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A Weighting Factor-Fuzzy logic based Transformer Residual Life Estimation Model

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Abstract— **Further utilization of ageing fleet of power system assets can be enhanced by acquiring better knowledge of life-threatening factors. In this paper, further exploration of power transformer residual life estimation is articulated. Previously, focus has been on diagnostic capabilities and degradation agencies in forecasting the remnant life of a power transformer. In this study, a weighting factor approach cascaded with fuzzy inference system was adopted in realizing the residual life of a power transformer. Instead of using individual attributes, the proposed model utilizes the grouping factor of technical life threatening agencies. A multi-criteria analysis was employed in developing the model, whereby the outcome of the model is accomplished by including the collective effect of distinct sub outcomes using fuzzification of all the active grouping attributes. Assessment of the developed residual life model was confirmed by utilization of data set attained from several in-service mineral oil immersed transformers. The simulation results were comparable with utility expert's outcome, thus confirming the applicability of the proposed model.**

Keywords— End of technical life, insulation degradation, remnant life estimation, life mapping, weighting factor

I. Introduction

The most critical development that led to the widespread supply and limitless use of electric energy is the invention of power transformer. Ideally, the power transformers serve as the fulcrum between the energy sources and the grid. Their great importance is only equalled by their high costs incurred in purchasing and maintaining them [1]. This makes power transformer failure a subject of great concern in electrical engineering. However, like other machines and equipment, transformers are not expandable. Without proper maintenance or if subjected to strenuous conditions (electrical, thermal, chemical or mechanical) which are out of the design characteristic, they are prone to failure. Their failures are especially detrimental as they cripple electric grid systems and the dependent faculties with unexpected outages which are usually indefinitely long. Consequently, it is vital to pay necessary attention to their maintenance, diagnostic and prognosis of life span issues [2].

A power transformer is designed to have a technical life of at least 40 years. However, this is not the ultimatum life, since life is dependent on numerous variables. The back bone of transformer life is its insulation life. However, being a function of voluminous divergent attributes, the design feature, varying operational conditions, and diverse maintenance policies and approach, a perfect assertion of the criteria governing the residual power transformer life estimation remains a complex phenomenon. Nevertheless, this intricate situation does not call off model estimation of residual life of transformers. Consequently, more variables that can affect life estimation models need more exploration.

Owing to hitches in diagnosis and prognosis, a noteworthy number of transformers are not meeting the probable technical life. Additionally, as power transformer ages, they are prone to fatigue leading to frequent failure rates thus; calling for untimely maintenance and repair till it reaches its end of life [3]. Though conditioned based maintenance approaches can extend equipment residual life, it can be monetary intensive for assets approaching their end of life. This has called for strategies to project the remaining useful life of power system assets. The transformer insulation failure has been the indicator of diminishing life of a transformer, thus models based on insulation conditions have been developed to map the transformer remnant life [3], [5]-[11]. Extreme, insulation stress levels, ageing and degradation, premature and poor asset management approaches and severe environments can lead to transformer catastrophe. Furthermore, agents like excessive moisture content, high oxygen levels, heat, and incipient faults can expedite the ageing and degradation of transformer insulation system [4].

In literature, the subject of transformer life estimation issues centered on different approaches not limited to mathematical and soft-computing based models linking some condition monitoring attributes and parameter lab tests (gases and oil quality lab tests) [3], [5]-[13] have been addressed. The degree of complexity for mathematical based model scales up as number of attributes considered increases. Thus, most of mathematical models are limited to few parameters overlooking some accelerating ageing and degradation factors which may lead to inaccurate prognosis of the transformer residual life [3], [11]. Consequently, intelligent based remnant life models managed to produce peculiar and interesting results that have managed to overcome some shortfalls of mathematical based models.

In [11], [13], a comprehensive multi-attribute remnant life estimation model based on fuzzy logic was established. However, some factors inclusive of failure history, maintenance data, loading regimes have been overlooked in

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establishing the remnant life of a power transformer. Subsequently, the underlying factors utilized in life estimation was taken at individual basis which might compromise the outcome since there parameters are correlated. Therefore, there is still room to improve the existing models to enable a probable true reflection of transformer residual life.

