Machine Learning Approaches for Estimating the Degree of Polymerization of Paper Insulation Impregnated with Uninhibited Insulation Oils

Martua Mario Gultom[1,2*], Tobias Kinkeldey[3], Peter Werle[3], Suwarno[4]

[1] School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Bandung, 40132, Indonesia.

[2] PT. PLN (Persero), Jakarta, 12160, Indonesia.

[3] Leibniz Universität Hannover, Institute of Electric Power Systems, Hannover, Germany.

[4] School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Bandung, 40132, Indonesia.

* Corresponding author. Tel.: +628115777559; email: martua.mario@gmail.com
Manuscript submitted May 16, 2021; accepted August 5, 2021.
doi: 10.17706/ijmse.2021.9.4.59-70.

Abstract: The condition of the oil-impregnated paper is an essential point of life diagnostics for a power transformer. The degree of polymerization (DP) of paper insulation is considered as a good indicator for the determination of the deterioration level of the insulation paper that indicates the remnant life of the transformer. In these years, researchers have been able to implement classification analysis methods on a power transformer through a database of measurement data. Further studies related to the development of machine learning for the assessment of power transformers must be accomplished in order to formulate a comprehensive model.

The objective of this paper is to develop a reliable algorithm to determine the current state of the oil-paper insulation based on the monitoring characteristics. With nominal classification base and numerically base using Fuzzy Inference System (FIS) and Back Propagation Neural Network (BPNN), and study its behavior. Both methods evaluate dielectric characteristic parameters, i.e., acidity and interfacial tension (IFT), of the insulating oil, and dissolved gas analysis (DGA) measurement results; the concentration of carbon monoxide (CO) and carbon dioxide (CO2), and four possible combinations variable input.

This paper describes the structure of FIS and BPNN and gives a comparison of both methods to the performance to data sets of a real transformer fleet. The result shows that both models can be used to predict the value of DP accurately and to improve the reliability of the result.

Key words: Transformer, degree of polymerization, dissolved gas, dielectric characteristic, FIS, back-propagation neural network.

1. Introduction

Transformer is generally known as key electrical equipment [1]. It is of high importance to estimate the transformer condition precisely to avoid unwanted outages of the transformers. Because the unexpected failure of a transformer unit also involves high consequential costs [2]. If a defective transformer is part of a distribution system, the customer will be left without power. The cost of replacing the transformer itself is high, but the resultant cost can be considerable, potentially approaching a few time the cost-price for the transformer.

To increase of the availability of transformers, failures need to be detected at their initial stages. The condition of the transformer insulation determines the remaining life of the asset [3]. Various methods for artificial intelligence implementation have been proposed for estimating the condition of transformer or the Degree of Polymerization, i.e. Machine Learning based CO_2 & Acidity [4], Fuzzy method based IFT and Acidity [3], Fuzzy method based CO & CO_2 [5], ANFIS model based fault diagnosis [6], ANFIS to RSME comparative based DGA data [7], Support Vector Machine (SVM) based Oil measurement [8] and the newest is DP estimation with FIS based on ID3 algorithm decision tree [9].

In this paper, the objective is to develop a reliable algorithm to determine the current state of the oil-paper insulation based on the monitoring characteristics with nominal classification base and numerically base using FIS and BPNN, and study its behavior. Both methods evaluate dielectric characteristic parameters, i.e., acidity and interfacial tension (IFT), of the insulating oil and dissolved gas analysis (DGA) results; concentration of carbon monoxide (CO) and carbon dioxide (CO_2), and four possible variable combinations.

2. Methodology

2.1. Data Preparation

The data provided in this research originally came from measurement data of oil insulation from Schering Institute Laboratories-Leibniz University of Hanover (as a training data), and measurement data of post mortem (PM) oil insulation, samples of an service company (as a test data).

The data input is limited to measurement data of Acidity and IFT, due to the acidity and the IFT value are quite appropriate indicators to determine the condition of the insulation paper [10]. And the concentration of CO and CO_2, as these variables have the greatest correlation with the Degree of Polymerization value [9]

2.2. Fuzzy Inference System

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic [11]. The process of fuzzy inference involves membership function (MF), logical operation and If-Then rules. The inference process consists of the following steps:

a. Fuzzification.
b. Degree of activation
c. Implication
d. Aggregation
e. Defuzzification

The rule, generated through C4.5 algorithm decision tree, are implemented in the fuzzy inference system. The full description of this process is provided in the Fig. 1:

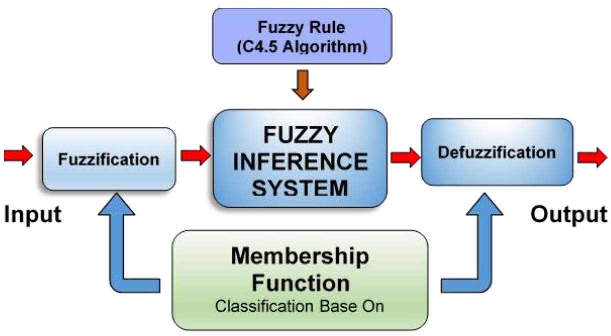

Fig. 1. Fuzzy inference system process.

