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Application of Multilayer Perceptron Neural Network for Transformer Health Index Monitoring

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ABSTRACT

Dissolve Gas Analysis (DGA) is a method of diagnosis employed in the assessment of transformers, enabling the distinction between transformers in optimal operating condition and those requiring scheduled repair. The primary objective of DGA is to accurately identify and characterise the issues arising from different gas forms within transformers. The Key Gas Method (KGM) analysis is a commonly employed approach within the field of DGA. The KGM method is employed for predicting the health index of transformers by analysing the production of gases within the transformer. The study involved the arrangement of many classifiers to achieve optimal performance, taking into consideration four specific configuration parameters. The multilayer perceptron (MLP) network, K-Nearest Neighbourhood (KNN), Linear Discriminant Analysis (LDA), and Support Vector Machine (SVM) algorithms are used to classify the data. The accuracy of the MLP network surpasses that of other classifiers, achieving a rate of 90.67%. Additionally, the mean squared error (MSE) for the MLP network is 0.92. Three distinct training algorithms were chosen for the purpose of training a MLP using the Backpropagation (BP), Lavenberg Marquardt (LM), and Bayesian Regularisation (BR) training procedures. At the conclusion of the simulation, the BR training algorithm demonstrates superior performance, achieving an accuracy rate of 91.25% and a MSE value of 0.93.

1. Introduction

Power transformers are the most valuable assets inside a power grid, thereby constituting a substantial proportion of the overall investment in a power delivery system. The necessity of conducting planned observations and general maintenance as preventive measures should be considered due to the potential consequences of a malfunctioning transformer, such as power outages. These outages can lead to substantial financial losses for plant owners, as they are unable to generate energy [1–2]. Furthermore, the presence of defective transformers can lead to

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potentially perilous circumstances, including the generation of excessive noise, power outages, and combustion, ultimately resulting in the emission of smoke from the transformers. Consequently, ensuring the appropriate functioning of a transformer is imperative to mitigate potential ramifications for its health.

Power transformers are operating at levels of load that are approaching their nominal limits due to the ongoing increase in demand. This raises the likelihood of potential failure or inability to perform their intended function. This research primarily focuses on utilising a neural network to tackle the challenge of health monitoring in power transformers. Hence, expeditiously identifying the problem with the transformer is imperative to uphold the optimal balance between maintenance expenses, capital investment prices, and the expenses associated with ensuring a secure working environment [3].

In the latter part of the 19th century, the process of computing the health index (HI) underwent significant advancements, rendering it increasingly valuable in assessing the state of transformers. The HI is a reliable and efficient technique used to assess the condition of power transformers by considering multiple characteristics. The HI was determined by considering and integrating several components throughout the procedure. The provided data encompassed comprehensive information pertaining to the current of a transformer, as well as additional test outcomes, expert evaluations, and data acquired through field inspections. To achieve cost reduction, it is imperative to minimise the quantity of necessary experiments that need to be conducted. Artificial neural networks (ANN) are employed for the purpose of predicting HI. To eliminate tests that are deemed to be of minimal significance, the feature-based exhaustive technique is utilised [4].

In contemporary times, the expeditious advancement of computer science and data processing has resulted in the emergence of novel HI methodologies for the analysis of huge datasets, which are based on machine learning algorithms. The quick advancements in technology have facilitated the development of these novel approaches [5]. The researchers investigated an ANN that utilised the HI approach. The ANN incorporated data obtained from dissolved gas analysis, furan testing, and oil testing to assess the overall health condition of many transformers that were already operating at an optimal level [6]. The study employed ANN to assess the health index of power transformers. The data used in this research was obtained from one of electrical provider in Malaysia and was derived from a sample of 50 transformers located in the Klang Valley region.

2. Literature Review

In general, the transformer health index can be regarded as a measurement or assessment of the condition and performance of the transformer. Typically, the evaluation process entails an inspection of various factors, such as temperature, oil quality, insulation condition, winding resistance, and further diagnostic tests. Through the inspection of these properties, researchers and professionals can assess the overall condition of a transformer as well as determine the remaining lifespan of the equipment. This capability allows them to discern possible malfunctions and, consequently, arrange preparation for maintenance or replacement procedures. The transformer HI is a single factor that considers information from operational observations, field inspections, and lab tests to come up with the best asset management choice for transformers. According to the source cited as [7], this choice has the potential to successfully maintain the operational efficiency of transformers.

