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Transformer Paper Expected Life Estimation Using ANFIS Based on Oil Characteristics and Dissolved Gases (Case Study: Indonesian Transformers)

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Abstract: This article presents an algorithm for modelling an Adaptive Neuro Fuzzy Inference System (ANFIS) for power transformer paper conditions in order to estimate the transformer's expected life. The dielectric characteristics, dissolved gasses, and furfural of 108 running transformers were collected, which were divided into 76 training datasets and another 32 testing datasets. The degree of polymerization (DP) of the transformer paper was predicted using the ANFIS model based on using the dielectric characteristics and dissolved gases as input. These inputs were analyzed, and the best combination was selected, whereas CO + CO_2, acidity, interfacial tension, and color were correlated with the paper's deterioration condition and were chosen as the input variables. The best combination of input variables and membership function was selected to build the optimal ANFIS model, which was then compared and evaluated. The proposed ANFIS model has 89.07% training accuracy and 85.75% testing accuracy and was applied to a transformer paper insulation assessment and an estimation of the expected life of four Indonesian transformers for which furfural data is unavailable. This proposed algorithm can be used as a furfural alternative for the general assessment of transformer paper conditions and the estimation of expected life and provides a helpful assistance for experts in transformer condition assessment.

Keywords: ANFIS; furanic compounds; degree of polymerization; paper insulation; remaining life; dissolved gas analysis; dielectric characteristic

1. Introduction

A power transformer is a piece of equipment that is designed for years of usage and generally has good reliability, with a life expectancy up to 40 years or more. The condition of the transformer naturally decreases as it is operated because of the processes of aging. However, it may become damaged faster than normal. During operation, transformers experience things that accelerate aging such as increased water content, temperature, and oxidation [1]. Without proper maintenance, the aging agents such as oxygen, heat, and moisture will cause acid formation and other materials that negatively impact cellulose insulation. Thus, these transformers may become unreliable and incapable of functioning as expected. The remaining life of a power transformer is an important aspect that the owner of the transformer needs to know. A good transformer assessment will give better insights on the condition of the transformer for maintenance purposes. This will result in better power transfer efficiency because of the smaller loss of opportunity resulting from power outages.

Aging power transformers have become a great concern for providers of electric power around the world, along with the growing needs of the power system. The oil-cellulose insulation in transformers will continue aging over a lifetime, and the cellulose insulation cannot be replaced. The aging of oil-immersed cellulose insulation decreases the mechanical strength and further limits the operation of the transformer [2].

Many data confirm that most of the damage to the transformer is related to the failure of the insulation system, while the life of the cellulose insulation is the life of the transformer [3]. Failures of transformers that are operating are commonly dominated by events such as a short circuit or a lightning strike. Due to the aging on the transformer, the mechanical strength of the paper insulation will decrease, and short circuit events like this can cause the ultimate failure of the transformer. Due to their random occurrence, we cannot be certain when the final failure of the transformer is going to happen. However, if the strength of the latest paper insulation can be known, it is possible to make an estimation of when these events might occur [1].

Different methods of diagnosis have been used to estimate the insulation degradation rate, i.e., dissolved gas analysis (DGA) and the estimation of the aging based on the loading history. Furanic compounds have been a concern in the past 20 years because they offer measurement of specific chemical compounds that can be transformed directly into an indicator of the aging of the transformer's paper insulation [4].

Furfural testing data of transformers in Indonesia is limited, unlike DGA and dielectric characteristics. Therefore, it is necessary to find an alternative way to do transformer paper insulation condition assessments using other test parameters. This study collected 108 transformer testing datasets, consisting of dielectric characteristics, Dissolved Gas Analysis (DGA), and furfural (2FAL).

Several different approaches to paper insulation condition prediction have been reported such as a Fuzzy based method using interfacial tension and acidity as the input in [5], a Fuzzy Logic model using CO and CO_2 as the input in [6], a ML (Machine Learning) approach using CO_2 and acidity as the input in [7]. The research in [8,9] shows the possibility of using neural networks to predict the furfural level. Another study uses the loading and temperature history to calculate and predict the degree of polymerization of the transformer paper, as reported in [10].

ANFIS has been used as estimator in several studies for many purposes. For transformer diagnosis purposes, various studies report the use of ANFIS to do dissolved gas analysis and complement the existing methods as shown in [11–13]. For its good purpose as an ultimate estimator [14], this article presents the development of an ANFIS model to help the experts in transformer paper condition assessment using widely available data, dielectric characteristics, and dissolved gasses as the input variables when furfural data is unavailable.

2. Methodology

This study used power transformer test data consisting of dielectric characteristics, dissolved gas analysis, and furfural. The transformers that were included in this study were 108 transformers with the nominal voltage of 150 and 500 kV and a capacity of 10 up to 100 MVA. There were 38 units under 30 MVA, 25 units between 30 and 60 MVA, and 45 units 60 MVA and more. All of the transformers used were mineral-oil immersed free breathing transformers with conservators. The transformers discussed in this article were already in operation for at least two years up to 53 years. These transformers underwent routine tests once a year and, if necessary, a few times a year. Dielectric characteristics and dissolved gas analysis tests are routinely performed, and the test datasets were collected. There are a lot of factors that influence transformer paper aging; the effects of nominal voltage, capacity, and the design of transformer on the aging of the paper are beyond the scope of this research and will further be ignored. Figure 1 shows one of the transformers included in the study. The ANFIS modelling process will be elaborated below.

Figure 1. Example of 150/20 kV transformer with a capacity of 60 MVA.

2.1. Transformer Paper Deterioration Indicator

The degree of polymerization test is done in order to measure precisely the degradation of the paper insulation used in the transformer. Cellulose, which is used as solid transformer insulation, is a linear polymer molecule consisting of hundreds of glucose units. DP is the average number of glucose molecules that make cellulose chains. The DP value decreases by the time proportional to the broken cellulose molecule. The deterioration rate is highly dependent on the temperature. Based on IEEE C57 140 standard, DP values vary from about 1200 for new paper to at least 100 for aging paper. At DP 200, the paper has lost about 70% of the initial tensile strength. At this point, the paper becomes brittle and the transformer is considered at the end of its life because it has lost its mechanical strength.

