Neural networks applied to the design of dry-type transformers: an example to analyze the winding temperature and elevate the thermal quality

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Summary
Much of the cost of manufacturing transformers is related to the complexity in the development of its project, which involves many variables, such as different types of materials, methods, and manufacturing processes. Also, it is notoriously difficult to establish standards that relate the transformer characteristics with these design variables, since each, almost always, variable is calculated empirically. One of the most important design variables is the internal temperature of the transformers, which directly influences the lifetime of such equipments. So, a computational tool is under development whose purpose is to automate the design of cast resin dry-type transformers and minimize the time taken for its completion, by means of artificial neural networks. In this article, we present some results of this tool, which relate some geometrical parameters of the specific transformer with the temperature of its windings. For this, the winding losses and total losses are also estimated. The training of the neural network was done with the test data of about 300 dry-type transformers from the same manufacturer, so, with the same constructive features. Nevertheless, our results show that the technique is promising because the neural networks were well fitted and its results present errors lower than 1% when compared with data from tests with real transformers. Evidently, the proposed methodology is dependent on the constructive technique; that is, once trained, the neural network can be used only in the design of dry-type transformers of the same constructive technique as those whose results of the tests were used to train the network. Nevertheless, even if only used to provide the initial parameters for a more complex design tool, the proposed method is useful since it is rapid and has low computational cost.

KEYWORDS
artificial intelligence, epoxy resin, magnetic losses, transformers design automation, winding losses, winding temperature

1 INTRODUCTION

Power transformers are essential components in electric power distribution systems and industries. Suitable for indoor installations that require safety and reliability, the dry-type transformers are the focus of this paper. These transformers have smaller dimensions than the ones with oil insulation. Also, they have advantages such as a higher mechanical robustness; the possibility of installation close to the load point; does not require transformation wells for oil collection, fire fighting systems, fireguard walls, and oil supervision accessories; and the lowest level of internal partial discharges (owing to its vacuum encapsulation). Therefore, they are typically used where there is the presence of people, for example, in industries, residential buildings, and hospitals. However, dry-type transformers are more expensive and have
power and voltage limitations. In this sense, failures on these equipments imply great financial and social losses. So, they must be designed and manufactured so as to meet the specific usage needs, respecting the limits set in international standards such as the IEC-76 and the IEEE C57.12.50-1981. Unfortunately, designing a transformer is not trivial. The importance of balancing lifetime, performance, and costs, besides the increasing development and evolution of various materials, methods, and manufacturing processes, cause the design of power transformers to be a highly complex process. Part of this complexity is also due to the large number of variables and their interrelationships.3,4

In the design of transformers, a major goal is to reduce the internal power losses. These are related to the losses in the winding and iron and are dependent on parameters such as internal temperature, resistance of windings, working current, nominal voltage, load, and quality of the aluminum used. Evidently, these losses affect the machine's temperature regime, which directly influences the efficiency and lifetime of the transformer.5 This is because the thermal stress is a major cause of failures, since it causes the deterioration of the insulating material.6 Therefore, estimating the value of the internal temperature (or the value of the temperature increase) is one of the most complex tasks in the transformer design.3,7,8

Usually, transformers designers use either some design patterns curves or the thermal network method to estimate the temperature increase in the windings of this kind of equipment. Also, several studies have attempted to predict the internal temperature of the windings using empirical and mathematical models and computational intelligence techniques, which have obtained different degrees of success.9 In these cases, the advantage is that the temperatures can be foreseen when the operating conditions change, for example, with the design of a new transformer. In this sense, several studies deal with oil transformers, so as to minimize production costs and find core losses, winding losses, and no-load losses.10-20 However, in the case of dry-type transformers, there are only a few thermal models available and related researches.21 Besides, for example, Srinivasan and Krishnan22 also point out that there are few theoretical and practical studies on estimating hot spot temperature and calculating the average temperature of the windings of dry-type transformers. So they developed a computational modeling for this purpose using statistical methods, such as multiple variable regression, multiple polynomial regression, and computational techniques, such as artificial neural networks (ANN) and adaptive neuro-fuzzy inference system. In that paper, Srinivasan and Krishnan22 used as input variables cold resistance, ambient temperature, and temperature rise. The results were verified based on temperature rise tests in a dry-type transformer of 55 kVA. In another example, Lee et al21 developed a thermal model for foil-type winding for ventilated dry-type power transformers rated at 2000 kVA, to calculate the electrical losses. Temperature distributions were obtained in 3 different loads by the coupled electromagnetic-thermal model with the aid of a 2D transient finite element analysis, determined by the finite element method.

