to build, where the nature of the input-output relationship is neither well defined nor easily computable. Over the last few years, artificial neural network techniques have seen increased usage in various areas such as in the fields of industry, electronics, robotics, and medicine. The recent extensive research in neural classification has established that neural networks are a promising alternative to various conventional classification methods.

In the case of winding material selection problem, there is no simple relationship among the parameters involved in the solution. Artificial neural networks, due to their highly nonlinear capabilities and universal approximation properties, are proposed to select the appropriate winding material that results in optimum distribution transformer design. This means that the considered problem is a problem of classification into two classes: Cu or Al. At the training stage, the proper artificial neural network architecture (e.g., number and type of neurons and layers) is selected. In addition, an adaptive training mechanism allows the artificial neural network to learn from its mistakes and correct its output by adjusting the parameters (weights) of its neurons. The adaptive training process enhances the performance of the proposed method as additional training data become available. It is important to note that normalization of data is a crucial stage for training the ATNN. In doing so, it not only facilitates the training process but also helps in shaping the activation function. It should be done so that the higher values do not suppress the influence of lower values and the symmetry of the activation function is retained.

Moreover, we divide the knowledge base into training, validation, and test sets. The selection of the size of these sets is important for the ATNN behavior. Since our goal is to find the neural network having the best performance on new data, the simplest approach to the comparison of

table 3. The results of the experiments in brief.

13 Attributes		6 DT Attributes	
1 hidden layer	CSR on TS	1 hidden layer	CSR on TS
70%LS - 30%TS:	92.28%	70%LS - 30%TS:	92.16%
50%LS - 50%TS:	95.92%	50%LS - 50%TS:	94.28%
2 hidden layers		2 hidden layers	
70%LS - 30%TS:	94.48%	70%LS - 30%TS:	92.59%
50%LS - 50%TS:	95.73%	50%LS - 50%TS:	94.58%

LS: learning set, TS: test set, CSR: classification success rate different neural networks is to evaluate the error function using data that is independent of that used for training. Various neural networks are trained by minimization of an appropriate error function defined with respect to a training data set. This function defines the classification failure rate of the winding selection problem. The performance of the neural networks is then compared by evaluating the error function using an independent validation set, and the network having the smallest error with respect to the validation set is selected. Since this procedure can itself lead to some over-fitting to the validation set, the performance of the selected network should be confirmed by measuring its performance on a third independent set of data called a test set (Figure 6). Consequently, in our case, we use a learning set that is always split into a training set and a validation set. After training, each of the different neural network architectures is tested on the basis of an independent test set. Finally, the neural network architecture with the minimum classification failure rate (maximum classification success rate) on the test set is selected, which is the optimum ATNN for the winding material selection problem. In this article, the research of the optimum ATNN architecture is conducted by using the MATLAB Neural Network Toolbox. When new FODs are coming, the neural network is retrained following the above-mentioned training mechanism.

Selection of the Optimum Training and Transfer Function for the Neural Network

To select the best training and transfer function for the neural network, we follow the procedure below. Taking into consideration initial investigation that showed that the 13-13-1 architecture (13 input neurons, 13 neurons in the hidden layer, and one single neuron in the output layer) achieved the highest classification success rate on the test set, we use all the possible combinations of training and transfer

