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Implementation of Artificial Neural Networks for Determining Power Transfomer Condition

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Abstract—**Power transformer is one of the most critical and expensive components in power grid which occupies almost 60% of total investment. Due to the expensiveness of power transformer investments, monitoring and maintenance of transformer condition are the important tasks in the field. There exist various diagnostic methods to monitor transformer health condition in the literatures. However, these methods fail to interpret the condition when multiple faults are occurred. Moreover, the appearance of artificial intelligence attracts many interests of researchers. In this paper, the 2-tier multi-layer neural network as a family of AI is proposed to be used for diagnosing transformer health condition. By using this method, the accuracy of interpretation on tier-1 and tier-2 analysis achieves 92.4% and 99.5%, respectively. The proposed method is also validated using *k*-fold cross-validation.**

Keywords: ANN, cross-validation, health index, transformer

I. INTRODUCTION

POWER transformer is one of the most critical and expensive components in power grid. They occupy almost 60% of total investment in high-voltage substations [1]. Monitoring and maintenance of power transformer become an important task in many power utilities to enhance the financial and technical performances of power transformer. One of the important aspects in the monitoring and maintenance activities is health condition. Health condition of the transformer can be used as a parameter to improve reliability and assist in determining appropriate asset management decisions benefits, enable operators to develop effective maintenance and replacement strategies based on the condition of the transformer, identify transformers that could benefit from life extension measures [2]. The health condition is influenced by several factors such as, chemical, electrical and mechanical parameters [3]. The purpose of the asset condition assessment is to detect and quantify long-term degradation and to provide a tool of quantifying remaining life of the asset.

Various techniques were proposed to diagnose the health condition of power transformer. Dissolved Gas Analysis (DGA) [4], Degree of Polymerization (DP) measurement [5], [6] and Furan analysis [7] are very commonly used by electric utilities.

Dissolved Gas Analysis (DGA) is the most common technique to diagnose the faults of transformer such as low and medium temperature thermal fault, high temperature thermal fault, discharge of low energy, arcing, and partial discharge. These faults are detected by analyzing the concentration of dissolved gases such as Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4), Acetylene (C_2H_2), Carbon Monoxide (CO), and Carbon dioxide (CO_2). The interpretation techniques of these faults have been established in various industrial standards, such as IEEE and IEC [9], [10].

However, the DGA fails to estimate transformer end of life. Hence, another technique namely furan analysis is proposed. Furans are organic compounds in the transformer oil which are formed by degradation of paper insulation. By measuring the furan compounds concentration, remaining life of paper insulation can be estimated. Furans measurement is also related to the IFT and acid number.

Another diagnosis technique which is usually used in the assessment namely insulation test. The transformer insulation test includes insulation power factor test and excitation current test [11]. Besides that, key gas method and ratio method [8]-[10], [12] have also been used to interpret the condition of transformer.

Currently, artificial intelligence technique is proposed to be used as a diagnostic tool for diagnosing the power transformer health. By using artificial intelligence, the rule can be generated automatically and the decision would be made. One of the benefits of artificial intelligence is to minimize the subjective perspective of the diagnosis. The uses of intelligence diagnostic methods were reviewed in [13].

Fuzzy logic and artificial neural network are the most commonly used artificial intelligence techniques for power transformer diagnosis. However, there is a significant difference between fuzzy logic and artificial neural network. In Fuzzy Logic, the rule of diagnosis has to be defined in advance and cannot learn directly from data samples, while the Artificial Neural Network can learn directly from data samples through a set of training samples and update the knowledge of diagnosis directly.

The first step of diagnosing transformer health condition is determining the health index of transformer. Several techniques are proposed to determine the health index of the transformer conditions. In [1], clear steps of calculating the transformer health condition are presented. However, during the calculation of the health index the presented methods give the measurements of winding resistance and oil quality more weight than the measurement of total furans which is an important indication to the degree of polymerization of the solid insulation. The degradation of solid insulation (paper) can be considered the primary reason for a transformer end of life [14], [15]. The work done in [16] includes all parameters affect the health of the transformer; however, the paper did not reveal the method used in the calculation of the health index. The total furan in the transformer oil is ignored in the method presented in [17].

