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Research Article

Multiparameter-Based Fuzzy Logic Health Index Assessment for Oil-Immersed Power Transformers

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The health index scheme can be the most fundamental tool that unifies all transformer condition status information into a singular outcome, thereby enhancing the power transformer asset management and life longevity strategies. This study aims at establishing a multiple parameter-dependent transformer health index estimation model cascaded with a fuzzy logic inference system. This strategy is centered on the effect of dynamic loading regime, varying hotspot temperatures and multiple attesting results of the insulation system. Furthermore, a nonintrusive degree of polymerization (DP) model based on furans and carbon oxide ratios as DP pointers is also factored in developing the health index model. The general outcome of the health index depends on entirely considered elements, but not on any isolated attribute. Data obtained from in-service transformers were used to validate the proposed model. The outcome of the model mirrors the practical condition of the evaluated transformers. Therefore, the proposed health index model can be a vital tool to asset managers and power utilities.

1. Introduction

Ageing infrastructure of electrical energy systems has lately calls for concern and challenge to power utilities around the globe. Catastrophic failures of ageing electrical equipment, especially power transformers in a power grid, can cause interruptions which result in both social and economic losses. Therefore, it is very important to pay sufficient attention to their maintenance and diagnostic and life span issues [1]. Due to the extensive investment in power transformers and their prominence as key elements which can affect system availability, the transformer asset management system is presumed to be the key aspect of equipment asset management in the field of power engineering [1–3].

Transformer health index can be utilized as an asset management decision support tool, residual life valuation, risk pointer, and as a blueprint of maintenance scheme [4–6]. The health index (HI) has emerged to be the most fundamental tool that unifies all transformer condition status information into a singular outcome [6]. The HI highlights a threshold centered principle that allows power utilities to classify the condition of an individual transformer from being in an excellent to a degraded state of operation. Accordingly, asset maintenance, refurbishment, or replacement decisions can be centered on a conjoint pointer. Based on the information gathered during transformer operation not limited to physical transformer and auxillary equipment tests, transformer fault history, parameter lab tests (oil quality lab tests), loading history, and a power transformer health index can be established [1, 7].

Different health index models have been established in different literature based on synthesis of different developers using information attained from the insulation system in order to minimize transformer outages [1, 5, 7–15]. Nevertheless, transformers are exposed to different stresses which act simultaneously inside the transformer making the analysis challenging. This makes it difficult to assess and accurately interpret the power transformer's health condition as well as estimate its technical end of life. Due to these complications in diagnosis, a significant number of transformers are failing before attaining the expected technical life. However, being able to establish transformer health index can avert possibilities of transformer outages. The weighting factor approach of data extracted from field tests, laboratory, and operation history of transformers has been the most used technique is computation of transformer HI. Nevertheless, health index based on soft-computing techniques have brightened the future of many power utilities as these HI methodologies are easy to comprehend. As highlighted in [1, 9–15], fuzzy logic HI approach based on several transformer tests have been proposed in transformer condition and health index assessment. Additionally, probabilistic approaches [16], Bayesian networks [17], and artificial neural networks have been used in determining health index [18].

Since there is no standardized approach in defining the scores and weights given to input parameters for health index calculation based on weighting factor, the HI outcome will differ as per the developer. However, this subjective scoring and weighting strategy can be merged with intelligence-based algorithms to mimic the utility experience in determining the asset health index. Even though the fuzzy logic models conveyed in different texts have their peculiar significance in defining the overall HI of transformers, most of them consider limited variables which are influential in deciding the health state of power transformers [14]. However, a multicriterion [1] and multiattribute [5] transformer condition based on fuzzy logic was proposed. In [1], the strategy was centered on the data-correlated auxillary equipment and physical condition of the transformer. However, in this technique, substantial diagnostic information related to internal transformer degradation and ageing was overlooked. Additionally, the limitation of the approach used in [5] arises when a thermally upgraded insulation paper comes into play. Thus, some variables such as the degree of polymerization (DP) and operational stress should be factored in when calculating transformer health index. Furthermore, as observed in [13], it is also essential to include the impact of transformer age and loading profile as pointers in establishing an overall transformer health index. However, DP measurement is an intrusive test which requires de-energizing of the power transformer and take paper samples, thereby disrupting continuity of power supply. Furthermore, gas evolution can be due to insulation ageing or through incipient faults. Thus, the impact of the evolved gases should be considered in determining the health index by also assessing the origin of gas manifestation. Accordingly, implementation of a probable health index calls for great caution in choosing the variables that have great significant effect on the index outcome such that a reasonable and reliable transformer condition is estimated.

This paper aims at developing a multiparameter-dependent transformer health index estimation model established upon an integrated fuzzy inference system. It considers the effect of loading regime, varying hotspot temperatures and all attesting results of the insulation system. The general outcome of the established HI centers on entirely reflected elements, not on any sole attribute. Additionally, a nonintrusive DP estimation based on indicating factors, furans and carbon oxides ratio, is also factored in the health index model. Having a reasonable health index can facilitate power transformer reliability and also enhance its residual life span.

2. Transformer Health Index Pointers

In order to formulate a probable health index model of a power transformer, careful determination and analysis of the influencing parameters that leads to deterioration of a transformer needs to be performed first. The significance and interpretations of some of the parameters that have influence in the life span and insulation degradation of power transformers in service are summarized in this section.

2.1. Oil Quality Analysis (OQA). Attesting oil quality is usually authenticated by a variety of electrical, physical, and chemical tests conducted on oil test samples. Methods and standards used in this study to measure and determine the oil characteristics are highlighted in Table 1.

2.2. Dissolved Gas Analysis (DGA). Interpretation of DGA techniques was performed after testing samples of transformer oil to quantify the composition of principle fault gases. Internal electrical or thermal faults manifest through insulation decomposition producing gases such as H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, CO, and CO_2. Manifestation of CO_2 and CO discloses paper degradation-related faults whilst C_2H_4 and C_2H_6 are significant indicators of oil thermal activities inside the transformer. Faults due to partial discharge can be detected through increase of H_2 and CH_4, whereas arcing can be can be mirrored by the progression of C_2H_2 and H_2. In this paper, DGA data acquired using a Total Oil Gas Analyzer (TOGA) gas chromatography technique was used in quantifying the concentration of dissolved gases.

2.3. Furanic Content in Oil Analysis (FA). Although furans can exist in five different forms [19, 20], this study focused on 2-FAL since it has been found that its concentration in oil is directly correlated with the DP of the solid insulation that relates to transformer age. 2-FAL content in the transformer mineral oil was detected and well quantified by using the high-performance liquid chromatography (HPLC) under ASTM D-5837 test standards.

2.4. Degree of Polymerization (DP). The degree of polymerization is a valuable indicator of the degradation condition of the transformer insulation paper and its mechanical properties [19, 21]. DP measurement is an intrusive test that requires sampling of insulating paper from a disassembled transformer, thus making it impossible to do on-line measurements. Moreover, this approach requires utmost care, labor intensive, and is pricey and time consuming. This has led to alternative techniques of DP

Table 1: Oil quality parameters.

