Integrated Life Estimation and Asset Management Decision Model for Power Transformers Using ANFIS

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ABSTRACT

Power transformer is a critical asset in electrical transmission and distribution networks that need to be carefully monitored during its entire operational life. Considering the fact that a significant number of worldwide in-service power transformers have approached the end of expected operational life, utilities have adopted various transformer condition-based maintenance techniques to avoid any possible catastrophic failure of the equipment. Pre-mature ageing of power transformers mainly depends on accumulated impacts of three aging processes, including pyrolysis, hydrolysis and oxidation. The extent of transformer insulation system ageing can be quantified through measuring several diagnostic indicators such as interfacial tension number of the insulating oil which has a strong correlation with the number of transformer operating years. Moisture and furanic compounds generated due to paper insulation degradation are indicators for solid insulation ageing. While several papers investigating various estimation models for transformer remnant life can be found in the literatures, all presented models are solely based on static expert system rules without taking into account the adaptive modification of these rules based on accumulated history and experience of the practical measurements. This paper introduces a new adaptive neuro fuzzy logic-based model to estimate the life of a power transformer based on the values of insulating oil interfacial tension number, furan content in oil and the moisture content within the cellulose insulation. Also, an integrated asset management decision model is proposed. Results of the proposed model are validated against practical data collected from utility and industry power transformers of different ratings, designs, operating conditions and lifespans.

Index Terms — **power transformers, condition monitoring, asset management and life estimation, adaptive neuro fuzzy logic inference system.**

1 INTRODUCTION

The day-by-day increase in load demand along with the significant number of aged power transformers have led to high failure rate during the last two decades [1]. Statistic survey conducted by the IEEE indicates that during a 16-year period, 10% of oil-immersed power transformers in a fleet are expected to exhibit a catastrophic failure [2]. This motivated worldwide utilities to adopt more reliable condition-based maintenance techniques rather than time-based maintenance schemes [3]. A CIGRE survey indicates failure rate of transformers owing to issues originating from the insulation system is 11% [4]. Thus, in order to formulate a reliable condition-based maintenance strategy, comprehensive understanding of insulation system ageing mechanism and quantifying the extent of its integrity are inevitable. Ageing of the transformer insulation system is attributed to several factors, including temperature, moisture content, and oxygen concentration along with electrical and mechanical stresses within the transformer [5]. Although insulation system ageing is an unavoidable process, exposure of transformer to excessive levels of above mentioned ageing contributors results in accelerated aging. Limitation of economic resources emphasizes the necessity for utilities to adopt reliable and cost effective models for transformer life estimation and asset management decision. Some models were put forward by IEEE [6] and IEC [7] organizations to estimate remaining life of transformers based on the operating temperature of the transformer insulation system. Although the advancement of online condition monitoring technologies have facilitated utilities to collate temperature data of their assets in a more practicable way; still, there is no confident perception of temperature distribution within transformers. Furthermore, a lifetime estimation model based on the insulation temperature does not reflect the impact of other ageing factors such as oxygen and moisture, which leads to less credibility and reliability of that model. A power transformer asset management decision model was proposed in [2], which is based on fuzzy logic inference system. In spite of being a comprehensive model for the purpose of asset management decision, some criticisms can be directed toward the

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applicability of such model on a regular basis as this model includes some parameters that are not measured during transformer routine testing. Furthermore, in order to measure some of the parameters deployed in this model, such as sweep frequency response analysis, transformer needs to be taken out of service. Moreover, all developed models in the literature for power transformer remnant life estimation and asset management decision are based on either static artificial neural network models or fuzzy logic rules without giving much attention to enhancing these rules based on the future measurements and feedback of the models outcomes. This paper is aimed at introducing an age estimation model for power transformers, developed by utilizing adaptive neuro fuzzy logic inference system (ANFIS) that can facilitate the improvement of model accuracy through the continuous evaluations of the measured parameters and the model's outcome. The parameters used in this model are routinely measured diagnostic indicators, including interfacial tension number, 2-Furfuraldehyde (2-FAL) content in oil and moisture content within cellulose insulation, which are strongly correlated with the transformer aging. Furthermore, an integrated asset management decision model is developed based on diagnostic parameters that are frequently measured during routine inspections.