Furans concentration is a very important aging indicator for the evaluation and life assessment of transformers in service [15,16]. Furanic compounds are easier to get than DP and TS (Tensile Strength) because we only need to test an oil sample rather than taking paper samples of in service transformers. The furanic compound is one of the byproducts of the aging of oil-immersed cellulose paper and can be directly correlated to the degree of polymerization. Furfural (2FAL) is a compound that is tested to determine the aging rate of transformer paper. For non-upgraded kraft paper transformers, 2-Furaldehyde (2FAL), or so-called furfural, can be linked to the degree of polymerization by Chendong [17] Equation (1).

$$DP = \frac{\mathrm{Log}_{10}(2FAL_{ppm}) - 1.51}{-0.0035} \quad (1)$$

For a thermally upgraded paper transformer, Stebbins proposed that Equation (2), a modified Chendong equation, be used.

$$DP = \frac{\mathrm{Log}_{10}\left(2FAL_{ppb} \times 0.88\right) - 4.51}{-0.0035} \quad (2)$$

2.2. Adaptive Neuro-Fuzzy Inference System

The architecture and learning procedure underlying ANFIS (adaptive neuro fuzzy inference system) is a fuzzy inference system implemented in the framework of adaptive networks [13]. By using a hybrid learning procedure, the proposed ANFIS can construct an input-output mapping based on both human knowledge (in the form of fuzzy logic if-then rules) and stipulated input-output data pairs [18].

Two of the first parts of the process of fuzzy logic, the fuzzification of the input parameters and the use of the use of membership functions (MF), are used in ANFIS. The difference is in the output of the membership functions of Sugeno system, which can be either linear or constant.

The structures of two input ANFIS models are shown in Figure 2. By using the input-output data sets, ANFIS makes a FIS (Fuzzy Inference System). The MF parameters are set by training using a hybrid algorithm, which is combination of backpropagation and least squares. This led to the ability of the FIS system to learn the training data.

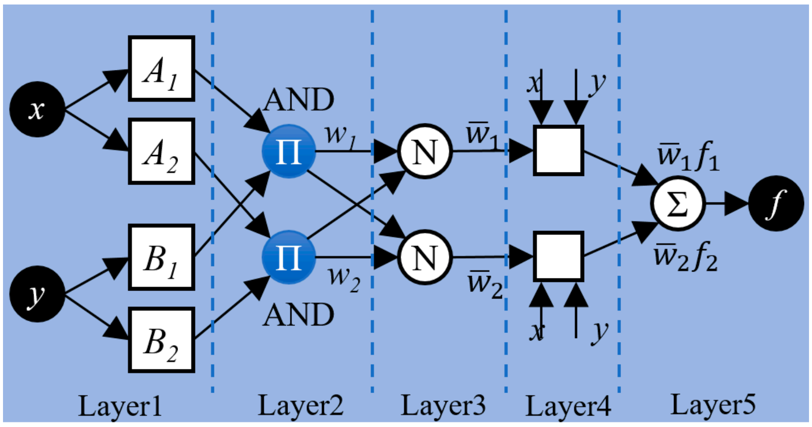


Figure 2. Network structure of an Adaptive Neuro Fuzzy Inference System (ANFIS) model.

The training obtains as many rule numbers as does the training data as shown below.

Rule 1: IF x is A1 AND y is B1 THEN $f_1 = 1$
Rule 2: IF x is A2 AND y is B1 THEN $f_2 = 2$
Rule 3: IF x is A1 AND y is B2 THEN $f_3 = 3$
Rule 4: IF x is A2 AND y is B2 THEN $f_4 = 4$
. . . . and so on

where x and y are the input of the fuzzy logic, and f_i is the output of a constant.

At the first layer, all nodes are adaptive or the parameters can be changed by Equation (3).

$$O_{1,i} = \mu_{A_i}(x) \text{ for } i = 1,2 \text{ or} \\ O_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i = 3,4 \tag{3}$$

With x (or y) as the input from the first node, while A_i or B_i is a linguistic label (high, low, medium), μ_{A_i} and μ_{B_i} are the membership functions of each node.

At the second layer, each node is labelled Π, which is non-adaptive. This is obtained by multiplying each input signal to generate an output signal using Equation (4).

$$O_{2,i} = w_i = \mu_{A_i}(x).\mu_{B_i}(y) \text{ for } i = 1,2 \tag{4}$$

Each output node represents the degree of activation. In the third layer, each node is non-adaptive, labelled N, and its function is to normalize the degree of activation by calculating the ratio of the first node of the previous layer to all layers of the previous output. Equation (5) is as follows.

$$O_{3,i} = \overline{w}_i = \frac{w_1}{w_1 + w_2} = \frac{w_i}{\sum w_i}, \text{ for } i = 1,2 \tag{5}$$

In the fourth layer, each node is adaptive, by the following Equation (6).

$$O_{4,i} = \overline{w}_i.f_i = \overline{w}_i(p_i x + q_i y + r_i) \text{ for } i = 1,2 \tag{6}$$

f_1 and f_2 are fuzzy logic if-then functions, $\overline{w}_i$ is the output of the third layer, and $(p_i x + q_i y + r_i)$ is an adaptive parameter.

In the fifth layer, each node in this layer is non-adaptive, labelled Σ; this node generates the output function of the ANFIS system by Equation (7).

$$O_{5,i} = \Sigma_i \overline{w}_i . f_i = \frac{\Sigma_i w_i . f_i}{\Sigma_i w_i} \quad (7)$$

2.3. Potential Input Variables

The dielectric characteristics and a dissolved gases test dataset of the transformers were collected and analyzed in this study.

2.3.1. Dielectric Characteristics

Temperature, water, and oxygen are the main agents of cellulose degradation as well as the oxidation of the oil. Insulation decomposition is a chemical phenomenon. The three mechanisms of degradation, namely, hydrolysis, pyrolysis, and oxidation, act simultaneously. Hydrolysis is the decomposition of a chemical compound by reaction with water. Pyrolysis is the decomposition or transformation of a compound caused by heat. Oxidation is the combination of a substance with oxygen [1].