Serial no.	Oil quality parameter	Testing method/instrument	Standards
1	Breakdown voltage (kV)	Megger OTS100AF and Foster OSTS100F (0–100 kV)	IEC 60156
2	Water content moisture (ppm)	Karl Fischer Titration (KFT) method Moisture-in-oil sensor	ASTM D1533
3	Acidity	Chemistry neutralization method	ASTM D947
4	Colour and appearance	Transmitted light and visual inspection	IEC-ISO 2049 ASTMD-1524
5	Dielectric dissipation factor (DDF)	Oil tan delta & resistivity test kit ex. MOTR	IEC 60247
6	Interfacial tension (IFT)	Tensiometer	ASTM D-971

Table 2: Transformer standard parameter limits [1, 26].

Category	Parameter	Condition			
		Normal	Caution	Alarm	Failure
DGAF					
	Dissolved gases				
	H_2 (ppm)	0–100	101–700	701–1800	>1800
	CH_4 (ppm)	0–120	121–400	401–1000	>1000
	C_2H_2 (ppm)	0–1	2–7	7–35	>35
	C_2H_4 (ppm)	0–50	51–100	101–200	>200
	C_2H_6 (ppm)	0–65	66–100	101–150	>150
	CO (ppm)	0–350	351–700	701–1400	>1400
	CO_2 (ppm)	0–2500	2501–4000	4001–10000	>10000
OQF					
	Oil quality				
	BDV (kV)	100–50	49–40	39–30	<30
	IFT (mN/m)	50–30	30–23	23–18	<18
	Moisture (ppm)	0–15	16–20	21–25	>25
	Acidity (mg KOH/g)	0–0.05	0.051–0.1	0.11–0.2	>0.2
	DDF	0-0.1	0.1–0.5	0.5–1	>1
	Colour	0–1.5	1.5–2	2–2.5	>2.5
FF					
	Furans				
	Furans (ppm)	0–0.1	0.1–1	1–10	>10

estimation through usage of chemical indicators such as furans, and/CO_2/CO concentration ratio, and methanol concentration in oil [19, 22–25]. In addition, mathematical models based on relationships between 2-FAL concentration and DP values have been formulated, and some of them are summarized in [19]. Although, exclusive furan analysis being the most dominant method of DP value estimation in transformer insulation, its results are inconsistent depending on the type of insulation paper, loading regime, and location of the transformer. In this paper, an alternative of DP estimation is proposed as highlighted in the foregoing sections.

3. Transformer Health Index Estimation

Estimation of the HI was centered on the fuzzy inference tool based upon the calculation of five cumulative factors that signifies the transformer condition established on DGA, OQA, furans, DP, and operational ageing stress (OAS). The final HI value is the linguistic output of the fuzzy logic model. The assigned inputs are based on the aggregation of each of the subsystem factor with respect to scores, weights, or impact on the transformer's insulation condition. Data used to validate the HI model was obtained from transformers from different substations in South Africa and Zimbabwe.

3.1. Fuzzy Inference Health Index Model

3.1.1. Determination of Parameter Score. Several attributes of a transformer can be used in ascertaining its health index. The fuzzy logic HI model inputs are centered on the concentration of dissolved gases factor (DGAF), oil quality factor (OQF), furan content factor (FF), degree of polymerization (DP), and the operational ageing stress factor (OASF). DGAF comprises seven variables, OQF involves six attributes, OASF consists of two parameters. DP is a result of the estimated value from furan content and carbon oxide ratios while furans represent FF. Power utilities can differ on the limits of transformer attributes. Accordingly, variation in transformer health index for similar data can be observed, depending on which organization limits are implemented.

Table 3: Weights assigned to each of the parameters of the four conditions.

Condition	Condition representation	Weights (w)
Normal	Good	$[w \leq 2.5]$
Caution	Acceptable	$[2.5 < w \leq 5.0]$
Alarm	Poor	$[5.0 < w \leq 7.5]$
Failure	Worst	$[7.5 < w \leq 10]$

The commonly accepted transformer attribute thresholds are highlighted by IEEE, IEC, Dornenburg, California State University Sacramento, and Bureau of Reclamation [1, 26]. In this paper, the IEEE standard C57.104–2008 parameter limit was adopted as summarized in Table 2. Using data from different transformers, fuzzy logic HI was established initially by transforming the inputs into dimensionless variables between 0 and 1. This was attained by normalizing the data using limits that symbolize normal and extreme values which are highlighted in Table 2. Additionally, the ranges of the variables have been partitioned into four conditions. Accordingly, by subjective reasoning, the four conditions of each parameter are given suitable weights (w) spanning between 0 and 10, as indicated in Table 3.

Computation of the exact weight of the variable of a given concentration was performed by using equations (1), [5], and (2).

$$\text{Parameter score} = K_i + \left[\left(\frac{x_i - a_i}{b_i - a_i}\right) \times 2.5\right]. \qquad (1)$$

Equation (2) only corresponds with breakdown voltage (BDV) and interfacial tension (IFT) parameters whose values the higher the better and vice versa and thus (1) had to be modified by rearranging it presented as follows:

$$\text{Parameter score} = K_i + \left[\left(\frac{b_i - x_i}{b_i - a_i}\right) \times 2.5\right], \qquad (2)$$

where, K_i signifies the assigned minimum weight in the four conditions of the parameters, x_i is the current value of the parameter considered (x_i is represented by x_i' for DGAF parameters, x_i'' for FF parameter, and x_i''' for OQF parameters), a_i and b_i are the lower and the upper limits of the conforming cluster of the parameter, and $(x_i - a_i)/(b_i - a_i)$ denotes normalization expression of assessing inputs, whilst normalization of BDV and IFT was done using $(b_i - x_i)/(b_i - a_i)$.

3.1.2. DP Estimation Model. The main byproducts of transformer solid insulation considered in this paper mirror the DP value of paper insulation constitute of furans (2-FAL), CO_2, and CO concentration. To map the transformer insulation DP values, the proposed fuzzy logic model is developed under MATLAB/Simulink platform. The model is shown in Figure 1, where furan (2-FAL) and CO_2/CO are the model inputs, whilst the output represents the insulation DP value.

The associated membership functions as input attributes are set based on the concentration of furan (2-FAL) considered on a scale of 0–12 (ppm) and amount of CO_2 and CO as a ratio from 0–12 based on various transformer test data,

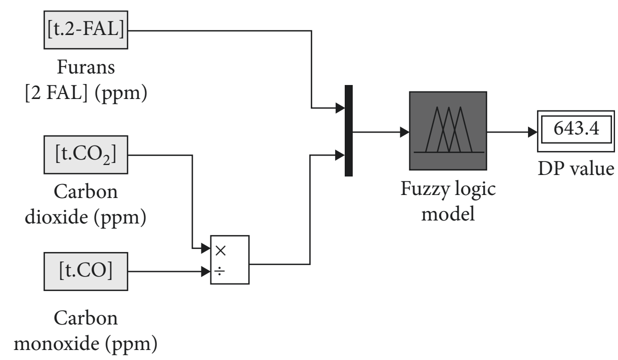

Figure 1: Fuzzy logic model for DP estimation.