2 Transformer Ageing Mechanism

It is widely accepted that the health condition of a transformer is highly dependent on the overall health of its insulation system. Degradation of the oil-immersed transformer insulation system comprised of paper and electrical insulating oil occurs through complex and sophisticated multi-factorial process due to interdependent relation between ageing factors and their additive effect [8]. The accumulative effect of temperature, moisture, acids and oxygen within a transformer is identified as the major cause of transformer aging mechanism. As insulation system ages, several by-products are generated. Acids are one of these by-products, resulted from both oil oxidation and cellulose degradation [9]. Despite the fact that oil oxidation produces several types of acids, only some specific acid types having low solubility in oil are aggressive and accelerate the aging rate of paper insulation [10]. Cellulose insulation acid hydrolysis also yields another aging by-product recognized as furanic compounds [11]. Furans are one of the diagnostic tools used in evaluating the health level of transformer paper insulation. In spite of the availability of other cellulose degradation indicators, such as dissolved gas analysis (through carbon-oxide concentrations and their ratio) [12], furan content in the oil is widely accepted as an indicator to reflect the degree of polymerization (DP) of cellulosic chain [11, 13].

Table 1. Degree of polymerization and 2-FAL concentration correlation

DP Value	2-FAL (ppm)	Significance
1200-700	0-0.1	healthy insulation
700-450	0.1-1.0	moderate deterioration
450-250	1-10	extensive deterioration
<250	>10	end of life

Extensive research was conducted to establish the correlation between 2-Furfuraldehyde (2-FAL) furanic compound, which has higher production rate than other furan compounds and DP [5]. The relationship between DP and 2-FAL concentration in the oil along with their significance in the interpretation of paper insulation ageing level is highlighted in table 1 [14].

As another decisive contributor to the insulation system degradation, moisture content plays an integral role in the reliability of transformer operation. Moisture content within a transformer can be sourced by several means, such as penetration of moisture due to atmospheric leaks, paper or pressboard degradation, and insufficient drying out of cellulose insulation throughout manufacturing process [8]. Because of hygroscopic nature of paper, cellulose insulation tends to absorb almost all existing moisture within a transformer. Moisture accelerates the ageing rate of paper insulation, triggers partial discharge between windings and may even cause flashover within the transformer [5, 15]. Considering detrimental effect of moisture on the insulation system of a transformer, not only fastidious drying-out process during manufacturing procedure should be conducted, but also excessive moisture content of in-service suspected units should be removed by means of on-line drying-out methods, such as the application of heat and vacuum, cellulose cartridge filters or molecular sieves [15]. A transition of moisture between the paper insulation and insulating oil occurs when the transformer operating temperature alters until an equilibrium status is reached [16]. Although absolute moisture content within transformer oil sample is measured, in parts per million (ppm), during routine inspection, relative saturation of the oil is used for determining the criticality level of the moisture. Relative saturation of the oil depends on oil temperature and indicates the capacity of the oil to hold moisture before it becomes saturated and free water drops are visible within the oil solution [17]. Utilizing moisture equilibrium curves [5], an estimation of the water content within the paper insulation can also be calculated using relative saturation of the oil.

The third diagnostic indicator of transformer insulation system decomposition, included in the proposed model in this paper is the interfacial tension number of the insulating oil. Interfacial tension number with the unit of mN/m provides an indication of the level of polar contaminants and ageing by-products within the oil solution [18]. As explained above, the accumulation of acids in the insulation system has a retroactively adverse impact on the ageing rate of transformers. With a strong correlation observed between the IFT number and acidity level of transformer oil [19], interfacial tension number can fully represent the contribution of acids to the ageing of transformer insulation system in the proposed model. Table 2 [8, 18] includes diagnostic categorization of the paper insulation moisture content and interfacial tension number of the insulating oil.

Table 2. Diagnostic categorization of the paper insulation moisture content and IFT number of the insulating oil

Paper Insulation Moisture Content (%M/DW)	Interfacial Tension Number (mN/m)	Significance
0.5-1.5%	>27	healthy insulation
1.5%-2.5%	24-27	entering in medium risk zone
2.5%-4%	18-23	entering in high risk zone
>4%	<18	entering in imminent failure zone

3 TRANSFORMER LIFE MODEL

Over the course of transformer multi-factorial ageing, ageing factors participate in a retrospective and synergistic way, making this mechanism complex. Due to this complexity, developing a precise mathematical model for insulation system degradation behavior is extremely difficult. In this paper, Adaptive Neuro Fuzzy Inference System (ANFIS) is implemented to estimate transformer life and provide a proper asset management decision based on some diagnostic parameters, which yields higher precision in the model output.