This paper aims to explore avenues of improving the existing methodologies on estimation of residual life of new and aged transformers through linking transformer oil and paper attesting results. Additionally, some maintenance data and winding temperature profile are also considered in this study. The weighting factor method of data extracted from insulation system attesting results, maintenance data and degradation accelerating agents are merged with a fuzzy logic inference system so as to compute the residual life for a power transformer. However, weighting factor technique depends on the designer's subjective reasoning. The overall outcome of the estimation depends on all considered features and variables as a whole, but not on any solitary parameter. The fuzzy logic-based residual life estimation value is established upon the dissolved gas factor (DGAF), oil quality factor (OQF), maintenance data factor (MF), degradation accelerants (ACCF), contaminants factor (CONTF) and degree of polymerization factor (DPF). Having a practical remaining useful life value can facilitate power utilities to enhance their asset management criterion, thus planning strategies to retire or shuffle transformers to less loading factors before end life can be realized.

II. Transformer Residual Life Estimation

The life estimation model is established on the fuzzy inference tool initiated upon the calculation of seven integrated cumulative factors that indicate the transformer status and degradation state. The variables are categorized into different classifications namely, dissolved gas (DGAF), oil quality (OQF), furans, (FF), maintenance data (MF), degradation accelerants (ACCF), contaminants (CONTF) and degree of polymerization factor (DPF). The DGAF, OQF, FF, and MF are utilized in mapping the transformer status whilst ACCF, CONTF and DPF are indicators of transformer life mappers. The DGAF involves seven attributes, OQF consists of five attributes, MF entails five attributes, FF represents furans whilst ACCF contains three variables and CONTF has two variables. The final residual life estimation value is the linguistic output of the fuzzy logic model. The allocated inputs are based on the combination of each of the sub-model factor with respect to scores, weights, and influence on the transformer's performance.

IEEE, IEC, Dornenburg, California State University Sacramento, and Bureau of Reclamation [14]-[16] have articulated the parameter ranges that can be acceptably utilized by power utilities. With that same notion, remnant life predication or transformer health condition can vary depending on the standards followed [16]. To achieved a practical residual life value from a fuzzy logic inference system, normalization of inputs was attained by using parameter limits that signifies normal and extreme ranges obtained from [14]-[17]. Furthermore, the variables ranges have been divided into four groups and conditions. Consequently, by subjective reasoning, the four settings of respective parameter are assigned appropriate weights (w) on a scale ranging from 0 to 10, as shown in Table 1.

Table 1: Parameter weights assigning.

Description	*Condition*	*Weights (w)*
Group A	*Good*	$[w \leq 2.5]$
Group B	*Okay*	$[2.5 < w \leq 5.0]$
Group C	*Poor*	$[5.0 < w \leq 7.5]$
Group D	*Critical*	$[7.5 < w \leq 10]$

A. Parameter Score and Weight Determination

The weight and score assigned to each variable was calculated based on the quantified value from the experiments and observation data and inputted in expression highlighted in equations *(i)* [16], [17] and *(ii)* [16]:

$$Variable\ score = K_i + \left[\left(\frac{x_i - y_i}{z_i - y_i}\right) \times 2.5\right] \quad (i)$$

Rearranging equation *(i)* gives an expression in *(ii)* to cater for variables whose higher values are preferred rather than lower values:

$$Variable\ score = K_i + \left[\left(\frac{z_i - x_i}{z_i - y_i}\right) \times 2.5\right] \quad (ii)$$

where, K_i indicates the minimum weight in the four settings of the variables, x_i is the present quantified value of the variable measured (x_i, is signified by x_i^a for DGAF variables, x_i^b for FF, x_i^c for OQF variables, x_i^d for MF variables, x_i^e for DPF, x_i^f for CONF variables and, x_i^g for ACCF variables), y_i and z_i are the lower and the upper limits of the matching group of the variables, $\left(\frac{x_i - y_i}{z_i - y_i}\right)$ symbolizes normalization expression of assigned inputs governed by equation *(i)*, whilst normalization of BDV, IFT and Core to ground resistance was accomplished through $\left(\frac{z_i - x_i}{z_i - y_i}\right)$.

