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A New Model for Predicting the Remaining Lifetime of Transformer Based on Data Obtained Using Machine Learning

*M.K.K. Alabdullh, M. Joorabian**, S.G. Seifossadat, M. Saniei

Department of Electrical Engineering, Faculty of Engineering, Shahid Chamran University of Ahvaz, Ahvaz, Iran

Abstract— *Transformers are one of the most important parts of the electric transmission and distribution networks, and their performance directly affects the reliability and stability of the grid. Maintenance and replacing the faulted transformers could be time-consuming and costly and accordingly, a solution should be proposed to prevent it. This led to studies in the field of transformer lifetime management. As a result, estimating the remaining lifetime of the transformer is a crucial part for the mentioned solution. Therefore, this paper aims to tackle this issue through employing a new algorithm to estimate the lifetime of a transformer by combining selection methods and Artificial Intelligence (AI)-based techniques. The main goal of this method is to reduce the estimation error and estimation time simultaneously. The proposed approach assesses transformers based on environmental conditions, power quality, oil quality, and dissolved gas analysis (DGA). Consideration of additional factors overcomes the disadvantage of traditional methods and gives a meticulous result. In this respect, the collected data from the power transformer of Iran and Iraq as well as regions with different conditions are employed in the studied algorithm. Several combinations of algorithms are investigated to choose the best one. Principal Component Analysis (PCA) is employed in the next step for weighing the various parameters to improve the accuracy and decrease execution time. Results show that the Bayesian neural network provides the best performance in the predicting remaining lifetime of the transformer with an accuracy about 98.4 %.*

Keywords— Machine learning, Predicting, Transformer.

1. Introduction

Both power transformers and distribution transformers are the key equipment of the distribution and transmission networks [1]. The mentioned transformers are responsible to deliver the appropriate level of voltage to the final consumer. The consumer expects to have a reliable and stable system since system failures cause disruptions at different levels and pose a serious threat to the entire system. Consequently, the reliability of the system becomes important. Reliability of the system is one of the most crucial parameters that should be considered in the design. The power grid is designed so that electricity could be distributed at the highest possible reliability and finally, delivered to the consumers with the highest possible quality and accessibility. Equipment aging is one of the most important factors that affect network reliability. The aging of system equipment reduces the level of reliability of both equipment and the entire system. Therefore, estimating the lifetime of the equipment of the power system is playing an important role.

Companies try to precisely estimate the lifetime of key utilities in a different part of the grid such as transformers. This estimation allows the necessary actions to be taken before a major fault occurs in the power grid and this leads to the network reliability improvement. In addition, recognizing the possible transformer faults helps to prevent aging. Generally, the importance of lifetime estimation for transformers can be summarized as follows:

1) Improving the reliability of both distribution and transmission networks.
2) Reinvestment reduction in transformers due to the high cost of its components.
3) Scheduling a plan to replace new transformers.
4) Planning for transformers operation time to prevent aging.
5) Scheduling a plan for the maintenance of transformers.

In recent years, different methods have been presented to estimate the lifetime of the transformer. Some of them analyzed the effect of hot spot temperature on the lifetime of the transformer, while others focused on proposing a solution to determine the Degree of polymerization (DP) of the insulation. Three IEEE C57-91 [2], IEC 60076-7 [3], and IEEE C57-110 [4] discussed a method in order to calculate the hot spot temperature and Loss of Life (LOL). Partial discharge (PD) [5] [6] and dissolved gas analysis (DGA) [7] are two methods that can be employed to clarify the transformer insulation status and determine the DP value [8].

One of the most common methods to obtain the Health Index (HI) of power transformer is the scoring-weighting method. The mentioned method mainly consists of two steps. First, a comparison between each parameter and scoring table is conducted, and according to its importance, an appropriate weight will be assigned to each parameter. It is worth mentioning the weights are determined by expert personnel [9–15]. The scoring-weighting of parameters and aspects are attained by using analytical hierarchy process. This method is constructed based on the decision of five professionals with comprehensive experience in transformer condition monitoring, fault analysis and benefit management [16, 17].

Second, the combination of each score with the index that indicates the health condition of the transformer. Dealing with the data uncertainty, with the aid of current methods for HI identification, is quite complex and a challenging task. New approaches are presented for HI on the basis of machine learning algorithms for big data analysis, thanks to the recent development of both computer science and data processing [18, 19]. In [20], DGA, oil test data, and furan parameters are used to develop

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* Corresponding author:
E-mail: mjoorabian@scu.ac.ir (M. Joorabian)
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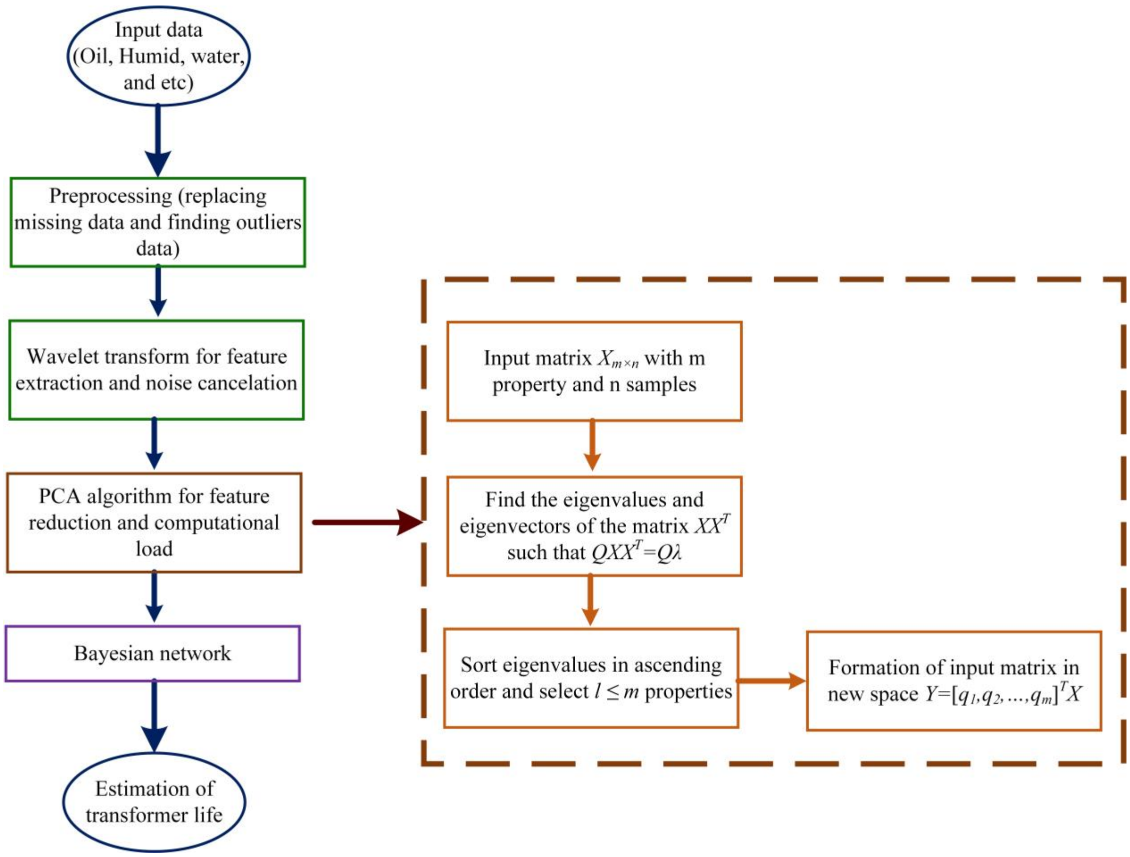