The typical structure of the fuzzy inference system is elaborated in [14, 18, 20, 21, 26]. Fuzzy inference system is deployed to model systems whose rule structure is defined as per the perception of the user from attributes of the presented data. The parameters of membership functions are selected haphazardly with merely looking at the data. With using ANFIS method, one can tailor the membership functions to the values of input and output data in order to account for all their characteristics and variations. Membership functions in a fuzzy logic system are defined by the parameters determining the shape of each membership function and the interval they cover. On the other hand, ANFIS method enables adaptive adjustment of the membership functions through adjusting their parameters with any change in the input data. Therefore, in the case of condition monitoring and asset management decision, membership functions and fuzzy rules can be modified based on the variations in the input and feedback from output data.

The fundamentals of neuro-adaptive learning technique are identical to those of artificial neural networks, ANN. Acquiring satisfactory results after being utilized in self-learning as well as solving complex problems, ANN has been deployed in pattern recognition and trend prediction [22], [23]. For the proposed model in this paper, input data including 2-FAL content in the oil, moisture content within the paper insulation, interfacial tension number of the oil and the actual age of the investigated transformers calculated based on their commissioning date are collated from different transformers of different ratings, operational conditions, lifespans and designs. This data is divided into two groups for training and testing, involving 60 and 40 sets, respectively. ANFIS method is employed to adjust membership functions parameters through the Levenberg-Marquardt back propagation-optimizing algorithm. Using historical data of input and output variables, this algorithm optimizes the parameters of membership functions by employing random weights which are computed and adapted through the learning process so as to minimize the error between the actual and estimated result [24].

Figure 1 depicts the training error in years, which is the difference between the actual (based on designated remnant operational life) and estimated age (based on abovementioned diagnostic parameters) of the transformers over the course of training. As can be seen in Figure 1, training error decreases to a value of 1 year at the epoch of 2000. The architecture of the developed ANFIS model is shown in Figure 2 in which input variables to the system are oil interfacial tension number, 2-FAL content in the oil and moisture content within the paper insulation while the output variable is the transformer estimated age.

