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Health index for power transformer condition assessment: A comparison of three different techniques

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Abstract: In practice, the condition state of Power Transformers (PT) is quantified by using Health Index (HI). This paper analyzes and compares three different state-of-the-art algorithms to compute HI. The first one uses a Weighted Sum Model (WSM), the second is based on a Fuzzy Inference System (FIS), and the third combines both techniques, i.e., WSM and FIS. These three approaches are tested in a PT fleet composed of 30 units. Results show that each approach produces different HI values for the same PTs. Therefore, decision making regarding the PT fleet will depend on the selected approach for HI calculation. This work proposes merging the knowledge involved in each analyzed approach by using a K-means clustering technique to overcome this drawback. This solution could help the asset manager to make adequate decisions regarding the maintenance scheduling of PT when there is uncertainty about the appropriate approach to be selected

Keywords: Health index, power transformers, fuzzy logic, condition assessment

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1. Introduction

Power Transformers (PTs) constitute one of the most critical assets in power systems (Rønneberg, 2017). For this reason, special attention must be taken to reduce the PT failure rate to the minimum possible level.

Powe transformer condition assessment represents a key indicator to make adequate maintenance/replacing decisions, thus reducing the failure rates. Several techniques (Romero-Quete et al., 2017; Scatiggio et al., 2018; Vasquez & Jayaweera, 2020; Zeinoddini-Meymand & Vahidi, 2016) have been developed to assess the condition of PT. Health Index (HI) is one of these techniques, it uses as input parameters different criteria such as ageing of oil-impregnated paper (Liang et al., 2017), apparent age (Tamma et al., 2020), or the condition of other PT subsystems (e.g., load tap changer, bushings, cooling system) (Jian et al., 2020).

The development of a HI does not only include measurable parameters but, expert knowledge is also required to attain a more robust and reliable result (Bohatyrewicz et al., 2019). Even though HI tends to use almost the same input framework, employed algorithms take different approaches to process input data. For instance, main algorithms include systems based on Weighted Sum Models (WSM) (Jahromi et al., 2009; Jian et al., 2020; Naderian et al., 2008; Tamma et al., 2020), systems based on the Markov chain model (Yahaya et al., 2017), fuzzy logic systems (Cerón et al., 2015; Mharakurwa & Goboza, 2019; Rosero-Z et al., 2018), and systems based on artificial neural networks (Islam et al., 2017).

Despite the several and different techniques to compute a HI for PT, a simple question can arise for an asset manager in charge of a PT fleet: which one is the adequate tool to compute HI. Having in mind the above question, and after an in-depth review of the HI techniques listed in the previous paragraph, three of them were selected to be compared in this article, i.e.,(Cerón et al., 2015; Li & Song, 2014; Mharakurwa & Goboza, 2019). The selection of the HI techniques was supported by the fact that these use clearly defined quantities, measures, and test regularly done by PT owners during routine inspections.

There are some differences between the three HI calculation techniques. Although (Li & Song, 2014) and (Cerón et al., 2015) use almost the same input parameters, (Li & Song, 2014) makes use of WSM to process data, while (Cerón et al., 2015) employs fuzzy logic. On the other hand, (Mharakurwa & Goboza, 2019) presents some differences in the set of input parameters regarding the other two techniques, and combines the weighting technique and the fuzzy logic methodology to reach the final HI score.

In this context, this work aims to analyze the three methods to determine the influence of the algorithm technique chosen and discern how the decisions made by the authors affect the evaluation of the condition of the PT. This will be particularly useful to attain a major understanding of the importance of the algorithm used for processing the input data and how this can influence the final HI value.

Section II presents a brief description of the weighting technique and the Fuzzy Inference System (FIS) technique. Section III introduces the three models studied in detail, meanwhile, Section IV explains the proposed comparison method, the results, and discussions.

2. Health index calculation

The Health Index is a magnitude that quantifies and easily provides an understanding of the general condition of a PT. HI is calculated by using most of the representative elements of PT diagnosis (Gorgan et al., 2010). Most of the methodologies to calculate HI employ WSMs. A WSM establishes linear relationships among a number of decision criteria (e.g., results of tests, diagnostics, visual inspections, etc.). Then, each criterion is assigned with a representative or performance value and a specific weight according to its importance. Finally, results of products between performance value and weight, for each criterion, are added into a summation which provides the resultant HI. Approaches based on WSM tend to use different relations to calculate the final value of the HI, but most of them are a variant of the formula used in (Naderian et al., 2008).

A Main drawback of WSM is that the definition of the criteria weights may differ from an expert to another since expert judgment is invariably required to construct the final HI formula. This variance of weights causes a different HI final score between the formulas proposed by different authors.

To overcome the above drawback, some authors (Idrees et al., 2019; Patil et al., 2019; Ranga et al., 2017) propose a different approach to the way the input data is processed. Based on the uncertainty generated by the different opinions of the experts when assigning weights to HI calculation criteria, they propose the use of the FIS to calculate the HI.

The implementation of a FIS-based methodology requires the fuzzification of input data for each criterion, which is often given in numerical values. The fuzzification process involves the definition of membership functions (i.e., related with linguistic variables as good, fair, bad, etc.) which represents states of condition for each criterion into its numerical range of variation.

To process the fuzzified data a FIS relies on inference rules based on non-numerical expressions. This characteristic allows to set aside the issue of assigning weights to the state elements, however, to design the inference rules is required to discern the level of criticality of each criterion and how they are related to the general PT condition, in (Ross, 2010; Singh, 2012; Trillas & Eciolaza, 2015) more detailed information about fuzzy systems can be found.

