Determination of Leakage Reactance in Monophase Transformers Using by Cascaded Neural Network

H. S. Nogay

***Abstract*—In this study, the artificial neural networks method was used in order to determine the leakage induction coefficient using known constants of the transformer. It is important to reach the leakage reactance through guessing. For this purpose, two types of ANN models were used in the study and were compared to one another. These two ANN models are cascaded ANN model and the conventional model. Testing data were used to measure the efficiency of these two models. Testing data are the same for both models. When the models were compared to each other, it was concluded that Cascaded ANN model was more successful. However, it is a fact that both models produce estimation around 99%. The main reason why the ANN model is used in the study is to ensure a more practical and quicker attainment of leakage reactance or leakage induction coefficient by looking at the fixed and measurable values of the transformer than calculation method.**

***Index Terms*— Transformator, Leakage Induction Coefficient, Cacaded Neural Network, Backpropagation Learning Algorithm.**

I. Introduction

Investigating of transformers which have a great deal of importance for production, transmission and distribution of electrical energy begins with inventing flux distribution. In this distribution various fluxes can be distinguished from each other. Leakage flux rung with only one winding plays an important role in the theory of electrical machines and transformers. Determination of the leakage field distribution in transformers is required to calculate inductances, the force applied to the windings, additional losses occuring in the windings and iron. Icreasing energy consumption and the growing generator power required large power transformers. Despite the restrictions of materials, dimensions and weight, performing suitable transformers production has been made possible with advances of leakage flux determination [1, 2].

Leakage flux generated by primary and secondary windings currents give rise to internal voltage in primary and secondary windings. Hence leakage fluxes decrease the useful fluxes. As a result voltage reduction is seen in output of secondery windings. Voltages created by leakage fluxes is full inductive and 90 degree ahead from current.

H.S. NOGAY, works in University of Erciyes, Kayseri, Turkey, (e-mail: hidirselcuknogay@gmail.com , nogay@erciyes.edu.tr).

Hence fluxes leakages are showed as reactances which connected to transformer circuit as serial and named leakage reactance[2,3].In this study, the leakage induction coefficient in mono-phase transformers was estimated using two different artificial neural network estimation model. It is possible to find out the leakage reactance value that is supposed to be found through calculation in order to design a transformer of any type or power capacity by using the numerical values of transformer coil width, fictive iron frame height, coil height, type of coil used and the thickness of no conducting layer. It has a great deal of importance for designers to determine the leakage currents in transformers. Leakage induction coefficient can be calculated based on the different winding types and core types of the transformer. In addition, it is of great importance that a designer has an opinion on the leakage reactance of all transformers without delay. Software or prediction software that will allow the designer to save time and will apply to all types of mono-phase transformers is an essential need for designers and producers. There are a number of estimation and prediction software and as many estimation methods on the market. The most commonly used estimation method is the artificial neural networks. Of many ANN prediction models, the most efficient and the most common model is the multi-layer back propagation ANN model. In this study, the multi-layer back propagation ANN model is defined as the conventional ANN model. The ANN model recommended in line with the purpose of the study the Cascade ANN prediction model which guarantees prediction with a higher accuracy level compared to the conventional ANN prediction model. In this study, both methods were used and the results were compared. The most important feature of the study is that, both the conventional ANN and cascade ANN ultimately form a basis for a generalized design program. In other words, both ANN models are of types that may easily serve the designer in the design of a mono-phase transformer of any type. Based on the results of the study, there is an significant difference between the cascade ANN prediction model and the conventional ANN prediction model in favor of the cascade model [4-6].

The architecture of the study is as follows:

In the second part of the study, a mathematical expression of leakage reactance was given for all coil types in mono-phase transformers.

In the third part of the study, basic information was given on artificial neural network models and the selection of ANN model architectures used in the study, formation of the data set and performance of ANN model testing was explained.

In the fourth part of the study, the results attained from the study were evaluated and discussed.

In the fifth part, which is the final part is the conclusion. The result of the study is explained in plain terms.