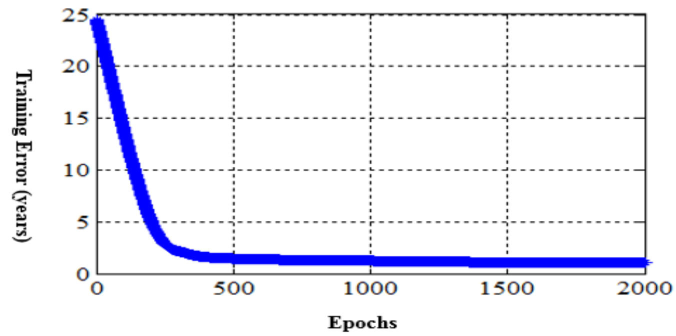

Figure 1. Training error against the number of epochs

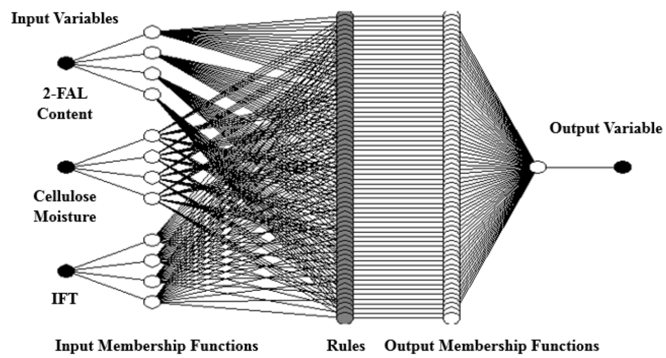

Figure 2. The architecture of the proposed ANFIS model

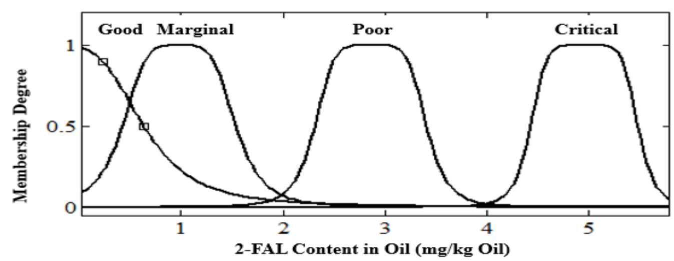

Figure 3. Adapted membership functions of 2-FAL content in oil

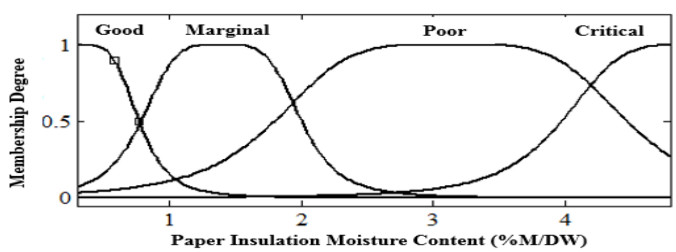

Figure 4. Adapted membership functions of cellulose moisture content

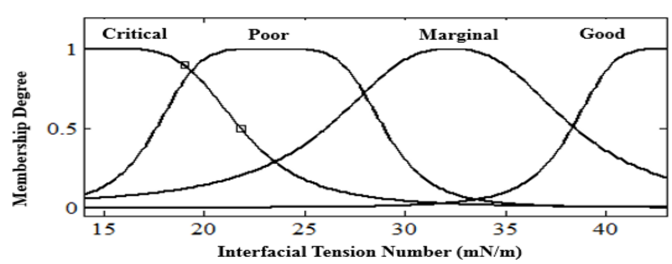

Figure 5. Adapted membership functions of interfacial tension number

As shown in the model structure of Figure 2, input variables are mapped through input membership functions and subsequently through output membership functions and their associated parameters into output variable. Once the training concludes, the outcome will be the required ANFIS-based model and its optimized membership functions. Adjusted bell-shape membership functions of the proposed ANFIS-based model are shown in Figures 3, 4 and 5. In contrary to fuzzy logic models, these membership functions are optimized every time ANFIS training is performed which facilitates continuous improvement in the model's accuracy. The entire range of every parameter used in the ANFIS-based model is selected based on the input data, while the interval covered by each membership function is determined by the optimized parameters calculated by the ANFIS training method. Figure 6 shows graphical illustration of the automated rules associated with the developed ANFIS model.

Validation of the developed model is accomplished using the designated testing data. As documented in Figure 7, actual ages of the transformers that are allocated to this set of data are displayed in blue circles along with the age estimated by the developed ANFIS-based model in red stars. The figure reveals a satisfactory level of precision of the proposed model.

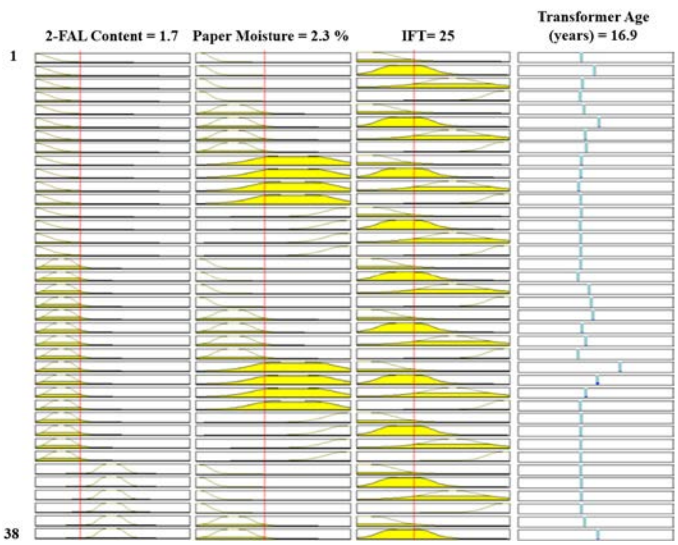

Figure 6. Developed rules by the ANFIS method for the proposed transformer life estimation model