Fig. 1. Flow chart of proposed Model for estimating life time

an artificial intelligence (AI)-based HI approach to study the health condition of transformers. The accuracy of the mentioned estimation method is limited to 56.3%, due to the limited available data.

In another study [21], a HI sensitivity analysis was conducted on a transformer by utilizing a self-adaptive neuro-fuzzy inference system (ANFIS) and the parameters were tuned by a partial swarm optimizer (PSO) algorithm. The future condition of a transformer is predicted in [22] using the Probabilistic Markov chain model which is based on HI calculation with a non-linear optimization algorithm. Another HI-based condition assessment was proposed in [23] using a support vector machine by considering several factors, the judgment of utility experts, and standards of the industry. In [24] a new AI-based method was proposed to classify the transformer condition into four different classes: 1. good, 2. fair, 3. poor, and 4. very poor. In the mentioned method, general regression neural network (GRNN) was employed. Another study employed two analytical hierarchy process (AHP) and principal component analysis (PCA) methods were proposed in order to predict the health condition of the transformer by virtue of expert empirical formula [25], [26].

In previous literature, AI-based methods have been studied to estimate the transformer lifetime. Random forest (RF), k-nearest neighbor (kNN) artificial neural network (ANN), static vector machine (SVM), and decision tree are examples of the AI-based methods that are used in [23] to make the assessment process automatically.

Although previous literature covered the AI-based methods to estimate the transformer lifetime, still the accuracy of studied methods is need to be improved due to the unavailability and uncertainty of the data. In [27] compared numerous machine learning algorithms to assess the lifetime of power transformers through probabilistic basis. A method is obtainable in [28] that compared the performance of several AI approaches in recognizing transformer HI. However, regardless the many AI approaches proposed in the literatures to estimate the transformer lifetime, more thorough studies are still essential to improve the accuracy of methods, in specific with the uncertainty or unavailability of the used data. Reference [29] adopts a normal method to define the uncertainty, and a 95% accuracy was provided for the estimated lifetime; however, the supposed algorithm did not always match the actual condition.

In [30], the effect of data uncertainty on the reliability and accuracy of the lifetime estimation is studied. The main cause for the uncertainty is the inadequate existing data. In [31] informed the consequence of data unavailability and proposed a helpful method constructed on RF to forecast the missing data and improve the scoring-weighting lifetime. However, the expansion and study of AI-based lifetime model in management data uncertainty has not yet investigated carefully with recognized implementation probability.

According to the above-mentioned discussions, there are several motivations to conduct this research as listed below:

- A considerable number of AI-based methods are presented to estimate the lifetime of the power transformers. However, their accuracy is still not acceptable and might not be reliable.
- No estimation method is still acceptable since their accuracy is highly dependent on data and as a result, their reliability is not appropriate due to the data uncertainty.
- Accordingly, the main contributions of the presented paper are:
- Develop an AI-based approach to modify the traditional HI scoring-weighting method for transformer lifetime estimation.
- Utilizing several AI models to process the testing data for the power transformer insulation system in order to improve the accuracy of the HI calculation.
- Presenting an appropriate and practical correlation for the parameters that are involved in transformer HI calculation.

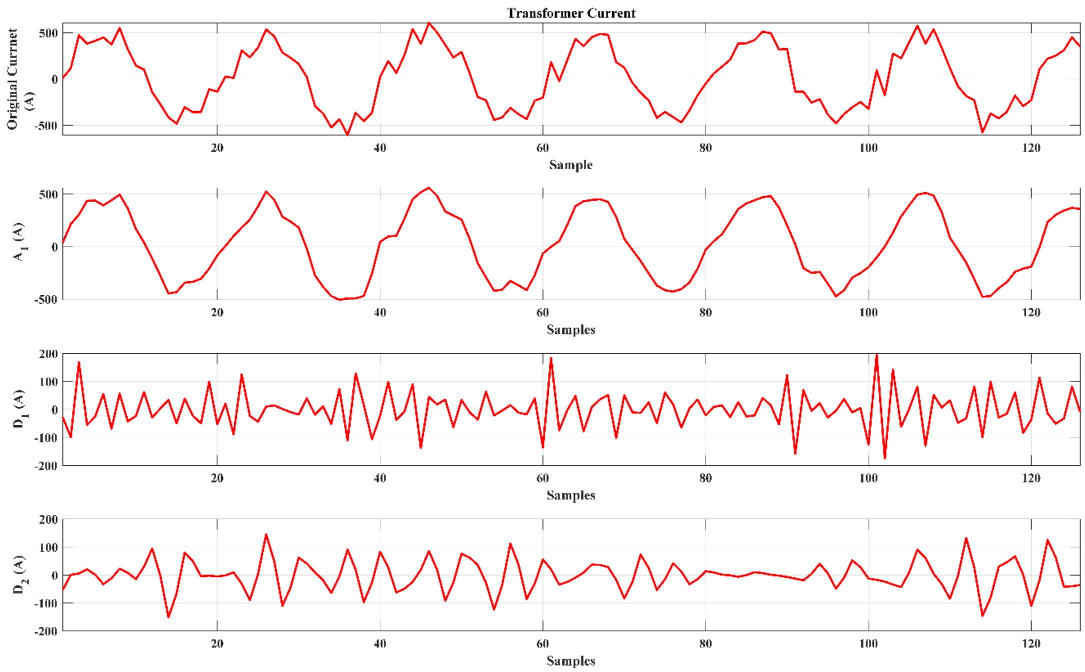

Fig. 2. Applying the wavelet transform on the input current of the transformer

- Proposing the ideal AI-based combination in order to solve the data uncertainty problem and outlier and missing values.
- Using the IQR algorithm to find outliers and anomaly data. Outliers data is information whose value is unreasonably much larger or smaller than other data. This data causes a substantial error during the training of the Bayesian neural network, as well as making the training process difficult.
- In order to extract better and more effective features data that are continuous, such as transformer current, are decomposed by wavelet transform into two sub-signals, one of which contains high-frequency signal information and the other containing low-frequency signal information.
- To reduce the characteristics of variables such as oil and environment temperature, and as a result of reducing the number of neural network inputs and simplifying the model, the PCA algorithm is applied.