II. MATHEMATICAL EXPRESSION OF LEAKAGE REACTANCE IN TRANSFORMERS

A. SIMPLE CYLINDRICAL COIL FORM

Leakage flux of most common medium centered cylindrical coil transformers under normal operation conditions and short circuits is shown in Figure 1. Leakage self-induction coefficients of primery and secondery windings is as follow .

$$l_1 = 4\pi.\omega_1^2 \varepsilon_{10}\, e_0 .10^{-9} \quad \text{H} \tag{1}$$

$$l_2 = 4\pi.\omega_2^2 \varepsilon_{20}\, e_0 .10^{-9} \quad \text{H} \tag{2}$$

Leakage induction coefficient (N_2) reduced to secondary winding can be expressed as follow [7, 8]:

$$N_2 = \frac{8\pi^2 \omega_2^2 r}{h} k_R \left(\delta + \frac{3}{a_1 + a_2} \right) 10^{-9} \quad \text{H} \tag{3}$$

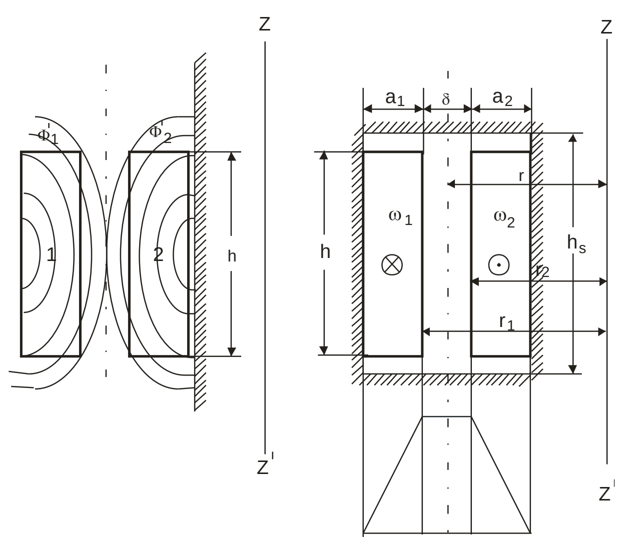

Fig. 1. Leakage field for simple cylindrical coil form

B. TWO LAYERED CYLINDRICAL COIL FORM

In the common medium centered winding as shown in Figure 2, there are two equal δ nonconductive layer between them and the fact that the section shown in the figure is symmetrical to Y-Y’ axis in terms of form and leakage area and it can be divided to two magnetic circuits which are not connected to each other in terms of leakage magnetic circuit one of which is on the left and the other is the right side of the Y-Y' axis provides a conclusion by adding up all the results obtained by considering these magnetic circuits separately in calculations.

So, considering that both parts divided into two with the Y-Y′ axis is not different from the simple cylindrical coil form that we previously examined, the leakage induction coefficient of the secondary winding can be expressed as follows [8].

$$N_2 = \frac{4\pi^2 \omega_2^2 r}{h} k_R \left(\delta + \frac{a_1 + a_2}{3} \right) 10^{-9} \quad \text{H} \tag{4}$$

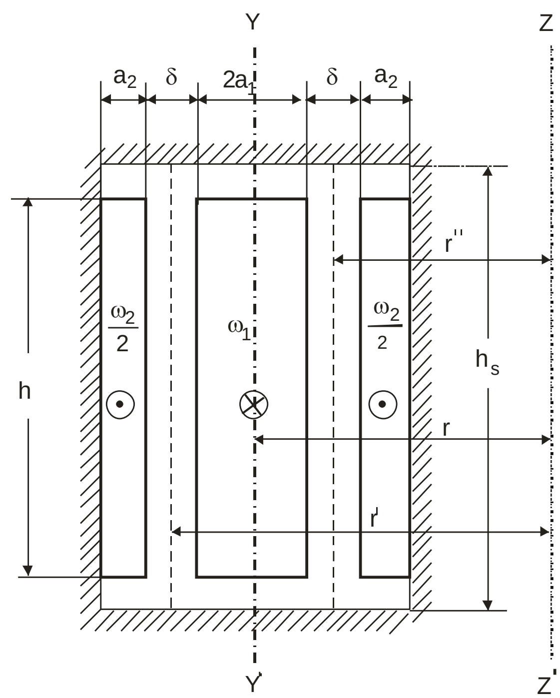

Fig. 2. Leakage field for two -layered cylindrical coil form

C. SYMMETRIC SLICE, MIXED COIL FORM

As can be seen in Figure 3, if this type of winding more symmetrical than the horizontal X-X’ axis in the form of magnetic circuit form which has not connection to it as many as the number of its nonconductive layers or the section form of which intersects this in terms of magnetic area and form, then it can be considered as the two-layered cylindrical winding section made side-by-side as *m* which is the number of high voltage coils (90º rotated). Also, *m* number of high voltage coils and low voltage coils are connected in series among themselves, considering the number of windings of one of these section parts, the formula for the two-layer cylindrical winding transformer (4) is written down, multiplied with *m* and the leakage induction coefficient can be expressed as follows [8].

