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 makes physical assets safe, productive, efficient, and cost effective. Asset Management (AM) framework is defined by ISO55001 to ensure electrical network operators are delivering best quality of services by operating their network at high performance, low cost while managing unexpected risks.

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. According to (Jahromi, 2009), there are a small number of electrical utilities around the globe who capture data using recent technologies that work in line with information best practice which serve large fleet of Power Transformers (PTs). The implementation of strategic AM standard ISO55001 framework is considered for the HI tool in this research. 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 is developed to examine HI as an important section in AM, it is considered the HI as a building block in AM process. It 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 Electrical Electronics & Engineers (IEEE) C57.104 transactions on industrial informatics. Preliminary analysis for data management using Python Programming Language (PPL) is considered.

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

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Biographical notes: Khamis Salim Al-Romaimi has over 15 years employment experience and moved to various roles in his career as started as electrical engineer in electricity and water industries. During his work experience in this field, he involved in operation and maintenance practices, data analysis, strategic planning, program management, asset planning, economics, system studies, design, projects, load dispatch, risk management, business continuity and international best practices for asset management development for PAS55 and ISO55001 certifications. He received his MSc in Electrical Engineering, from Curtin University of Technology, Australia. His BEng. in Automatic Control System Engineering, University of Sheffield. His research interests focus on asset management, electrical engineering, power transformer condition assessment, artificial intelligence, and transformer aging.

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Dr Derek Dixon has a PhD in Engineering Maintenance. He also has a degree in Manufacturing Systems Engineering. He began his career as a Maintenance Technician and further developed his industrial experience as an Engineer in the manufacturing sector. This included roles in product design and process engineering. Following this, he spent a number of years in the education sector. This included lecturing, pedagogical development and department management.

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. This research considers AM framework which defined in ISO55001 Asset

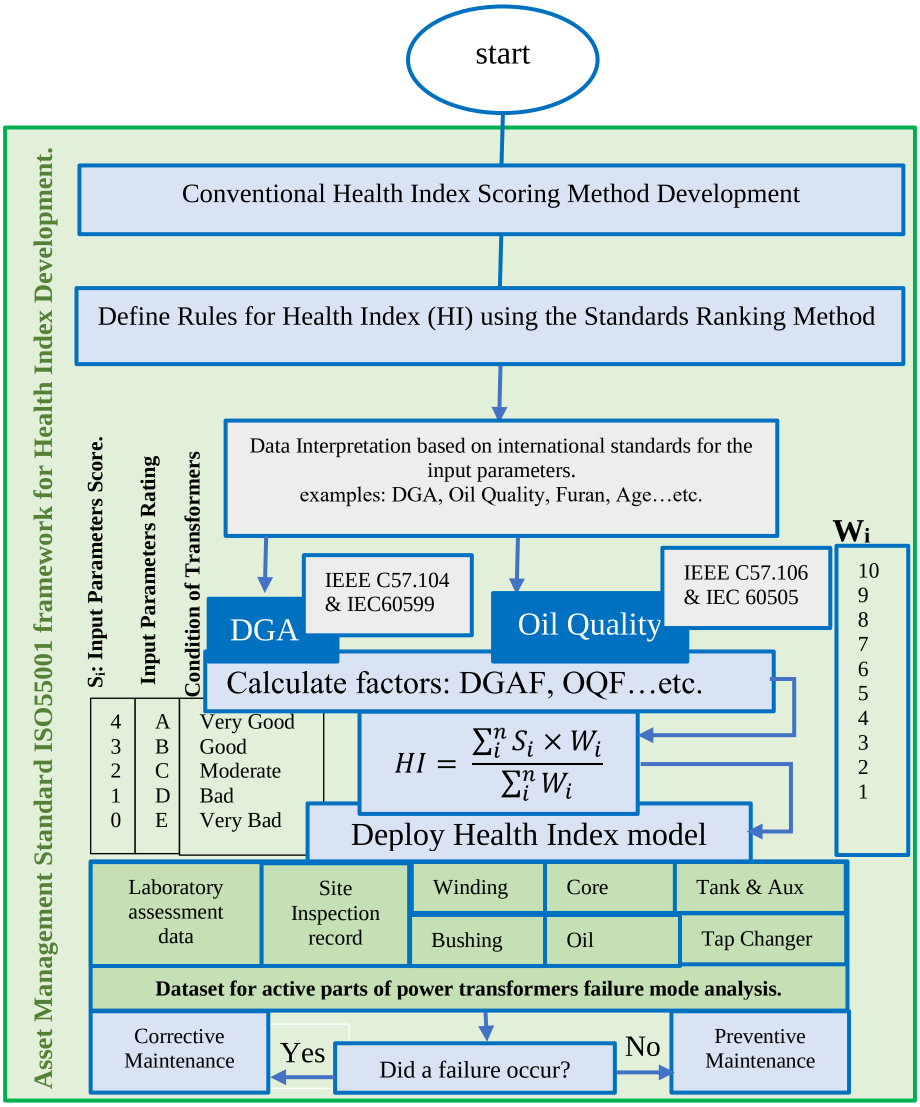
Management standard (2014) for the development of the HI tool. This research also considers the HI as a building block to the broader AM process. Based on the recent development, the HI calculation method become a popular tool to many researchers working in the electrical industry based on (Kadim et al.,2018; Vermeer et al.,2015; Islam et al.,2018; Jahromi et al.,2009; Abu-Elanien et al.,2012; Naderian,2008). This paper assist 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 it is own scoring method. The various methods to calculate the health index in research are not same as well as in practice (Islam et al.,2017). This based on many factors including agreed scoring and weighting factors for each input parameters, the methods which used for data interpretation and the standards IEEE C57.104 (2019), IEC60599 (2022), IEEE C57.106 (2015) & IEC 60505 (2011) that considered for the ranking method (Jahromi et al.,2009). The most famous three popular basic health condition methods are: degradation modelling, condition assessment using monitoring data, and statistical end-of-life modelling (Foros & Istad, 2020). 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 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 joint by expert finding if statistical figures are incorrect.