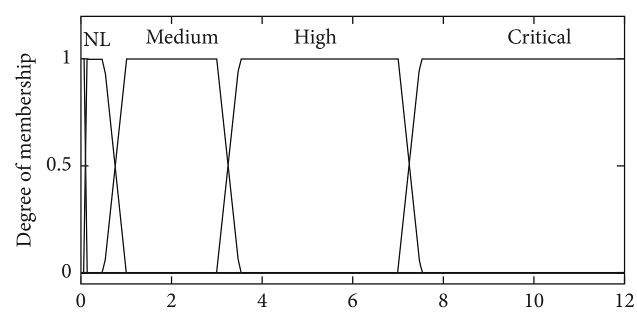

Figure 2: Input parameter membership function-furans (2-FAL) (ppm).

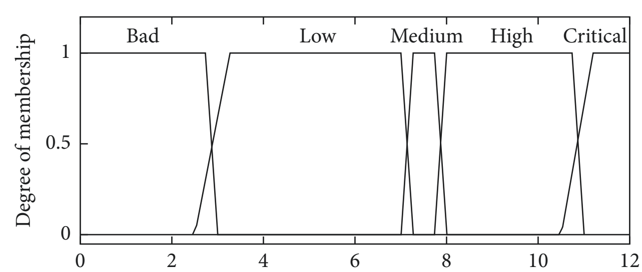

Figure 3: Input parameter membership function-CO_2/CO ratio.

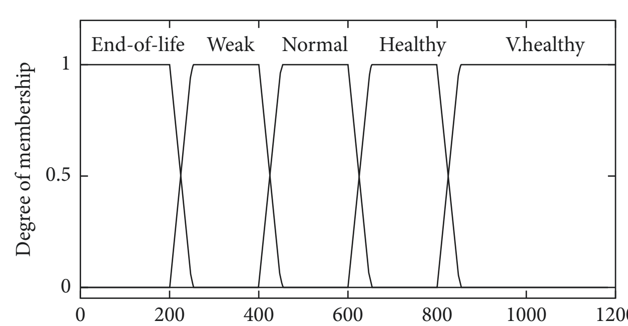

Figure 4: Output variable membership function-DP value.

as shown in Figures 2 and 3, respectively. The five trapezoidal membership linguistic values considered for the furan input variable are normal (N), low (L), medium, high, and critical, whilst CO_2/CO input variable uses bad, low, medium, high, and critical.

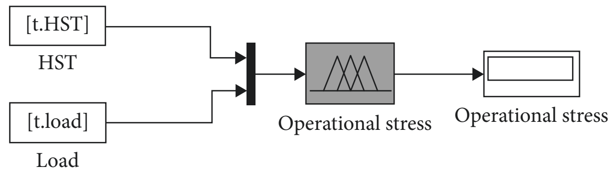

FIGURE 5: Fuzzy logic model for operational ageing stress.

TABLE 4: Ranges obtained for summed parameters.

Summed parameters	Input category ranges			
	Low (L)	Moderate (M)	High (H)	Critical (C)
DGAF	0 ≤ 17.5	17.5 < M ≤ 35	35 < H ≤ 52.5	52.5 < C ≤ 70
OQF	0 ≤ 15	15 < M ≤ 30	30 < H ≤ 45	45 < C ≤ 60
FF	0 ≤ 2.5	2.5 < M ≤ 5	5 < H ≤ 7.5	7.5 < C ≤ 10

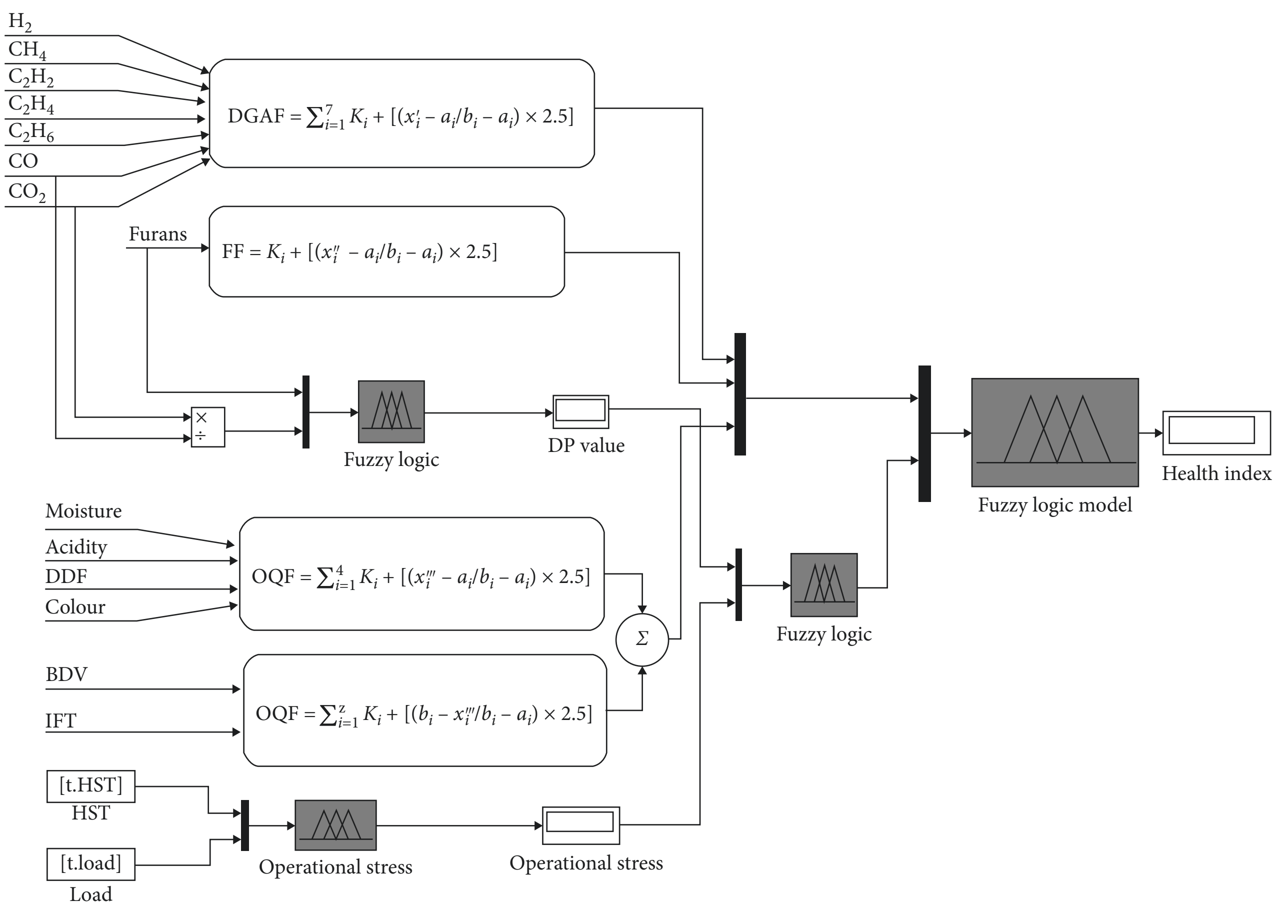

FIGURE 6: Fuzzy-based transformer health index model.