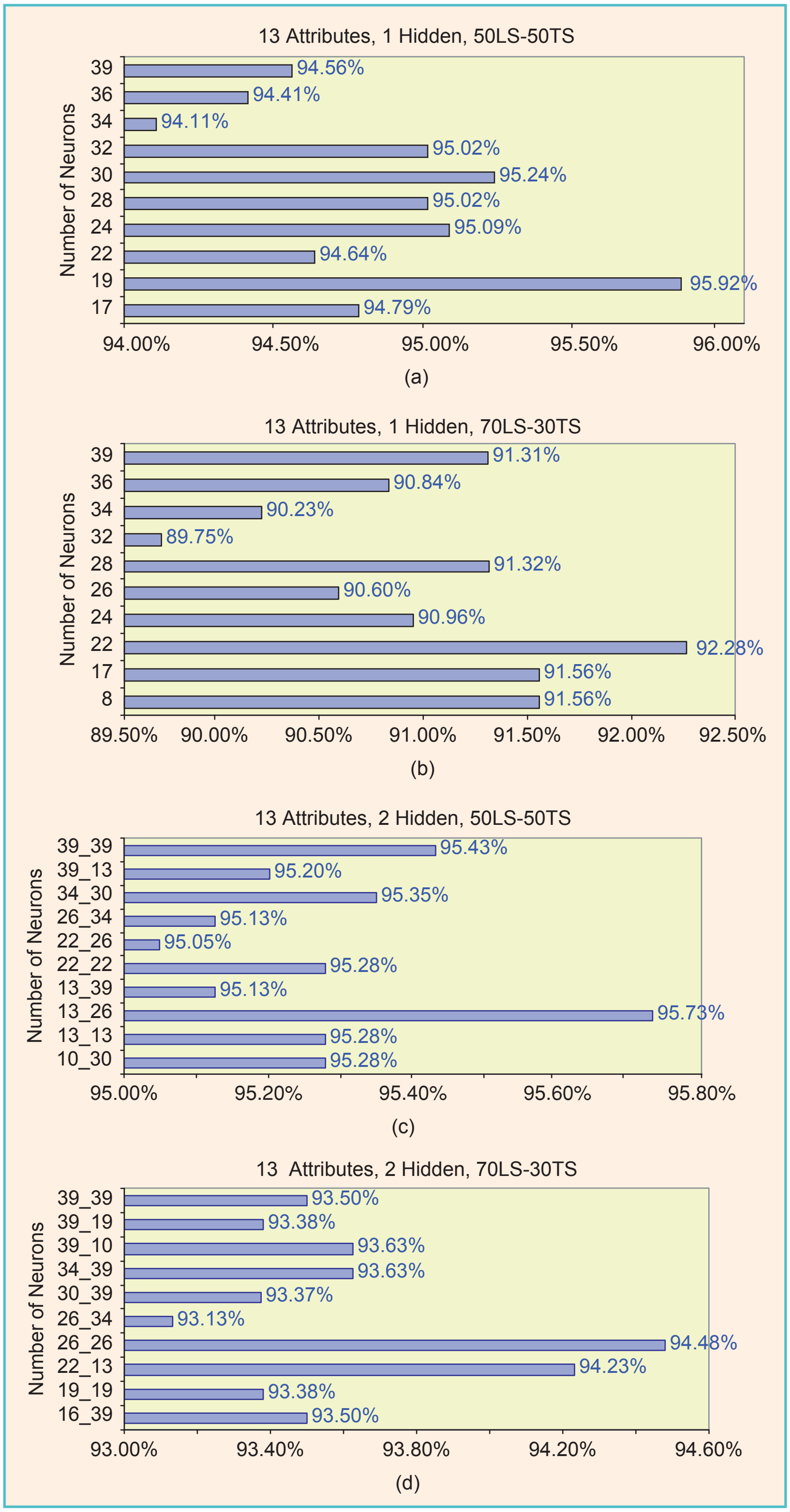

figure 10. The best ten results (according to the highest classification success rate on test set) of each case are presented using 13 attributes and two different cases as concerns the sizes of learning and test set. (a) One hidden layer with 50% LS and 50% TS. (b) One hidden layer with 70% LS and 30% TS. (c) Two hidden layers with 50% LS and 50% TS. (d) Two hidden layers with 70% LS and 30% TS.

