Artificial Intelligence Combined with Hybrid FEM-BE Techniques for Global Transformer Optimization

Eleftherios I. Amoiralis[1], Pavlos S. Georgilakis[1], Themistoklis D. Kefalas[2], Marina A. Tsili[2], and Antonios G. Kladas[2]

[1]Department of Production Engineering and Management, Technical University of Crete, GR-73100, Greece
[2]Faculty of Electrical and Computer Engineering, National Technical University of Athens, Athens GR-15780, Greece

The aim of the transformer design optimization is to define the dimensions of all the parts of the transformer, based on the given specification, using available materials economically in order to achieve lower cost, lower weight, reduced size, and better operating performance. In this paper, a hybrid artificial intelligence/numerical technique is proposed for the selection of winding material in power transformers. The technique uses decision trees and artificial neural networks for winding material classification, along with finite-element/boundary element modeling of the transformer for the calculation of the performance characteristics of each considered design. The efficiency and accuracy provided by the hybrid numerical model render it particularly suitable for use with optimization algorithms. The accuracy of this method is 96% (classification success rate for the winding material on an unknown test set), which makes it very efficient for industrial use.

***Index Terms*—Adaptive training, artificial intelligence (AI), artificial neural networks (ANNs), decision trees (DTs), finite-element method–boundary-element (FEM–BE) techniques, transformer design optimization, transformer winding.**

I. INTRODUCTION

TRANSFORMER design optimization is primarily determined by minimizing the overall transformer manufacturing cost, which includes the cost of materials and the labor cost. However, this minimization must take into account constraints related to international technical specifications and transformer user needs.

Over the last years, in order to predict the transformer design characteristics and achieve an optimum transformer design, various artificial-intelligence (AI) techniques have been proposed [1]–[3]. In the context of transformer design optimization, the selection of the winding material, which can be copper (Cu) or aluminum (Al), is an important, complex, and time-consuming task. Since Cu and Al materials are stock exchange commodities and their prices can significantly fluctuate through time, in some transformer designs, it is more economical to use Cu windings instead of Al and, in others, vice versa. In this paper, decision trees (DTs) and adaptive trained neural networks (ATNNs) are proposed with the aim of automatically selecting the appropriate winding material so as to design an optimum transformer, eliminating the need to optimize the transformer twice.

II. TRANSFORMER DESIGN OPTIMIZATION

It is essential to find an optimum transformer that satisfies the technical specifications and the customer needs at the minimum manufacturing cost. Three-phase wound-core power transformers are considered, whose magnetic circuit is of a shell type. In the considered industrial environment, the optimum transformer is calculated with the help of a suitable computer program, which uses 134 input parameters in order to make the transformer design as parametric as possible [4]. Among the acceptable solutions, the optimum transformer with the minimum manufacturing cost is selected. Some of these 134 input parameters, such as the unit cost (U.S. dollars per kilogram) of the magnetic material and the type of winding material, have a very strong impact on the characteristics of the optimum transformer.

III. FEM–BE TECHNIQUE

The role of the finite-element method–boundary-element (FEM–BE) analysis in the optimization process is to provide the solution and the performance measure of the current design, helping the optimization method to navigate in search of the optimum. The hybrid numerical technique is therefore used as a basic tool in the analysis, constituting an important part of the proposed methodology framework. Moreover, it is directly linked to the proposed AI techniques, as it is employed for the creation of the knowledge base, containing the learning, test, and validation sets of the DT and the ATNN techniques.

The efficiency of numerical techniques, along with the vast improvement in computers performance, enhances the ability to incorporate them in a search scheme in order to locate the optimum in a multidimensional parameter space. Since the evaluation of the transformer performance parameters is realized iteratively in the optimization process, significantly increasing the computational requirements, the adoption of a hybrid FEM–BE technique for the transformer 3-D representation, is able to reduce the total time needed for the

Digital Object Identifier 10.1109/TMAG.2006.892258

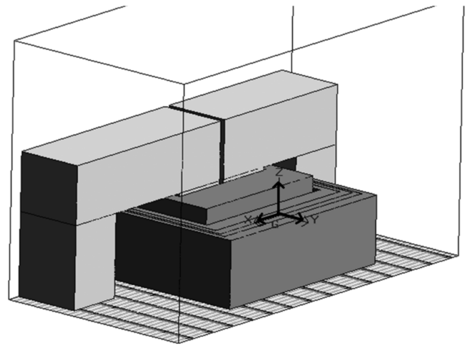

Fig. 1. Perspective view of the transformer FEM–BE model.

optimal solution search, while it benefits from the great accuracy provided by the mixed finite-element–boundary-element formulation. Therefore, the FEM–BE model used for the field solution of each design is crucial for the performance of the AI technique, since it establishes the interface that joins the search and solution algorithms [5].