3. Techniques under analysis

3.1. Health index based on a weighted sum model

Developed by Li and Song (2014) and based on WSM, HI_{WSM} is computed as the result of adding four health subindices, each one of the following criteria: 1) age of the PT, 2) the insulating paper, 3) Dissolved Gas Analysis (DGA) 4) Oil Quality Factor (OQF). The method involves a process where the input parameters are quantified and normalized employing linear functions. The tables concerned with the corresponding relationship to calculate the normalized parameters for each of the four parts and tables for the assigned weights can be consulted in (Li & Song, 2014).

The first health subindex HI_{age} is concerned with the age and loading of the PT and is given by Equation (1).

$$HI_{age} = HI_o \cdot e^{B\cdot(T_2 - T_1)} \quad (1)$$

Where HI_0, is the initial value, B is the aging coefficient calculated by the equations given in (Li & Song, 2014), T_1 is the year corresponding to HI_0, which is usually the year that the PT was put into operation, T_2 is the year that the PT condition is analyzed, can be the current year or some year into the future.

The insulating paper subindex HI_{iso} considerers the overall insulation aging characteristics and is constituted by two parts: subindex HI_{CO} formed by the contents of carbon and oxygen, and subindex HI_{fur} formed by the Furfural Content (FC). DGA and FC analysis are the tests needed to obtain the input parameters to calculate the HI_{iso}.

The subindex HI_{CO} consists of three parameters $F_{CO}(i)$, the three factors are considered to be equally important and all the weights are set as ω=0.333. The HI_{CO} is calculated using Equation (2).

$$HI_{CO} = \sum_{i=1}^{3} \omega_i \cdot F_{CO}(i) \quad (2)$$

HI_{fur} reflects the FC results and it is given by (3).

$$HI_{fur} = 3.344 \cdot (C_{fur})^{0.413} \quad (3)$$

The resultant HI_{iso} can be obtained by adding HI_{CO} and HI_{fur} together with their respective weights. In this paper, the weights are set to be 0.3 and 0.7, respectively. The index HI_{iso} is shown in Equation (4).

$$H_{iso} = 0.3 \cdot HI_{CO} + 0.7 \cdot HI_{fur} \quad (4)$$

The subindex HI_{CH} based on DGA uses five gases, H2, CH4, C2H6, C2H2 and C2H4, to assess the health state of the PT. The subindex is calculated using Equation (5), which is a function of five hydrocarbon factors $F_{CH}(i)$.

$$HI_{CH} = \sum_{i=1}^{5} \omega_i \cdot F_{CH}(i) \quad (5)$$

The subindex based on OQF HI_{oil} analyses the proprieties of oil and how it is correlated with the overall state of the PT. Considered properties are moisture content, acid value, dielectric loss, and breakdown voltage (BV), each of them is represented by $F_{oil}(i)$ and are linear functions.

The index HI_{oil} is calculated using Equation (6) and the weights given (Li & Song, 2014).

$$HI_{oil} = \sum_{i=1}^{4} \omega_i \cdot F_{oil}(i) \quad (6)$$

To compute the final HI_{WSM}, Equation (7) is used.

$$HI_{WSM} = 0.569HI_{age} + 0.266HI_{iso} + 0.095HI_{CH} + 0.07HI_{oil} \quad (7)$$

The overall condition of the PT based on the value of HI is presented in Table 1.

Table 1. PT condition based on HI.

HI_{WSM}	Condition
0-3.5	Very good
3.5-5.5	Good
5.5-7	Bad
7-10	Very Bad

3.2. Health index based on fuzzy inference system

Proposed by Cerón et al. (2015) the second HI employs the FIS methodology to process the input data. It uses six parameters to calculate the final value, HI_{FIS}, which are: BV, moisture content (humidity), acidity, power factor, FC and DGA. A membership function is designed for each input. The author employs (IEEE Std C57.152-2013, 2013) and (IEC 60422, 2013) to establish the limits to score the input data. The set of membership functions for the input parameters can be consulted in (Cerón et al., 2015).

The membership functions corresponding to the output HI_{FIS} are presented in Figure 1.

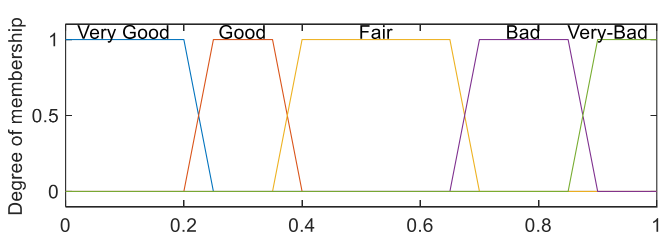


Figure 1. Membership functions for the HI_{FIS}.

A Mamdani FIS composed by 80 rules is used to integrate the six linguistic inputs with the output. Once the output membership function is obtained, a defuzzification process takes place to convert the linguistic HI into a numerical value. The complete HI fuzzy model can be observed in Figure 2.

