Applications of ANFIS to Estimate the Degree of Polymerization Using Transformer Dissolve Gas Analysis and Oil Characteristics

Kharisma Utomo Mulyodinoto[1,2],
Suwarno[2],
Rahman Azis Prasojo[2] and
Abu-Siada A[3]*

1   PLN (Persero), Jl. Trunojoyo Blok M I/135 Kebayoran Baru, 12160, Jakarta, Indonesia

2   School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Indonesia

3   Electrical and Computer Engineering Department, Curtin University, Australia

Abstract

Degree of Polymerization is a reliable parameter that can identify the health condition and remaining operational life of the paper insulation within power transformers. Measuring this parameter is a challenging process due to the difficulty in acquiring paper samples from hot spot locations of operating transformers. Insulation oil characteristics and dissolved gas analysis (DGA) of power transformers have become powerful tools to overcome this limitation, because these tests are regularly performed by utilities in Indonesia, unlike furfural and degree of polymerization measurements. This paper presents a novel Adaptive Neuro Fuzzy Inference System (ANFIS) approach to estimate the paper degree of polymerization based on dissolved gas analysis and oil characteristics. In this context, data of oil insulation characteristics, DGA, and furan compounds of 200 150/20 kV and 42 500/150 kV operating transformers are collected from PT. PLN (Persero). The Calculated degree of polymerization from furan data of each investigated transformer is analyzed using the corresponding oil insulation characteristics and DGA data. Results show that carbon oxides compounds, acidity number, interfacial tension, and colour of the oil are statistically correlated with the degree of polymerization of the insulation paper. Parameters that highly correlated with the degree of polymerization are used as input parameters to the proposed ANFIS model to estimate the degree of polymerization value. The results of the developed ANFIS model reveal an overall accuracy more than 86% for the two investigated transformers' data. The accuracy of the proposed ANFIS model can be enhanced through tuning the model using future obtained results.

Keywords: Power transformers; Degree of polymerization; Oil insulation characteristics; DGA; Fulfral compound; ANFIS

*Corresponding author: Abu-Siada A

✉ A.AbuSiada@curtin.edu.au

Senior Member, IEEE, Electrical and Computer Engineering Department, Curtin University, AustraliaElectrical and Computer Engineering Department, Curtin University, Australia.

Tel: +61 8 9266 7287

Introduction

Power transformers are critical links within transmission and distribution networks which play important role to maintain continuity and sustainability of the electricity grids. Reliable and effective condition monitoring and diagnostic techniques must be employed to avoid unplanned outages of the equipment. Early diagnosis and detection of specific dissolved gases in transformer oil has become the fastest technique in detecting incipient faults within the power transformer [1-5]. Dissolved Gas Analysis (DGA) uses several specific gases concentrations that are produced due to oil decomposition and insulating paper degradation [1-5]. Several factors are considered as accelerating aging factors for power transformers such as water content in solid and liquid insulation, operating temperature and oil oxidation [6-8]. The presence of moisture, oxygen and acids are due to de-polymerization and decomposition of cellulose chains that lead to the paper insulation degradation itself [9-12]. Several statistical surveys confirmed that most of the failures in power transformers are attributed to the insulation system degradation, in particular paper insulation as the remaining life of operating transformer is equivalent to the life of its solid insulation [10].

Quality of the solid insulation system can be assessed through its degree of polymerization (DP) [8-11]. However, it is impractical to collect paper insulation samples from operating power transformers especially from hot spot locations. As such, several correlations between DP and Furanic compounds that are generated in the insulating oil due to cellulose decomposition have been published in the literatures [13,14]. These correlations are not consistent as they may lead to different DP value for the same Furan concentration. Moreover, the correlation between DP and Furan is not valid for thermally upgraded papers and when biodegradable insulation oil is used. This paper investigates the correlation between the DP and other routinely measured parameters such as oil dielectric characteristics and DGA data. The commonly measured parameters that have high correlation with DP can be used as an alternative way to estimate DP value

of solid insulation in case that furfural data are not available (e.g. in Indonesia).

Several research in transformer diagnosis based on artificial intelligence have been conducted especially in predicting the life of operational transformers using interfacial tension (IFT) and acidity number data [15]. The relationship between DGA data especially carbon oxides and the paper insulation's quality was investigated [16] using fuzzy logic model. It is to be noted that while the carbon oxides may provide an idea about the degradation level in paper insulation, it is not very accurate as carbon oxides may be generated due to atmospheric leak or oil oxidation [16]. While the work presented [17,18] investigated the relationship between the DP of transformer paper insulation and the DGA within the transformer oil, it did not take into account the impact of transformer rating and size which is the main focus of this paper.

Research Methodology

Data such as dissolved gas analysis, dielectric oil characteristics and furfural compounds are collected from two operating transformers at PT. PLN (Persero), Indonesia. Data were collected from 200 transformers of rating 150/20 kV, 60 MVA and 30 MVA and 42 transformers of 500 MVA and 166.66 MVA, 500/150 kV rating.

Parameters of the dielectric oil characteristics used in this paper include the voltage breakdown in kV based on IEC 60156-02 [19-22], water content in ppm based on IEC 60814 [23], acidity number in mg KOH/g based on IEC 62021-1 [24], interfacial tension value in dyne/cm based on ASTM D 971-99a [25] and power transformer oil colour based on ISO 2049 [26].