The variation in the cost of the materials used in transformer manufacturing has a direct impact on the design of the technically and economically optimum transformer.

functions of the MATLAB Neural Network Toolbox to reach the best result. Figures 7 and 8 show the training and transfer function results, respectively, using 1350 FODs, from which 675 FODs composed the learning test and the remaining 675 FODs the test set. As shown in Figures 7 and 8, the best three training functions are traincgb, traingdx, and trainbfg, and the best three transfer functions are tansig, satlins, and logsig, respectively. Based on these training and transfer functions, we conducted new experiments among all the possible combinations of them. As shown in Figure 9, the highest classification success rate is achieved by using the traincgb as training function and the satlins as transfer function. Traincgb is a network training function that updates weight and bias values according to the conjugate gradient backpropagation with Powell-Beale restarts, and satlins is a symmetric saturating linear transfer function. Figure 9 shows that this combination achieved 95.71% classification success rate on the test set, which is not only the best classification performance but also considered as very high for the transformer winding material selection problem. It should be noted that the classification success rates of Figure 9 resulted from the average of ten different executions of the algorithm.

Selection of the Optimum Adaptive Trained Neural Network

In this section, we introduce the results of the experiments of the winding material selection in distribution transformers. Table 3 contains the results in brief. The primary goal is to find the optimum architecture of the ATNN that has the highest classification success rate on test set, solving successfully the problem of the winding material selection.

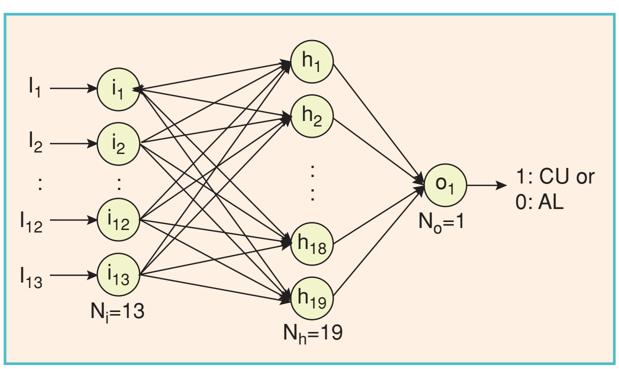

figure 11. The optimum ATNN architecture.

To achieve our goal, we introduce an extensive research in ATNN. To be more precise, we carry out experiments by studying ATNN behavior when we have all the 13 attributes as input neurons and when we have six attributes, which are stemmed from DT methodology ($I_3, I_4, I_5, I_7, I_8, I_{13}$). Both cases have one single neuron in the output layer that represents the type of winding (Cu or Al) that corresponds to each FOD. Concerning the hidden layer(s), we present a thoroughness research by investigating numerous possible topologies of the ATNN. To be more precise, one and two hidden layers are explored by trying a wide range of candidate number of neurons. More specifically, in the cases of 13 attributes and six DT attributes with one hidden layer, we examine 18 different numbers of neurons (2, 4, 6, 8, 10, 13, 15, 17, 19, 22, 24, 26, 28, 30, 32, 34, 36, and 39 neurons). In case of two hidden layers, when we have 13 attributes, we investigate 81 different combinations for the number of neurons of the two hidden layers (namely all the possible combinations of the following numbers of neurons: 10, 13, 16, 19, 22, 26, 30, 34, and 39 neurons), whereas in case of the six DT attributes, we investigate 64 different combinations of candidate solutions (namely all the possible combinations of the following numbers of neurons: 3, 6, 9, 12, 15, 18, 21, and 24 neurons). It should be noted that the classification success rate in each case of the learning and test set resulted in the average of five different executions of the algorithm.

In addition, the split of the knowledge base into learning set (training set and validation set) and test set has been investigated through the following two different cases: in the first case, the learning set is composed of 50% of total FODs and the remaining 50% compose the test set (different than the FODs of the learning set), while in the second case, the learning set is composed of 70% of total FODs and the remaining 30% compose the test set. In addition, it is important to mention that we checked the test case that has 30% of total FODs as learning set and 70% of total FODs as test set. But, in this case, the behavior of the ATNN was unstable and the classification success rate on the test set was approximately 80%, which is quite low in comparison with the other test cases. This observation is reasonable due to the fact that the ATNN does not have enough data concerning the learning set, implementing poor training of the ATNN.

