Artificial Intelligence-Based Power Transformer Health Index for Handling Data Uncertainty

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ABSTRACT Power transformer is a critical and expensive asset in electric transmission and distribution networks. It is essential to monitor the health condition of all power transformer fleet in such networks to avoid unwanted outages. The health index (HI) is a quick and efficient way to assess the condition of power transformers based on multi-criteria. While Power transformer HI method has been well presented in the literature, not much attention was given to handle the uncertainty and reliability of this method due to unavailability of used data. Therefore, this paper aims to tackle this issue through employing Artificial Intelligence (AI)-based techniques to reveal the health condition of power transformers with high accuracy and at the same time handling data uncertainty. The proposed HI approach assesses the power transformer insulation system based on oil quality, dissolved gas analysis (DGA), and paper condition. In this regard, collected data from 504, 150-kV transformers are used to establish the proposed AI-models. Seven AI algorithms including k-Nearest Neighbor (kNN), Support Vector Machine (SVM), Random Forest (RF), Naïve Bayes (NB), Artificial Neural Network (ANN), Adaptive Boosting (AdaBoost), and Decision Tree are investigated. A performance comparison of the proposed AI-based HI models is carried out using the scoring-weighting-based HI method as the reference. Results show that RF model provides the best performance in predicting power transformer HI with an accuracy of 97.3%.

INDEX TERMS Power transformer, health index, insulation system, condition monitoring, artificial intelligence.

I. INTRODUCTION Power transformers are among the most critical and expensive assets within the electrical transmission and distribution networks. With the continuous increase in the load demand, power transformers are operating close to their nominal ratings and becoming more prone to failures. Therefore, power transformers need to be continuously monitored during their entire operational life to avoid sudden and catastrophic failures. Over the past two decades, several condition monitoring techniques have been developed for power transformers [1]. Among these techniques, insulation system has been a common key component to identify transformer health state and estimate its useful remnant life [2]. Several papers to explain the aging mechanism of the transformer oil and paper insulation have been published in the literatures [3]–[7]. The health condition and remnant life of power transformers have been assessed through various parameters of the insulation system [8], [9].

Reliable and cost effective condition monitoring and asset management techniques are essential for electric utilities in preparing an appropriate financial plans to estimate the future cost of maintenance, repair, and replacement of their power transformer fleet. In this regard, much research effort has been conducted to help utility companies optimize their asset maintenance costs. Transformer asset management (TAM) practice has been explained in [10]–[12] in which strategic plans for future maintenance and replacement activities based on various diagnostic testing methods are presented. The diagnostic testing methods can be generally categorized into...
condition monitoring (CM) and condition assessment (CA) techniques. CM techniques employ electrical, chemical, and physical tests to be collectively used by the CA tools to determine the health condition of the transformer.

The transformer health index (HI), as primarily explained in [13], is a single factor that utilizes the information from operating observations, field inspections, and laboratory tests to provide a reliable TAM decision. Majority of the data used in the HI model are based on the insulation system testing. Oil insulation tests include dissolved gases analysis (DGA), oil quality analysis (OQA), and furan analysis (FFA). Due to the high electric and thermal stress within operating transformers, oil and paper insulation decomposes and releases some gases that dissolve in the oil and decrease its dielectric strength. These gases include hydrogen (H₂), methane (CH₄), ethylene (C₂H₄), acetylene (C₂H₂), ethane (C₂H₆), carbon monoxide (CO), and carbon dioxide (CO₂). DGA test is conducted to quantify these gases from which internal transformer electrical and thermal faults can be identified [14]. Considering the guideline in [15], the OQA is determined by analyzing the oil breakdown voltage (BDV), acidity, water content, interfacial tension (IFT), dielectric dissipation factor (DDF), and color. FFA is conducted to measure furan compounds that are generated due to cellulose degradation and dissolve in the transformer oil [16]. Among the 5 furan compounds, furfuraldehyde (also known as furfural/2FAL) dominates the measurements and is correlated to the degree of polymerization of the paper insulation [17].