The analysis of the variables that have the most significant impact on the transformer health index has garnered considerable interest among numerous researchers. The primary sources of uncertainty in a simulation are attributed to the levels of the data source and diagnostics. Measurement uncertainties have a significant impact on the available data sources, manifesting in several types of errors, such as measurement and quantization inaccuracies. These deficiencies are evident in the available data sources. The presence of accurate knowledge or stochastic uncertainties both contribute to the influence of modelling uncertainties on diagnostic models. This phenomenon is true irrespective of the specific form of uncertainty that is encountered. Fig. 1 displays the framework of the transformer health index that was constructed and executed.

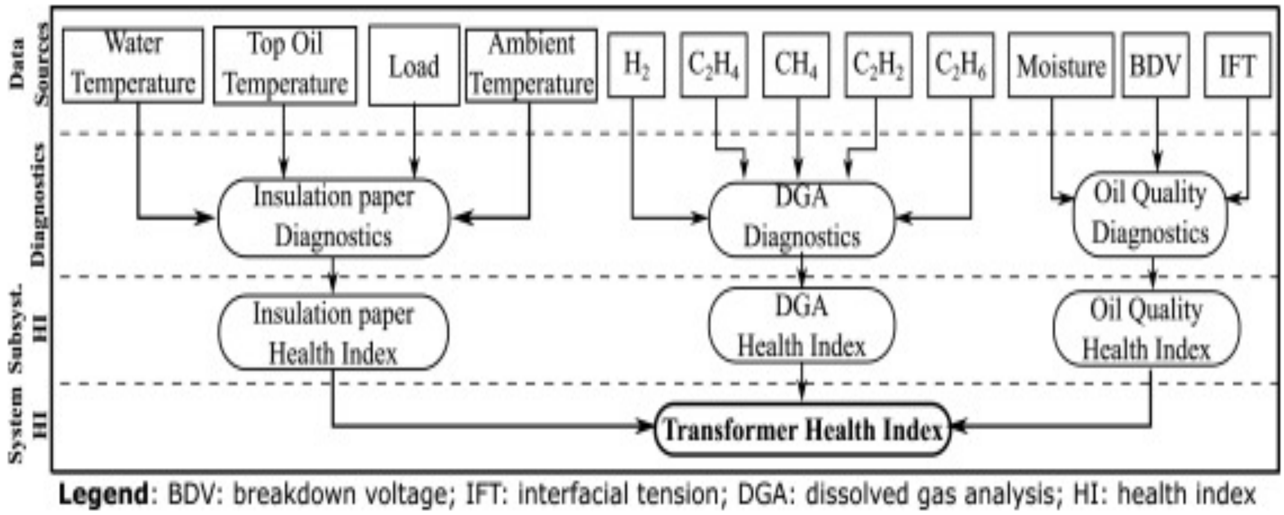

Fig. 1. Transformer health index soft computing framework [8]

Furthermore, the impact of many sources of uncertainty, which are analysed inside different subsystems of the transformer, is propagated to the higher level of the transformer health index. This facilitates the enhancement of the final decision-making process and renders it suitable for use inside systems characterised by measurement and process uncertainty. Moreover, it renders it appropriate for utilisation inside decision-making procedures that are enveloped by ambiguity. The diagnostic approach known as DGA is commonly employed to assess the operational status of electrical power transformers and ascertain their overall health. To accomplish this duty, it is necessary to do measurements and investigations on the gas concentrations that have been dissolved in the insulating oil of a transformer. The generation of these gases occurs within the transformer because of various defects and abnormalities present in the internal components of the device. The device exhibits several defects and abnormalities. The DGA is a diagnostic technique commonly employed for the routine assessment of transformer conditions [9]. This is since prior empirical evidence has indicated that the DGA is a very effective tool [10].

Techniques constructed in the field of artificial intelligence were employed to derive an approximation of the HI of the transformers. The developmental trajectory of an ANN-based HI model is reminiscent of the chronological sequence depicted in Fig. 2, available at the provided location. The utilisation of artificial intelligence in assessing the state of power transformers proves to be highly advantageous in the analysis of extensive datasets pertaining to transformers [13].

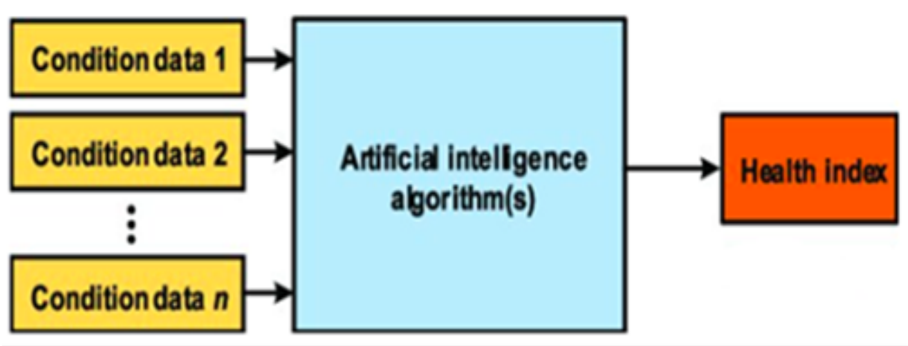

Fig. 2. Assessing transformer health index using ANN principle [13]