Fig. 1 illustrates the 3-D one phase part model of the considered three-phase, wound core power transformers, consisting of the low-voltage (LV) and high-voltage (HV) winding of one phase as well as the iron cores that surround them. The model is divided in two regions: The active part (FEM region), represented by a tetrahedral finite-element mesh and the area between the active part and the tank walls (BEM region), represented by a triangular mesh of its boundaries [6].

IV. 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 set, the validation set (in the case of the ATNN), and the test set. In order to generate these sets, six transformer power ratings (250, 400, 630, 800, 1000, and 1600 kVA) are considered, and nine categories of losses are taken into consideration, namely AA', AB', AC', BA', BB', BC', CA', CB', and CC' (according to CENELEC harmonization document 428.1 S1, 1992). For example, a 250-kVA transformer with the AC' category of losses has 3250 W of load losses and 425 W of no-load losses. Seven different unit costs (in U.S.$/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, employing a heuristic transformer design optimization technique [4]. For each design, either the Cu design or the Al design is the final optimum design (with the least cost). In total, $6 \cdot 9 \cdot 7^2 = 2646$ final optimum designs (FOD) are collected and stored in databases. The performance parameters of each considered design (short-circuit impedance, no-load loss, etc.) are calculated with the use of the particular hybrid FEM–BE model of Section III. The use of the model is incorporated in the iterative optimization process required for the extraction of each FOD. To obtain each FOD, approximately 2 h are required for a transformer designer who is familiar with the use of the transformer design software considered [4]. The optimization algorithm requires an average of 25 iterations for the convergence to the optimum solution, resulting in a mean calculation time of 4.8 min per iteration: approximately 90% of this time corresponds to the time needed to obtain a solution from the 3-D FEM–BE model (i.e., 4.3 min in a PC of average computational capability). The knowledge base is composed of sets of FOD 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 (Table I) are selected based on extensive research and design experience. The output pairs comprise the type of winding material that corresponds to each FOD.

TABLE I
CANDIDATE ATTRIBUTES

Symbol	Attribute Name	Symbol	Attribute Name
I_1	Cu unit cost (€/kg)	I_7	Guaranteed Fe losses (W)
I_2	Al unit cost (€/kg)	I_8	Guar. winding losses (W)
I_3	I_1/I_2	I_9	I_7/I_8
I_4	Fe unit cost (€/kg)	I_{10}	Rated power (kVA)
I_5	I_4/I_1	I_{11}	Guar. short-circuit voltage (%)
I_6	I_4/I_2	I_{12}	I_7/I_{10}
		I_{13}	I_8/I_{10}

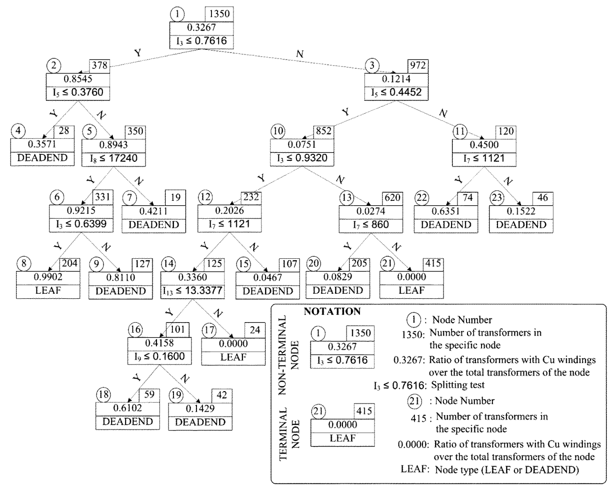

Fig. 2. DT for selection of winding material in power transformers.