A scoring-weighting (also called weighted-sum) is the most commonly used method to calculate the HI of power transformers [13], [18]–[23]. The approach starts by comparing each parameter to a scoring table, then weighting each parameter based on its importance. The weights are usually identified by expert personnel. The individual scores are combined into a single index that reveals the overall health condition of the transformer.

As the HI is a linear combination of different scores and weighted measurement data, it is a challenging task to deal with the uncertainty of the used data through the current utility practice to identify the HI.

The rapid development of computer science and data processing has resulted in new HI approaches based on machine learning algorithms for big data analysis [9]. Artificial Intelligence (AI)-based HI approach was presented in [24] using DGA, furan, and oil test data to assess the health condition of several in-service transformers. However, due to the limited available data, the prediction accuracy of the developed neuro-fuzzy model has only been 56.3%. The study in [25] conducted a transformer HI sensitivity analysis using self adaptive neuro-fuzzy inference system (ANFIS) whose parameters were tuned using particle swarm optimizer (PSO). In [26], probabilistic Markov chain models were used to predict the future condition of the transformer based on HI calculation using a non-linear optimization technique. AI with a fuzzy-based support vector machine (SVM) was employed in transformer HI-based condition assessment using several factors, industry standards, and utility expert judgment [27]. AI-based general regression neural network (GRNN) was introduced in [28] to calculate the HI based on four-class transformer conditions; very poor, poor, fair, and good. In [29], AI-based HI using Bayesian network was proposed to quantify the parameters contribution through score-probability and population failure statistics. In [30], principal component analysis (PCA) and analytical hierarchy process (AHP) were proposed to determine the transformer health condition based on an expert empirical formula.

The use of AI methods to define transformer health index has been presented in the literatures. For instance, decision tree, random forest (RF), static vector machine (SVM), artificial neural network (ANN), and k-nearest neighbor (KNN) methods were used in [27] to automate the assessment process. A study in [31] compared several machine learning algorithms such as ANN, SVM, and Gaussian bayesian networks (GBN), to evaluate the health condition of power transformers through probabilistic HI framework. An approach is presented in [32] that compared the performance of various AI methods such as naive Bayes (NB), multinomial logistic regression (MLR), ANN, SVM, kNN, one rule (OneR), decision tree (J48), and RF in identifying transformer health index. However, regardless the various AI methods proposed in the literatures to calculate the transformer HI, more thorough studies are still required to improve the accuracy of such methods, in particular with the uncertainty or unavailability of the used data.

As discussed in [9], data uncertainty is the main shortcoming of the HI method which affects its reliability and accuracy. Data unavailability is the main reason of uncertainty. The study in [33] reported the effect of data unavailability and proposed a remedial approach based on RF to predict the missing data and improve the scoring-weighting HI. However, the development and investigation of AI-based HI model in handling data uncertainty has not yet discussed thoroughly with proven implementation feasibility.

**TABLE 1. Summary of previous researches.**

| Ref. No. | Main Contribution | Remarks |
|---------|-------------------|---------|
| [13], [18]–[23] | Scoring-weighting based transformer HI | Complete parameters is needed to achieve high accuracy in determining HI |
| [24]–[30] | Non-conventional AI-based transformer HI | The effect of some unavailable data to HI accuracy have not been reported |
| [31], [32] | Performance comparison of various AI algorithms to assess transformer HI | The use of AI algorithms to support HI when some data unavailable has not been investigated |
| [33] | Certainty level introduced to be reported alongside the HI when unavailable data observed | |

Table 1 shows the summary of the previous researches. From the above discussion, the gaps in this area of research can be summarized as below:

- despite the several AI-based methods used to identify the HI of power transformers, accuracy of such methods is still relatively low.
• there is no reliable and widely accepted technique to deal with data uncertainty which affects the reliability of the current HI practice.

As such, the main contribution of this paper is to:
• construct an AI-based approach to enrich the current conventional HI scoring-weighting method for power transformers.
• improve the accuracy of the HI calculation using multi-AI models to process most common routine testing data for power transformer insulation system.
• develop an effective correlation for all used parameters in calculating the transformer HI.
• identify the best AI-based combination for dealing with data uncertainty and missing values.

