International Journal of Energetica (IJECA)
https://www.ijeca.info
ISSN: 2543-3717 Volume 9. Issue 1. 2024 *Page 10-16*

Prediction of the Insulating Paper State of Power Transformers Using Artificial Neural Network

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Abstract – *Power transformers are considered the heart of power systems. The malfunction or undesirable outage of the power transformer will cause a tremendous revenue loss for the utilities. Therefore, a regular or preventive test must be accomplished on the transformer to check its state. Some standards, such as the American Transformer Diagnosis Guide and the American Society for Testing and Materials, have instructions for testing the transformers. The current works addressed which tests can be accomplished to predict the insulating paper state, which is the indicator of transformer aging. Furthermore, ANN model will be constructed to use it as a prediction tool of the paper state when the water content (WC), acidity (ACI), interfacial tension (IFT), oil color (OC), and 2-furfuraldehyde (2-FAL) were known. The ANN results indicated that the ANN's prediction accuracy was 93.87%.*

Keywords: Power transformer, insulating paper, Degree of polymerization, Artificial neural Network, preventive tests.

Received: 23/04/2024 – Revised: 12/06/2024 - Accepted: 18/06/2024

I. Introduction

Power transformers are considered essential assets in the power system. However, most transformer issues can be attributed to electrical, thermal, and mechanical stress due to a malfunction in its insulating system [1-3]. Therefore, the insulation system indicates the health condition of overall power transformers. The health index can be evaluated via valuable measurements for variables such as furan, dissolved gas analysis, water content, breakdown voltage, interfacial tension, acidity, and oil color scale [4,5]. In addition, insulating paper degradation is vital for transformer aging and can be used to assess its remaining life [6-9]. Therefore, regular tests must be accomplished to maintain the transformers' reliability and monitor their condition to avoid an undesired outage [10, 11]. Furthermore, as the insulating paper is hard to acquire, an inspection of the oil state can indicate the paper state through the type tests because it is easy to collect and test the transformer oil when the fault occurs [12-14]. Evaluation of the transformer's condition, aging, and remaining lifetime relies on the insulating paper because the transformer oils can be replaced when it deteriorates [15,16].

The technical condition of the transformer determines the operational risks associated with it. The transformers' state can be determined using the methods indicated in the instructions observed in each country or the operator, such as the instructions for the test methods found in the American transformer diagnosis guide [17,18]. These methods are used periodically when performing transformer maintenance or when a transformer malfunction is suspected. These methods include oil condition diagnosis, insulation resistance tests, and turn ratio measurement [19,20]. Therefore, the standard evaluation of the technical condition of the transformer depends on the periodic tests because it is the easiest method, and the oil insulation test and the analysis of dissolved gases are among the essential methods [21]. In addition, some advanced techniques were used in transformer fault diagnoses, such as Frequency Domain Spectroscopy (FDS), Frequency response analysis (FRA), and partial discharge measurement [22-24].

The condition of the transformers can be identified via periodic tests. These tests are categorized into (i) oil quality tests such as Breakdown Voltage (BDV), Water content (WC), Interfacial tension (IFT), and oil colors (OC), (ii) Dissolved gas analysis (DGA), which measures the concentration of hydrocarbon gases, which develops due to several stresses on the transformer (electrical and thermal stresses), (iii) the furan analysis (2-FAL), which is the indicators to the degradation of the insulating paper, and (iv) the CO and CO_2, which develops due to deterioration of the insulating paper [25].

The test issue is the cost due to the advanced equipment used to perform these tests. So the importance of the current work was focused on which tests were essential to indicate the paper condition and then the transformer aging and its lifetime. Furthermore, is the furan analysis only responsible for identifying the insulating paper's DP? In addition, an artificial neural network (ANN) was used to determine the transformer condition based on the results of the crucial tests. The results indicated high accuracy of the ANN to identify the transformer state (93%).

II. Methodology and experimental tests

When a transformer malfunction occurs or is suspected, the maintenance and testing team quickly checks the transformer's condition through several tests. These routine tests follow the instructions of existing specifications such as IEEE and IEC, including electrical, dissolved gas, and oil quality tests. Unfortunately, these tests consume a lot of time, effort, and cost. Transformer aging assessment is based on the determination of the insulation paper's degree of polymerization (DP). The value of DP is determined based on the results of measurements and tests of transformer oil, so the oil quality tests and furan analysis are the main tests in determining DP.