2.2.1. C4.5 Algorithm Decision Tree

The decision tree algorithm builds a flowchart-like mechanism where each internal node denotes an attribute test, each branch corresponds to the test result, and each external (leaf) node denotes a class prediction. These systems are supported by several cases, each being in the same small categorize, that are described by their values for a specific set of attributes and provide a classifier that can predict the class to which a new case belongs [12].

C4.5, an extension of ID3, is a well-known decision tree algorithm to select the best attribute for classification [13]. C4.5 algorithm uses Gain Ratio while ID3 uses Information Gain. With the same procedure, C4.5 Algorithm calculates the Entropy (S) and the Information Gain (S,A), Splitting info (S,A) and Gain Ratio (S,A).

$$E\ (S) = -\sum_{i=1}^{n} p_i \cdot log_2\, p_i \tag{1}$$

$$Gain\ (S, A) = E(S) - \sum_{i=1}^{n} \frac{|S_i|}{|S|} \cdot E(S_i) \tag{2}$$

$$Gain\ Ratio\ (S, A) = \frac{Gain\ (S,A)}{Split\ Info\ (S,A)} \tag{3}$$

$$Split\ Info\ (S, A) = -\sum_{i=1}^{n} \frac{|S_i|}{|S|} \cdot log_2 \frac{|S_i|}{|S|} \tag{4}$$

where:

p_i = frequentist probability of an element/class i.

S = Collection of training examples

A = Attribute

$|S_i|$ = Number of elements in S_i

$|S|$ = Number of elements in S

i = All the possible values of the attribute

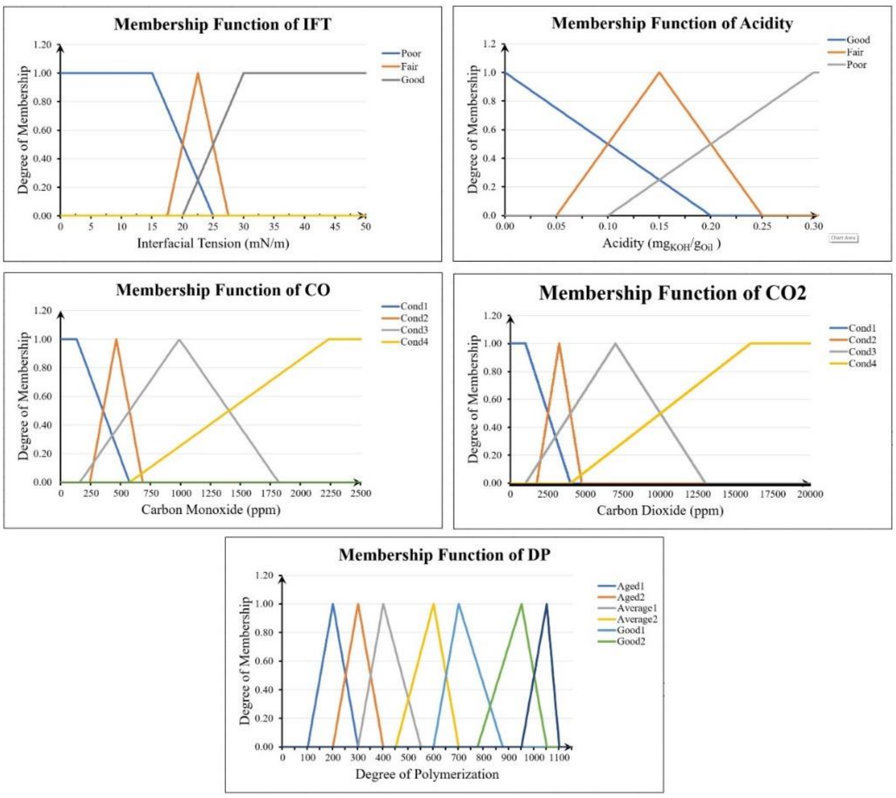

Fig. 2. Membership function of fuzzy system.

