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Probabilistic Health Index-Based Apparent Age Estimation for Power Transformers

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ABSTRACT This paper proposes a probabilistic health index-based method for estimating the apparent age of power transformer. Compared with the conventional weighted-score-sum based health index, the probabilistic health index is calculated as a data fusion result of kinds of transformer condition monitoring data through a constructed Bayesian belief network. The regression result of such a probabilistic health index is then applied to estimate the apparent age of the transformer through a few steps listed in the paper. The apparent age not only embodies an overall health status a transformer but also helpful for sorting a transformer fleet based on the estimated apparent age or even make it easy to make comparisons between transformer fleets. The estimated apparent age can be taken as a reference for power utilities to prioritize transformers and pay attention to the unit who owns the maximum apparent age among a fleet, thus helps to schedule replacement plans. Case studies with different transformers verify the usability and prove the advantages of the proposed method.

INDEX TERMS Apparent age, Bayesian belief network, condition monitoring data, health index, power transformer.

I. INTRODUCTION

In the electrical power system, the transformer plays a very important role in energy conversion and distribution. So far, a large number of power transformers in-service are almost approaching their designed life (25-30 years in general). However, for economic and other safety considerations, most of them are not replaced and still functioning satisfactorily. As the insulation material of the transformer usually exposes in a multi-stress coexisting condition including the thermal, the electrical, and the mechanical effect as well as the chemical erosion during service, degradation of the insulation and aging of the transformer is inevitable [1], [2]. It thus becomes crucial to evaluate the "real age" or "real life" of a transformer for scheduling its retirement, and also helps to schedule the maintenance and replacement plan.

As two coupled parts for the oil-paper insulation system of the oil-immersed transformers, the kraft paper usually coordinates with mineral oil or nature ester to ensure the safe and stable operation of the transformer. The kraft paper, formed with 90% cellulose, 6%-7% lignin, and pentosans, can become very brittle once exposed to thermal, electrical stresses, or both of them within a specified period [3]–[5]. For cellulose, the depolymerization process can reduce its chain length of polymer molecular during long-term service, thus resulting in a decrease of the mechanical strength. Usually, the loss in mechanical strength of the kraft paper can be measured by the degree of polymerization (DP). For newly manufactured paper, its DP typically varies from 1100 to 1600 [6], [7], which can be reduced along with its aging. Once the value of DP decreases to 200, it is considered the kraft paper almost reaches its end-of-life.

During aging, the insulating paper can generate some feature byproducts like furaldehyde and furans compounds as a single or synthetic effect of pyrolysis, hydrolysis, and oxidation [8]–[10]. Most of such hydrocarbon byproducts will be absorbed in Kraft paper only with a small portion dissolved in oil, which has been utilized as one of the reliable and effective indicators for aging assessment of the insulating paper [4], [11]. Once incipient faults (both the

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electrical and the thermal) like arcing, corona, discharges, sparking, and overheating occurred, the mineral oil would be decomposed, and combustible gases, carboxy compound might be released consequently. The main components of these gases are hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane (C_2H_6), carbon monoxide (CO), and carbon dioxide (CO_2) [12]–[14]. By utilizing such byproducts obtained from oil tests and routine inspection, it is feasible to conduct a comprehensive health condition assessment of the oil/paper insulation system or even an entire transformer.

Although studies prove that the gas ratio of CO_2 and CO is useful for a rough estimation of the service life for insulating paper [15], [16], it is still hard to determine the service life of a transformer based on such ratio since this value can vary greatly for different units. Approaches like the IEEE/IEC method, the kinetic model, and some statistical techniques are mainly focused on the thermal effect on the insulation of the transformer [17]–[19], so a complete load and temperature profile are thus needed. Such information, however, is always incomplete. Sometimes the estimated life of a transformer through these approaches can be very old and even reaching the end-of-life, but they are still functioning well, while a particular transformer with an estimated younger life may have kinds of defects or even retired before that time.

For power utilities, the managers may pay more attention to the health condition of a transformer group, or namely, their focus is on which unit exhibits the most miserable state in the fleet. Face with this, the health index is thus regarded as an effective tool for achieving such a goal [20]–[32]. By combining condition monitoring data obtained from types of measurements, routine tests, maintenance records, failure statistics, and also the experience summarized from human experts, it is feasible to implement a comprehensive health assessment of power transformer. From the health index result of all transformers, it is possible to rank a single unit among the fleet. Furthermore, one can also judge whether the condition of a single unit is beyond or below the average health level of the population through regression of the health index results. This will give a more intuitive reflection of a single unit's health condition, and thus provides a reference to maintainers pay more attention to those below the average.

