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Review

Review of Transformer Health Index from the Perspective of Survivability and Condition Assessment

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Abstract: As a critical indicator for assessing the survivability and condition of transformers in a fleet, the transformer health index has attracted attention from both asset owners and international organizations like CIGRE and IEEE DEIS/PES. To provide a systematic and comprehensive review for further study or to guide transformer asset management, this paper summarizes the state-of-the-art of the transformer health index, from the early proposed weighted-score-sum approaches to the more recently proposed artificial intelligence algorithm-based methods. Firstly, different methods for determining the transformer health index are reviewed. Each of these is specified as belonging to a certain type on the basis of its formulation and composition schematic. Subsequently, the steps to determine each type of health index are summarized, and examples derived from literature are provided for further illustration. Comparisons are finally carried out in order to better understand the pros and cons of different types of transformer health index, and the future development trends for transformer health indexes are also discussed. This work can serve as a valuable reference for the survivability and condition assessment of transformers in the power industry.

Keywords: weighted-score-sum; artificial intelligence; condition assessment; health index; information fusion; power transformer

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1. Introduction

Transformer failures and outages can result in significant economic losses and have a considerable social impact. Accurate condition assessment of in-service transformers is essential for ensuring their reliable operation. Concerns regarding transformer health condition assessment have been raised for a long time in both industry and academia. In practice, a variety of online and offline monitoring techniques have been developed and applied to perform condition assessment and asset management of transformers. These techniques include diagnostic oil testing (e.g., dissipation factor, breakdown voltage, etc.), dissolved gas analysis (DGA) [1,2], frequency domain spectroscopy (FDS) testing [3,4], recovery voltage measurement (RVM) [5,6], polarization and depolarization current measurement (PDC) [7], frequency response analysis (FRA) [8,9], partial discharge (PD) detection [10], by-product analysis (e.g., water in oil, furan content, etc.) [11,12], and other testing and measurement methods [13,14].

However, each of the above techniques generally focuses on evaluating the health condition of a transformer in terms of a single aspect. Given the complicated construction of a transformer and the measurement errors of each diagnostic technique, it is becoming apparent that it is impossible to perform a reliable health condition assessment using only a single type of measurement. A practical and reliable condition assessment should be performed based on a fusion of data and information, integrating all available pieces of evidence from online and offline measurements regarding operation and maintenance, failure statistics, on-site inspection, and past experiences of human experts. In combination with such condition data, an assessment of the overall health condition of a power transformer, named the health index, has been developed.

The merit of a health index is its ability to provide a quantitative evaluation of the overall condition of a transformer or even a whole transformer fleet, and thus to provide asset managers with an intuitive understanding on the basis of a single index [15,16]. In both utilities and academia, investigations into the transformer health index have been carried out for years. Current methods for health index calculation can be classified into two main categories: the weighted-score sum (WSS)-based methods and artificial intelligence (AI) algorithm-based methods. Schematic diagrams of these two types of approach are given in Figure 1.

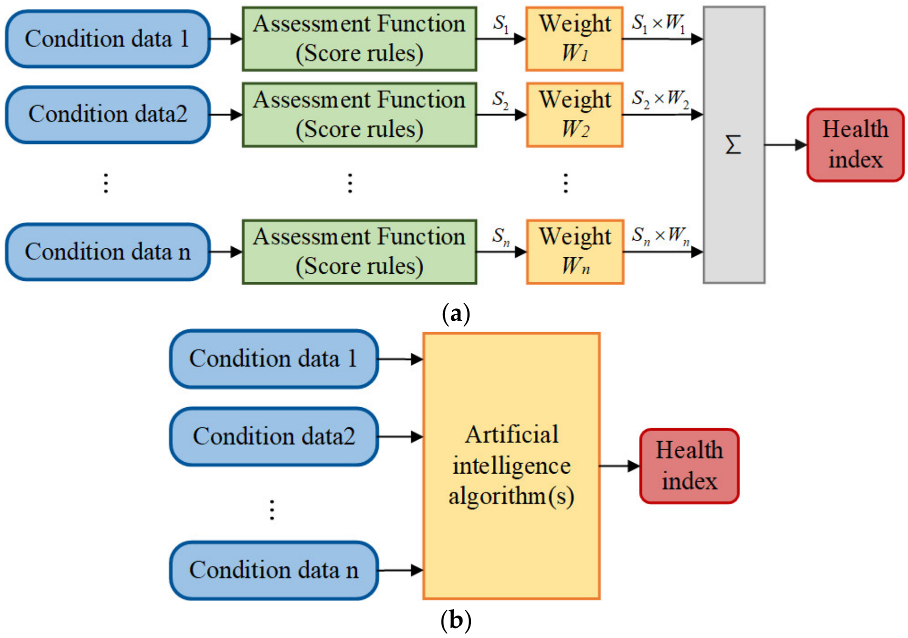


Figure 1. Schematic diagram for transformer health index calculation. (**a**) Transformer health index based on weighted-score sum, (**b**) artificial intelligence (AI)-based transformer health index.

For WSS-based approaches [15–52], transformer health index is determined as a weighted scoring of different types of condition data, namely:

$$HI = \sum_{i=1}^{n} S_i W_i, \quad (1)$$

Monitoring data are determined using relevant standards [53–60]. S_i represents the evaluation score for the monitoring data, and W_i is the corresponding weight indicating the significance of these condition monitoring data to the overall state of the transformer. In comparison, the AI-based transformer health index uses intelligent algorithms, e.g., artificial neural networks (ANN), support vector machine (SVM), fuzzy logic, or expert criteria-based methods to approximate the underlying relationship between different types of condition data and the transformer health index [61–93]. This kind of relationship can be described as follows:

$$HI = f(v_1, v_2, \cdots, v_i, \cdots, v_n), \quad (2)$$

where v_i represents the i-th type of condition monitoring data, and n is the total number of pieces condition monitoring data.

The rest of this paper is organized as follows. In Sections 2 and 3, the WSS-based and AI-based transformer health index approaches are reviewed. Then, typical examples derived from published papers are adopted to illustrate the steps required for the realization of each type of health index. Section 4 presents the ongoing research on the realization of a probabilistic health index for transformers using Bayesian fusion, from its orientation to its implementation, as well as relevant case studies, and discussions on the advantages and disadvantages of the existing methods for calculating the health index are also summarized in this section.

2. Weighted-Score-Sum-Based Methods

In weighted-score-based methods, the calculation of the transformer health index is performed as a summation of the weighted scores of different types of condition data. In this process, relevant standards are adopted to help determine the score of every type of condition data. The health index can be determined by multiplying it by a weighting, indicating the relative important of each item to the overall transformer (or part of the transformer). More generally, weighted-score sum approaches can be categorized into three groups:

- The transformer health index is calculated as a weighted-score summation of different test items. Each test item (also known as condition data) is essential to transformer condition monitoring. In this paper, this kind of health index is classified as Type-I.
- The transformer health index is calculated as a weighted-score summation of all of the transformer's components. This kind of health index is classified as Type-II.
- The transformer health index is calculated as a mathematical score adding different causes of stress degradation (e.g., electrical, mechanical, chemical, etc.). The score of each type of degradation is calculated as a weighted-score summation of several types of condition data that contribute to it. This kind of health index is classified as Type-III.

The above three scenarios will be detailed in the following sections. In addition, examples derived from the literature will be provided for each method for the purpose of illustration. Apart from these three categories, other forms of weighted-score-sum-based health index are also reviewed at the end of this section.

2.1. Type-I Health Index

In terms of the transformer health index, a straightforward approach is to judge different types of condition data (e.g., online measurements, offline test data, maintenance records, etc.) and combine them into one index. In this kind of approach, each type of condition data is firstly converted to a score according to the relevant standards (e.g., IEEE/IEC or CIGRE). Then, a weight indicating its significance to the health condition of the entire transformer is assigned on the basis of experts' experience or the relevance to standard codes, or a combination of both [16–30]. Finally, a summation of all of these weighted scores is performed, which provides the health index of the transformer of interest.

Recent efforts by Kinectrics [16–18], US and Thai utilities [19], Hydro-Québec [20,21], Wuhan University [22], University of Cambria [23], Ann University [24], as well as other utilities and research institutes can be classified as belonging to this type of health index [25–29]. A schematic for realizing the so-called Type-I health index is presented in Figure 2.