To assess the robustness of the proposed model, another set of data collected from various in-service transformers is used to compare the transformer age estimated by the proposed ANFIS model with that of a model established based on fuzzy inference system. Actual age which is calculated based on commissioning date of the transformers, estimated age of the transformers obtained through the proposed ANFIS-based model, and that estimated by fuzzy logic inference system (FIS) model along with the estimation error of each model (calculated as per (1)), are listed in Table 3.

$$\%Error = \left| \frac{Age(Actual) - Age(Estimated)}{Age(Actual)} \right| \times 100 \qquad (1)$$

By comparing the results of the ANFIS and FIS models, one can conclude that the ANFIS-based model is able to estimate transformers life with much higher accuracy. For example, a 39-year transformer having 2-FAL content of 5.3 (mg/kg Oil), paper moisture content of 4.6 (%M/DW) and IFT number of 15 (mN/m), is estimated to have 38 years of age by the ANIFS model with an error of 2.6%, while the error is 6.2% when FIS is used to estimate the age of this transformer. This high accuracy is referred to the optimization of membership functions parameters when ANFIS is employed. These parameters are arbitrarily determined by the user when FIS is employed.

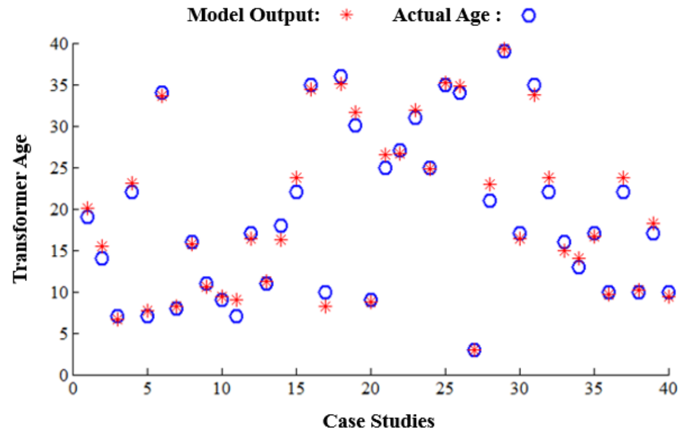

Figure 7. Validation of the developed ANFIS transformer-aging model

Table 3. Error between Actual and Estimated Life of Transformers by ANFIS and FIS models

Category	2-FAL Content (mg/kg Oil)	Paper Moisture Content (%M/DW)	IFT Number (mN/m)	Actual Transformer Life	FIS-Estimated Life	Error (%)	ANFIS-Estimated Life	Error (%)
End-life Transformers	5.3	4.6	15	39	36.6	6.2	38	2.6
	5.6	4.6	17	36	36.9	2.5	37	2.8
	5.4	4.2	17	35	36.8	5.1	35.5	1.4
	4.9	4	18	34	32.7	3.8	33.7	0.9
	5	3.3	19	32	34.8	8.8	31.3	2.2
	4.3	3.5	17	31	27.9	10	30.8	0.65
Near-end-life Transformers	4	3.2	18	29	27.9	3.8	27.7	4.5
	3.6	3.1	19	27	27.5	1.85	26.9	0.4
	4.1	3.3	18	27	27.9	3.3	27.7	2.6
	2.3	2.9	20	24	20.1	16.3	24.9	3.8
	3	2.7	22	22	24	9.1	23.8	8.2
Middle-age Transformers	1.2	2.4	25	19	15.5	18.4	17.9	5.8
	0.9	2.1	22	17	15.1	11.2	16.4	3.5
	1.7	2.3	25	17	19.1	12.4	16.9	0.6
	1.6	2	26	15	17.6	17.3	13.4	10.7
	1.3	1.9	26	12	15.1	25.8	12.1	0.8
New Transformers	1	1.8	28	10	13.2	32	10.3	3
	0.4	0.8	34	8	9.2	15	8.2	2.5
	0.05	0.9	40	7	6.1	12.9	7.45	6.4
	0.03	0.5	43	3	3.7	23.3	3.02	6.7

4 Asset Management decision model

As the parameters used in the life estimation model can reflect transformer's general health condition, model shown in Figure 8 is established using these parameters along with dissolved gases in the oil, which are also measured during continuous routine inspection [28]. This model consists of several ANFIS models trained in the same procedure as elaborated above. In the proposed model, overall criticality of a transformer is determined as a result of insulating oil, paper insulation and electrical criticalities. Oil insulation criticality output indicates the extent of risk that the insulating oil poses to the transformer and is determined based on interfacial tension number, acidity level and moisture content with considering the effect of temperature on the moisture equilibrium process.