1.1. Transformer Health Condition

The process of transformer aging is quite complex and complicated to understand. The deterioration and the aging of the transformers is a function of the electric field intensity, temperature, humidity, oxygen with impurities, water, and many other things. The factors that affect the aging process of a transformer are not independent of each other. Moreover, passing the current with a large amplitude could cause heat and increase the losses [32–35].

The aging topic is discussed for different equipment. Generally, the lifetime of equipment is affected by electrical, thermal, and environmental factors, which are defined below:

1) Overload with harmonic voltage and harmonic current that cause the temperature to rise above nominal value.
2) Life expectancy is reduced, due to periodic use.
3) Mechanical stress also enhance the aging speed (for instance, machine vibration due to load changes)
4) Environmental factors such as humidity are also strongly effective on equipment aging.

Transformers aging has an impact on many other factors such as power outages, the environment, and electricity companies. Excessive transformer loading and harsh environmental conditions are the main reasons that damage the transformer insulation and also accelerate the aging process. Furthermore, not detecting the defects and faults of the equipment at the right time and lack of maintenance affect the aging of transformers. Damaged insulation is associated with malfunctions and undesirable physical parameters changes. For example, the deterioration of paper and oil insulations produces moisture, which accelerates the transformer's aging. When a transformer wears out, its maintenance cost increases dramatically. One of the most important indicators for replacing a transformer is the life of mentioned equipment [36, 37].

Changes in polymerization coefficient, load, and harmonics in the network are playing a major role in the aging process of transformers. Also, factors such as radiation intensity, ambient temperature, and wind are also involved in the aging rate of the transformer [38, 39].

2. Proposed Approach

In this paper, a new method is proposed to properly estimate the remaining life of the transformer by considering various effective factors. In addition to the high accuracy of the model, this method has other features such as interpretability, flexibility in facing new data types, flexibility on complex databases, and the capability to deal with an outlier. For this, data parameters such as oil temperature, gases dissolved in oil, ambient temperature, hot spot temperature, etc. are considered as inputs. Also, employing selection algorithms and suitable features are selected and the lifetime of the transformer is estimated by combining neural networks and other efficient methods.

On the other hand, in the collected data, sometimes the measurement has been taken irregularly. Occasionally, the transformer oil is refined and sampled at indefinite intervals. From time to time, for some reasons, the data does not follow a logical course. As a result, the collected data need to be processed carefully. After processing the data, a study is conducted on the different classification methods and reviewing various modeling with their advantages and weaknesses. In the next step, an appropriate analytical model with high accuracy is developed for the transformer considering effective factors. The flowchart of the proposed method is displayed in Fig. 1 and its different steps are described below.

2.1. Collecting data

In this paper, the real data of the transformers of the electric grid of Iran and Iraq have been used, which are about 500 in total. Data collection was performed at different time intervals and environmental conditions. Used data are listed below:

- Load
- Transformer current peak-peak, RMS, Average, and Max
- Ambient temperature
- Humidity
- Ambient pressure
- Transformer capacity
- Oil temperature
- Harmonic content of voltage and current
- Oil impurities
- Dissolved gases in transformer oil including methane, hydrogen, carbon dioxide, ethylene, ethane, acetylene, propylene, propane, oxygen, nitrogen, and carbon monoxide
- Manufacturing year of the transformer

2.2. Data pre-processing

Used to develop a model. Data processing is quite time-consuming and complex since the collected data included deleted measurements, noise, and outliers. If the processing would have done without recognizing this data, the quality of the model outputs will be decreased significantly. In this paper, the wavelet transform method is utilized to modify and reduce the error. The transformer current is applied during the investigation of the two-level wavelet transform. This action causes to have three signals instead of one. The first signal, which is usually represented by the symbol A1, expresses the behavior of the main signal and its steady state. On the other hand, the D1 signal represents the high-frequency behavior of the main signal, which has the main changes. Also, the D2 signal expresses the high-frequency behavior, but the changes of this signal are less compared to the D1 signal.

The Fig. 2 shows a part of the current waveform of one of the phases of the transformer. (To display and express the idea on a limited number of current samples, wavelet transform has been applied). As can be seen, the A1 signal is very similar to the original signal, in which noises have been removed. Furthermore, D1 and D2 signals form the high-frequency signals of the main current. After applying the Wavelet transform, the features in the following are calculated for each of these signals and are used as input to the Bayesian neural network.

- RMS
- Average
- Peak-Peak
- Max

2.3. Weighting and feature selection

Classification methods require an appropriate function that assigns a specific input pattern to one of the existing classes. Feature selection depends on the accuracy of the function, required time, set of training data, and implementation cost. In this paper, the PCA algorithm method is used for weighting purposes.

2.4. Modeling and determining the data class

In this paper, classification methods are used to develop the analytical model. The classification method is the way in which for each piece of information recorded in the explored data set, there is a label that indicates the information of the problem; Therefore, classification methods belong to the supervised algorithms. In these algorithms, a model is taught in the training phase. Then in the analysis stage, the performance and accuracy of the taught model are evaluated. In this paper, a Bayesian neural network is used to classify different classes.

At this stage, the lifetime of transformers is divided into 5 selected categories.

Table 1. Classifying Transformers according to remaining life time

Analysis	Estimate the remaining lifetime in percent	Estimated Degree of Polymerization (DP)
Normal aging rate	100	800
	90	700
	79	600
Accelerated aging	66	500
	50	400
	46	380
	42	360
Impermissible danger	38	340
	33	320
	29	300
High risk of failure	24	280
	19	260
End of the expected lifetime of paper insulation and transformers	13	240
	7	220
	0	200

3. Brief Description of the Utilized Networks

In the following, the utilized methods are briefly described.

3.1. Wavelet transform

One of the preprocessing tools for data processing is wavelet transform (WT). In this transform, unlike the Fourier transform (FT), there is no frequency parameter involved. Instead, there is a scale parameter that is inversely related to the frequency. Scaling, as its meaning implies, is a mathematical operator that expands and shrinks the signal. Similar to the concept of scale in the map, high scales correspond to the overall view, and the details of the signal are neglected (equivalent to the low frequencies) and small scales correspond to the detailed view of the signal (equivalent to the high frequencies) [40, 41]. At this stage, as shown in Table 1 the lifetime of transformers is divided into 5 sub-categories based on DP.