Based on the health index mentioned above, a new approach for estimating the ''apparent age'' of power transformer using the results of a probabilistic health index given in [33] is proposed in this paper. The apparent age can be useful for making a judgment of a single transformer fleet, and also makes it easy to select the poorest condition unit from a transformer group. Therefore, it is helpful for ranking transformers among a fleet and useful for guiding maintenance, replacement, and investment strategy. There are essential differences between the proposed apparent age and the traditional service life or transformer age since the former can be taken as a metric for assessing the overall health condition of a single transformer among a large group. It is different from traditional methods for transformer life

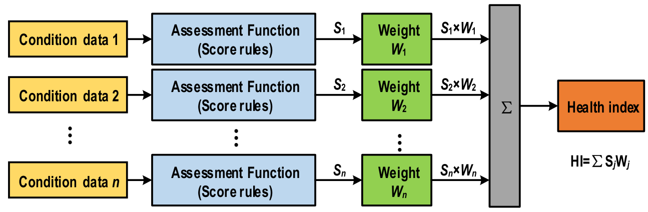

FIGURE 1. Schematic for transformer health index based on weighted-score sum approaches.

calculation since condition data from different sources are taken into consideration, which covers most of the stresses that can result in the aging of a power transformer.

The rest of the paper is organized as follows: Section II presents the realization of a probabilistic health index based on Bayesian information fusion followed by a brief review of transformer health index, Section III details the estimation of transformer apparent age from health index results calculated in Section II. Case studies and discussions are carried out in Section IV. Finally, conclusions are drawn in Section V.

II. REALIZATION OF PROBABILISTIC HEALTH INDEX

This section will briefly introduce how a probabilistic health index is created based on the Bayesian information fusion theory. A brief review of general approaches to calculating the health index is firstly given in Section A. By summarizing the shortcomings of general health indices, a probabilistic health index is then proposed in Section B.

A. BRIEF REVIEW OF TRANSFORMER HEALTH INDEX

The transformer health index is a comprehensive index that integrates a variety of condition monitoring data to indicate the overall health condition of a transformer. Since various new techniques and advanced measures have been applied for transformer condition monitoring, the health index thus becomes more and more reliable.

So far, different types of health indices have been developed. Among all, the weighted-score-sum based health index has been widely accepted and put into service by power utilities [20]–[24], while the artificial intelligence (AI) algorithms-based health index is more popular in academia [25]–[32]. The realization of the two different categories of health index is summarized below.

1) WEIGHTED-SCORE-SUM BASED HEALTH INDEX

The weighted-score-sum based transformer health index can be realized as a summation of weighted-score for different types of condition monitoring data, e.g., in [20], seven gases (H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, CO, and CO_2), six oil test parameters (including dielectric strength, IFT, acid number, water content, color, dissipation factor), furan compound, dissolved gas analysis (DGA) of on-load tap changer (OLTC), loading profiles, and maintenance records are taken into consideration to calculated the transformer health index. As illustrated in Figure 1, such health index is easy to be realized

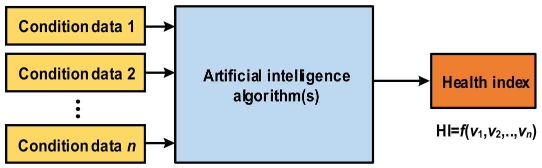

FIGURE 2. Artificial intelligence (AI) algorithms based transformer health index.

using the following equation.

$$HI = \sum_{i=1}^{n} k_i \times HI_i, HI_i = \sum_{j=1}^{m} S_j w_j / \sum_{j=1}^{m} w_j \tag{1}$$

where HI_i is the local health index of the transformer, i.e. health index for oil or tap changer, k_i is the corresponding weight of HI_i with $\sum w_i = 1$, S_j is the score of a specific condition monitoring data and w_j is the identical weight factor, n is the number of condition monitoring data.

The condition score S_j is generally determined according to assessment functions (or score rules) that have been defined in published papers or relevant guidelines/standards or subjectively assigned by human experts, or even a synergy of them. In Figure 1, the condition data can be either digital or textual (e.g., the water content in the oil is digital, but maintenance records of a bushing are in text).

For the weighted-score-sum based health index, the local or partial health index HI_i can refer to different items, it can either represent a sub-index of a number of condition monitoring data with similar attributes or stand for the local health condition of a certain part/component of a transformer. For example, the HI_i mentioned in [22] indicated the overall condition of different gases dissolved in transformer oil. However, in [23], it was used as a local index to represent the condition of the transformer winding.

2) ARTIFICIAL INTELLIGENCE ALGORITHMS-BASED HEALTH INDEX

Except for the abovementioned weighted-score-sum based approaches, some AI algorithms that applied for fault classification, regression or prediction, fuzzy synthesis, and probability inference, etc., also show their applicability in transformer health index calculation. For these approaches, the AI algorithms usually act as an inference engine, while kinds of transformer condition monitoring data and the health index are taken as their input and the output, respectively. This kind of health indices are shown in Figure 2 and can also be realized through the following formula (2).

$$HI = f\left(v_1, v_2, \cdots, v_i, \cdots, v_n\right) \tag{2}$$

where v_i is the i-th type of condition monitoring data collected from the power transformer, while f is a nonlinear mapping relationship between the input (condition monitoring data) v_i and the output (health index HI).