Paper insulation and thermal criticality are determined based on the level of 2-FAL content in the oil, heating gases (ethylene C_2H_4 and ethane C_2H_6), and the quantity of carbon-oxide concentrations in the oil measured by dissolved gas analysis, DGA, along with carbon-oxides ratio, CO_2/CO. Carbon-oxides ratio can be used as an indicator of the excessiveness of paper insulation degradation as recommended by the IEC [29] and IEEE [30] standards. This ratio is used when carbon-oxide concentrations exceed the recommended limits [29, 30]. When this ratio is less than three or more than eleven, it indicates significant cellulose degradation.

Electrical criticality is determined by considering partial discharge and arcing criticalities. Partial discharge activity within a transformer can be detected by monitoring the concentration of hydrogen (H_2) and methane (CH_4) gases while acetylene (C_2H_2) concentration is an indicator for sustained arcing [31]. Based on the model overall criticality and transformer life estimation, asset management decision (D) ranging between 0% (new transformer) to 100% (imminent risk condition) is recommended as shown in Table 4.

Table 5 provides a comparison between the developed asset management model and practical management decisions (assessed by expert asset management utility team).

For instance, for the sixth case study in the imminent failure category in Table 5, the proposed model has revealed an asset management decision criticality of 99.1%, with an error of 0.1% compared to the asset management number decided by an expert asset management utility team based on the provided diagnosing parameters. Having an oil criticality of 91%, paper criticality of 98%, electrical criticality of 19%, and the overall criticality of 99%, this transformer is categorized within the imminent failure zone. To elaborate more on this, very high oil criticality of this transformer originates form the excessive amount of acidity as well as moisture in the oil, which yields high level of moisture within the paper insulation. The IFT number of this transformer has entered in the imminent failure zone as per the diagnostic categories provided in Table 2. In addition, carbon-oxide concentrations are outside IEEE recommended limits, which together with carbon-oxides ratio of 12.3 reveal excessive degradation of the cellulose insulation. This may be attributed to the improper cooling of this transformer due to the formation of sludge within the oil solution as the IFT number drops below 22. Over time, the formed sludge within the oil solution deposits on the transformer's internal components, resulting in reduced cooling efficiency of the transformer. Moreover, excessive degradation of this transformer is due to the extensive level of moisture within the paper insulation, which together with the acids accelerate degradation rate of the paper insulation, producing out-of-limits carbon-oxide concentrations. Electrical criticality of this transformer however is estimated to be at a satisfactory level as there is no evidence of partial discharge activity or sustained arcing within the transformer and Hydrogen, Methane and Acetylene concentrations are within the IEEE recommended limits. The overall criticality of this transformer along with the estimated life, 91%, provides asset management decision number of 99.6%. According to table 4, this transformer needs to be immediately taken out of service for an internal thorough investigation. Final decision on whether this transformer should be retired or scrapped is made based on the engineering judgment from the inspection outcome as well as degree of polymerization (DP) testing of the paper samples taken from the winding insulation.

Table 4. Management Decisions Associated with the Proposed Model Output

Asset Management Decision Model Output	Management Decision
0 % < D < 25 %	• normal operation • normal monitoring regime
25 % < D < 50 %	• normal operation • planning diagnostics • specific monitoring
50 % < D < 65%	• operation capacity reduction (below 80% nominal capacity) • strict overall monitoring scheme • more frequent sampling intervals • planning specific diagnostics • planning required remedial actions
65% < D < 75%	• operation capacity reduction (below 60% nominal capacity) • strict overall monitoring scheme • more frequent sampling intervals • planning specific diagnostics • planning required remedial actions
75% < D < 85%	• operation capacity reduction (below 50% nominal capacity) • strict overall monitoring scheme • more frequent sampling intervals • planning specific diagnostics • planning required remedial actions • deciding on relocation if justified
85% < D < 95%	• operation capacity reduction (below 50% nominal capacity) • strict online monitoring scheme • more frequent sampling intervals • planning specific diagnostics • planning required remedial actions • internal off-line detailed inspection • deciding on relocation or retirement
95% < D < 100%	• take transformer out of service • specific diagnostics with internal off-line detailed inspection • deciding on retirement or scrapping

