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Estimation through ANN of Voltage Drop Resulting from Overloads on Power Transformers

Onur Akar[1*]

[1*]Marmara University, Department of Electronics and Automation, Istanbul, Türkiye. (e-mail: onur.akar@marmara.edu.tr).

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Corresponding author: *Onur Akar*

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ABSTRACT

Along with the increasing population, technological developments and industrialization in the world, the need for electrical energy shows rapid increase day by day. For that reason, it is very important to ensure permanence in the process from the generation of electrical energy to its transmission to consumers. One of the most significant components of power systems is the power transformer, and it plays an important role in the process of energy transmission and distribution. Thus, continuous operation of the power transformers should be ensured for the quality and reliability of the power systems. Despite the institutions in charge of electric power generation, transmission and distribution carry out inspections for the continuous operation of the power transformers, failures resulting from voltage drop arise due to overloads. In this study, the estimation through Artificial Neural Network (ANN) of voltage drop resulting from overloads was performed using the data of power transformers of different quality. It was observed that the values obtained as the result of estimations through ANN were correct with a rate of 99%. It is considered that this study will set an example for other studies in the field.

1. INTRODUCTION

Electrical energy is one of the essential requirements of our lives along with today's technological developments. The quality of electrical energy is a significant issue that concerns the producer and distributor companies as well as the consumers in the competitive energy market. In general, quality of energy is important in terms of problems causing changes in current, voltage and frequency that can result in misoperation or failure of consumers' devices **[1,2]**. Low quality energy is able to cause problems on the electronic devices as well as the electrical home appliances. Sensitive devices such as computers and televisions are greatly affected especially from voltage and frequency changes. The quality of electrical energy also affects the production quality and efficiency at industrial facilities. The electrical appliances cannot show the required performance when they are fed with interrupted energy, or with an energy different than the required values. For such reasons, the quality of energy is important at all points of consumption of electrical energy and at all kinds of voltage levels. In addition, the harmonics, overvoltage and undervoltage are among the most frequently encountered problems. The voltage drop is defined as short-term reductions in the voltage amplitude. According to IEEE Std 1159-1995, the voltage drop remains between 10% and 90% of the nominal voltage, and the period of drop is able to change between half a period and one minute. The voltage drop's waveform and range is as shown in Fig. 1 **[3-6]**.