Figure 10 presents the best ten classification success rate results for 13 attributes, one or two hidden neurons, and the two different splits of the knowledge base (50%LS-50%TS and 70%LS-30%TS). In Figure 10, when there are two hidden layers, we symbolize them, for example, as 13_26, which means that the first hidden layer has 13 neurons and the second hidden layer has 26 neurons. Thus, in this particular example, the architecture of the ATNN is 13-13-26-1, i.e., 13 neurons in the input layer, 13 neurons in the first hidden layer, 26 neurons in the second hidden layer, and one single neuron in the output layer. It is important to note that the input data is normalized by dividing the value of each attribute by its maximum value, which contributes to the efficient training of the neural network.

As shown in Figure 10(a), we achieve the highest classification success rate on test set (95.92%) using a fully connected three-layer feed-forward system with the following topology: 13-19-1 (13 input neurons in the input layer, 19 neurons in the hidden layer, and one single neuron in the output layer). Figure 11 presents the optimum neural network mentioned above. In this case, 50% of the FODs is used as learning set and the remaining 50% of the FODs as test set. In addition, when there are two hidden layers, the best ATNN topology is 13-13-26-1 (13 input neurons in the input layer, 13 neurons in the first hidden layer, 26 neurons in the second hidden layer, and one single neuron in the output layer), with 95.73% classification success rate on test set [Figure 10 (c)]. Consequently, both cases show balanced behavior, approaching significant classification success rate on the test set.

Moreover, when we use 70% of the FODs as learning set and the remaining 30% of the FODs as test set, the result is not as good as in the previous cases. For instance, the ATNN topology of 13-22-1 achieves 92.28% classification success rate on test set (the best with one hidden layer), whereas the

