Health Index Assessment for Power Transformer Strategic Asset Management in Electrical Utilities

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Abstract:

The use of Health Index (HI) has helped in driving electrical utilities decision making for strategic investment planning including operation, and maintenance (O&M) programmes. This approach increases the ability of the business to implement robust investment decision objectives that make physical assets safe, productive, and efficient. and cost effective. Asset Management (AM) framework is defined by British Standards PASSS and ISO55001/2 to ensure electrical network operators are delivering best quality of services by operating at high performance, low cost while managing unexpected risks (38, 39).

Data monitoring and recording have improved but still robust master dataset is either limited or not available due to a range of factors including huge costs for capturing live data, the lack of monitoring tools, limited or no data collection and, data uncertainty challenges. there are a small number of electrical utilities [31] around the globe who capture data using recent technologies that work in line with information best practice which serve a large fleet of Power Transformers (PTs).

Specific tools such as Artificial Intelligence (Al) have helped to address problems associated with limited or missing data uncertainty issues, data capturing process, and therefore impact the accuracy of a HI calculation. Recently, innovative systems became an alternative approach in structuring big data to support condition assessment and condition monitoring tools which are reliant on various data sources.

This paper discusses HI scoring for transformer condition assessment using conventional methods that can add value to the AM practice. This includes defining HI model requirements. Power transformer health index data interpretation analysis will be considered using international standard: Institute of Electric-al Electronics & Engineers (IEEE) C57.104 transactions on industrial informatics. Preliminary analysis for data management using Python Programming Language (PPL) is considered. The authors hope to provide an up-to-date review of the current literature to allow academia and industry to question and challenge a preconceived perception that large datasets are difficult to obtain and review to support the development of new decision-making investment activities.

Keywords: Power Transformer, Asset Management, Health Index, Artificial Intelligent, Electrical Utility, Decision Making, Strategic Investment Planning, Python Programming Language.

1. Introduction

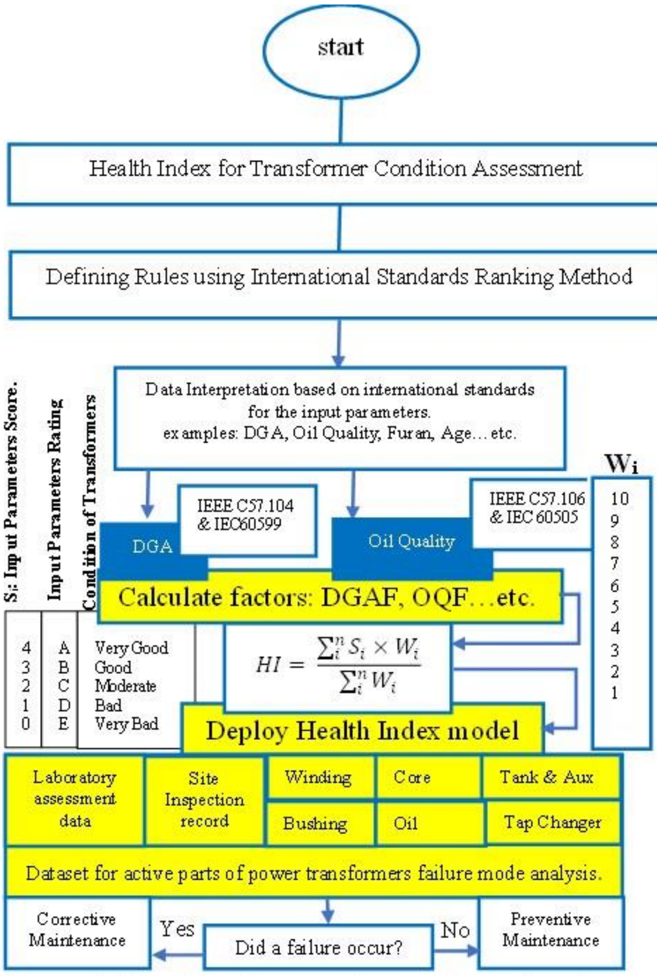
Electrical power transformers are considered as one of the most significant assets in electrical power grid. Electrical utilities are considering these assets as vital and reliable in delivering energy quality. The "health index" is applied to assess and categorise transformers health conditions that includes upgrading, replacement, or routine maintenance decisions. The AM framework defined in [38,39) considers HI as a building block to the broader AM process. Based on the recent development, the HI calculation method has become a popular tool to many researchers working in the electrical industry [1, 5, 8, 9, 10, 19, 31, 36, 37, 40].