2.2.2. Membership Function

Membership function is constructed from symmetrical triangle curve on which assigned to condition class of each variable. Membership functions allow us to represent a fuzzy set graphically. The x-axis represents the value of the variable, whereas the y-axis represents the degrees of membership in the [0,1] interval.

Membership function curve of this research shown in Fig. 2, is based on the standard as follows:

a. IEC Std. 60422:2013 for Breakdown Voltage, Acidity, and Interfacial Tension.

b. IEEE Std. C57.104:2008 for CO and CO2

c. IEC Std. 60450:2007 for Degree of Polymerization.

2.3. Back Propagation System

The input information spreads to hidden layer nodes and is calculated by Sigmoid activation - the output information from the hidden layer nodes distributed to the output layer nodes. If the output layer cannot provide the preferred output value, return the error signal between the actual value and the desired output value along the original connection path.

2.3.1. Data Normalization

Before the training process is carried out, the data must be normalized. Normalization is to change the values of numeric data in the dataset to use a common scale, without distorting differences in the ranges of values or losing information. In this step, the data will be normalized into the range 0.1 to 0.9 using the equation:

$$X' = \frac{0.8(X-b)}{(a-b)} + 0.1 \tag{5}$$

where:

X' = normalized data

X = original data / initial data

a = the maximum value of the original data

b = minimum value of original data

2.3.2. Architecture of BPNN

The architecture used in the data training process uses a neural network with two hidden layers. The first hidden layer contains four neurons, and the second hidden layer contains three neurons. The architecture provided in the Fig. 3.

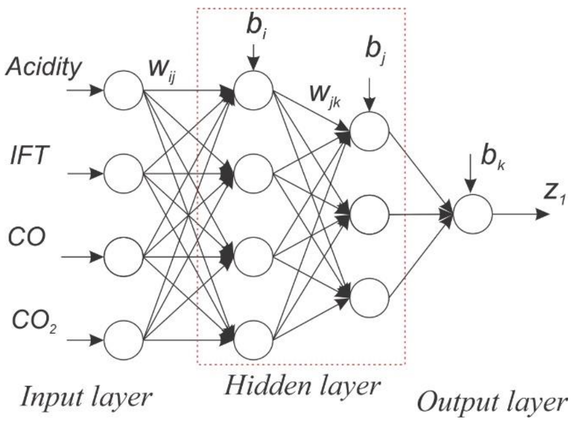

Fig. 3. Architecture of training neural network.

Initial weight and bias parameters are determined to the same value in order to obtain a similar training process to achieve balanced treatment for each combination input. Weight and bias values are obtained from the best training process, with four variables in the training process. These weights and biases are as follows:

Weight value from input to hidden layer 1:

$$w_{ij} = \begin{bmatrix} 0.040959 & 0.8357 & 0.94896 & 1.2494 \\ -0.099996 & 1.5659 & -3.1865 & -0.89014 \\ 1.1885 & -0.87322 & 1.0287 & -1.4767 \\ 0.49817 & -0.9258 & 0.010561 & -1.5137 \end{bmatrix}$$

Weight value from input to hidden layer 2:

$$w_{jk} = \begin{bmatrix} 1.3919 & 1.1426 & -0.21703 & -0.27904 \\ -0.73053 & 1.5742 & -0.42707 & 0.56075 \\ 0.81115 & -1.8702 & 1.1144 & -0.64249 \end{bmatrix}$$

Weight value from input to output:

$$[w_{ki} = -0.32446 \quad -1.3657 \quad -2.0853]$$

Bias value for each layer:

$$b_i = \begin{bmatrix} -1.9974 \\ 0.12593 \\ 1.6932 \\ 2.1984 \end{bmatrix}$$
$$b_j = \begin{bmatrix} -2.0225 \\ -0.69793 \\ 1.5575 \end{bmatrix}$$
$$b_k = [-0.093792]$$

In MATLAB, the neural network is trained for a given iterations number to verify the validity and performance of the network model. The model training process ends when the number of iterations has been reached, there is a lack of validity or the satisfaction of performance criteria. The performance curve of training regression is shown in Fig. 4 below.