II. METHODOLOGY
The study in this paper is conducted in accordance to the workflow of Figure 1. Diagnostic data of 504, 150kV-power transformers including oil characteristics, furan content, and DGA were collected from in-service units of various life spans and health conditions. The assessment data are used to calculate the power transformer insulation system HI using the conventional Scoring-Weighting (SW) method. At the same time, data are used to establish the AI-based HI method. The performance of various AI algorithms is compared to identify the best performing AI algorithm through comparison with the SW method as a reference. The effect of unavailable data on the accuracy of both conventional SW and the identified best performing AI-based HI is evaluated by adjusting the complete data into 50 missing data scenarios. A preprocessing approach is then proposed to enhance the ability of the AI-based HI model to deal with such unavailable data and provide an accurate HI value.

A. TRANSFORMER POPULATION
The data used in this study were collected from PT. PLN PERSERO, an Indonesian state electricity company. Data are collected from 504 units, all with a specific high voltage of 150 kV with a low voltage of either 70 kV or 20 kV. Majority of these transformers use Kraft paper insulation and they are periodically inspected in a condition-based maintenance scheme by checking their insulation properties through DGA and dielectric characteristics (oil quality analysis). Dielectric characteristics include oil breakdown voltage (BDV), water content, interfacial tension (IFT), acidity, and color. In addition, 2-FAL measurement are provided for some units. Normally, the oil testing is conducted once a year or more frequent, if needed. Data used for the analysis in this paper are the same year data when HI is calculated, therefore omitting the uncertainty caused by outdated data. The age classification of the observed population sample is shown in Figure 2.

B. TRANSFORMER HEALTH INDEX
There are many methods to calculate the transformer HI score that reflects the overall health condition of the power transformer. Generally, there are two main approaches to determine the HI:

Scoring-Weighting: This approach starts with a scoring and weighting process conducted by expert personnel. As shown in Figure 3, condition data are processed into scores by comparing them to the scoring tables. Then, individual scores are weighted and aggregated into a single index value revealing the overall transformer health condition. A final health index is a linear combination of different scored and weighted measurement data. Therefore it is a challenging task to conduct a consistent and reliable HI process in case of some of the data are unavailable. In this regard, this paper highlights the
drawback of the conventional scoring-weighting models in handling unavailable data using the certainty level and output accuracy as proposed in [33].

Artificial Intelligence: various AI methods have been employed to estimate the transformers HI. The typical AI-based HI model development is as shown in Figure 4. In this method, training database including various diagnostic measurements conducted on several transformers at different health condition levels must be carefully prepared. The training dataset is used to establish the AI model to estimate the overall transformer health condition. As discussed above, various artificial intelligence algorithms have been used to establish such model including ANN, ANFIS, SVM, GRNN, decision trees [34]. The use of AI in power transformer condition assessment is useful especially for analysing large transformer datasets [35].

C. POWER TRANSFORMER INSULATION SYSTEM HI

The HI is developed based on the transformer reliability survey published by CIGRE TB 642 [36] that is discussing the failure modes of high voltage power transformers. The survey results show that the most common fault location for power transformer is the winding, with a dominant fault mode within the dielectric system. The main cause of failures includes aging and external short circuit. Therefore, this study focuses mainly on the integrity of the power transformer insulation system. The structure of the proposed HI method is divided into three-layers as shown in Figure 5 which is based on previously proposed method in [20]. The HI is equipped with scoring tables to score each measurement, as well as weighting factors based on the reliability and criticality of each parameter. These tables and weighting factors can be continuously adapted based on new information, experience, and recent international guidelines. The layers in Figure 5 include:

Data layer: this layer consists of frequently measured diagnostic data such as key gases of DGA, BDV, water content, IFT, acidity, oil color, 2FAL, and transformer age.