A comprehensive transformer diagnosis was also presented in [11]. In this diagnostic method, all transformer parameters are involved with DGA and furan as the main parameter to determine the transformer condition. Besides that, a two tier diagnoses is used to represent primary and secondary parameter in transformer diagnosis.

In this paper, an implementation of artificial neural network for diagnosing transformer health presented in [11] is proposed. The use of artificial neural network is to evaluate the health condition of power transformer by using 2-tier neural network. The artificial neural network is used to diminish personal distraction of choosing transformer diagnostic methods which are available in various approaches. Using the proposed method, operator could determine condition of transformer from the measurement data directly with no more calculation to obtain health index. Afterwards, the performance of proposed method in terms of accuracy is evaluated using measurement data taken from the Distribution System of State Electric Company at Indonesia.

The rest contents of this paper are organized as follow. Section II describes the Transformer Diagnostic Parameters while the proposed diagnostic method is presented in Section III. Discussions of results and Conclusions are elaborated in Section IV and Section V, respectively.

II. The Proposed Diagnostic Method

The idea behind the proposed diagnostic method comes from the fact that conventional fault detection methods, such as Roger Ratio or Doernenburg ratio, which are usually used in DGA diagnostic technique, fail to give appropriate diagnostic. This condition occurs when the transformer experiences multiple faults since the generated gases from different faults are mixed up resulting in confuse ratio between different gas components.

This drawback can be overcome by using artificial intelligence such as, artificial neural network (ANN). ANN is an information processing paradigm that is inspired by the biological nervous system in human brain [18]. ANN has a sophisticated ability to derive meaning from complicated or imprecise data. They can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

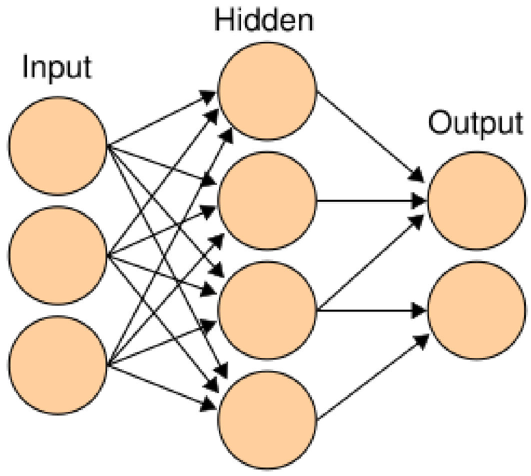

Figure 1 Multi-layer perceptron Neural Network

In this paper, one of the ANN class, namely Multi-Layer Perceptron with Back Propagation is proposed to estimate the health condition of a transformer. In the multi-layer perceptron, the neural network consists of several layer including input layer, output layer, and hidden layers. In the hidden layer, there exists an activation function. Whereas, Back Propagation is a learning algorithm which usually used by the perceptron to adjust the weight of nodes in order to obtain the target value. Figure 1 represents the multi-layer perceptron neural network.

A multi-layer perceptron neural network is implemented to the transformer health diagnostic mechanism presented in [11] which has 2-tiers of calculations. Accordingly, the proposed method is also designed by using 2-tiers of neural networks, as depicted in Figure 2. Transformer health parameters which are fed into the first tier input are DGA, furan, transformer power factor, age of transformer, operation and maintenance history. Each of combustible gasses involved in DGA analysis are considered as tier-1 input separately. The second tier is activated when the tier-1 result indicates the transformer condition of warning or poor. Transformer health parameters which are involved in the second tier are the measurement result of turn ratio test, short circuit impedance, direct current winding resistance, frequency response analysis (FRA) and degree of polymerization (DP).

