Power Losses Analysis in a Three-Phase Distribution Transformer Using Artificial Neural Networks

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ABSTRACT

This research article presents the analysis of power losses in a three-phase distribution transformer, 100 kVA 22 kV-400/230 V by using artificial neural networks that can analyze the power losses in distribution transformers faster and use fewer variables than the original method. The measurement data were collected for 100,000 sets at the transformer manufacturer factory by setting the current flow from 1% to 100% at temperatures: 30 °C, 35 °C, 40 °C, 45 °C, 50 °C, 55 °C, 60 °C, 65 °C, 70 °C, and 75 °C to calculate the power losses in a distribution transformer. The collected data were divided into 80,000 sets to use for training in order to find the parameters of the artificial neural networks, and 20,000 sets were used for the artificial neural network input in order to calculate power losses in a distribution transformer. From comparing the power losses in the distribution transformer of artificial neural networks compared with the calculated values from the measurement, the percentage error was at a satisfactory level and can be applied to design a test of power losses in the distribution transformer in the future.

Keywords: Distribution Transformers, Power Losses, Artificial Neural Networks

1. INTRODUCTION

The distribution transformer is an important equipment in a distribution system, which transfers power through adjusting up-down voltage with the appropriate level for the specified use or users. There are some losses in the distribution transformer system called power losses that consist of core losses and copper losses. These losses have a lot of factors such as voltage, current, resistance, temperature, load and transformer quality. These problems are difficult and complicated processes to consider, we also need to find out the effect on transformer temperature due to the change of load. In the test, A. N. de Souza et al. [1] presented the application of using artificial neural networks to calculate power losses in the single phase distribution transformer, using 6 variables input into the artificial neural network model. This could reduce the difficulty of calculating power losses. N. Suttisinthong and C. Pothisan [2] proposed the application of using artificial neural networks to calculate power losses in a single phase distribution transformer using 3 variable inputs into an artificial neural network model that could reduce the difficulty of calculating power losses but the percentage error was very high. K. N. Souza et al. [8] presented the application of using artificial neural networks to specify core losses in a three phase transformer.

N. Suttisinthong and C. Pothisan [2] presented the application of using artificial neural networks to calculate values of losses in a three phase distribution transformer at 100 kVA 22 kV-400/230 V using 5 variable inputs into an artificial neural network model, which can reduce the difficulty of calculating power losses and lower the percentage error.

2. POWER LOSSES IN A TRANSFORMER

Power loss in the transformer is no load loss and load loss, which consists of core losses and copper losses in the first equation [1]–[3]

$$P_T = P_{Core} + P_{CU} \tag{1}$$

where P_T is the total loss in distribution transformer, P_{Core} is the core losses, and P_{CU} is the copper losses.

2.1 Core losses

Fig. 1 is a test to determine the core losses due to hysteresis loss and eddy currents where the core losses have constant values in every condition as in Eq. 2 [1]–[3].

$$P_{Core} = P_H + P_E \tag{2}$$

where P_{Core} is core losses, P_H is the hysteresis losses, and P_E is the eddy-current loss.

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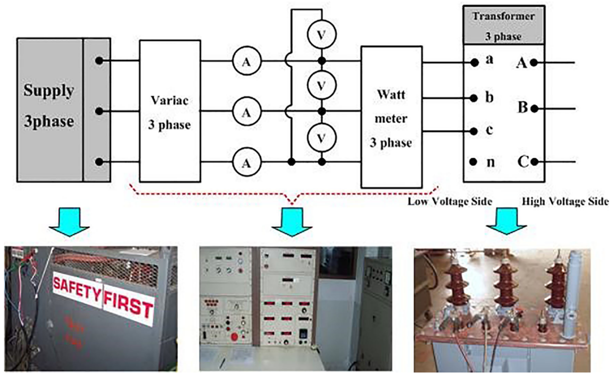