V. DT Technique

The DT methodology is a nonparametric technique that is able to produce classifiers in order to reduce information for new and unobserved cases [7]. The attractiveness of the DT is that it solves a classification problem by creating IF-THEN-ELSE rules, which are readily comprehended by humans. The DT is a tree 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.

The learning set is composed of 1350 sets of FOD and the test set has 1296 independent sets of FOD. Fig. 2 illustrates the DT for the selection of the winding material, which is automatically constructed by using the learning set of 1350 FOD with the 13 attributes (Table I). Each terminal node of the DT produces one decision rule, on the basis of its Cu index (i.e., the ratio of Cu designs over the FOD of that node).

It is also important to note that, among the 13 attributes, the DT method automatically selects the six most important ones, which are the attributes I_3, I_5, I_7, I_8, I_9, and I_{13} that appear

TABLE II
CLASSIFICATION SUCCESS RATE ON THE TEST SET FOR THE DT

Node number	Cu Index	Transformer designs	Correctly classified transformer designs	Classification success rate (%)
4	0.3571	27	17	62.96
7	0.4211	18	11	61.11
8	0.9902	196	194	98.98
9	0.8110	122	100	81.97
15	0.0467	103	98	95.15
17	0.0000	23	23	100.00
18	0.6102	57	36	63.16
19	0.1429	40	37	92.50
20	0.0829	197	180	91.37
21	0.0000	398	397	99.75
22	0.6351	71	47	66.20
23	0.1522	44	37	84.09
	Total	1296	1177	90.82

in the various test nodes of the DT (Fig. 2). The selection of the above six attributes is reasonable and expected, since they are all related to the selection of the winding material in transformers. Thus, taking for granted the values of the above six attributes, the DT of Fig. 2 estimates the appropriate material from which the transformer has to be designed, achieving a total classification success rate (CSR) of 90.82% on an unknown test set of 1296 FOD (Table II). Although I_3, I_5, I_6, I_9, I_{12}, and I_{13} depend on other attributes, it is very important to consider them; otherwise, the DT would not select them [7] and the CSR on the test set would be only 84.26%.

VI. Adaptive Trained NN Technique

Techniques based on artificial neural networks (ANNs) are especially effective in solving 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 [8].

In the case of the winding material selection problem, there is no simple relationship among the parameters involved in the solution of this problem. ANNs are proposed in order to select the appropriate winding material that results in optimum power transformer design. At the training stage, the proper ANN architecture (e.g., number and type of neurons and layers, etc.) is selected. In addition, as new training data become available, an adaptive training mechanism is activated that allows the ANN to learn from its mistakes and correct its output by adjusting the parameters (weights) of its neurons.

A. Selection of the Optimum Training and Transfer Functions

In order to select the best training and transfer functions for the ANN, the following procedure is proposed and used: the number of hidden layers and the numbers of neurons in each hidden layer are parameters to be defined by trial and error. After numerous experiments, the ANN with the 13-13-1 architecture (13 input neurons, 13 neurons in the hidden layer, and one single neuron in the output layer) was found to be sufficient for this work with high CSR on the test set. Taking into account this ANN architecture, all possible combinations of the 17 different training functions and 12 different transfer functions of the MATLAB NN toolbox are considered in order to reach the best result, using 1350 FOD from which 675 FOD composed the learning set and the remaining 675 FOD composed the test set. Among the 204 combinations of the training and transfer functions of MATLAB, the CSR results show that the best training function is traincgb and the best transfer function is satlins. Traincgb is a network training function that updates weight and bias values according to the conjugate gradient back propagation with Powell–Beale restarts, and satlins is a symmetric saturating linear transfer function [9]. The combination of traincgb and satlins achieved 95.44% CSR on the test set. This is not only the best classification performance but also this CSR is considered to be very high for the transformer winding material selection problem.

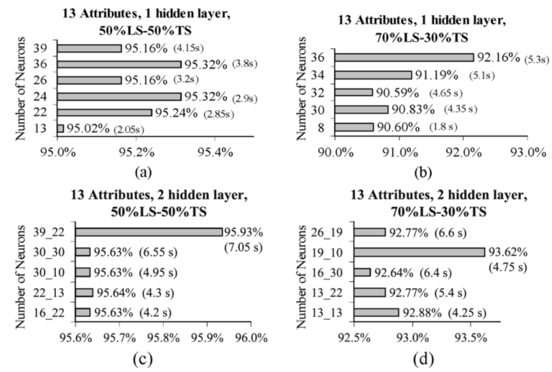

Fig. 3. Best five results (according to the highest CSR on TS) of each case are presented using as input neurons the 13 attributes of Table I and two different cases regarding the sizes of LS and TS. (a) One hidden layer with 50% LS-50% TS. (b) One hidden layer with 70% LS-30% TS. (c) Two hidden layers with 50% LS-50% TS. (d) Two hidden layers with 70% LS-30% TS. Elapsed ATNN training times (in seconds) are given in parentheses.