Among the AI algorithms, the neural network and its modified methods [25], [26], as well as the support vector machine (SVM) [27] are usually taken as classifiers or regressors in the case of a certain number of labeled condition monitoring data (with known health index) are available. Such labels (health index), generally, are firstly determined by the weighted-score-sum based health index through formula (1). Similar to ANN or SVM, such labeled data are also essential to the regression-based health index [28], [29]. The goal of this type of health index is to find the optimal curve that can fit the relationship between the condition data and the health index to the greatest extent. Either the ANN/SVM method or the regression-based method health index relies less on expert experience. In contrast, the fuzzy-logic-based health index mainly depends on the knowledge of human experts [30], [31]. To realize this type of health index, a membership function needs to be assigned to each of the condition data according to relevant standards or regulations firstly, after then the knowledge of human experts is transformed to a number of fuzzy-logic rules, which can be used for fuzzy synthesis and the final health indices are thus derived.

In order to get a reliable transformer health index, either using those weighted-score-sum based approaches or AI algorithms, the experience of human experts cannot be ignored, i.e. the determination of the weights in weighted-score-sum based health index relies on the expertise of human experts, although kinds of feature selection methods are applied to reduce the subjectivity. Additionally, label identification (a specific health index) of the transformer condition data also depends on experts' judgment. Therefore, the results of such health indices are subjective in nature as human experience varies from person to person, which significantly affects the calculated health index as a consequence.

Confront with such an issue, a probabilistic health index based on Bayesian information fusion is proposed in [33], where a probabilistic graphical model is constructed and applied to infer the relationship between the condition data and the health index of a transformer. This probabilistic health index is more objective since it emphasizes on the use of a variety of different types of transformer condition data, including the online monitored, the offline measured, as well as the failure statistics. A brief review of this health index will be given below.

B. REALIZATION OF PROBABILISTIC TRANSFORMER HEALTH INDEX

In the field of data fusion, the graph-based method for inferencing cause-effect relationships like the Bayesian belief network (BBN) is widely used [34]. Its probabilistic structure, in combination with the fault tree of power transformer [35], can fit the calculation of health index very well. The fault tree given in [35] defines the cause-effect relationship between the condition monitoring data and the health status of a transformer's component is thus referenced for establishing a four-layer BBN shown in Figure 3.

Once a BBN is established and its structure parameters are fixed, the transformer health index can then be calculable if a new set of condition monitoring data is available. The main

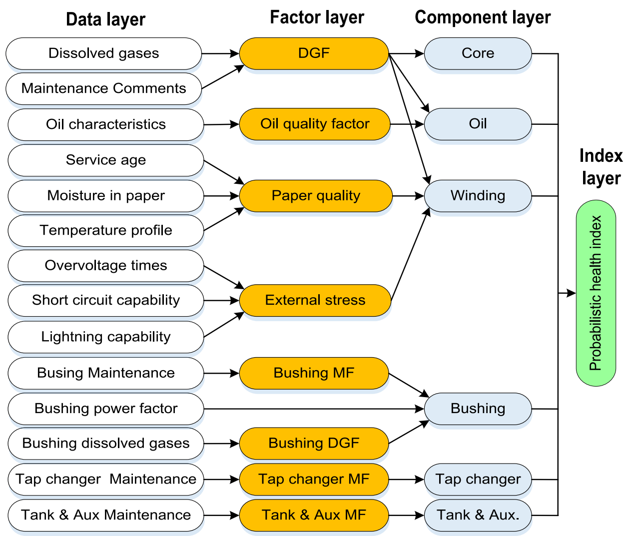

FIGURE 3. BBN implemented for probabilistic health index calculation as a result of dynamic information fusion.

procedures for realizing such a probabilistic health index are as follows.

1) CONSTRUCTION OF THE BBN FOR PROBABILISTIC INFERENCE

For the constructed four-layer BBN, various condition monitoring data of power transformer like online monitored DGA, offline routine tests, maintenance records, as well as failure statistics can be utilized for determine its structure parameters, i.e., the prior probability of father nodes (the nodes that arrows start from) and the conditional probability table (CPT) for child nodes (the nodes that arrows pointed) in Figure 3.

In this four-layer BBN, each node in the data layer stands for one kind of condition data, the condition of a node in the factor layer is usually decided by several nodes in the data layer. Similarly, the state of an individual component can be determined by several nodes in the factor layer. The health index of a transformer is a combined result of all components' condition. In the BBN, six components are considered, i.e. transformer winding, core, oil, bushing, tap changer, and the combination of tank and auxiliaries. Note that in data layer, the node "Dissolved gases" represents seven types of gases dissolved in oil (H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, CO, and CO_2), while the node "Oil characteristics" includes four types of test data, i.e. dielectric strength, acid number, moisture in oil and dissipation factor. Similarly, the node "Bushing dissolved gases" indicates four dissolved gases (CH_4, C_2H_2, C_2H_4, and C_2H_6).