Fig.1: *Open circuit test.*

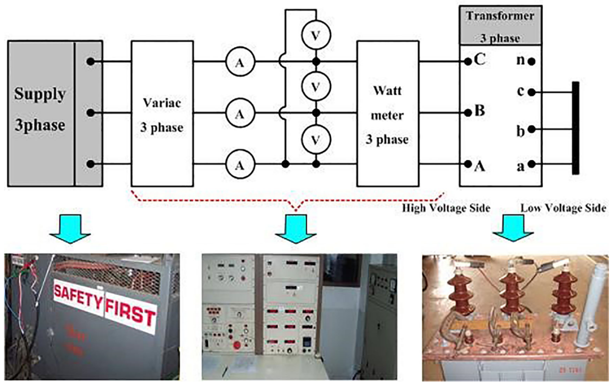

Fig.2: *Short circuit test.*

The hysteresis loss is given by Eq. 3 [1]–[3].

$$P_H = K_S \cdot B^{1.6} \cdot f \tag{3}$$

where K_S is the coefficient of core, B is the maximum flux density, and f is the frequency.

The eddy-current loss is given by Eq. 4 [1]–[3].

$$P_E = K_e \cdot f^2 \cdot B^2 \cdot d^2 \cdot 10^{-3} \tag{4}$$

where K_e is a constant, d is the thickness of the laminated core, B is the maximum flux density, and f is the frequency.

2.2 Copper losses

Fig. 2 shows a test to find the copper losses by short circuit test shown as Eq. 5 [1]–[3].

$$P_{CU} = 3\left(I_{HV}^2 \cdot R_{HV} + I_{LV}^2 \cdot R_{LV}\right) \tag{5}$$

where R_{HV} is the winding resistance of the high-voltage coil, I_{HV} is the current of the high-voltage coil, R_{LV} is the winding resistance of the low-voltage coil, and I_{LV} is the current of the low-voltage coil.

Figs. 3 and 4 show the measuring of winding resistance by Wheatstone bridge with high accuracy [4], [11], [12].

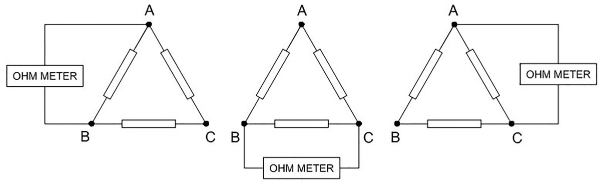

Fig.3: *Measurement of winding resistance of the high-voltage coil (primary).*

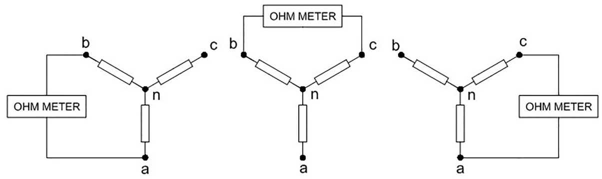

Fig.4: *Measurement of winding resistance of the low-voltage coil (secondary).*

Calculating the resistance of the coil (Resistor/phase, R/ph) in the high voltage side is shown as Eq. 6 and the low voltage side as Eq. 7.

$$R_{HV} = R/ph = \frac{3}{2} R_{WB(HV)} \tag{6}$$

$$R_{LV} = R/ph = \frac{1}{2} R_{WB(LV)} \tag{7}$$

where R_{HV} is the resistance of the high voltage side (primary), R_{LV} is the resistance of the low voltage side (secondary), R_{WB} is the resistance measured by Wheatstone Bridge.

Finding the required coil resistance, and coil temperature is shown in Eq. 8 [2]–[4].

$$R_r = R_a \left(\frac{235 + \theta_r}{235 + \theta_a}\right) \tag{8}$$

where R_r is the require coil resistance at coil temperature (θ_r), R_a is the coil resistance at ambient temperature (θ_a).

3. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are one type of artificial intelligence that is developed through computer technology. Artificial neural networks have high-speed processing systems because they are connected in parallel point to point, have nonlinear processing and have flexibility in calculations by adjusting the input and output data that work with nonlinear and complex structures. Artificial neural networks [5]–[10] can be applied to the problems that cannot be represented by mathematical equations.