Factor layer: This layer has three categories that are derived from data layer/ measurement:
1. Oil Quality Factor (OQF) that consists of oil parameters; BDV, water content, IFT, acidity, and color.
2. Faults factor (FF), which consists of gas evolution, gas concentration level, and Duval’s pentagon DGA interpretation method (DPM), which is shown in Figure 6.
3. Paper condition Factor (PCF): This factor consists of the operating age, CO/CO₂ ratio, and 2FAL concentration.

Health Index layer: in this layer the HI calculation is conducted to provide a single value that reveals the overall health condition of the investigated transformer.

D. SCORING-WEIGHTING-BASED HI

All of the data used to calculate the transformer HI are determined by international standards limits [37], [38]. The scoring-weighting based HI for each factor is calculated as in (1).

\[
HI_{\text{each factor}} = \sum_{i=1}^{n} S_i W_i
\]

where \( n \) is the number of parameters used in every factor. The value of \( S_i \) is based on the scoring for each parameter based on standard scoring tables, and \( W_i \) is the weighting factor that describes the importance of every parameter.
The assessment methods are based on Tables 2 through 7, along with Figure 6. The final HI value is calculated using (2).

\[ HI_{\text{final}} = \frac{\sum_{j=1}^{n} SF_j W_j}{\sum_{j=1}^{n} W_j} \times 100\% \]  

(2)

where \( SF_j \) is the parameter’s scoring factor and \( W_j \) is the weighting factor.

The weighting parameters and factors are obtained by using AHP. This technique is built based on the judgment of five experts with in-depth experience in transformer condition monitoring, fault diagnosis and asset management [39], [40].

The health index category and description is classified as shown in Table 8. A more detailed explanation of the scoring-weighting method can be found in [20].
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FIGURE 7. A flowchart for the AI-based HI model's development.

FIGURE 8. Flowchart of the proposed multi-AI approaches to calculate HI.

FIGURE 9. Dealing the uncertainty with AI-based HI.

E. AI-BASED HI DEVELOPMENT
To establish the AI-based HI model, the collected transformer data have been divided into 354 training and 150 testing data sets. Each set comprises data of transformers of different aging, operating, and health conditions.

The output of the AI model is the overall HI which is validated using the corresponding HI calculated by the scoring-weighting method. If the AI model does not provide satisfactorily accuracy, additional tuning process is conducted through more training. On the other hand, if the accuracy has met the criteria, the final HI is calculated as per the process shown in Figure 7. Various AI algorithms are employed to establish the proposed HI model; this includes kNN, SVM, RF, NB, ANN, Adaptive Boosting (AdaBoost), and Decision Tree (Tree). The proposed method to calculate the transformer HI using multi-AI approaches is shown in Figure 8. The performance of these approaches is compared based on:

- **AI-SW**: which is based on factors category stage (OQF, FF, and PCF), then scoring-weighting-based in HI category stage.
- **AI-Full**: which is based on all classification stages (OQF, FF, PCF, and HI category) of the AI model.

F. DEALING WITH DATA UNCERTAINTY
All assessments of transformers include a non-avoidable level of uncertainty. Unavailability of the data, erroneous, or obsolete data will adversely affect the assessment results and increase the uncertainty of the obtained outcomes. The uncertainty within available data is due to different reasons such as incorrect data entry, erroneous or questionable test results, uncertainty in the condition assessment, and obsolete data [9].

A solution to manage the unavailability of the data is by employing machine learning to estimate the missing parameters based on historical data and well training process. Following the characteristics of the data, several methods can be used to preprocess the missing values. In this study, the
average/most frequent value is used to handle the issue of unavailable data as shown in Figure 9.

Three methods are used to implement the proposed approach namely; scoring weighting (SW), random forest (RF), and Random forest with preprocessing-based (RFwP).

The certainty level (CL) is calculated as below [33]:

\[
CL_i = WP_i \times WF_i
\]  

\[
CL = \frac{\sum\text{(AvailableCLi)}}{\text{Max.CL}} \times 100 
\]  

CL<sub>i</sub> is the certainty level for each parameter (i), WP<sub>i</sub> is the weighting parameter, and WF<sub>i</sub> is the weighting factor.