This paper assists in understanding the development of the conventional HI method. Preliminary analysis using Python Programming Language (PPL) is used for analysing and validating the collected data from the local electrical utility in Sunderland, UK. It shares recent progress in this research profundity offering in detail a range of articles reflected to the conventional HI method. Each electrical utility has its own scoring method. The various methods to calculate the health index in research are not the same as in practice. This is based on many factors including agreed scoring and weighting factors for each input parameter, the methods which are used for data interpretation and the standard that considered for the ranking method [10, 14, 19, 20, 25, 29, 30]. The most famous three popular basic health condition methods are: degradation modelling, condition assessment using monitoring data, and statistical end-of life modelling [18]. The first method applies a physical model which predicts the degradation and the insulation paper residual lifetime utilising operational historical record. Whereas the second method evaluates condition monitoring data. This condition assessment method typically sums these data into a numerical measure that describes the current condition of power transformer, and this method is known as HI. HI method is derived reliant on advanced mathematical modelling as well the HI scores, weighting factors and results that requires involvement of power transformer specialist to insure consideration of the right decision within the required timeframe. Additionally, the third method is the calculation of the power transformer projected residual life from the present age. This method requires a contrast using statistical figures that are joined by expert's findings if statistical figures are incorrect.

There are advantages and disadvantages to using either of the previous three condition assessment methods. For instance, the degradation modelling method allows calculation of residual life but does not reflect condition monitoring data. The condition assessment using monitoring data method allows altogether current condition monitoring data to be involved but predicting residual life from this is complicated. The statistical end-of-life modelling method allows a stochastic model to be developed by using statistical data but does not consider any other data than the transformer age. The validity using this method relies on the value and representability of the presented statistical data.

2. Health Index Formulation

The development of condition-based HI requires relative degree of importance for different condition factors in determining the health condition of the power transformer. This research method investigation is novel, new and potentially the most useful tool which is Figure 1 describes the research workflow of HI methodology that are required for developing conventional HI scoring method. The most important step is defining ranking method scoring rules for the input parameters and HI scoring equation.



$$HI = \frac{\sum_i^n S_i \times W_i}{\sum_i^n W_i}$$

Figure 1: Workflow for transformer HI methodology.

The rules of ranking method are considered based on relevant IEEE/IEC standards. The weighting and scoring factors are different for every electrical utility practice. The collected data must fulfill the requirements to identify power transformer health condition.

2.1 Health Index Scoring & Weighting Factor for Ranking Method

HI mathematical scoring and weighting practices are applied for all diagnostic analysis data in the type of multicriteria analysis to analyse HI findings for all PTs. With both factors, the real PT condition is valued in the way of ratio indicators. The scoring method is applied for classifying PT condition into numerous conditions such as score'1' for "normal" condition, score '2' for "suspect" condition, and score '3' for "poor" condition, as this can vary to 5-7 different conditions depending on the required HI condition classifications. The score states are defined with applying the advised threshold of numerous international standards like IEEE, International on Electrotechnical Commission (IEC), and International Council on Large Electric Systems as in French stands for Conseil International des Grands Réseaux Electriques (CIGRE) guides [23] that identifies the ranking method rules. These linguistic terms are simplified expressions of the transformer condition. The weighting factor is used for ranking the degree of importance or contribution of any parameter that affects the condition of a transformer. The rating code starts with Weight ‘1’ for very low importance, Weight ‘2’ for low importance, Weight ‘3’ for moderate importance, Weight ‘4’ for high importance, Weight ‘5’ for very high importance [24]. Determination of the weight/score factors for each diagnostic analysis requires the experience of transformer experts.

2.2 Health Index Calculation Formula

A computed scoring and weighting method can typically be put into correctly signify the PT health condition. Power Transformer Health Index (PTHI) includes the following main steps:

1. Allocated scores/existing condition deterioration assessments are defined into health scores in a distinct scale.
2. Significance weighting factor is allocated to all test constraint in a scale from "very bad" to "very good".
3. Analyzing the limit probable score by adding up the multiples

   of steps 1 and 2 for all condition test factors [19].

4. Finally, the total HI is computed using equation (1):

$$\mathrm{HI} = \frac{\sum_{i=1}^{n} S_i \times W_i}{\sum_{i=1}^{n} S_{max} \times W_i} \times 100\% \tag{1}$$

Where HI is the final HI metric, Si is the score factor for all PT health condition obtained from diagnostic test shown on table 1, W, is the weight factor for the relative importance of the diagnostic test parameters and Smox-i represent maximum score among all the diagnostic tests, n represents the number of tests included for PTHI calculation [19, 31, 40]. The rating (A, B, C, D, E) described (Green: Very Good, Blue: Good, C Fair, Orange: Bad, Red Very Bad) respectively. This is converted to HI factor which ranges between 4 and O respectively as shown in table 1. HI design contains dividing its overall condition score by its highest condition score, then multiplying by 100.