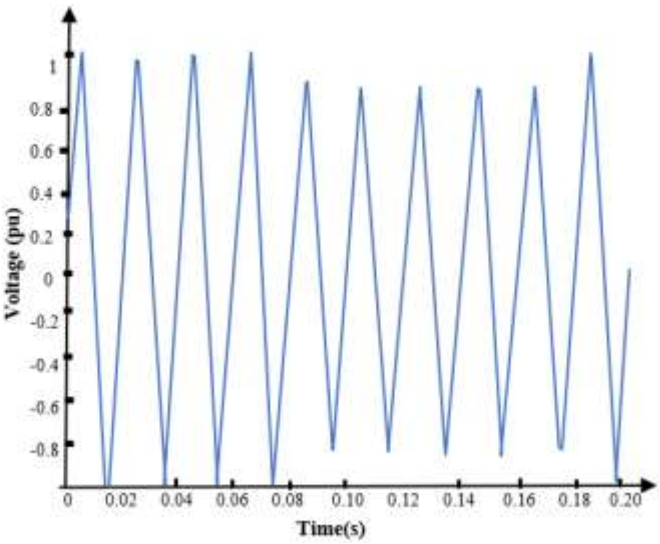

Figure 1. Waveform of voltage drop

Short-term voltage drops affects sensitive loads in industrial distribution systems. In addition, the voltage drop is also relevant to balanced and unbalanced failures in distribution systems, location, and different transformer connection groups **[3,4,7]**. In principle, the root cause of voltage drop is all the circumstances causing current increase in the system. Three main causes are indicated for the occurrence of voltage drop. These are short circuit, failures occurring superficially in the systems, and high current drawn during commissioning of high power motors and of power transformers, respectively [8-10]. The power transformer is one of the most significant parameters constituting the energy transmission and distribution system. Smooth operation of power transformers is a very important criterion in ensuring the continuity and stability of demand guarantee in the energy system. The power transformers encounter different types of failures, and the repair and elimination of such failures are being highly expensive and time-consuming [11,12]. But the transformers' lifetime is able to be extended up to 60 years through proper maintenance and monitoring. But knowing the effect of voltage drops caused by such failures in transmission and distribution systems on large industrial loads and on engines provides great ease regarding the characteristics of short-term voltage drops in distribution systems [13,14]. It was observed that the transformers reach saturation following the occurrence of voltage drop. It is known that the root cause of transformers' saturation is the magnetizing current 10-20 times the nominal current drawn by the transformer from the mains in spike occurring following the finalization of voltage drop. Magnetizing current is at very high levels and causes harmonic distortion during energizing of transformer as unloaded or under low load. In some cases, similar magnetizing current occurs through return of voltage to its normal value following voltage drop, and in other cases, it occurs as the result of high amplitude harmonic distortion due to saturation of the transformer [15-19].

In the studies performed, methods based on measurement with respect to voltage drop against loading of power transformers were examined. In this study, it was intended to estimate voltage drop of transformers under full load through the ANN model developed by the use of specific input variables of the transformers. In this manner, the estimation through ANN of voltage drops resulting from overloads on transformers was performed.

2. MATERIAL AND METHOD

2.1. Transformers' Data

In this study, the values of power, rated voltage, idle leakage current, loss at full load, idle loss, short circuit voltage, voltage drop at full load, and efficiency at full load of power transformers with different characteristics were used as specified in Table I [20].