**G. PROPOSED RANDOM FOREST**

Random forest algorithm is a method consisting of a collection of tree-structured classifiers \{h(x, Θk), k = 1, . . .\} where \{Θk\} represent independent identically distributed random vectors. Each tree casts a unit vote for choosing the most popular class at input x [41]. An ensemble of the classifiers h<sub>1</sub>(x), h<sub>2</sub>(x)...h<sub>K</sub>(x), is given, and the training data are drawn randomly from the distribution of the random vector X, Y and the margin function is defined as:

\[
mg(X, Y) = av_k I(h_k(X) = Y) - \max_{j \neq Y} av_k I(h_k(X) = j)
\]  

The generalization error is given by:

\[
P_{E^*} = P_{X,Y}(mg(X,Y) < 0)
\]  

In RF, h<sub>k</sub>(X) = h(X,Θ<sub>k</sub>). Almost all sequences Θ<sub>1</sub>…PE* converge to:

\[
P_{X,Y}(P_Θ(h(X,Θ) = Y) - \max_{j \neq Y} P_Θ(h(X,Θ) = j) < 0)
\]  

This explains why random forests do not overfit as more trees are added and produce a limiting value for the generalization error [41].

**H. EVALUATION**

The evaluation of the model is based on the accuracy of the prediction of the transformer HI category. The classification accuracy (CA) is the proportion of correctly classified data as given by (8).

\[
\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)}
\]  

where TP is true positive, TN is true negative, FP is false positive, and FN is false negative. This calculation is based on the confusion matrix of binary classification in which the evaluation is considered as a multi-class classification problem.

**III. RESULTS AND DISCUSSION**

**A. TRANSFORMER HEALTH INDEX**

The HI is calculated for the investigated 504 units using the scoring-weighting method. As shown in Figure 10, the most frequent category of HI transformer is very good condition (VG) that represents 174 units or 35% of the population.

The other categories are good condition (G) for 104 units (21%), caution condition (C) for 134 units (27%), poor condition (P) for 82 units (16%), and very poor condition (VP) for 10 units (2%). This HI assessment is used to highlight faulty transformers and to construct strategies for maintenance plans.

**B. DATA MANAGEMENT**

The data used to develop the AI-based HI models are the same data classified in the above section to ensure the correctness and availability of all data. The distributions of the used parameters are shown in Figure 11 and a matrix correlating these parameters is shown in Figure 12. As shown in Figure 12, the IFT and color have the highest correlation value of -0.69. Sequentially, the significant correlation is found between C<sub>2</sub>H<sub>4</sub> and CH<sub>4</sub> (0.65), 2FAL and color (0.65), IFT and acidity (−0.63), color and acidity (0.55), and age and color (0.53). These results reveal that several parameters have a dependency relationship and influences each other.

Furthermore, the correlation of parameters with HI score, as shown in Figure 13, can be described from the highest to the lowest by applying a threshold limit above 0.2, which are...
as follows: color (−0.778), IFT (+0.638), 2FAL (−0.568), age (−0.51), acidity (−0.45), CO (−0.413), CO2 (−0.335), water content (−0.278), BDV (+0.268), and C2H2 (−0.218). The HI score has a limit value of 1, which means HI category has an equal relationship with the HI score. Therefore HI scores and maximum level are derived from the value of the parameter (data layer), then in the subsequent discussion, HI maximum score and LvMax will be ignored. The correlation of parameters helps to reduce the number of features without reducing the accuracy significantly as will be elaborated below.

C. EVALUATION OF DEVELOPED AI-BASED HI MODELS

To evaluate the performance of the developed AI-based HI models, the data were divided into training and testing sets. Using the training data, random forest algorithm was found to produce the highest classification accuracy (CA) of 91.2% in OQF and 92.1% in PCF. The tree decision excels at predicting FF categories with about 100% of CA. In the HI-layer model, the AdaBoost algorithm produces the highest CA of 97.2%.