2.3 What Diagnostic Parameters Must be Unified in Power Transformer Health Index?

The extra diagnostic parameters are employed, the extra dependable and correct PTHI must be. However, considering all the input parameters [12]. Figure 2 shows the waterfall diagram that links the HI platforms from identified data sources all through analytic platform towards failure modes classification. The feedback loop considering the sanity check is supporting the final HI calculation that indicates the origin data [13].

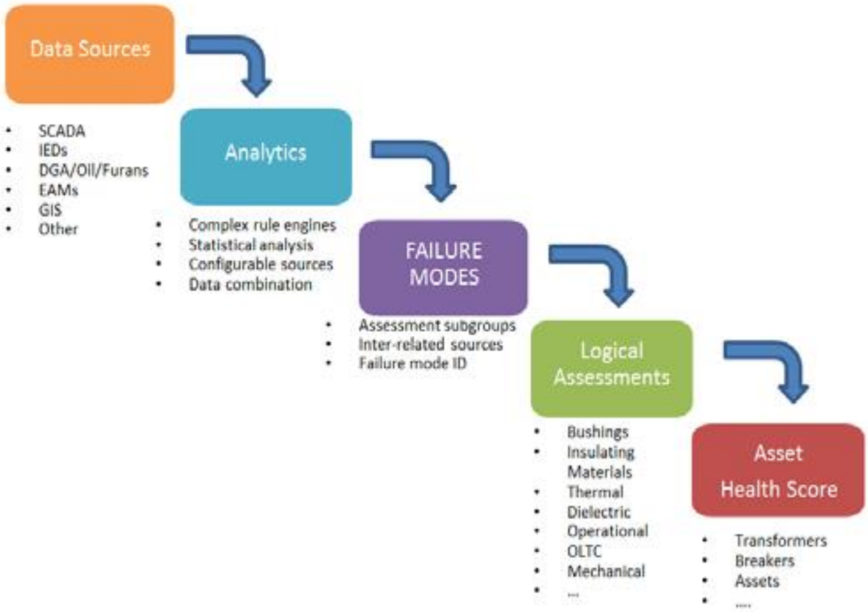


Figure 2: Waterfall stages to move from data source to HI score.

There are various patterns are attributing condition data to basic data. IEEE C57.104 [14] has a good interpretation for DGA degrees in PT oil, that permit the operator to categorize a cause as individual of four data. Considering four input data, the IEEE C57.104 approach might be the required standard [14]. HI method works to prioritize decisions reliant on asset condition.

2.3.1 Health Index Diagnostic Parameters Analysis

Table 1 shows 27 diagnosis inputs in four groups to compute HI.

Table 1: Health index scoring using conventional method.

#	Diagnostic Tests	W_i	Condition					S_i				
1	DGA	10	A	B	C	D	E	4	3	2	1	0
2	Load History	10	A	B	C	D	E	4	3	2	1	0
3	Power Factor	10	A	B	C	D	E	4	3	2	1	0
4	Infrared thermography	10	A	B	C	D	E	4	3	2	1	0
5	Tx Oil Quality	6	A	B	C	D	E	4	3	2	1	0
6	Overall Tx Condition	8	A	B	C	D	E	4	3	2	1	0
7	Furans Content or Age	5	A	B	C	D	E	4	3	2	1	0
8	Turns ratio	5	A	B	C	D	E	4	3	2	1	0
9	Leakage reactance	8	A	B	C	D	E	4	3	2	1	0
10	Winding resistance	6	A	B	C	D	E	4	3	2	1	0
11	Core-to-ground	2	A	B	C	D	E	4	3	2	1	0
12	Bushing Condition	5	A	B	C	D	E	4	3	2	1	0
13	Main Tank Corrosion	2	A	B	C	D	E	4	3	2	1	0
14	Cooling Equipment	2	A	B	C	D	E	4	3	2	1	0
15	Oil Tank Corrosion	1	A	B	C	D	E	4	3	2	1	0
16	Foundation	1	A	B	C	D	E	4	3	2	1	0
17	Grounding	1	A	B	C	D	E	4	3	2	1	0
18	Gaskets, seals	1	A	B	C	D	E	4	3	2	1	0
19	Connectors conser	1	A	B	C	D	E	4	3	2	1	0
20	Oil Leaks	1	A	B	C	D	E	4	3	2	1	0
21	Oil Level	1	A	B	C	D	E	4	3	2	1	0
22	Conductivity factor (k_c)	10	A	B	C	D	E	4	3	2	1	0
23	Polarization index (k_p)	10	A	B	C	D	E	4	3	2	1	0
24	Loss factor tg8 at (f = 1mHz)	10	A	B	C	D	E	4	3	2	1	0
25	DGA of LTC	6	A	B	C	D	E	4	3	2	1	0
26	LTC Oil Quality	3	A	B	C	D	E	4	3	2	1	0
27	Overall LTC Condition	5	A	B	C	D	E	4	3	2	1	0
28	Others*	3	A	B	C	D	E	4	3	2	1	0

*Vator tank, PT / CT, cable box, manufacture, protection equipment.