When the transformer insulation undergoes degradation, the dielectric characteristics of the oil will change from the initial value. The dielectric characteristics parameters used in this article consist of

- Breakdown voltage in kV (IEC 60156-02)
- Water content in ppm (IEC 60814)
- Acidity in mg KOH/g (IEC 62021-1)
- Interfacial tension in dyne/cm (ASTM D 971-99a)
- Color (ISO 2049)

According to [19] acidity, has a relationship with the DP value through the oxidation of insulation oil that degrades the insulation paper through a hydrolysis process. In a transformer, we expect that paper aging is the main source of low molecular weight acids. Oil acidity is measured as the sum of all acids and expressed as the total acid number [2].

Paper aging decomposition is also related to interfacial tension, which is sensitive to the presence of soluble polar contaminants from solid insulating material [3]. The interfacial tension of oil in a transformer is the object of one of the tests done to assess the water content in solid insulation according to [1]. As the time elapsed, the degradation of the oil as well as the paper was indicated by the darker color of the aged oils [20].

2.3.2. Dissolved Gas Analysis

Dissolved gas analysis (DGA) was used to identify the gasses released in the paper-oil composite insulation as the results of the thermal aging process [20]. Normal operation will also result in the formation of some gases. In fact, it is possible for some transformers to operate throughout their useful life with substantial quantities of combustible gases present [21].

Operating a transformer with large quantities of combustible gas present is not a normal occurrence but it does happen, usually after some degree of investigation and an evaluation of the possible risk.

The concentration of gasses detected by the DGA test used in this article are:

- H_2 (hydrogen)
- CH_4 (methane)
- N_2 (nitrogen)
- O_2 (oxygen)
- CO (carbon monoxide)
- CO_2 (carbon dioxide)
- C_2H_6 (ethane)
- C_2H_4 (ethylene)

- C_2H_2 (acetylene)
- Tdcg (Total Dissolved Combustible Gas)

CO and CO_2 are a result of the thermal aging of paper insulation through an oxidation process [2,3,20]. The amount of dissolved carbon monoxide and carbon dioxide in oil could be correlated with the degree of polymerization and the tensile strength of the paper. When insulating papers are degraded, their degree of polymerization decreases, and CO and CO_2 are generated. The higher the temperature, the more gasses are generated [22].

2.4. Modelling ANFIS for Transformer Paper Condition

The proposed algorithm for building an ANFIS model for transformer paper condition estimation is shown in Figure 3

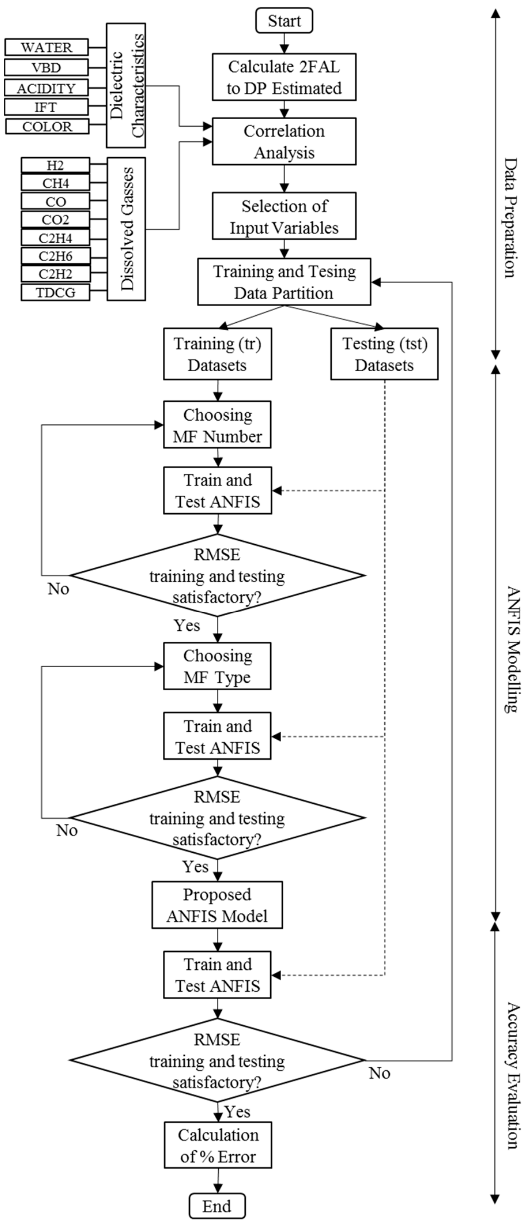


Figure 3. Adaptive neuro-fuzzy inference system (ANFIS) flowchart for modelling transformer paper condition estimations.

(1) Data Preparation: In the first stage, DP is estimated from 2FAL using Equations (1) and (2). The correlation of estimated DP and potential variables consists of dielectric characteristics, and the dissolved gases of transformer oil are analysed. The best combination of input variables for predicting DP is selected. The data from 108 transformers are then divided into training and testing datasets. 76 datasets will be used for training, and 32 datasets will be used to evaluate the proposed model.

(2) ANFIS Modelling: The training dataset is used for building the ANFIS model. The next step is to find the optimal combination of the Membership Function (MF). The number and type of MF for each input variable is selected, the model of each combination is trained using the training dataset, and each model is tested to find the satisfactory combination.

(3) Accuracy Evaluation: The proposed model is tested using the testing datasets, and then the error is calculated both from training and testing.

2.5. Prediction Accuracy and Evaluation

There are several criteria that can be used to do the performance evaluation of a transformer paper condition model. The accuracy of the proposed model has been evaluated using these different methods.

2.5.1. Mean Absolute Error (MAE)

This error evaluation criterion measures the difference between the estimated DP and the target DP.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|f_i - t_i| \tag{8}$$

Equation (8) calculates MAE where f_i and t_i are respectively the average difference of the estimated and target DP values of the i transformer, whereas N is the amount of DP predicted [23].