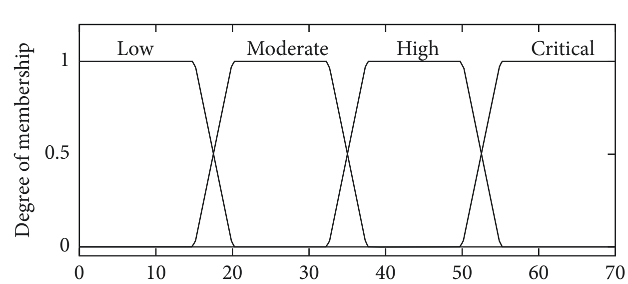

FIGURE 7: Input variable membership function-DGA Factor (DGAF).

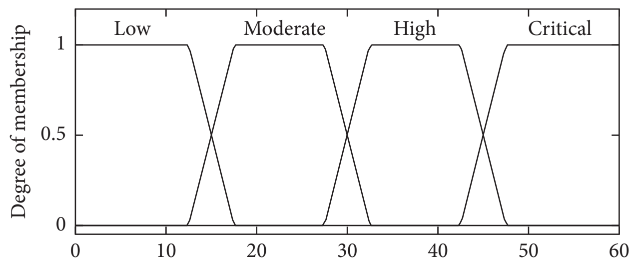

Figure 8: Input variable membership function-oil quality Factor (OQF).

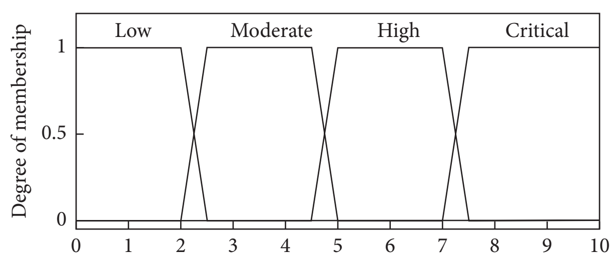

Figure 9: Input variable MF-furans content factor (FF).

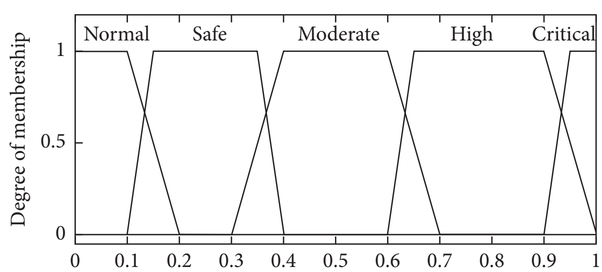

Figure 10: Input variable MF-operational ageing stress factor (OASF).

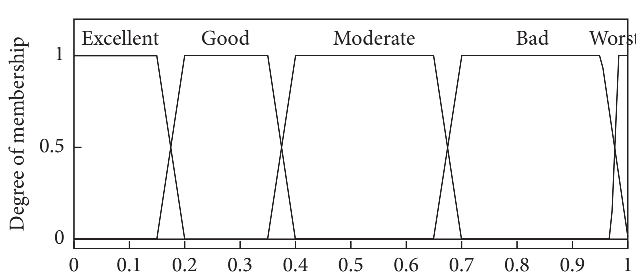

Figure 11: Output variable MF-health index.

The membership functions of the output variable signifying the DP value are established on a scale of 0 to 1200 where linguistic values of End-of-life, Weak, Normal, Healthy, and Very Healthy are used as indicated in Figure 4.

A set of "*IF-THEN*" statements as rules governing the mapping of inputs into outputs were formulated. Illustrations of the conveyed rules for DP estimation are as follows:

IF (Furans is normal) and (CO_2/CO is low) THEN (DP is V.Healthy)

IF (Furans is medium) and (CO_2/CO is medium) THEN (DP is Normal)

IF (Furans is high) and (CO_2/CO is bad) THEN (DP is End-of-Life)

3.1.3. Operational Ageing Stress Factor (OASF). Transformer loading profile and temperature variations (hotspot temperatures (HST)) are the characteristic

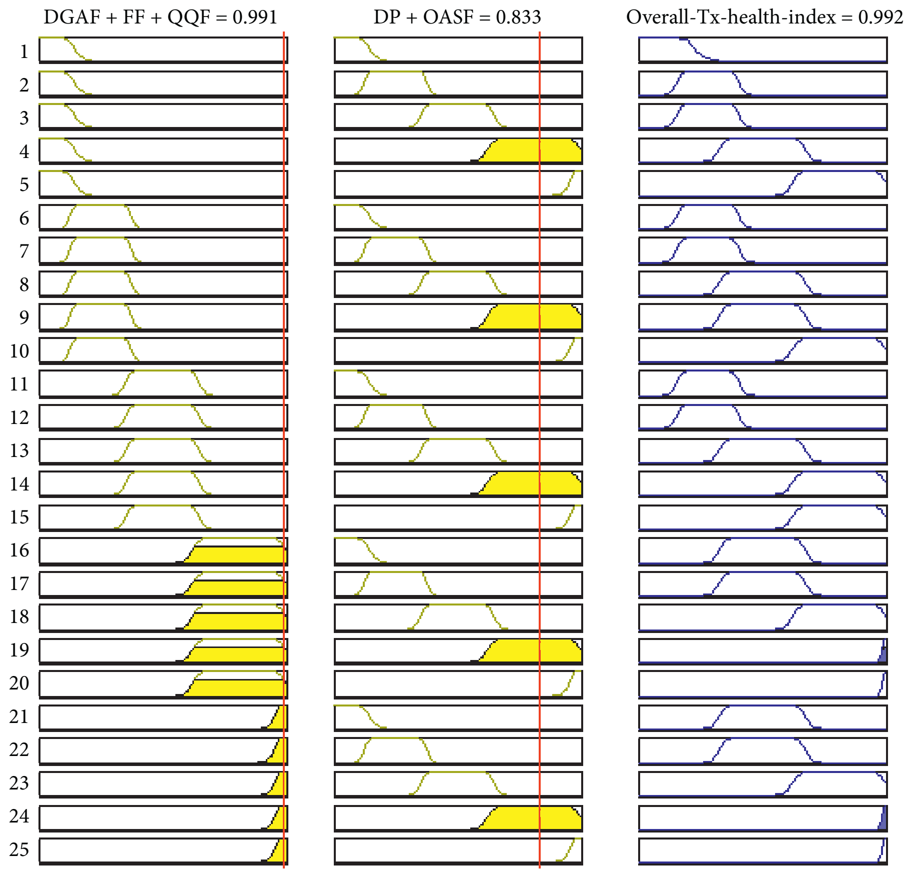

Figure 12: Rules for the developed fuzzy logic-based transformer health index model.