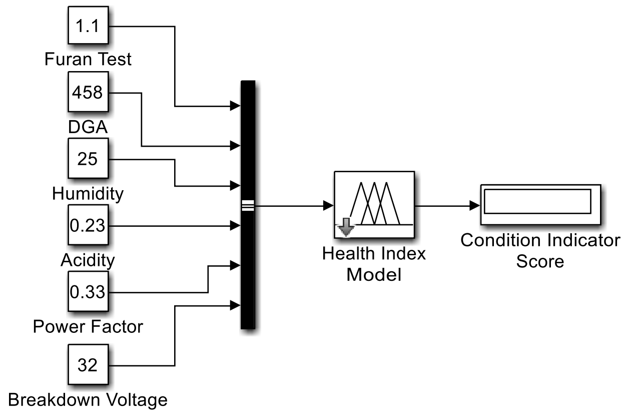


Figure 2. HI fuzzy model.

3.3. Health index based on hybrid WSM-FIS

The third approach to compute a HI was proposed by Mharakurwa and Goboza (2019). It combines WSM with four FIS to assess the PT condition. The general approach is shown in Figure 3.

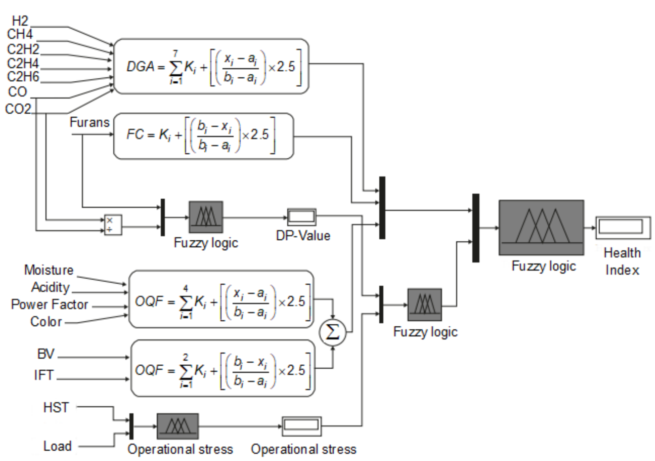


Figure 3. Health index calculation method based on WSM and FIS.

The WSM component scores results of DGA, OQF and FC analysis, while the four FISs are implemented for different purposes. The first FIS evaluates the degree of polymerization (DP) based on the FC and the carbon dioxide (CO2) and carbon monoxide (CO) ratio. The second one assesses the operational stress of the PT, which depends on the load and the hotspot temperature. The third FIS combines the results of the previous two FISs, i.e., it combines the obtained scores for DP and operational stress. Afterwards, the four and last FIS uses the outputs of the WSM and the third FIS to obtain $HI_{WSM\text{-}FIS}$ finally.

To calculate the scores of DGAF, OQF and FC, tables given in (Mharakurwa & Goboza, 2019) are employed. After that, Equations (8) and (9) are applied in order to obtain the normalized score to be used in the fuzzy logic model.

$$\text{Parameter Score} = K_i + \left[\left(\frac{x_i - a_i}{b_i - a_i}\right) \cdot 2.5\right] \tag{8}$$

$$\text{Parameter Score} = K_i + \left[\left(\frac{b_i - x_i}{b_i - a_i}\right) \cdot 2.5\right] \tag{9}$$

Where K_i corresponds to the assigned minimum weight in the four conditions, x_i is the current value of the parameter analyzed, a_i and b_i are the lower and upper limits of the conforming cluster of the parameter.

In order to compute the operational stress; hotspot temperature and load are taken into account. To calculate the DP value the furan content and CO_2/CO will be considered. The membership functions for both parameters and the output can be consulted in (Mharakurwa & Goboza, 2019).

In Figures 4 to 6, the membership functions for the final HI value which combines the DGAF+OQF+FF and the DP-value+Operational stress are introduced.

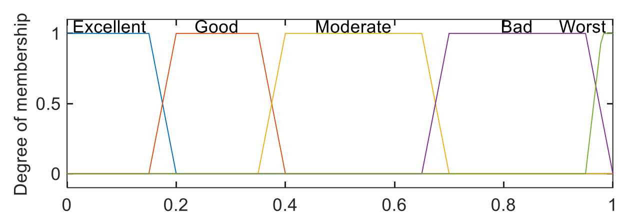


Figure 4. Membership functions for DGAF+OQF+FF.

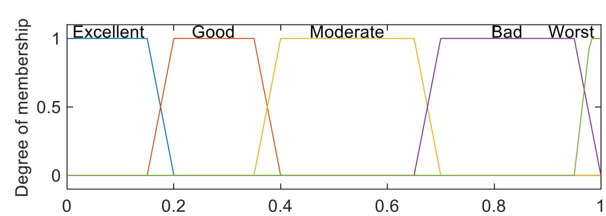


Figure 5. Membership functions for DP value+Operational stress.

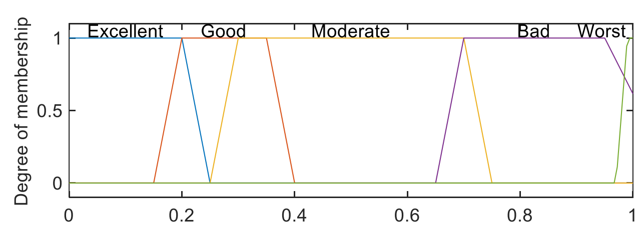


Figure 6. Membership functions for the final HI.

4. Case Study

4.1. Description of the performed comparison

Figure 7 presents a flowchart with the major key points of the methodology used to compare the different HI techniques.