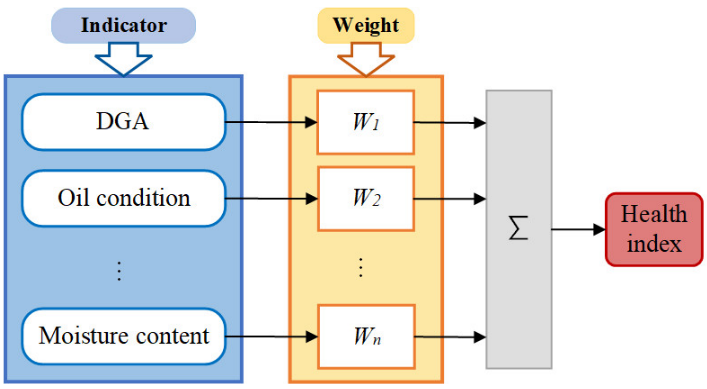


Figure 2. Schematic of the Type-I health index.

As shown in Figure 2, three critical components constitute the Type-I health index, e.g., the indicator, the weighting, and the final health index. The indicator represents different kinds of condition data that partially indicate the condition of the transformer (e.g., trace water in oil, indicating the condition of the transformer oil). According to the IEEE/IEC standards and the CIGRE recommendations, each indicator is then converted into a numerical score (e.g., an integer value between 1 and 4, if the standard defines four levels for the state of the condition data). The weight of each indicator in this kind of health index is often determined by the experience of human experts. After determining the indicators and associated weights, a summation of the weighted score of different indicators is then taken as the final health index of the transformer. Note that the indicators may vary among implementations employed by different utilities. Table 1 provides a summary of the indicators used by different utilities to calculate this type of health index.

Table 1. Availability of indicators of different HI methods.

Indicator	Kinectrics	Hydro Québec	US &Thai Utilities	Ann University
Family failure rate		•	•	•
Solid insulation aging		•		
Age of transformer			•	•
Load history	•		•	
DGA [1]	•	•	•	•
Oil condition	•	•	•	•
Oil leaks	•	•	•	•
Oil tank	•			
Oil level	•			
Bushing condition	•	•	•	•
Bushing power factor			•	
OLTC [2] condition	•	•	•	•
OLTC oil quality			•	
DGA of OLTC			•	
Moisture content		•		•
Power factor	•		•	•
Infra-red	•			
Main tank	•			
Main tank cabinets & controls			•	•
Accessory condition	•	•		
Cooling equipment	•		•	
Foundation	•		•	
Grounding	•			
SFRA [3]			•	•

[1] DGA refers to analysis of seven gases dissolved in transformer oil, including H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, and CO_2; [2] OLTC—on-load tap changer; [3] SFRA—sweep frequency response analysis.

A typical example of a Type-I health index is represented by Kinectrics's experience with transformer fleet assessment. In Kinectrics's health index model, statistical data and diagnostic results are adopted. Its implementation is shown in Figure 3. From the left side to the right side, the main elements in this health index model are: (1) the inputs or indicators; (2) the weights; (3) the partial summation of the weighted score; and (4) the adding rules for finalizing the health index. Details of each part in this model will be introduced in the next section.

2.1.1. Inputs and Weights

This model utilizes 19 types of condition data to calculate the health index. Note that items like the DGA factor, the oil quality factor (OQF), the DGA of OLTC, and the OLTC oil quality in Figure 3 are already a mixture of several different types of condition data. For example, the DGA factor (DGAF) is calculated using [25,30,31]:

$$DGAF = \frac{\sum_{i=1}^{7} S_i W_i}{\sum_{i=1}^{7} W_i}, \quad (3)$$

where S_i is the condition score of the i-th gas, and W_i represents the corresponding weight. The condition score for each gas, in this case, is determined by the IEC/IEEE standards [53,54] and is given in Table 2. The score of the DGAF calculated by (3) is also divided into five levels, which are provided in Table 3. This criterion is applied to all inputs shown in Table 3.

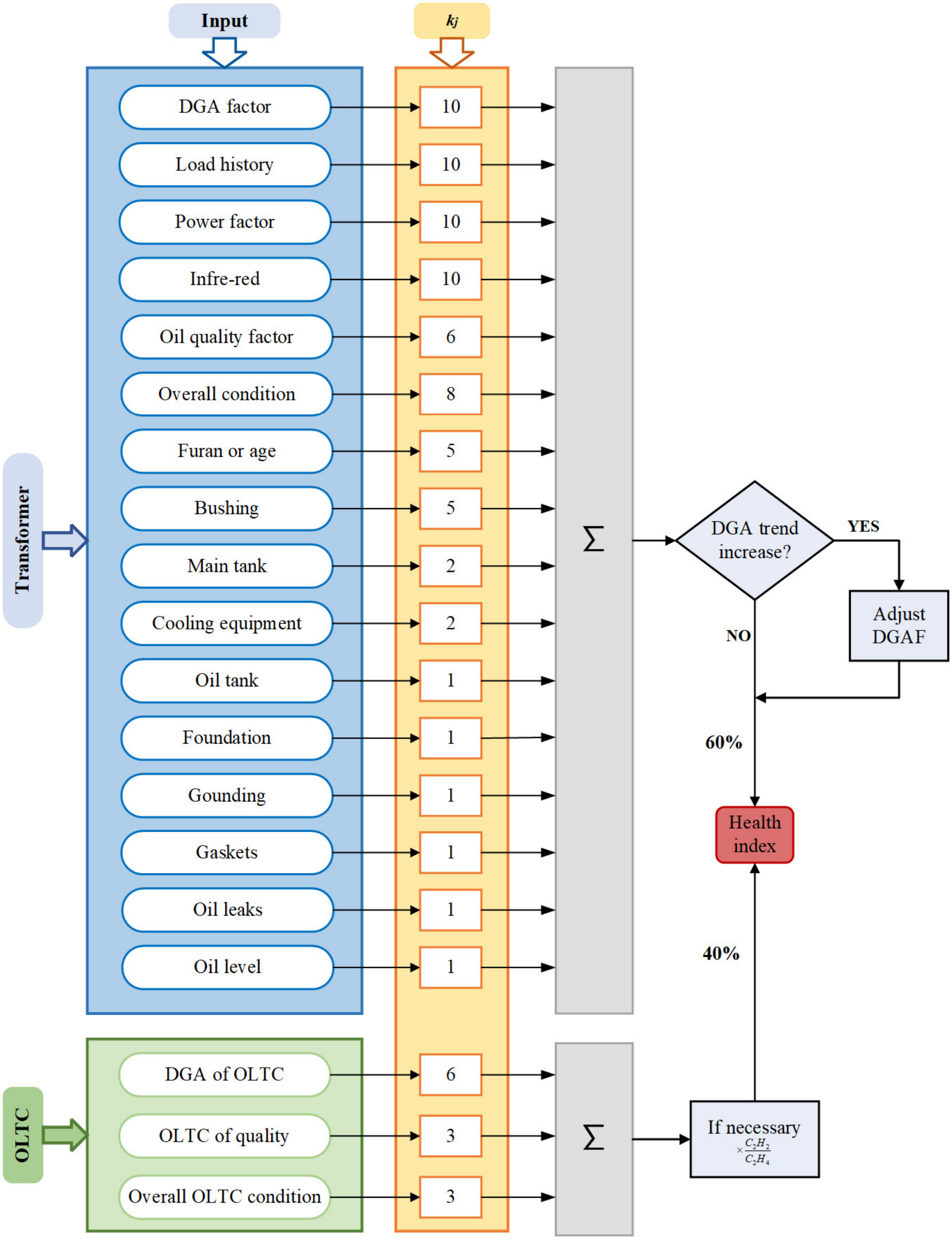


Figure 3. Implementation of the Hydro-Québec health index [17].

Table 2. Scoring rules and weights of gasses dissolved in oil.

Gas	Score						Wi
	1	2	3	4	5	6	
H2	≤100	100–200	200–300	300–500	500–700	≥700	2
CH4	≤75	75–125	125–200	200–400	400–600	≥600	3
C2H6	≤65	65–80	80–100	100–120	120–150	≥150	3
C2H4	≤50	50–80	80–100	100–150	150–200	≥200	3
C2H2	≤3	3–7	7–35	35-50	50–80	≥80	5
CO	≤350	350–700	700–900	900–1100	1100–1400	≥1400	1
CO2	≤2500	≤3000	≤4000	≤5000	≤7000	≥7000	1

Table 3. DGA factor ranking.