Results of DGA tests used in this paper include H_2 (Hidrogen), CH_4 (Methane), CO (carbon monoxide), CO_2 (carbon dioxide), C_2H_6 (Ethane), C_2H_4 (Ethylene) and C_2H_2 (Acetylene), all in ppm.

For all collected oil data, 2-Furaldehyde (2FAL) furan compound was also measured. Stebbins equation below is used in PT. PLN (Persero) to estimate the paper DP value for non-upgraded kraft paper using the 2FAL concentration [14]:

$$DP = \frac{log_{10}\left(2FAL_{ppm}\right) - 1.51}{-0.0035} \tag{1}$$

Correlation analysis using basic multiple regression is usually applied to find a correlation between multiple parameters [21].

In this paper, the basic linear regression method is employed to examine the correlation between the investigated parameters and the paper DP. The range of the correlation coefficient paramater (r) is from -1 to +1 whereas the closer of r value to - 1 or +1, the correlation between two parameters becomes more significant. T-test with α=0.05 is applied to ensure and verify the correlation; α is a reference parameter used as an indicator of significancy level of the performed linear regression. If the value of P, a parameter produced by the linear regression process called Pearson correlation coefficient [20], is less than α the linear regression result becomes significant.

Adaptive Neuro Fuzzy Inference System (ANFIS) provides the benefits of both ANN (Artificial Neural Networks) and the fuzzy

logic for computation and logical analysis. This system can set up an input-output mapping based on fuzzy if-then rules in the human knowledge and set out input-output data pairs [19]. The fuzzification of the input parameters and the membership functions (MF) are the first two steps in developing ANFIS models.

Figure 1 shows two-input ANFIS model's structure. Hybrid algorithm, a combination of least squares and backpropagation method is used to train the MF. Input of the model are x and y while f is the output parameter. All nodes are adaptive at the first layer, A_i and B_i defined as linguistic label (high, low,…), μ_{Ai} and μ_{Bi}, represent the membership function of each node. Each node called Π is non-adaptive at the second layer. At second layer, each output node stands for the degree of activation. At the third layer, N is nonadaptive and its role is to normalize the degree of activation by counting the ratio between the first node of the previous layer to all layers. At the fourth layer, each node is adaptive. Fuzzy if-then function are labelled as f_1 and f_2, the output of the third layer defined as $\overline{w_i}$ and $(p_i x + q_i y + r_i)$ is an adaptive parameter. At the fifth layer, each node labelled Σ is nonadaptive. Overall output of the ANFIS model is generated at the fifth layer [19].

In ANFIS, calculations are repeated per epoch using the feedforward and reverse pass calculations until the maximum number of epochs is reached or the respective error function is not further minimized. Each epoch sets training, input, and target vectors to a network and calculates new parameters of the MFs.

The accuracy of the proposed ANFIS model in estimating the DP is computed based on the RMSE (Root Mean Squared Error) value, MAE (Mean Absolute Error) value and MAPE (Mean absolute percentage error) value [27].

In eqn. (2), the *RMSE* is measured for a target sequence t and forecast sequence f with N time steps.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(t_i - f_i\right)^2} \tag{2}$$

MAE criterion calculates the gap between the estimated and the target DP.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|f_i - t_i\right| \tag{3}$$

On the other hand, *MAPE* evaluates the prediction error as a percentage between the actual DP to the target DP value.
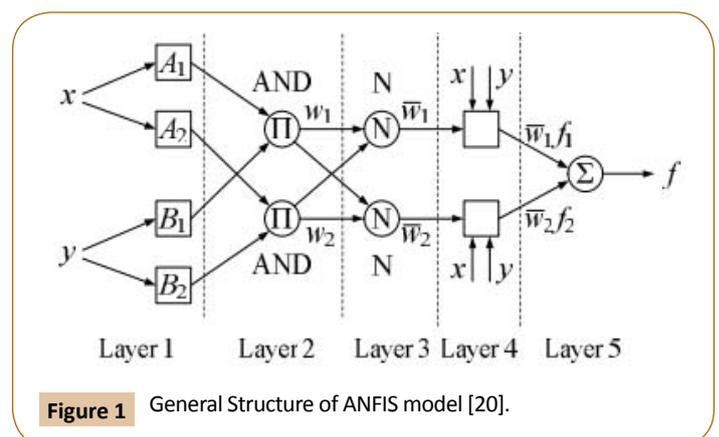
Figure 1 General Structure of ANFIS model [20].

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} \frac{|f_i - t_i|}{t_i} \qquad (4)$$

Linear regression is also conducted to get the best combination subsets of several parameter. Some criteria like R^2 criteria (*R-sq*, *R-sq[adj]*, and *R-sq [pred]*), s^2 and Cp-Mallows value are applied.

Coefficient of multiple determination, R^2 or R(sq) defined as a ratio of sum of squares is calculated as [20,21]:

$$R_p^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \overline{y})^2} \qquad (5)$$

R(sq)-adj or commonly called the adjusted coefficient of multiple determination is calculated from [20,21]:

$$R_{adj}^2 = 1 - \left(\frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \overline{y})^2} \right) \left(\frac{n-1}{n-p-1} \right) \qquad (6)$$

R(sq)-pred or generally called the predicted coefficient of multiple determination is calculated as below [20,21]:

$$R_{adj}^2 = 1 - \left(\frac{\sum_1^n \left(\frac{e_i}{1 - h_i} \right)^2}{\sum_1^n (y_i - \overline{y})^2} \right) \qquad$$

R_{adj}^2 takes the number of parameters n in the model into account.