B. Translation of model inputs into fuzzy variables

The principal inputs to the fuzzy logic model were attained from the summed scores for seven transformer variable groupings obtained from expressions *(i)* and *(ii)*. However, the two sub-models (transformer status model and life mapping model) were initially developed, then their outputs were integrated to map the transformer residual life. The related membership function range and assigned linguistic indications for the totaled inputs are summarized in Table 2. Additionally, the partitioned ranges also represent the ranges for the membership functions for the fuzzy logic inputs for different factors. Computation of these membership ranges was achieved by multiplying the lower and upper limits of weights of the four settings by number of attributes in each grouping. For both inputs and outputs, the trapezoidal membership functions were of choice and the centroid defuzzification method was used to map the residual transformer life.

Table 2: Summed parameter ranges

Totalized variables	Input category ranges			
	Safe (S)	*Moderate(M)*	*High(H)*	*Critical (C)*
DGAF	$0 \le 17.5$	$17.5 < M \le 35$	$35 < H \le 52.5$	$52.5 < C \le 70$
OQF	$0 \le 15$	$15 < M \le 30$	$30 < H \le 45$	$45 < C \le 60$
FF	$0 \le 2.5$	$2.5 < M \le 5$	$5 < H \le 7.5$	$7.5 < C \le 10$
MF	$0 \le 10$	$10 < M \le 20$	$20 < H \le 30$	$30 < C \le 40$
DP	$0 \le 2.5$	$2.5 < M \le 5$	$5 < H \le 7.5$	$7.5 < C \le 10$
CONF	$0 \le 5$	$5 < M \le 10$	$10 < H \le 15$	$15 < C \le 20$
ACCF	$0 \le 7.5$	$7.5 < M \le 15$	$15 < H \le 22.5$	$22.5 < C \le 30$

The proposed sub-models for fuzzy logic transformer status condition and transformer degradation state are portrayed in Fig. 1. The prognosis of transformer residual life was accomplished after cascading transformer condition status factor with life mapping factor model. The output (estimated transformer residual life) membership functions were normalized on a scale of 0-1. The projected transformer residual life spans on a scale of 0% (end-of-life) to 100% (excellent) of its technical in-service life span which is typically 40 years. Thus, the results are based on a 40-year projection timeline. Henceforth, this model can be applied to different transformer design life time. The overall residual life estimation Simulink generated model is depicted in Fig. 2.