$$N_2 = \frac{4\pi^2 \omega_2^2 r}{hm} k_R \left(\delta + \frac{a_1 + a_2}{3} \right) 10^{-9} \quad \text{H} \tag{5}$$

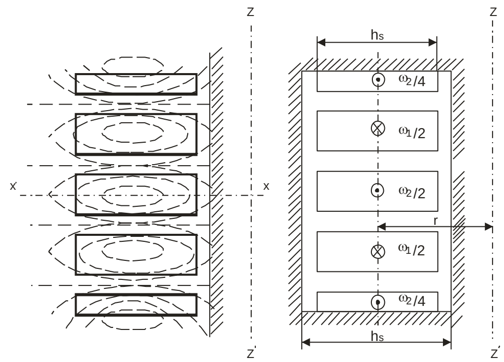

Fig. 3. Leakage field for symmetric slice, mixed coil form

D. Zig-Zag Coupling Two Layered Cylindrical Coil Form

Since the low voltage winding is to be zigzag-connected, this winding consists of two parts in the form of two interlaced cylinders as shown in Figure 4 and the currents on these parts are currents of two different phases. That is why, with the consideration that it would be simpler to express the N1 self-induction coefficient translated to the primary winding as the leakage self-induction coefficient to be calculated in the case of this type of winding, the expression of this coefficient is proven to be made in a similar way to the one that is followed in the case of simple cylindrical coil [8 - 11].

$$N_1 = \frac{8\pi^2 \omega_1^2 r}{h} k_R \left(\delta + \frac{a_1 + a_2}{3} + \frac{\delta'}{3} + \frac{a_2}{36} \right) 10^{-9} \ \mathrm{H} \qquad (6)$$

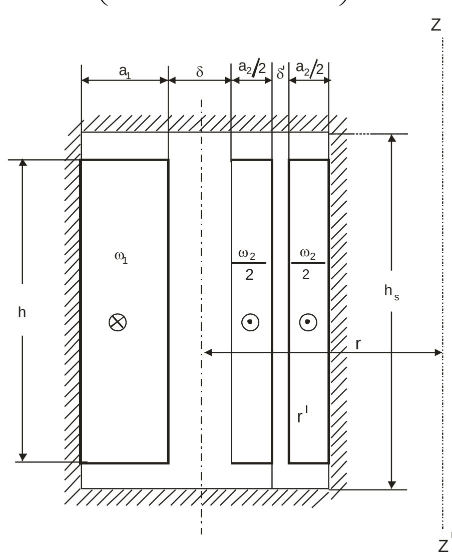

Fig. 4. Equivalent Leakage Magnetic Circuit for Zig-Zag Coupling Transformer

III. Development of the ANN Forecasting Models

A. Artificial Neural Network (ANN)

Artificial neural networks are parallel and distributed data processing structures developed with inspiration from the human brain, connected to each other with weighting connections and consisting of processing components each having a memory of its own. In other words, artificial neural networks are computer programs that imitate the neural networks.

Artificial neural networks are self-learning mechanism which does not require conventional abilities from a programmer.

There are a number of artificial neural networks and the use of some is more common than that of others. The most common artificial neural network model is Back propagation ANN.

Two types of ANN were used in this study. Both ANN models are of back propagation ANNs. The ANN model consisting of a single model was named the “conventional model” in this study. The model connected to one of the outputs of four ANN models was named "Cascaded ANN model"

Cascaded ANN model has no difference from the conventional model in terms of model type. The only difference is that it consists of the multiple ANN models. The more the number of input parameters affecting the result is in artificial neural networks, the quicker and more accurate the model learns. Therefore, it is of great importance that the number of input variables is high in ANN models. And the input number used in the only ANN model used as the conventional model in this study is 6. In cascaded model, 10 input numbers were used in total, since each ANN model that is used would produce one input number. The most significant advantage of the cascaded model over the conventional model is that it may have more inputs [12].

Type of models used for this paper is multi-layered back-feed ANN models. These ANN models are used in many of the studies based on prediction. The multi-layered artificial neural networks learn from back propagation learning algorithm. As learning algorithm, Levenberg – Marquardt learning algorithm, one of the back propagation learning algorithms, has been used [13].