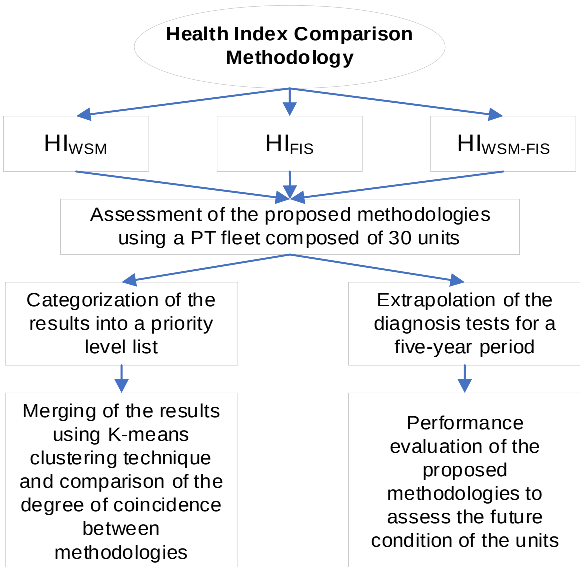


Figure 7. Flowchart of the proposed comparison methodology.

The three approaches presented in the previous section were tested in a PT fleet composed of thirty units. Table 2 summarizes the main results of the diagnostic tests for the complete fleet.

According to Hughes (2003) and Jürgensen et al. (2017), HI is an indicator that enables an effective prioritization/ranking of the assets, in order to support maintenance and replacement decisions.

Therefore, by using the computed HIs, the transformer fleet will be categorized into groups based on level of priority following the guidelines presented in Table 3.

Table 3. Decision-making categorization groups.

Index Value	Condition	Recommended action
0-3.5	Good	Continue the maintenance scheme.
3.5-6.5	Normal	Increment the number of inspections, a transition to condition-based maintenance (CBM) is suggested.
6.5-10	Bad	Implement CBM, degradation indicates approaching end of life.

Then, the results of the three methods are combined using the well-known K-means clustering technique to obtain a final categorization ranking and performing a comparison with the rest of the rankings previously obtained.

Finally, in a second stage, to assess how the HIs evolve with time, an extrapolation for five years is performed for the PT diagnosis test. For this purpose, the normal limits for oil condition given by IEEE Std C57.106™-2002, (2003) are employed and normalized for a yearly increase according to the equations suggested by Irungu et al. (2017). The change rate per year for the oil condition is calculated based on a normally expected life span for a PT, which is 40 years. To extrapolate FC, acidity, moisture, and power factor equation (10) is used. The normal rate of change for BV and interfacial tension is calculated based on (11).

$$x(yearly) = \frac{x_{extreme} - x_{normal}}{40} \quad (10)$$

$$x(yearly) = \frac{x_{normal} - x_{extreme}}{40} \quad (11)$$

The normal rate of increment for the dissolved gases in parts per million per year and per day can be found in IEC 60599, (2015) and Gray (2009) respectively. The consequent values for normal increment for both oil condition and DGA are presented in Table 4.

Table 4. Rate of increment limits.

Yearly rate of change for oil condition parameters	
Ageing indicator	Normal limits (per yr.)
Furans (ppm)	<0.0225
Acidity (mg KOH/g)	<0.00125
Moisture (ppm)	<0.25
IFT (dynes/cm)	<0.2
BV (kV)	<0.5
PF (%)	<0.0225
Yearly rate of change for dissolved gases	
Gas type	Normal limits (per yr.)
H_2 (ppm)	35-132
CH_4 (ppm)	10-120
CO (ppm)	260-1060
C_2H_4 (ppm)	32-146
C_2H_6 (ppm)	5-90
C_2H_2 (ppm)	0-37
CO_2 (ppm)	1700-10000

4.2. Results and discussions

Table 5 shows the HI ranking obtained from each approach for the assessed fleet. From HI results, it is noted that the three methods produce different rankings. Moreover, from Table 5, it can be inferred that also different decisions will be made depending on the approach selected by the asset manager.

There is a level of coincidence between methods 2 and 3, but there are cases where important differences between them can be found. Method 1 returned the lowest HI values for all PTs and always maintained a margin of difference in relation to methods 2 and 3. For the fleet of thirty PTs, the three methods only agreed in the ranking in four cases, i.e., PTs: T2, T22, T24, and T30.

Table 2. Results of the diagnostic tests for the PT fleet.