There are advantages and disadvantages using any 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 rely on the value and representability of the presented statistical data.

2. Health Index Formulation: Research Methodology

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 as using strategic AM standard ISO55001 framework by conducting a detailed health check and gap analysis to make the HI, new and potentially the most useful and effective tool in AM. This is to clearly articulate the condition and risk of assets; it is imperative first to understand the components of the strategic AM process in ISO55001 as the main part of any business objective. Figure 1 describes the research workflow of HI methodology that is required for developing conventional HI. The most important step is defining the ranking method and scoring rules for the input parameters and HI scoring equation. This is developed by defining the rules using international standards, for example, IEC C57.106 for DGA gas interpretation and IEC 60505 for oil quality utilizing a ranking method with a score range from 0 to 4 and a weight range from 1 to 10. Then by calculating factors for each test like DGAF, OQF, furan, age ...etc. Then using the HI formula (1) to obtain the final HI value. The HI model is deployed by using the HI value obtained to define whether a failure has occurred or not for better decision-making, whether it is corrective maintenance which includes two actions: refurbishment or replacement. Also, it can be as a preventive maintenance action like performing regular inspections and conducting related maintenance. 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 fulfil the requirements to identify power transformer health condition.

Figure 1 Workflow of the study: Health Index methodology.



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 analyze 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 by 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 that identifies the ranking method rules (Leauprasert et al., 2020). 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 (Pompili & Scatiggio, 2015). 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. Analysing the limit probable score by adding up the multiples of steps 1 and 2 for all condition test factors.
4. Finally, the total HI is computed using equation (1):

$$\mathrm{HI} = \frac{\sum_{i=1}^{n} S_i \times W_i}{\sum_{i=1}^{n} S_{max} \times W_i} \times 100 \qquad (1)$$

Where HI is the final HI metric, S_i is the score factor for all PT health condition obtained from diagnostic test shown on table 1, W_i is the weight factor for the relative importance of the diagnostic test parameters and S_{max-i} represent maximum score among all the diagnostic tests, n represents the number of tests included for PTHI calculation (Jahromi et al., W., 2009; Naderian et al., 2008). 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 0 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, and the extra dependable and correct PTHI will be. However, considering all the input parameters is not possible as it is doubtful that the organization will have a complete set of information about each transformer in the real world, therefore HI could be generated with a subset of these tests.

There are various patterns are attributing condition data to basic data. IEEE C57.104 (2019) 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 (2019) approach might be the required standard. 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 the required 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 (McGrail, 2015). 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:

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

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 (Jahromi et al., 2009).

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 factors for gas levels parts per million (PPM) (Jahromi et al., 2009).

	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

	Score (S)						W_i
Gas	1	2	3	4	5	6	
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 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 (2022) offers a coded catalogue of defects, obviously by DGA and IEEE Std C57.104 (2019) presents a four level reasons to group threats to transformers, for constant operation and maintenance at numerous burnable gas levels (Duval, 2002; Pompili and Scatiggio, 2015).

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 (Duval, 2002).

Numerous standard analysis skills are utilized for DGA of power transformers over the previous 3 decades by Rogers, Durenburg, and Duval Triangle (Jahromi et al.,2009).