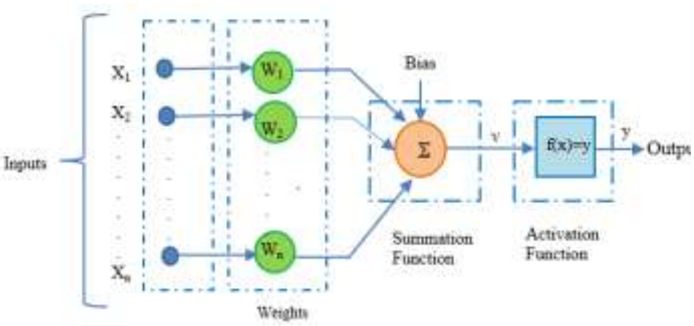

Figure 2. Structure of artificial neuron

TABLE I

TECHNICAL SPECIFICATIONS OF POWER TRANSFORMERS

Power (kVA)	*Rated Voltage (kV)*	*Idle Current (% Io)*	*Loss at Full Load (W)*	*Idle Loss (W)*	*Short Circuit V(%Uk)*	*V. Drop at full Load(%)*	*Efficiency at Full Load (%)*
25	6.3	2.5	550	65	4	3.773	9.02
25	10.5	2.5	550	65	4	3.773	97.02
25	15.8	2.5	550	65	4	3.773	97.02
25	33	3.15	700	110	4.5	4.360	96.11
40	6.3	2.4	650	80	4	3.512	97.77
40	10.5	2.4	650	80	4	3.512	97.77
40	15.8	2.4	650	80	4	3.512	97.77
40	33	2.92	900	135	4.5	4.153	96.87
50	6.3	2.3	750	90	4	3.446	97.94
50	10.5	2.3	750	90	4	3.446	97.94
50	15.8	2.3	750	90	4	3.446	97.94
50	33	2.76	1050	160	4.5	4.086	97.06
63	6.3	2.25	900	110	4	3.407	98.04
63	10.5	2.25	900	110	4	3.407	98.04
63	15.8	2.25	900	110	4	3.407	98.04
63	33	2.62	1225	195	4.5	4.012	97.26
80	6.3	2.2	1050	125	4	3.342	98.20
80	10.5	2.2	1040	125	4	3.342	98.20
80	15.8	2.2	1050	125	4	3.342	98.20
80	33	2.5	1400	225	4.5	3.913	97.52
100	6.3	2.1	1250	145	4	3.306	98.29
100	10.5	2.1	1250	145	4	3.306	98.29
100	15.8	2.1	1250	145	4	3.306	98.29
100	33	2.27	1600	270	4.5	3.859	97.66
125	6.3	2	1475	175	4	3.264	98.38
125	10.5	2	1475	175	4	3.264	98.38
125	15.8	2	1475	175	4	3.264	98.38
125	33	2.14	1900	330	4.5	3.787	97.82
160	6.3	1.9	1700	210	4	3.193	98.53
160	10.5	1.9	1700	210	4	3.193	98.53
160	15.8	1.9	1700	210	4	3.193	98.53
160	33	2	2150	390	4.5	3.686	98.05
200	6.3	1.9	2025	255	4	3.162	98.58
200	10.5	1.9	2025	255	4	3.162	98.58
200	15.8	1.9	2025	255	4	3.162	98.58
200	33	1.9	2575	470	4.5	3.652	98.10
250	6.3	1.6	2350	300	4	3.117	98.69
250	10.5	1.6	2350	300	4	3.117	98.69
250	15.8	1.6	2350	300	4	3.117	98.69
250	33	1.8	3000	550	4.5	3.600	98.26
315	6.3	1.5	2800	365	4	3.084	98.76
315	10.5	1.5	2800	365	4	3.084	98.76
315	15.8	1.5	2800	365	4	3.084	98.76
315	33	1.7	3575	670	4.5	3.559	98.34
400	6.3	1.5	3250	430	4	3.034	98.86
400	10.5	1.5	3250	430	4	3.034	98.86
400	15.8	1.5	3250	430	4	3.034	98.86
400	33	1.7	4150	790	4.5	3.498	98.48
500	6.3	1.4	3950	520	4	3.020	98.89
500	10.5	1.4	3950	520	4	3.020	98.89
500	15.8	1.4	3950	520	4	3.020	98.89
500	33	1.6	4850	950	4.5	3.455	98.56
630	6.3	1.4	4600	600	4	2.980	98.98
630	10.5	1.4	4600	600	4	2.980	98.98
630	15.8	1.4	4600	600	4	2.980	98.98
630	33	1.6	5500	1100	4.5	3.392	98.71
800	6.3	1.3	6000	650	4	4.264	98.98
800	10.5	1.3	6000	650	4	4.264	98.98
800	15.8	1.3	6000	650	4	4.264	98.98
800	33	1.50	7000	1300	4.5	4.350	98.72
1000	6.3	1.20	7600	770	4	4.271	98.96
1000	10.5	1.20	7600	770	4	4.271	98.96
1000	15.8	1.20	7600	770	4	4.271	98.96
1000	33	1.40	8900	1450	4.5	4.360	98.72
1250	6.3	1.20	9500	950	4	4.271	98.97
1250	10.5	1.20	9500	950	4	4.271	98.97
1250	15.8	1.20	9500	950	4	4.271	98.97
1250	33	1.40	11500	1750	4.5	4.810	98.69
1600	6.3	1.10	12000	1200	4	4.264	98.98
1600	10.5	1.10	12000	1200	4	4.264	98.98
1600	15.8	1.10	12000	1200	4	4.264	98.98
1600	33	1.30	14500	2200	4.5	4.371	98.71
2000	6.3	1.10	15000	1450	4	4.264	98.98
2000	10.5	1.10	15000	1450	4	4.264	98.98
2000	15.8	1.10	15000	1450	4	4.264	98.98
2000	33	1.20	18000	2700	4.5	4.367	98.72
2500	6.3	1.00	18500	1750	4	4.257	99.00
2500	10.5	1.00	18500	1750	4	4.250	99.00
2500	15.8	1.00	18500	1750	4	4.250	99.00

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2.2. Artificial Neural Network (ANN)

The artificial neural networks consist of artificial neurons indicated in Fig. 2. The artificial neurons are the data processing technology formed by simulating the biological nervous system as being inspired from the information processing technique of human brain and real neurons. ANN is a method frequently used in the solution of complex problems [21-25].

In artificial neural networks, the data is given to the network from the input layer. The information reaching the network as being processed in interlayers is converted to output by the use of network's weight values. For the network to be able to generate the correct outputs for the inputs, it is required for the weights to have correct values. The operation of determining the correct weights is called network training. The required number of value items in input and output layers is determined considering the problem. There is no method indicating the required number of items in each layer along with the number of interlayers. In general, it is found with the trial and error method [26-28].