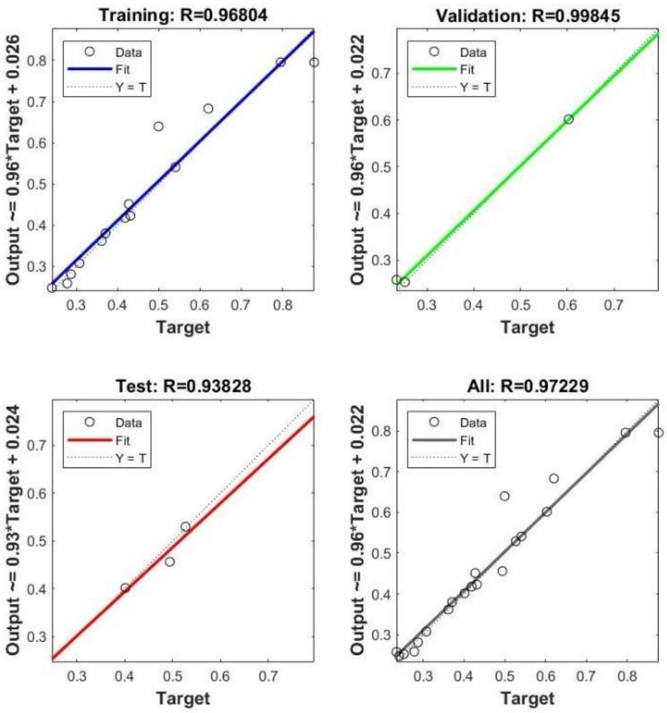

Fig. 4. Performance curve regression training via MATLAB.

2.4. Evaluation Method

This research has 3 (three) types of evaluation methods to know the performance of the estimation of each instance. The evaluation methods are based on DP class rate estimation, based on DP value deviation, and by Mean Absolute Error (MAE).

2.4.1. Evaluation based on DP estimated class

The outcome of both methods is evaluated by comparing the estimated DP class result with the actual DP class, which is defined by the *IEC 60450*. If the class estimation result is the same as the actual DP class, it is evaluated as "precise". If the estimation result is one class that varies above or below the actual DP class, it is graded as "close". If the estimation result is different in two classes above or below, it is evaluated as "Incorrect."

2.4.2. Evaluation based on DP value

In this assessment method, the estimation result is evaluated by deviation or error of the estimated DP from the actual DP measurement according to the criterion in Table 1.

Table 1. Evaluation Criterion by DP Value Error/Deviation

No.	DP value deviation	Evaluation
1	DP deviation < 75	Precise
2	75 ≤ DP deviation ≤ 150	Close
3	DP deviation > 150	Incorrect

2.4.3. Evaluation using MAE

Estimation result in this research is evaluated by Mean Absolute Error (MAE) to measure the accuracy, because MAE is the most natural measure of average error magnitude and give unambiguous measure of average error magnitude [14]. The MAE are calculated for the data set as:

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} = \frac{\sum_{i=1}^{n}|e_i|}{n} \tag{6}$$

where

y_i = prediction

x_i = true value

3. Result and Discussion

3.1. C4.5 Decision Tree

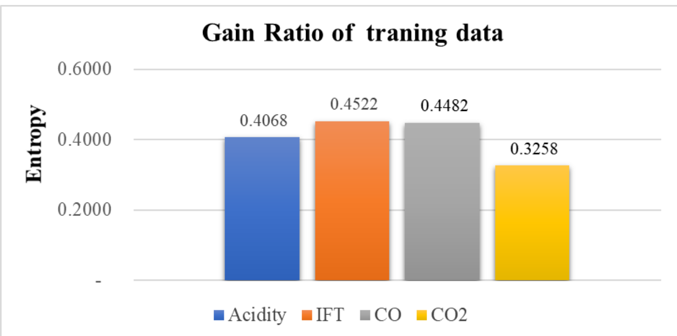

Fig. 5. Gain Ratio for each input variable

The calculation method for developing the decision tree that has been presented above gives the Gain Ratio value for each variable input, as shown in Fig. 5.

IFT has the highest gain ratio with 0.4522 against the other variable, so IFT becomes the root of the decision tree. The further step is to divide the data based on the IFT as a root of the tree. The classification of IFT divide into 3 (three) classes; there are Good, Fair, and Poor. Then, calculate the Gain Ratio of each group of data to find out the highest Gain Ratio for each class of IFT Condition. Then divide the new groups into smaller groups. This process should be performed till pure groups are reaches which cannot be divided into a purer group. The Decision tree is shown in Fig. 6.