attributes governing the operational ageing stress of the transformer insulation system. A fuzzy logic model for determining the transformer operational stress level is established upon load and HST as inputs on membership function scaling of 0–1.2 pu (load) and 0–140°C (HST). The loading and temperature regime were taken to be of equal significance during fuzzy logic rule formulation. The magnitude and rate of change of these parameters determines the pace of operational criticality. The operational stress level of the transformer is upon a scale of 0 to 1 in which the worst condition is reflected by values nearing 1. The transformer fuzzy logic model for operational ageing stress is shown in Figure 5.

3.2. Transformation of HI Model Inputs into Fuzzy Variables. Instead of using individual parameters as inputs to the HI fuzzy logic model, summed scores for three transformer parameter categories obtained using equation (1) and (2), DP, and operation ageing stress factor were employed as the underlining fuzzy inputs. These inputs are mapped into five assessing fuzzy logic variable states using simple and computational efficacy trapezoidal membership functions (MF). These assessing states (Excellent, Good, Moderate, Bad, and Worst) signify the health index of transformer insulation. Excellent designates the best condition whereas worst signifies immediate attention to the transformer. The associated membership function scale and their linguistic labels for the summed inputs are shown in Table 4. These scales are calculated by multiplying the lower and upper limits of weights of the four conditions by the number of parameters in DGAF, OQF, and FF. Furthermore, the DP and OASF membership function was established upon a scale of 0–1200 and 0-1, respectively. The crisp HI output was obtained through the center of gravity defuzzification method. Although the centroid method is computationally intensive, it was chosen due to its intuitive plausibility [27].

The proposed fuzzy logic health index model for the power transformer condition assessment process is depicted in Figure 6. Figures 4 and 7–10 show the inputs membership functions utilized in mapping the health index output, whereas Figure 11 depicts the membership functions for the established transformer health index output, whilst Figure 12 shows the established rules associated with the proposed fuzzy logic model. The output of the DP model shown in Figure 4 was also used as an input to HI.

4. Results and Discussions

Test data from different transformers and sources highlighted in Table 5 were used in validation of the developed model. The validation was based on a linguistic label (Worst, Bad, Moderate, Good, and Excellent) assigned to different outcome states of the transformer after inputting test data from the sampled in-service transformers. Table 6 shows the

Table 5: Test data of 20 transformers rated between 20MVA and 175MVA (88 kV–420 kV).

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)	Furans (ppm)	Moisture (ppm)	Acidity (mg KOH/g)	BDV (kV)	DDF (%)	IFT (dynes/cm)	Colour	HST (°C)	Load (pu)
Tx1	1996	234	300	52	56	29	5495	700	0.25	22	0.07	52	0.14	30	1.5	60	0.58
Tx2	—	607	119	3	257	67	2011	189	1.37	23	0.13	44	0.264	24	2	61	0.6
Tx3	1996	32.5	45.8	17	25.54	21.31	3685	697	0.49	16.5	0.058	61	0.174	27	2	49	0.57
Tx4	1986	74	347	35	194	172	22789	8197	4.5	28	0.18	40	0.266	20	2.5	78	0.61
Tx5	—	71	65	18	127	79	4567	582	1.1	19	0.15	38	0.185	23	2.5	58	0.44
Tx6	2000	107	129	0	55	68	7038	892	0.1	26	0.09	48	0.249	25	1.5	66	0.65
Tx7	1981	979	236	112	183	180	2492	1843	5.76	23.2	0.251	51.7	0.458	26	3	75	0.72
Tx8	1976	1498	395	26	323	395	12371	1582	3.9	33	0.19	35	0.593	25	4	66	0.48
Tx9	1996	294	748	6	212	1348	6764	669	0.83	9	0.08	49	0.1	35	2.5	77	0.75
Tx10	—	163	106	9	298	1517	2348	299	4.48	42	0.22	46	0.221	21	3.5	64	0.45
Tx11	1998	151	8	8	151	10	2323	297	0.22	6	0.13	64	0.566	27	2	68	0.5
Tx12	—	678	368	163	92	108	1139	162	0.16	11	0.05	70	0.113	38	1	81	0.82
Tx13	2015	893	724	1	6	18	1883	242	0.03	9	0.04	71	0.068	45	0	56	0.55
Tx14	1995	195	660	22	127	79	3347	356	0.09	6	0.03	66	0.207	41	1	53	0.6
Tx15	1990	440	522	183	31	62	5382	685	0.31	12	0.05	65	0.319	28	2	50	0.66
Tx16	2010	15	8	0	9	5	7135	902	0.1	10	0.03	55	0.15	42	1	61	0.44
Tx17	2005	1176	4	1	4	10	4991	637	0.83	10	0.09	62	0.733	29	1.5	53	0.5
Tx18	—	441	678	55	73	62	13345	1695	5.1	32	0.25	55	0.328	26	3	77	0.62
Tx19	2000	75	44	0	106	13	7846	261	2.4	40	0.092	31	0.416	22	3	61	0.55
Tx20	2002	181	79	21.1	56	29	713	192.6	8.91	21.2	0.349	33.5	0.257	20	3	50	0.5

Table 6: Corresponding scores obtained as per the values of the test data and HI results.