In order to be able to make estimation with ANN, it is first required to train the ANN to be formed. In this study, the variables used for ANN training were input (weight) values, and output (target) values. These values are shown in Table II. As ANN's input values, the values of power, rated voltage, idle leakage current, loss at full load, idle loss, short circuit voltage, voltage drop at full load, and efficiency at full load of power transformer were used. The transformer's voltage drop at full load (%) was assigned as ANN's output value.

TABLE II
ANN INPUT AND OUTPUT VALUES

Inputs	Weight and Target Data	Max.Values	Min. Values
X1	Transformer Power(kVA)	2500	25
X2	Rated Voltage(kV)	33	6.3
X3	Idle Current(%Io)	3.15	1
X4	Loss at full Load (W)	22500	550
X5	Idle Load (W)	3200	65
X6	Short Circuit Voltage (%Uk)	4.5	4
X7	Efficiency at Full Load (%)	99	96.11
Y1	Voltage Drop at Full Load (%)	4810	2980

3. IMPLEMENTATION

The input (weight) and output (target) values of the ANN model formed in order to estimate the transformers' voltage drop at full load are shown in Fig. 3. In ANN, it is required to convert the verbal data to digital data. Without the conversion, it will not be possible for us to introduce these values to ANN. The operation of making the training of ANN more efficient by subjecting the weight and target data, to be used in the training of network, to specific operations is called the normalization operation. In this study, the training data was reduced to the range of (0, 1) by the use of min.-max. Equation 2 was used to reduce the training data to this interval. The data obtained as the result of normalization is as shown in Table III [29-31].

$$X' = \frac{(X_i - X_{min})}{(X_{max} - X_{min})} \qquad (1)$$

In the Equation;

X'	is the normalized value,
X_i	is the input value of ANN,
X_{min}	is the smallest value of input value,
X_{max}	is the greatest value of input value

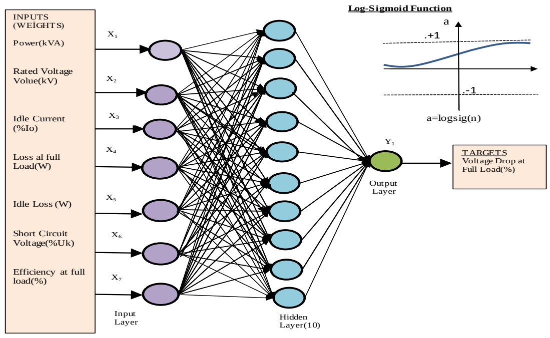


Figure 3. Weight and target values of the ANN model for the estimation of transformer voltage drop

TABLE III
NORMALIZED WEIGHT AND TARGET VALUES USED IN ANN TRAINING

Inputs	Weight and Target Data	Max.Values	Min. Values
X1	Transformer Power(kVA)	1	0
X2	Rated Voltage(kV)	1	0
X3	Idle Current(%Io)	1	0
X4	Loss at full Load (W)	1	0
X5	Idle Load (W)	1	0
X6	Short Circuit Voltage (%Uk)	1	0
X7	Efficiency at Full Load (%)	1	0
Y1	Voltage Drop at Full Load (%)	1	0

The graphs between the normalized data and transformer's voltage drop are shown in the part from Fig. 4 to Fig. 10.

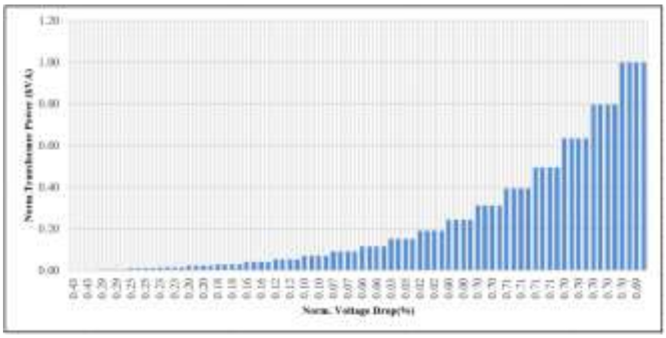


Figure 4. Graph between Norm.Transformer Power (kVA) and Norm.Transformer Full Load Voltage drop (%)