2) DETERMINATION OF THE PRIOR PROBABILITY

For each node in the data layer of the BBN in Fig.3, its condition state is categorized into four levels, i.e., Good, Fair, Poor, and Faulty. The prior probabilities of these state levels of each node are determined according to relevant standards and the experience of human experts. Details can refer to [33].

TABLE 1. Determination of condition state levels – An example.

Condition data	Condition state level			
	Good	Fair	Poor	Faulty
Data A [unit]	[0, a1]	(a1, b1]	(b1, c1]	(c1, ∞)
Data B [unit]	[a2, ∞]	[b2, a2)	[c2, b2)	[0, c2)
H_2 [ppm]	≤100	100-300	300-700	≥700
DP	≥800	500-800	300-500	≤300

TABLE 2. Prior probability from data statistics – An example.

Condition data	Condition state level			
	Good	Fair	Poor	Faulty
DP	>800	500-800	300-500	<300
Prior probability [%]	A%	B%	C%	D%
H_2 [ppm]	≤100	100-300	300-700	≥700
Prior probability [%]	88.6%	9.8%	1.0%	0.6%

Hence, the final form of the heath index from the BBN represented as the probability of an individual state, which is unique from the conventional health index formatted as a score.

To illustrate how the condition state level is determined, an example is given in Table 1. In the Table, the condition state levels of Data A and Data B are divided into different intervals, where "a1", "b1", "c1", "a2", "b2" and "c2" represents limits defined in relevant standards. For example, Data A usually represents the indices, which are the smaller the better. Namely, when the data value bellows "a1", then it can be categorized as "Good," while the data locates between "a1" and "b1", it is then classified as "Fair", etc. In contrast, Data B stands for the indices of the bigger, the better. For illustration, the condition data of H_2 and DP are given here.

Once the condition state level is determined, the statistics of available data can then be used for determining the prior probability, as illustrated in Table 2.

After the condition state levels defined in Table 1, the condition data can be classified into different groups concerning each condition state level. For Data A in Table 2, the sum of the prior probability belongs to each state is 1, namely, A%+B%+C%+D%=1. For example, the prior probability of H_2 that will be used for the case study in Section IV-B, is determined according to the collected data of onsite transformers, which is 88.6% for "Good", 9.8% for "Fair", 1.0% for "Poor" and 0.6% for "Faulty".

3) DETERMINATION OF CONDITIONAL PROBABILITY TABLE

Here, a serial relationship between two elements in factor layer (the DGA factor and oil quality factor) and a component in component layer (Oil) in Fig.3 is taken as an example to illustrate the determination of a CPT. In Fig.3, the condition of "Oil" is decided by "DGA factor (DGAF)" and "Oil quality factor (OQF)", while the importance of each of them to the oil condition is assigned as 40% and 60%, respectively. Such an "importance degree", however, is decided by human experts. Thus, a condition score table is derived in Table 3 to show the transform from condition score to probability.

TABLE 3. Condition score and corresponding probability of "Oil".

DGAF	OQF	Score of Oil in "Good"	Corresponding probability $p(x)$			
			Good	Fair	Poor	Faulty
Good	Good	1.0	1.00	0	0	0
	Fair	1.7	0.25	0.75	0	0
	Poor	2.4	0	0.655	0.345	0
	Faulty	3.1	0	0	0.99	0.01
…	…	…	…	…	…	…
Faulty	Good	1.9	0.01	0.99	0	0
	Fair	2.6	0	0.345	0.655	0
	Poor	3.3	0	0	0.82	0.18
	Faulty	4.0	0	0	0	1

*DGAF and OQF are abbreviations of DGA factor and Oil quality factor.

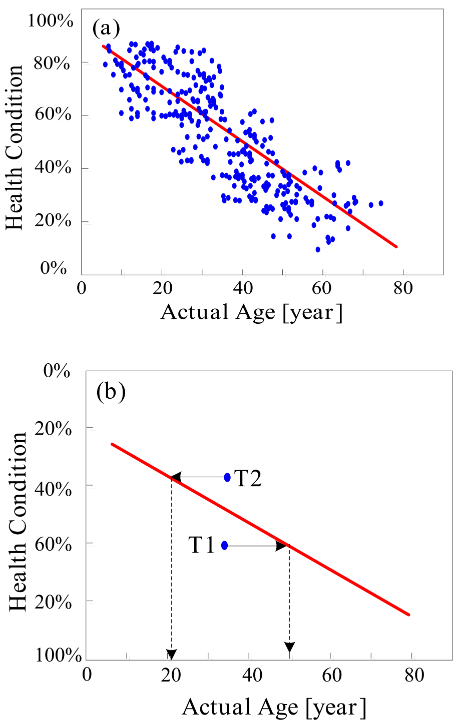

FIGURE 4. Calculation of the transformer apparent age. (a) Overall condition of a transformer fleet as a function of age, (b) Apparent age from health condition.

In Table 3, when the condition of DGAF is "Good", given "Poor" to the state of OQF, the calculated condition score is 2.4 with a weighted-score sum given in [33]. According to Fig.4, the corresponding probability is [0, 0.655, 0.345, 0]. Namely, the likelihood of Oil in a "Fair" state is 0.655, in a "Poor" state is 0.345, and 0 for both "Good" and "Faulty" state.