No.	Age	Color	Moisture (ppm)	BV (kV)	IFT (dynes/cm)	Acidity (mgKOH/g)	PF (%)	H2 (ppm)	CH4 (ppm)	CO (ppm)	C2H4 (ppm)	C2H6 (ppm)	C2H2 (ppm)	CO2 (ppm)	HST (°C)	Furans (ppm)	DCG (ppm)
1	23	1.5	22	52	30	0.07	0.14	234	300	700	29	56	52	5495	60	0.25	671
2	24	2	23	44	24	0.13	0.264	607	119	189	67	257	3	2011	61	1.37	1053
3	23	2	16.5	61	27	0.058	0.174	32.5	45.8	697	21.31	25.54	17	3685	49	0.49	142.15
4	33	2.5	28	40	20	0.18	0.266	74	347	8197	172	194	35	22789	78	4.5	822
5	24	2.5	19	38	23	0.15	0.185	71	65	582	79	127	18	4567	58	1.1	360
6	19	1.5	26	48	25	0.09	0.249	107	129	892	68	55	0	7038	66	0.1	359
7	38	3	23.2	51.7	26	0.251	0.458	979	236	1843	180	183	112	2492	75	5.76	1690
8	43	4	33	35	25	0.19	0.593	1498	395	1582	395	323	26	12371	66	3.9	2637
9	23	2.5	9	49	35	0.08	0.1	294	748	669	1348	212	6	6764	77	0.83	2608
10	22	3.5	42	46	21	0.22	0.221	163	106	299	1517	298	9	2348	64	4.48	2093
11	21	2	6	64	27	0.13	0.566	151	8	297	10	151	8	2323	68	0.22	328
12	19	1	11	70	38	0.05	0.113	678	368	162	108	92	163	1139	81	0.16	1409
13	4	0	9	71	45	0.04	0.068	893	724	242	18	6	1	1883	56	0.03	1642
14	24	1	6	66	41	0.03	0.207	195	660	356	79	127	22	3347	53	0.09	1083
15	29	2	12	65	28	0.05	0.319	440	522	685	62	31	183	5382	50	0.31	1238
16	9	1	10	55	42	0.03	0.15	15	8	902	5	9	0	7135	61	0.1	37
17	14	1.5	10	62	29	0.09	0.733	1176	4	637	10	4	1	4991	53	0.83	1195
18	18	3	32	55	26	0.25	0.328	441	678	1695	62	73	55	13345	77	5.1	1309
19	19	3	40	31	22	0.092	0.416	75	44	261	13	106	0	7846	61	2.4	238
20	17	3	21.2	33.5	20	0.349	0.257	181	79	192.6	29	56	21.1	713	50	8.91	366.1
21	13	1.5	13.9	48	39.25	0.025	0.003	1638	12242	139	17755	8647	5	1296	54	0.01	40287
22	15	6	19.46	33	21.47	0.139	0.9	5	35	964	41	21	1	4002	60	0.033	103
23	11	1.5	12.4	44.4	31.27	0.025	0	4	13	102	22	10	0	1274	35	0.036	49
24	15	5.5	13.6	30	29.8	0.085	0.2	10	8	542	46	2	0	2346	61	0.066	66
25	15	2.5	12.5	56.2	26.2	0.065	0.101	4	13	102	22	10	0	1274	56	0.017	49
26	13	2	10.9	56.2	39.5	0.02	0	160	176	156	7	58	0	2763	60	0.01	401
27	16	1.5	11.9	58.1	38.95	0.009	0.1	225	116	401	146	29	28	2757	58	0.01	544
28	18	0.5	7.1	50.4	47	0.008	0	14	12	271	27	6	0	7454	40	0.01	59
29	16	2	12.1	54.8	38.96	0.042	0.04	3	16	136	1	6	0	2669	53	0.01	26
30	13	1.5	9	58	35.94	0.015	0.038	6	1	240	25	0	3	2059	56	0.01	35

As mentioned above, a clustering technique was applied to combine HI results. Figure 8 shows the clusters representing the three methods and the centroids of the k-means technique.

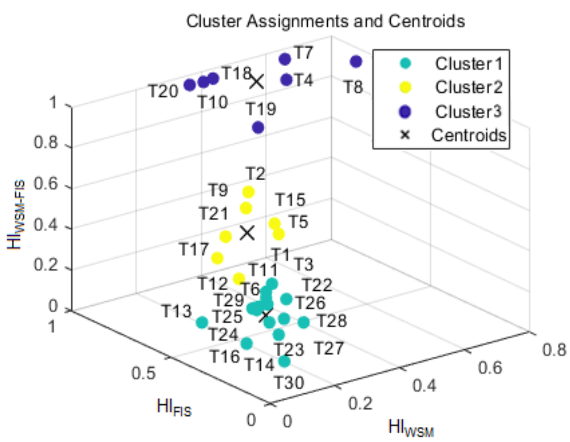


Figure 8. Cluster for the categorization groups of PT conditions.

Table 6 presents the categorization groups for the three methods and the inclusion of the k-means merged results. Clear differences can be observed in how the methods categorized the PT fleet.

Table 6. Categorization groups in agreement with Table 3.

Condition	Method 1	Method 2	Method 3	Merged Method
Good	25	12	17	16
Normal	4	12	6	7
Bad	1	6	7	7
% of coincidence	60.00%	83.30%	96.67%	

The first method ranks almost all units in good condition and only one of them receives a bad score, method 2 and 3 showed different results as well. The degree of coincidence between method 1 and 2 is around forty percent as for method 3 the value increases to sixty percent; for method 2 the level of agreement with method 3 is eighty percent. Thus, the overall coincidence of the three methods was around forty percent. The k-means method presented a ranking similar to the one proposed in method 3, the degree of coincidence with method 2 and 3 is greater than eighty percent and for method 1 is placed around sixty percent.

On the other hand, in Figure 9, an individual analysis for each method is developed to simulate how each type of HI varies with time, by using the extrapolated values for the diagnosis tests.