When evaluated using the testing data, as shown in Figure 14, random forest excels with the PCF classification accuracy of 97%. The decision tree excels with the OQF classification accuracy of 96%, and the FF is 100% accurate. The AdaBoost excels at predicting HI categories with about 100% of CA.

The results show that the best prediction models are the tree-based classifiers such as random forest, decision tree and AdaBoost.

The performance of the RF classifier for the HI category is shown in the confusion matrix. The comparison between actual and predicted values is used to evaluate the classification accuracy of AI-based HI. The classification accuracy for RF is 97.3%. Furthermore, the random forest model only has four incorrect classifications, as shown in Table 9. The accuracy of other models are: decision tree (96%), AdaBoost (94.8%), neural network (91.3%), SVM (89.3%), Naïve Bayes (70.7%), and kNN (70%). In addition, an AI-SW-based model, which uses AI in the factor level, and weight-sum calculation in the HI level has been also developed. The model provides a classification accuracy results of 98%. Figure 15 shows a comparison of the performance of all developed models in terms of the HI calculation accuracy. Results attest that AI-based tree-structured classifiers produces better HI calculation accuracy than other algorithms.

D. EFFECTS OF UNAVAILABLE DATA

In this study, a comparison is done to evaluate the effect of uncertainty as a result of unavailable data to the accuracy of the HI calculation. Three main methods were compared: SW, RF, and RFwP. The missing data scenarios in Table 9 were assumed to conduct this analysis.
Figure 16 shows the accuracy with the certainty level of parameters. The results show that the RF is significantly influenced by a low certainty level due to particular missing parameters. With a low certainty level, the accuracy of RF also decreased. In contrast, RF with preprocessing (RFwP), due to missing value using the average or most frequent value, can maintain the classification accuracy at an acceptable level of at least 95%.

Then, the effect of missing factor on the HI calculation accuracy is examined according to the scenarios shown in Table 11. The uncertainty due to missing factor significantly affects the HI classification accuracy as shown in Figure 17. In this case, the observed factor conditions were divided into OQF, FF, and PCF. The most significant effect of missing value is observed in the RF-based paper condition factor (PCF). The lowest accuracy value is 60.7% using RF based on the missing of the paper condition factor. Using RFwP, the classification accuracy can be increased to 82%. Therefore, it can be concluded that the RFwP model can maintain the classification accuracy of HI categories with missing factor.

After evaluating the effect of missing each parameter and factor on the HI accuracy, the next analysis is conducted to investigate various scenario of unavailable data. The correlation of the certainty level and the classification accuracy of multi-parameters is constructed, as shown in Appendix 1. The aim is to measure the causal effect between certainty level and resulting HI accuracy for each of the three developed model: SW-based HI, RF-based HI, and RFwP-based HI. This analysis is helping to define efficient and precise ways to deal with the data uncertainty.

1) SCORING-WEIGHTING (SW)-BASED HEALTH INDEX

When evaluated using the testing data in Appendix 1, the SW-based HI is affected by the uncertainty due to unavailable data as shown in Figure 18. This is indicated by the coefficient of determination ($R^2$) of 0.917. From Figure 18, the correlation of the accuracy ($y$) and certainty level ($x$) can be approximated using (9).

$$y = 0.6554x + 0.2573$$

The challenges of this method is that if there are many missing values, the classification accuracy of the HI category would be significantly affected.
will be decreased significantly. The range of the classification accuracy in HI categories will have a value above 80% if the certainty level is above 85%.

The color categories in terms of the accuracy indicator are green for high (H) accuracy level, yellow for medium (M) accuracy level, and red for low (L) accuracy level.