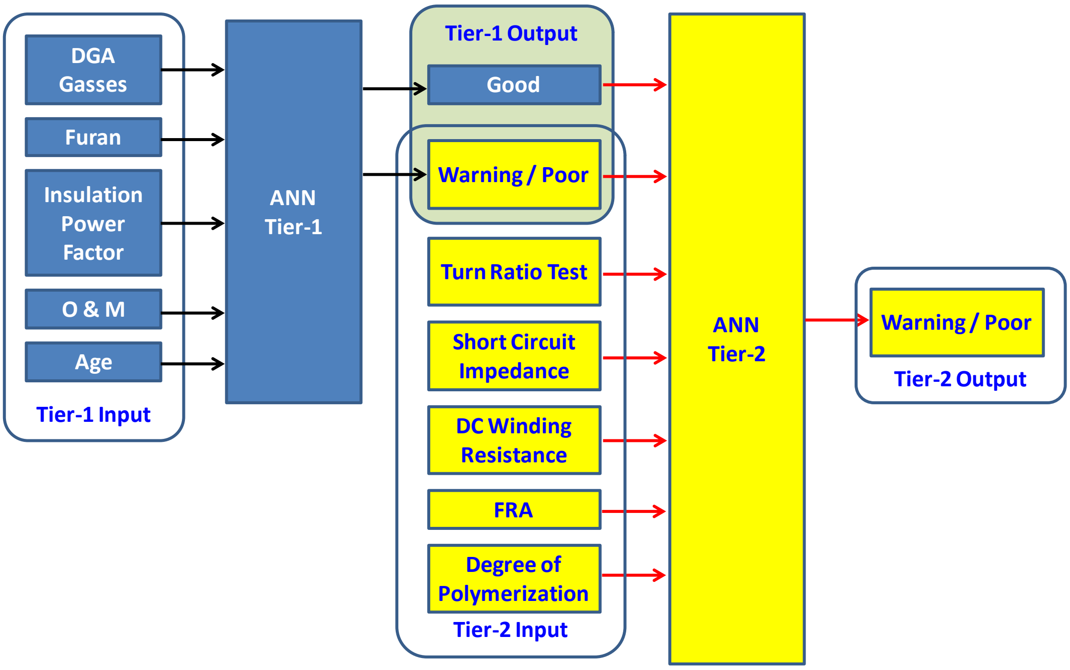

Figure 2 A 2-tier Multi-layer perceptron neural networks

The ANN in each tier is designed by using two hidden layers to increase the ability of information learning. Each hidden layer consists of several nodes which influence the performance of neural network. Hence, the number of nodes should be determined appropriately. Table 1 shows the influence of the number of nodes in each hidden layer to the ANN performance. From the table, information can be extracted that by using 10 nodes for both hidden layer 1 and hidden layer 2 the performance and accuracy of ANN tier-1 will achieve 0.043 and 91.3%, respectively. There is also another possibility to increase the accuracy of ANN tier-1 by choosing 15 nodes in hidden layer 1 and 10 nodes in hidden layer 2. However, we should deal with the complexity of computation when choosing this scenario. Furthermore, by similar mechanism, the number of nodes for ANN tier-2 can also be determined. By using 10 nodes in both layer 1 and layer 2, the performance and accuracy achieves 0.0048 and 99.5%, respectively.

Table 1 The influence of node number to the performance of ANN Tier-1

Node Layer 1	Node Layer 2	Performance	Accuracy
10	10	0.043	91.3 %
5	10	0.079	82.2 %
15	15	0.048	91.6 %
5	5	0.055	89.5 %
15	10	0.043	92.9 %
15	5	0.053	91.1 %
5	15	0.082	82.5 %
20	10	0.041	92.4 %

III. DISCUSSIONS

Implementation of the proposed method is divided into two steps, namely health index calculation and artificial neural network design. As the key aspect of determining transformer condition, the health index of transformer can be calculated using classification index of transformer quality of each transformer diagnostic technique. Several quality classifications of each technique have been defined in [11]. Additionally, to complete the quality classification of transformer condition, the State Electric Company of Indonesia is also proposed the quality classification of transformer which is considered as confidential in this paper.