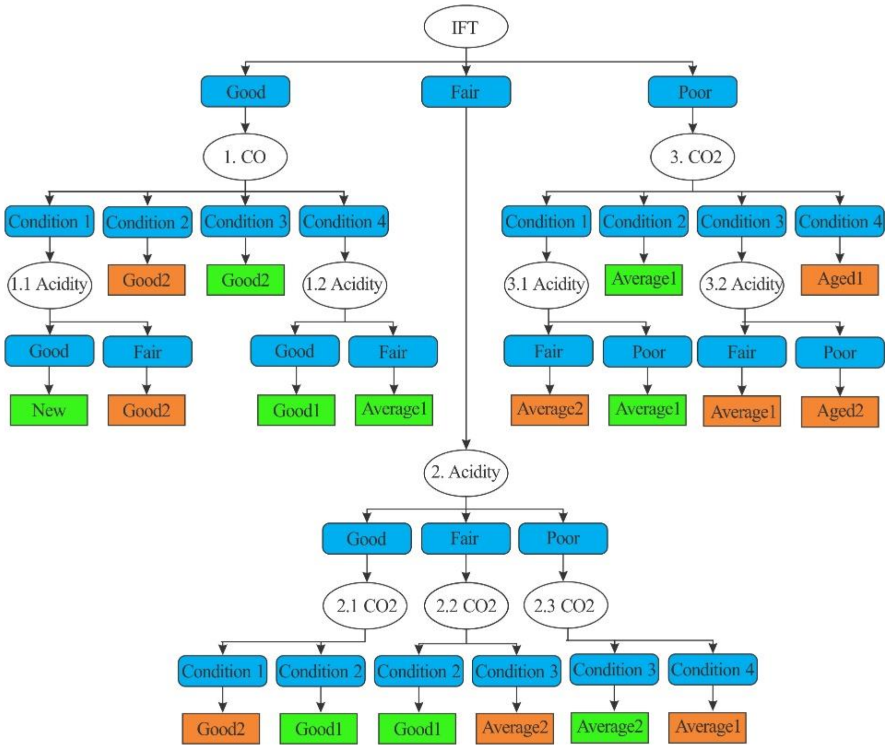

Fig. 6. Decision tree C4.5 algorithm.

Table 2. Fuzzy Rule Sets

Rule	Expression
1	If IFT is Good, CO is Con-1, and Acidity is Good then DP is New
2	If IFT is Good, CO is Con-1, and Acidity is Fair then DP is Good2
3	If IFT is Good, and CO is Con-2, then DP is Good2
4	If IFT is Good, and CO is Con-3, then DP is Good2
5	If IFT is Good, CO is Con-4, and Acidity is Good, then DP is Good1
6	If IFT is Good, CO is Con-4, Acidity is Fair, then DP is Average1
7	If IFT is Fair, and Acidity is Good, CO_2 is Con-1 then DP is Good2
8	If IFT is Fair, and Acidity Good, CO_2 is Con-2 then DP is Good1
9	If IFT is Fair, and Acidity Fair, and CO_2 is Con-2 then DP is Good1
10	If IFT is Fair, and Acidity Fair, CO_2 is Con-3 then DP is Average2
11	If IFT is Fair, and Acidity Poor, CO_2 is Con-3 then DP is Average2
12	If IFT is Fair, and Acidity Poor, CO_2 is Con-4 then DP is Average1
13	If IFT is Poor, CO_2 is Con-1, and Acidity Fair then DP is Average2
14	If IFT is Poor, CO_2 is Con-1, and Acidity Poor then DP is Average1
15	If IFT is Poor, CO_2 is Con-2, then DP is Average1
16	If IFT is Poor, CO_2 is Con-3, and Acidity Fair then DP is Average1
17	If IFT is Poor, CO_2 is Con-3, and Acidity Poor then DP is Aged2
18	If IFT is Poor, CO_2 is Con-4, then DP is Aged1

The colored orange parts are based on expert decisions due to the limited number of training data and to accommodate classes that are not covered. From C4.5 tree in Figure above, generate out 18 rules to control the fuzzy logic as shown in the Table 2. The rule are implemented in the fuzzy inference system.

The estimation results from the two algorithm method discussed above, the FIS estimation system and the Back Propagation Neural Network estimation system, will be evaluated. How much is the deviation/error between the actual data and the predicted data from the DP value, and the accuracy in determining the class category.

3.2. FIS Estimation Result

The performance of the FIS estimation system to estimate 20 data sets of post mortem (PM) insulation data can be seen in the Table 3 below.