This study proposes a tool to obtain the internal temperature of the windings, as well as winding losses and the total losses, of dry-type transformers. The applied methodology uses ANN in parts of the transformer design, where the relationship between the variables is not well defined and the design parameters are obtained empirically.23 The main justification for using ANN is its ability to learn to relate a complex set of data, which may be unnoticed by the designer.5 Moreover, these networks have a quick assessment and precision to resolve problems.24 The type of ANN chosen was the feed-forward multilayer perceptron. To train the ANN, we used a database with tests results of 225 similar dry-type transformers with power outputs between 15 and 150 kVA and voltage classes equal to either 15 or 25 kV. Building data of the transformer under design and the environment temperature conditions, to which it will be subject to during operation, are inputs of the neural networks. In the data validation step, we used another 75 transformers with the same characteristics of those used in the training. The results show that the technique is very promising. This is because the results show that the proposed tool provides the designer the possibility of testing various design conditions prior to manufacturing the transformer. Thus, the generated results allow the adequacy of the constructive variables to the environmental condition of the equipment operation, ensuring the construction of dry-type transformers with better performance and lifetime. Evidently, this makes the design more efficient when it takes to preparation time and specificity.

The model presented is simple. However, it works because it applies only to the design of dry-type transformers based on the constructive technique of those transformers of the tests, ie, transformers of which test results were used to train the neural network. In this case, the neural network was shown to be able to model the constructive technique very well. Furthermore, by following the methodology discussed here, the readers may conduct their own tests and train a neural network that models their own constructive technique, which can lead to great results. Also, another application of the proposed tool is to provide the initial parameters for a more complex design software. This can be done rapidly and with low computational cost.

2 | MATERIALS AND METHODS

Not all steps of a dry-type transformer project have the same degree of subjectivity or uncertainty. So, in this paper, to test the use of ANN in modeling this type of problem, we opted to model the temperature in the windings (referred to as T) of this type of transformer. Such quantity is a function of
the following variables: area of the conductors (in this paper, referred to as Sections and given in mm²); thickness of the windings sheets (referred to as Thickness and given in mm); number of winding channels (Channels), and the electrical losses (referred to as $L_T$ and given in W). So, to calculate $T$, first it is necessary to know $L_T$. In turn, the quantities that are part of the process of $L_T$ are defined as follows: high-voltage coil resistance (referred to as $R_{HV}$ and given in Ω); low-voltage coil resistance ($R_{LV}$, Ω); the environment temperature ($T_A$, °C); the excitation current ($I_{EX}$, A); the core losses or the no-load losses (referred to as $L_C$, given in W); and the winding losses ($L_{AI}$, W). Thus, to calculate $L_T$, it is necessary first to calculate $L_{AI}$. In turn, the main variables that influence $L_{AI}$ are as follows: the resistances of the high-voltage and low-voltage coils, the temperature $T_A$, and the short-circuit impedance ($Z_{CC}$, given in %).

Based on the above, the developed tool as well as the stages where the neural networks are applied and their purposes can be seen in Figure 1. The neural network on the left (Winding Losses Network) is intended to estimate the winding losses ($L_{AI}$), a variable that is used in the next neural network (Total Losses Network), so as to estimate the total losses ($L_T$). Since the system aims to determine the internal temperature of the transformer, the Temperature Network takes as inputs, in addition to the conductor section, the thickness of the core constituent plates and the number and dimensions of ventilation channels, besides the output of the Total Losses Network. All these networks are discussed in detail in Section 3.

For the training and validation of the 3 neural networks developed in this paper, we used a database with tests results of 300 dry-type transformers, with power outputs from 15 to 150 kVA and voltages classes equal to either 15 or 25 kV. To prepare the database, we performed the following tests with a 3-phase transformer in a laboratory: no-load test, short-circuit test, and winding resistance test. These tests are discussed in detail below.