2.5.2. Symmetric Mean Absolute Percentage Error (SMAPE)

This criterion evaluates the prediction error as a percentage of the actual or target DP value using Equation (9) [24,25].

$$\mathrm{SMAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\frac{|f_i - t_i|}{(|f_i| + |f_i|)/2} \tag{9}$$

Provided that the data are strictly positive, a better measure of relative accuracy can be obtained based on the log of the accuracy ratio, log (Ft/At). This measure is easier to analyze statistically and has valuable symmetry and unbiasedness properties [26].

2.5.3. Root Mean Squared Error (RMSE)

RMSE is a measure of accuracy to compare the forecasting errors of different models for a particular variable and not between variables, as it is scale-dependent [27]. This is a criterion that minimizes the variance of the error distribution. For a target sequence t and forecast sequence f with N time steps, it is calculated by Equation (10).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{\mathrm{i}=1}^{N}(t_i - f_i)^2} \tag{10}$$

2.6. Transformer Paper Expected Life Estimation

The result of the ANFIS model is DP prediction. This DP value indicates the condition of the transformer paper. The life of the paper insulation is the life of the transformer [3]. Estimated percentage remaining life (%Eprl) can then be calculated using Equation (11).

$$\%\mathrm{Eprl} = 100 - \left\{ \frac{[\mathrm{Log}_{10}(\mathrm{DP}) - 2.903]}{-0.00602} \right\} \tag{11}$$

The DP value of cellulose decreases from its initial value (DP_0) due to cellulosic chain termination. The relationship between chain scission (η) and measured DP is calculated using Equation (12).

$$\eta = \frac{\mathrm{DP}_0}{\mathrm{DP}_t} - 1 \tag{12}$$

The Arrhenius Equation (13) about the aging of paper is shown below.

$$\frac{1}{\mathrm{DP}_t} - \frac{1}{\mathrm{DP}_0} = \mathrm{A} \,.\, e^{-\frac{\mathrm{Ea}}{\mathrm{RT}}} .t \tag{13}$$

R is the molar gas constant (8.314 J/mole/K), T is the absolute temperature in Kelvin, and Ea is the activation energy in kilojoules per mole. A is a constant that is dependent on the chemical conditions.

The chemical degradation of cellulose can be described, as above, by the above equation, which can be reconstituted into the equation below to determine the residual life of the transformer. In order to calculate expected life estimation of the transformer in years, Equation (14) is used.

$$\text{Remnant Life} = \frac{\frac{1}{\mathrm{DP}_t} - \frac{1}{\mathrm{DP}_0}}{\mathrm{A} \times 24 \times 365} \times e^{\frac{\mathrm{Ea}}{\mathrm{RT}}} \; [\text{years}] \tag{14}$$

Equation (15) is completed with coefficients that are needed.

$$\text{Remnant Life} = \frac{\frac{1}{200} - \frac{1}{\mathrm{DP}_0}}{\mathrm{A} \times 24 \times 365} \times e^{\frac{111 \times 1000}{8.314 * 30 + \mathrm{HST} + 273}} \; [\text{years}] \tag{15}$$

A is a constant using the results of [28,29], which are 2×10^8 for non-upgraded kraft paper and 0.67×10^8 for thermally upgraded paper. HST is the hot spot temperature rise from the hot spot of the winding. The standard HST in Indonesia is 68 K from IEC (International Electrotechnical Commission) 60076-2 [30] which set the HST of transformer at 78 K and was then corrected using K^a -10. Ea is the activation energy, which is uncertain depending on the presence of oxygen and water. Based on [31], which models the remaining lifetime of the power transformer derived from the result of previous research [28,29], the energy activation used for expected life estimation is 111 kJ/mol.

2.7. Transformer Dielectric Characteristics and Dissolved Gases Data

The predicted DP from the ANFIS model can be used as an alternative expected life estimation calculation for the transformer paper insulation if the current furfural level is unknown. Tables 1–4 show the dielectric characteristics and dissolved gases data from the three transformers to be assessed in this paper.

Table 1. Transformer #1.

Voltage (kV)	Rated Power (MVA)	Phase	Running Time (Years)
150/20	20	3	25
Dielectric Characteristic	**Value**	**DGA**	**Value (ppm)**
Water (ppm)	5.64	H_2	0
VBD (kV)	92.10	CH_4	25
Acidity (mg KOH/g)	0.19	C_2H_4	0
IFT (dyne/cm)	13.30	C_2H_6	0
Color (0–10)	3.40	C_2H_2	19
-	-	CO	1628
-	-	CO_2	1119
-	-	TDCG	1673

Table 2. Transformer #2.

Voltage (kV)	Rated Power (MVA)	Phase	Running Time (Years)
150/70	100	3	21
Dielectric Characteristic	**Value**	**DGA**	**Value (ppm)**
Water (ppm)	3.93	H_2	40
VBD (kV)	66	CH_4	0
Acidity	0.06	C_2H_4	0
IFT (dyne/cm)	30.60	C_2H_6	0
Color (0–10)	2.30	C_2H_2	0
-	-	CO	96.05
-	-	CO_2	2250.10
-	-	TDCG	96.05

Table 3. Transformer #3.

Voltage (kV)	Rated Power (MVA)	Phase	Running Time (Years)
150/20	60	3	4
Dielectric Characteristic	**Value**	**DGA**	**Value (ppm)**
Water	2.86	H_2	0
VBD	65.90	CH_4	30.37
Acidity	0.019	C_2H_4	0
IFT	30.20	C_2H_6	57.67
Color	0.50	C_2H_2	0
-	-	CO	167.84
-	-	CO_2	2787.33
-	-	TDCG	249.90

Table 4. Transformer #4.

Voltage (kV)	Rated Power (MVA)	Phase	Running Time (Years)
150/20	60	3	20
Dielectric Characteristic	**Value**	**DGA**	**Value (ppm)**
Water	2.80	H_2	23
VBD	80	CH_4	0
Acidity	0.02	C_2H_4	0
IFT	19.89	C_2H_6	0
Color	4.80	C_2H_2	0
-	-	CO	910.62
-	-	CO_2	7115.37
-	-	TDCG	910.62

3. Results and Discussion

From transformed DP based on furfural data collected, a correlation analysis was performed on each of the dielectric characteristics, as shown in the Table 1. Figure 4 shows the scatterplots of acidity, interfacial tension, and color. Those three parameters have higher correlation with the DP value than do water content and voltage breakdown, which is proven by r (correlation coefficient).