First of all, measurement errors are modified with the aid of the wavelet transform Wavelet transform of $x(t)$ can be defined as (1):

$$C_{x,\phi}\left(a,b\right)=\int_{-\infty}^{\infty}x\left(t\right)\phi^{*}{}_{a,b}\left(t\right)dt \tag{1}$$

where $\varphi_{a,b}$ can be calculated as (2):

$$\varphi_{a,b}\left(a,b\right)=\frac{1}{\sqrt{a}}\varphi\left(\frac{t-b}{a}\right) \tag{2}$$

where $\varphi\left(t\right)$ is the mother wavelet function, a is a defined scale, and b is a shift.

In discrete wavelet transform, the signal is passed through a series of high-pass filters for high-frequency analysis and through a series of low-pass filters for low-frequency analysis. The signal itself is divided into two different parts. The part of the signal that passes through the high-pass filter, which contains high-frequency information (including noise) and is called details, and the part that passes through the low-pass filter, which contains low-frequency information and identity of the signal and is called general.

The dataset of each parameter (load, voltage, temperature, humidity, etc.) are collected during the 20 years observation. In this case, each of these parameters is considered as a signal. By using the wavelet transform, each of these parameters is converted into several sub-signals that represent the transient and steady state of the main signal. This method is usually employed for parameters such as load and voltage since their transient state must be analyzed carefully.

3.2. Principal component analysis (PCA)

The problem regarded to a large number of variables is generally known as a multidimensional problem. Principal Component Analysis (PCA) is a multivariate technique whose main purpose is to reduce the dimension (number of variables) of a multivariate data set the extent that the changes of the primary variables in the data set could still be explained. This goal is achieved by converting the primary variables into a new set of uncorrelated variables called principal components, which are linear combinations of the primary variables and are arranged in such a way that the first few components compute the greatest variability in the principal variables [42].

Equation (3) shows the general transformation that map each row vector of data matrix to a new vector of principal component scores.

$$Y = Q^T X \tag{3}$$

Where *X* is data matrix, *Y* is new vector of principal components, and Q is vector of weights by which determine equations (4), (5) based on PCA algorithm.

$$X = [x_1, x_2, \ldots, x_n] \tag{4}$$

$$x_i \in \Re^m, x_i = [x_{i1}, x_{i2}, \ldots, x_{im}]^T \tag{5}$$

It is expected that input data matrix is equal to zero, since no information has been lost by the assumption. If the mentioned condition is not satisfied, the inputs can be easily subtracted from the mean values.

$$E\{X\} = 0 \tag{6}$$

$$E\{Y\} = E\left\{Q^T X\right\} = Q^T E\{X\} = 0 \tag{7}$$

In property space, maximum resolution is achieved when the data have the highest variance in the coordinate axes. The variance of the data in the input space is called *R*, therefore:

$$E\left\{XX^T\right\} = R \tag{8}$$

$$\begin{aligned} E\left\{YY^T\right\} &= E\left\{\left(Q^T X\right)\left(Q^T X\right)^T\right\} \\ &= E\left\{Q^T X X^T Q\right\} = Q^T E\left\{XX^T\right\} Q = Q^T R Q \end{aligned} \tag{9}$$

If the following equation holds, $\varphi(Q)$ becomes maximized when Q matrix corresponds to the eigenvectors of *R* matrix.

$$\varphi(Q) = Q^T R Q \tag{10}$$

If the eigenvalues of the R matrix are sorted in descending order so that λ_1 corresponds to the largest eigenvalue and λ_m corresponds to the smallest eigenvalue, then:

$$\begin{aligned} \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \\ q_1 \geq q_2 \geq \cdots \geq q_m \end{aligned} \tag{11}$$

Generally, Y matrix has M number of properties. In order to reduce the number of properties, l number of the properties that have the most variance is selected and create the $\hat{Y}$matrix. The mentioned matrix provides the highest resolution.

$$\hat{Y}_i = [q_1, q_2, ..., q_l]^T X_i \tag{12}$$

3.3. Bayesian regularization-backpropagation method

Usually, the goal of training is to reduce the sum of square errors [43]. However, regularization adds new conditions to the objective function, which is expressed in the following equation:

$$F = \beta E_D + \alpha E_\omega \tag{13}$$

Which$E_D$represent the sum of the error squares, E_ω is the sum of the squares of the network weights, $\alpha$and$\beta$are the components of the objective function. The relative amplitude of the objective function components indicates the training process. If $\alpha \ll \beta$, the training algorithm makes the error smaller. If $\alpha \gg \beta$, the training algorithm reduces the weights at the expense of network error and accordingly, creates a smoother network response.

The main problem with implementing regularity is setting the integer values for the objective function components. In the Bayesian framework, network weight is considered as a random variable. After collecting the data, the weight density function can be updated according to Bayes' law:

$$P(w|\, D, \alpha, \beta, M) = \frac{P(D|\, w, \beta, M)\, P(w|\, \alpha, M)}{P(D|\, \alpha, \beta, M)} \tag{14}$$

Where D represents a set of data, M is the specific employed neural network model, and w is the weight vector of the network. $P(w|\, \alpha, M)$is the previous density, which indicates our knowledge of weights before collecting any data.

$P(D|\, w, \beta, M)$ is a probability function, which indicates the probability of the data occurring with respect to the weight w. $P(D|\, \alpha, \beta, M)$is a normalization factor that guarantees the overall probability is equal to 1.

4. Case Study

In this paper, 500 transformers from Iran and Iraq electricity networks have been selected and sampling has been done in different climatic conditions during several different years. The confusion matrix is one of the most common methods of describing the performance of a classification model on a described database. The simplest way of calculating the accuracy of a model is obtained from the following equation.

$$Acc = \frac{n_T}{n_T + n_F} \tag{15}$$

where n_T , $n_F$are two parameters that describe the number of classes that are incorrectly and correctly labeled, respectively. One of the serious drawbacks of this method is the assessment of non-segregation errors between classes. For example, in this case, it cannot be recognized how many data that the model has assigned them to label A have been labeled correctly. Conversely, how many labeled A/ data have been labeled properly. This is important when a class of data is notable. In the proposed confusion matrix of this paper that has shown in Fig. 3, the labels placed on the row of this matrix represent the label that has been assigned by the model, and the data placed on the column represent the actual label of the model.

Among of 70 transformers belonging to the category of transformers with "normal aging" (sum of the numbers in the first column), 69 are correctly labeled and only one of the transformers belonging to the category of "normal aging" is incorrectly assigned to the category of "accelerated aging". Thus, only 1.5% of transformers with "normal aging" are incorrectly labeled as "accelerated aging". In other words, 100% of the transformers that the model has assigned as "normal aging" are correctly labeled.