The current study was established based on Dissolved gas analysis (DGA) and quality oil test results. The dissolved gas analysis is one of the necessary tests, which measures the concentration of the hydrocarbon gases developed from the degradation of insulating oil and papers. Hydrocarbon gases are categorized as combustible and incombustible gases. The combustible gases are Hydrogen, Methane, Ethan, ethylene, and acetylene. On the other hand, incombustible gases are carbon monoxide and carbon dioxide. Carbon monoxide and carbon dioxide are developed due to cellulose decomposition, which is used as the weight parameters to diagnose the paper state. The transformer oil deteriorates during the regular operation of the transformer due to electrical and thermal stresses. The oil quality is identified based on dielectric strength, acidity, interface tension (IFT), power factor, and color. So, In this work, we shed light on the investigation of the essential variables that determine the state of insulation paper to ensure the lowest possible cost for these tests. Gas chromatography is used to separate the gases between the stationary and mobile layers based on the instructions of ASTM D3612-2 [26]. In addition, High-performance liquid chromatography can be used to detect the furanic components based on the instructions on ASTM D5837 [27]. The oil's water content (WC) can be measured based on Karl Fisher's Approach using the 899 Coulometer device. A Baur oil tester was used to measure the breakdown voltage (BDV), and the oil's acidity (ACI) was measured in terms of mgKOH/mg using an acidity kit.

A total of 147 data samples were collected from the Saudi Electricity Company maintenance section in Jedda. For the transformer under investigation, the transformer oils drew and sent to the central chemical laboratory for analysis and tested. All sample results were collected as in Table 1, which illustrates some of these results.

Table 1. Some of the data samples result from 147 data samples

CO (ppm)	CO2 (ppm)	BDV (kV)	WC (ppm)	ACI (mg KOH/mg)	IFT (mN/m)	OC	2-FAL (ppm)
187	2887	38	4	0.08	21	4	2.062
164	2650	28	9	0.08	20	4	3.929
326	5263	57	6	0.24	18	5	13.236
491	2150	21	6	0.09	25	3	0.24
416	2089	24	6	0.05	27	2.5	0.046
383	5394	28	6	0.016	36	0.5	0.117

730	6545	30	7	0.25	18	6	6.884
683	6168	20	7	0.24	18	5.5	6.063
363	1571	15	30	0.03	31	1.5	0.026
606	3423	41	19	0.09	24	3.5	0.21
235	1957	49	2	0.01	39	0.5	0.018
242	1892	34	4	0.01	39	0.5	0.013
708	3340	36	4	0.1	32	2	0.221
976	6734	43	7	0.06	32	1.5	0.152
1548	9457	38	6	0.03	35	1.5	0.093
301	4181	41	11	0.21	18	4.5	8.647
362	3917	48	5	0.16	21	4.5	1.754
198	2627	52	8	0.16	20	4.5	4.661

Table 2 shows how the paper state can be categorized based on the magnitude of the DP [28]. The distribution of the 147 dataset samples is illustrated in Table 3. In this table, 94 data samples are categorized as category 1, referring to the normal aging rate, 11 for accelerating aging rate, 30 for Excessive aging danger zone and high risk of failure, and 12 for samples for End of expected life.

Table 2. The classification categories of the insulating paper state are based on DP value and its description

DP	**>600**	**<600-400**	**<400-200**	**<200**
Class	1	2	3	4
Description	Normal aging rate	Accelerating aging rate	Excessive aging danger zone and high risk of failure	End of expected life

Table 3. Distribution and number of the data samples That were used in this study

Category	**Number of samples**
1	94
2	11
3	30
4	12
Total	147

The distribution of the magnitude of each test variable against the samples can be illustrated in Figures 1-9. Figure 1 shows the Paper state based on the DP class in Table 2. The distribution of the carbon monoxide (CO) through the samples is shown in Figure 2.

The nonlinearity distribution of the CO through the samples was observed, and refer that CO has no relation to determining the paper state class and relates only to the degradation of the cellulose.

Figure 3 illustrates that CO2 also has no connection to the paper state class due to the nonlinearity distribution through the samples compared to the paper state class in Figure 1.