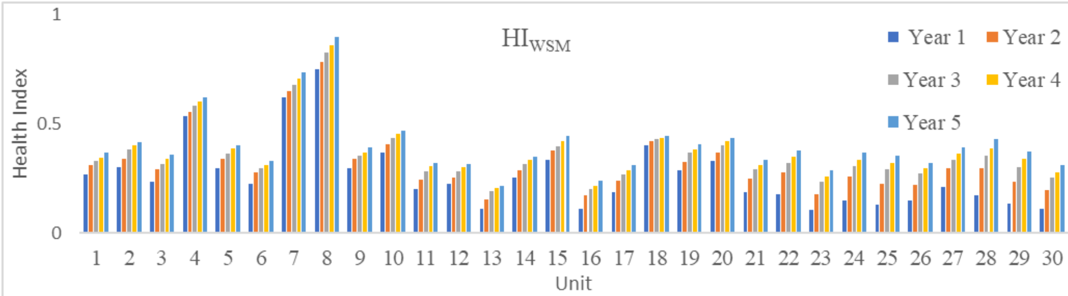
For method 1, the HI rose every year, the increment rate shaped a quasi-linear function as the sample ages. The growth can be explained due to the weight assigned to the age of the PT (56%), in contrast, DGA and oil condition were given much lower weights (26% and 9%). Method 2 presented a different perspective during the five-year period, only fifty percent of the samples presented changes, the rest remained at the same value, this can be attributable to the nature of the trapezoidal fuzzy membership functions (TFMF), where they maintain the same value unless the input value moves to an interception zone between membership functions or another function at all.

It is important to note that this method does not consider, age, load or CO_2/CO relation but shows good performance Method 3 was a particular case, it showed similar results with method 2, but during the five years, there were some samples whose HI experimented a decrease in value (samples 2,9 and 19). The reason for that decrement was the change in the CO_2/CO relation, which has an essential role in the final value in the degradation level of the insulating paper. Also, it can be observed a stiffer rate of change than in method 2, this behavior responds to the nature of the TFMF that is amplified by the multi-FIS scheme employed in the method.

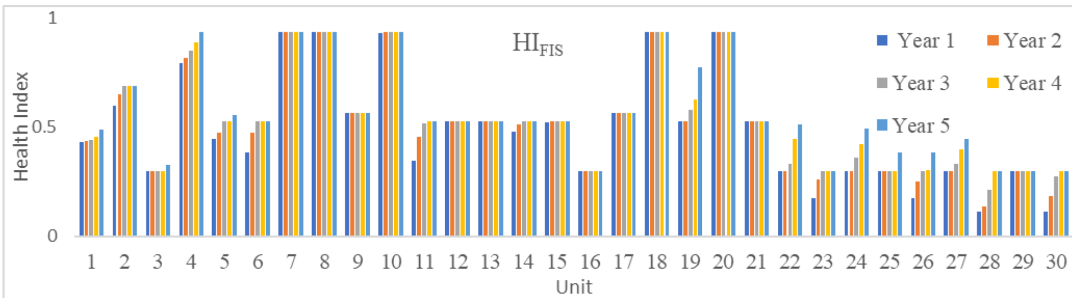
Table 5. Comparison of the HI ranking for the assessed fleet for years 1 and 5.

Order	HI_{WSM}		HI_{FIS}		$HI_{WSM-FIS}$	
1	T23	0.10357	T28	0.1104	T27	0.1104
2	T30	0.11042	T30	0.1104	T30	0.1104
3	T16	0.11072	T26	0.1719	T16	0.1104
4	T13	0.11135	T23	0.1739	T13	0.1104
5	T25	0.12812	T3	0.3	T14	0.129
6	T29	0.13396	T27	0.3	T23	0.275
7	T26	0.14722	T16	0.3	T26	0.275
8	T24	0.1487	T24	0.3	T24	0.275
9	T28	0.16993	T25	0.3	T25	0.275
10	T22	0.17511	T22	0.3	T22	0.275
11	T21	0.18422	T29	0.3	T29	0.275
12	T17	0.18449	T11	0.3464	T11	0.275
13	T11	0.1993	T6	0.3862	T6	0.275
14	T27	0.20965	T1	0.4297	T1	0.275
15	T6	0.22354	T5	0.4442	T28	0.275
16	T12	0.22528	T14	0.4816	T12	0.275
17	T3	0.23301	T15	0.5222	T3	0.275
18	T14	0.25386	T12	0.525	T17	0.375
19	T1	0.26838	T13	0.525	T5	0.5
20	T19	0.28424	T19	0.525	T15	0.5
21	T9	0.29509	T21	0.525	T21	0.5
22	T5	0.29801	T17	0.5672	T9	0.556
23	T2	0.30052	T2	0.5996	T2	0.634
24	T20	0.32773	T9	0.6033	T19	0.992
25	T15	0.33322	T8	0.7879	T8	0.992
26	T10	0.36696	T4	0.7945	T4	0.992
27	T18	0.39995	T10	0.9334	T10	0.992
28	T4	0.53692	T7	0.9364	T7	0.992
29	T7	0.61924	T18	0.9392	T18	0.992
30	T8	0.74717	T20	0.9392	T20	0.992

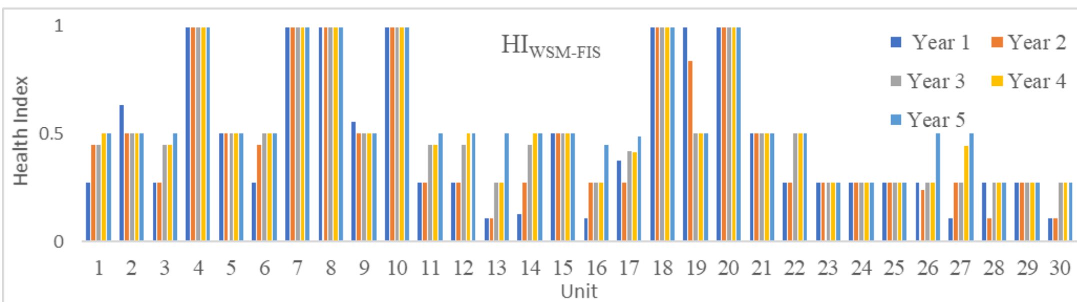
● General Coincidence ●Coincidence for Methods 1 and 2 ●Coincidence for Methods 1 and 3 ●Coincidence for Methods 2 and 3



a)



b)



c)

Figure 9 a) to c). Individual comparison for the three methods for the five-year period.
a) Health index based on a weighted sum model. b) Health index based on fuzzy inference system.
c) Health index based on hybrid WSM-FIS.