Ranking	Condition	Description	HIFj
A	Good	DGAF $\leq$ 1.2	4
B	Acceptable	1.2 $\leq$ DGAF $\leq$ 1.5	3
C	Need caution	1.5 $\leq$ DGAF $\leq$ 2	2
D	Poor	2 $\leq$ DGAF $\leq$ 3	1
E	Very poor	DGAF $\geq$ 3	0

The total score of the OQF is calculated in a similar manner. The score of different oil parameters, including the dielectric strength, IFT (Interfacial Tension), acid number, water content, color, and dissipation factor, are determined with reference to IEEE C57.106-2006 and IEC 60505 [55,56]. The calculation of OQF is similar to that of DGAF in (3), and is given by (4). The scoring rules and weights of different oil parameters and the OQF ranking are given in Ref. [60].

$$OQF = \frac{\sum_{i=1}^{6} S_i W_i}{\sum_{i=1}^{6} W_i}, \tag{4}$$

where S_i is the i-th oil parameter score, W_i represents the corresponding weight.

2.1.2. Calculation of Health Index

In this model, a total of 19 types of condition data are utilized to calculate the health index. From (5), the health index of a transformer ranging from 0 to 100% can be determined.

$$HI = 60\% HI_{Trans.} + 40\% HI_{OLTC} = 60\% \frac{\sum_{j=1}^{21} K_i HIF_j}{\sum_{j=1}^{21} 4K_i} + 40\% \frac{\sum_{j=22}^{24} K_i HIF_j}{\sum_{j=22}^{24} 4K_i}, \tag{5}$$

where Kj is the weight factor, which indicates the significance of each input to the final health index (the second column in Figure 3), and $HIFj$ is the health index factor of each input, as shown in Table 4.

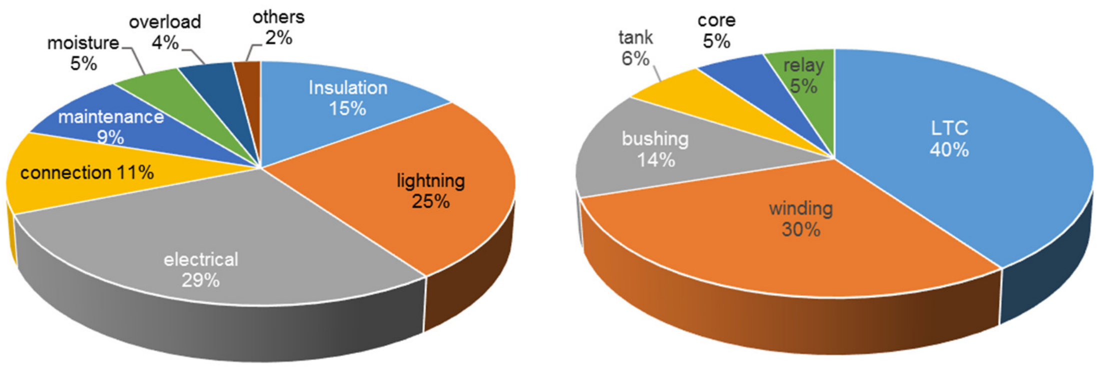
Table 4. Health condition level divisions for Kinectrics' health index.

HI [%]	Condition	Description	Expected Lifetime [Year]
85~100	Very good	Some aging or minor deterioration of a limited number of components	≥15 years
70~85	Good	Significant deterioration of some components	≥10 years
50~70	Fair	Widespread significant deterioration or severe deterioration of specific components	≤10 years
30~50	Poor	Widespread serious deterioration	≤3 years
0~30	Very poor	Extensive serious deterioration	At the end-of-life

The calculation results of the health index are helpful for dividing the operation status of the transformer into different levels, as shown in Table 4. This is convenient for providing practical operators with an understanding of the actual status of the transformer.

2.2. Type-II Health Index

Since a transformer is constituted of different components (e.g., winding, iron core, oil tank, bushing, oil, OLTC and other accessories), its health index can be calculated as the composite result of the different components. Finally, a weighting is assigned to each component that identifies its significance to the entire transformer. Unlike in the case of the method introduced in Section 2.1, this weight is determined on the basis of a combination of the results of both transformer failure statistics and the experience of human experts [32,33]. Figure 4 provides a typical survey of the statistics of transformer failures from CIGRE.



(a) **(b)**

Figure 4. Statistics of transformer failures and defective components. (**a**) Causes of transformer failure; (**b**) defective transformer components.

A typical way of realizing the Type-II health index is shown in Figure 5a, and this has been adopted by several utilities [32,34–36]. For such a health index, the score of each component is taken as a sub-index. The final health index is the sum of the weighted values of each sub-index. Usually, the score of each component is determined by several "items", and the condition of each item is determined on the basis of at least one type of condition data. For example, in the Norwegian health index model [32], the transformer oil is one of the components constituting the transformer. Its condition is determined by two items: the OQF and the oil maintenance effect. In addition, the state of OQF is decided by six oil characteristics (condition data).

The procedure for realizing the Type-II health index is illustrated in Figure 5b, and consists of four steps: (1) scoring of each type of condition data; (2) calculation of the condition score for each item; (3) sub-index calculation; and (4) health index synthesis from sub-index. Details of each step will be demonstrated after that. Note that the first step is similar to realizing the Type-I health index, which will be neglected here.

2.2.1. Item Score and Sub-Index Score Calculation

For each sub-index in Figure 5b, its condition score S_{2j} can be calculated by:

$$S_{2j} = \sum_{i=1}^{n} S_{1i} W_{1i}, \tag{6}$$

where S_{1j} is the condition score for each item that belongs to a sub-index.

There are two scenarios when calculating the score of S_{1i}: (1) one item is determined by one type of condition data only; and (2) one item is determined by k ($k \geq 1$) types of condition data v_i. For the first scenario, the score can be directly determined by converting the condition data according to relevant standards, while for the second scenario (e.g., the

DGA factor, which is determined by seven gases, H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, and CO_2), S_{1i} is calculated in the same way as S_{2j}, where the score of each gas, denoted as S_{0i}, is assigned a weight W_{0i}. The score S_{1i} is the sum of the weighted scores for each gas:

$$S_{1i} = \sum_{i=1}^{k} S_{0i} W_{0i}, \tag{7}$$

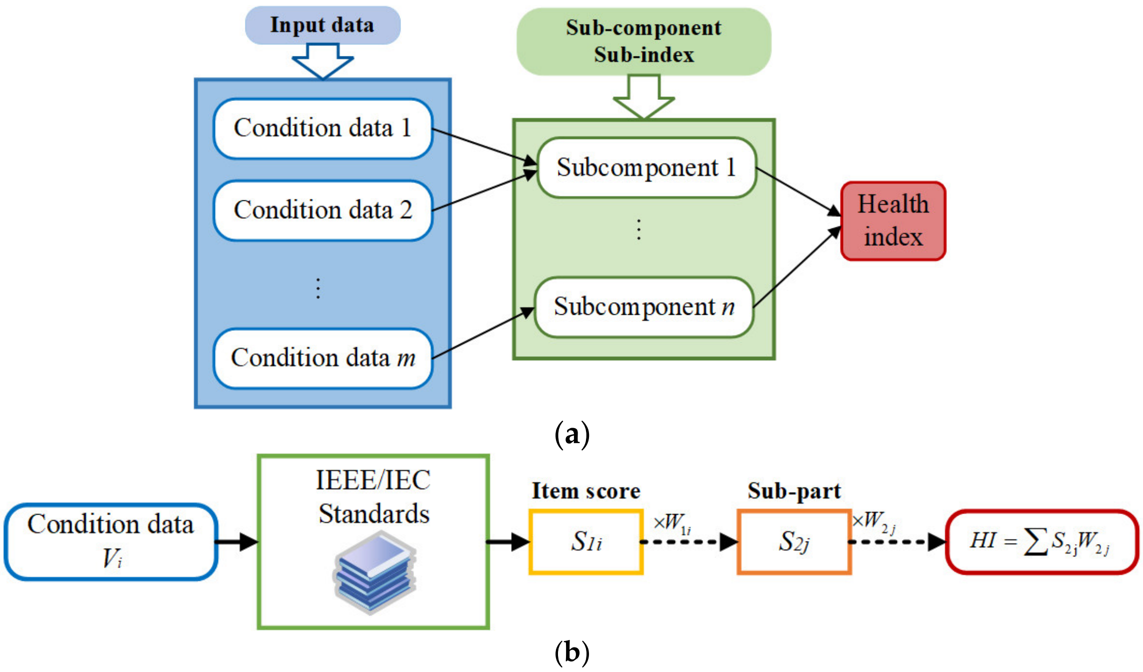


Figure 5. Schematic of transformer health index calculation (Type-II). (**a**) Schematic diagram of a Type-II health index, (**b**) Type-II health index calculation procedure.