The back-propagation learning algorithm is presented below in brief. For each neuron in the input layer, the neuron outputs are given by

$$n_i = o_i \qquad (7)$$

where n_i is the input of neuron *i*, and o_i the output of neuron *i*. Again for each neuron in the output layer, the neuron inputs are given by

$$n_k = \sum_{j=1}^{N_j} w_{kj} o_j \qquad k = 1,2,3,\ldots, N_k \qquad (8)$$

where w_{kj}, is the connection weight between neuron *j* and neuron *k*, and N_j, N_k the number of neurons in the hidden layer and output layer, respectively. The neuron outputs are given by

$$o_k = \frac{1}{1+\exp[-(n_k+\theta_k)]} = f_k(n_k, \theta_k) \qquad (9)$$

where θ_k is the threshold of neuron k, and the activation function f_k is a sigmoidal function. For the neurons in the hidden layer, the inputs and the outputs are given by relationships similar to those given in Eqs. (8) and (9), respectively.

The connection weights of the feed-forward network are derived from the input–output patterns in the training set by the application of generalized delta rule. The algorithm is based on minimization of the error function on each pattern p by the use of steepest descent method. The sum of squared errors E_p which is the error function for each pattern is given by

$$E_P = \frac{1}{2}\sum_{k=1}^{N_k}(t_{pk}-o_{pk})^2 \qquad (10)$$

where t_{pk} is the *target* output for output neuron k, and o_{pk} the calculated output for output neuron k. The overall measure of the error for all the input–output patterns is given by

$$E = \sum_{p=1}^{N_p} E_p \qquad (11)$$

where N_p is the *number* of input–output patterns in the training set. When an input pattern p with the target output vector t_p is presented, the connection weights are updated by using the following equations:

$$\Delta w_{kj} = \eta\delta_{pk}o_{pj} + \alpha\Delta w_{kj}(p-1) \qquad (12)$$

$$\delta_{pk} = (t_{pk}-o_{pk})o_{pk}(1-o_{pk}) \qquad (13)$$

where η is the learning rate, and α is the momentum constant. Again, the connection weights between input layer neuron i and hidden layer neuron j can be updated by using the following equations:

$$\Delta w_{ji} = \eta\delta_{pk}o_{pj} + \alpha\Delta w_{ji}(p-1) \qquad (14)$$

$$\delta_{pj} = o_{pj}(1-o_{pj})\sum_{k=1}^{N_k}\delta_{pk}w_{kj} \qquad (15)$$

It is important to note that the threshold θ of each neuron is learned in the way same as that for the other weights. The threshold of a neuron is regarded as a modifiable connection weight between that neuron and a fictitious neuron in the previous layer which always has an output value of unity [14 - 16].

In order to use the ANN simulator for any application, first the number of neurons in the layers, type of activation function (purelin, tansig, logsig), the number of patterns, and the training rate must be chosen.

ANN designing process involves five steps. These are gathering input data, normalizing the data, selecting the ANN architecture, training the network, and validation-testing the network. In this paper, the data were normalized according to (16), also these values ranged from 0.1 to 0.9 for all ANN models.

$$\overline{N}_2(t) = \frac{0.1\cdot(N_{2\max}-N_2(t)) - 0.9\cdot(N_{2\min}-N_2(t))}{N_{2\max}-N_{2\min}} \qquad (16)$$

Where : N2 and $\overline{N}_2$ are the Leakage Induced coefficient of conventional ANN model time series non-normalized and normalized, respectively; Nmax and Nmin are the maximum and the minimum absolute value of the Leakage Induced coefficient respectively. This normalization function was used for the other ANN models in this study. [17]

B. Creation of Dataset

In this study, a single data set was used for two types of ANN models. In the first YSA model called the conventional ANN, 6 inputs or, in other words the [6x341] matrix and 1 output of [1x341] was used. Inputs and output used in the conventional model can be seen in Table 1.

TABLE I. INPUTS AND OUTPUTS OF CONVENTIONAL ANN MODEL

Inputs		Output
R		N2
h	Coil height (mm)	Leakage Induced coefficient
hs	Fictive iron frame height (mm)	
a1	Width of the first winding (mm)	
a2	Width of the second winding (mm)	
Cf	Coil form	
δ	Insulating layer (mm)	

Input matrix used for the conventional model forms the input of the first ANN in the first layer of the Cascaded ANN model. In other words, the input matrix used for both ANN systems are the same. Cascaded model consists of four ANN models connected to each other and outputs to inputs. The first ANN model in the Cascaded ANN model has two outputs.

Inputs and outputs of four ANN models in the Cascaded ANN system is given in Table 2 below [17, 18].