Table 3. FIS Estimation Result for Testing Data

Name	DP Actual	DP Estimation	Deviation	Class DP Actual	Class DP Estimation
PM0	705.00	848.76	143.76	Good	Good
PM1	765.00	662.29	102.71	Good	Good
PM2	1,192	1,029	163.00	New	New
PM3	910.00	1,029	119.00	Good	New
....	....	....	....	....	....
PM14	1,008	921.51	86.49	New	Good
PM15	1,004	924.49	79.51	New	Good
PM16	898.00	924.49	26.49	Good	Good
PM17	925.00	1,029	104.00	Good	New
PM18	1,182	1,029	153.00	New	New
PM19	925.00	880.54	44.46	Good	Good
Max. Deviation			**164.34**	**Accuracy 75 %**	
MAE			**81.28**		

Table III show the result of the estimation, with maximal deviation/error estimation is 164.34, MAE 81.28, and accuracy class estimation is 70%.

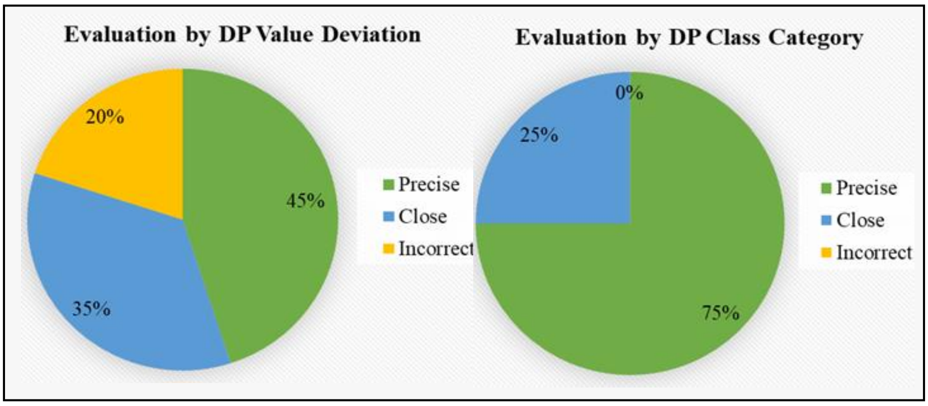

Fig. 7. Evaluation for FIS estimation result.

Fig. 7 show the evaluation by deviation provide accuracy 45 % “precise”, 35 % “close”, 20 % “incorrect”. For evaluation by DP class estimation, the accuracy is 75 % “precise”, 25 % “close”, and there is no evaluation as incorrect.

3.3. BPNN Estimation Result

The performance of the BPNN estimation system to estimate 20 data sets of post mortem (PM) Insulation data can be seen in the Table 4 below.

Table 4. BPNN Estimation Result for Testing Data

Name	DP Actual	DP Estimation	Deviation	Class DP Actual	Class DP Estimation
PM0	705.00	864.81	159.81	Good	Good
PM1	765.00	848.87	83.87	Good	Good
PM2	1,192	1,002	189.60	New	New
PM3	910.00	906.60	3.40	Good	Good
....	....	....	....	....	....
PM14	1,008	1,036	28.33	New	New
PM15	1,004	866.62	137.38	New	Good
PM16	898.00	866.17	31.83	Good	Good
PM17	925.00	999.81	74.81	Good	Good
PM18	1,182	956.82	225.18	New	Good
PM19	925.00	879.91	45.09	Good	Good
Max. Deviation			**247.30**	**Accuracy 75 %**	
MAE			**105.63**		

Table IV show the result of the estimation with BPNN, with maximal deviation/error estimation is 247.30, MAE 105.63, and accuracy class estimation is 75 %.

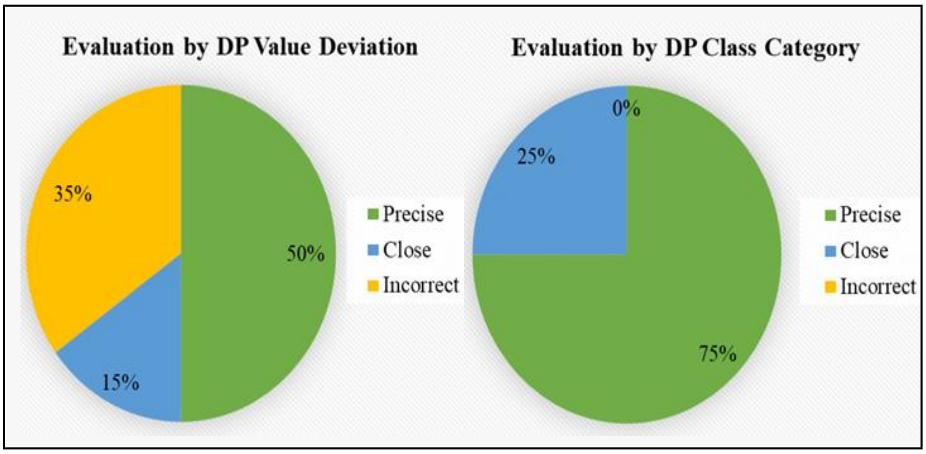

Fig. 8. Evaluation for BPNN estimation result.