5. Conclusions

The three methods yielded to different HI results and individual analysis was necessary to understand these differences.

The method based on WSM showed the least promising results. In this approach, the weighting distribution is dominated by the PT age criterion. Then for those cases of PTs with average calendar ages, the resulting HI will show good condition health despite the poor performance of other criteria such as OQF and DGA.

The method based on FIS presented more consistent results and the increment of the HI during the five years was normal. A certain grade of inelasticity was found, but this can be attributed to the nature of the membership functions on a FIS. As an improvement recommendation, the method should consider the age and the load of the unit.

The hybrid method WSM-FIS, even though it encloses the highest number of diagnosis criteria, showed an irregular behavior specifically during the five-year analysis. The CO_2/CO relation played a major role in its performance. A grade of inelasticity, higher than method 2, was also noted, the multi-FIS employed in the model was responsible for that level of stiffness.

In summary, FIS-based approaches showed the most promising results. Although both methods exhibited a certain degree of inelasticity, this can be reduced by using a higher number of membership functions by criterion or by replacing the trapezoidal with triangular or Gaussian distribution functions.

The health index is mainly a tool for decision-making support into an asset management framework. In this context, this paper demonstrated that decision-making depends on the adopted approach for HI calculation. To overcome this problem, a good compromise solution is to combine the results of different techniques by using clustering techniques, such as the K-means technique.

Several experts advise electrical utilities in developing their own HI approach for PT, in agreement with their needs and available data. However, a good understanding of the different techniques proposed in the literature could help these utilities to choose the most suitable alternative, or even more to select a set of approaches and combine their HI outputs, as it is proposed in this work.

Conflict of interest

The authors have no conflict of interest to declare.

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References

Bohatyrewicz, P., Płowucha, J., & Subocz, J. (2019). Condition assessment of power transformers based on health index value. *Applied Sciences*, *9*(22), 4877. https://doi.org/10.3390/app9224877

Cerón, A. F., Echeverry, D. F., Aponte, G., & Romero, A. A. (2015). Índice de salud para transformadores de potencia inmersos en aceite mineral con voltajes entre 69kV y 230kV usando lógica difusa. *Información tecnológica*, *26*(2), 107-116.

https://doi.org/10.4067/S0718-07642015000200013

Gorgan, B., Notingher, P. V, Badicu, L. V, & Tanasescu, G. (2010). Calculation of Power Transformers Health Indexes. Annals of the University of Craiova, Electrical Engineering Series, 34, 13–18.

Gray, I. (2009). A guide to transformer oil analysis. *Transformer Chemistry Services*, 1–12.

Hughes, D. (2003). 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) (Vol. 5, No. 1, pp. 5-15).

Idrees, M., Riaz, M. T., Waleed, A., Paracha, Z. J., Raza, H. A., Khan, M. A., & Hashmi, W. S. (2019). Fuzzy Logic Based Calculation and Analysis of Health Index for Power Transformer Installed in Grid Stations. *RAEE 2019 - International Symposium on Recent Advances in Electrical Engineering*, *4*, 1–6. https://doi.org/10.1109/RAEE.2019.8887016

Iec 60422, i. e. c. (iec). (2013). iec 60422 : mineral insulating oils in electrical equipment - supervision and maintenance guidance. In *61010-1 © Iec:2001* (4th ed.). International Electrotechnical Commission (IEC).

IE 60599, International Electrotechnical Commission. (2015). Mineral oil-filled electrical equipment in service–Guidance on the interpretation of dissolved and free gases analysis. *IEC, 60599*, 2015.

IEEE Std C57.106™-2002. (2003). IEEE Guide for Acceptance and Maintenance of Insulating Oil in Equipment. In *Communications Society* (Vol. 2002, Issue April).

IEEE Std C57.152-2013. (2013). IEEE Guide for Diagnostic Field Testing of Fluid-Filled Power Transformers , Regulators , and Reactors. In *IEEE Std C57.152-2013* (Vol. 2013). https://doi: 10.1109/IEEESTD.2013.6544533

Irungu, G. K., Akumu, A. O., & Munda, J. L. (2017, September). Transformer condition assessment for maintenance ranking: a comparison of three standards and different weighting techniques. In *2017 IEEE AFRICON* (pp. 1043-1048). IEEE. https://doi.org/10.1109/AFRCON.2017.8095626

Islam, M. M., Lee, G., & Hettiwatte, S. N. (2017). Application of a general regression neural network for health index calculation of power transformers. *International Journal of Electrical Power and Energy Systems*, *93*, 308–315. https://doi.org/10.1016/j.ijepes.2017.06.008

Jahromi, A. N., Piercy, R., Cress, S., Service, J. R. R., & Fan, W. (2009). An approach to power transformer asset management using health index. *IEEE Electrical Insulation Magazine*, *25*(2), 20–34. https://doi.org/10.1109/MEI.2009.4802595