From the study of artificial neural networks, we can find the power losses in transformers [8]–[11]; it can also be found that Feed-forward multilayer

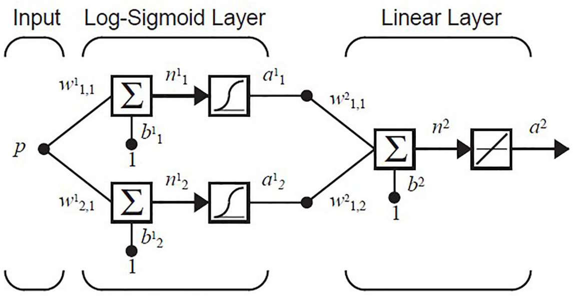

Fig.5: *Feed-forward multilayer perceptron MLP.*

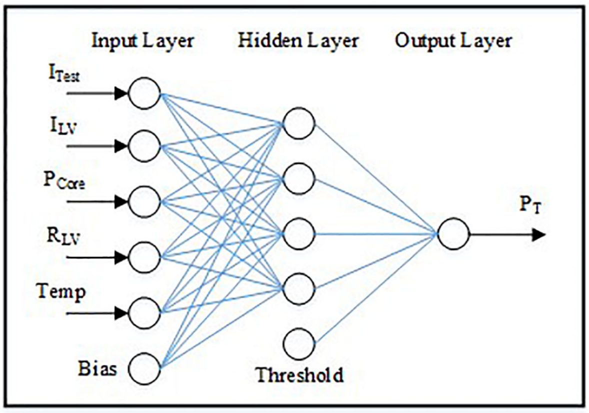

Fig.6: *Model of Artificial Neural Networks 5-4-1.*

perceptron MLP and Error back-propagation are suitable for calculating power loss values in transformers by neural network architecture (MLP) as shown in Fig. 5.

3.1 Application of Artificial Neural Networks

Souza et al. [1] determined the power losses in a transformer using 6 input data, which consist of: temperature (T), resistance of high voltage and low voltage (R_{HV} and R_{LV}), core loss (P_{Core}), copper loss (P_{CU}) and test current (I_{Test}).

This research article uses only 5 input data, which consist of temperature (T), resistance of low voltage (R_{LV}), core loss (P_{Core}), low voltage current (I_{LV}), and magnetizing current (I_{Test}) as inputs to artificial neural networks.

The artificial neural networks in this research consist of 5 inputs and 1 output, as shown in Fig. 6, using data from the measurement and data collection at the transformer manufacturer factory. By setting the current flows from 1% to 100% at 30 °C, 35 °C, 40 °C, 45 °C, 50 °C, 55 °C, 60 °C, 65 °C, 70 °C, and 75 °C we are able to calculate the power losses in the distribution transformer. The collected data was divided into 80,000 sets to use for training the artificial neural networks in order to find the parameters of artificial neural networks, and 20,000 sets were used for the artificial neural networks input

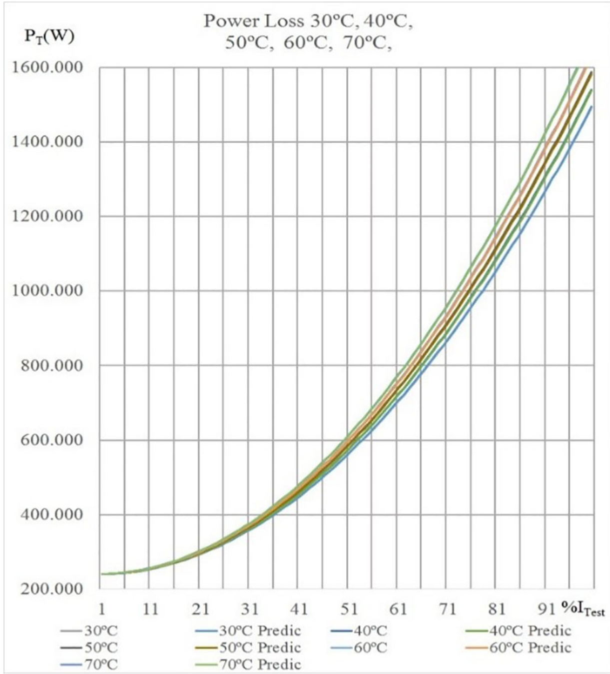

Fig.7: *The relationship between the values from the simulation and the actual measured values at various temperatures: 30 °C, 40 °C, 50 °C, 60 °C, and 70 °C.*