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4) CALCULATION THE JPD AND DATA FUSION USING BBN

With the CPT of each child node determined, the JPD can be readily calculated through (3). Once new condition data becomes available, its health index can be calculated through the above constructed BBN.

Apparently, by applying the BBN, various kinds of data can be integrated by multi-source information fusion. This means the BBN acts a function F and has the ability to process the transformer data set $\boldsymbol{x}_i$ through information fusion within it [36]:

$$F(x_i) = F(e) = \frac{\sum_{U\backslash\{X_i\}} P(U, e)}{P(e)} \tag{3}$$

where $F(x_i)$ is the fusion result based on the evidence e. In this paper, e refers to different types of measurement or condition monitoring data of a transformer.

The output Θ is the posterior probability of hypotheses that need to be inferred. In this paper, it is the final health index, which can be expressed as:

$$\Theta = P(X_i|e) \tag{4}$$

Obviously, for traditional approaches, the importance of a single condition monitoring data to the overall condition of a transformer is represented by the "weight" assigned by human experts. While for the BBN, this is delivered by the CPTs defined from layer to layer, which are mainly developed from the statistics of condition monitoring data, test results, but only partially relies on the experience of human experts. It means human experts cannot be ignored in the development of CPT for BBN, but their subjectivity can be greatly reduced since the proposed BBN introduces the CPT.

III. TRANSFORMER APPARENT AGE

The transformer apparent age is a combination of a transformer's service age and its health condition, which first originated from the need for asset overhaul, retirement, replacement, and investment decision [37]. The apparent age is an adjusted value given the condition of all transformers among a fleet is known, the process of estimating the transformer apparent age from the results of health condition is illustrated in Figure 4.

As an example, the transformer's health condition of 180 units is calculated and drawn in Figure 4a (the blue dot). Note that the health condition of the transformer is defined in percentage, e.g., 100% means a transformer in an excellent condition while 0% stands for a transformer in bad condition. In order to find a formula to describe the correlation between the actual age of transformer and its corresponding health condition, linear regression was adopted and the result can be seen in Figure 4a. The red regression line indicating the condition of the entire transformer. Thus, the blue dots below the line means the state of the corresponding transformer is worse than average, and vice versa.

With such regression curves available, the transformer apparent age can be readily determined as shown in Figure 4b. The actual age of either transformer T1 or T2 is all 33 years, but the health condition of T1 is worse than T2 as it is located under the red line in Figure 4b. The arrow line originated from either T1 or T2 has a point of intersection with the regression

TABLE 4. Basic information for transformers used for case study.

Parameter	Transformer						
	T1	T2	T3	T4	T5	T6	T7
Voltage[kV]	138	300	305	300	300	304	144
Power[MVA]	80	300	160	200	300	125	30

line, the corresponding value in abscissa is 50 and 21, which means the apparent ages for T1 and T2 are 50 years and 21 years, respectively.

Sometimes, the estimated apparent age may have extreme abnormal values like the difference of apparent age and actual age is too large, two measures are suggested to avoid that: 1) disregarding the outliers stand for extreme values in regression, and 2) applying the limit values proposed in [37] to adjust the final apparent age. Such measures can be summarized in one, namely, the maximum difference between the apparent age and the actual age should be smaller than 15 years.

IV. CASE STUDY AND DISCUSSION

To illustrate the proposed transformer apparent age, case studies with both data collected from publications and real transformer condition monitoring data are presented in this section, respectively. Comparison between the apparent age estimated from the BBN based probabilistic health index and other types of conventional health indices are provided, as well as that between different transformer groups is also provided in this section.

A. CASE STUDY WITH LITERATURE PUBLISHED DATA

Condition monitoring data of seven transformers [23] are adopted to implement the proposed transformer apparent age, including contents of dissolved gases, oil test results, textual maintenance records, service age, oil temperature profiles, and records of transformer external stresses are provided. Essential information like voltage and power of seven transformers are given in Table 4.

Considering some of the condition data like moisture in oil, DP, bushing power factor, bushing maintenance records of the bushing, OLTC, tank, and auxiliaries are unavailable, a rough estimate of DP is obtained through (5) with transformer winding temperature profiles provided in [38]. The content of moisture-in-paper (MIP) is transformed from the moisture equilibrium curves given in [39]. In addition to DP and MIP, other missing information that cannot be ignored is replaced with statistical results from condition monitoring data of a large number of power transformer. The data of 192 transformers in China is adopted for such purpose. For the calculation of DP, this paper uses:

$$\frac{1}{DP_0}\left(\frac{DP_0}{DP_t}-1\right) = A \times e^{\frac{-E_A}{RT}} \times T \tag{5}$$

where A is a constant relating to the chemical environment (2×10^8), R is the molar gas constant, T is the absolute temperature in Kelvin, E_A the activation energy (111KJ/mol),