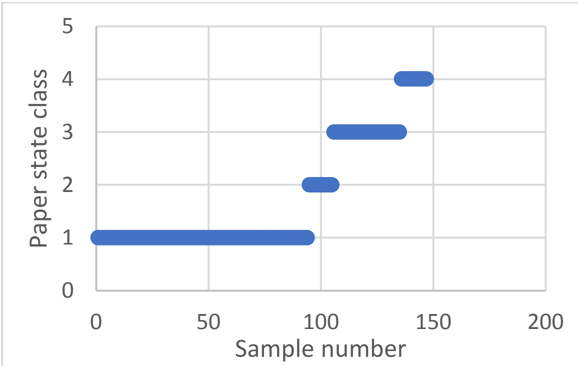

Figure 1. Paper state class

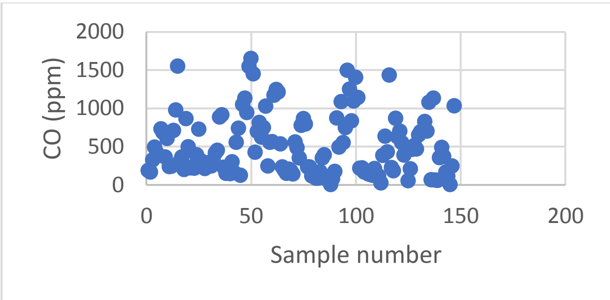

Figure 2. Distribution of the CO concentration against sample number

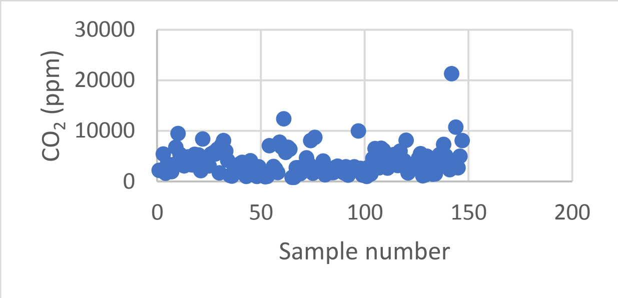

Figure 3. Distribution of the CO2 concentration against sample number

The breakdown voltage (BDV) misses the linearity with the paper state class as in Figure 4, so no link between the breakdown voltage and paper state class. Figure 5 shows the relation between the paper state class and the water content (WC) where an increase of the water content refers to excessive aging of the insulating paper and leads to the end of the expected life of the paper and then to the transformer.

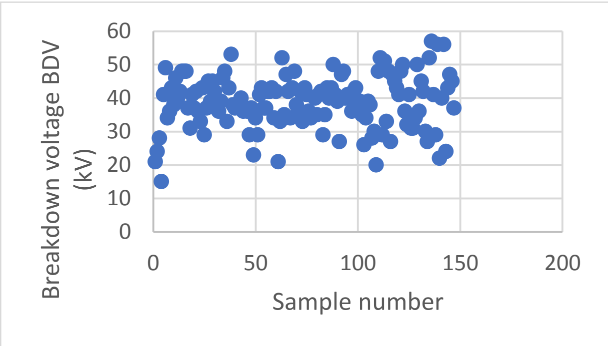

Figure 4. Distribution of the BDV against sample number

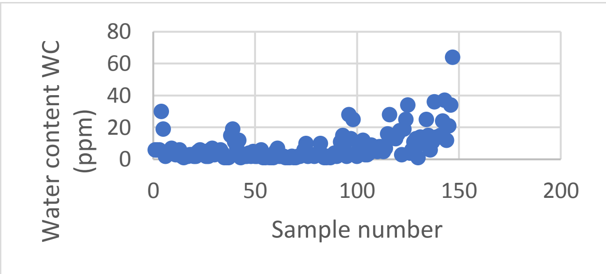

Fig. 5. Distribution of the WC concentration against sample number

The acidity (ACI) and oil color (OC) have the same trend as WC, referring to a relation between their magnitude and the paper state class. An increase in ACI and OC results in a dangerous state of the insulating oil and then in the transformer state. These facts are indicated in Figures 6 and 8.

On the other hand, Figure 7 refers to an inverse proportion between the oil's interfacial tension and the paper's state; a decrease of the interfacial tension refers to the dangerous state of the insulating paper.