Further, the 2-tier artificial neural network is designed using those calculation results. The input and target dataset of artificial neural network are derived from the calculation of transformer health index above. Input dataset come from the measured data of each transformer diagnostic technique, while target dataset of artificial neural network uses the health index of transformer.

In this paper, designing the artificial neural network are conducted using 15910 measurement data from the transformer monitoring system of Distribution System of State Electric Company of Indonesia. The Distribution System consists of high-voltage transformers which have primary voltage of 150 kV. These measurement data are obtained through either different transformer or a transformer measured in different time. These measurement data are then manually calculated to obtain health index of transformer.

After calculation the measurement data, a multi-layer perceptron neural network is trained using 12728 measurement data. This training process is conducted to train the system in order to be able to estimate the condition of transformer. Afterwards, 1591 data are used to validate the system and the remaining data are used to test the system. Validation process is conducted to evaluate each of the obtained artificial neural network model. The model with highest accuracy is selected. Then, the selected artificial neural network model is evaluated using test data [19].

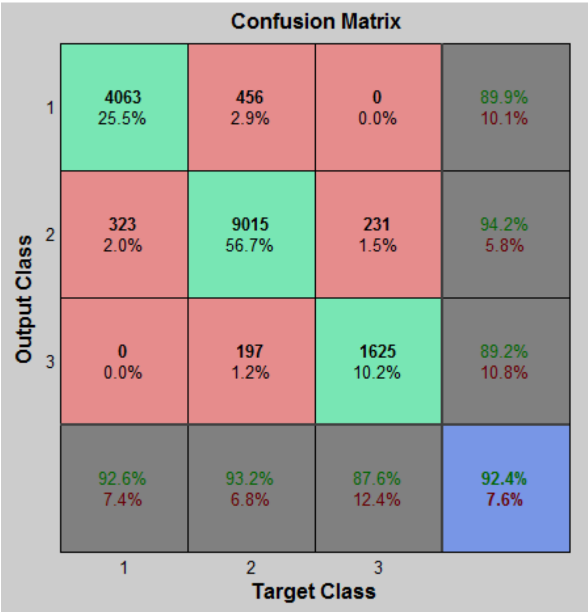

Figure 3 ANN Result of Tier-1

The output of selected ANN model is obtained through the numerical analysis as depicted in Figure 3 and Figure 4 for tier-1 and tier-2 results, respectively. As shown in these figures, a horizontal axes indicates the target of ANN that has been determined through calculation process, while the vertical axes represents the output of ANN. Further, the green and red blocks represent the matching and un-matching results between target and output of ANN. Class 1, 2 and 3 shown in the figure indicate the classification condition of transformer, namely Good, Warning and Poor, respectively. The bottom row indicates the accuracy of ANN output to determine the transformer condition to each class of target.

The result of each figure can be described as follow. Generally, Figure 3 shows that from tier-1 of ANN the majority of transformers are operated in warning or moderate condition. The accuracy of ANN interpretation for this system is around 92.4%. As shown in Figure 3, 4063 output of ANN exactly match to the target class of ANN, with error around 323 data or 2.0%. While 9015 data and 1625 data are exactly match to the second and third target class of ANN respectively.

The confusion matrix of tier-2 output is shown in Figure 4. Contrary to Figure 3, number 1, 2 and 3 in output or target class axes indicate poor, warning and good condition of transformer, respectively. The third column and row of the table show value of zero since in tier-2 of ANN there is no more good condition to be considered. The ANN tier-2 is only used to further diagnose the transformer operated in warning or poor condition.