The proposed scoring or weighting factors for each diagnostic are presented for each input are discussed, and its levels are given in table 2 and 3. A consideration, whether power transformer failure causes are detected need more study like conducting a detailed laboratory investigation analysis which are considered by electrical utility [13]. HI needs to formulate the needs over the period. A two examples of analysis parameters are provided as follows:

2.3.1.1 Power Transformer Dissolved Gas Analysis (DGA)

Power transformer DGA analysis is used to compare the contents of gas in the oil in contrast to the scoring and waiting factors. DGA results shows that for each gas is given a score. The scores are reliant on international standard. For example, the HI scores reliant on Dorenburg, IEC, IEEE, and Reclamation standards. By applying equation 2, the density of the Dissolved Gas Analysis Factor (DGAF) is calculated as follows:

$$DGAF = \frac{\sum_{I=1}^{n} S_i W_i}{\sum_{i=1}^{7} W_i} \qquad (2)$$

Where, S_i is the score of each gas and W_i is the weight factor of each gas. The DGAF rating and condition are given in Table 2. Table 3 includes the ranking limits for each individual gases to calculate the DGAF.

Table 2 Transformer rating based on DGA factor analysis [22].

Rating Code	Condition	Description
A	Good	DGAF < 1.2
B	Acceptable	1.2 ≤ DGAF < 1.5
C	Need Caution	1.5 ≤ DGAF < 2
D	Poor	2 ≤ DGAF < 3
E	Very poor	DGAF ≥ 3

Table 3 Scoring weight factors for gas levels parts per million (PPM) [22].

	Score (S)						
Gas	1	2	3	4	5	6	W_i
H_2	≤100	100-200	200-300	300-500	500-700	>700	2
CH_4	≤75	75-125	125-200	200-400	400-600	>600	3
C_2H_6	≤65	65-80	80-100	100-120	120-150	>150	3
C_2H_4	≤50	50-80	80-100	100-150	150-200	>200	3
C_2H_2	≤3	3-7	7-35	35-50	50-80	>80	5
CO	≤350	350-700	700-900	900-1100	1100-1400	>1400	1
CO_2	≤2500	≤3000	≤4000	≤5000	≤*7000*	>7000	1

This technique is not intended as a diagnostic test, it is as a test to investigate the quality of the oil over the long-term period. The amount of the gas that produced in the transformer oil is very dangerous for the transformer's life and it require an urgent action. When a drop of a final HI score occurs, it means if the three successive gas samples display a 30% rise or more, or it means if a 20% rise or more is inspected for five successive samples.

IEC Std 60599 offers a coded catalogue of defects, obviously by DGA and IEEE Std C57.104 presents a four level reasons to group threats to transformers, for constant operation and maintenance at numerous burnable gas levels [20, 24].

Theoretically, when using DGA, it is expected to recognise inner defects like partial discharge, severe overloading, low-energy sparking, arcing, and insulation system overheating issues.

Practically, DGA data means it does continually offer adequate data to certain degree from which to assess the transformer system reliability. Routine operation can show some effect in the development of several gases. Knowledge about the history of a transformer in terms of maintenance, loading practice, previous faults, manufacturer data, and so on are an essential element of the data needed to conduct HI assessment. The certainty is conceivable for certain transformers to run during effective life cycle with significant measures of burnable gases present [20].

Numerous standard analysis skills are utilized for DGA of power transformers over the previous 30 years by Rogers, Durenburg, Duval Triangle, and modified Durenburg May/June 2002 [20].

Table 4 contrasts the suggested alarm level of gases from various standards. The facts are related, apart from the IEEE thresholds for acetylene and carbon dioxide.

Table 4 DGA gas limits references PPM by many standards [23].

Gas	Dorenburg	IEC	IEEE	Bureau of Reclamation
H2	200	100	100	500
CH4	50	75	120	125
C2H6	35	75	65	75
C2H4	80	75	50	175
C2H2	5	3	35	7
CO	500	700	350	750
CO2	6000	7000	2500	10000

2.3.1.2 Power Transformer Oil Quality Analysis

The power transformer oil quality analysis is obtained using Oil Quality Factor (OQF) which is resultant by the scoring oil properties. The OQF is calculated using equation (3).