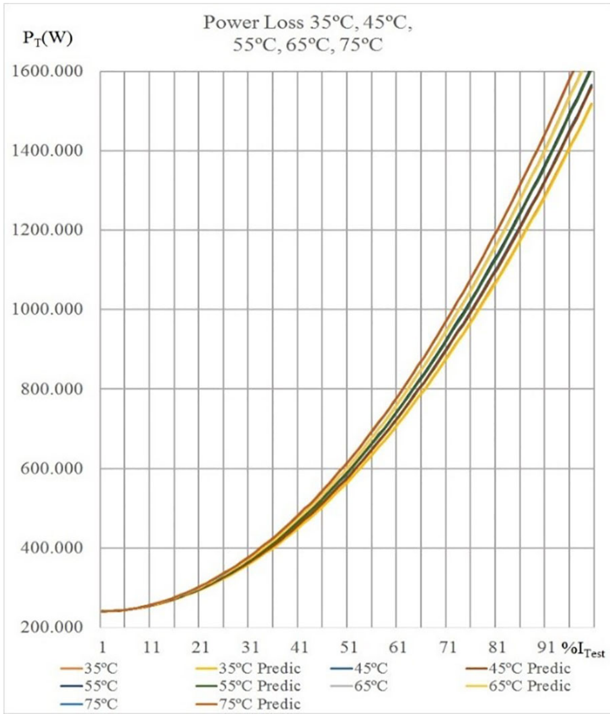

Fig.8: *The relationship between the values from the simulation and the actual measured values at various temperatures: 35 °C, 45 °C, 55 °C, 65 °C, and 75 °C.*

in order to calculate power losses in a distribution transformer as shown in Table 1, which is used as a reference (Look-Up Table).