### Table 12. Scenarios of data unavailability.

| HI Scenarios | Oil Quality Factor (OQF) | PCF | Fault Factor (FF) - DGA | Certainty Level (%) |
|--------------|--------------------------|-----|-------------------------|---------------------|
| HI-0         | 1 1 1 1 1 1 1 1 1 1 1 1 1 |     |                         | 100                 |
| HI-1         | 0 1 1 1 1 1 1 1 1 1 1 1 1 |     |                         | 96                  |
| HI-2         | 1 0 1 1 1 1 1 1 1 1 1 1 1 |     |                         | 94                  |
| HI-3         | 1 1 0 1 1 1 1 1 1 1 1 1 1 |     |                         | 95                  |
| HI-4         | 1 1 1 0 1 1 1 1 1 1 1 1 1 |     |                         | 96                  |
| HI-5         | 1 1 1 1 0 1 1 1 1 1 1 1 1 |     |                         | 96                  |
| HI-6         | 1 1 1 1 1 1 0 1 1 1 1 1 1 |     |                         | 88                  |
| HI-7         | 1 1 1 1 1 1 1 0 1 1 1 1 1 |     |                         | 84                  |
| HI-8         | 1 1 1 1 1 1 1 0 1 1 1 1 1 |     |                         | 85                  |
| HI-9         | 1 1 1 1 1 1 1 1 1 1 0 0 0 |     |                         | 65                  |
| HI-10        | 1 1 1 1 1 1 1 1 1 1 1 1 1 |     |                         | 80                  |
| HI-11        | 1 0 1 1 1 1 1 0 1 1 1 1 1 |     |                         | 78                  |
| HI-12        | 1 0 1 1 1 1 0 1 1 1 1 1 1 |     |                         | 79                  |
| HI-13        | 1 1 1 0 1 1 0 1 1 1 1 1 1 |     |                         | 79                  |
| HI-14        | 1 1 1 1 0 1 0 1 1 1 1 1 1 |     |                         | 80                  |
| HI-15        | 1 1 1 1 1 1 1 0 1 1 1 1 1 |     |                         | 71                  |
| HI-16        | 1 1 1 1 1 1 1 0 1 1 1 1 1 |     |                         | 68                  |
| HI-17        | 1 1 1 1 1 1 1 0 1 1 0 0 0 |     |                         | 49                  |
| HI-18        | 1 1 0 1 0 1 1 0 1 1 1 1 1 |     |                         | 76                  |
| HI-19        | 1 1 1 0 0 1 1 0 1 1 1 1 1 |     |                         | 74                  |
| HI-20        | 1 1 1 1 1 1 0 1 0 1 1 1 1 |     |                         | 75                  |
| HI-21        | 1 1 1 1 0 0 1 1 1 1 1 1 1 |     |                         | 76                  |
| HI-22        | 1 1 1 1 0 0 1 0 1 1 1 1 1 |     |                         | 67                  |
| HI-23        | 1 1 1 1 1 1 0 1 0 1 1 1 1 |     |                         | 64                  |
| HI-24        | 1 1 1 1 1 1 0 0 1 0 1 0 0 |     |                         | 45                  |
| HI-25        | 1 1 1 1 1 1 0 1 0 1 1 1 1 |     |                         | 72                  |
| HI-26        | 1 1 1 1 1 1 0 0 1 0 1 1 1 1 |     |                         | 70                  |
| HI-27        | 1 1 1 1 1 1 0 0 1 0 1 1 1 1 |     |                         | 71                  |
| HI-28        | 1 1 1 1 1 1 0 0 0 1 1 1 1 1 |     |                         | 64                  |
| HI-29        | 1 1 1 1 1 1 0 0 0 1 1 1 1 1 |     |                         | 61                  |
| HI-30        | 1 1 1 1 1 1 0 0 0 1 1 1 1 1 |     |                         | 60                  |
| HI-31        | 1 1 1 1 1 1 0 0 0 1 1 1 1 1 |     |                         | 67                  |
| HI-32        | 1 1 1 1 1 1 0 0 0 1 1 1 1 1 |     |                         | 65                  |
| HI-33        | 1 1 1 1 1 1 0 0 0 1 1 1 1 1 |     |                         | 59                  |
| HI-34        | 1 1 1 1 1 1 0 0 0 1 1 1 1 1 |     |                         | 56                  |
| HI-35        | 1 1 1 1 1 1 0 0 1 0 1 0 0 0 0 0 0 36 |
| HI-36        | 0 0 0 0 0 0 0 1 0 1 1 1 1 1 1 1 |     |                         | 62                  |
| HI-37        | 1 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 |     |                         | 53                  |
| HI-38        | 1 0 0 0 0 0 0 0 1 0 1 1 1 1 1 1 50 |
| HI-39        | 1 0 0 0 0 0 0 1 0 1 0 0 0 0 0 31 |
| HI-40        | 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 50 |
| HI-41        | 0 0 0 0 0 0 1 0 1 1 1 1 1 1 1 47 |
| HI-42        | 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 19 |
| HI-43        | 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 |
| HI-44        | 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 6 |
| HI-45        | 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 5 |
| HI-46        | 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 |
| HI-47        | 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 |
| HI-48        | 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 12 |
| HI-49        | 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 16 |
| HI-50        | 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 15 |