TABLE II. INPUTS AND OUTPUS OF CASCADED ANN MODEL

Models	Inputs	Outputs
YSA1	R: Inputs of Conventional Model	ω_1 : Number of turns of the first winging
		ω_2 : Number of turns of the second winging
YSA2	R1 : ω_1, ω_2, R	r : The average radius of the windings
YSA3	R2 : R1, r	k_R : Rogowski Coefficient
YSA4	R3 : R2, k_R	N_2 : Leakage Induced coefficient

Structural values of transformers used in the data set being s, h, ω2, ω1, δ, Cf, r ,a_1 and a_2 were formed according to the restrictions in Table 3. Data set was formed based on the transformer sizes that can be designed to form a data set, increasing the section of the conductor with 0.2, and calculating the sizes corresponding to the increase on the sections of each conductor. The wider the range of data set is kept, the more the transformer sizes which the study addresses [18, 19].

TABLE III. SUMMARY OF THE DATA SET USED FOR ANN MODELS

Abbreviation	Max.	Min.
s	3	2
h	1000	200
ω2	5328	100
a2	48	2
a1	96	4
ω1	2656	50
a1+a2+δ	146	8
k	12.5	3.424658
kR	0.987261	0.953503
δ	2	2
Cf	4	1
hs	1048.764	202.5806
r	222	141
N2	6.124687	0.001372

C. SELECTING THE ANN ARCHITECTURE

The input and output patterns used in the first model that is conventional model are arranged with 6 inputs and one output as shown in Fig. 5. The best number of neurons in the hidden layer that better adapted to the dataset was selected among different architectures for all model in the study. The architecture with 20 hidden nodes presented smaller error on the validation set during the trainings. Therefore, the architecture of the selected ANN was 6 -20 -1 for the conventional model. All ANN models used in this study were developed using Multi-Layer Perceptron network with three layers: input layer; hidden layer, and the output layer. Hyperbolic tangent sigmoid function for all of the layers was used. The architecture of the proposed cascaded system was created using by four ANN models [20, 21].

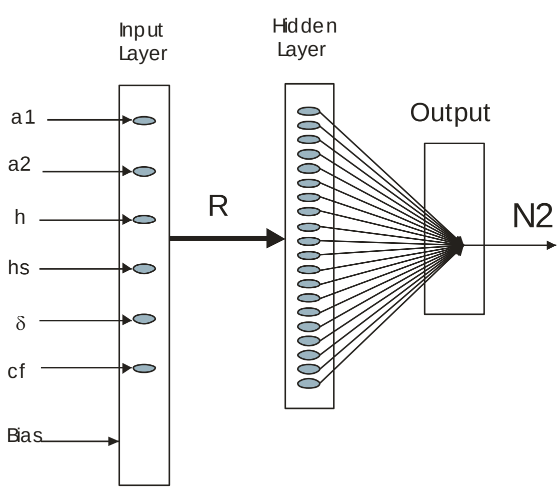

Fig. 5. Tradional ANN Model

The input and output patterns used in the cascaded system for the first step ANN model that named ANN 1 are arranged with the same inputs of conventional ANN model and two outputs that represent the forecasting ω_1 and ω_2. Inputs and outputs for the other steps of cascaded system are illustrated as shown in Fig. 6 [22].

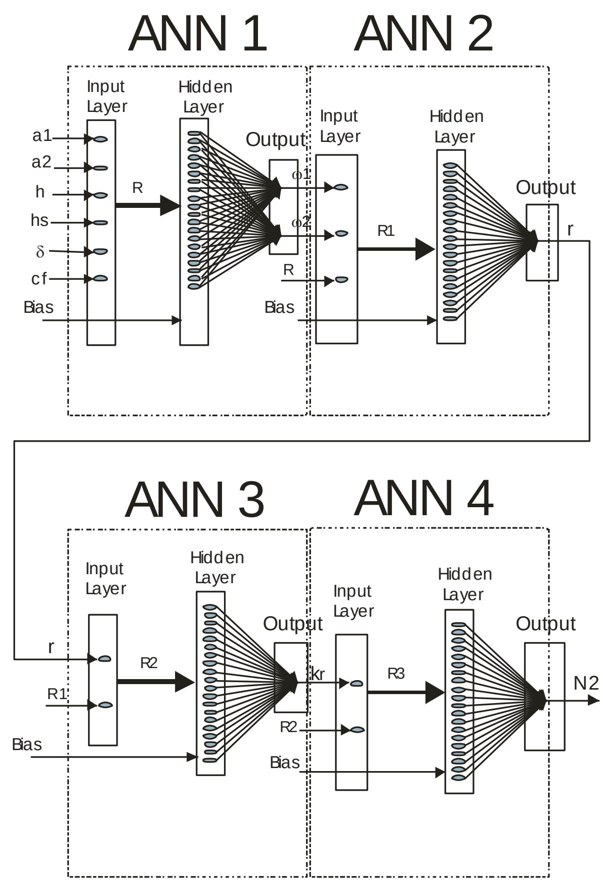

Fig. 6. Proposed Cascaded Neural Network

D. TRAINING THE ANN MODEL

Neural Networks learn from examples and are generated to be able to generalize the acquired knowledge during the training. A suitable strategy for training the neural networks can affect substantially their generalization ability. In this study all ANN models were trained with the back propagation (Levenberg – Marquardt) training algorithm. In the training process of this study, the actual outputs of ANN models were compared with the desired outputs [22].