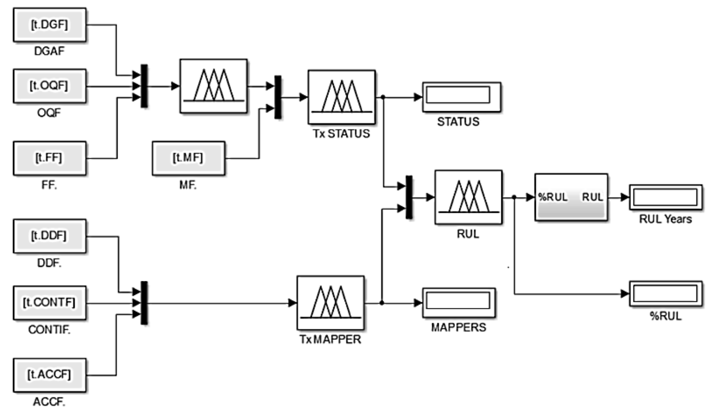

Fig. 2: Residual life estimation model

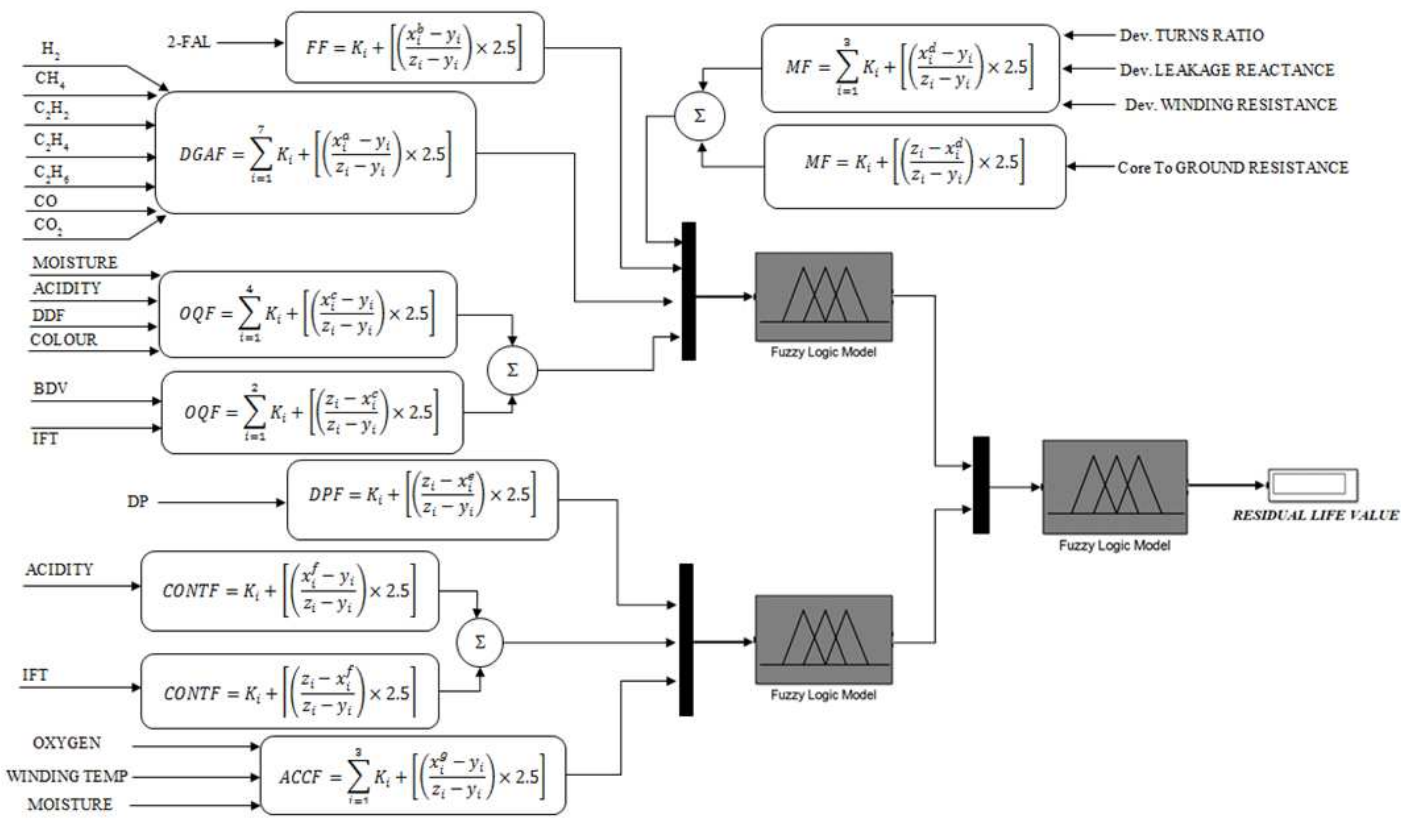

Fig 1: Proposed Fuzzy logic model for Residual transformer life estimation status

III. Model Validation Results and Discussion

Validation of the designed model was conveyed through use of test data (Table 3) attained from different in-service power transformers. In Table 4, the corresponding scores calculated as per the individual transformer attributes are highlighted. Henceforth, Table 5 represents totalized scores for the different groupings and residual useful life (RUL) simulation results for the sampled transformers. The totalized scores were used as inputs to the model. Additionally, comparisons between different remnant life estimation model outputs and utility life estimated values for the different transformers are tabulated in Table 5. The model considered in [18], had a relative low accuracy compared to other models because it was based on single attribute (DP) thereby overlooking other relevant life-threatening factors. Based on this single variable, the results obtained were an overestimation of the transformer remaining life. As noted in [19] wet insulation paper exposed to high oxygen levels may degrade 37 times faster than when dry paper was aged in low oxygen.