Mallow constant C_p is specified as the predicted value obtained from a regression equation based on a subset of variables that are commonly biased. It can be calculated from [20,21]:

$$C_p = \frac{\left((1 - R_p^2)(n - T) \right)}{(1 - R_T^2)} - \left(n - 2(p+1) \right) \qquad (7)$$

s value or commonly called Residual Mean Square is defined as [20,21]:

$$s = \sqrt{MSE} = \frac{\sum (y_i - \hat{y}_i)^2}{(n - p - 1)} \qquad (8)$$

where:

$y_i = i^{th}$ observed response value

$\overline{y} = mean\,response$

$\hat{y}_i = i^{th}\,fitted\,response$

n=number of observations

p=number of terms in model

$e_i = i^{th}$ residual

$h_i = i^{th}$ diagonal element of $X(X'\,X)^{-1}X'$

X=design matrix.

Correlation Analysis

Data statistical analysis are performed using Pearson correlation coefficient to investigate the correlation between dissolved gases, oil characteristic data and the DP of paper insulation that is calculated from the 2-FAL data based on eqn. (1). Data collected from two transformer fleets of different ratings are used in this analysis as elaborated below.

30 MVA and 60 MVA, 150/20 kV transformers

Oil samples collected from 200 transformers of 30 MVA and 60 MVA, 150/20 kV ratings were collected and the DGA, furfural, acidity, and IFT were measured following the respective standards. The paper DP value for each transformer was calculated using eqn. (1). Correlation analysis was performed for each dissolved gas and the results are listed in **Table 1**. Results in **Table 1** shows that the value of P is less than 0.05 in case of H_2, CO, CO_2. The r value on the other hand, is closer to ±1 in case of CO_2, CO and H_2. This reveals the strong correlation between CO_2, CO, H_2 and the DP value. Combining CO and CO_2 leads to better correlation as shown in **Figure 2 and Table 1** that depicts the scatter plots for $CO+CO_2$ against the DP value. Results show that more concentration of $CO+CO_2$ in the oil sample indicates more deterioration in the cellulose and hence a reduced value for the DP.

Each dielectric oil characteristic and the DP value are processed using correlation analysis as shown in **Table 2**. Results in **Table 2**

Table 1 Correlation Coefficient of DP and dissolved gases data of 200 oil samples (150/20 kV transformers).

Gasses from DGA test	r (correlation coefficient)	p value
H_2 (Hidrogen) in ppm	-0.200156231	0.004
CH_4 (Methane) in ppm	-0.132735397	0.061
CO (Carbon Monoxide) in ppm	-0.359815467	0
CO_2 (Carbon Dioxide) in ppm	-0.454084816	0
$CO+CO_2$ in ppm	-0.499712213	0
C_2H_4 (Ethylene)	-0.111333276	0.117
C_2H_6 (Ethane)	-0.097799442	0.168
C_2H_2 (Acetylene)	-0.137760631	0.052
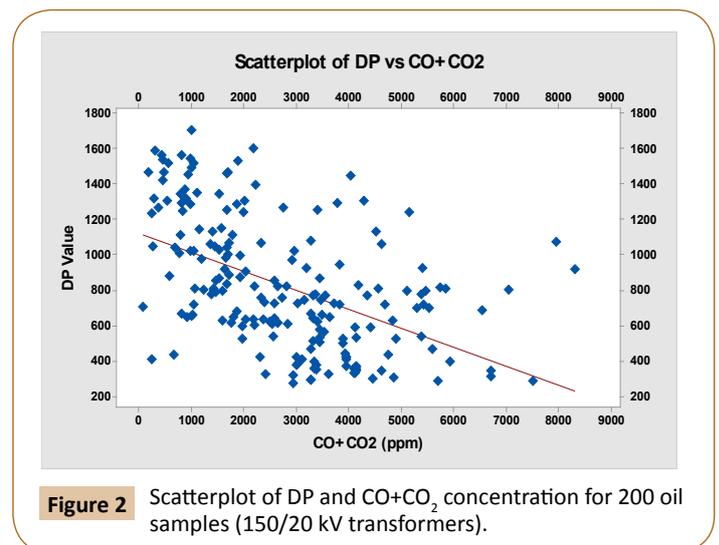
Figure 2 Scatterplot of DP and $CO+CO_2$ concentration for 200 oil samples (150/20 kV transformers).

Table 2 Correlation Coefficient of DP and dielectric characteristic data of 200 oil samples (150/20 kV transformers).

Oil Dielectric Characteristic	r (correlation coefficient)	p value
ACIDITY Number in mgKOH/g	-0.502554956	0
WATER CONTENT in ppm	-0.245657978	0
IFT (Interfacial Tension) in dyne/cm	0.680202495	0
VBD (Voltage Breakdown) in kV	0.29923926	0
OIL COLOUR	-0.820097054	0

indicates highly correlated parameters with the DP value are acidity number, interfacial tension (IFT), and oil colour parameters as revealed from the correlation coefficients. On the other hand, water content and voltage breakdown (VBD) of the oil are of less correlation to the DP value. **Figures 3-5** show the scatter plots for acidity, interfacial tension, and colour and the DP value. Results show that, the DP value will be reduced for higher acidity and less IFT numbers. From the correlation analysis, several independent variables are found to have close relationship with the DP value, so multicollinearity test should be performed [20]. Results of multicollinearity test shown in **Table 3** reveal that CO_2 and $CO+CO_2$ have correlation coefficient values close to 1 and p-value less than 0.05 so independent parameter CO_2 is eliminated from the chosen parameters to predict the DP Value.