$$DGAF = \frac{\sum_{I=1}^{n} S_i W_i}{\sum_{i=1}^{7} W_i} \qquad (2)$$

Where S_i is the score of the unlike properties and W_i is the conforming weight. The final OQF is calculated in a similar technique. Which is used for DGAF. It is considered, the dissipation factor and breakdown voltage boundaries for the HI model is reliant on other measurements of international standards. Dielectric dissipation factor is referred to 25°C based on IEEE C57.106-2006 standard [28], whereas laboratories reference of this measurement is 90°C based on IEC60156 standard [29]. Furthermore, the dielectric breakdown voltage boundaries are measured via an electrode gap of 2 mm based on the IEEE C57.106-2006 [28]. And as per the IEC60156 standard with a gap of 2.5 mm which can be confirmed with local utility. All inputs values will be utilized for on service aged oil. Table 5 summaries the advised oil analysis criteria reliant on the American Society Testing Materials (ASTM) standard recommended by IEEE and the IEC standard recommended by CIGRE [14, 25, 30], A pattern of electrical, physical, and chemical tests is made to verify preventive maintenance techniques, prevent premature breakdown and expensive power failures, and preventive maintenance plan like oil replacement plan [27, 28, 29, 30, 40].

Table 5 Gas limit references based on OQA assessment [22].

Parameter	ASTM recommended by IEEE [110,48]	IEC recommended by CIGRE [110,75]
Dielectric Breakdown	D877 D1816	IEC60156
Water content	D1533	IEC 60814
Power Factor	D924	IEC247
IFT	D971	ISO 6295
Acidity	D644 D974	IEC62021
Colour	D1500	ISO 2049

ASTM advised by IEEE Std C57.106-2006 [28], "IEEE Guide for Acceptance and Maintenance of Insulating Oil in Equipment", and IEEE Transformers Committee, 2006. IEC advised by CIGRE Working Group 05, "An international survey on failures in large in service power transformers," Electra, no. 88, May 1983 [19]. The highest threshold references for oil parameters are classified reliant on the level voltage in both IEEE and IEC standards [28, 30]. Table 6 is the utilized ranking technique for each oil quality assessment parameter. A related scoring technique to DGA is utilized for oil quality. It is critical to mention that these rates are advised for constant application of service-aged insulating oil excluding new oil.

Table 6: Ranking Method for oil analysis - IEEE C57.106-2006 [22].

	U<=69kV	69 kV < U < 239 kV	230 kV < U	Score (Si)	Wi
Dielectric Strength kV (2 mm gap)	≥ 45	≥ 52	≥ 60	1	3
	35-45	47-52	50-60	2	
	30-35	35-47	40-50	3	
	≤ 30	≤ 35	≤ 40	4	
IFT dyne/cm	≥ 25	≥ 30	≥ 32	1	2
	20-25	23-30	25-32	2	
	15-20	18-23	20-25	3	
	≤ 15	≤ 18	≤ 20	4	
Acid Number	≤ 0.05	≤ 0.04	≤ 0.03	1	1
	0.05-0.1	0.04-1.0	0.03-0.07	2	
	0.1-0.2	1.0-0.15	0.07-0.10	3	
	≥ 0.2	≥ 0.15	≥ 0.10	4	
Moisture (ppm)	≤ 30	≤ 20	≤ 15	1	4
	35-35	20-25	15-20	2	
	35-40	25-30	20-25	3	
	≥ 40	≥ 30	≥ 25	4	
Color	≤ 1.5			1	2
	1.5-2.0			2	
	2.0-2.5			3	
	≥ 2.5			4	
Dissipation factor (%) 25 C)	≤ 0.1			1	3
	0.1 - 0.5			2	
	0.5 - 1.0			3	
	≥ 1.0			4	

2.4 Preliminary Analysis Using Python Programming Language:

2.4.1 Data Management and Analysis

The data management and analysis section cover data collection, preparation, analysis, and findings. Currently the investigation includes data records of total of 1231 from a utility in UK considering all voltage levels records as shown in table 15. The data are classified based on transformer voltage level using earlier IEC & IEEE standards for the related diagnostics parameters. Explanatory Data Analysis (EDA) is conducted using Python for the collected data, to explore the dataset. This indicates the amount of missing data to enable considering the right action towards solving the issue of missing data. So firstly, to describe data in terms of minimum, maximum, shape of how many records in dataset in terms of rows and columns of what is missing.

Table 7 shows preliminary investigation for the collected data.

	Age	Moisture	Acidity	BDV	DGA	Furfuraldehyde	Health Index
mean	41.669198	21.957598	0.132945	63.772151	267.298246	0.187878	3.153503
std	17.164061	170.009150	0.905780	12.619900	301.143476	0.445652	1.532753
min	5.000000	5.000000	0.010000	14.000000	0.000000	0.000000	0.620434
25%	25.000000	13.000000	0.033333	57.666700	100.000000	0.001000	1.710821
50%	49.000000	16.000000	0.080000	65.000000	220.000000	0.055000	3.245311
75%	55.000000	19.000000	0.136667	70.333300	340.000000	0.200000	4.269388
max	70.000000	5861.000000	23.050000	302.000000	2600.000000	6.876670	5.500000

Table 8 shows the classification of collected data.