The proposed model results and those of fuzzy logic in [8], [11] were in the boundaries of the life estimated by the power utility experts. These models considered the ageing accelerants and contaminants. However, the model in [11] further considered the transformer condition determined by fault and ageing stress criticality in life estimation as compared to paper criticality (mapped by furans factor) in [8]. Accordingly, in the proposed model, the factor of solely depending on individual variables in life estimation was removed, thus the grouping and weighting factor which maps the reality of transformer functionality was realised.

IV. CONCLUSIONS

As the ageing fleet of power system equipment approaches the ending timeline of their technical usefulness, malfunctions and sometimes catastrophic failures often emerges. However, knowledge of remaining useful life of these assets can avert these technicalities from happening. In this paper, a power transformer residual life estimation model was established based on groupings of the life-threatening agencies. A weighting factor approach cascaded with a fuzzy logic inference system was utilized in formulating the model. Based on a 40-year technical life span, simulation results of the model were comparable with utility expert results. It was observed that the grouping of attributes that mirrors the performance and condition of the transformer merged with maintenance data can lead to apt prognosis of the remaining useful technical life of a power transformer. Henceforth, results presented direct a trend towards achieving a feasible life estimation model for power transformers.

Table 3: Test Data

Tx No	*Year of Installation*	*H_2 ppm*	*CH_4 ppm*	*C_2H_2 ppm*	*C_2H_6 ppm*	*C_2H_4 ppm*	*CO_2 ppm*	*CO ppm*	*O_2 ppm*	*Furans ppm*	*Moisture ppm*	*Acidity mg KOH/g*	*BDV kV*	*DDF %*	*IFT dynes/cm*	*Colour*	*WT °C*	*Turns Ratio (TR) Δ%*	*Leakage Reactance (Δ%)*	*Core to Ground Resistance (GΩ)*	*Winding Resistance (Δ%)*	*DP*
Tx1	1996	234	300	52	56	29	5495	700	8865	0.25	22	0.07	52	0.14	30	1.5	60	0.92	0.48	3.56	1.03	650
Tx2	2010	15	8	0	9	5	7135	902	1672	0.1	10	0.03	55	0.15	42	1	61	0.01	0.67	5	0.56	750
Tx3	2012	793	704	1	8	18	1873	245	5300	0.03	9	0.04	71	0.068	45	0	56	0.023	0.21	5.82	0.22	840
Tx4	1987	82	344	37	202	162	22589	8197	20971	4.53	28	0.18	40	0.266	20	2.5	78	1.33	1.78	0.74	2.44	220
Tx5	1998	151	8	8	151	10	2323	297	14620	0.22	6	0.13	64	0.566	27	2	68	0.52	0.33	4.6	1.08	680
Tx6	2000	107	129	0	55	68	7038	892	5013	0.1	26	0.09	48	0.249	25	1.5	66	0.04	0.56	2.3	0.84	780
Tx7	2015	102	38	3	8	15	1077	165	679	0.02	3	0.01	82	0.083	45	0	60	0.02	0.36	5.02	0.3	1030
Tx8	1978	1498	395	26	323	395	12371	1582	25623	3.9	33	0.19	35	0.593	25	4	66	1.02	2.81	0.55	3.1	260
Tx9	2005	1176	4	1	4	10	4991	637	3892	0.83	10	0.09	62	0.733	29	1.5	53	0.35	1.33	2.2	1.2	600
Tx10	2002	181	79	21.1	56	29	713	196	10032	2.91	21.2	0.349	33.5	0.257	20	3	50	0.63	-	1.53	0.98	375
Tx11	2018	75	6	0	3	10	1020	257	598	0.01	2.5	0.05	86	0.072	44	0	52	0.01	0.1	7.02	0.13	1090