From 242 transformers labeled "accelerated aging", one of these transformers is mistakenly classified as "Impermissible danger". Thus, 99.5% of the transformers that had "accelerated aging" were labeled correctly by the model. As can be seen in the second row of the matrix, 99.2% of the 244 transformers that the model

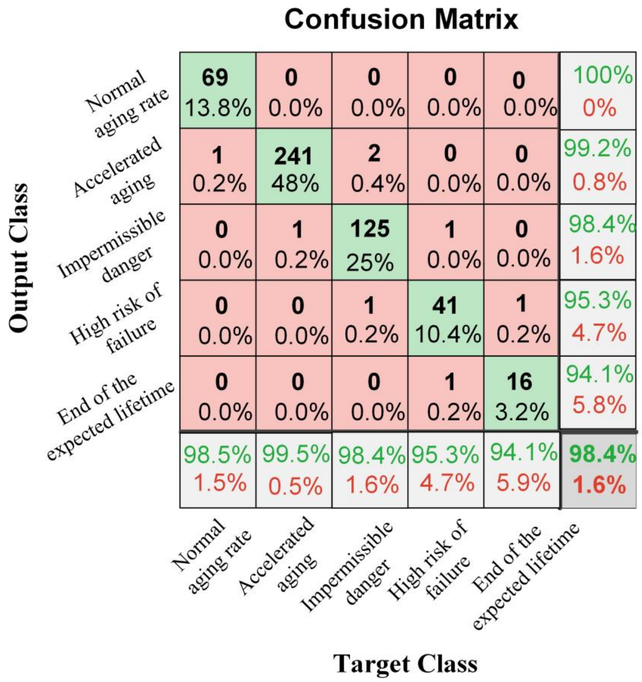

Fig. 3. Confusion Matrix of Proposed model

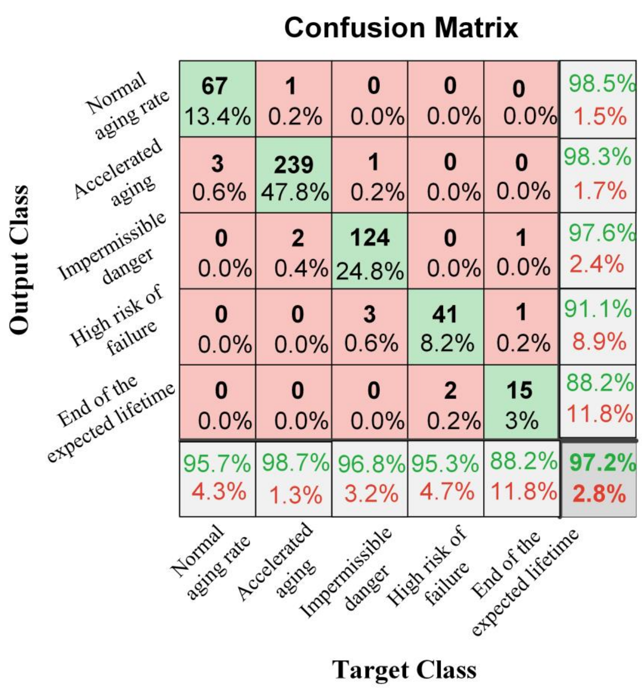

Fig. 4. Confusion Matrix of Bayesian NN without Applying Preprocessor

labeled as “accelerated aging” are correctly classified. (2 cases labeled as " Impermissible danger" and 1 case labeled "normal aging").

Similarly, 97.6% of the 128 transformers were correctly labeled with "Impermissible danger", and 3 transformers were incorrectly classified in other categories ("accelerated aging" and "high risk of failure"). 125 out of 127 transformers categorized in the "Impermissible danger" were correctly labeled and only 2 transformers were incorrectly labeled (one labeled as "high risk of failure" the other one labeled as "Impermissible danger"). Therefore, the accuracy of the model for this group of transformers is equal to 98.4%.

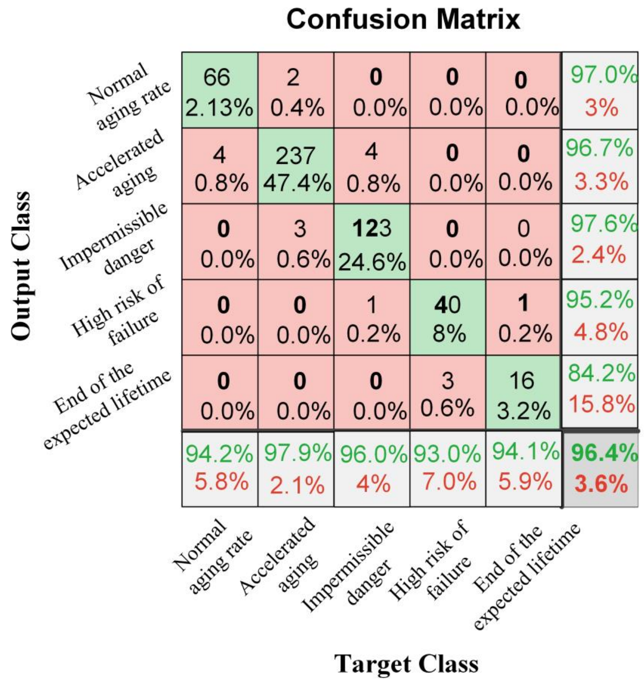

Fig. 5. Confusion Matrix of Multilayer perceptron with Preprocessor

For 43 "high risk of failure" transformers, 41 cases were correctly labeled and two transformers were incorrectly classified as "Impermissible danger" and "end of expected lifetime”. Thus, 95.3% of transformers are properly labeled with a "high risk of failure" status. In other words, only 2 transformers out of 43 transformers that the model has labeled "high risk of failure" belong to other categories ("end of life expectancy" and "Impermissible danger") and as a result, the accuracy becomes 95.3%.

Finally, out of 17 transformers in the "end of expected lifetime" category, only one is labeled in the other categories. In better words, 94.1% of the transformers are correctly labeled "end of expected lifetime".

Finally, 94.1% of the transformers labeled "end of expected lifetime” were labeled correctly by the model and only one transformer incorrectly labeled "high risk of failure".

It should be noted that the numbers in the green and red cells of the matrix indicate the percentage out the of total 500 transformers.

In order to validate the proposed method in the paper, a simulation without wavelet transform is performed once again. Due to the removal of the wavelet transform algorithm, all parameters are considered as input without any processing. Some of these parameters have errors and inaccuracies that are caused by various factors. Then, with these parameters, the life of the transformer is estimated. As can be seen in Fig. 4, the result indicated the accuracy of the proposed method decreased considerably (about 1.2%) without the wavelet transform.