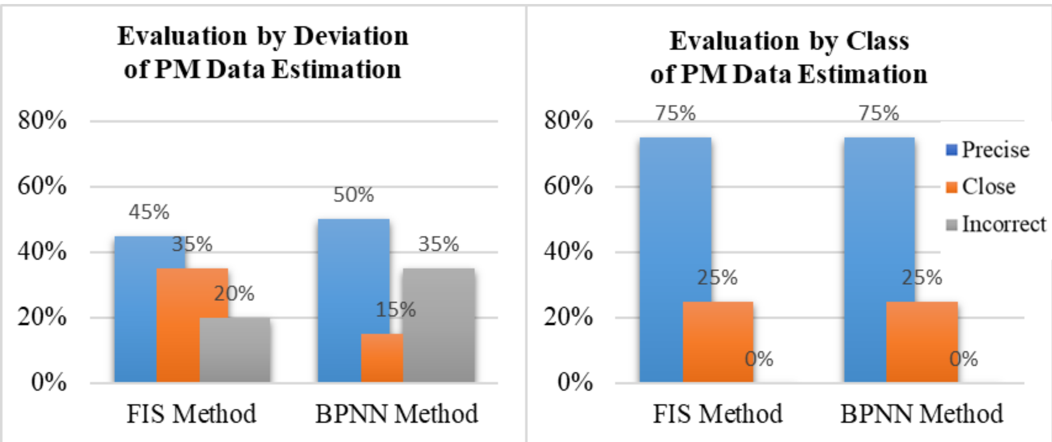

Fig. 9. Comparison evaluation for PM estimation result.

BPNN system shown in Fig. 8 determines an estimation of PM insulation data. The performance is 50 % "precise", 15 % "close" and 35 % "incorrect" evaluated by deviation. Accuracy 75 % "precise", 25 % "close", and no "incorrect" assessed by class estimation result.

Fig. 9 show the representation of the evaluation comparison for post mortem (PM) oil insulation data estimation result.

4. Conclusion

In the above-shown investigations, different methods have been developed in order to automatically analyze the condition of the paper insulation of power transformers based on oil parameters

The C4.5 algorithm performs better at developing an acceptable outcome hierarchical structure in the process of creating a decision tree that allows users easily to add artificial decisions for experts when required.

FIS systems tend to be better at estimation performance for comparison between FIS and BPNN estimation result. Moreover, BPNN accuracy in estimating DP value is lower than FIS; this is demonstrated by the number of maximal deviation and Mean Average Error.

In this research, a comparison of the BPNN estimation system is also made with a combination of three input variables. The result show that the IFT variable has the highest impact to achieving improved estimation accuracy. This observation in line with the C4.5 algorithm that presents IFT as the root in the decision tree.

Further investigations could be carried out using more data and used the transformer's field data, with the integration of multiple architectures of the neural network to get higher accuracy of estimation.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors had approved the final version.

Acknowledgment

The authors would like to express their gratitude to GRIDINSPECT GmbH and AiF/ZiM for the financial support as well as Weidmann Electrical Technology AG for the support with insulation materials and Analysen Service GmbH Leipzig for the DP analysis. Furthermore, the authors would like to thank the company ABB for the provision of comparative data.

References

[1] Li, Y., Tang, M.-J., Wu, F.-J., Zhang, G.-J., Wang, S.-H., & Suwarno, S. (2013). Aging assessment of power transformer using multi-parameters. *IJEEI, 5(1),* 34–44.

[2] IEEE Guide for Application for Monitoring Equipment to Liquid-Immersed Transformers and Components. (2012). *IEEE Std C57.143-2012* (pp. 1–83).

[3] Forouhari, S., & Abu-Siada, A. (2015). Remnant life estimation of power transformer based on IFT and acidity number of transformer oil. *Proceedings of 2015 IEEE 11th International Conference on the Properties and Applications of Dielectric Materials (ICPADM)* (pp. 552–555).

[4] Shaban, K. B., El-Hag, A. H., & Benhmed, K. (2016). Prediction of transformer furan levels. *IEEE Transactions on Power Delivery, 31(4),* 1778–1779.

[5] Malik, H., Kushwaha, N., Suryakant, & Yadav, A. K. (2011). Paper insulation deterioration estimation of power transformer using fuzzy-logic. *Proceedings of 2011 Annual IEEE India Conference* (pp. 1–5).