2.2.2. Final Health Index Calculation

Once the condition score S_{2j} and its associated weight W_{2j} for each sub-index has been determined, the transformer health index can be readily obtained as a summation of the weighted scores of the sub-indexes:

$$HI = \sum_{j=1}^{m} S_{2j} W_{2j}, \tag{8}$$

The NTU's method for determining the transformer health index is a typical example [32]. The NTU's health index is calculated as the sum of the weighted scores of the different components, including the winding, core, oil, tank, bushing, and tap changer. Apart from these components, external stress is also considered as a component in the example, as shown in Figure 6.

In this example, the health index is calculated using a four-layer model (Figure 6). From left to right, these layers are: input data, scoring data of items belonging to different components, the components of the transformer, and the final health index. Firstly, each type of condition data is taken as an input in this model, and is then converted to a specific score according to the relevant scoring criteria. After that, the condition score for each component is calculated by summing the weighted score of different condition data relating to its health condition. Finally, the health index of the transformer is calculated as the summation of the weighted scores of various components. Since the number of subcomponents of a transformer is countable, the weights of these components can be easily determined, either using failure statistics or on the basis of experts' experience, or a combination of both. In this example, all weight factors are determined by human experts.

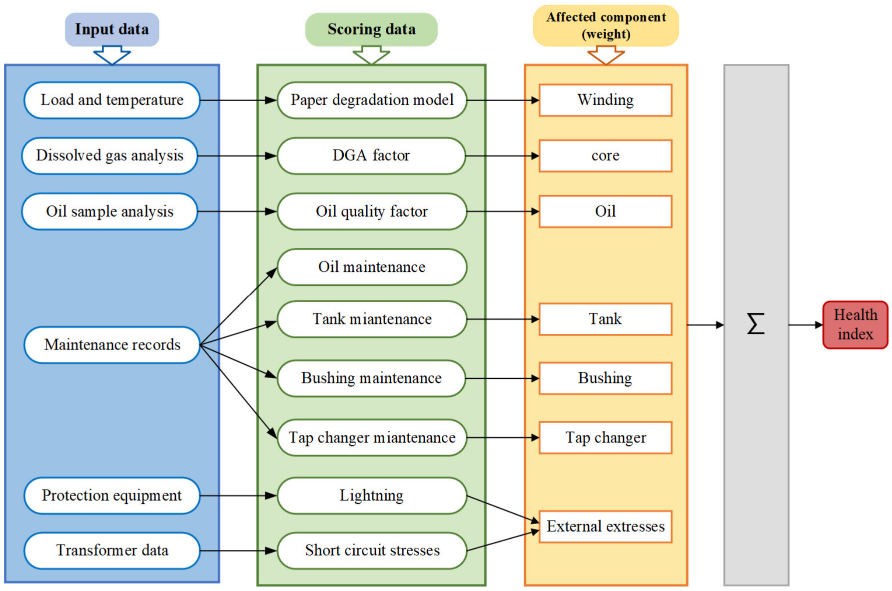


Figure 6. Structure of the Norwegian transformer health index.

2.3. Subsection

Usually, the deterioration in a transformer's health condition can be attributed to different types of stresses, like electrical, mechanical, or thermal stress, or a synergistic combination of several of them, as well as some chemical reactions. Therefore, in some situations, the transformer health index can be calculated as a synthesis of such causes, which can be realized using:

$$HI = \sum_{j=1}^{m} S_{2j} W_{2j}, \tag{9}$$

where N is the number of different types of condition data [37,38], or a maximum score [39].

Unlike the Type-I and Type-II health indexes, the final form of the health index no longer needs the weightings to indicate the importance of various causes of degradation, but rather a mean of their values. In industry, such methods have been adopted by utilities like ABB and TERNA [37,40]. In TERNA's transformer health index [37], transformer condition data are classified into four degradation categories:

- Those related to dielectric and thermal degradation are derived from DGA. They include electrical faults (i.e., PD, low energy discharges, arcing) and thermal faults.
- Those related to the purely thermal condition of solid insulation are derived from CO_2, CO, and Furans.
- Those related to the mechanical condition of the transformer are derived from on-site electrical tests (i.e., inductance, SFRA, PDC/FDS).
- Those related to the health of the insulating oil are derived from water, acidity, BDV and DDF.

With this method, the final health index is the average of the weighted ranking of N types of condition data, similar to (9). Here, it is calculated according to the following equation.

$$HI = \frac{HI_{Diec} + HI_{Therm} + HI_{Mech} + HI_{Oil}}{4}, \tag{10}$$

where HI_{Oil} is the health sub-index of transformer oil, which can be calculated by:

$$HI_{Oil} = \sum_{i=1}^{n} WR(i) = \sum_{i=1}^{n} \sum_{j=1}^{m} W_j f(j), \tag{11}$$

where WR (i) represents the weighted rank of each type of condition data, W_j is the condition weight factor, f (i) is the active function, n is the number of different types of condition data, and m is the number of different condition states. The process of calculating the WR (3) of the water content is given in Table 5.

Table 5. Example of weighted ranking.

Test Item	IEC 60422, for >170 kV	Weight	Active Function	Rank
Water	Good < 15	0	(0) No	0
	Fair 1~20	0.15	(1) Yes	0.15
	Poor > 20	0.3	(0) No	0
	Weighted rank for water content =			0.15

2.4. Other Types of Health Index Based on Weighted Scores

Some methods use weighting in the calculation of the health index [15,40–44]. For example, in Ref. [40], the final health index is called the status indicator factor (xSIF), which is an average of the weighted rankings of N types of condition data and is similar to the Type-I health index in (5).

$$HI_{Oil} = \sum_{i=1}^{n} WR(i) = \sum_{i=1}^{n} \sum_{j=1}^{m} W_j f(j), \tag{12}$$

where K_i is the weight of the xSI (status indicator), and $xSIC_i$ represents the status indicator code of the i-th type of condition monitoring test.

For example, $xSIC_2$ stands for the status indicator of the oil characteristic test, which is:

$$\chi SIC_2 = \frac{\sum_{i=1}^{6} S_i \times W_i}{\sum_{i=1}^{6} W_i}, \tag{13}$$

where S_i and W_i represent the classification value (or condition score) and corresponding weight of a specific test item (e.g., breakdown voltage, dissipation factor, etc.).

Unlike the calculation of Type-I, Type-II and Type-III health indexes, the condition score S_i in this health index is converted from a physical value using a segmentation function. Figure 7 from [40] is redrawn here to illustrate how the condition score of the service age is determined in this kind of health index.

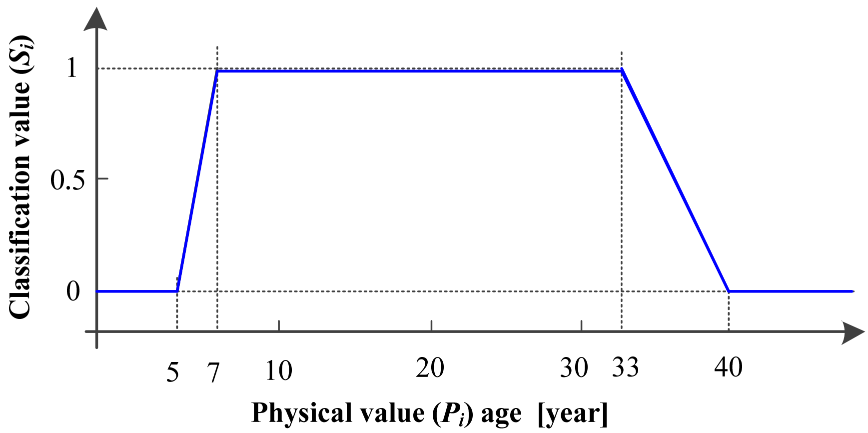


Figure 7. Condition score determination of the service age.