Tx. no	H_2	CH_4	C_2H_2	C_2H_6	C_2H_4	CO_2	CO	Moisture	Acidity	BDV	DDF	IFT	Colour	HST (°C)	Load pu	DP*	DGAF	OQF	FF	Health index	
Tx1	3.06	4.1	9.02	2.15	1.45	5.63	5	6	3.5	2.4	2.75	2.5	2.5	60	0.58	643.4	30.41	19.65	2.92	0.278	Good
Tx2	4.61	2.48	3.39	9.7	3.32	2.01	1.35	6.5	5.75	4	3.53	4.64	5	61	0.6	443.5	26.86	29.42	5.1	0.657	Moderate
Tx3	0.81	0.95	5.89	0.98	1.07	4.48	4.98	3.25	2.9	1.95	2.96	3.57	5	49	0.57	725.1	19.16	19.63	3.58	0.28	Good
Tx4	1.85	4.53	5	8.23	6.79	12.83	31.78	9	7	5	3.54	6.5	7.5	78	0.61	172.7	71.01	38.54	5.97	0.992	Worst
Tx5	1.78	1.35	3.48	6.33	3.93	5.24	4.15	4.5	6.25	5.5	3.03	5	7.5	58	0.44	524.8	26.26	31.78	2.53	0.498	Moderate
Tx6	2.53	2.57	0	2.12	3.37	6.27	5.68	8	4.5	3	3.43	4.29	2.5	66	0.65	786.3	22.54	25.72	2.5	0.275	Good
Tx7	5.63	3.53	14.38	9.15	6.99	2.49	9.08	6.6	8.78	2.42	4.74	3.93	12.5	75	0.72	109.9	51.25	38.97	6.32	0.944	Bad
Tx8	6.81	4.96	6.7	16.15	12.38	8.49	8.15	11.5	7.25	6.25	5.47	4.29	15	66	0.48	262.5	63.64	49.76	5.81	0.992	Worst
Tx9	3.12	6.45	4.5	10.6	36.2	7.82	4.78	1.5	4	2.75	2.5	1.88	7.5	77	0.75	494.8	73.47	20.13	4.53	0.528	Moderate
Tx10	2.76	2.21	5.18	14.9	40.43	2.35	2.14	16	8	3.5	3.26	6	12.5	64	0.45	248.7	69.97	49.26	5.97	0.991	Worst
Tx11	2.71	0.17	5.09	7.55	0.5	2.32	2.12	1	5.5	1.8	5.33	3.58	5	68	0.5	665.7	20.46	22.21	2.83	0.248	Good
Tx12	4.91	4.71	18.93	4.41	5.18	1.14	1.16	1.83	2.5	1.5	2.58	1.5	1.67	81	0.82	725.2	40.44	11.58	2.67	0.275	Good
Tx13	5.44	6.34	2.5	0.23	0.9	1.88	1.73	1.5	2	1.45	1.7	0.63	0	56	0.55	992.8	19.02	7.28	0.75	0.12	Excellent
Tx14	2.89	6.08	3.84	6.32	3.93	3.91	2.54	1	1.5	1.7	3.17	1.13	1.67	53	0.6	725.1	29.51	10.17	2.25	0.121	Excellent
Tx15	3.91	5.51	20.71	1.19	3.06	7.24	4.89	2	2.5	1.75	3.87	3.21	5	50	0.66	638.3	46.51	18.33	3.09	0.525	Moderate
Tx16	0.38	0.17	0	0.35	0.25	7.97	5.72	1.67	1.5	2.25	2.81	1	1.67	61	0.44	756.2	14.84	10.9	2.5	0.12	Excellent
Tx17	6.08	0.08	2.5	0.15	0.5	7.08	4.55	1.67	4.5	1.9	6.17	2.86	5	53	0.5	594.4	20.94	22.1	4.53	0.348	Good
Tx18	3.92	6.16	9.29	3.01	3.06	8.89	8.55	11	8.75	2.25	3.93	3.93	12.5	77	0.62	217.4	42.88	42.36	6.13	0.991	Worst
Tx19	1.88	0.92	0	5.26	0.65	8.23	1.86	15	4.6	7.25	4.8	5.5	12.5	61	0.55	325	18.8	49.65	5.31	0.931	Bad
Tx20	2.84	1.65	6.25	2.15	1.45	0.71	1.38	5.6	11.23	6.63	3.48	6.5	15	50	0.5	109.9	16.43	48.44	7.2	0.992	Worst

Table 7: Health index status by different methods for 20 different test transformers.

Tx. No	Transformer health index level and description						
	Utility estimation	Method in [8]		Method in [5]		Proposed method	
Tx1	Good	0.275	Good	0.275	Good	0.278	Good
Tx2	Moderate	0.552	Moderate	0.572	Moderate	0.657	Moderate
Tx3	Excellent	**0.120**	Excellent	**0.143**	Excellent	**0.28**	Good
Tx4	Worst	0.936	Worst	0.972	Worst	0.992	Worst
Tx5	Moderate	0.5	Moderate	0.452	Moderate	0.498	Moderate
Tx6	Good	0.273	Good	0.275	Good	0.275	Good
Tx7	Worst	0.832	Bad	0.894	Bad	0.944	Bad
Tx8	Worst	0.991	Worst	0.99	Worst	0.992	Worst
Tx9	Moderate	**0.752**	Bad	**0.52**	Moderate	**0.528**	Moderate
Tx10	Bad	**0.899**	Bad	**0.934**	Bad	**0.991**	Worst
Tx11	Good	0.225	Good	0.233	Good	0.248	Good
Tx12	Good	0.264	Good	0.273	Good	0.275	Good
Tx13	Excellent	0.083	Excellent	0.083	Excellent	0.12	Excellent
Tx14	Excellent	0.12	Excellent	0.122	Excellent	0.121	Excellent
Tx15	Moderate	0.45	Moderate	0.51	Moderate	0.525	Moderate
Tx16	Excellent	0.08	Excellent	0.104	Excellent	0.12	Excellent
Tx17	Good	0.25	Good	0.278	Good	0.348	Good
Tx18	Worst	**0.887**	Bad	**0.9**	Bad	**0.991**	Worst
Tx19	Worst	0.913	Bad	0.926	Bad	0.931	Bad
Tx20	Worst	0.98	Worst	0.983	Worst	0.992	Worst

corresponding scores calculated as per the values of transformer parameters and the health indices calculated for a sample of 20 in-service transformers. Using Transformer 8 as an illustration, the established model health index output signifies that the transformer is in the worst state. Its corresponding totals are DGAF = 63.64, OQF = 49.76, FF = 5.81, DP = 262.5, and OASF = 0.25. From Table 4, it is noted that DGAF and OQF fall in the critical range, whereas, FF exists in the high range. Additionally, the estimated DP value (through fuzzy logic sub model) approaches the end-of-life category. The critical state of DGAF is as a result of evolved gases surpassing their limited thresholds. Furthermore, most of the transformer oil quality tests (moisture, BDV, DDF, colour, and acidity) were in high ranges thereby resulting in worst transformer state. In addition, the results of both test data and HI output can be justified as the transformer was installed in 1976, and thus it was 37 years old at the time of the tests (2013).

The test data used in validating the proposed model were also used in validating some of the models for health index proposed in the literature. A comparative analysis of four approaches is highlighted in Tables 7 and 8. The utility Health index estimation was based on Furans analysis and oil quality factors, whereas the model in [8] was centered upon seven inputs which are, moisture, acidity, BDV, DF, Furans calculated DP, and TDCG, whilst a weighting factor of three inputs based on transformer oil and paper tests was established in [5]. It has been observed that though many attributes were used in [8], it was cumbersome to formulate many rules although three membership functions were used in which different experts decision can compromise the accuracy of the model by using fewer membership functions. In [8], the number of rules was reduced; however, variables like DP and loading effect should also be considered in HI estimation of which in [5] they were overlooked. The proposed model utilized the various transformer tests and integrated them into influential factors that mirror the transformer health index. Additionally, loading regime, DP, and hotspot temperatures were considered in HI estimation. In Table 8, different HI estimation methods have been presented. It is observed that some transformers show different health status whereas some show same HI status, but the magnitude of the condition differs by using same data. Bold values indicate where the HI differs for the compared models.