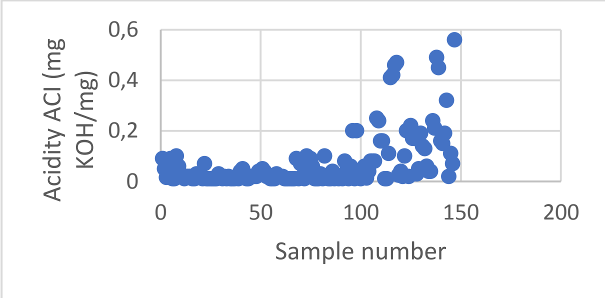

Figure 6. Distribution of the Acidity (ACI) against sample number

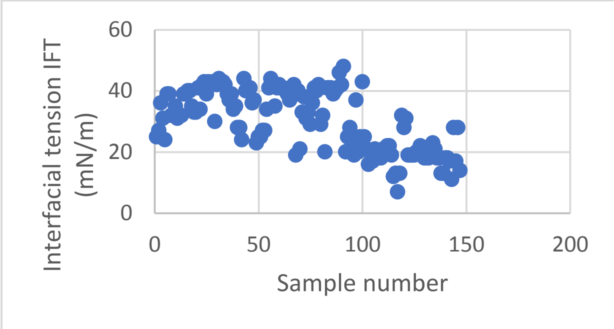

Figure 7. Distribution of the IFT against sample number

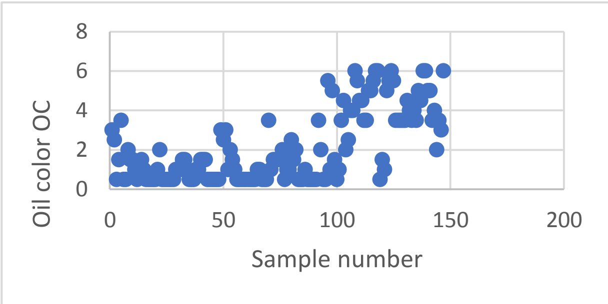

Figure 8. Distribution of the OC against sample number

Figure 9 explains the distribution of the 2-FAL through the sample number, it gives a good trend with the paper state class. An increase in the 2-FAL is a good indicator of the degradation of the insulating paper. Therefore, the results indicate a good linear relationship among WC, ACI, IFT, OC, and 2-FAL with the paper state. So, an artificial neural Network can be used as a diagnostic tool to get the paper state easily based on using WC, ACI, IFT, OC, and 2-FAL as input variables to the ANN.

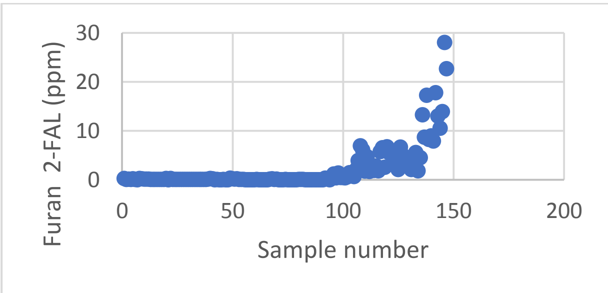

Figure 9. Distribution of the 2-FAL concentration against sample number

III. Artificial Neural Network (ANN)

The relation among the paper state class and the five other parameters WC, ACI, IFT, CO, and the 2-FAL can be mapped using the ANN, considered a powerful tool. A feed-forward back propagation ANN type was used based on the Matlab tool (nntool). First, the weighted inputs with a bias value are operated with a prechosen approximator, which refers to the transfer function so that the output can be compared with the target output. In each iteration, the errors will be reduced by alternating the weight.

The structure of the feed-forward backpropagation ANN was designed to develop high accuracy, as shown in Figure 10. There are input and output nodes with two layers, the hidden and output layer. The input node receives the five variables WC, ACI, IFT, CO, and 2-FAL, one hidden layer with 10 neurons, the output layer, and finally, the output node. The selected feed-forward backpropagation is a standard structure with high pattern recognition ability [29-30].

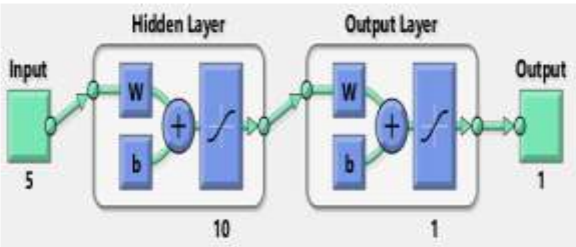

Figure 10. The ANN structure

The information on the feed-forward backpropagation ANN can be explained as follows,

- The training function is TRAINLM, which is the function that updates weight and bias values according to Levenberg-Marquardt optimization. It considers the fastest backpropagation algorithm in the toolbox but needs more memory.
- The adaptation learning function is LEARNGDM, which refers to Gradient descent with momentum weight and bias learning function.
- Performance function is MSE, which uses the mean squared errors to measure the network performance.
- The transfer function is TANSIG, which refers to the Hyperbolic tangent sigmoid transfer function used to compute the layer's output from the net input.