Table 4: Corresponding scores obtained as per the values of the test data

Tx No	*H_2*	*CH_4*	*C_2H_2*	*C_2H_6*	*C_2H_4*	*CO_2*	*CO*	*O_2*	*Furans*	*Moisture*	*Acidity*	*BDV*	*DDF*	*IFT*	*Colour*	*WT*	*TR*	*Leakage Reactance*	*Core to Ground Resistance*	*Winding Resistance*	*DP*
Tx1	3.06	4.1	9.02	1.45	1.45	5.62	5	4.65	2.92	5.63	3.47	2.4	2.75	2.5	2.5	3.44	4.78	1.6	1.81	2.55	3.33
Tx2	0.38	0.17	0	0.35	0.25	6.31	5.72	2.09	2.5	1.67	1.5	2.25	2.81	1	1.67	3.54	0.25	2.23	1.39	1.4	2.5
Tx3	5.21	6.26	2.5	0.31	0.9	1.87	1.75	3.53	0.75	1.5	2	1.45	1.7	0.63	0	3.02	0.56	0.4	1.16	0.55	2
Tx4	2.05	4.5	7.68	12.75	6.54	12.75	31.8	10.93	5.98	9.34	6.75	5	3.54	6.5	7.5	5.21	5.83	3.93	3.16	4.9	7.8
Tx5	2.71	0.17	5.09	10.05	0.5	2.32	2.12	6.44	2.83	1	5.56	1.8	5.29	3.57	5	4.27	3.67	0.44	1.5	2.63	3.08
Tx6	2.53	2.57	0	2.12	3.37	6.27	5.68	3.44	2.5	8.13	4.49	2.78	3.43	4.29	2.5	4.06	1	1.87	2.14	2.1	2.33
Tx7	2.51	0.79	3	0.31	0.75	1.08	1.18	0.85	0.5	0.5	0.5	0.9	2.08	0.63	0	3.44	0.5	1.2	1.38	0.75	0.94
Tx8	6.81	4.96	6.7	18.83	12.42	8.49	8.15	12.38	5.81	12.5	7.22	6.11	5.42	4.29	15	4.06	5.13	5.31	3.64	5.6	7.38
Tx9	6.08	0.083	2.5	0.15	0.5	5.41	4.55	3.09	4.53	1.67	4.49	1.9	6.14	2.86	2.5	2.71	3.19	3.33	2.17	2.8	3.75
Tx10	2.83	1.65	6.26	2.15	1.45	0.71	1.4	5.01	5.53	5.13	11.64	6.53	3.48	6.5	10	2.5	3.97	-	3.35	2.45	5.94
Tx11	1.88	0.13	0	0.12	0.5	1.02	1.84	0.75	0.25	0.42	2.5	0.7	1.8	0.75	0	2.6	0.25	0.33	0.83	0.33	0.61

Table 5: Summed scores and Simulation Results

Tx. No	SUMMED PARAMETER SCORES							REMNANT LIFE ESTIMATION (YRS)				
	DGAF	OQF	FF	MF	DPF	CONF	ACCF	Utility estimation	Sen's Model [18]	Fuzzy logic model [8]	Fuzzy logic model [11]	*Proposed Model*
Tx1	29.7	19.25	2.92	10.74	3.33	5.97	13.72	29.8	41.2	31.6	28	30.2
Tx2	13.18	10.9	2.5	5.27	2.5	2.5	7.3	30.2	46.6	33	29.4	29.3
Tx3	18.8	7.28	0.75	2.67	2	2.63	8.05	34	50.6	30.4	32.8	35.6
Tx4	78.07	38.63	5.98	17.82	7.8	13.25	25.48	5	1.1	9.2	6.03	5.1
Tx5	22.96	22.22	2.83	8.33	3.08	9.13	11.71	28	43.1	25	25.6	28.7
Tx6	22.54	25.62	2.5	7.11	2.33	8.78	15.63	30	47.9	28.4	28	28.5
Tx7	9.62	4.61	0.5	3.83	0.94	1.13	4.79	40	57.3	35.8	35.3	39.6
Tx8	66.36	50.54	5.81	19.68	7.38	11.51	28.94	8	9.6	12.4	9.2	9.5
Tx9	19.27	19.56	4.53	11.49	3.75	7.35	7.47	25	38.7	22.8	24.3	22.4
Tx10	16.71	43.28	5.53	9.77	5.94	18.14	12.64	15	22.2	17.3	12.5	18.6
Tx11	5.49	6.17	0.25	1.74	0.61	3.25	3.77	40	59.6	36.9	38.3	39.8

The empirical remnant useful life model of the mineral oil-immersed could be enhanced by including the aspect of the transformer failure statistics and considering the effects from other ageing failure mechanisms, for example the transformer electromagnetic degradation due to geomagnetic disturbances.

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