Taking the Utility HI estimation as the bench-mark, Table 8 depicts the accuracy comparison between the fuzzy logic models in [5, 8] and the present proposed method. The three methods showed accuracy levels of 92.5% [8], 93.3% [5], and 95.5% (proposed method) against the utility HI estimation. This shows that all three methods have the capabilities of estimating the health index that can be embraced by utility expects for asset management. The criticality of the estimated HI was based on the parameter threshold values highlighted in Table 2.

From Table 7, refurbishment, replacement, decision on retirement, or scrapping the transformers in the worst state is recommended since these transformers can fail untimely. However, for transformers in bad state, proper diagnostic measures and condition-based maintenance are suggested and planning for their short term replacement or other remedial actions. Transformers in moderate condition pose for long-term refurbishment or replacement. However, their condition does not promote them to be sidelined for monitoring and diagnosis. Additionally, more frequent sampling intervals should be administered in new transformers in moderate state, so as to investigate any abnormalities that may result in accelerated insulation degradation and ageing. Subsequently, the likelihood of failure for transformers in excellent or good state is very low; thus, only regular maintenance can be practiced as they operate within nameplate specifications.

Table 8: HI comparison accuracies for different methods for 134 test transformers.

Status	HI comparison of 134 test case transformers			
	Utility estimation	Method in [8]	Method in [5]	Proposed method
Excellent	7	9	9	6
Good	28	26	26	27
Moderate	65	66	64	64
Bad	11	13	14	13
Worst	23	20	21	24
Total transformers	**134**	**134**	**134**	**134**
Overall % error against utility HI		**7.5%**	**6.7%**	**4.5%**

In a nutshell, the variances in transformer health status might be due to variations in loading patterns, the harmonic content of the loads, differences in maintenance strategies, different stresses subjected to the transformers, partial-discharge activities, and problems in the cooling mechanisms or difference in ageing and degradation rate.

5. Conclusions

To improve on the consistency of the transformer insulation health index model output, an intelligent health index model was developed based on the transformer multiattributes cascaded with an inference system which relies on the interpretation of an experienced expert. The computation of the HI was centered on the fuzzy inference tool based upon the calculation of cumulative factors that signifies the transformer insulation condition established on dissolved gas analysis factor, oil quality analysis factor, Furans content factor, degree of polymerization (DP), and operational ageing stress factor. The DP value was established from a fuzzy logic-based model using Furans (2-FAL) and carbon oxides ratio as the inputs. The operational ageing stress was framed from the transformer loading and transformer hot spot temperature profile. The overall resultant of the health index assessment was governed by all considered parameters as a whole, not on any specific individual parameter. Hence, this approach reflects a reliable and truthful insulation health index for the transformers. However, transformer health status evaluation can be enhanced by using the rate of change of dissolved gases and oil characteristics. However, in this paper, the data for rate of change of the variables were not available. Having a reasonable health index can facilitate in power transformer reliability and also enhance its residual life span.

Data Availability

Table 5 in this article provides the data used in achieving the findings of this study.

Conflicts of Interest

The authors affirm no conflicts of interest concerning the publication of this article.

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References

[1] A. Jahromi, R. Piercy, S. Cress, J. Service, and W. Fan, "An approach to power transformer asset management using health index," *IEEE Electrical Insulation Magazine*, vol. 25, no. 2, pp. 20–34, 2009.

[2] A. E. B. Abu-Elanien and M. M. A. Salama, "Asset management techniques for transformers," *Electric Power Systems Research*, vol. 80, no. 4, pp. 456–464, 2010.

[3] S. Forouhari and A. Abu-Siada, "Application of adaptive neuro fuzzy inference system to support power transformer life estimation and asset management decision," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 25, no. 3, pp. 845–852, 2018.

[4] D. Hughes, "The use of health indices to determine end of life and estimate remnant life for distribution assets," in *Proceedings of the 17th International Conference on Electricity Distribution (CIRED)*, pp. 5–15, Barcelona, Spain, May 2003.

[5] C. Ranga, A. K. Chandel, and R. Chandel, "Condition assessment of power transformers based on multi-attributes using fuzzy logic," *IET Science, Measurement & Technology*, vol. 11, no. 8, pp. 983–990, 2017.

[6] J. H. Jürgensen, A. Scheutz Godin, and P. Hilber, "Health index as condition estimator for power system equipment: a critical discussion and case study," in *Proceedings of the 24th International Conference & Exhibition on Electricity Distribution (CIRED)*, vol. 2017, no. 1, pp. 202–205, Glasgow, UK, June 2017.

[7] H. Zeinoddini-Meymand and B. Vahidi, "Health index calculation for power transformers using technical and economical parameters," *IET Science, Measurement & Technology*, vol. 10, no. 7, pp. 823–830, 2016.

[8] R. D. Medina, J. P. Lata, and D. P. Chacón, "Health index assessment for power transformers with thermal upgraded paper up to 230kV using fuzzy inference systems," in *Proceedings of the 51st International University Power Engineering Conference (UPEC)*, pp. 1–6, Coimbra, Portugal, September 2016.