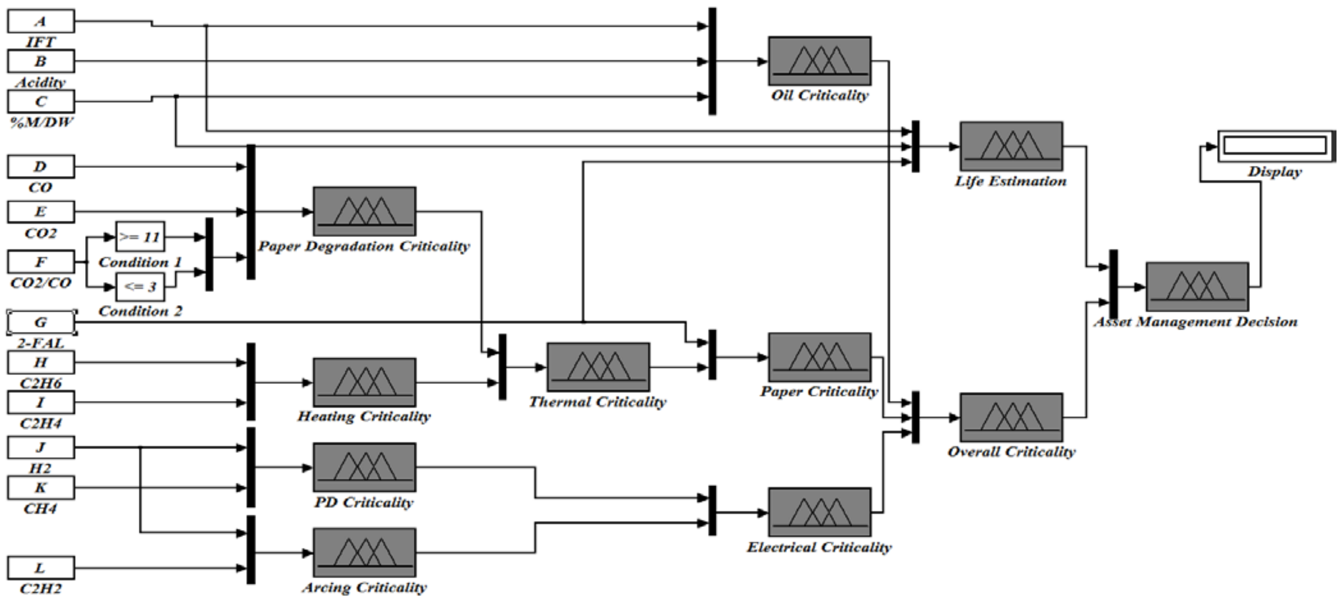

Figure 8. Developed ANFIS-based asset management decision model

Table 5. Results of the developed Asset Management Decision Model

Category	IFT	Acidity	%M/DW	%Oil	CO	CO2	CO2/CO	%Paper Degradation	C2H6	C2H4	%Heating	%Thermal	2-FAL	%Paper	H2	CH4	C2H2	%PD	%Arcing	%Electrical	%Overall	%Life Estimation	%D (Model Output)	%D (Actual)	%Error
Low Risk Zone	30	0.01	0.3	3	21	421	20	1	6	4	1	1	0.06	1	12	2	1	12	2	12	12	3	11.7	12	2.5
	40	0.01	0.9	11	54	526	9.7	7	26	16	7	7	0.08	7	42	25	1	7	13	13	14	11	14.3	14	2.1
	30	0.02	1.6	17	76	652	8.6	10	22	16	10	10	0.85	11	54	33	1	15	14	15	17	20	17.1	17	0.6
	40	0.02	0.9	12	96	1210	12.6	12	23	14	12	12	0.05	13	84	42	1	19	18	19	19	10	19.3	19	1.6
	34	0.02	0.8	9	114	2210	19.4	20	23	12	20	20	0.4	22	35	22	1	7	12	12	22	7	22.3	22	1.4
	40	0.01	1	13	212	1256	5.9	19	27	17	19	19	0.1	20	87	42	1	19	19	20	23	12	23.3	24	2.9
Medium Risk Zone	27	0.05	1.8	30	86	1395	16.2	12	31	18	12	12	1.2	28	20	12	1	7	6	7	30	26	30.7	30	2.3
	28	0.04	1.8	25	212	1120	5.3	19	21	16	19	19	1	30	32	22	1	6	12	12	32	25	32.4	32	1.3
	29	0.02	2.1	27	124	1283	10.3	14	25	16	14	14	1.9	32	76	22	1	23	17	23	34	36	34.3	34	0.9
	26	0.05	2.4	37	64	860	13.4	10	3	1	10	10	1	25	16	5	1	10	4	10	37	44	37	37	0
	29	0.02	0.6	7	135	1640	12.1	16	23	12	16	16	0.1	17	642	215	1	39	22	39	39	5	39	39	0
	24	0.07	2.3	41	121	973	8	12	26	12	12	12	2	29	34	14	1	8	12	12	41	45	40.8	41	0.5
	26	0.07	1.9	33	475	3280	6.9	49	4	1	49	49	1.3	49	16	22	1	5	4	5	49	27	48.8	49	0.4
High Risk Zone	42	0.01	1	13	102	1562	15.3	14	41	28	14	14	0.8	15	878	453	1	53	23	53	53	13	52.9	53	0.2
	33	0.02	1.7	22	597	5421	9.1	63	112	146	63	63	0.7	59	82	57	1	14	18	18	59	22	59.4	59	0.7
	22	0.12	2.1	51	125	980	7.8	12	10	8	12	12	0.9	14	1520	340	1	63	24	63	63	37	62.5	63	0.8
	38	0.04	1.3	16	825	2650	3.2	66	102	163	66	66	0.4	60	820	276	9	58	49	58	64	17	63.5	64	0.8
	25	0.08	1.8	37	345	3221	9.3	57	84	66	57	57	1.2	73	146	124	3	28	33	37	73	26	73.6	73	0.8
	25	0.07	2.4	47	1350	10600	7.9	54	41	21	54	54	1.2	73	980	125	1	69	23	69	74	46	76.6	74	3.5
Imminent Failure Zone	25	0.07	1.9	33	322	6421	19.9	77	43	29	77	77	1.6	81	83	67	1	14	18	18	82	29	81.3	82	0.9