3. Artificial-Intelligence-Algorithm-Based Transformer Health Index

In addition to the approaches for realizing the transformer health index mentioned above, artificial intelligence (AI) algorithms have also been applied in transformer health index calculation, including artificial neural works (ANNs) [61–65], back-propagation neural networks (BP-NNs) [66], general regression neural networks (GRNNs) [67], fuzzy support vector machine (FSVM) [68,69], fuzzy logic [70,71], wavelet networks [72], binary logistics, and Bayesian networks [73–75]. A common characteristic of all of these methods is all of them ordinarily use historical condition data as their input variables, while a particular health state is taken as the output. The hidden relationship between the input and the outcome can be approximated using available condition data through the training process. After training, this algorithm can process new condition data and evaluate the health condition of the corresponding transformer according to the learned relationship.

Generally, AI algorithm-based approaches can be classified into three categories: classification-algorithm-based approachs, fuzzy logic approaches, and inference-based approaches. These three types of method will be detailed in the following subsections.

3.1. Classification-Algorithm-Based Health Index

The representative algorithms for the application of classification algorithms in health index calculation are ANN, back-propagation neural networks (BP-NNs), general regression neural networks (GRNN), SVM, and some improved algorithms [61–69,76–80]. As depicted in Figure 1b and mentioned in the introduction, the merits of this kind of method are the approximation of the underlying relationship described in (2) between the inputs (the condition data $v_1 \sim v_n$) and the output (the health index). There are two steps in realizing the health index in this manner: (1) network training, and (2) testing with several labeled datasets with known health indexes. During the network training, the input–output relationship can be "learned" from the labeled data and then applied to determine the health index of new unlabeled datasets.

Figure 8 presents a schematic of the ANN-based health index calculation model [63,64]. This model applies a four-layer feed-forward ANN to calculate the transformer health index, including one input layer, one output layer, and two hidden layers. The inputs of this network are eleven types of condition data, collected from 59 transformers, while the output is a single specific health condition (e.g., Good, Fair, or Poor). Here, the health condition of the condition datasets used for network training is decided by human experts. After training the network, condition data from 29 transformers are used for testing.

Similar to ANN, GRNN can also be applied to calculate the transformer health index. It allows multi-dimensional condition data to be combined through an optimal weighting and score mechanism [68]. In this method, a smoothly interpolated continuous function is used for the weighting assignment of each type of condition data. Since GRNN is a probability-based neural network, the main task in health index calculation is to approximate the joint probability distribution function (PDF) $f\,(X,Y)$ of a random variable vector X and a scalar random variable Y using nonparametric Parzen window estimation from a finite set of datasets. Given X is an M-dimensional condition dataset of transformer $X = [x_n]$, $x_n \in \mathbf{R}^{\mathrm{m}}$ and $Y = [y_n]$ is the corresponding health index, the conditional expectation of health index can thus be expressed as:

$$E[Y|X] = \frac{\int_{-\infty}^{+\infty} Y f(X,Y) dy}{\int_{-\infty}^{+\infty} f(X,Y) dy}, \tag{14}$$

Once different kernel functions have been adopted, e.g., the Gaussian kernel function, the basic equation for the GRNN can finally be calculated as follows:

$$g(x) = \frac{\sum_{n=1}^{N} Y \exp(-\frac{D_n^2}{2})}{\sum_{n=1}^{N} \exp(-\frac{D_n^2}{2})}, \tag{15}$$

where $D_{2n} = (x - X_n)^{\mathrm{T}} \sum^{-1} (x - X_n)$ is the squared Mahalanobis distance between the training datasets and the output.

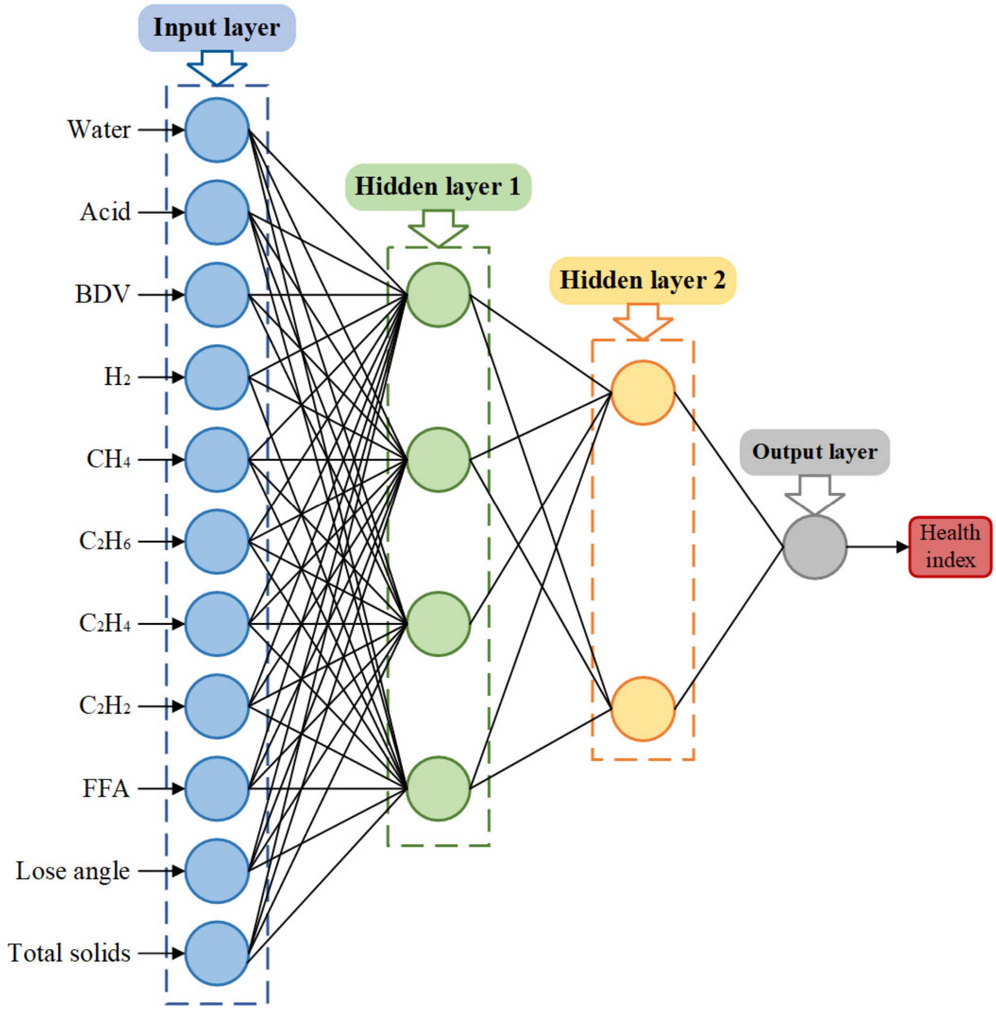


Figure 8. ANN-based transformer health index calculation model [63].

In (12) and (13), the inputs X include the total dissolved combustible gases of five dissolved gases (e.g., H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, and CO) and six characteristic parameters of oil (dielectric strength, acidity, water content dissipation factor, furan). Output Y is one of the five-level condition states: excellent, good, moderate, bad and very bad.

Another classification approach that has been applied in health index calculation, as proposed in Ref. [69], is the FSVM. This method uses the condition data from 181 transformers with specific oil test results (health index level) for network modeling. The test results are interpreted by utility experts on the basis of industry standards, Duval's triangle, and other methods. The input of this approach mainly consists of three main factors: the DGAF, the OQF, and the paper insulation factor. Denoting these inputs as $X = [x_1, x_2, \ldots, x_l]$, each sample belongs to one of the k health index levels $[y_1, y_2, \ldots, y_k]$. FSVM works to help separate the samples into different categories by constructing a hyperplane. This hyperplane is then used to classify new samples into certain health index levels. Details on how FSVM works are not provided here.

3.2. Fuzzy-Logic-Based Health Index

For conventional HI approaches, the HI level is determined by the score interval to which the calculated score belongs, usually consisting of four or five intervals. However, as mentioned before, these approaches have several limitations; in particular, the determinations of the weights of the condition data are in most cases more or less subjective (decided by utility experts). In addition, the thresholds between different health levels are too rigid (and are always determined by industry standards and the experience of utility experts. These thresholds vary from utility to another.