At the beginning, the artificial neural network will

Table 1: *Look-up table.*

No.	P_T (W)	I_{Test} (%)	I_{LV} (A)	P_{Core} (W)	R_{LV} (mΩ)	Temp. (°C)	No.	P_T (W)	I_{Test} (%)	I_{LV} (A)	P_{Core} (W)	R_{LV} (mΩ)	Temp. (°C)
1	240.125	1	1.443	240	10.5	30	50001	240.337	1	1.443	240.2	11.5	55
2	240.501	2	2.887	240	10.5	30	50002	240.749	2	2.887	240.2	11.5	55
3	241.127	3	4.33	240	10.5	30	50003	241.434	3	4.33	240.2	11.5	55
4	242.004	4	5.774	240	10.5	30	50004	242.395	4	5.774	240.2	11.5	55
5	243.131	5	7.217	240	10.5	30	50005	243.629	5	7.217	240.2	11.5	55
6	244.509	6	8.66	240	10.5	30	59995	1477.05	95	137.1	240	11.5	55
7	246.137	7	10.1	240	10.5	30	59996	1503.23	96	138.6	240	11.5	55
8	248.016	8	11.55	240	10.5	30	59997	1529.69	97	140	240	11.5	55
9	250.146	9	12.99	240	10.5	30	59998	1556.41	98	141.5	240	11.5	55
10	252.525	10	14.43	240	10.5	30	59999	1583.42	99	142.9	240	11.5	55
9995	1371.33	95	137.1	240.2	10.5	30	60000	1610.69	100	144.3	240	11.5	55
9996	1395.27	96	138.6	240.2	10.5	30	60001	240.34	1	1.443	240.2	11.7	60
9997	1419.46	97	140	240.2	10.5	30	60002	240.758	2	2.887	240.2	11.7	60
9998	1443.9	98	141.5	240.2	10.5	30	60003	241.456	3	4.33	240.2	11.7	60
9999	1468.59	99	142.9	240.2	10.5	30	60004	242.432	4	5.774	240.2	11.7	60
10000	1493.53	100	144.3	240.2	10.5	30	60005	243.688	5	7.217	240.2	11.7	60
10001	240.328	1	1.443	240.2	10.7	35	69995	1498.38	95	137.1	240	11.7	60
10002	240.711	2	2.887	240.2	10.7	35	69996	1525.01	96	138.6	240	11.7	60
10003	241.349	3	4.33	240.2	10.7	35	69997	1551.92	97	140	240	11.7	60
10004	242.243	4	5.774	240.2	10.7	35	69998	1579.11	98	141.5	240	11.7	60
10005	243.392	5	7.217	240.2	10.7	35	69999	1606.58	99	142.9	240	11.7	60
19995	1391.74	95	137.1	240	10.7	35	70000	1634.33	100	144.3	240	11.7	60
19996	1416.11	96	138.6	240	10.7	35	70001	240.342	1	1.443	240.2	11.9	65
19997	1440.74	97	140	240	10.7	35	70002	240.768	2	2.887	240.2	11.9	65
19998	1465.63	98	141.5	240	10.7	35	70003	241.477	3	4.33	240.2	11.9	65
19999	1490.77	99	142.9	240	10.7	35	70004	242.47	4	5.774	240.2	11.9	65
20000	1516.16	100	144.3	240	10.7	35	70005	243.747	5	7.217	240.2	11.9	65
20001	240.33	1	1.443	240.2	10.9	40	79995	1519.71	95	137.1	240	11.9	65
20002	240.72	2	2.887	240.2	10.9	40	79996	1546.79	96	138.6	240	11.9	65
20003	241.371	3	4.33	240.2	10.9	40	79997	1574.16	97	140	240	11.9	65
20004	242.281	4	5.774	240.2	10.9	40	79998	1601.81	98	141.5	240	11.9	65
20005	243.452	5	7.217	240.2	10.9	40	79999	1629.74	99	142.9	240	11.9	65
29995	1413.07	95	137.1	240	10.9	40	80000	1657.96	100	144.3	240	11.9	65
29996	1437.89	96	138.6	240	10.9	40	80001	240.344	1	1.443	240.2	12.1	70
29997	1462.98	97	140	240	10.9	40	80002	240.777	2	2.887	240.2	12.1	70
29998	1488.32	98	141.5	240	10.9	40	80003	241.498	3	4.33	240.2	12.1	70
29999	1513.93	99	142.9	240	10.9	40	80004	242.508	4	5.774	240.2	12.1	70
30000	1539.8	100	144.3	240	10.9	40	80005	243.806	5	7.217	240.2	12.1	70
30001	240.332	1	1.443	240.2	11.1	45	89995	1541.04	95	137.1	240	12.1	70
30002	240.73	2	2.887	240.2	11.1	45	89996	1568.57	96	138.6	240	12.1	70
30003	241.392	3	4.33	240.2	11.1	45	89997	1596.39	97	140	240	12.1	70
30004	242.319	4	5.774	240.2	11.1	45	89998	1624.51	98	141.5	240	12.1	70
30005	243.511	5	7.217	240.2	11.1	45	89999	1652.9	99	142.9	240	12.1	70
39995	1434.39	95	137.1	240	11.1	45	90000	1681.59	100	144.3	240	12.1	70
39996	1459.67	96	138.6	240	11.1	45	90001	240.347	1	1.443	240.2	12.3	75
39997	1485.21	97	140	240	11.1	45	90002	240.786	2	2.887	240.2	12.3	75
39998	1511.02	98	141.5	240	11.1	45	90003	241.52	3	4.33	240.2	12.3	75
39999	1537.09	99	142.9	240	11.1	45	90004	242.546	4	5.774	240.2	12.3	75
40000	1563.43	100	144.3	240	11.1	45	90005	243.865	5	7.217	240.2	12.3	75
40001	240.335	1	1.443	240.2	11.3	50	99990	1426.83	90	129.9	240	12.3	75
40002	240.739	2	2.887	240.2	11.3	50	99991	1453.35	91	131.3	240	12.3	75
40003	241.413	3	4.33	240.2	11.3	50	99992	1480.17	92	132.8	240	12.3	75
40004	242.357	4	5.774	240.2	11.3	50	99993	1507.27	93	134.2	240	12.3	75
40005	243.57	5	7.217	240.2	11.3	50	99994	1534.67	94	135.7	240	12.3	75
49995	1455.72	95	137.1	240	11.3	50	99995	1562.37	95	137.1	240	12.3	75
49996	1481.45	96	138.6	240	11.3	50	99996	1590.35	96	138.6	240	12.3	75
49997	1507.45	97	140	240	11.3	50	99997	1618.63	97	140	240	12.3	75
49998	1533.72	98	141.5	240	11.3	50	99998	1647.2	98	141.5	240	12.3	75
49999	1560.26	99	142.9	240	11.3	50	99999	1676.07	99	142.9	240	12.3	75
50000	1587.06	100	144.3	240	11.3	50	100000	1705.22	100	144.3	240	12.3	75