If the PCA is removed from the proposed method, the simulation time would be too long due to the great number of data, which is not reasonable.

In this paper, various methods and combinations have been tested to select the most appropriate algorithm that has the best overall performance. Therefore, in the latter case that has shown in Fig. 5, wavelet transform and PCA are present, but the MLP neural network is used instead, which is obviously less accurate than the presented network.

In this proposed model, a considerable amount of time is spent on data collection, and other algorithm steps (such as training, testing, and execution) do not require much time. In addition, in the proposed model, the goal is not to improve the speed

Table 2. Comparing the accuracy of the proposed model with some other models

Model	Accuracy
Propose Model	98.4%
K nearest neighbors' algorithm (KNN)	92%
Support vector machine	93%
multilayer perceptron neural network (MLPNN)	96.4%
Bayesian neural network without pre-processor	97.2%
decision tree	89%

because no analysis is supposed to happen online and in real-time. Therefore, the issue of the speed of the proposed model is not very important. Also, the number of inputs considered for the prediction model is as follows.

- The average loads connected to the transformer every month;
- Average, RMS, maximum, peak-peak, and such third to seventh-order harmonics resulting from 3-level wavelet transform on voltage and transformer current every month;
- Other parameters mentioned in the text of the paper are monthly averages over twenty years.

Furthermore, almost all the parameters affecting the lifetime of the transformer have been taken into account. Despite the fact that most references only focus on one specific factor, it is not a fair comparison between this proposed method and other presented models. However, using all the data and parameters used for the proposed model, several other benchmark models have been considered. Table 2 shows the comparison of the proposed model with several other methods. At First, life is estimated separately for both countries, Iran and Iraq, with considering all parameters. In this case, the accuracy of the proposed algorithm was 98.43 for Iran and 98.39 for Iraq. Since the environmental conditions and accordingly, the performance of transformers in Iran and Iraq are different from each other. Also, the factors that play a major role in the accuracy of lifetime estimation will also be different. As a result, the effect of various factors on the performance of the transformers of Iraq and Iran will be investigated separately in order to study the sensitivity of lifetime estimation based on the climate of the region.

4.1. The effect of environmental conditions on the performance of the transformer

The normal operating conditions of the transformer are defined in accordance with IEC60076 standard, as follows. 40 degrees Celsius is the maximum temperature
-25 degrees Celsius is the minimum air temperature
30 degrees Celsius is the average temperature in the warmest month
20 degrees Celsius is the average annual temperature
The height of the installation site is 1000 meters above sea level
Iran and Iraq have completely different environmental conditions according to the provided meteorological data over the years for both countries. Therefore, to conduct a sensitivity analysis of the parameters, one of the meteorological parameters is not considered in each stage, then the lifetime is estimated. The results are displayed in Fig. 6. For example, the maximum temperature is not considered in the inputs of the proposed algorithm. Also, Iraq has more days with higher temperature than Iran. As a result, as shown in Figure 6, without considering this parameter, the accuracy of transformer lifetime estimation is higher for Iran than Iraq. In other words, lifetime estimates for transformers located in Iraq are more dependent on the maximum temperature.

As can be concluded from Fig. 6 the accuracy of the lifetime estimation for Iraq is more dependent on meteorological parameters since Iraq has a tropical climate. Iran has more pollution and higher installation height, so the mentioned parameters have a considerable impact on the accuracy of the estimation in Iran.

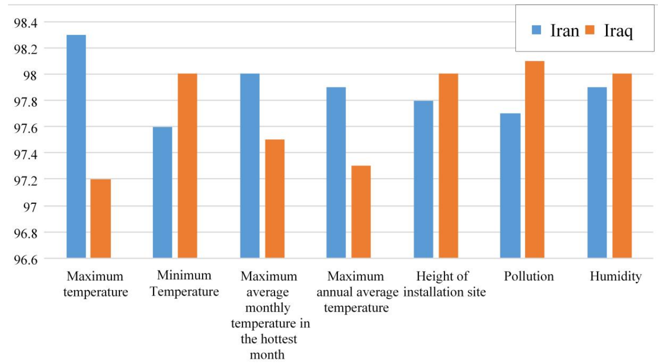

Fig. 6. The effect of environmental conditions on the performance of the transformer

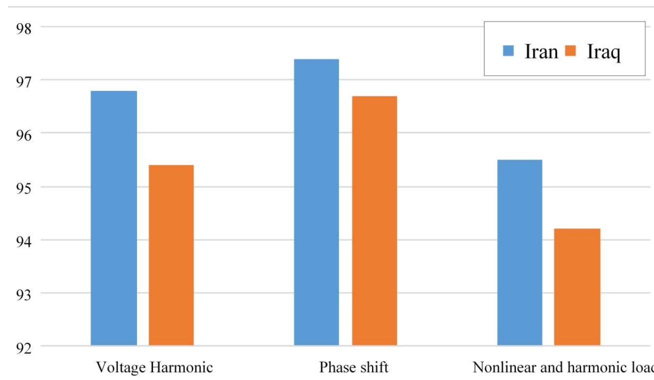

Fig. 7. The effect of power quality parameters on the accuracy of life estimation

4.2. Power Quality

Harmonics have a considerable impact on transformers, especially in the distribution sector. Transformers are designed to operate at the rated frequency and are connected to the linear loads. Grid harmonics inevitably increase the losses and temperature of the transformer simultaneously and consequently, reduce the lifetime of the transformer.

Voltage harmonics increase the winding losses and enhance the hot spot temperature of the coils as well. Thus, the rate of transformer aging increases. The IEEE C57-110 standard describes the harmonic effect on transformer losses and hotspot temperatures in detail.

Also, one of the parameters that affect the aging rate of the transformer is the total load and its type. The higher the load connected to the transformer, the higher the losses and the hot spot temperature. As a result, load characteristics should be taken into account since it has an impact on the aging rate of the transformer. IEEE standards C57-91 and IEC60076-7 analysed the aging rate of the transformers according to the type of load.

In Fig. 7, the lifetime of the transformer is estimated for both countries considering different power quality conditions. As seen in Figure 7, Iraq is much more dependent on these parameters than Iran due to the low power quality. From this section, it can be concluded that in developed countries, power quality parameters can be ignored in the lifetime estimation without a significant decrease in the accuracy of the algorithm.