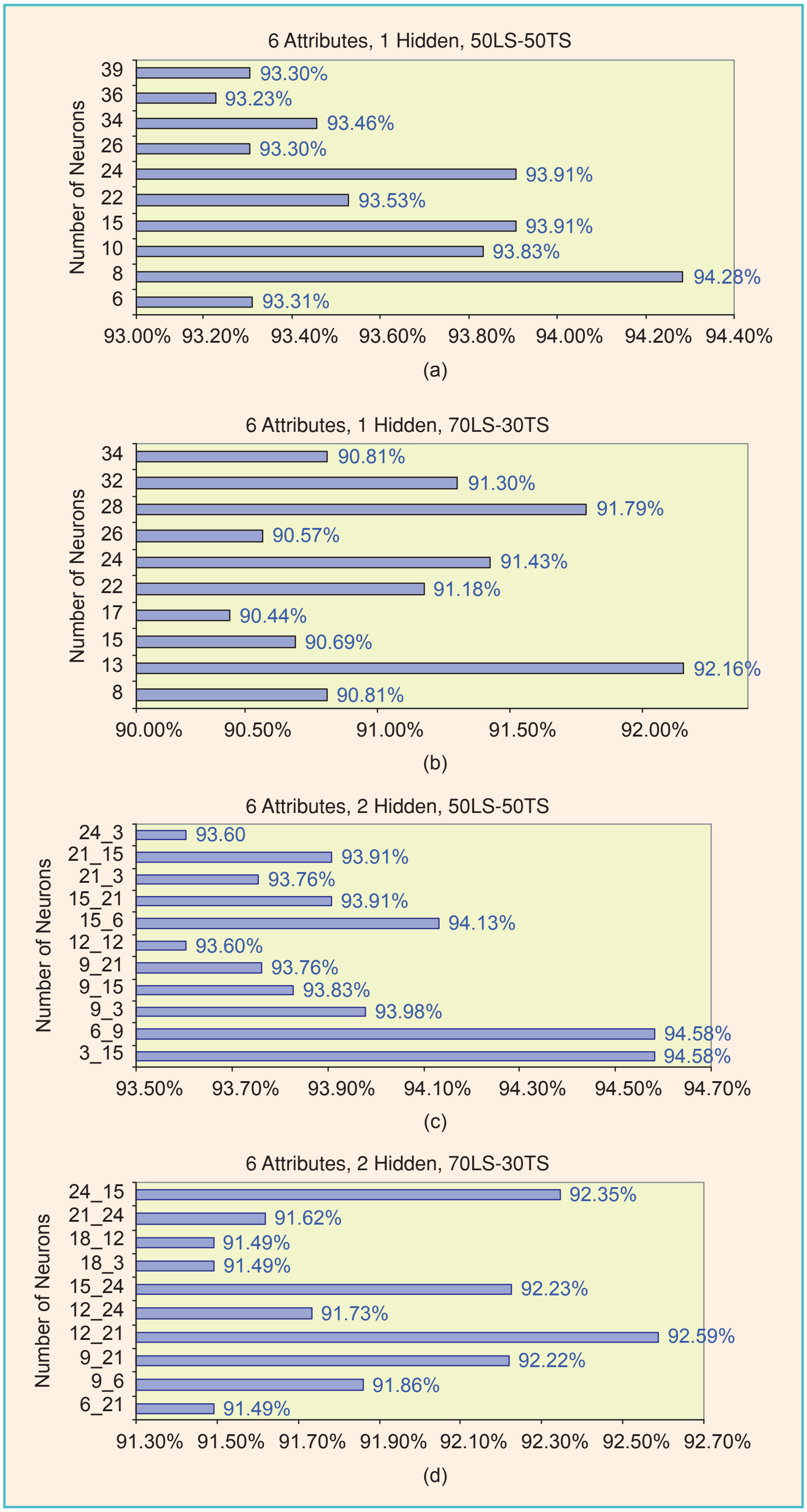

figure 12. The best ten results (according to the highest classification success rate on test set) of each case are presented using six DT attributes and two different cases as concerns the sizes of learning and test set. (a) One hidden layer with 50% LS and 50% TS. (b) One hidden layer with 70% LS and 30% TS. (c) Two hidden layers with 50% LS and 50% TS. (d) Two hidden layers with 70% LS and 30% TS.

architecture of 13-26-26-1 implements quite better results, namely 94.48% classification success rate on test set (the best with two hidden layers).

Figure 12 illustrates the results using the six attributes that have been selected by the DT, namely there are six input neurons in the input layer. In this case, the results are slightly worse in comparison with 13 attributes. Figure 12(a) and (c) shows that the neural network achieves classification success rate of 94.28% (6-8-1 architecture, the best with one hidden layer) and 94.58% (6-6-9-1 and 6-3-15-1, the best with two hidden layers), respectively, using 50% of the FODs as learning set and 50% of the FODs as test set. Although we use different topologies, we obtain almost the same performance, which proves the efficiency of the proposed methodology. However, when we use 70% of the FODs as learning set and the rest as test set, the result is approximately 2% worse, as it is shown in Figure 12(b) and (d).

Conclusions

In this article, we propose the DT and ATNN methodologies with the aim of the appropriate selection of winding material for optimum transformer design. A rich knowledge base is constructed that is composed of 2,646 FODs. Each individual FOD requires approximately two hours to be built. This knowledge base is used to classify the selection of winding material (Cu or Al) in distribution transformer designs, based on 13 attributes. These attributes are selected by extensive research and transformer design experience.

We present the DT methodology with the aim of creating simple IF-THEN rules for solving the winding material selection problem in distribution transformers. This technique achieves 90.92% classification success rate on the test set. In addition, the ATNN technique is also presented for winding material classification in distribution transformers. The performance of the ATNN was found to be exceptional, which emerged this method as an important tool for classification. More specifically, the classification success rate on the learning set was 97.97% and 95.92% on the test set using all 13 attributes. These performances are approximately 1.5% lower when we use the six attributes selected by the DT as inputs to the ATNN model. The result that is achieved by the ATNN is highly suitable for industrial use, because of its accuracy and implementation speed, since the ATNN method eliminates the need to optimize the transformer twice.

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For Further Reading

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