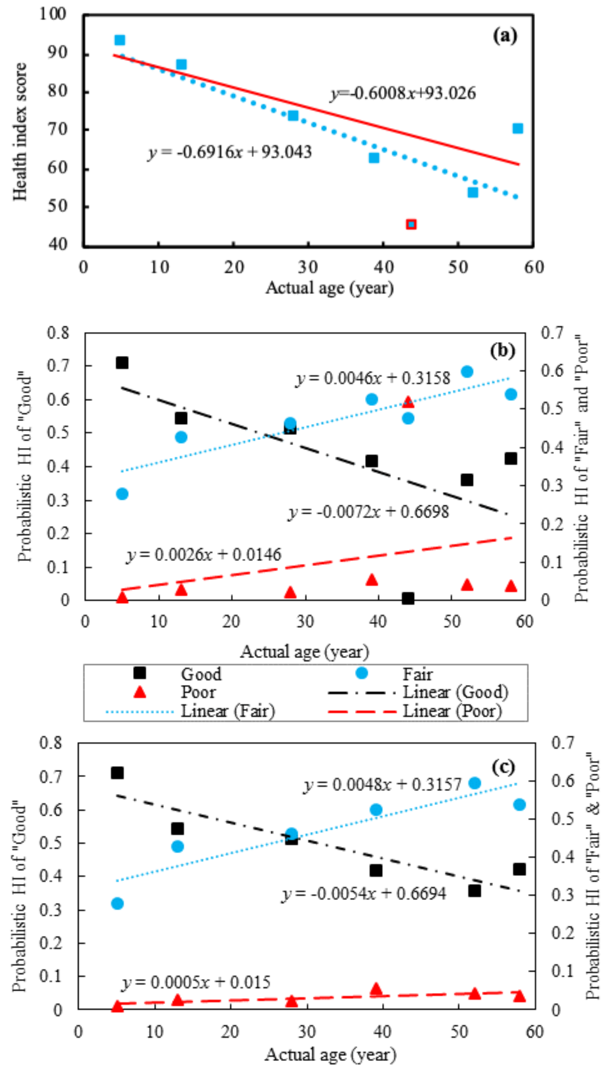

FIGURE 5. Linear regression for health index results. (a) Results of HI score from [23], (b) Results of probabilistic HI of seven transformers, (c) Results of probabilistic HI of transformers (exclude the one with the inferior condition).

DP_0 and DP_t are the initial and the current DP value, respectively.

To estimate the proposed apparent age, the probabilistic health indices of seven transformers were firstly calculated through GeNIe [40], the apparent age was then obtained follow the procedures mentioned in Section 3. Details for the realization of the probability health index can refer to [33].

For comparative study, the transformer apparent ages were also calculated using a weighted-score-sum based health index proposed in [23]. Calculated results of health index and estimated apparent age were summarized in Table 5 and shown in Figure 5. The probabilistic health indices with proposed BBN (Figure 5b, the probability of HI = "Good") have a good agreement with that derived from the weighted-score-sum based health index (Figure 5a). When a linear regression was performed for the calculated health index for all transformers (defined as original, Table 5), the regression equation

TABLE 5. Probabilistic health indices and apparent ages of seven transformers.

Trans. No.	Actual age (year)	HI score [24]	Expected condition [24]	Apparent age (year)		Probabilistic health index				Potential condition	Apparent age (year, original)			Apparent age (year, adjusted)		
				Original	Adjusted	Good	Fair	Poor	Faulty		HI=Good	HI=Fair	HI=Poor	HI=Good	HI=Fair	HI=Poor
T1	5	93	Very good	0.06	0.04	0.712	0.278	0.010	<0.001	Good	<0	<0	--	0	0	0
T2	13	87	Unknow	8.38	10.03	0.544	0.428	0.028	<0.001	Good	17.47	24.52	--	23.22	23.40	26
T3	28	74	Unknow	27.53	31.67	0.513	0.464	0.023	<0.001	Good	21.78	42.87	--	28.96	30.90	16
T4	39	63	Unknow	43.44	49.97	0.418	0.527	0.055	<0.001	Fair	34.97	45.91	--	46.56	44.02	80
T5	44	45	Very poor	69.47	59	0.007	0.476	0.521	0.006	Poor	--	34.83	59	--	33.40	59
T6	52	54	Poor	56.45	64.95	0.359	0.597	0.043	<0.001	Fair	43.17	61.13	--	57.48	58.60	56
T7	58	70	Acceptable	33.32	48	0.424	0.539	0.037	<0.001	Fair	31.14	48.52	--	45.44	46.52	44

in Figure 5a (above the red line) indicates the initial state of this fleet has an excellent condition, owning a health score up to 93.026. The health condition of this fleet deteriorates with a rate of 0.6008/year, along with the service time (actual age). In contrast, the regression result in Figure 5b (under the black dash line) shows this fleet initially has a probability of 0.6698 in a "Good" condition, which decreases with a likelihood of 0.0072/year against the service time. Besides, the probability health index also shows this fleet initially has a probability of 0.3158 and 0.0146 in a "Fair" and "Poor" condition, and the situation worsens with a rate of 0.0046/year and 0.0026/year, respectively.