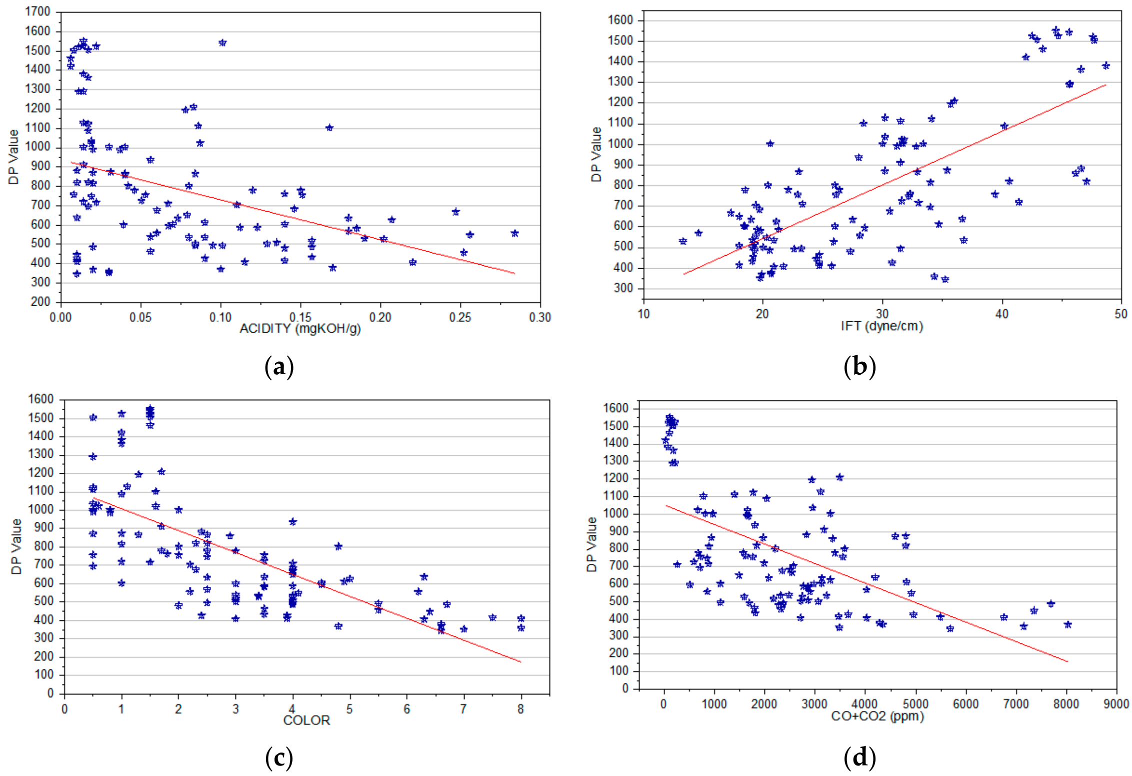


Figure 4. Scatterplots of DP (Degree of Polymerization) estimated versus input variables. (**a**) DP versus Acidity; (**b**) DP versus Interfacial Tension; (**c**) DP versus Color; (**d**) DP versus CO + CO_2.

3.1. Input Selection

3.1.1. Correlation Analysis

Correlation analysis is a highly general and therefore very flexible data analytic system. Basic linear regression may be used whenever a quantitative variable, the dependent variable is to be studied as a function of, or in relationship to, any factors of interest, the independent variables [32].

Linear regression is used in this study to find the highly-correlated parameters of dielectric characteristics and DGA to make a transformer paper condition assessment model. A correlation coefficient is a number that quantifies a type of correlation and dependence, meaning statistical relationships between two or more values in fundamental statistics. The correlation coefficient r is in the value range of −1 and +1. The closer 'r' is to −1 or +1, the more significant the correlation. If the value of 'r' is closer to +1, this means that the correlation between two variables is positive. Otherwise, if the value of 'r' is closer to −1, this means that the correlation between two variables is negative.

In this study, the correlation is verified by a *t*-test with $\alpha = 0.05$. If the value of 'P' < α, this means that the result of linear regression is significant.

Table 5 shows that acidity, interfacial tension, and color are correlated with DP and are potential as transformer paper condition predictors. According to [19], acidity has a relationship with DP value through the oxidation of the insulation oil that degrades the insulation paper through a hydrolysis process. Interfacial tension is sensitive to the presence of soluble polar contaminants from solid insulating material [3]. As the time elapsed, the degradation of the oil as well as the paper was indicated by the darker color of the aged oils [20].

Table 6 shows the correlation analysis of the DGA values, which resulted in TDCG, CO, and CO_2 having relatively high correlation with the DP value. TDCG (Total Dissolved Combustible Gasses) is not used as a potential predictor because it is originally the sum of H_2, CH_4, CO, C_2H_2, C_2H_4, and

C_2H_6. The highest concentration of TDCG comes from CO, which makes a high multicollinearity of CO and TDCG.

Table 5. The correlation coefficients of DP against the dielectric characteristics for oil-filled transformers.

Dielectric Characteristic	r	*p*-Value
Water Content (ppm)	−0.244	0.007
Voltage Breakdown (kV)	0.199	0.029
Acidity (mg KOH/g)	−0.432	0.000
Interfacial Tension (dyne/cm)	0.732	0.000
Color (Scale 0–10)	−0.686	0.000

Table 6. The correlation coefficients of DP against the dissolved gasses for oil-filled transformers.