In the conventional model; the training set consists of six input and one output data. The number of data was 341. 70% of this data (239) were used for training.

In the Cascaded system; the training set consists of six input data that same as the conventional model's inputs and two output data for the first step ANN 1. For the second step ANN 2, the training set consists of eight input and one output data, for the third step ANN 3 , the training set consists of nine input and one output, finally for the forth step ANN 4 the training set consists of ten input and one output data. The number of data was same to conventional model in the all cascaded steps [22, 23].

The network adjusted the weighting coefficients that began with random set. The training process has been stopped when the error has become stable. Training process of the conventional ANN model and cascaded system are shown in Fig. 7 and Fig. 8 respectively. ANN simulator has been trained through the 37 epochs in the conventional system and 84 epochs in the final step of the cascaded system, as shown in Figure 7 and Fig. 8 respectively.

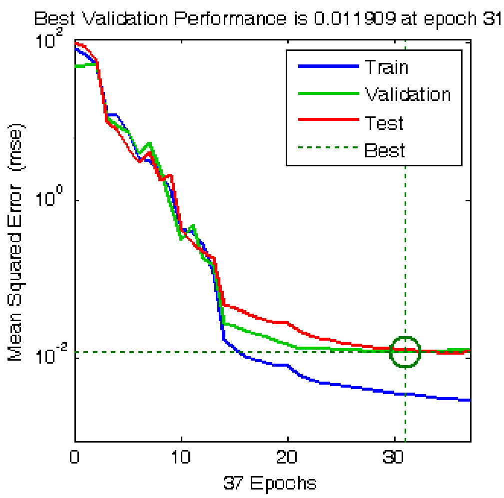

Fig. 7. Training process of the conventional ANN model

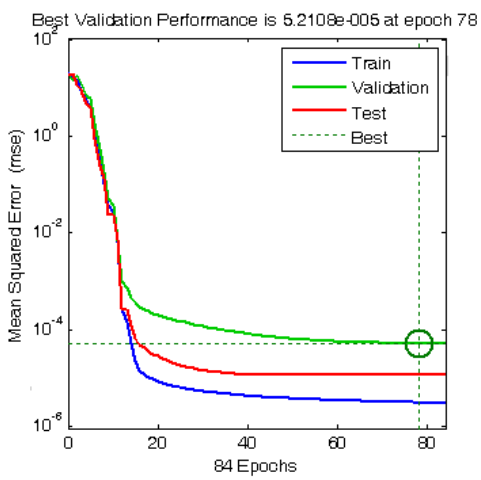

Fig. 8. Training process of the cascaded system

E. Testing the ANN Model

At the test stage, 51 data selected as a random set from the entire dataset were used for all ANN models in this study as shown in Table 4. In order to be positive about the test result, validation data were used at 51 pieces. According to the result of test conducted, as can be inferred from Table 4, a prediction rate of 97.7% was achieved in the conventional model, and 99.9% was achieved in the proposed system. In Fig. 9 comparison of the target and ANN results for testing is illustrated. In Fig. 10 and 11, the regression curve obtained from testing is presented for conventional model and cascaded model respectively [23, 24].