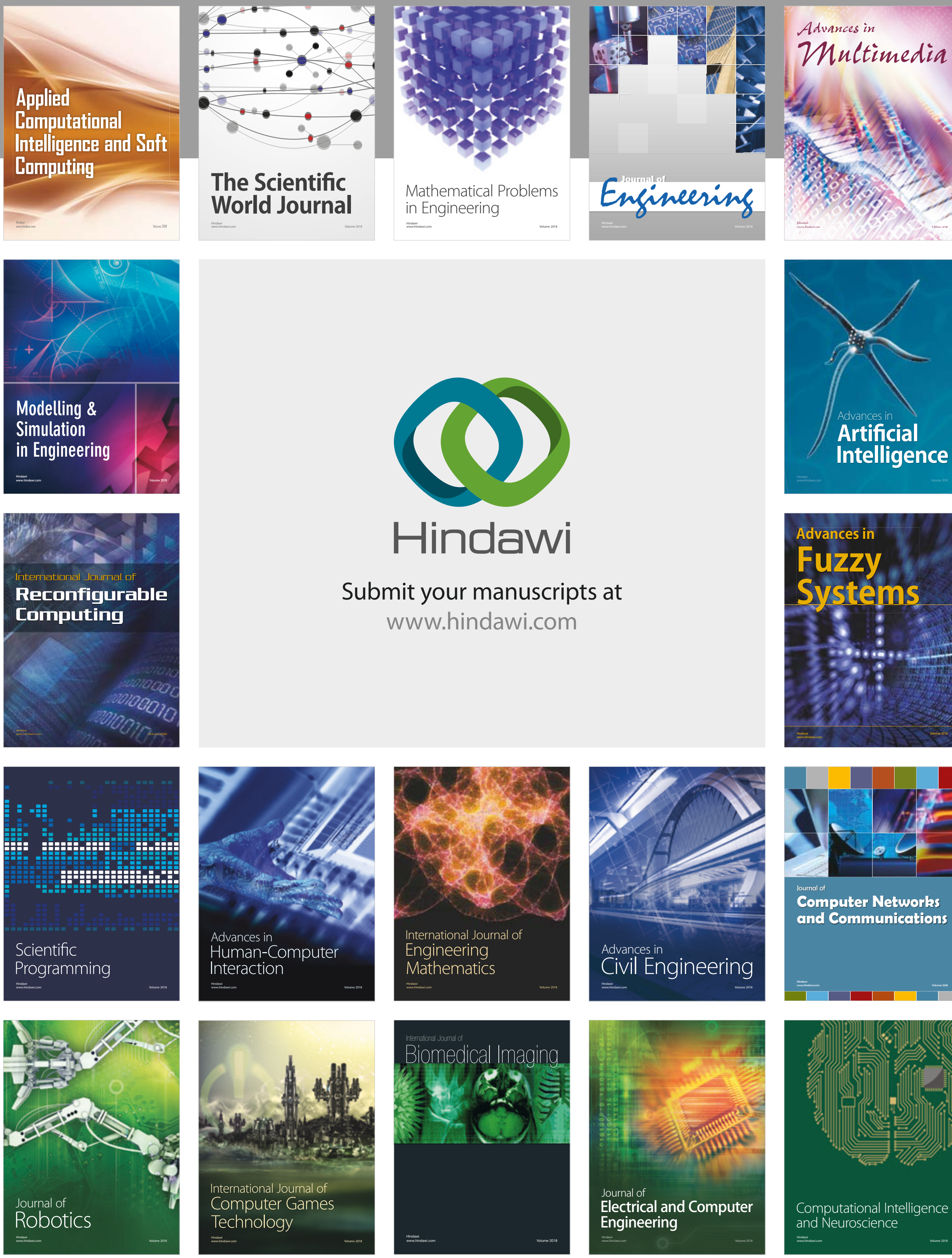
[9] A. Abu-Siada, S. Hmood, and S. Islam, "A new fuzzy logic approach for consistent interpretation of dissolved gas in oil analysis," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 20, no. 6, pp. 2343–2349, 2013.

[10] A. Abu Siada, M. Arshad, and S. Islam, "Fuzzy logic approach to identify transformer criticality using dissolved gas analysis," in *Proceedings of the IEEE Power and Energy Society General Meeting*, pp. 1–5, Providence, RI, USA, July 2010.

[11] A. E. B. Abu-Elanien, M. M. A. Salama, and M. Ibrahim, "Calculation of a health index for oil-immersed transformers rated under 69 kV using fuzzy logic," *IEEE Transactions on Power Delivery*, vol. 27, no. 4, pp. 2029–2036, 2012.

[12] B. Gorgan, P. Notingher, L. Badicu, and G. Tanasescu, "Calculation of power transformers health indexes," *Electrical Engineering Series*, vol. 34, pp. 13–18, 2010.

[13] M. Arshad, S. Islam, and A. Khaliq, "Fuzzy logic approach in power transformers management and decision making," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 21, no. 5, pp. 2343–2354, 2014.
[14] W. H. Tang and W. Hu, *Condition Monitoring and Assessment of Power Transformers Using Computational Intelligence*, ISBN 978-0857290519, Springer, London, UK, 2011.
[15] A. D. Ashkezari, H. Ma, T. K. Saha, and C. Ekanayake, "Application of fuzzy support vector machine for determining the health index of the insulation system of in-service power transformers," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 20, no. 3, pp. 965–973, 2013.
[16] S. Li, G. Hu, B. Gao, Y. Yang, and G. Wu, "A probabilistic framework for transformer health condition assessment," in *Proceedings of the 12th IEEE International Conference on the Properties and Applications of Dielectric Materials*, pp. 212–217, Xi'an, China, May 2018.
[17] W. Zuo, H. Yuan, Y. Shang, Y. Liu, and T. Chen, "Calculation of a health index of oil-paper transformers insulation with binary logistic regression," *Mathematical Problems in Engineering*, vol. 2016, Article ID 6069784, 9 pages, 2016.
[18] A. E. B. Abu-Elanien, M. M. A. Salama, and M. Ibrahim, "Determination of transformer health condition using artificial neural networks," in *Proceedings of the International Symposium on Innovations in Intelligent Systems and Applications (INISTA'11)*, pp. 1–5, IEEE, Istanbul, Turkey, June 2011.
[19] A. Teymouri and B. Vahidi, "CO_2/CO concentration ratio: a complementary method for determining the degree of polymerization of power transformer paper insulation," *IEEE Electrical Insulation Magazine*, vol. 33, no. 1, pp. 24–30, 2017.
[20] L. Cheim, D. Platts, T. Prevost, and S. Xu, "Furan analysis for liquid insulation in power transformers," *IEEE Electrical Insulation Magazine*, vol. 28, no. 2, pp. 8–21, 2012.
[21] M. Arshad and S. Islam, "Significance of cellulose power transformer condition assessment," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 18, no. 5, pp. 1591–1598, 2011.
[22] M. Duval, A. D. Pablo, I. Atanasova-Hoehlein, and M. Grisaru, "Significance and detection of very low degree of polymerization of paper in transformers," *IEEE Electrical Insulation Magazine*, vol. 33, no. 1, pp. 31–38, 2017.
[23] A. Abu-Siada, S. P. Lai, and S. M. Islam, "A novel fuzzy-logic approach for furan estimation in transformer oil," *IEEE Transactions on Power Delivery*, vol. 27, no. 2, pp. 469–474, 2012.
[24] P. K. Pandey, Z. Husain, and R. K. Jarial, "ANFIS based approach to estimate remnant life of power transformer by predicting furan contents," *International Journal Electrical and Computer Engineering (IJECE)*, vol. 4, no. 4, pp. 463–470, 2014.
[25] A. Schaut, S. Autru, and S. Eeckhoudt, "Applicability of methanol as a new marker for paper degradation in power transformers," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 18, no. 2, pp. 533–540, 2011.
[26] G. K. Irungu, A. O. Akumu, and J. L. Munda, "Transformer condition assessment for maintenance ranking: a comparison of three standards and different weighting techniques," in *Proceedings of the IEEE Africon 2017 Proceedings*, pp. 1043–1048, Cape Town, South Africa, September 2017.
[27] F. O. Karray and C. W. De Silva, *Soft Computing and Intelligent Systems Design: Theory and Applications*, Pearson/Addison-Wesley, Boston, MA, USA, 2004.



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