Considering the health condition of transformer T5 is the worst among all, a new regression (exclude T5 as an outlier) is then conducted. The result is shown in Figure 5a (equation under the red dot line) and Figure 5c. Corresponding apparent ages are also calculated in Table 5. Table 5 shows that, after adjustment, the sequence for the apparent age of above seven transformers estimated from the weighted-score-sum based health index is {T6> T5> T4> T7> T3> T2> T1}. In contrast, that sequence for the proposed method is {T5> T6> T7> T4> T3> T2> T1}.

Obviously, from the perspective of asset prioritization for overhaul and replacement purposes, the apparent age is more persuasive since the transformer T5 already exhibited with the most unsatisfactory condition. Its apparent age ought to be the oldest among all. For transformer T6, based on the result of conventional weighted-score-sum based health index or that from the probabilistic health index, its status is believed better than transformer T5 since its apparent age is 58.6 years as estimated. This can be largely attributed to the probabilistic health index used for apparent age estimation integrates different sources of condition monitoring data of the transformer.

B. CASE STUDY WITH FIELD COLLECTED DATA

To further verify the effectiveness of the proposed apparent age, condition monitoring data collected from a group of 192 transformers in China are utilized for the case study. The data include dissolved gases, oil characteristic tests, age, and failure statistics. The transformer group has 116 transformers rated at 220kV (with actual age varies from 0 to 35) and 76 transformers rated at 330kV (with actual age ranges from 0 to 65). The calculation result is given in Figure 6.

In Figure 6a, the calculated probabilistic health indices of all transformers are presented. Considering the probability of condition, "Faulty" of almost all transformers is below 0.001 (except eight transformers with known faults), which was disregarded in the figure. For the purpose of prioritizing transformers with the highest apparent age to the lowest and comparing the overall health condition of two fleets, the apparent ages of these transformers against actual age are presented in Figure 6b. In Figure 6b, the linear regression results (solid line) of the relationship between the apparent age and actual age are above the dash-dot line $y = x$ representing the apparent age is equal to the actual age.

From Figure 6b, it is evident that the average apparent age of this transformer fleet is older than the actual age, which means these transformers are aged with an accelerated speed. The apparent ages of most transformers are below 42 years. Whereas some of them even exceed 120 years as the actual age of the oldest transformer is only 65 years, which indicates that most transformers are working satisfactorily. However, some of them should be paid close attention and even overhaul or replaced.

Once separates these transformers by the voltage ratings, the relationship between the apparent age and the actual age of the 220/330kV fleets are much different from each other, as summarized in (6).

$$\begin{cases} L_{\text{apparent}} = 0.9504 L_{actual} + 5.0044 \text{ (220kV)} \\ L_{\text{apparent}} = 1.4122 L_{actual} - 14 \text{ (330kV)} \end{cases} \tag{6}$$

with L_{apparent}, L_{actual} represents the apparent age and actual age of the transformer, respectively.

Since the faulty transformers can enlarge the apparent age of the transformers, three 220kV transformer and five 330kV transformers in a faulty condition are screened out, and the final fitted relationships are redrawn in Figure 6d as the equations are given below.

$$\begin{cases} L_{\text{apparent}} = 1.0496 L_{actual} + 3.8727 \text{ (220kV)} \\ L_{\text{apparent}} = 1.1469 L_{actual} - 8.3816 \text{ (330kV)} \end{cases} \tag{7}$$

It indicates that the transformers of the 220kV fleet are more prone to retirement than that of the 330kV fleet, which can mainly attribute to the 220kV fleet contains more new transformers than the 330kV fleet. This can be validated by the transformer statistics provided in Figure 7.