### 2.1 No-load test

No-load tests of transformers aim to determine the following quantities: core losses ($L_C$), no-load excitation currents ($I_{EX}$), transformation ratio, and parameters related to the magnetizing branch. Also, it is possible to analyze the nonsinusoidal shape of the no-load current and of the transient magnetizing current. It is the safest test to determine those characteristics, by applying the nominal operating voltage of the transformer. Figure 2 shows the block diagram of the no-load test, characterized by the Aron connection (2-wattmeters method). This test is characterized by open high-voltage terminals ($V_{HI}$). $V_L$ are the low-voltage terminals; $W_1$ and $W_2$ are wattmeters (which indicate the losses in W); $V$ represents the voltmeter; $A_1$, $A_2$, and $A_3$ are ammeters; and $F$ is a frequency meter.

### 2.2 Short-circuit test

This test is normally used to determine stray losses, but its results also allow to determine the short-circuit impedance ($Z_{CC}$), as well as the internal resistance and reactance of transformers. For this, the low-voltage terminals ($V_L$) are short-circuited, and a voltage applied to the high-voltage terminal is varied so that the primary current observed on the ammeter (Figure 3) is equal to the nominal current. This voltage, referred to as $V_{CC}$, represents from 10% to 15% of the rated voltage ($V_R$) of the high-voltage side ($V_{HI}$). Under these conditions, the core losses, which vary with the square of the voltage, can be neglected. Thus, through the readings of power, voltage, and short-circuit current, the variables of interest may be determined and applied in the determination of the winding losses. More specifically, the impedance $Z_{CC}$ will be considered in percentage, where $Z_{CC} = 100V_{CC}/V_R$.

### 2.3 Winding resistance test

The windings of the primary and secondary of a transformer have an electrical resistance, as any conductor. Respectively, such resistances are usually indicated by $R_1$, $R_2$, $R_3$, and $R_4$, $R_5$, $R_6$ (1 for each phase). In this paper, we consider $R_1$, $R_2$, and $R_3$ as being equal to each other and referred to as $R_{LV}$. Similarly, $R_4$, $R_5$, and $R_6$ are referred to as $R_{HV}$. These resistances exert a double effect on the operation of the transformer: determining an ohmic power loss in the primary and the secondary and producing a loss of energy...
by Joule effect. To reduce this winding loss to limits established by technical standards, it is necessary to make such resistances small enough. This is done by appropriately choosing the section of the winding conductors. In conducting this test, the electrical resistances of each winding must be registered, phase to phase, as well as the terminals where they have been measured and their respective temperatures. This procedure is performed by means of the Wheatstone bridge. It is also important to note that the resistance values should always be obtained at the reference temperature, which is generally set at 115°C for dry-type transformers.

After obtaining the experimental data and preparing the database, these data have been used for training the neural networks, as shown below.

3 | IMPLEMENTATION OF THE PROPOSED TOOL

All neural networks implemented in this work have an input layer, a single hidden layer, and 1 output layer with a single neuron. In addition, for each of the neural networks, the heuristic defined by Kolmogorov was applied to determine the maximum number of neurons in the hidden layer, considering a feed-forward multilayer perceptron network. Since the structure of Figure 1 has been defined, it was necessary to train each neural network individually. For this, from the total of the transformers design data, only 75% were used. The remaining 25% were used for validation of this training. Also, this training was performed by the modified Levenberg-Marquardt algorithm as learning rule. In the Winding Losses Network and Total Losses Network (Figure 1), we used the tangent sigmoid activation function. In the Temperature Network (Figure 1), in turn, we used the hyperbolic tangent activation function.

3.1 Winding losses network

The architecture of the neural network responsible for identifying the processes related to the transformer winding losses is shown in Figure 4. The variables that make up the input vectors of this neural network were defined through the short-circuit and windings resistance tests. Among these variables, $T_A$ represents the environment temperature in Celsius. On the other hand, the output vector of the neural network consisted of a single variable, $L_{AL}$, which represents the winding loss in watts. Based on the method of Kolmogorov and considering this number of inputs, the maximum number of neurons in the hidden layer was set equal to 9. However, it was empirically determined that the best results were obtained when we used only 5 neurons in the hidden layer.