Figure 11 illustrates the training performance of the ANN. The network errors decrease after more epochs of training, but it increases on the validation data when the network fits the training data. Normally, the training will stop when six consecutive increases in validation error are observed. Therefore, the best network performance can be considered when the validation error is the lowest. In our study, the best network performance occurs after 11 epocs, as shown in Figure11.

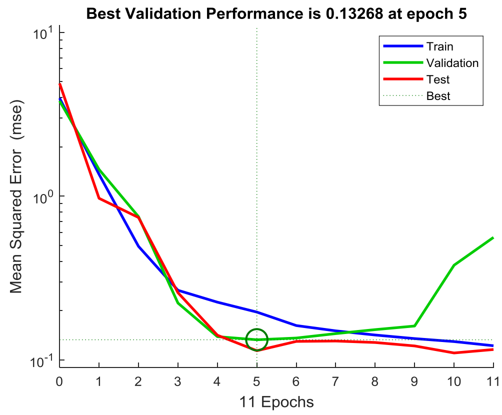

Figure 11. ANN network performance

Figure 12 shows the four plots that present the training, validation, testing, and overall accuracy result. In these figures, the dashed line refers to the perfect result when the output is equal to the target, and the solid line indicates the best fit of the linear regression between the outputs and the desired targets. R-value explains the relationship between output and the targets. If R is equal to one, it means a linear relationship between the outputs and the targets; if it is zero, it refers to no relationship between the outputs and the targets. Our study's overall relationship between the outputs and targets indicates 92.4%.

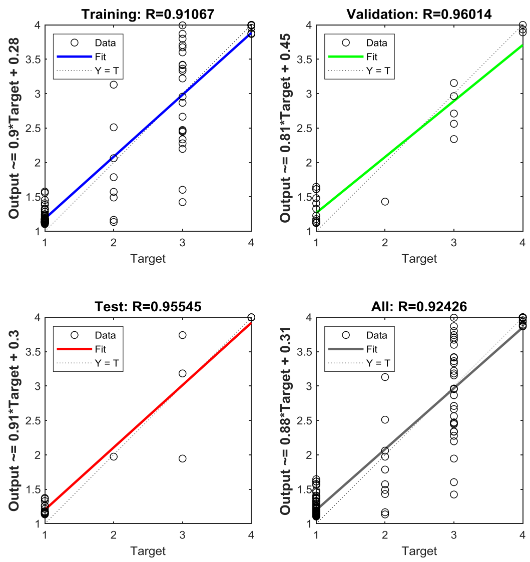

Figure 12. Neural network training regression

A total of 147 data samples were used in the training process of the ANN model. After training, the weighted matrix (ANN network for testing) was called in Matlab command and testing the input data again to determine the prediction accuracy of the constructed ANN.

Table 4 illustrates the prediction accuracy of the constructed ANN model when using the input data as the testing data samples. In addition, Table 4 shows how many corrected prediction samples are in each class, how many incorrect predicted samples are, and which class are. For example, the corrected number of the predicted sample of class 1 is 93, and the incorrect sample is only 1 and belongs to class 2. Therefore, the prediction accuracy of class 1 is 98.93%. On the other hand, the accuracy of class 2 is 54.54, the correct predicted samples is 6 from 11 samples, and the other 5 incorrect samples are categorized as 4 samples for class 1 and one sample for class 3.

Table. 4. The prediction accuracy of each paper state class.

Paper state class					**accuracy%**
	1	2	3	4	
1	**93**	1	0	0	98.93
2	4	**6**	1	0	54.54
3	0	5	**24**	1	80
4	0	0	0	**12**	100
Overall prediction accuracy					**93.87**

IV. Conclusion

Regular and maintenance tests are essential to check the transformer state. The insulating state paper state can be used as the indicator of the transformer aging and predict the expected lifetime. More tests can be used to identify the transformer state, but it is costly. Therefore, this study focused on which test is required to check the insulating paper and transformer state. The current research recognized that WC, ACI, IFT, CO, and the 2-FAL are the crucial tests that influence the paper state. Feed-forward back propagation was used to construct a prediction model to identify the paper state based on the training of 147 data samples with known DP value. So it was categorized into several paper states class as mentioned in the text. The prediction accuracy of the ANN model was 93.87%, which referred to the ability of the model to predict the paper state reasonably.

Declaration

- The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.
- The authors declare that this article has not been published before and is not in the process of being published in any other journal.
- The authors confirmed that the paper was free of plagiarism

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