To overcome the above limitations, applications of the fuzzy logic method for transformer HI estimation were implemented in Refs. [69,70,81–91]. These papers utilized the membership function to divide the condition data into different health levels. Different health levels were described using other membership functions. Once the fuzzy logic (FL) rules had been defined, a fuzzy synthesis operation was able to deduce the final membership function for transformer HI. Expert knowledge is fully integrated with the inference process in such approaches.

In calculating the FL-based health index, there are four essential steps:

- Determination of fuzzy rules and membership functions. The fuzzy rules are a set of "If–Then" sentences that integrate the experience of human experts.
- Fuzzification. For each type of condition data, a membership function is assigned based on relative industry standards (e.g., IEEE, IEC, or CIGRE). These membership functions (varying in the range of 0~1) indicate the transformer's partial condition (e.g., good, moderate, bad, or more states).
- Fuzzy inference. Membership functions were synthesized using the fuzzy rules while employing the Mamdani maximum–minimum inference method to derive the output membership function.
- Defuzzification. Different methods (e.g., the centroid method) of the output membership function were used to find a crisp value for the output that indicates the health index of the transformer.

However, one deficiency of this kind of method is that fuzzy-logic rules are entirely dependent on expert experience.

3.3. Regression-Method-Based Health Index

In addition to the neural-network- and SVM-based methods for calculating the transformer health index, regression methods have also been applied in transformer health condition assessment, especially in health index calculation, such as binary logistic regression, multivariate analysis, and general regression neural networks, or a combination thereof [67,73,74,93,94]. For regression methods, health index calculation is a type of task that explores the best-fitting model in order to describe the relationship between a set of condition data $\{x_i\}$ and the health index $HI(x) = f(x_i)$. During this process, correlation analysis can be utilized to reduce the number of input condition data that make little contribution to the health index of the transformer.

In Ref. [73], binary logistic regression was applied to calculate the health index of the transformer by considering the oil breakdown voltage, the total acidity of the oil, the 2-furfuraldehyde content, the water content and the dissolved combustible gases. The logistic regression model used in that paper is reproduced in Figure 9a. The health index is taken as the probability that the transformer belongs to a specific condition (i.e., healthy or unhealthy, in this paper), and the input condition data are taken as the variable x_i. Thus, the transformer health index can be expressed as follows:

$$HI(x) = \frac{1}{1 + e^{-(\beta_0 + \int_{i=1}^{n} \beta_i x_i)}}, \tag{16}$$

where β_0 is a constant and β_i is a coefficient reflecting the contribution of each type of condition data x_i to the health index, which can be estimated using the maximum likelihood criterion to avoid subjective assignment in weighted-score-based health index methods.

In Ref. [74], typical factor analysis was first implemented on seven dissolved gases and five oil characteristics in order to identify the interdependency between the condition data from the correlation patterns. After that, the effect of each common factor on the health index was analyzed using structural equation models, a method that combines regression and factor analysis. The model for health index calculation using multivariate analysis is provided in Figure 9b.

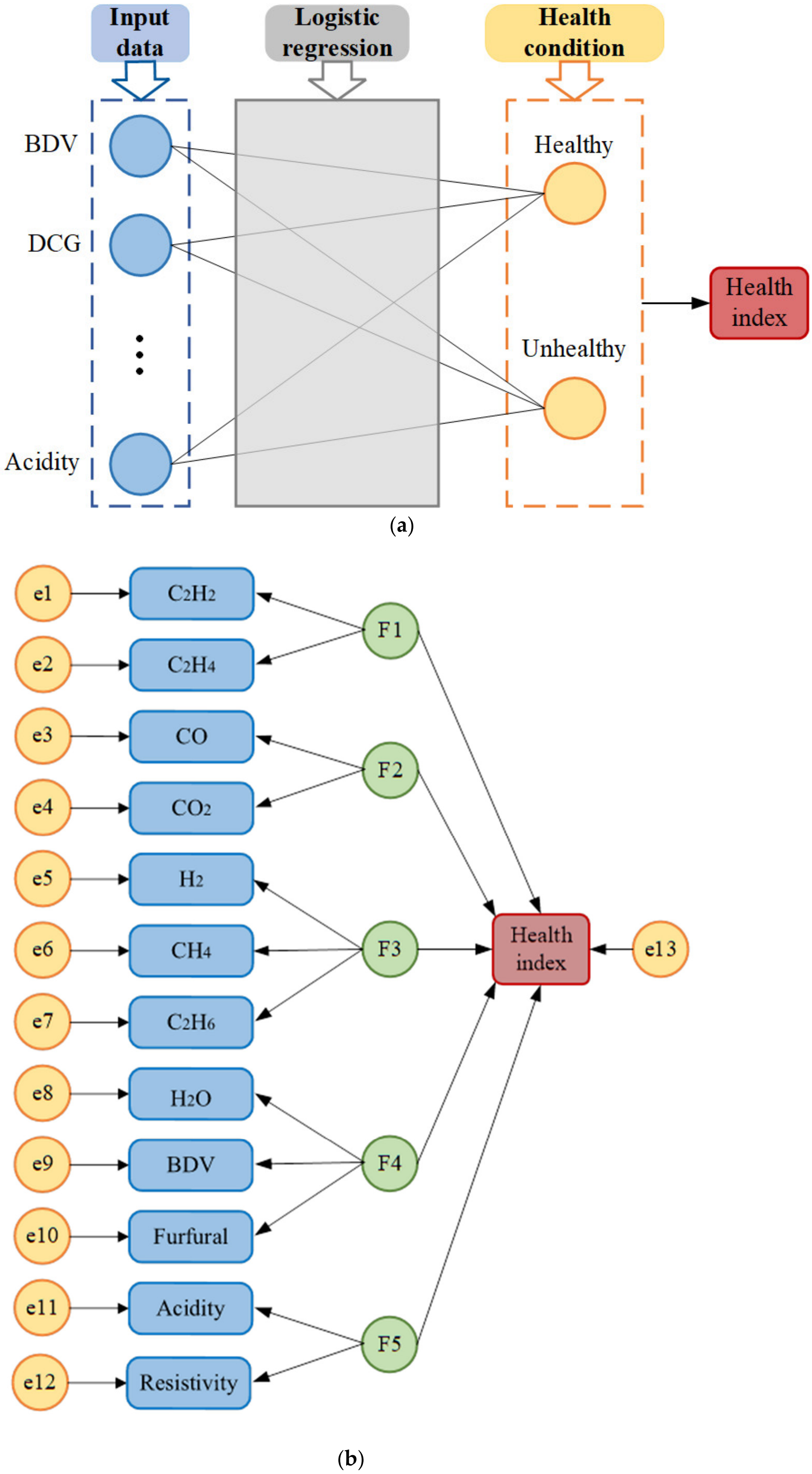


Figure 9. Transformer health index calculated as the sum of causes of degradation. (**a**) Binary logistic regression model [73]. (**b**) Multivariate analysis model [74].

However, for binary logistic regression or multivariate analysis, determining the significance or weighting of each type of condition data with respect to the health index or the common factor requires many datasets: the greater the number of datasets, the more credible the weightings.

3.4. Probabilistic Method-Based Health Index

In cases when condition data are not complete, or even when some are unavailable, neither weighted-score-based methods nor those based on ANN, fuzzy logic or regression methods are capable of adequately calculating the health index of the transformer (fleet) of interest. Under such circumstances, probabilistic-based techniques like Monte Carlo simulation and Bayesian belief networks are superior for handling the missing information and uncertainties in transformer health index calculation [49,95–100].

The method used by DNV GL Energy to calculate health index is to use the remaining lifetime to derive the health index, which is taken to be a single indicator representing the condition of an asset with respect to its specified performance and lifetime. Therefore, the core of DNV GL Energy's model consists of the assessment using functions to estimate the asset's remaining lifetime from the available data. This estimation is based on whatever information is available, including asset type, failure data, age, utilization data, maintenance and condition data, etc. [96].

Three different assessment functions have been developed, including the statistical assessment function, the utilization assessment function, and the condition assessment function. Using these three functions, three different remaining lifetimes can be calculated for the transformer of interest by using different data types. Finally, a folding function is applied to select the most critical value derived by the three functions. A schematic for the calculation of this type of health index is reproduced in Figure 10.