B. Selection of the Optimum ATNN Architecture

In order to find the optimum ATNN architecture, simulations are carried out by studying ATNN behavior for two different numbers of input neurons: 1) all of the 13 attributes of Table I and 2) the six attributes that are derived from the DT method. Both cases have one single neuron in the output layer that represents the type of winding material that corresponds to each FOD. Furthermore, both one and two hidden layers are explored by trying a wide range of potential numbers of neurons. The CSR in each case resulted in the average of ten different executions of the algorithm.

In addition, the split of the knowledge base into the learning set (training and validation set) and test set has been investigated through the cases that are illustrated in Figs. 3 and 4. It should be mentioned that the case (not shown in Figs. 3 and 4) that has 30% of total FOD as the learning set (LS) and 70% of total FOD as the test set (TS) has a low CSR (approximately 80%) in comparison with the other test cases.

Fig. 3 presents the best five CSR results for 13 input attributes, 1 or 2 hidden layers, and the 2 different splits of the knowledge base (50%LS-50%TS, 70%LS-30%TS). In Fig. 3, when there are 2 hidden layers, they are represented as x_y, which means that the first hidden layer has x neurons and the second hidden layer has y neurons. Observing Fig. 3(c), the highest CSR on the test set (95.93%) is achieved using a fully connected four-layer feedforward ANN with topology 13-39-22-1 (i.e., 13 input neurons, 39 neurons in the first hidden layer, 22 neurons in the second hidden layer, and one output neuron). In this case, 50%

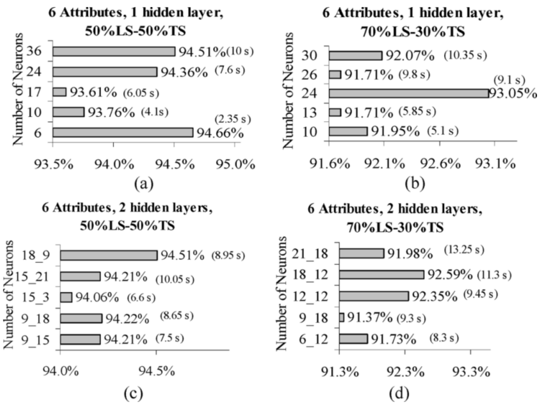

Fig. 4. Best five results (according to the CSR on TS) of each case are presented using as input neurons the six attributes selected by the DT and two different cases regarding the sizes of LS and TS. (a) One hidden layer with 50% LS-50% TS. (b) One hidden layer with 70% LS-30% TS. (c) Two hidden layers with 50% LS-50% TS. (d) Two hidden layers with 70% LS-30% TS. Elapsed ATNN training times (in seconds) are given in parentheses.

TABLE III
OPTIMUM ATNN ARCHITECTURE AND ITS PERFORMANCE

Parameter	Value	Parameter	Value
Input neurons	13	Epochs	100
Hidden layers	2	Size of training set (FOD)	337
Neurons of 1st hidden layer	39	Size of validation set (FOD)	338
Neurons of 2nd hidden layer	22	Size of test set (FOD)	675
Training function	*traincgb*	CSR on training set	97.97%
Transfer function	*satlins*	CSR on test set	95.93%

of the FOD is used as a learning set and the remaining 50% of the FOD as a test set. In addition, in the case of one hidden layer, the best ATNN topology is 13-36-1 or 13-24-1 with 95.32% CSR on the test set [Fig. 3(a)]. In conclusion, the cases mentioned before show balanced behavior, approaching significant CSR on the test set. However, when 70% of the FOD is used as a learning set and the remainder is used as a test set, the result is not as good as in the previous cases.