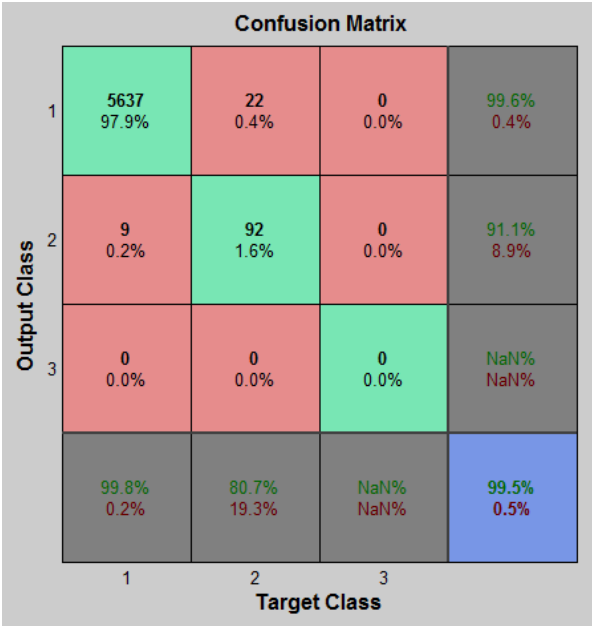

Figure 4 ANN Result of Tier-2

Generally, the accuracy of ANN to interpret the condition of transformer in tier-2 analysis is around 99.5%. After conducting tier-2 ANN analysis, 5673 transformers are operated in poor condition. This condition indicates that those transformers have to be considered for replacement of transformer to the new one with good condition to keep the production running well.

Furthermore, to evaluate the robustness of the selected artificial neural network, *k*-fold cross-validation scheme is used. Cross-validation is widely used in machine learning applications as reported in [19]-[21]. In *k*-fold cross-validation, the available data are divided into *k* subsets of the same size. One subset is used as test data, while the remaining (*k*-1) subsets are used as training data. Each subset is used exactly once as the test data. The cross-validation yields mean error or accuracy of estimation.

The calculated health index obtained from measurement data are then divided into 10 subsets and applied consecutively to the selected ANN model to obtain mean error or accuracy value. Each subset consists of 1591 measurement data.

From the numerical analysis, the average accuracy of the selected artificial neural network by k-fold cross-validation for tier-1 and tier-2 of ANN are obtained. The average of accuracy interpretation of ANN tier-1 is around 91.4% with the range of accuracy from each iteration between 91.2-91.6%. Whereas, The average of accuracy interpretation of ANN tier-2 is around 99.6% with the range of accuracy from each iteration between 92.4-92.8%. Its mean that selected neural network is stable to estimate the condition of power transformer.

IV. CONCLUSIONS

The usage of one of artificial intelligence type, namely multi-layer perceptron neural network with back propagation to diagnose transformer condition is addressed. In order to increase the ability of information learning, the node number selection is also considered. A 2-tier neural network to interpret transformer condition from measurement data is implemented. By using these methods, the accuracy of interpretation on tier-1 and tier-2 analysis achieves 92.4% and 99.5%, respectively. Besides that, the selected neural network has also been validated by using *k*-fold cross-validation with *k* equal to 10.

REFERENCES

[1] A. Jahromi, R. Piercy, S. Cress, J. Service and W. Fan, "An approach to power transformer asset management using health index," *IEEE Electrical Insulation Magazine*, vol. 25, pp. 20-34, 2009.

[2] D. Hughes, G. Dennis, J. Walker and C. and Williamson, "Condition based risk management (CBRM)- enabling asset condition information to be central to corporate decision making," in *Proc. of the First World Congress on Engineering Asset Management* (WCEAM), Gold coast, Queensland, Australia,11-14 July, 2006.

[3] X.Zhang and E. Gockenbach, "Asset-Management of Transformers Based on Condition Monitoring and Standard Diagnosis [Feature Article]," *IEEE Electrical Insulation Magazine*, vol. 24, pp. 26-40, 2008.