Table 2: *Improved neural network.*

	Hidden 1			
	Node 1 (Sigmoid)	Node 2 (Sigmoid)	Node 3 (Sigmoid)	Node 4 (Sigmoid)
I_{Test} (%)	–3.228	–1.225	–1.306	–0.972
I_{LV} (A)	–3.183	–1.237	–1.334	–1.004
P_{Core} (W)	0.088	–0.005	0.129	–0.013
R_{LV} (mΩ)	0.033	–0.131	–0.223	–0.031
Temp. (°C)	–0.014	–0.117	–0.159	–0.024
Bias	–7.213	3.116	–1.939	0.384
	Output			
	Regression (Linear)			
Node 1	0.121			
Node 2	–2.497			
Node 3	0.120			
Node 4	–1.476			
Threshold	2.726			

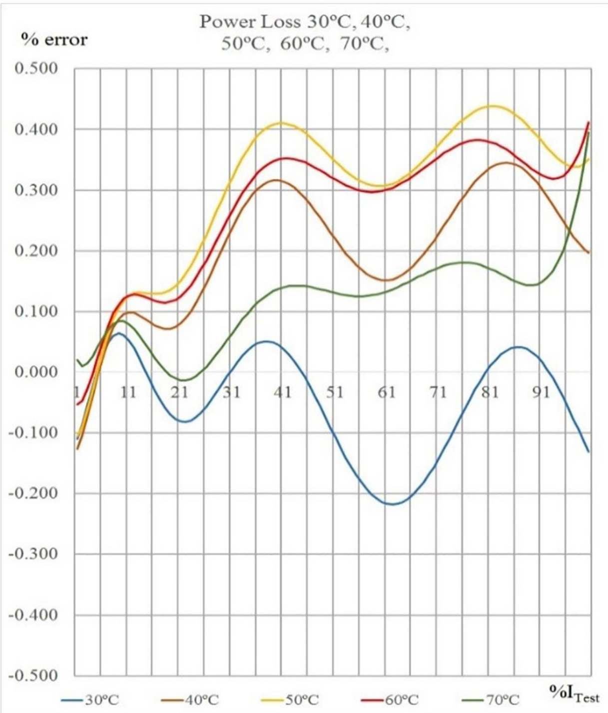

Fig.9: *The percentage errors at various temperatures: 30 °C, 40 °C, 50 °C, 60 °C, and 70 °C.*

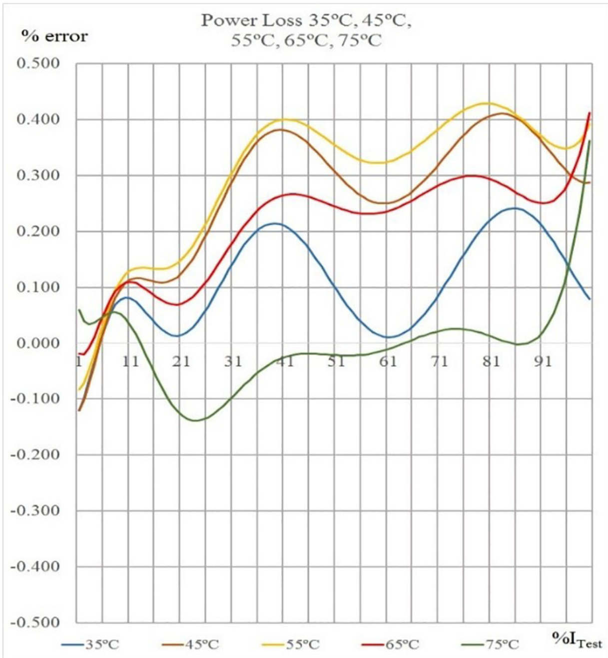

Fig.10: *The percentage errors at various temperatures: 35 °C, 45 °C, 55 °C, 65 °C, and 75 °C.*