4.3. Transformer Oil

Transformer oil must be free of any mechanical Particulates, moisture, bitumen, and other materials with poor electrical properties. Impurities and moisture reduce the dielectric breakdown voltage of transformer oil. Since the transformer oil is a mineral

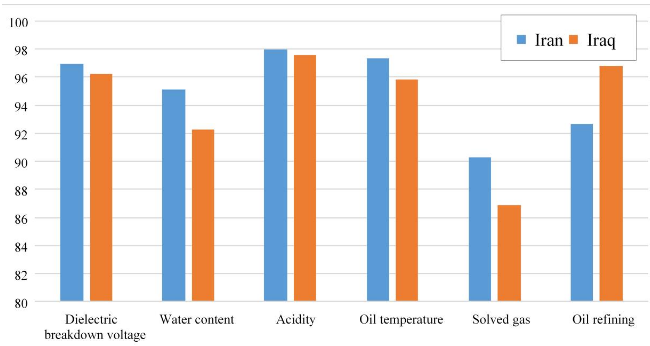

Fig. 8. The effect of oil quality parameters on the accuracy of life estimation

compound, it is vulnerable to heat and oxygen. due the fact that, the oil is oxidized and polar and acidic compounds are produced in their presence.

Regular maintenance and refining of transformer oil could significantly improve the performance and lifetime of the transformer. The quality and purity of the oil are considered as one of the major factors in the lifetime of the transformer. The impure and dirty oil is one of the reasons that cause the transformer to catch fire. One of the appropriate methods to monitor the status of the transformer is to study the soluble gases in the transformer oil. These gases are created by mechanical, thermal, and electrical stresses inside the transformer and usually include methane, carbon monoxide, hydrogen, ethylene, acetylene, carbon dioxide, and ethane. According to IEC61599, the amount of each of these gases in the transformer oil indicates a specific problem in the transformer, and ignoring these gases can cause great damage. Moisture also could deteriorate the quality of the power transformer oil and affects its insulation as well. The life of insulation is proportional to the amount of moisture absorption. Also, increasing humidity in areas with high electric field intensities causes a partial discharge and finally, imposes serious damage to power transformers.

Figure (8) shows the oil quality of Iran and Iraq and their effect on the lifetime of the studied transformer.

5. Conclusion

Transformers are one of the most crucial and expensive power grid equipment. Nowadays, a lot of research is done in the field of transformer maintenance. According to the previous reports, a great number of transformers wear out completely before they reach the end of their expected lifetime. Furthermore, any disturbance and problem in the transformer hugely affect the network. It can be concluded that fast transformer fault detection and diagnosis will improve the reliability of the grid and prevent power outages. Therefore, providing a solution to present an accurate lifetime estimation for the power transformer is essential and it's the main topic and purpose of this paper.

In this paper, the development and implementation of artificial intelligence methods has been presented to estimate the lifetime of a transformer with considering numerous factors, and IEEE recommendations for all specified condition parameters of a transformer. The main goal of this method is to reduce the estimation error and computational burden as well. This algorithm uses collected and pre-processed data for the estimation. Pre-processing has been proposed to overcome the data uncertainty by considering the missing values with the wavelet transform. The impact of missing data on the model has been evaluated, and the proposed method performed better than other methods. A comparison of various methods is investigated and using the PCA for weighing the various parameters to improve the accuracy and decrease execution time. Based on comparison, the Bayesian neural network is chosen as the proposed method with the highest accuracy to predict the transformer remaining lifetime.

1) The benefits of the proposed method are summarized as below:
2) Using the combined method in order to reduce the estimation time
3) Accurate modelling of transformers and factors affecting its performance
4) Flexibility of the proposed method against new and outlier data.

References

[1] A. Schijndel, J. Wetzer, and P.A.A.F. Wouters, "Forecasting transformer reliability," *IEEE Conf. Elec. Insul. Dielectric Phenom.*, pp. 577–582, 2006.

[2] IEEE guide for loading mineral-oil-immersed Transformers and Step-Voltage Regulators, pp. 1–123, 2012.

[3] IEC loading guide for oil immersed power transformers, pp. 60076–7, 2005.

[4] IIEEE Recommended Practice for Establishing Liquid-Immersed and Dry-Type Power and Distribution Transformer Capability When Supplying Nonsinusoidal Load Currents, pp. 1–68, 2018.

[5] E. Müllerová, J. Hrůza, J. Velek, I. Ullman, and F. Stříska, "Life cycle management of power transformers: results and discussion of case studies," *IEEE Trans. Dielectr. Electr. Insul.*, Vol. 22, No. 4, pp. 2379–2389, 2015.

[6] G.C. Montanari, "Aging and life models for insulation systems based on PD detection," *IEEE Trans. Dielectr. Electr. Insul.*, Vol. 2, No. 4, pp. 667–675, 1995.

[7] "Mineral oil-impregnated electrical equipment in service: guide to the interpretation of dissolved and free gases analysis," *IEC Stand.*, Vol. 44, p. 60599, 2013.

[8] M. K. Pradhan and T. S. Ramu, "On the estimation of elapsed life of oil-immersed power transformers," *IEEE Trans. Power Deliv.*, Vol. 20, No. 3, pp. 1962–1969, 2005.

[9] A. Jahromi, R. Piercy, S. Cress, J. Service, and W. Fan, "An approach to power transformer asset management using health index," *IEEE Electr. Insul. Mag.*, Vol. 25, No. 2, pp. 20–34, 2009.

[10] A. Naderian, S. Cress, R. Piercy, F. Wang, and J. Service, "An approach to determine the hHealth iIndex of power transformers," in *Conf. Rec. IEEE Int. Symp. Elec. Insul.*, pp. 192–196, 2008.

[11] I.G.N.S. Hernanda, A.C. Mulyana, D.A. Asfani, I.M.Y. Negara, and D. Fahmi, "Application of health index method for transformer condition assessment," in *IEEE Region 10 Conf.*, pp. 1–6, 2014.

[12] W.R. Tamma, R.A. Prasojo, and Suwarno, "High voltage power transformer condition assessment considering the health index value and its decreasing rate," *High Volt.*, Vol. 6, No. 2, pp. 314–327, 2021.

[13] W.R. Tamma, R. Azis Prasojo, and S. Suwarno, "Assessment of high voltage power transformer aging condition based on health index value considering its apparent and actual age," in 12^{th} *Int. Conf. Informa. TechNo. Elec. Eng. (ICITEE)*, pp. 292–296, 2020.

[14] L. En-Wen and S. Bin, "Transformer health status evaluation model based on multi-feature factors," in *Int. Conf. Power Sys. Techno.*, pp. 1417–1422, 2014.

[15] K. Taengko and P. Damrongkulkamjorn, "Risk assessment for power transformers in PEA substations using health index," in 10^{th} *Int. Conf. Elec. Eng. Electron. Computer, Telecommu. Inform. Techno.*, pp. 1–6, 2013.