**Figure 18.** Effect of certainty level due to unavailable data on the accuracy of SW-based HI.

**Figure 19.** Effect of certainty level due to unavailable data on the accuracy of RF-based HI.

**Figure 20.** Effect of certainty level due to unavailable data on the accuracy of RFwP-based HI.
2) RANDOM FOREST-BASED
The AI-based RF algorithm also suffers when predicting transformers HI with many unavailable data as confirmed by Figure 19 in which $R^2$ is 0.7614. The correlation of the accuracy and certainty level for this model can be approximated as below.

$$y = 0.7542x + 0.1232 \quad (10)$$

In some cases, RF model can predict the HI with an accuracy above 80% even though the certainty level is only 70%. Nevertheless, the accuracy will be better if the certainty level is above 80%.

3) RANDOM FOREST WITH PREPROCESSING
The RFwP is slightly affected by unavailable data. In this case $R^2$ is 0.8079 and the accuracy-certainty level correlation can be approximated from Figure 19 as in (11).

$$y = 0.5407x + 0.4904 \quad (11)$$

The RFwP model has performed better than SW and RF, resulting in the highest accuracy value in classifying the HI category even at a low certainty level. When the certainty level is, in the worst-case below 10%, the accuracy is still above 50%. In some instances, the accuracy can reach a value above 80% even with a certainty level of only 50%. The best condition is when the certainty level is above 70% which results in an accuracy reaches 90%.

For instance for scenario HI-13 in the Appendix, furan and IFT parameters are unavailable. Based on the data observation, furan and IFT have the highest frequency of data unavailability. The assessment value of the certainty level for HI-13 scenario is 79%, and when evaluated based on 150 transformers data, the classification accuracy using the scoring-weighting method is 78%. It can be observed that the RF model can achieve 80.7% accuracy while the RFwP classification accuracy is 96%.

As shown in Figure 20, the RFwP model achieves medium to high accuracy levels in almost all instances. This reveals the ability of RFwP to solve the issue of data uncertainties in estimating the transformer HI.

IV. CONCLUSION
The development and implementation of artificial intelligence-based health index model to assess the power transformer insulation system conditions has been presented. The proposed method is aimed to simplify, speed up, and reduce error due to data uncertainty. A comparison of various AI algorithms is carried out and evaluated using the classification accuracy in reference to the scoring-weighting-based HI calculation that is widely used by worldwide utilities. Based on this comparison, the random forest-based model is chosen as the proposed method with the highest accuracy to predict the transformer HI. Results show that random forest does not overfit as it produces a limiting value of generalization error. As such, random forest with preprocessing has been proposed to handle the data uncertainty by considering the missing values with the average or the most frequent value. The impact of missing data on the model has been evaluated, and the proposed RFwP performed better than other investigated methods and resulted in a satisfactory classification accuracy even with low certainty levels. This solves the current common issue of calculating the transformer HI with unavailable data. Results in this paper pave the way to adopt AI-based methods in calculating the transformer HI. However, implementing such techniques calls for more validation and feasibility studies on large transformer population with several scenarios of unavailable data.

APPENDIX
SCENARIOS OF UNCERTAINTY MULTI-PARAMETER
See Table 12.

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