[6] Hu, W., Wang, X., & Yin, X. (2008). Study on fault diagnosis for transformer based on adaptive fuzzy inference system. *Proceedings of 2008 China International Conference on Electricity Distribution* (pp. 1–4).

[7] Nasution, E. F., Prasojo, R. A., Suwarno, Kinkeldey, T., & Werle, P. (2018). Estimation of the degree of polymerization (DP) in oil-paper insulation system based on dielectric and DGA data using fuzzy logic algorithm. *Proceedings of 2018 Conference on Power Engineering and Renewable Energy (ICPERE), Solo, Indonesia,* (pp. 1–6). doi: 10.1109/ICPERE.2018.8739284.

[8] Prasojo, R. A., & Suwarno, S. (2018). Power transformer paper insulation assessment based on oil measurement data using SVM-classifier. *IJEEI, 10(4),* 661–673.

[9] Nugraha, B. H., Kinkeldey, T., Münster, T., Werle, P., & Suwarno. (2019). Algorithm for Estimating the degree of polymerization of paper insulation impregnated with inhibited insulating oil. *Proceedings of 2019 2nd International Conference on High Voltage Engineering and Power Systems (ICHVEPS)* (pp. 1–6).

[10] Münster, T., Kinkeldey, T., Werle, P., Hämel, K., & Preusel. J. (2018). Investigation on Ageing Parameters of a Thermally Accelerated Aged Paper-Oil-Insulation in a Hermetically Sealed System. *2018 Condition Monitoring and Diagnosis (CMD),* 1–6.

[11] MathWorks, M. (2019). *MATLAB Fuzzy Logic Toolbox User's Guide.* The MatWorks, Inc, Retrieved Sep. 2019, from www.mathworks.com.

[12] Quinlan, J. R. (1986). Induction of decision trees. *Mach. Learn., 1(1),* 81–106.

[13] Quinlan, J. R. (1996). Improved use of continuous attributes in C4.5. *J. Artif. Intell. Res., 4,* 77–90.

[14] Willmott, C., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Clim. Res., 30,* pp. 79–82.

Martua Mario Gultom, S.T, M.T was born in Gisting, on March 30, 1984. He studied electrical engineering at Electrical Engineering at University of Lampung. In 2020, he received his M.T in School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Indonesia and conducting the thesis research in Leibniz Universität Hannover, Germany through a scholarship program from PT. PLN (Persero).

His research is in the field of asset management and condition monitoring of transformers, especially the determination of the ageing condition of transformers using AI algorithms. Currently, he is an engineer at PT. PLN Persero), Indonesia.

Tobias Kinkeldey studied electrical engineering at Leibniz University of Hannover, Germany. In 2015 he received his diploma in electrical engineering. Since May 2015 he is research assistant and PhD student of the Schering-Institute for High Voltage Engineering and Asset Management of the Leibniz University in Hannover.

He is member of the VDE. His research is in the field of asset management and condition monitoring of transformers, especially the determination of the ageing condition of transformers using AI algorithms. In this area he is author or co-author of 25 national or international publications.

Peter Werle studied electrical engineering at the University of Hannover and made afterwards his PhD at the Schering-Institute in Hannover, Germany.

From 2003 to 2014 he was with ABB Transformer Service in different national and international positions. From 2010 to 2014 he was the general manager of the Transformer Service in Germany and responsible for the workshops in Halle (Saale), Neusäss (close to Augsburg), and Nauen (close to Berlin) with over 200 employees.

Since October 2014 he is the executive director of the Schering-Institute for High Voltage Engineering and Asset Management of Leibniz University in Hannover.

He is a member of the VDE, DKE K 182, CIGRÉ, and IEC and active in CIGRÉ as Liaison officer between A2 and IEC TC 10 and between A2 and CIRED. Furthermore, he is the head of the Advisory Group AG A2.8 and therefore a member of the A2 strategy board and he is active in various working groups of CIGRÉ and IEC TC 10. He is the inventor of more than 20 patents and is the author or co-author of more than 350 publications in the area of high voltage testing, partial discharge diagnosis, condition monitoring, and asset management.

Suwarno, M.T received B.Sc. and M.Sc. from the Department of Electrical Engineering, Institut Teknologi Bandung, Bandung, Indonesia in 1988 and 1991 respectively. He received the PhD from Nagoya University, Japan in 1996 in the field of high voltage electrical insulation.

He is a professor in the School of Electrical Engineering and Informatics, Institut Teknologi Bandung and currently he is the Chairman of Electrical Power Engineering Research Group and a senior member of IEEE.