Fig. 4 illustrates the results using as input neurons the six attributes that have been selected by the DT. In this case, the results are slightly worse than they are using 13 attributes. Fig. 4(a) and (c) show that the ANN achieves a CSR of 94.66% (6-6-1 architecture, the best with one hidden layer) and 94.51% (6-18-9-1, the best with two hidden layers), respectively, using 50% of the FOD as the learning set and 50% of the FOD as the test set. Although different topologies are used, almost the same performance is obtained, which proves the efficiency of the proposed methodology. However, when 70% of the FOD is used as a learning set and the rest as the test set, the result is about 2% worse, as it is shown in Fig. 4(b) and (d). In conclusion, an unnecessarily large training set reduces the generalization capability of the ATNN.

Table III presents the architecture and the performance of the proposed optimum ATNN for the selection of winding material in power transformers. After setting the number of hidden layers/neurons, the 204 combinations of training/transfer functions (Section VI-A) are considered, and traincgb/satlins are still found to be the best. The elapsed training time of the optimum ANN is 7.05 s [Fig. 3(c)], which is comparable to the 8.62-s training time of the DT.

VII. CONCLUSION

This paper proposes artificial intelligence combined with hybrid FEM–BE techniques with the aim of the appropriate selection of winding material for optimum transformer design, based on 13 attributes which are selected by extensive research and transformer design experience. The FEM–BE model is particularly suitable for use with optimization algorithms, as it reduces the total time needed for the magnetic-field calculation during each iteration and provides high accuracy, which is crucial during the design stage. The iterative use of the model in the transformer optimization technique and the creation of FODs that constitute the knowledge provides a combination between numerical and AI techniques. The DT methodology solves the winding material selection problem in power transformers, achieving 90.82% CSR on an unknown test set. The performance of the ATNN was found to be exceptional and better than the DT method. The ATNN methodology provides 95.93% CSR on the test set using all of the 13 potential attributes as input neurons. The proposed 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. Future research will focus on the integration of mathematical and AI optimization techniques [5], such as genetic algorithms, simulated annealing, and Tabu search, in order to improve the existing heuristic solution technique [4] that is used in the industrial environment under consideration.

ACKNOWLEDGMENT

This work was supported by the General Secretariat for Research and Technology of Greece under PENED Grant 03ED045.

REFERENCES

[1] P. S. Georgilakis, N. D. Hatziargyriou, and D. Paparigas, “AI helps reduce transformer iron losses,” *IEEE Comput. Appl. Power*, vol. 12, no. 4, pp. 41–46, Oct. 1999.

[2] C. Nussbaum, H. Pfützner, T. Booth, N. Baumgartinger, A. Ilo, and M. Clabian, “Neural networks for the prediction of magnetic transformer core characteristics,” *IEEE Trans. Magn.*, vol. 36, no. 1, pp. 313–329, Jan. 2000.

[3] N. Tutkun and A. Moses, “Design optimisation of a typical strip-wound toroidal core using genetic algorithms,” *J. Magnet. Magn. Mater.*, vol. 277, no. 1–2, pp. 216–220, 2004.

[4] P. S. Georgilakis, M. A. Tsili, and A. T. Souflaris, “A heuristic solution to the transformer manufacturing cost optimization problem,” *J. Mater. Process. Technol.*, vol. 181, no. 1–3, pp. 260–266, 2007.

[5] Y. Rahmat-Samii and E. Michielssen, *Electromagnetic Optimization by Genetic Algorithms*. New York: Wiley, 1999.

[6] M. A. Tsili, A. G. Kladas, P. S. Georgilakis, A. T. Souflaris, and D. G. Paparigas, “Geometry optimization of magnetic shunts in power transformers based on a particular hybrid finite element—Boundary element model and sensitivity analysis,” *IEEE Trans. Magn.*, vol. 41, no. 5, pp. 1776–1779, May 2005.

[7] L. Wehenkel, *Automatic Learning Techniques in Power Systems*. Norwell, MA: Kluwer, 1998.

[8] G. Zhang, “Neural networks for classification: a survey,” *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 30, no. 4, pp. 451–462, Nov. 2000.

[9] H. Demuth and M. Beale, *Neural Network Toolbox for Use With MATLAB*. Natick, MA: MathWorks, 2001, user’s guide, ver. 4.

Manuscript received April 22, 2006 (e-mail: kladasel@central.ntua.gr).