3.2 Total losses network

This neural network was used to identify processes related to the transformer’s total losses, which include both the winding losses (considered variables) and the core losses (considered fixed). Its architecture is shown in Figure 5. The network input vectors were defined from the short-circuit and no-load tests, besides the power lost due to the winding losses, estimated by neural network discussed in the previous section. More specifically, the input variables of this network were defined as follows: $R_{HV}$, $R_{LV}$, $T_A$, $I_{EX}$ (which represent the excitation current in amperes), and $L_{AI}$ and $L_C$ (which represent the core loss in W). However, owing to their similarities, $R_{HV}$ and $R_{LV}$ were considered equal. In turn, the output vector of the neural network has a single output, $L_T$, which represents the total loss. Finally, based on the Kolmogorov method, considering the number of inputs, the maximum number of neurons in the hidden layer was set to 11. However, empirically, it was determined that the best results were obtained when we used 10 neurons in this layer.

3.3 Temperature network

Figure 6 shows the neural network used to estimate the temperature. The input variables of this neural network are as follows: the cross-sectional area of the conductors used in the windings (in mm$^2$), referred to as Sections; thickness of the winding sheet (in mm), referred to as Thickness; and...
and the number and dimensions of ventilation channels (Channels) and the output of the Total Losses Network (Section 2), referred to as $L_T$. In the output of this neural network, the estimated variable is the temperature inside the transformer, which indicates the temperature rise of the windings. This temperature must be added to the environment one, thus determining the temperature of the winding in nominal operating conditions. Again, using the Kolmogorov method, the indicated maximum number of neurons in the hidden layer is 9. However, the final implemented hidden layer has only 8 neurons.

Unfortunately, the presented model allows only to foresee the temperature of a single point of the transformer. However, when performing a test on the transformer, for example, a short-circuit test, one can verify that the temperature of the transformer is not homogeneous, existing in higher-temperature zones. Therefore, in the training of the neural network, it is important not to consider an average temperature. This is because during normal operation of the transformer, the temperature in a hot spot may increase excessively, to the point of damaging the equipment. So, naturally, in this work, for the training of the neural network, the considered temperature is the one with the hottest point in the transformer. In turn, the hottest point was determined experimentally with the aid of a set of thermocouples during short-circuit tests.

It is also important to note that the proposed methodology is dependent on the constructive method of the transformer. Especially, with respect to the ventilation ducts, dry-type transformers based on a given construction method have no ventilation ducts with different geometries and positions. Normally, such parameters are well defined in the constructive methodology. This does not mean that these parameters do not influence the internal temperature of the transformers. Instead, simply, it is not necessary to include them in the neural network input parameters because, as stated, these parameters correspond to the construction methodology of each manufacturer. Thus, with respect to the ventilation ducts, the only unknown is, in fact, the number of ducts.

In the following sections, the results of training of all developed neural networks are presented.

4 | RESULTS

In this section, we present the results of the training and execution of the 3 neural networks implemented in the present work.

4.1 | Winding losses network

Figure 7 shows the results of the winding loss generalization done by the Winding Losses Network. In this graph, the values obtained experimentally and the ones obtained by the neural network are compared. One can check that the relative error is very small. In fact, it was calculated that the average relative error $\mu = 0.267\%$, the standard deviation $\sigma = 0.204\%$, and the variance just $\sigma^2 = 0.042\%$. These results show that the neural approach could adequately model the winding losses processes.