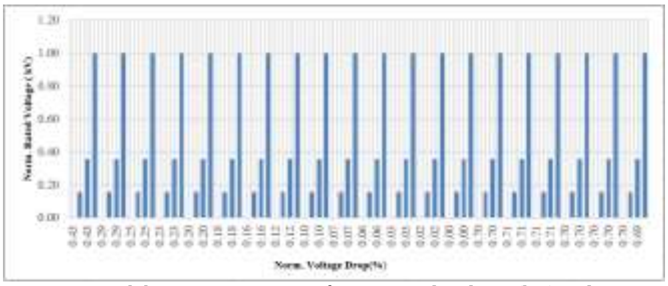


Figure 5. Graph between Norm.Transformer Rated Voltage (kV) and Norm.Transformer Full Load Voltage drop (%)

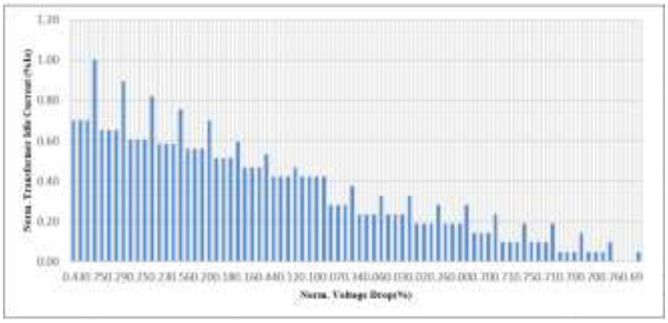


Figure 6. Norm. Transformer No-load Current (%Io) and Norm. Graph between transformer Voltage drop (%) at full

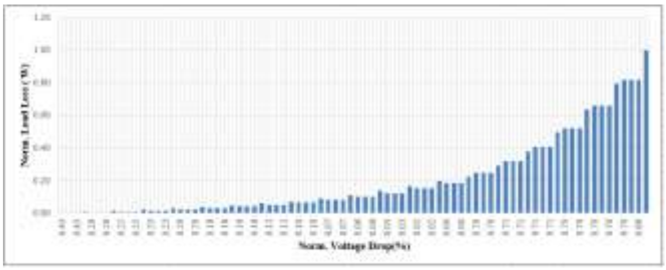


Figure 7. Graph between Norm.Transformer Load Loss (W) and Norm.Transformer Full Load Voltage Drop (%)

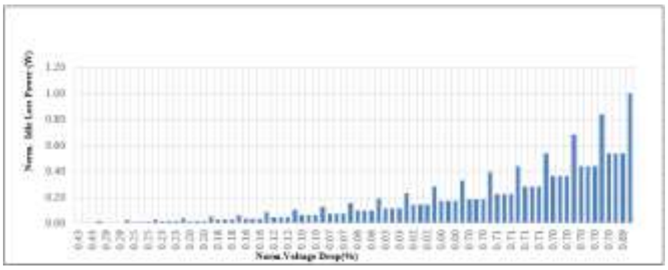


Figure 8. Norm. Graph between the No-load Loss power (W) of the transformer and the Norm.Transformer full load voltage drop (%)

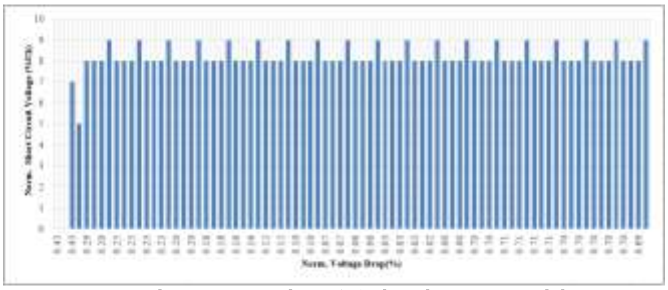


Figure 9. Norm. Short Circuit Voltage (%)Uk with Norm. Graph between transformer Voltage drop (%) at full load