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 (Jahromi et al.,2009).

Gas	Dorenburg	IEC	IEEE	Bureau of Reclamation
H_2	200	100	100	500
CH_4	50	75	120	125
C_2H_6	35	75	65	75
C_2H_4	80	75	50	175
C_2H_2	5	3	35	7
CO	500	700	350	750
CO_2	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).

$$OQF = \frac{\sum_{i=1}^{n} S_i W_i}{\sum_{i=1}^{n} W_i} \qquad (3)$$

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 (2015) standard, whereas laboratories reference of this measurement is 90°C based on IEC60599 (2022) standard.

Furthermore, the dielectric breakdown voltage boundaries are measured via an electrode gap of 2 mm based on the IEEE C57.106 (2015). And as per the IEC60156 (2018) standard 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 (IEEE C57.104, 2019; ABB, 2007; IEC 60505, 2011) , 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 (Wang et al., 2002).

Table 5 Gas limit references based on OQA assessment.

Parameter (Jahromi et al., 2009)	ASTM recommended by IEEE	IEC recommended by CIGRE
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 (2015), "IEEE Guide for Acceptance and Maintenance of Insulating Oil in Equipment", and IEEE Transformers Committee. IEC advised by CIGRE Working Group 05 (1983), through an international survey on failures in large in-service power transformers. The highest threshold references for oil parameters are classified reliant on the level voltage in both IEEE C57.106 (2015) and IEC 60505 (2011) standards. 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 C57.106,2015; Jahromi et al., 2009).

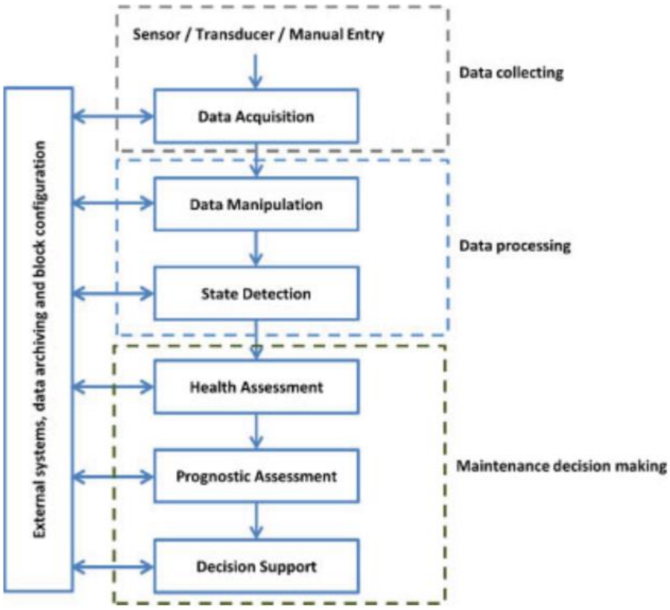
	U<=69kV	69 kV < U < 239 kV	230 kV < U	Score (Si)	Wi
Dielectric Strength kV (2 mm gap)	≥ 45	≥ 52	≥ 60	1	3
	35-45	47-52	50-60	2	
	30-35	35-47	40-50	3	
	≤ 30	≤ 35	≤ 40	4	
IFT dyne/cm	≥ 25	≥ 30	≥ 32	1	2
	20-25	23-30	25-32	2	
	15-20	18-23	20-25	3	
	≤ 15	≤ 18	≤ 20	4	
Acid Number	≤ 0.05	≤ 0.04	≤ 0.03	1	1
	0.05-0.1	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 Utilizing OSA/CBM framework

Open system architecture for condition-based maintenance (OSA-CBM) is one of the commonly used standards that have been implemented in various condition-based maintenance systems (Guillén et al., 2016). It has six universal operational layers which are data acquisition, data manipulation, condition recognition, health assessment, diagnosis, and maintenance decision making layer as shown in figure 2.

Figure 2 OSA-CBM data processing layers - source: (Al-Douri and Tretten, 2016).



In this paper, OSA-CBM is chosen to be the basic building block of implementing HI assessment as OSA/CBM framework is utilized in delivering objectives that are essential to use HI assessment as it offers flexibility for safeguarding third-party confidentiality strategies within viable modules as it is supported by different external systems and data sources. However, all steps are not considered in this paper, and it is only considered the data manipulation and analysis which it is experimented with using Python programming language. The data was received from the utility in various spreadsheets. Data cleaning and analysis were carried out in Python programming language with the aim to understand and validate these data. It is believed, the data processing applied in this paper can also be applied in the data pipeline and can be automated in the future. This is a complete utility decision to automate the data collection process by adding the required sensors on the related systems and the investment in the servers for saving the historical records without compromising in cost savings targets.