DGA	r	*p*-Value
H_2 (ppm)	−0.069	0.452
CH_4 (ppm)	−0.087	0.343
C_2H_4 (ppm)	−0.242	0.008
C_2H_6 (ppm)	−0.044	0.631
C_2H_2 (ppm)	−0.196	0.033
TDCG (ppm)	−0.471	0.000
CO (ppm)	−0.511	0.000
CO_2 (ppm)	−0.536	0.000
CO + CO_2 (ppm)	−0.578	0.000

CO and CO_2 are a result of thermal aging of paper insulation through oxidation process [2,3,20]. Figure 5 shows the scatterplot of CO + CO_2 as opposed to the DP value. The correlation coefficient (r) of CO + CO_2 is the highest for the DGA values, making it a better potential variable as a transformer paper condition predictor than other forms of DGA.

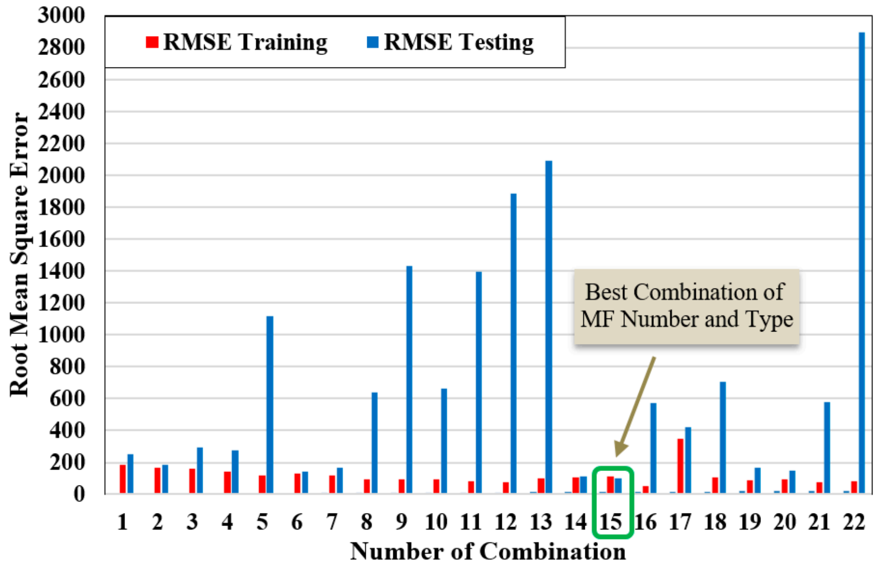


Figure 5. Root mean square error (RMSE) graph of 22 membership function combinations.

Figure 4 shows the scatterplots of estimated DP versus potential independent variables. The correlation of DP and acidity was statistically obtained with a correlation coefficient r of −0.432 and a *p*-value less than 0.05. This means that acidity has negative correlation with DP when the transformer paper is getting worse, the DP value is going down, and the acidity of the oil insulation is increasing.

The correlation of DP and interfacial tension was statistically obtained with a correlation coefficient r of 0.732 and a *p*-value less than 0.05. This means that interfacial tension has positive correlation with DP; when the DP value decreased, the interfacial tension of the oil insulation decreased.

The correlation of DP and color was statistically obtained by a correlation coefficient r of −0.686 and a *p*-value less than 0.05. This means that color has a negative correlation with DP; as the DP value decreases, the color of the oil insulation is getting darker.

The correlation of DP and CO + CO_2 was statistically obtained by a correlation coefficient r of −0.578 and a *p*-value less than 0.05. This means that CO + CO_2 has a reversed correlation with DP; as the DP value decreases, the amount of CO + CO_2 dissolved in the transformer oil is increased.

From dielectric characteristics, after content and voltage breakdown have relatively low correlation with the estimated DP. In dissolved gases, H_2, CH_4, C_2H_2, C_2H_4, and C_2H_6 have low correlation with the estimated DP [33]. Therefore, these parameters are not included as further potential input variables.

3.1.2. Various Combination of Input Variables

From the correlation analysis, several independent variables were statistically obtained, including CO + CO_2, acidity, interfacial tension, and color. The various combinations of these independent variables were then tested to get the best predictors. Parameters such as R-Sq, R-Sq (adj), R-Sq (pred), and Mallows Cp are the specifications used in choosing the best predictor model. From Table 7, the best combination of variables is number 13, which consists of CO + CO_2, acidity, IFT (Interfacial Tension), and color with the highest R-Sq, while the R-Sq (pred) value is not far from R-Sq (adj), and the mallows Cp is close to the number of predictors plus one.

Table 7. Various combinations of independent variables for DP prediction.

Number of Combination	R-Sq	R-Sq (Adj)	R-Sq (Pred)	Mallows Cp	CO + CO_2	Acidity	IFT	Color
1	33.6	33.0	31.3	33.2	x			
2	18.6	17.9	16.2	66.8		x		
3	53.6	53.3	51.9	50.7			x	
4	46.9	46.4	45.3	75.0				x
5	61.7	60.7	58.7	7.8			x	x
6	53.9	53.1	51.6	3.0		x	x	
7	47.9	47.0	45.5	3.0	x	x		
8	60.4	59.4	57.4	10.6	x		x	
9	51.2	50.4	48.9	3.0	x			x
10	50.0	49.1	47.9	3.0		x		x
11	64.6	63.2	61.3	3.6	x		x	x
12	63.0	61.5	59.4	7.1		x	x	x
13	68.0	66.9	65.6	5.0	x	x	x	x

3.2. Membership Functions Selection

The MF number of each input into the ANFIS model influences the accuracy of DP prediction. To obtain the optimal ANFIS model, various combinations of membership functions have been tested. Table 8 shows various combinations of MF numbers used as considerations for selecting the MF number in creating the ANFIS model.

Table 8. Various combinations of membership function (MF) numbers.