After validating the neural network, we examined the relationship between the winding losses process and the short-circuit impedance and temperature. The results are shown in Figures 8 and 9. Figure 8 shows the behavior of the winding loss relating to the short-circuit impedance variation. In this simulation, the environment temperature was considered constant, and mean values were used for the resistance of high-voltage and low-voltage bobbins ($R_{HV}$ and $R_{LV}$, see neural network architecture in Figure 4). One can observe in this graph that in the intervals between 1.6% and 1.8% of short-circuit impedance, there is an increasing winding loss. Beyond this range, the curve remains constant. That behavior is due to the thermal effect inside the transformer. Generally,
this slight variation in impedance is more difficult to be observed experimentally, with this kind of detail, in traditional designs of transformers. However, this information is important because this quantity numerically represents the relationship between the circuit voltage and the nominal voltage of the transformer. In turn, Figure 9 shows the maximum winding loss relating to the variation in the transformer temperature. To generate this graph, we considered average values for $Z_{CC}$ and for the high-voltage and low-voltage impedances, while varying the room temperature. This graph shows that there is a direct dependency between the temperature and the winding losses. In the intervals between 12°C and 15°C, the values of the winding loss have rapid and uniform increases, reaching 1250 W, which is an accepted value according to standards.

From this temperature until 34°C, the losses remain constant. This is due to the inertia of the thermal process, in which the saturation threshold of the material is reached and then the loss becomes constant with the temperature increase. This identification is very important for the designer to select the most suitable type of aluminum, based on the knowledge of the temperature maximum limit related to the degree of purity of the material. However, it would be difficult to be observed in detail in experimental measurements without the aid of the proposed tool.

4.2 | Total losses network

Figure 10 shows the results of the total loss generalization done by the Total Losses Network, comparing the values obtained experimentally with the ones obtained by the neural network. One can see that the output values of the neural network approached the values obtained in laboratory tests, which show the success of this application for this type of problem. Comparing experimental data with the output of the neural network, one can see that the relative error is very small. In fact, it was calculated that the average relative error $\mu = 0.774\%$, with standard deviation $\sigma = 0.567\%$, and variance $\sigma^2 = 0.322\%$. 

FIGURE 7  Network behavior for the winding losses

FIGURE 8  Variation of the winding loss versus impedance

FIGURE 9  Variation of the winding loss versus temperature

FIGURE 10  Behavior of the total loss network
After validating the Total Losses Network, we examined the dependence of the total losses regarding the no-load losses, winding losses, and excitation current, as presented in Figures 11–13, respectively. For this, with the aid of the validated neural network, we simulated the total losses considering the minimum, average, and maximum values of the following quantities: $R_{HV}$, $R_{LV}$, $I_{EX}$, $L_{AL}$, and $L_{C}$ (Section 2). In each graph, 3 curves are shown, which represent the maximum, medium, and minimum of the input variables. It is noteworthy that the simulations with the maximum and average values are hypothetical, so as to identify possible problems in the project, both in the constructive aspects and in the quality of the material used.

Figure 11 shows the behavior of the total loss relating to the no-load loss, considering 3 different values for $R_{HV}$, $R_{LV}$, $T_A$, $I_{EX}$, and $L_{AL}$. In this graph, one can verify a linear trend in all 3 curves, which indicates a thermal effect. It was also observed that the curves of “maximum values” and “medium values” show total loss values close to each other, even considering the average and maximum values of the quantities already mentioned. This behavior shows that the estimation of phenomena was performed satisfactorily, because if there were any nonlinearity in the simulations, it would represent that the network had not learned the process for various situations. In this regard, it is essential to mention that the simulated values in the curves are in disagreement with the values recommended by standard. However, this condition is an extreme project situation that provides valuable information to the designer, since it identifies the worst condition to the transformer’s design. This kind of detail would be almost impossible to verify through either conventional tools or experimental testing. This type of identification is also valuable so as to provide information to the transformers designer so that the project will be set neither below the blue curve (minimum values) nor above the black curve (maximum values). This is because it is preferable to dimension the transformer so that it has a better performance at an operation midpoint. Thus, it will continue to be efficient at a point above or below the normal.

Figure 12 shows the behavior of the total loss relating to the winding loss, considering different values for the quantities $R_{HV}$, $R_{LV}$, $T_A$, $I_{EX}$, and $L_{C}$. One can observe that the behavior of the total losses is similar to that in Figure 11. The difference is that the average and maximum values are farther. This analysis shows the sensitivity of the developed neural tool. This observation is also very particular, because it presents the contribution of the winding losses over the total losses of a transformer.