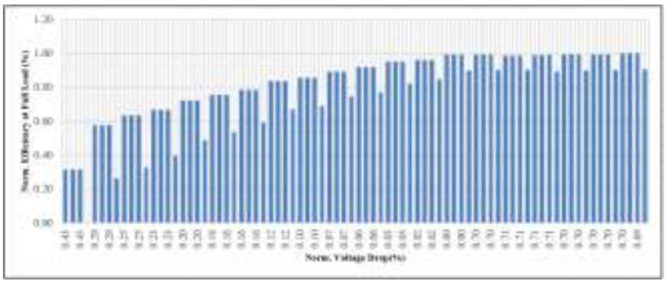


Figure 10. Norm. Transformer Full Load Voltage Drop (%) and Norm. Graph between Transformer Efficiency (%) at full load

In the defined model, feed-forward back propagation was selected as ANN model for the estimation of the transformer's voltage drop at full load. As seen in Table IV, TRAINLM was selected as the training function, and LEARNGDM was selected as the adaptive learning function. The MSE (Mean Squared Error) specified in equation (2) was used as the performance function. LOGSIG (Log-Sigmoid Transfer Function) was used as the transfer function.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\frac{(y_1 - y_2)^2}{n} \tag{2}$$

In the Equation;

n is the number of data points

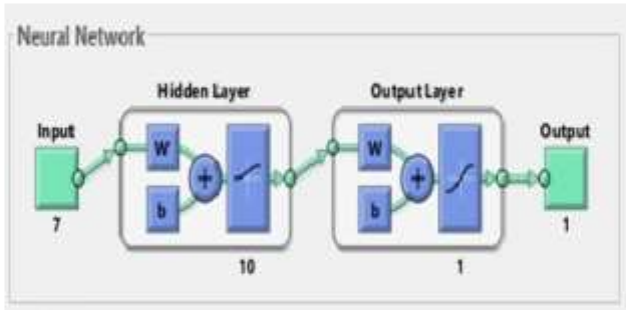
y_1 represents observed values

y_2 represents predicted values

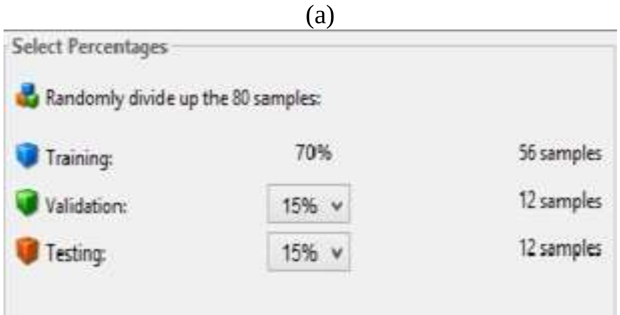
TABLE IV
FUNCTIONS AND DATA SELECTED IN THE ANN TRAINING

Network Properties		
Network Type	:	Feed-Forward backpropagation
Training function	:	TRAINLM
Adaption learning function	:	LEARNGDM
Performance function	:	MSE
Number of layers	:	2
Properties for	:	Layer 1
Tranfer Function	:	LOGSIG

The functions and data used in ANN training were as shown in Table 4. In Fig. 11.a, ANN model having 7 input values and 1 output value is shown. During the development of the model formed for ANN estimation, technical information of 560 transformers according to 7 different input variables was used. In Fig. 11.b., the percentages of data used in ANN trainings are shown.



(a)