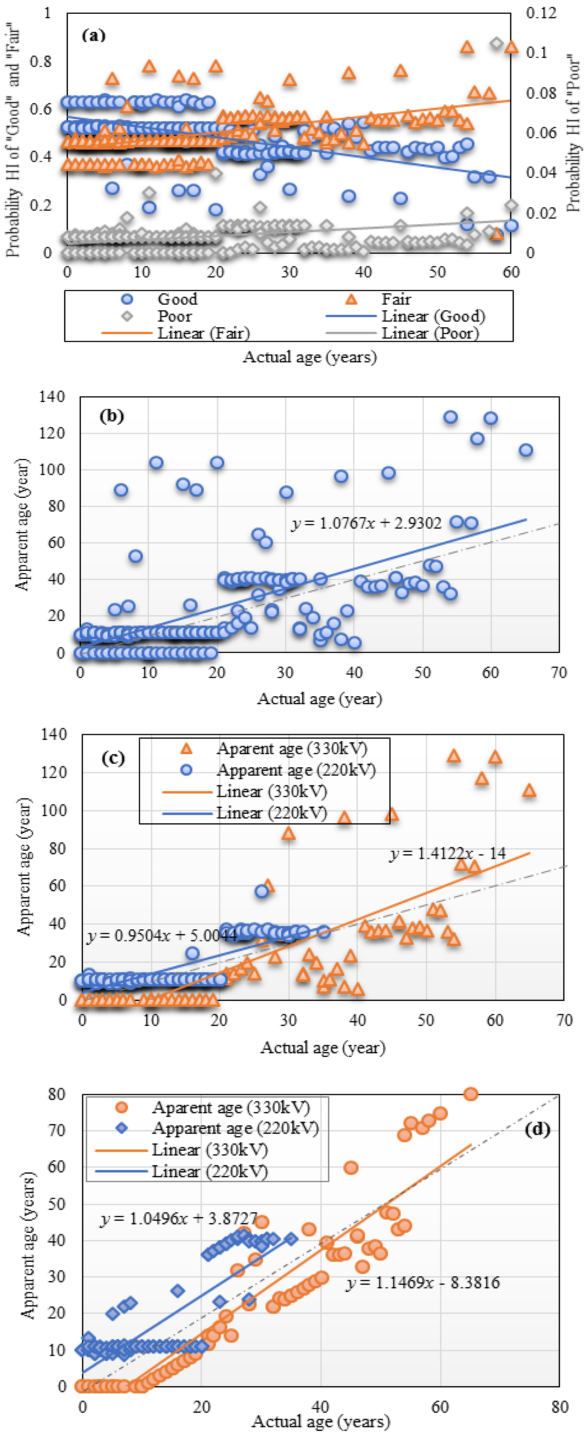

FIGURE 6. Apparent age calculated from the probabilistic HI-age. (a) Probabilistic HI of all 192 transformers, (b) Apparent age against actual age of 192 transformers, (c) Apparent age against actual age of 220kV (116 units) and 330kV transformers (76 units), (d) Apparent age against actual age of 220kV (113 units, excludes 3 units with known faults) and 330kV transformers (71 units, excludes 5 units with known defects).

According to the well-known bath curve, both inadequate and faulty specimens fail can result in a high infant mortality rate when the new equipment was put into service. When the equipment approaches the end of their lifespan or steps into its twilight years, it can also have an inferior condition due to wear out. As shown in Fig.7, the 220kV fleet has 52 units below ten years (red in Fig.7a), while the 330kV fleet only has 16 units below ten years and ten units above 50 years (red in Fig.7b). Such results are thus convincible as it is in line with the bath curve.

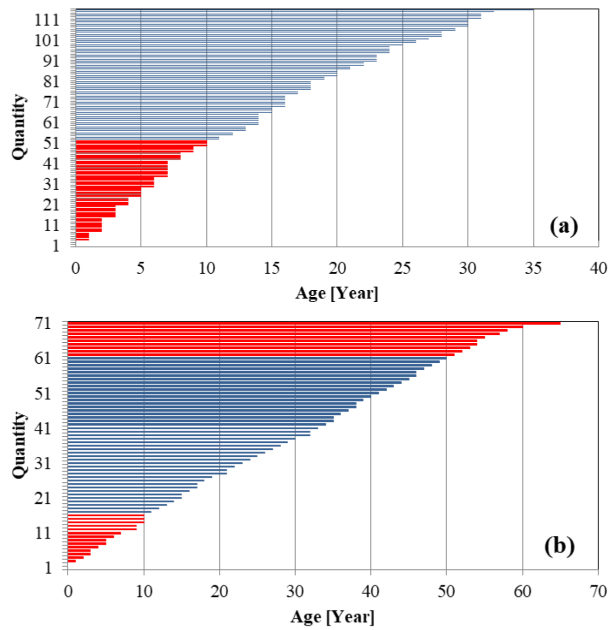

FIGURE 7. Quantity of transformers in two fleets. (a) the fleet of 220kV transformers, (b) the fleet of 330kV transformers.

From the case studies with either literature published data or field-collected data, it proves that the proposed transformer apparent age estimation approach is effective and useful for prioritizing units among a transformer fleet. The probabilistic health index based apparent age is not only a reflection of the real condition but also helpful for utility retirement, replacement schedule.

V. CONCLUSION

The applicability of the proposed apparent age estimation method for transformers based on the probabilistic health index was implemented in this paper. Different from the conventional transformer age or remaining life calculation approaches, the apparent age estimation method proposed in this paper used the results of the probabilistic health index as its basis through regression. The probabilistic health index was realized as a multi-source information fusion results within the BBN, with integrated kinds of condition monitoring data of the power transformer. The apparent age, therefore, can be taken as an indication of the ‘‘real service age’’ of a power transformer. For utility asset managers, the proposed apparent age can provide a reference for decision making of an overhaul, replacement or retirement for power transformers to a certain extent.

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Condition monitoring data of 192 transformers used for case studies in this paper can be downloaded from the link:

https://github.com/Greylee007/hello-world/raw/Greylee007-data-1/TRANSFORMER%20DATA%20-%20ver2.xlsx

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