Voltage Level	**No of Records**
132kV Transformers	217
33kV Transformers	692
66kV Transformers	322
Grand Total	1231

Transformer Percentage by Voltage Levels

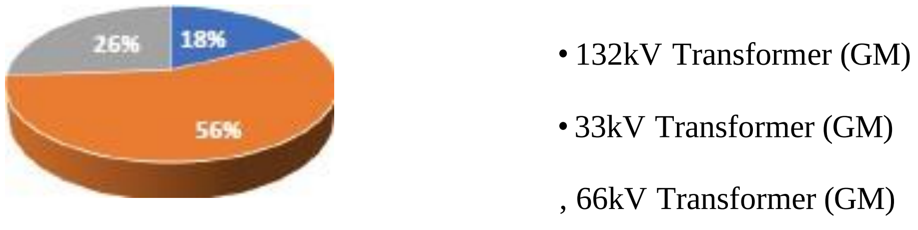


Figure 3: The percentage of Transformer by Voltage in the initial dataset.

995 records were missing including nine hundred values of DGA data from 1231 records. Then it is considered what if scenario of deleting the whole DGA record first especially the DGA record is collected as a total. Secondly, assuming the case that if decided to drop the missing data from dataset analysis before building machine learning model. This will enable to know the remaining data from the records, so it led to 236 complete records as show in table 9.

Table 9 shows deleting with null values that caused to lose around 1000 transformers records

Voltage Level	**No of Records**
132kV Transformer	40
33kV Transformer	128
66kV Transformer	68
Grand Total	236*

• Based on the collected data which are not including laboratory data.

Table 9 shows the collected records that remained after deleting the null values were not sufficient to build machine learning module especially it is intended to build two models, one for 132kV transformer using >69kV rules and one for 33kV and 66kV transformers using the <69KV rules based on IEC and IEEE standards. Therefore, the average could not be utilized to predict the missing values due to the huge number of missing values, especially for the DGA which was 900 records out of 1231 records.

To further study the available data records, a correlation matrix and pair plots are used to study the input diagnostic parameters and to understand the condition of power transformer based on age, moisture, acidity, break down voltage, dissolved gases analysis and furfuraldehyde parameters. These diagnostic parameters are reflected in the HI scoring system as shown in the Figures 4, 5 and 6 plots. Figure 4 shows that age has the highest positive correlation of 0.91. Also, a noticeable negative correlation is observed between BDV and HI Score of (-0.31), BDV and Moisture (-0.29) and DGA and HI (-0.21). Other parameters in this dataset show a very little association between each other and with HI Score. For example, the correlation of parameters with HI score are observed as: Moisture (0.036), Acidity (0.062), Furfuraldehyde (-0.0076).

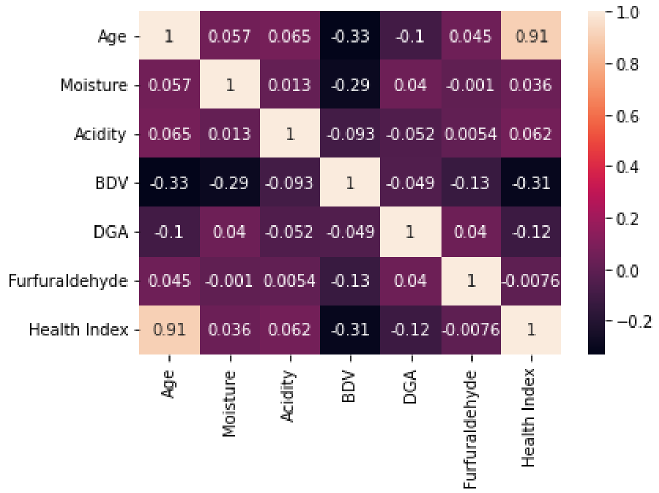


Figure 4 Correlation matrix of the observed parameters.

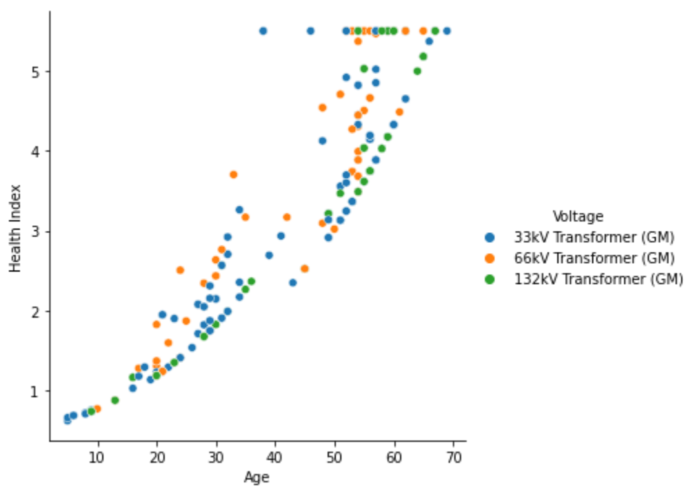


Figure 5 plot visualizing statistical interactions between age & HI.