be trained with the setting of 5 input nodes and 1 output node. During the training, the weight of each hidden layer will be adjusted by transfers function in hidden layer Lock-sigmoid function. The output layer will use a linear function. The experiment found that the hidden layer had 4 nodes as shown in Fig. 6 and the various parameters as shown in Table 2.

4. RESULTS

Power loss in a three phase distribution transformer 100 kVA 22 kV-400/230 V calculated from the artificial neural networks was compared with the measured power loss in a three phase distribution transformer 100 kVA 22 kV-400/230 V. The actual measurement result with the percentage error is shown in Table 3 [11]–[12].

From Table 3, the graphs of the relationship between the values from the simulation and the actual measured values at various temperatures, are shown in Figs. 7 and 8, and the percentage errors at various temperatures are shown in Figs. 9 and 10.

5. CONCLUSION

This research paper has presented a technique that helps to determine the power losses in a

Table 3: *Percentage error of electrical motor losses.*

No.	Temp. (°C)	I_{Test} (%)	P_T (W)	Prediction (P_T)	% Error	No.	Temp. (°C)	I_{Test} (%)	P_T (W)	Prediction (P_T)	% Error
1	30	1	240.125	240.390	–0.110	10001	55	1	240.337	240.536	–0.083
2	30	2	240.501	240.710	–0.087	10002	55	2	240.749	240.921	–0.071
3	30	3	241.127	241.263	–0.056	10003	55	3	241.434	241.550	–0.048
4	30	4	242.004	242.063	–0.024	10004	55	4	242.395	242.438	–0.018
5	30	5	243.131	243.118	0.006	10005	55	5	243.629	243.595	0.014
6	30	6	244.509	244.435	0.030	11995	55	95	1481.852	1479.531	0.157
7	30	7	246.137	246.017	0.049	11996	55	96	1508.184	1505.780	0.159
8	30	8	248.016	247.867	0.060	11997	55	97	1534.793	1532.245	0.166
9	30	9	250.146	249.986	0.064	11998	55	98	1561.677	1558.913	0.177
10	30	10	252.525	252.371	0.061	11999	55	99	1588.837	1585.770	0.193
1995	30	95	1377.947	1379.655	–0.124	12000	55	100	1616.272	1612.799	0.215
1996	30	96	1402.055	1404.037	–0.141	12001	60	1	240.340	240.467	–0.053
1997	30	97	1426.416	1428.683	–0.159	12002	60	2	240.758	240.873	–0.048
1998	30	98	1451.029	1453.588	–0.176	12003	60	3	241.456	241.526	–0.029
1999	30	99	1475.895	1478.743	–0.193	12004	60	4	242.432	242.440	–0.003
2000	30	100	1501.013	1504.141	–0.208	12005	60	5	243.688	243.627	0.025
2001	35	1	240.328	240.617	–0.120	13995	60	95	1503.304	1501.478	0.122
2002	35	2	240.711	240.946	–0.098	13996	60	96	1530.091	1528.075	0.132
2003	35	3	241.349	241.511	–0.067	13997	60	97	1557.158	1554.874	0.147
2004	35	4	242.243	242.323	–0.033	13998	60	98	1584.506	1581.860	0.167
2005	35	5	243.392	243.393	0.000	13999	60	99	1612.134	1609.018	0.193
3995	35	95	1396.041	1395.966	0.005	14000	60	100	1640.042	1636.330	0.226
3996	35	96	1420.558	1420.702	–0.010	14001	65	1	240.342	240.386	–0.018
3997	35	97	1445.331	1445.697	–0.025	14002	65	2	240.768	240.815	–0.020
3998	35	98	1470.361	1470.943	–0.040	14003	65	3	241.477	241.496	–0.008
3999	35	99	1495.648	1496.431	–0.052	14004	65	4	242.470	242.441	0.012
4000	35	100	1521.191	1522.152	–0.063	14005	65	5	243.747	243.662	0.035
4001	40	1	240.330	240.632	–0.125	15995	65	95	1524.757	1523.821	0.061