Several combinations of the investigated parameters are then tested to get the best combination to predict the DP value. R-q, R-sq (adj), R-sq (pred), Mallows Cp and S parameters are employed to identify the optimum combination of the investigated parameters. Selecting and evaluating the best regression equation is mainly based on the criteria: the maximum R (R-sq, R-sq[adj], and R-sq [$pred$]) and consistency of variables pattern with equations, the minimum s^2 and the value of Cp-Mallows
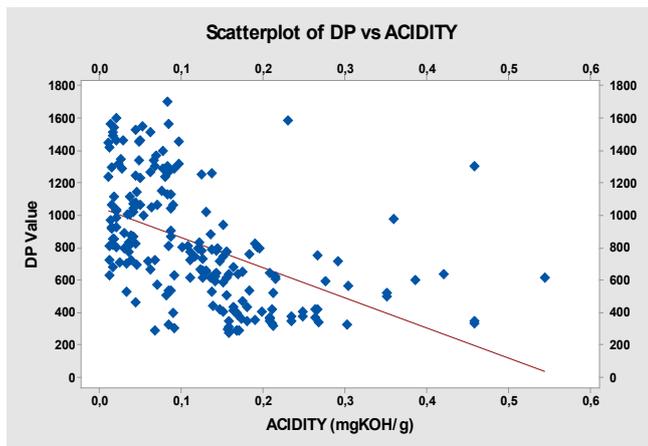
Scatter plot of DP and acidity number for 200 oil samples (150/20 kV transformers).
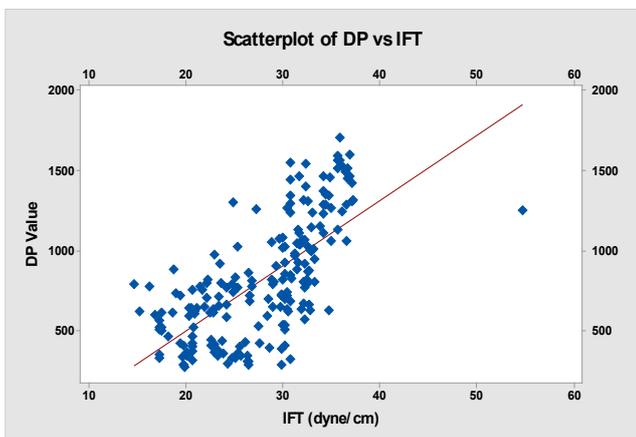
Scatter plot of DP and IFT number for 200 oil samples (150/20 kV transformers).
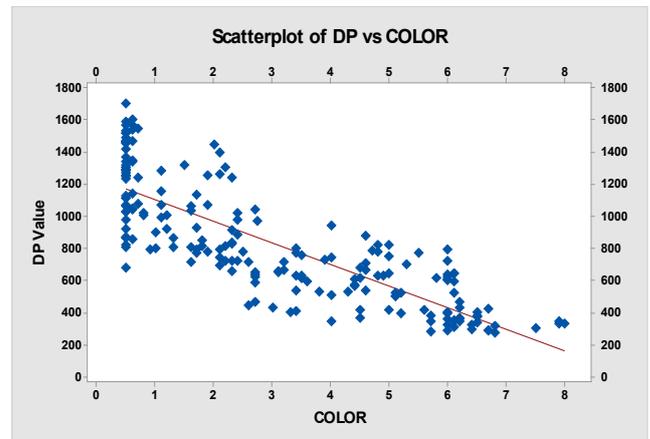
Scatter plot of DP and oil colour for 200 oil samples (150/20 kV transformers).

Table 3 Several Independent variables Multicollinearity test of 200 oil samples (150/20 kV transformers).

	TDCG	Acidity	IFT	CO	CO$_2$	CO+CO$_2$
ACIDITY	0.1					
	0.159					
IFT	-0.219	-0.652				
	0.002	0				
CO	0.703	-0.074	-0.032			
	0	0.3	0.649			
CO$_2$	0.394	0.139	-0.178	0.199		
	0	0.049	0.012	0.005		
CO+CO$_2$	0.513	0.116	-0.174	0.389	0.98	
	0	0.101	0.014	0	0	
COLOUR	0.376	0.593	-0.682	0.217	0.36	0.382
	0	0	0	0.002	0	0

which is the same with the number of regression parameter. Results in **Table 4** show that the optimum combination is number 15 in the table. This combination comprises total carbon oxide ($CO+CO_2$), acidity number, Interfacial Tension, and oil colour achieved the highest R-Sq. On the other hand, the value of R-sq ($pred$) is nearly equal to R-sq (adj) value and the mallows Cp value is exactly the same as the number of parameters used (CO, CO_2, IFT and colour). The S value is also the lowest among all of other combination groups.