Jian, W., Wenbing, Z., Chao, G., Demeng, B., & Kuihua, W. (2020). The New Developed Health Index for Power Transformer Condition Assessment. *Proceedings - 2020 5th Asia Conference on Power and Electrical Engineering, ACPEE 2020*, 1880–1884. https://doi.org/10.1109/ACPEE48638.2020.9136344

Jürgensen, J. H., Scheutz Godin, A., & Hilber, P. (2017). Health index as condition estimator for power system equipment: a critical discussion and case study. In *24th International Conference on Electricity Distribution-CIRED Glasgow, 12-15 June 2017* (Vol. 2017, pp. 202-205). Institution of Engineering and Technology. https://doi.org/10.1049/oap-cired.2017.1174

Li, E. W., & Song, B. (2014). Transformer health status evaluation model based on multi-feature factors. *POWERCON 2014 - 2014 International Conference on Power System Technology: Towards Green, Efficient and Smart Power System, Proceedings, Powercon*, 1417–1422. https://doi.org/10.1109/POWERCON.2014.6993723

Liang, G., Li, S., Liu, R., Cao, J., Hao, Y., & Chen, W. (2017). A probabilistic maintenance scheme evaluation method for transformer based on failure rate. *Proceedings - 2017 4th International Conference on Information Science and Control Engineering, ICISCE 2017*, 90–93. https://doi.org/10.1109/ICISCE.2017.29

Mharakurwa, E. T., & Goboza, R. (2019). Multiparameter-based fuzzy logic health index assessment for oil-immersed power transformers. *Advances in Fuzzy Systems*, *2019*, 7–15. https://doi.org/10.1155/2019/2647157

Naderian, A., Cress, S., Piercy, R., Wang, F., & Service, J. (2008). An approach to determine the health index of power transformers. *Conference Record of IEEE International Symposium on Electrical Insulation*, *July 2008*, 192–196. https://doi.org/10.1109/ELINSL.2008.4570308

Patil, A. J., Singh, A., & Jarial, R. K. (2019). A Novel Fuzzy Based Technique for Transformer Health Index Computation. *2019 6th IEEE International Conference on Advances in Computing, Communication and Control, ICAC3 2019*. https://doi.org/10.1109/ICAC347590.2019.9036845

Ranga, C., Chandel, A. K., & Chandel, R. (2017). Condition assessment of power transformers based on multi-attributes using fuzzy logic. *IET Science, Measurement and Technology*, *11*(8), 983–990. https://doi.org/10.1049/iet-smt.2016.0497

Romero-Quete, A. A., Gómez, H. D., Molina, J. D., & Moreno, G. (2017). Método práctico para la evaluación de riesgo en parques de transformadores de potencia. *DYNA (Colombia)*, *84*(200), 11–18. https://doi.org/10.15446/dyna.v84n200.54364

Rønneberg, T. (2017). Cost-Benefit Analysis of Maintenance Measures for Power Transformers (Master's thesis, NTNU).

Rosero-Z, L., Pavas, A., & Durán, I. C. (2018, September). Analysis of maintenance in transformers based on a fuzzy logic method. In *2018 IEEE PES Transmission & Distribution Conference and Exhibition-Latin America* (T&D-LA) (pp. 1-5). IEEE. https://doi.org/10.1109/TDC-LA.2018.8511772

Ross, T. J. (2010). Fuzzy Logic with Engineering Applications. In *Fuzzy Logic with Engineering Applications: Third Edition* (Third). Wiley. https://doi.org/10.1002/9781119994374

Scatiggio, F., Pompili, M., & Calacara, L. (2018, June). Transformers fleet management through the use of an advanced health index. In *2018 IEEE Electrical Insulation Conference (EIC)* (pp. 395-397). IEEE. https://doi.org/10.1109/EIC.2018.8481030

Singh, P. (2012). A new approach for the ranking of fuzzy sets with different heights. *Journal of Applied Research and Technology*, *10*(6), 941–949. https://doi.org/10.22201/icat.16656423.2012.10.6.354

Tamma, W. R., Prasojo, R. A., & Suwarno, S. (2020, October). Assessment of High voltage power transformer aging condition based on health index value considering its apparent and actual age. In *2020 12th International Conference on Information Technology and Electrical Engineering (ICITEE)* (pp. 292-296). IEEE. https://doi.org/10.1109/ICITEE49829.2020.9271778

Trillas, E. & Eciolaza, L. (2015). Fuzzy logic: an introductory course for engineering students (Vol. 1). Springer Publishing Company, Incorporated.

Vasquez, W. A., & Jayaweera, D. (2020). Risk-based approach for power transformer replacement considering temperature, apparent age, and expected capacity. *IET Generation, Transmission and Distribution*, *14*(21), 4898–4907. https://doi.org/10.1049/iet-gtd.2020.1006

Yahaya, M. S., Azis, N., Abidin Ab Kadir, M. Z., Jasni, J., Hairi, M. H., & Talib, M. A. (2017). Estimation of transformers health index based on the markov chain. *Energies*, *10*(11), 1–11. https://doi.org/10.3390/en10111824

Zeinoddini-Meymand, H., & Vahidi, B. (2016). Health index calculation for power transformers using technical and economical parameters. *IET Science, Measurement and Technology*, *10*(7), 823–830. https://doi.org/10.1049/iet-smt.2016.0184