No.	$CO + CO_2$	Acidity	IFT	Color	MF Type	RMSE Training	RMSE Testing
1	2	2	2	2	TrapMF	183.81	254.30
2	3	2	2	2	TrapMF	168.81	183.02
3	3	3	2	2	TrapMF	161.06	296.70
4	3	3	3	2	TrapMF	143.8	274.81
5	3	2	3	3	TrapMF	116.25	1114.95
6	3	3	2	3	TrapMF	131.53	141.31
7	3	3	3	3	TrapMF	117.58	169.15
8	4	3	3	3	TrapMF	94.08	639.51
9	4	4	3	3	TrapMF	93.71	1431.84
10	4	4	4	3	TrapMF	94.06	662.59
11	4	3	4	4	TrapMF	83.31	1395.16
12	4	4	4	4	TrapMF	77.43	1886.97
13	4	2	3	3	TrapMF	98.25	2089.57
14	4	2	3	3	TrapMF	107.09	110.55
15	5	2	3	3	TrapMF	110.60	98.77
16	5	5	5	5	TrapMF	53.17	569.61

A red row shows a high testing error even though the training error is very small. This shows the overfitting of the training model, wherein, when given a different transformer scenario, the tendency of error is very high. A combination of 15, the green line indicates a similarly low training error and testing error. This suggests that, although training can produce fairly high accuracy, when given different transformer scenarios, the resulting predictions are quite good.

The type of MF varies by shape. After the combination of variations in the number of MFs with the highest accuracy, MF type selection was performed with respect to training and testing RMSE. Table 9 shows the different shapes and types of MF.

Table 10 shows the various combinations of MF type. A red row shows a high testing error even though the training error is very small. This shows the overfitting of the training model, where, when given a different transformer scenario, the tendency of error can be very high.

Table 9. Different MF types and shapes.

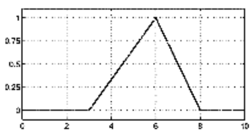
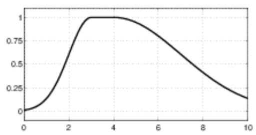
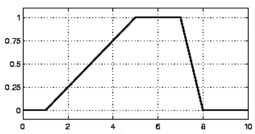
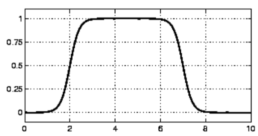
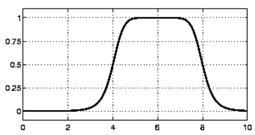
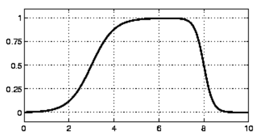
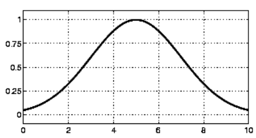
MF Type	MF Shape	MF Type	MF Shape
TriMF		Gauss2MF	
TrapMF		DsigMF	
GbellMF		PsigMF	
GaussMF		-	-

Table 10. Various combinations of MF types.

No.	$CO + CO_2$	Acidity	IFT	Color	MF Type	RMSE Training	RMSE Testing
15	5	2	3	3	TrapMF	110.60	98.77
17	5	2	3	3	TriMF	346.71	418.75
18	5	5	5	5	GbellMF	106.90	704.50
19	5	2	3	3	GaussMF	90.43	168.33
20	5	2	3	3	Gauss2MF	91.59	149.70
21	5	2	3	3	DsigMF	77.57	580.43
22	5	2	3	3	PsigMF	80.72	2893.2

From the selection of MF types, Table 10 shows that combination 15, with TrapMF (Trapezoid Membership Function), has the lowest RMSE training and testing values. Figure 6 shows the RMSE training and testing graph of various combinations of numbers and types of MF. The higher the graph, the greater the error that occurs. Combination 15 shows the lowest RMSE testing value, with a relatively low RMSE training value as well.

3.3. ANFIS Model Result and Evaluation

The various parameter inputs to the ANFIS model ($CO + CO_2$, acidity, IFT, and color) has been developed based on the 76 transformers that were used as a training data set with the membership function selection shown in Table 11.

Table 11. Membership function (MF) number and type of created ANFIS model.

Input Variable	MF Number	MF Type
$CO + CO_2$	5	TrapMF
Acidity	2	TrapMF
Interfacial Tension	3	TrapMF
Color	3	TrapMF

Figure 6 shows the structure of the ANFIS model developed. The prediction result from the ANFIS model tested uses the testing data set that consists of 32 different transformers from the training data set. Figure 7 shows the DP value target and the prediction result made by the ANFIS model, following the error from training and testing dataset.

Figure 7a,b show the estimated DP from the ANFIS model tested using the training dataset and the testing dataset. Blue dots show the targets of DP, and the red dots show the prediction results of the ANFIS model. Figure 7c,d show the residual value of the target and prediction results. It can be seen that the ANFIS is model able to predict the DP value using $CO + CO_2$, acidity, interfacial tension, and color as input variables.

The performance indicators in Table 12 suggest that the ability of the ANFIS model to predict DP from multiple parameters has an accuracy of 89.07% for the training dataset and 85.75% for the testing dataset.

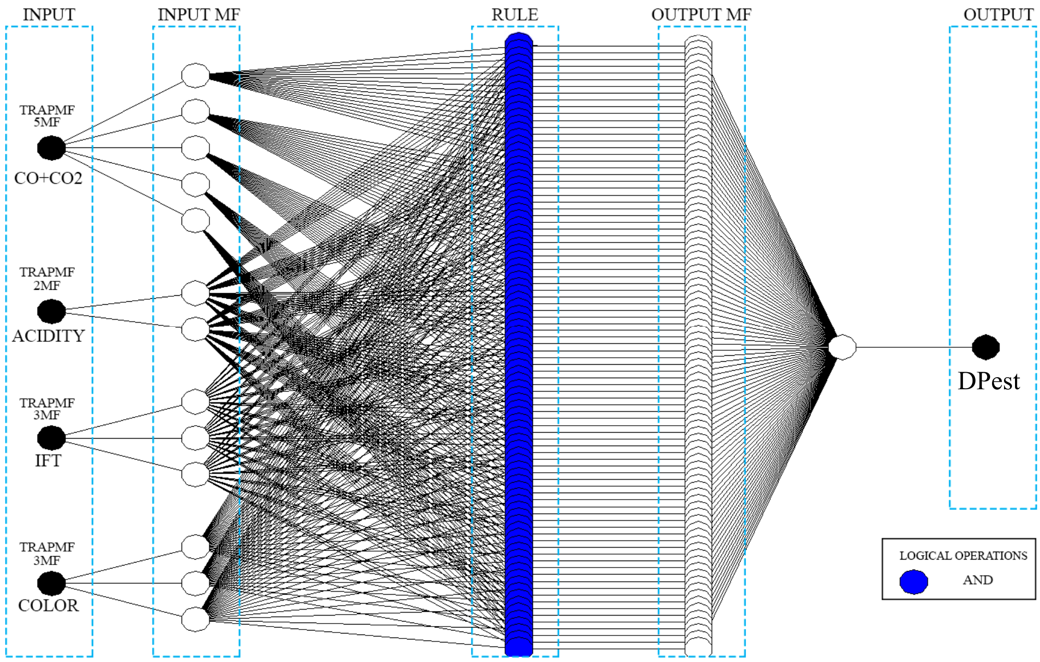


Figure 6. Proposed ANFIS model.