500 MVA and 166.67 MVA, 500/150 kV transformer

To investigate the impact of transformer rating on the proposed DP-oil characteristic correlation, same analysis explained above was performed on oil samples collected from 42 power transformers of 500 MVA and 166.67 MVA, 500/150 kV rating. **Table 5** shows the correlation coefficients between DP and various dissolved gases. Similar to the above case study, it can be seen that $CO+CO_2$ has significant correlation with the DP. This correlation is plotted in **Figure 6**. Correlation analysis of each oil dielectric characteristic and the DP value was also performed and results are listed in **Table 6**. Again, acidity, IFT and oil colour

Table 4 Various combinations of all selected independent variable for DP value Prediction (150/20 kV transformers).

Combination No.	R-Sq Value	R-Sq (adj) Value	R-Sq (pred) Value	Mallows Cp	S value	Total Carbon Oxide ($CO+CO_2$)	Acidity Number	Interfacial Tension (IFT)	Oil Color
1	25	24.6	23.1	392.2	317.2	X			
2	25.3	24.9	23.1	390	316.6		X		
3	46.3	46	44.9	225.3	268.44			X	
4	67.3	67.1	66.6	60.7	209.55				X
5	70	69.7	69.2	41.3	201.12			X	X
6	46.9	46.3	44.4	222.5	267.59		X	X	
7	45	44.4	42.6	237.2	272.27	X	X		
8	61.3	60.9	59.8	109.7	228.49	X		X	
9	71.3	71	70.5	30.9	196.64	X			X
10	67.3	67	66.4	62.4	209.96		X		X
11	61.9	61.3	59.8	107.1	227.33	X	X	X	
12	70.3	69.8	69.2	40.9	200.62		X	X	X
13	71.6	71.1	70.5	30.9	196.27	X	X		X
14	75	74.6	74.1	3.8	183.92	X		X	X
15	75.1	74.6	73.9	5	184.03	X	X	X	X

Table 5 Correlation Coefficient of DP and dissolved gases data of 42 oil samples (500/150 kV transformers).

Gasses from DGA test	r (correlation coefficient)	p value
H_2 (Hidrogen) in ppm	-0.023710916	0.861
CH_4 (Methane) in ppm	-0.196051018	0.213
CO (Carbon Monoxide) in ppm	-0.060570558	0.703
CO_2 (Carbon Dioxide) in ppm	-0.451567635	0.003
$CO+CO_2$ in ppm	-0.461077956	0.002
C_2H_4 (Ethylene)	-0.240100404	0.126
C_2H_6 (Ethane)	-0.214704174	0.172
C_2H_2 (Acetylene)	-0.05175006	0.745

Table 6 Correlation Coefficient of Degree of Polymerization value against dielectric characteristic data of 42 samples 500/150 kV transformers.

Oil Dielectric Characteristic	r (correlation coefficient)	p value
ACIDITY Number in mgKOH/g	-0.471047001	0.002
WATER CONTENT in ppm	0.006977088	0.965
IFT (Interfacial Tension) in dyne/cm	0.376374821	0.014
VBD (Voltage Breakdown) in kV	0.216165611	0.169
OIL COLOUR	-0.383317116	0.012
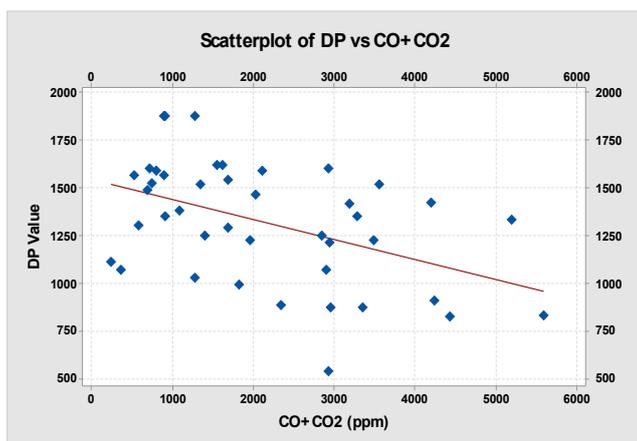
Figure 6 Scatter plot of DP and $CO+CO_2$ concentration for 42 oil samples (500/150 kV transformers).
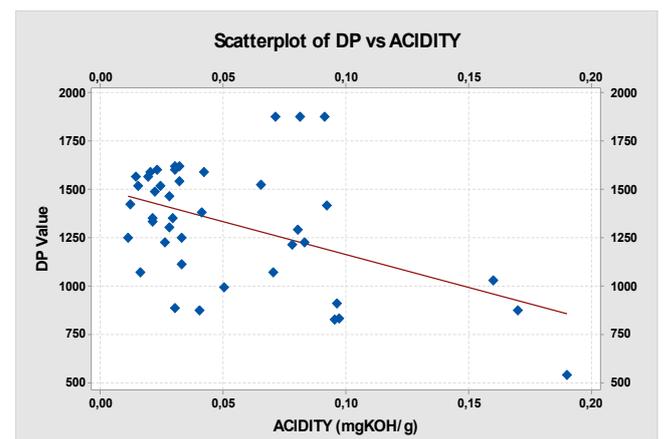
Figure 7 Scatter plot of DP and acidity concentration for 42 oil samples (500/150 kV transformers).

are considered to be the highly correlated parameters with the DP value than water content and oil voltage breakdown. The correlation between these three parameters and the DP value are depicted in **Figures 7-9**.