2.4.2 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 8. 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.

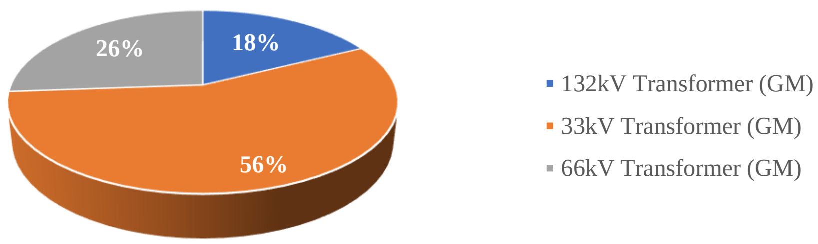
Table 7 shows preliminary investigation for the collected data.

	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

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 us 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 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.

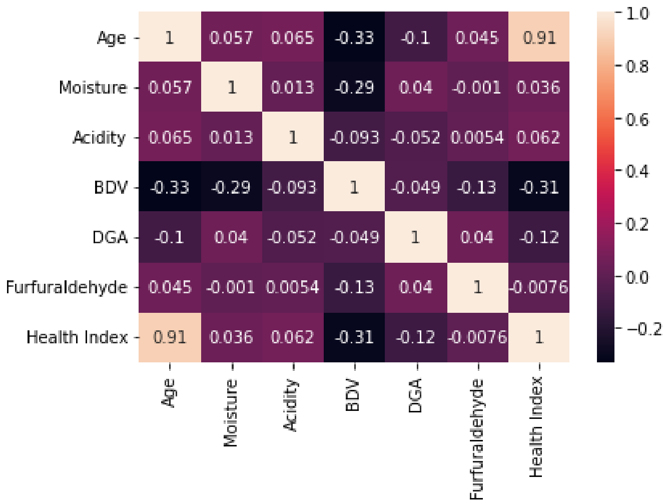
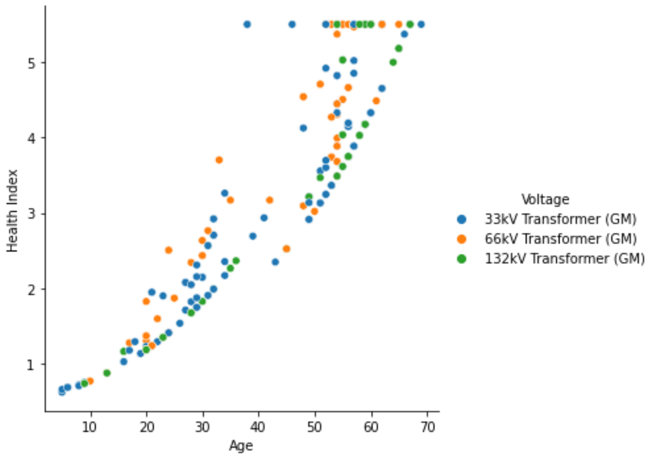
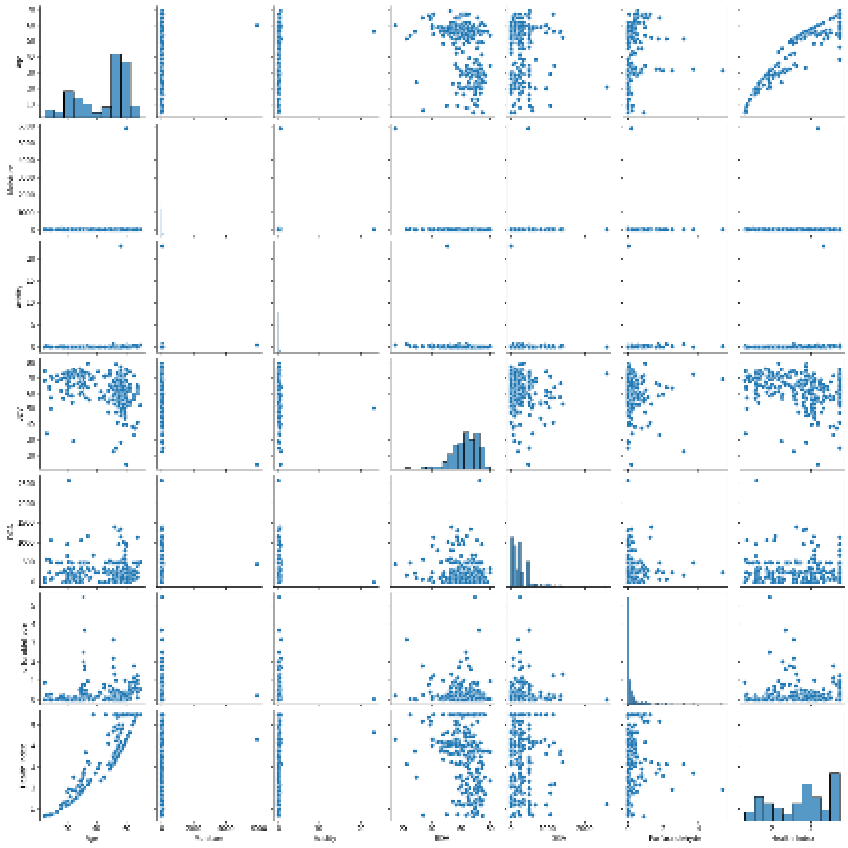