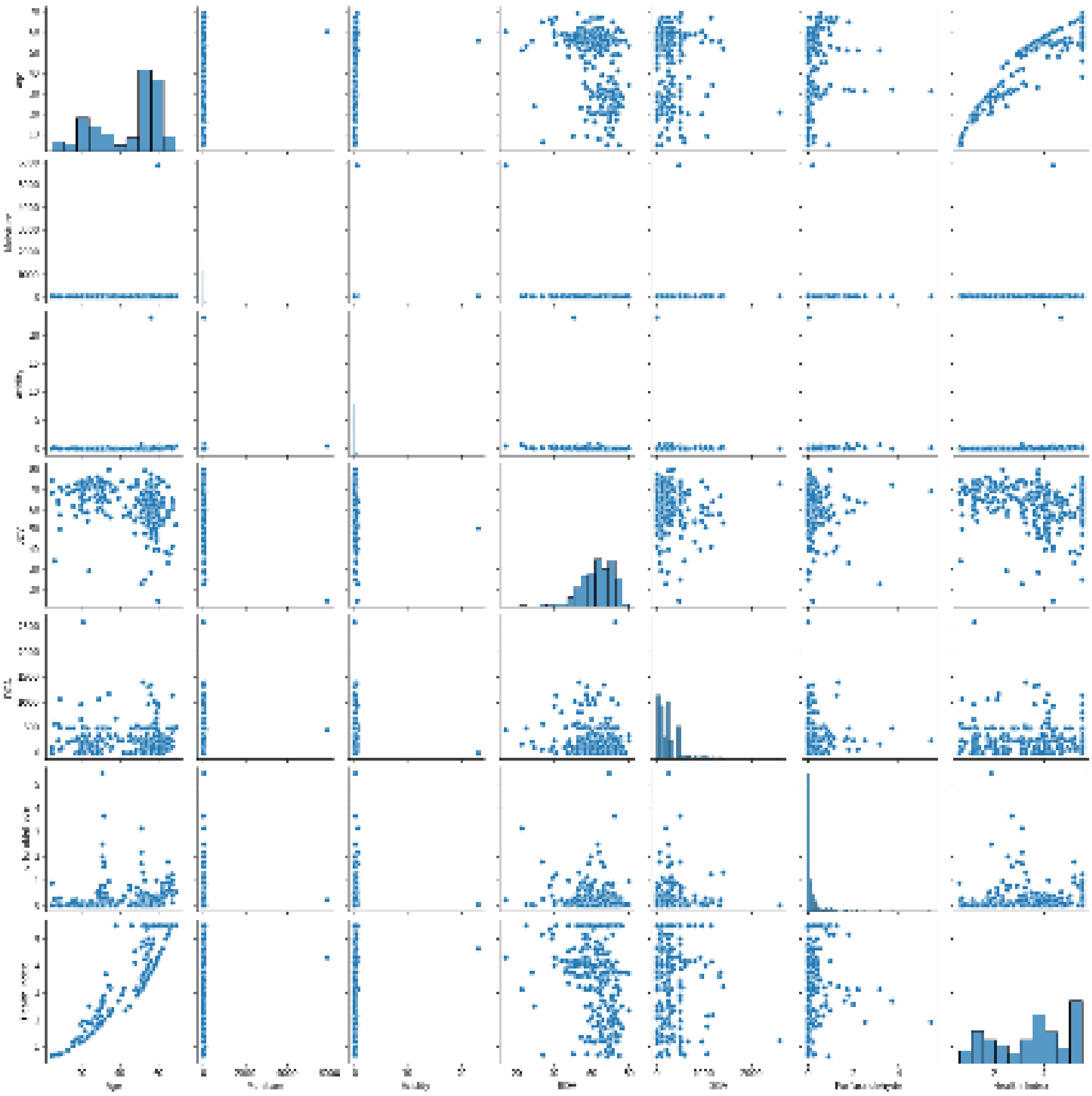


Figure 6 Pair plots show the considered outliners for action.

As a result of this analysis, and since many DGA values are missing, individual gases parameters from the laboratory files are to be included. Therefore, all the collected data are combined which includes the least records that collected at early stage, with the laboratory data records and all are used because DGA records were null. This decision enables all collected data and laboratory data to be combined to get more records that can be used for future machine learning for HI condition assessment investigation.