Table 7 shows that the optimum combination comprises total

carbon oxide ($CO+CO_2$), acidity number, Interfacial Tension, and oil colour based on the above mentioned statistical parameters.

From the correlation analysis and linear regression for the two investigated transformer fleets, the four optimum parameters; total carbon oxides, acidity number, Interfacial Tension, and oil colour are used as input to the proposed ANFIS model to predict the DP value as shown in **Figure 10**.

Table 7 Various combinations of all selected independent variable for DP value Prediction (500/150 kV transformers).

Combination No.	R-Sq Value	R-Sq (adj) Value	R-Sq (pred) Value	Mallows Cp	S value	Total Carbon Oxide (CO+CO$_2$)	Acidity Number	Interfacial Tension (IFT)	Oil Color
1	21.3	19.3	13.2	24.9	281.57	X			
2	22.2	20.2	14.5	24.1	279.9		X		
3	14.2	12	0	30.6	293.98			X	
4	14.7	12.6	6.4	30.1	293.07				X
5	34.8	31.5	20.5	16	259.41			X	X
6	26.8	23	7.6	22.5	274.95		X	X	
7	35.2	31.8	24.8	15.8	258.76	X	X		
8	32.1	28.6	15.6	18.2	264.74	X		X	
9	29.3	25.7	19.1	20.5	270.24	X			X
10	39.7	36.6	29.3	12.2	249.53		X		X
11	39.5	34.7	19.8	14.3	253.24	X	X	X	
12	47.7	43.6	30.9	7.7	235.35		X	X	X
13	46.5	42.3	34.9	8.7	238.13	X	X		X
14	44.9	40.6	29.4	10	241.63	X		X	X
15	53.7	48.7	35.7	5	224.56	X	X	X	X
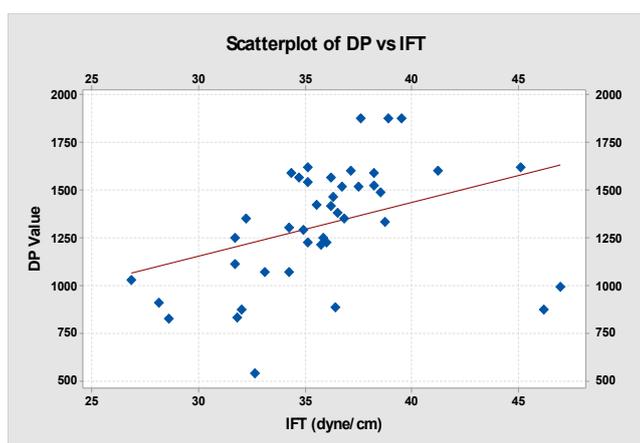
Figure 8 Scatter plot of DP and IFT concentration for 42 oil samples (500/150 kV transformers).
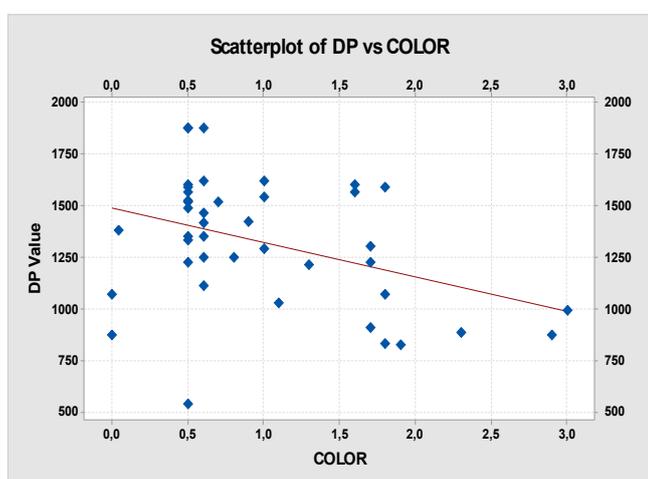
Figure 9 Scatter plot of DP and colour concentration for 42 oil samples (500/150 kV transformers).
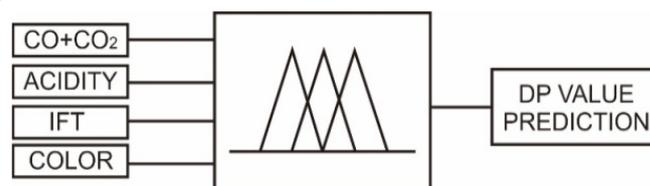
Figure 10 Proposed ANFIS model to predict DP value.

Table 8 The Best MF number and MF type of the proposed ANFIS Model.

Input of Independent Variable	MF Number	MF Type
Total Carbon Oxide (CO+CO$_2$)	5	trapmf
Acidity Number	4	trapmf
Interfacial Tension (IFT)	2	trapmf
Oil Colour	5	trapmf

Results and Discussion

The ANFIS toolbox in MATLAB is utilised to realize the mapping between input and output parameters shown in **Figure 10**. To create ANFIS model, 140 samples of transformers data as training data set are applied with membership function selection listed in **Table 8**. **Figure 11** presents the target DP value and the predicted DP value using the proposed ANFIS model during the testing stage using 60 samples. The results show that the error is insignificant and can be neglected which reveals the high accuracy of the proposed ANFIS model to predict the paper DP value based on oil dielectric characterics.