Figure 5 plot visualizing statistical interactions between age & HI.



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.

Figure 6 Pair plots show the considered outliners for action.



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 data modeling 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.

2.5 Health Index Results

HI model for under 69kV transformers was developed. The result from deploying the HI model is shown in the Figure 7. As it was found that 5 transformers are in very good condidtion, 769 transformers in good condition, 178 transformers in moderate condition, 5 transformers in bad condition and 19 transformers in very bad condition.

Figure 7 HI model result for PT health condition.

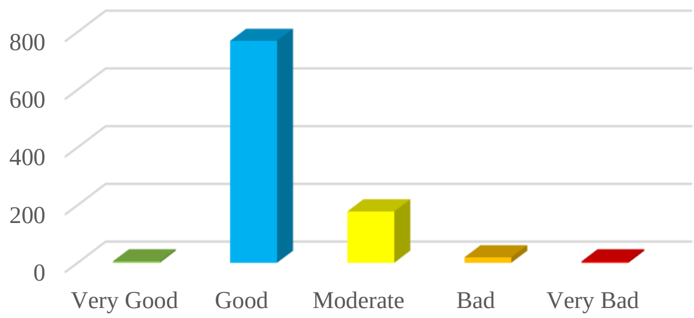
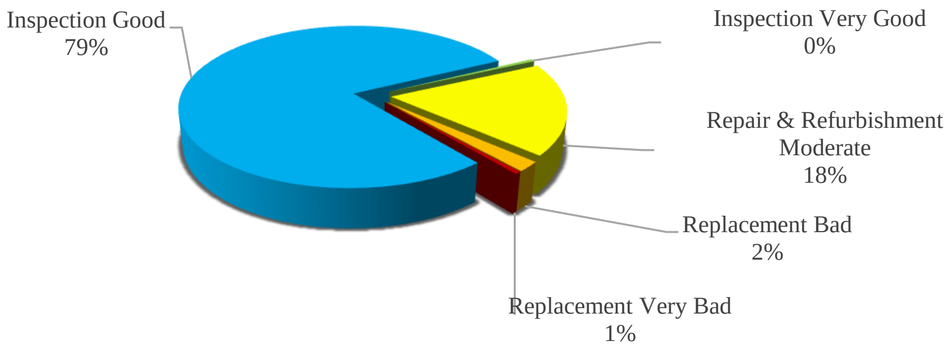


Figure 8 also describes the finding regarding transformer condition and decision to be taken as shown 79% of the data was in good condition and just due for normal inspection, and 18% are in Moderate condition and due for Repair and Refurbishment. Whereas 2% of the transformers are in Bad condition and due for Replacement and it is worth mentioning that the records of bad condition were stimulated as it was no bad records was found in the received datasets that is with the objective of ensuring the HI model can recognize transformers in bad condition.

Figure 8 show the HI model considered decision.



3. Discussion

This paper promotes consideration of AM standard ISO 55001 framework for the development of the HI condition assessment. This is based on the facts that the strategic AM standard ISO55001 framework is the key success for integrating the whole business together and achieving the required business objectives for effective and useful HI assessment decision making that serve the big picture of applying the AM process and achieving the required value. 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 used including the weighting factors. Such evaluations techniques based on the 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 as 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.

4. Conclusion

HI methods are important condition assessment in electrical utilities which apply AM practices 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 a correct and up to date datasets. This require 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/indirect measurements respectively from site inspection or laboratory diagnostic tests. The failure data are exposed to a failure mode that 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 are the most used within electrical utilities as less costly, but skills need. The formulation process of the HI model is a time consuming and require 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 AI, 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 require 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 successfully applied tool to assess and categorise transformers health condition for future enhancement that includes preventive and corrective maintenance work orders. HI is also 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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