[4] Duval M., ''Dissolved Gas Analysis:It Can Save Your Transformer'', *IEEE Electrical Insulation Magazine*, Vol. 5, No. 6, pp.22-27.1989.

[5] Shroff D. H. and Stannett A. W, ''A Review of PaperAgeing in Power Transformers'', *IEE Proc*., part C, Vol. 132, pp. 312-319, 1985.

[6] Oommen T. V. and Arnold L. N, ''Cellulose Insulation Materials Evaluated by Degree of Polymerization Measurements'', *IEEE Proceeding of 15th Conference on Electrical Electronics Insulation*, Chicago, IL, USA, pp. 257-261, 1981

[7] IEC, ''IEC 61198 1993-09, Mineral Insulating Oils Methods for the Determination of 2-furfural and Related Compounds'', 1993

[8] Rogers R.R, "IEEE and IEC codes to interpret faults in transformers, using gas in oil analysis", *IEEE Transaction of Electrical Insulation* Vol. 13, No. 5, pp. 349–354, 1978.

[9] IEC Publication 599, "Interpretation of the Analysis of Gases in Transformers and Other Oil-Filled Electrical Equipment in Service", first ed., 1978.

[10] IEEE, "IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed transformers", IEEE Standard C57.104-1991.

[11] Hydroelectric Research and Technical Services Groups - US Dept. of Interior, "Facilities, Instructions, Standards and Technique (FIST) - Transformers Diagnostic, "Vol. 3-31, June 2003.

[12] Dornenburg E., Strittmater W., "Monitoring oil cooling transformers by gas analysis", Brown Boveri Rev. 61 238–274, 1974

[13] A. Singh, P. Verma, "A review of intelligent diagnostic methods for condition assessment of insulation system in power transformers," in *Proc. of International Conference on Condition Monitoring and Diagnosis (CMD), 2008.* pp.1354-1357, Beijing, 21-24 April 2008

[14] M. K.Pradhan, T.S. Ramu, "Criteria for estimation of end of life of power and station transformers in service," *Annual Report Conference on Electrical Insulation and Dielectric Phenomena (CEIDP) 2004.* pp.220-223, 17-20 Oct. 2004

[15] H. Herman, M.J. Shenton, G.C. Stevens, R.J. Heywood, "A new approach to condition assessment and lifetime prediction of paper and oil used as transformer insulation," *Proceedings of the EEE 7th International Conference on Solid Dielectrics (ICSD) 2001,* pp.473-476, Eindhoven, 2001.

[16] N. Dominelli, "Equipment health rating of power transformers," *Conference Record of the 2004 IEEE International Symposium*, *Electrical Insulation*, pp. 163-168, 19-22 Sept. 2004.

[17] S. Miletic, "Asset condition assessment by health index benchmarking," in *Proc. of 20th International Conference and Exhibition on Electricity Distribution - Part 1 (CIRED) 2009*, pp.1-4, Prague, Czech Republic, 8-11 June 2009

[18] B. Coppin, *Artificial Intelligence Illuminated*. Sudbury, Massachusetts, USA: Jones and Bartlett Publishers, 2004

[19] H. Ishibuchi, H. Y. Nakashima, Y. Nojima, "Double cross-validation for performance evaluation of multi-objective genetic fuzzy systems," in *Proc. of IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems (GEFS) 2011*, pp.31-38, Paris, 11-15 April 2011

[20] Yong Liu, "Create Stable Neural Networks by Cross-Validation," in *Proc. of International Joint Conference on Neural Networks (IJCNN) 2006*. pp.3925,3928, Vancouver, 16-21 July 2006

[21] D.K. Barrow, S.F. Crone, "Crogging (cross-validation aggregation) for forecasting — A novel algorithm of neural network ensembles on time series subsamples," in *Proc. of International Joint Conference on Neural Networks (IJCNN) 2006*, pp.1-8, Dallas, 4-9 Aug. 2013.