To evaluate the precision of the proposed ANFIS model in predicting the DP value based on oil dielectric characteristics, 24 tested oil samples were collected from various operating transformers and the proposed ANFIS model was used to predict the DP paper value corresponding to each sample. Comparing the

Table 9 Accuracy test for the proposed ANFIS Model.

CO+CO$_2$	ACIDITY	IFT	COLOUR	2 FAL value (ppm)	DP calculated	DP predicted
4081.26	0.19	25.3	6.1	2091.96	355.70	337.53
1699.83	0.014	32	1.1	6.74	1067.67	1054.99
3325.509	0.167	25.5	6	1496.59	397.261	402.32
3049.77	0.248	20.6	6.5	1421.83	403.619	478.89
1860.79	0.163	26.6	4.5	151.02	681.85	720.28
3948.619	0.263	22.9	4.5	1272.81	417.35	499.34
776.47	0.037	31.6	0.5	4.65	1113.73	1176.26
1646.36	0.02	31.2	0.5	13.56	980.93	983.15
965	0.04	30	0.8	10	1018.72	1043.66
773.799	0.066	34.7	0.6	0.73	1343.48	1326.93
2320.591	0.049	32.2	0.5	6.75	1067.489	1066.16
464.81	0.028	36.9	0.6	0.27	1466.901	1430.88
1146.523	0.045	32.9	0.6	3.66	1143.43	1181.66
3374.773	0.234	23.3	5.7	2239.45	347.25	389.42
985.752	0.015	36.4	0.5	0.22	1492.31	1410.83
3595.829	0.302	25.1	6.4	2649.27	326.39	368.96
4111.72	0.458	17.2	7.9	2555.89	330.85	348.80
2727.92	0.183	21.7	3.5	83.21	755.81	717.92
935.488	0.096	36.6	0.5	0.3	1453.827	1452.93
896.699	0.014	36.2	0.5	0.12	1567.5246	1606.71052
3488.506	0.083	36	1.7	1.88	1226.1027	1295.50695
791.042	0.042	38.2	0.5	0.1	1590.1478	1606.71052
4201.722	0.012	35.5	0.9	0.39	1421.2722	1377.28022
1086.2	0.041	36.5	0.041	0.54	1380.8924	1407.1299

Table 10 Evaluation Criteria of the developed ANFIS Model.

ANFIS Evaluation	Transformer Voltage Rating			
	150/20 kV		500/150 kV	
	Training	Testing	Training	Testing
Root Mean Square Error (RMSE)	119.023	146.078	42.99	157.237
Mean Absolute Error (MAE)	75.46	111.03	17.44	127.001
Mean Absolute Percentage Error (MAPE)	9.15%	13.89%	1.26%	9.66%
Accuracy (100% - error)	90.85%	86.11%	98.74%	90.34%
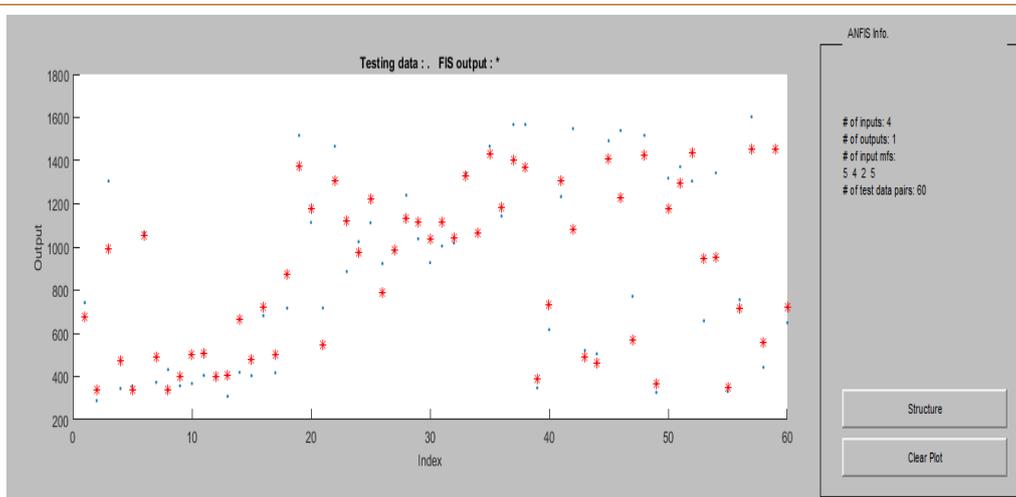
Figure 11 Test result of the proposed ANFIS model using 60 samples as testing data set.

calculated DP value and the predicted DP value using the developed ANFIS model in **Table 9** reveals the high accuracy of the model in predicting the DP value. Several evaluation criteria and performance indicators have been employed to assess the accuracy of the developed ANFIS model as shown in **Table 10**. The mean absolute error is found to be less than 14% and the overall accuracy of the proposed model is found to be higher than 86%.

Results reveal an acceptable accuracy level (over 86%) of the proposed ANFIS model to estimate the DP value of paper insulation. Thus the DP value can be estimated through the proposed four parameters: $CO+CO_2$, acidity, interfacial tension and transformer oil colour. Results show that the higher the value of $CO+CO_2$, the lower the DP value. On the other hand, the higher the value of oil interfacial tension, the higher the value of DP. Rapid estimation of the DP value can be also made with the information about transformer oil acidity and colour.