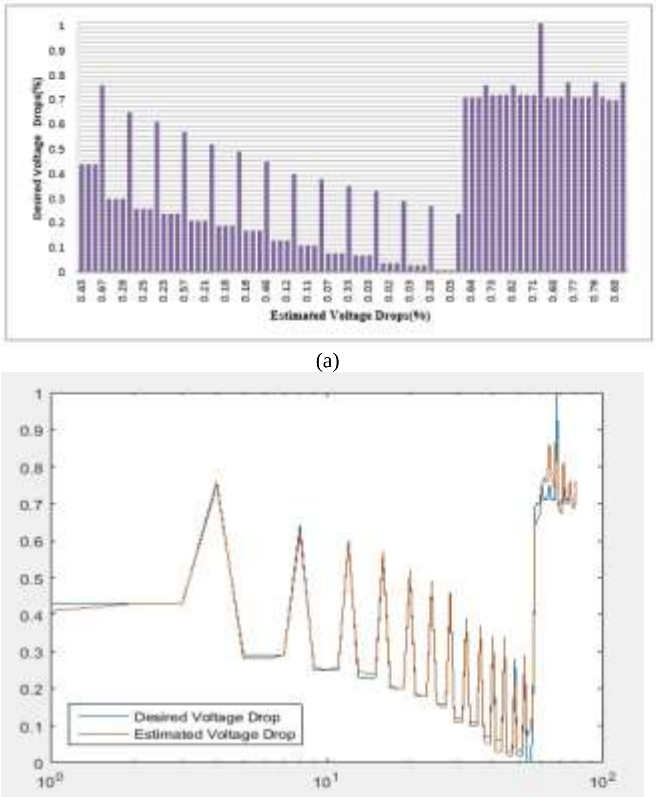


(b)

Figure 11. Defined ANN values and percentages

In the ANN training, the closest value was obtained in about the 114th iteration. As the result of this training, the values of training were found to be correct at a rate of 99.605%. It was observed that the validation values were correct at a rate of 98.651%, and that it was correct at a rate of 99.351% in ALL. As the correlation value

was equal to one, it was observed that there was perfect similarity between network output and target output.
After the completion of the training, it was observed that the known values and estimated values completely correspond with each other, and that they verify the requested estimation at a rate of 99%. There are also shown with Fig. 12 (a) column and Fig. 12 (b) line graphs.



(a)

(b)

Figure 12. Graphs showing that Desired Voltage Drop values and Estimated Voltage Drops overlap in (a) and (b) graphs.

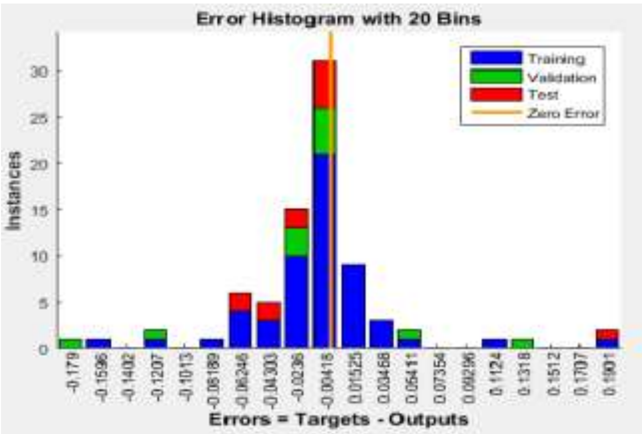


Figure 13. Error rate graph resulting from estimation

In Fig. 13, it is observed that the error rate between the estimations made with ANN after entry of the weight and target values in ANN, and the required values is about 1%.

4. CONCLUSION AND SUGGESTIONS

In this study, it was intended to show that it is possible to estimate the voltage drops through ANN as an alternative to theoretical and applied methods with respect to power transformers' voltage drop. It was observed that the ANN's estimation results and the known data were very close with an acceptable tolerance. In addition, in this study, less mathematical statements were used without having preliminary information regarding the system by the use of estimation method through ANN, and it was ensured to reach post-training results as faster and more accurately. By this study, it was observed that the real values and estimated values were very close, and that they were close to 1. It is considered that this will set a model for future similar studies.

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BIOGRAPHIES

Onur AKAR was born in 1981 in Giresun. He received his undergraduate, graduate and doctorate degrees from Marmara University in 2005, 2011 and 2020, respectively. He worked as a lecturer at Istanbul Gedik University between 2010-2020. He served as the Head of Electricity Program at Istanbul Gedik University between 2012-2015. He served as the Head of the Department of Electricity and Energy between 2021-2022 as an assistant professor in the Department of Electricity and Energy of the same university. He is still working as an Assistant Professor Marmara University, Vocational School of Technical Sciences. His research interests include Control Systems, Renewable Energy Systems, Power Systems and Lighting Systems.