[16] R. Azis Prasojo, Suwarno, N. Ulfa Maulidevi, and B. Anggoro Soedjarno, "A multiple expert consensus model for

transformer assessment index weighting factor determination," in 8^{th} *Int. Conf. Condition Monitoring Diagnosis (CMD)*, pp. 234–237, 2020.

[17] R.A. Prasojo, A. Setiawan, Suwarno, N.U. Maulidevi, and B. Anggoro Soedjarno, "Development of analytic hierarchy process technique in determining weighting factor for power transformer health index," in 2^{nd} *Int. Conf. High Volt. Eng. Power Sys. (ICHVEPS)*, pp. 1–5, 2019.

[18] R. Behkam, A. Moradzadeh, H. Karimi, M. S. Nadery, B. Mohammadi Ivatloo, G.B. Gharehpetian, and S. Tenbohlen, "Mechanical fault types detection in transformer windings using interpretation of frequency responses via multilayer perceptron," *J. Oper. Autom. power Eng.*, vol. 11, no. 1, pp. 11–21, 2022.

[19] N. Eskandari and S. Jalilzadeh, "Electrical load manageability factor analyses by artificial neural network training," *J. Oper. Autom. power Eng.*, vol. 7, no. 2, pp. 187–195, 2019.

[20] E. Kadim, N. Azis, J. Jasni, S. Ahmad, and M. Talib, "Transformers health index assessment based on neural-fuzzy network," *Energies*, Vol. 11, No. 4, p. 710, 2018.

[21] K. Ibrahim, R.M. Sharkawy, H.K. Temraz, and M.M.A. Salama, "Transformer health index sensitivity analysis using neuro-fuzzy modelling," in 2^{nd} *Int. Conf. Advanced TechNo. Appli. Sci. (ICaTAS)*, 2017.

[22] M. Yahaya, N. Azis, M. Ab Kadir, J. Jasni, M. Hairi, and M. Talib, "Estimation of transformers health index based on the markov chain," *Energies*, Vol. 10, No. 11, p. 1824, 2017.

[23] A.D. Ashkezari, Hui Ma, T.K. Saha, and C. Ekanayake, "Application of fuzzy support vector machine for determining the health index of the insulation system of in-service power transformers," *IEEE Trans. Dielectr. Electr. Insul.*, Vol. 20, No. 3, pp. 965–973, 2013.

[24] M.M. Islam, G. Lee, and S.N. Hettiwatte, "Application of a general regression neural network for health index calculation of power transformers," *Int. J. Electr. Power Energy Syst.*, Vol. 93, pp. 308–315, 2017.

[25] S. Li, G. Wu, H. Dong, L. Yang, and X. Zhen, "Probabilistic health index-based apparent age estimation for power transformers," *IEEE Access*, Vol. 8, pp. 9692–9701, 2020.

[26] S. Tee, Q. Liu, and Z. Wang, "Insulation condition ranking of transformers through principal component analysis and analytic hierarchy process," *IET Gener. Transm. Distrib.*, Vol. 11, No. 1, pp. 110–117, 2017.

[27] J. I. Aizpurua, B. G. Stewart, S. D. J. McArthur, B. Lambert, J. G. Cross, and V. M. Catterson, "Improved power transformer condition monitoring under uncertainty through soft computing and probabilistic health index," *Appl. Soft Comput.*, Vol. 85, p. 105530, Dec. 2019, doi: 10.1016/j.asoc.2019.105530.

[28] A. Alqudsi and A. El-Hag, "Application of Machine Learning in Transformer Health Index Prediction," *Energies*, Vol. 12, No. 14, p. 2694, 2019.

[29] J.I. Aizpurua, S.D.J. McArthur, B.G. Stewart, B. Lambert, J.G. Cross, and V.M. Catterson, "Adaptive power transformer lifetime predictions through machine learning and uncertainty modeling in nuclear power plants," *IEEE Trans. Ind. Electron.*, Vol. 66, No. 6, pp. 4726–4737, 2019.

[30] Condition Assessment of Power Transformers, *CIGRE*, Document 761, 2019.

[31] R.A. Prasojo, Suwarno, and A. Abu-Siada, "Dealing with data uncertainty for transformer insulation system health index," *IEEE Access*, Vol. 9, pp. 74703–74712, 2021.

[32] P.A.A. F. Wouters, A. Van Schijndel, and J.M. Wetzer, "Remaining lifetime modeling of power transformers: individual assets and fleets," *IEEE Electr. Insul. Mag.*, Vol. 27, No. 3, pp. 45–51, 2011.

[33] E.A. Mackenzie, J. Crossey, A. DePablo, and W. Ferguson, "On-line monitoring and diagnostics for power transformers," *IEEE Int. Symp. Elec. Insul.*, pp. 1–5, 2010.

[34] R. Zhang, M. Dong, G. Zhang, and Z. Yan, "Investigation of return voltage measurement for the assessment of power transformers," in *Int. Conf. Condition Monitoring Diagnosis*, pp. 902–905, 2008.

[35] Q. Hong, J. Zhang, Q. Xie, S. Liang, Y. Xu, S. Li, and W. Hu, "Transformer's condition assessment method based on combination of cloud matter element and principal component analysis," *Energy Power Eng.*, Vol. 09, No. 04, pp. 659–666, 2017.

[36] E. Fuchs and M. Masoum, Power quality in power systems and electrical machines, Elsevier Academic Press, 2008.

[37] C.T. Dervos, C.D. Paraskevas, P.D. Skafidas, and N. Stefanou, "Dielectric spectroscopy and gas chromatography methods applied on high-voltage transformer oils," *IEEE Trans. Dielectr. Electr. Insul.*, Vol. 13, No. 3, pp. 586–592, 2006.

[38] A. Elmoudi, M. Lehtonen, and H. Nordman, "Effect of harmonics on transformers loss of life," in *Conf. Rec. IEEE Int. Symp. Elec. Insul.*, pp. 408–411, 2013.

[39] P. Hari Mukti, F. Agung Pamuji, and B. Sofiarto Munir, "Implementation of artificial neural networks for determining power transfomer condition,", 5^{th} *Int. Symp. Advanced Control of Indu. Processes (ADCONIP 2014)*, pp. 4–8, 2014.

[40] R.M. Rao and A.S. Bopardikar, Wavelet Transforms: Introduction to Theory & Applications, Longman Pub Group, 1998.

[41] J.T. Olkkonen, *Discrete wavelet transforms-theory and applications*, *InTech*, 2011.

[42] M. Nadler and E. P. Smith, *Pattern recognition engineering*, *Wiley-Interscience*, 1993.

[43] F. Dan Foresee, and M.T. Hagan, "Gauss-newton approximation to bayesian learning," in Proc. of the *Int. Conf. Neural Net. (ICNN'97)*, Vol. 3, pp. 1930–1935 1997,