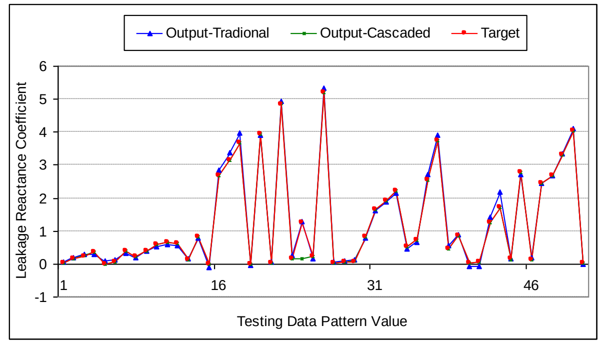

Fig. 9. Comparison of the target and ANN results for testing

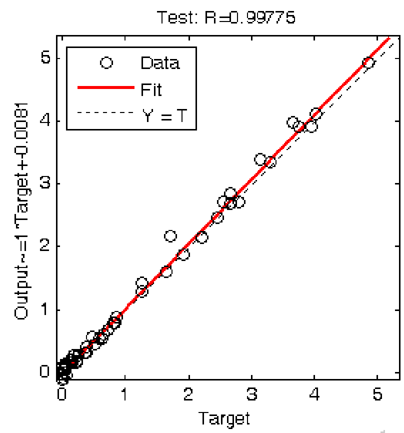

Fig. 10. Regression results of conventional ANN model for testing

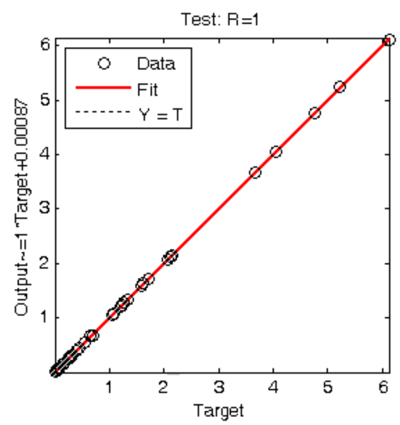

Fig.11 Regression results of cascaded ANN model for testing

TABLE IV. RESULTS OF THE ANN SYSTEMS

		Samples	**MSE**	***R***
Conventional ANN Model	Training	239	0.00352	*0.999454*
	Validation	51	0.0119	*0.997875*
	Testing	51	0.0125	*0.977540*
Cascaded ANN Model	Training	239	3.0594×10^{-6}	*0.999999*
	Validation	51	5.210×10^{-5}	*0.999994*
	Testing	*51*	1.180×10^{-5}	*0.999997*

IV. Results and Discussions

For a better evaluation of the study, 51 data used for the test were divided into five parts and five different charts were obtained. Figure 12 shows the comparison with the first ten of the testing data.

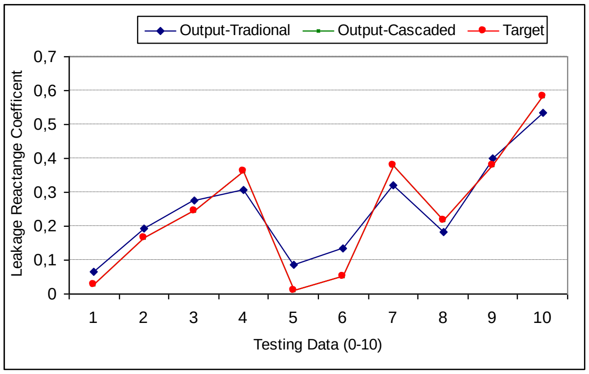

Fig. 12. Comparison of the ANN outputs and target for the first part of testing data

When we compare the results of the conventional system from the first parts of test results in Figure 12 with the target, it can be said that two charts are not consistent, though pretty much close to each other. In addition, when the cascaded system and the target is compared, the green-colored chart indicating the output of cascaded system is under the red-colored chart in Figure 12 and can not be seen. In other words, according to this first party of test results, the results of the cascaded system and the target are consistent. Based on this chart, the cascaded system can be said to be more successful in comparison with the conventional system for the first part.

If we examined Figure 13 obtained from the second part of test results; it can be seen that the results of the cascaded system are consistent with the target. On the other hand, the results of the conventional ANN model are not consistent with the target, though quite close to it. If we compare the first part of the test with the second, it can be said that the results of the conventional system in the second part seem to be more successful.

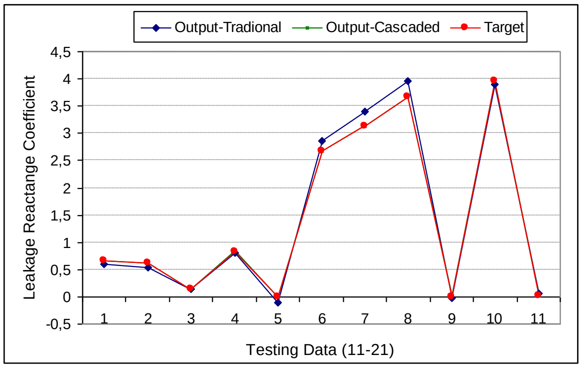

Fig. 13. Comparison of the ANN outputs and target for the second part of testing data

If we examine the chart in Figure 14 created from the third part of test results; it can be observed that the cascaded system indicated with green color in the data between 2-4 of the chart is distant from target, and is consistent with the target on other data spots. The results of the conventional system is not completely consistent with the target but pretty much close. In this chart, it can be understood that the cascaded system produces a more satisfactory prediction compared to the conventional system.