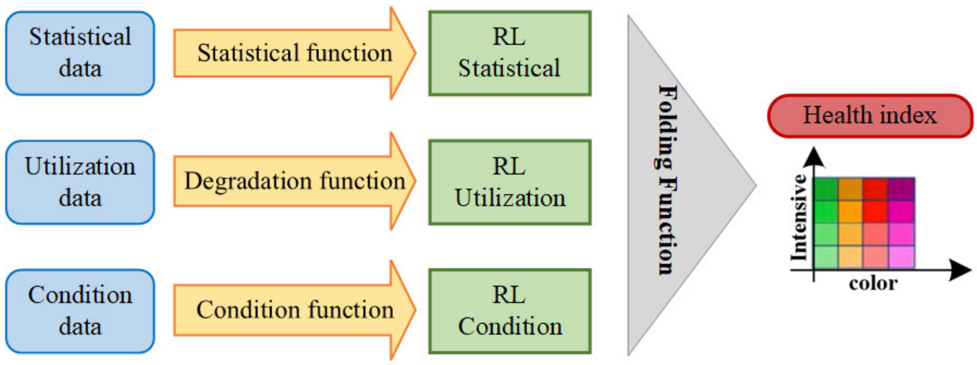


Figure 10. The transformer health index is calculated as the sum of degradation causes [96].

In this model, all input condition data are given by means of input distributions, which are set independently depending on the type of condition data. Thus, the inputs contain a certain level of uncertainty, and Monte Carlo simulation is used to estimate the distribution of the final health index. The details of this method, unfortunately, are not provided in the publications related to it.

In Ref. [99], by utilizing the method proposed in Refs. [16,17], the variations in the initial health index of specific transformers at different ages were determined. These were then used to determine the transition probability of the Markov chain. The constructed Markov chain was then used to predict the transformer health index in the future.

Recently, Bayesian belief networks (BBNs) were also applied in transformer asset health condition evaluation and management [75,76,95,98]. Since BBNs can provide the probability distribution function of the transformer's final health results, it is more intuitive and easier to understand. In Ref. [95], the health condition of the transformer was evaluated using the PoF, where the failure rate of each subcomponent was inferred using a BBN. More generally, the PoF is a health index that functions in coordination with those described in the foregoing text. The implementation of this health index model is illustrated in Figure 11.

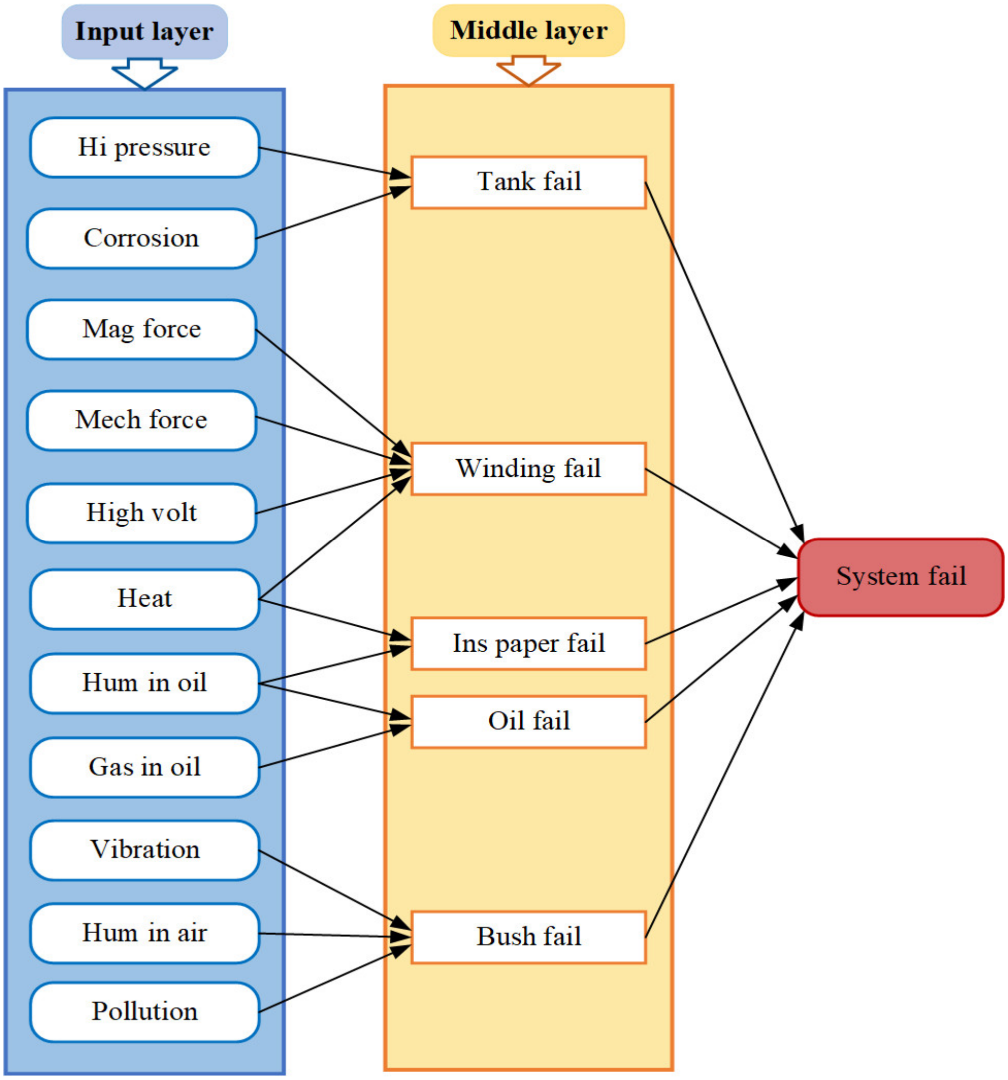


Figure 11. A model for evaluating the health of transformers through probability of failure (PoF).

In this model, the transformer health index is determined on the basis of five components, i.e., the bushing, the insulating oil, the kraft paper, the winding, and the tank. Similarly, the health condition of each component is determined by two or more types of condition data. Thus, this model has three layers: the input layer, the middle layer, and the output layer (from left to right). In Figure 11, each node X_i of the outer layer, representing one type of condition data, is characterized by several health states indicating its possible condition (in Refs. [95,98], only two conditions were employed). These nodes are connected using a unidirectional arrow. Here, the arrow direction reflects the probabilistic cause–effect relationships between two nodes. There are two types of node in the network: one has a parent node (nodes in the middle and output layer), and the other does not (input layer nodes). Those nodes with no parent usually have a probability distribution over all possible states, referred to as the prior probability.

Regarding those nodes with parents, the uncertainty of the effect of their parent node can be quantified through a conditional probability distribution table (CPT). Usually, these probabilities are evaluated using historical data, expert experience, or both. During the inference process, the joint probability distribution (JPD) of a set of connected variables $[X_i, i = 1, 2, \ldots, n]$ is inferred from observation. Once the CPTs of the variable group have been determined, the JPD can be calculated as a product of these CPTs using:

$$P(X_1, X_2, \ldots, X_n) = \prod_i P(X_i | X_{i-1}, \ldots, X_1), \tag{17}$$

When all of the probability distributions of each node have been assigned, the PoF can be calculated when specific values of X_i are available.

Since ref. [97] mainly focuses on identifying the failure condition of a transformer by calculating its PoF, it only provides a good scheme for realizing a probabilistic health index. Its method for calculating PoF, however, can serve as a reference. With this idea in mind, a probabilistic transformer health index based on Bayesian information fusion was proposed in Ref. [75]. In that study, an inference model was constructed using BBN, which integrates various data and information obtained from transformer measurements, maintenance records and failure statistics. As the hierarchical BBN was established with reference to the even tree of the transformer given by the IEEE standard [59] and the BBN structural parameters were determined based on both experts' experience and the statistical data, the results obtained from such a probabilistic framework are more objective and more persuasive. Similarly, in Ref. [75], a simplified Bayesian network was proposed to determine the transformer health index while accounting for possible classification error.

Using this method, the health index of the transformer is expressed in the form of probability, which can conveniently provide staff with an understanding of the state of the transformer in practical use. Before calculating the health index, it is necessary to obtain statistics for the fault location of the transformer and the factors influencing this location according to factors such as the use of the transformer and the cause of the fault and to establish a directed acyclic diagram. Compared with the previous health index calculation method, the probability-based health index calculation method is better able to consider the fault mechanism of the transformer, and the selection of the quantits of states is more in line with the actual use of the transformer.