Conclusion

Measuring the degree of polymerization of operating transformers is challenging. Instead, the current utilities practice to assess paper degradation is based on calculating the DP value based on Furan contents in transformer oil. However, Furan analysis is not a regular test in most of Indonesian Electricity utilities. As such, this paper presents a new technique to estimate the DP value based on oil dielectric characteristics. Correlation analysis shows that the total carbon oxides dissolved in transformer oil, oil colour, acidity and IFT are strongly correlated with the DP value. This correlation is realized using ANFIS model. Results of the proposed ANFIS model reveal its high accuracy in predicting the DP value. While the overall accuracy is found to be higher than 86%, it can be enhanced using future measurements due to the adaptive nature of the model.

References

1 Bakar NA, Abu Siada A, Islam S (2014) A review of dissolved gas analysis measurement and interpretation techniques. IEEE Electrical Insulation Magazine 30: 39-49.

2 Abu-Siada A, Hmood S (2015) A New Fuzzy Logic Approach to Identify Power Transformer Criticality using Dissolved Gas-in-Oil Analysis. Int J Electr Power Energy Syst 67: 401-408.

3 Abu-Siada A, Arshad M, Islam S (2010) Fuzzy Logic Approach to Identify Transformer Criticality using Dissolved Gas Analysis. IEEE PES General Meeting, USA.

4 Abu Bakar N, Abu-Siada A (2016) Fuzzy Logic Approach for Transformer Remnant Life Prediction and Asset Management Decision. IEEE Trans Dielectr Electr Insul 23: 3199-3208.

5 Abu-Siada A, Islam S (2012) A New Approach to Identify Power Transformer Critically and Asset Management Decision Based on Dissolved Gas-in-Oil Analysis. IEEE Trans Dielectr Electr Insul 19: 1007-1012.

6 Fabre J, Pichon A (1960) Deteriorating processes and products of paper in oil. Application to transformers. CIGRE Paper 137: 18.

7 Shroff DH, Stannett AW (1985) A review of paper aging in power transformers. Proc Inst Elect Eng C 132: 312-319.

8 Brochure C (2007) Ageing of cellulose in mineral-oil insulated transformers.

9 Kachler AJ, Hohlein I (2005) Aging of Cellulose Transformer Service Temperatures Influence of Type of Oil and Air on the Degree of Polymerization of Pressboard, Dissolved Gases and Furanic Compound in Oil. IEEE Electrical Insulation Magazine 21: 15-21.

10 Myers SD, Kelly JJ, Parrish RH (1981) A guide to transformer maintenance. Transformer Maintenance Institute.

11 Norazhar AB, Abu-Siada A, Islam S (2013) A review on chemical diagnosis techniques for transformer paper insulation degradation. Power Engineering Conference pp: 1-6.

12 Badicu LV (2011) Diagnosis and monitoring of power transformer's insulation systems. University Politehnica of Bucharest.

13 Cheim L, Platts D, Prevost T, Xu S (2012) Furan Analysis for Liquid Power Transformers. IEEE Electrical Insulation Magazine 28: 1-14.

14 Stebbins RD, Myer DS, Shkolnik AB (2003) Furanic Compound in Dielectric Liquid Samples: Review and Update of Diagnostic Interpretation and Estimation of Insulation Aging. 7th International Conference on Properties and Applications of Dielectric Material 3: 921-926.

15 Abu-Siada A, Lai SP, Islam S (2009) Remnant life estimation of power transformer using oil UV-Vis spectral response. Power Systems Conference and Exposition (PSCE'09), IEEE/PES pp: 1-5.

16 Fu Q, Wang M, Chen T, Li X, Li J, et al. (2016) The relationship between carbon oxides in oil and thermal aging degree of oil-paper insulation. High Voltage Engineering and Application (ICHVE) IEEE International Conference pp: 1-4.

17 Prasojo RA, Diwyacitta K, Gumilang H (2017) Transformer Paper Expected Life Estimation Using ANFIS Based on Oil Characteristics and Dissolved Gases (Case Study: Indonesian Transformers). Energ 10: 1135.

18 Prasojo RA, Diwyacitta K, Gumilang H (2017) Transformer Paper Condition Assessment Using Adaptive Neuro Fuzzy Inference System Model. International Conference on Electrical Engineering and Computer Science pp: 237-242.

19 Jang JSR (1993) ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Transactions on Systems, Man, and Cybernetics 23: 665-685.

20 Cohen J, Cohen P, West SG, Aiken LS (1975) Applied Multiple Regression/Correlation Analysis for the Behavioral Science. Taylor and Francis.

21 Karim ME (2014) Selection of the Best Regression Equation by sorting out Variables.

22 Korea Standards Association (2003) Insulating Liquids-Determination of the Breakdown Voltage at Power Frequency-Test Method.

23 IEC (1997) Insulating liquids—oil-impregnated paper and pressboard—determination of water by automatic coulometric Karl Fischer titration.

24 IEC (2003) Insulating Liquids – Determination of acidity Part 1: Automatic potentiometric titration.

25 American Society for Testing and Materials (1999) Standard test method for interfacial tension of oil against water by the ring method. ASTM International.

26 International Organization for Standardization (1996) Petroleum Product – Determination of colour (ASTM scale).

27 Erenturk K (2009) ANFIS-based compensation algorithm for current-transformer saturation effects. IEEE transactions on Power Delivery 24: 195-201.