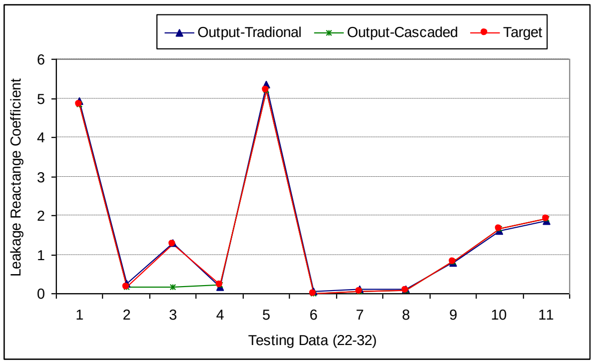

Fig. 14. Comparison of the ANN outputs and target for the thirth part of testing data

If we examine the charts obtained from the fourth and fifth party test results as shown in Figure 15 and Figure 16, it can be easily said that the cascaded model is completely consistent with the target and the conventional model produces predictions pretty close to the target.

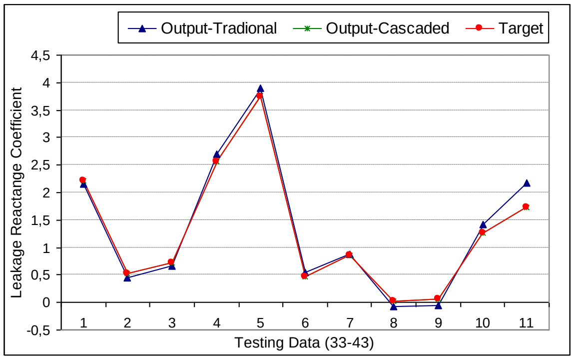

Fig. 15 Comparison of the ANN outputs and target for the forth part of testing data

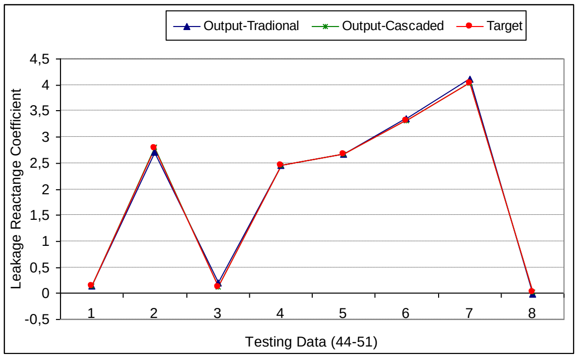

Fig. 16 Comparison of the ANN outputs and target for the fifth part of testing data.

V. CONCLUSION

In this study, leakage inductions (N2) in different coil forms of mono-phase transformers were predicted by using the artificial neural networks system. It is obvious that this study will lay the groundwork for the production of software that can be used in order to design mono-phased transformers. In this study, the cascaded model with can be attained by connecting the ordinary models end to end, instead of the ordinary ANN prediction model which is always used for prediction. Because, though the number of inputs is the same in the cascaded model, which means that ANN 1 has the same number of inputs with the conventional model, the result is in favor of the cascaded model. So, the prediction results generated in the cascaded model have proven more accurate than the conventional model. This forecasting model applies for all mono - phase transformers and is a very successful model in accelerating the designers working in this field and making their jobs easier through provision of preliminary ideas on future studies.

VI. List of Symbols and Abbreviations

N_2 : Leakage Induced coefficient
δ : Insulating layer
ω_1 : Number of turns of the first winding
ω_2 : Number of turns of the second winding
h : Coil height
h_s : Fictive iron frame height
k_R : Rogowski Coefficient
a_1 : Width of the first winding
a_2 : Width of the second winding
N_j, N_k : The number of neurons in the hidden layer and output layer
w_{kj} : Connection weight between neuron *j* and neuron *k*
n_i : Input of neuron *I*
o_i : Output of neuron *I*
θk : Threshold of neuron *k*
fk : Activation function
Ep : Sum of squared errors
α : Momentum constant
s : Cable section
r : The average radius of the windings
ANN : Artificial Neural Network
cf : Coil form

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Biography

SELCUK NOGAY was born in Isparta, Turkey. He received the B.S. and M.S degrees from the University of Marmara, Istanbul, Turkey. Since 2015, she is a Lecturer with the Erciyes University. Her research interests are in Electrical Machines, Renewable Energy and Artificial Intelligence.