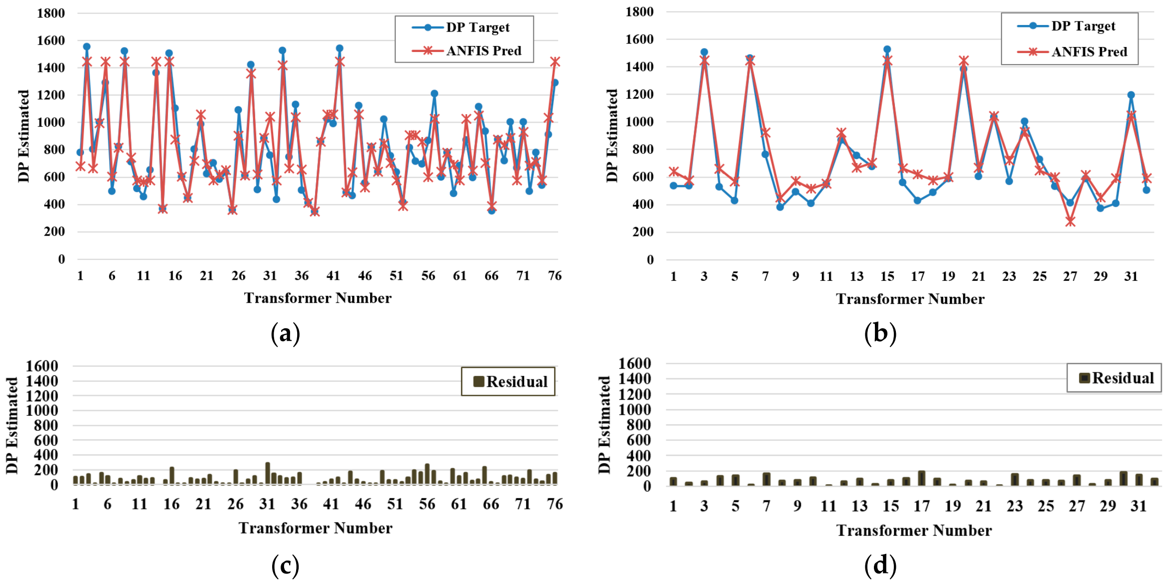


Figure 7. Results of the ANFIS model. (**a**) Degree of Polymerization prediction results of 76 training transformers; (**b**) Residual value of DP target and prediction results of 32 testing transformers; (**c**) Residual value of DP target and prediction results of 76 training transformers; (**d**) Residual value of DP target and prediction results of 32 testing transformers.

Table 12. Evaluation criteria of the model.

Criteria	Training	Testing
Mean Absolute Error (MAE)	85.57	85.52
Root Mean Square Error (RMSE)	110.60	98.77
Symmetrical Mean Absolute Percentage Error (SMAPE)	10.93%	14.25%
Accuracy (100–% error)	89.07%	85.75%

3.4. Expected Life Estimation of Transformer Paper Insulation

In order to estimate the expected life of four transformers in Tables 1–4, dielectric characteristics and dissolved gases data are used to predict the condition of transformer paper based on degree of polymerization. The ANFIS model proposed in this article is used to predict the DP of transformer paper. This predicted DP is then used to estimate the expected life of transformer paper using Equation (13). The result of the DP prediction and the expected life estimation is shown in Table 13.

Table 13. Expected life estimation.

Transformer	Running Time	DP Predicted (ANFIS)	Interpretation	%Eprl	Expected Life Estimated (Years)
#1	25 years	597.88	Accelerated Aging Rate	79.06%	8.05
#2	21 years	676.87	Normal Aging Rate	90.79%	8.67
#3	4 years	1044.46	Normal Aging Rate	119.25%	29.2
#4	20 years	369	Accelerated Aging Rate	44.25%	5.55

The results of expected life estimation from four Indonesian transformers show that Transformer #1 has 8.05 more years of life expectancy for transformer paper insulation. Transformer #2 is similar with 8.67 years, while Transformer #4 is in worse condition with 5.55 years of life expectancy. Transformer #3, on the other hand, has only been in use for four years and still has 29.2 years of life expectancy. Each estimated expected life span is result of the paper condition prediction using the ANFIS model based on using dielectric characteristics and dissolved gases as input variables. This expected life estimation result means that, as long as the hotspot temperature rise of the transformer is to be kept below 68 K (IEC 60076-2), the transformer paper life expectancy estimated should be more than that estimated in Table 13.

4. Conclusions

An algorithm for building an Adaptive Neuro Fuzzy Inference System (ANFIS) model for power transformer paper condition and expected life estimation is presented in this article. The combination of CO + CO_2, acidity, interfacial tension, and color were used as input variables to estimate the transformer paper condition. The proposed ANFIS model has 89.07% training accuracy and 85.75% testing accuracy and was applied to transformer paper insulation assessment and an expected life estimation of four Indonesian transformers for which furfural data is unavailable.

It can be seen that the proposed ANFIS model can be used to do a general estimation of the transformer paper condition and expected life when furfural data is unavailable. This algorithm acts as a helpful assistance for experts in transformer condition assessment. However, more confident engineering decisions on transformer paper condition assessment can be established when the transformers have furfural data as a main parameter.

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Conflicts of Interest: The authors declare no conflict of interest.

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