3.5. Other AI Algorithm-Based Types of Health Index

Apart from the AI algorithms described above, attempts have been made to apply the hybrid use of the classification algorithm, feature selection, and optimization methods to the determination of the transformer health index [101–103]. In Ref. [101], three feature selection methods—info-gain, relief, and correlation-based feature selection—were applied to identify the principal features that are able to represent the actual health condition of a transformer. First, algorithms like RForest SVM and kNN are used as classifiers to verify the validity of the selected features in estimating the transformer's health. Similar work is also provided in Ref. [102]. Then, the cat swarm algorithm is used to build an optimization model based on SVM to help select the most representative data from the among the various transformer tests to determine the health index. In comparison, G. C. Jaiswal et al. [103] proposed using the genetic algorithm to optimize the weighting formulation for the data from each sensor online. This would then improve the reliability of the calculated health index from an improved weighted-score sum method.

Unlike conventional methods, the above references emphasize the reliability of the condition data or features extracted from various tests to derive a health index, rather than numerical formulation or the extraordinary realization of the health index itself. Therefore, the calculation of the health index using such methods can be more reliable and accurate than conventional methods with implementing the sum of a weighted-score only. Furthermore, the optimization of the input data for a health index is extendable to all of the methods reviewed in Sections 2 and 3.

4. Summary and Outlook

4.1. Summary

The transformer health index provides an intuitive understanding of the overall condition of a single transformer or even a fleet of transformers. Compared with PoF, RUL (Remaining Useful Life) and other metrics for indicating the condition of a transformer, the health index is more comprehensive and practical for the purposes of asset management and maintenance. In addition, it integrates a variety of different types of condition monitoring data in order to reflect each subcomponent's condition in a single global index for assisting management decisions.

Table 6 summarizes all of the health index calculation methods. Among all of the methods for calculating the transformer health index, weighted-score-sum-based methods are widely accepted by utilities due to their practicability and the fact that they can be performed quickly. In contrast, scholars find AI algorithm-based methods preferable. Type-I and Type- II health indexes frequently use weighted-score-sum-based approaches. The key to obtaining a reliable health index using such methods relies on the reasonable determination of the weights. Therefore, the experience of human experts plays a decisive role in this process.

Table 6. Summary of different types of transformer health index.

	Type	Input Variables	Output Style	Advantages	Disadvantages
WSS-based HI	Type-I	Transformer routine test items, including DGA, infrared test, oil test, etc.	In percentage form, from 0 to 100%.	• Simple for calculation, the data needed are easy to collect and the weights are easy to determine. • Widely used in practice and has rich experience in field application.	• The collected data are not filtered to identify errors and missing data. • The amount of data selected is large, and does not take into account the measurement cost while ensuring the accuracy. • The weight is only determined by experts.
	Type-II	Composed of structural transformer components, such as winding, core, oil tank, bushing, oil, and other accessories.	In percentage form, from 0 to 100%.	• Strong operation logic and high operability, and has been used by many utilities. • The weight determination is considerably objective, as it combines the actual data and the expert's experience.	• The large amount of data collected is not screened, and wrong and missing data cannot be identified. • The calculation accuracy is considerably low.
	Type-III	Mathematical scores of different degradation causes or stresses (e.g., electrical, mechanical, chemical, etc.).	In percentage form, from 0 to 100%.	• Selection of input variables is reasonable, as it is referenced to the transformer fault mechanism. • Instead of relying solely on the weight to determine the health index, both weighted and average values are combined.	The final transformer health index adopts the average value of the weighted rank, which is not accurate enough.
	Other WSS-based	Transformer routine test items, including DGA, infrared test, oil test, etc.	In percentage form, from 0 to 100%.	• The operation is simple and convenient, and the types of test values are more concise. • According to the state indication factor, the service life can be obtained directly.	If there are wrong data present, they will directly affect the accuracy of the calculation results.

Table 6. *Cont.*

	Type	Input Variables	Output Style	Advantages	Disadvantages
AI algorithm-based HI	CA-based [1]	DGA and oil testing results.	Condition status, e.g., Good, Average, Poor, etc.	• With self-learning function, strong robustness and fault tolerance ability. • It is able to perform a large number of operations quickly.	• The accuracy greatly relies on the data amount and the calculation is complex. • The calculation process is a black box, so the accuracy of the calculation is in doubt.
	FL-based	Mainly focuses on the relevant testing results of fault-prone parts or DGA.	Membership degree, for determining failure probability.	• It is easy to operate and does not need an accurate mathematical model. • Strong robustness and fault tolerance ability.	Fuzzy logic is a black box, which cannot be established by a mathematical model for its internal structure and mechanism.
	RA-based [2]	Transformer routine test items, including DGA, infrared test, oil test, etc.	In probability form, from 0 to 1.	The mathematical models or formulations are simple and easy to understand.	• Unable to filter input data. • The accuracy is not satisfactory.
	PA-based [3]	Selecting test items related to failed components based on fault mechanism	In percentage form, from 0 to 100%.	The calculation results are accurate, and a directed acyclic diagram deeply analyzes the fault types of the transformer. Strong tolerance capability for data error or lack of certain information.	Needs a large number of calculations.
	Other AI-based	Transformer routine test items, including DGA, infrared test, oil test, etc.	In percentage form, from 0 to 100%.	• It is convenient and economical to simplify the traditional test data and extract the data for calculation. • High calculation accuracy and reliability.	The calculations are complex, and a large number of calculations is also needed.

[1] CA-based refers to the classification-algorithm-based health index; [2] RA-based refers to the regression-algorithm-based health index; [3] PA-based refers to the probabilistic-algorithm-based health index.

Comparatively speaking, AI algorithm-based methods rely more on data, whereas experts' experience is also non-negligible. For classification-algorithm- and regression-method-based health indexes, labeled data or a certain amount of transformer condition data with a known health index is indispensable. With a certain amount of data available, one should first decide the health condition of the corresponding transformer, and then use this for training and the determination of the algorithm parameters to be used for subsequent classification (or testing). In this regard, the experts' experience can significantly impact the classification performance, as Type-I and Type-II health index results are the basis for implementing the classification algorithm-based health index. Comparatively, the fuzzy-logic-based health index depends more on expert experience, since the expert rules directly decide the final health index. In contrast, the probability method-based techniques for realizing a health index rely less on specialist expertise, and focus more on the amount of data, e.g., large amounts of transformer condition data are needed to determine the algorithm parameters or the network. Such methods can be more objective, as they avoid the subjectivity of human experts' experience to the greatest extent.

The primary purpose of calculating the health index is to provide an assessment of the transformer's overall condition using a single indicator, which can also be considered a multi-attribute decision-making (MADM) problem [104–106]. Therefore, some conventional methods utilized for transformer condition assessment, like fuzzy logic, evidence theory, and analytical hierarchical process (AHP), or a combination of these, are also applicable for determining the health index of a transformer. To determine the final health condition of a transformer, MADM methods can be used to construct a multi-layer structure considering different types of condition data. They can also include ambiguous and uncertain information, similar to the BBN method. Both types of method have the ability to integrate different factors with varying or even conflicting evaluation results.

4.2. Future Trend of the Transformer Health Index

In the future, it is probably that new types of health index will be developed utilizing different methods and algorithms. However, the biggest challenge in realizing the health index may manifest in optimizing the available data and the objectiveness and practicality of the method. The primary issue can be solved by applying feature selection and optimization methods to eliminate data dimensions and improve data reliability. In terms of objectiveness and practicality, optimal weighting is an issue that can never be neglected, and is the final goal of the weighted-score sum methods. In contrast, the probability-algorithm-based health index will be a good choice in the future, since the rapid development and wide application of big data and machine learning technology will not only ensure the availability of the data itself, but will also render the realization of these algorithms no longer an obstacle in terms of engineers' understanding and use.

With changes in transformer service life, the weight of state quantity will change in accordance with the evolution of the internal mechanism. In the future, attention should be paid to the calculation of the variable-weight health index to improve the practicability and accuracy of health index calculation. Moreover, most of the calculation methods for calculating the health index have been realized in combination with various algorithms in recent years. They make up for each other's shortcomings, but their practicability needs further improvement.

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