	19	0.17	2.5	59	214	3459	16.2	76	24	16	76	76	2.9	85	63	34	1	18	15	18	85	50	86.2	88	2
	20	0.13	3	58	660	3210	4.9	62	178	112	62	62	3.2	76	86	42	1	19	19	20	76	60	91.6	92	0.4
	18	0.18	3.6	77	543	1243	2.3	95	164	121	95	95	4.5	99	732	146	18	65	67	73	99	76	95	95	0
	15	0.22	4.6	96	25	652	26.1	5	12	8	5	5	5.7	87	1620	452	1	60	24	60	96	97	98.4	98	0.4
	17	0.21	4.2	91	364	4485	12.3	85	121	53	85	85	5.4	98	72	34	1	19	17	19	99	91	99.1	99	0.1
	15	0.24	4.2	92	645	8422	13.1	100	435	322	100	100	5.3	100	620	421	1	29	22	29	100	90	99.6	100	0.4

5 CONCLUSION

Transformer insulation system decomposition is a complex procedure as the involved factors in this phenomenon have retroactive and synergistic effect on the ageing rate of the insulation system. This is the main difficulty for developing analytical equations explaining this mechanism. The developed models in this paper utilize diagnostic indicators that are regularly measured during transformer routine maintenance inspection. The adaptive neuro fuzzy logic-based integrated model put forward in this paper for estimating the age, overall criticality, and consequently asset management decision of a power transformer can be a great contribution to managing power transformers life cycle. It is expected that with the usage of this model, condition of transformers can be tracked more frequently with less financial cost during their operational lifetime. The proposed model utilizes the least possible number of essential key diagnostic parameters that are regularly measured during transformer routine inspection. ANFIS model provides more accurate results when compared to previously suggested fuzzy inference models. It also facilitates adaptive modifications of the rules based on the model's outcome and practical measurements. The proposed model can be implemented with feedback system that allows collecting, processing, and adapting model parameters in real time to continuously enhance the model accuracy and reliability.

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