4002	40	2	240.720	240.971	–0.104	15996	65	96	1551.998	1550.752	0.080
4003	40	3	241.371	241.548	–0.074	15997	65	97	1579.524	1577.868	0.105
4004	40	4	242.281	242.375	–0.039	15998	65	98	1607.335	1605.154	0.136
4005	40	5	243.452	243.463	–0.005	15999	65	99	1635.431	1632.593	0.174
5995	40	95	1417.494	1416.202	0.091	16000	65	100	1663.813	1660.166	0.219
5996	40	96	1442.464	1441.331	0.079	16001	70	1	240.344	240.296	0.020
5997	40	97	1467.697	1466.710	0.067	16002	70	2	240.777	240.753	0.010
5998	40	98	1493.190	1492.331	0.058	16003	70	3	241.498	241.465	0.014
5999	40	99	1518.945	1518.183	0.050	16004	70	4	242.508	242.444	0.026
6000	40	100	1544.962	1544.255	0.046	16005	70	5	243.806	243.704	0.042
6001	45	1	240.332	240.621	–0.120	17995	70	95	1546.210	1546.546	–0.022
6002	45	2	240.730	240.973	–0.101	17996	70	96	1573.904	1573.792	0.007
6003	45	3	241.392	241.565	–0.072	17997	70	97	1601.889	1601.208	0.043
6004	45	4	242.319	242.410	–0.038	17998	70	98	1630.164	1628.774	0.085
7995	45	95	1438.946	1436.881	0.144	17999	70	99	1658.728	1656.474	0.136
7996	45	96	1464.371	1462.394	0.135	18000	70	100	1687.583	1684.286	0.195
7997	45	97	1490.062	1488.148	0.128	18001	75	1	240.347	240.203	0.060
7998	45	98	1516.019	1514.132	0.124	18002	75	2	240.786	240.692	0.039
7999	45	99	1542.242	1540.334	0.124	18003	75	3	241.520	241.438	0.034
8000	45	100	1568.732	1566.742	0.127	18004	75	4	242.546	242.457	0.037
8001	50	1	240.335	240.588	–0.105	18005	75	5	243.865	243.759	0.044
8002	50	2	240.739	240.956	–0.090	19990	75	90	1431.340	1434.728	–0.237
8003	50	3	241.413	241.565	–0.063	19991	75	91	1458.015	1461.285	–0.224
8004	50	4	242.357	242.430	–0.030	19992	75	92	1484.985	1488.067	–0.208
8005	50	5	243.570	243.560	0.004	19993	75	93	1512.249	1515.062	–0.186
9995	50	95	1460.399	1457.994	0.165	19994	75	94	1539.808	1542.255	–0.159
9996	50	96	1486.278	1483.881	0.161	19995	75	95	1567.662	1569.633	–0.126
9997	50	97	1512.427	1509.998	0.161	19996	75	96	1595.811	1597.178	–0.086
9998	50	98	1538.848	1536.331	0.164	19997	75	97	1624.254	1624.873	–0.038
9999	50	99	1565.539	1562.869	0.171	19998	75	98	1652.992	1652.699	0.018
10000	50	100	1592.502	1589.597	0.182	19999	75	99	1682.025	1680.636	0.083
						20000	75	100	1711.353	1708.664	0.157

three-phase distribution transformer of 100 kVA 22 kV-400/230 V by applying artificial neural networks as the predictor. The results from 20,000 sets of test data showed that the percentage error was at satisfactory level with the range from –0.724 to +0.701.

From this research, it could reduce the number of parameters that needed to be measured and reduce the calculation processes. The experimental results also showed that the neural networks had good efficiency, accuracy, were close to reality so they can also be applied to design the distribution transformer in the future. This research can be applied to predict the loss of distribution transformers while overloading in the future.

The limitation of this research is that it can be used to predict the loss of distribution transformers up to 2000 kVA according to the Provincial Electricity Authority Thailand (PEA) standard.

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