This investigation took up to 5 months for data preparation as it requires a thorough study because within the collected data, the names of substations, voltages, inputs parameters were not identical. It also requires organizing the records to be efficient. The records were prepared based on industrial experience and academic research needs that are best suited for future research and modeling. Considering the facts that this HI development covers the following analysis input parameters that assumed sufficient to investigate PT health condition:

1. Oil Quality Sample Tests
2. DGA Sample Tests
3. Furan Sample Test.
4. Tap Changer:
5. Age

The future analysis using Al, will predict the missing data or simulate new data to train the algorithms to understand and work based on related IEC & IEEE rules.

5. Discussion

The discussed HI methods is an approach towards a successful HI formulation where both the accuracy of the data and the formulation process plays the difference. Formulation of HI is an interesting process although it takes time to develop. There are several approaches to calculate the HI in research and in practice as every researcher within the research area followed different methods which all are valid, but there is a need to manipulate the rules based on manufacturer reference, transformer type, voltage limitations, standards used and data interpretation approach by electrical utility. HI requires a justified Asset Maintenance Strategy (AMS) that improves the secured operation of the PT and decreases the operation costs. The achievement of these two targets leads to the development and implementation of a good HI.

The actual data quality is considered as the main challenge for a better outcome from the HI calculations scoring methods. This is mainly also relying on the analytics functions that are used including the weighting factors. Such evaluations techniques based on accurate service data are processed into a score that describes the overall condition of PT to enable supporting a quick response. Then, the HI scores will provide the needed practical decision for the intervention: what, and how soon, whether a maintenance or refurbishment or planned replacement to keep running the momentum of the PT whole life cycle cost effective and ensure the required future performance by each PT is continuously achieved and managed. The most important features influencing PTHI calculation methods, are:

- Failure modes.
- Diagnostic techniques.
- User's experience.
- Condition monitoring data.

Finally, all the information sources led to the importance of the database development to improve the long-term data reliability and accuracy which requires a frequent update by a dedicated field team. The HI is considered a good AM tool despite the facts of the differences among electrical utilities. The electrical utilities operate in-service PT effectively, efficiently and postpone the replacement plan of old PT through the decision making that must continuously seek ways to extend the lifetime of PT and defer unnecessary costs. However, it is important that PT are not operated to the point where it begins to affect energy supply or possibly a threat to the environment.

6. Conclusion

HI methods are especially important as AM tool for electrical utilities and for complex industrial automation processes. It can be time consuming and costly in the beginning, but the method pay back makes big saving into long term master planning investment.

The important of several fields collected datasets are proposed as long-term solution to improve the HI analysis tool and achieve a better timely decision despite the facts there is no standard method for designing HI. However, the authors have recommended the following:

1. HI investigation needs a practical focus reliant on using real data from users, transformer expert judgements and agreed practice.
2. Data management is the biggest challenge for HI development. It requires developing correct and up to date datasets. This requires a detailed process for data preparation, validation, and analysis to be considered but it is the key for better HI results using the most relevant actual data which was made to select a key indicator for developing the final HI. Obviously, the data was collected by direct and indirect measurements respectively from site inspection or laboratory diagnostic tests. The failure data are exposed to a failure mode that is used to identify the power transformers health condition that need more attention than others. HI classifies large fleet of power transformers based on the same set of the same manufacture, specification, serial numbers, and age that need to be studied together.
3. The HI conventional method is the most used within electrical utilities as less costly, but skills are needed. The formulation process of the HI model is time consuming and requires a complicated mathematical model and expert judgement. This requires so many factors to be calculated based on the relevant IEC/IEEE standards ranking method using the related scoring, weighting factors and their relative of importance.
4. HI using Al, machine learning, computer science is another tool to manage big data uncertainty like missing data and power transformer health condition classification.
5. HI is meaningless without integral into overall AM approach. This will ensure the value of a good HI is realized.
6. HI design requires ensuring the constructed model derives a probabilistic HI seeing unexpected uncertainties in data acquisition, interpretation, and modelling.
7. Utilities can benefit from academic researchers to ensure technologies suppliers are

developed with good accuracy and data structuring by supporting academia with the required data and knowledge sharing.

8. HI helps asset owners, operation, and maintenance team to schedule retirement, operate and maintain the transformers more reasonably at low cost by applying a justified HI approach.

The "Health Index" is a successfully applied tool to assess and categorise transformers' health condition for future enhancement that includes preventive and corrective maintenance work orders. HI is also an accountable tool towards a new investment that covers end of life asset replacement decisions. The difference of diagnostic test, factor and indicator plays strategic and technical roles to customise a good HI for optimising the required annual maintenance and capital plans. However, a good integration between HI and probability of failure is must to reflect with the available actual datasets and provide a good justification for the considered decision by electrical utilities.

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