In Figure 13, the total loss behavior with respect to the excitation current is presented, considering 3 different values of $R_{HV}$, $R_{LV}$, $T_A$, $L_{AL}$, and $L_{C}$. In Figure 13, one can see the influence of the excitation current in the overall result of the total loss. This detail would be almost impossible to be observed with conventional tools, owing to the complexity found in the mathematical modeling of the phenomenon. Generally, the weighing of the excitation current is restricted only to no-load core losses.
4.3 | Temperature network

The evolution of the error in the Temperature Network training process as a function of the number of iterations is shown in Figure 14. The training stopping criterion was the stabilization of the mean square error. With the completion of the network training, the project initial parameters estimated by the network are compared with the values actually used in the projects, through quantile-quantile graphs. A comparison between the results estimated by the Temperature Network and the real values obtained in the tests with 75 transformers (used to validate the proposed system) is shown in the quantile-quantile graphic of Figure 15, for the purpose of validating and testing the generalization quality of the network. In this graph, the output of the neural network fits the experimental data with a coefficient of determination $R^2 = 0.988$. These results confirm that the neural network is well fitted, having thus a good generalization. These facts demonstrate the ability of the Temperature Network to solve the problem.

5 | CONCLUSION

Currently, the design of dry-type transformers is almost entirely based on the designers’ experience. Typically, several attempts are necessary so as to achieve satisfactory results. This is mainly due to the large number of variables involved in calculations and to the fact that the relationships between these variables are not well defined. In this article, we evaluated the use of ANN in modeling the influence of various design parameters on the internal temperature of dry-type transformers. For this, we used results of practical tests with 300 transformers. Qualitative and quantitative results showed that ANN were able to model, with excellent accuracy, the relationship between various design parameters and the losses and internal temperature rise in dry-type transformers. Thus, by means of simulations using the validated neural networks, one could see details that are almost impossible to be observed with conventional tools, owing to the complexity in the mathematical modeling of phenomena involved. Thus, the developed system can be used to study the phenomena that define and relate the variables involved in the design. Evidently, this will have a direct influence on the quality of future transformers designs. This is because, based on the notion of behavior extracted via neural networks, it will be possible to obtain closer-to-real functions to model the interrelationships between the design parameters. Evidently, this work can be extended so that not only the internal temperature but also other dry-type transformers features could be modeled with the aid of ANN. Certainly, this would minimize the time taken in the design and increase the precision when estimating the final characteristics of this type of transformer. Unfortunately, the proposed methodology is dependent on the constructive method of the transformer. However, by following the methodology discussed here, the readers may conduct their own tests and train a neural network that models their own constructive technique.

6 | LIST OF SYMBOLS AND ABBREVIATIONS

6.1 | Abbreviations

- ANN: artificial neural networks
- Channels: number of winding channels
- FEA: finite element analysis
- Sections: area of the conductors
- Thickness: thickness of the windings sheets

6.2 | Symbols

- $\mu$: average relative error
- $A_1, A_2, A_3$: ammeters
\( I_{EX} \) \ no-load excitation current  
\( L_{AL} \) \ winding losses  
\( L_C \) \ core losses  
\( L_T \) \ electrical losses  
\( R^2 \) \ coefficient of determination  
\( R_{HV} \) \ high-voltage coil resistance  
\( R_{LV} \) \ low-voltage coil resistance  
\( R_1, R_2, R_3 \) \ electrical resistances of primary phase of the windings  
\( R_a, R_b, R_c \) \ electrical resistances of secondary phase of the windings  
\( \sigma \) \ standard deviation  
\( T_A \) \ environment temperature  
\( \sigma^2 \) \ variance  
\( V_{CC} \) \ voltage at the common collector  
\( V_H \) \ high-voltage terminals  
\( V_L \) \ low-voltage terminals  
\( V_R \) \ rated voltage  
\( W_1, W_2 \) \ wattmeters  
\( Z_{CC} \) \ short-circuit impedance  
\( F \) \ frequency meter  
\( kV \) \ kilovolt amperes  
\( kVA \) \ kilovolt-amps  
\( T \) \ Temperature  
\( V \) \ voltmeter  
\( W \) \ watts  

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