Computational systems that utilise artificial intelligence, such as ANN, have the capability to acquire knowledge on how to establish a correlation between the health index's response output and a distinct collection of associated inputs, such as values obtained from monitoring variables. The rapid advancement of technology and the resulting increase in the volume of raw data present a major challenge for artificial neural networks, which involves the extraction of meaningful features from the input. The increase in the quantity of unprocessed data has coincided with the swift progress of technology. According to the source cited as [15], the goal is to compute the HI of a transformer by simulating an ANN's operation. A feedforward artificial neural network and an empirical measurement of the working transformer were used to figure out the HI of the transformer. Furthermore, the authors [16–17] propose the use of a prognostication framework that is based on an algorithm designed for an ANN.

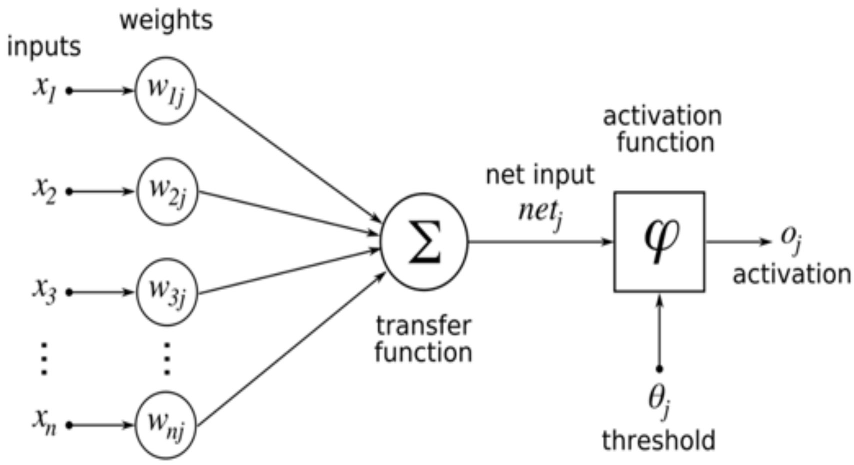

Fig. 3. Artificial neural model

The suggested system, called "distribution transformer failure prediction," would be put in place on the management plane so that real-time sensor data sent to our proposed cloud infrastructure could be used to make regular predictions. The forecast would rely on data gathered through the implementation of our proposed cloud infrastructure. This would enable the generation of periodic projections. Previous studies have employed ANN methodology and fuzzy logic approaches [18–20] to classify the state of the transformer by implementing typical condition tests.

3. Methodology

The employed research methodology is referred to as the integration of the KGM into a system designed for the analysis of transformer data obtained via DGA. The conditions outlined in Table I have functioned as the guiding framework for arranging this dataset. The determination of these circumstances is achieved through the execution of the TDCG computation, which entails the summation of the diverse gas concentrations. Subsequently, the TDCG is employed to define the criteria for structuring the data, utilising the data itself for this purpose. Subsequently, the values obtained from the TDCG are employed in the data sorting procedure.

The limit concentration identified in Table I, known as the TDCG, served as a benchmark for categorising the gathered data into four distinct groups. The term "Condition 1" refers to a transformer that satisfies all specified standards and is devoid of any discrepancies. The term "Condition 2" pertains to a condition that remains acceptable despite the existence of certain minor flaws, allowing for its utilisation despite the presence of these limited issues. The item is currently in a suboptimal condition, and it has been identified that there are issues that require fixing or maintenance within the upcoming six-month period. The ailment in question is identified as "Condition 3." The term "Condition 4" pertains to a critical situation wherein significant flaws necessitate quick fixing within a timeframe of three months or as soon as possible.

Table 1
Limit assigned as input

TDCG Limit	Condition
720	1
721-1920	2
1921-4630	3
>4630	4

The MLP uses data provided by the Transmission and Distribution Corporation, commonly referred to as the TNB, as its input. The MLP network has interconnected neurons, each possessing predefined weights and biases. The process of data transmission within a MLP network is commonly known as "feedforward." This phenomenon arises as data is transmitted from the input layer to the output layer. The term "procedure" is employed to refer to the ongoing process. The presence of one or several intermediary layers between the input and output layers of a MLP is contingent upon the specific implementation. The quantity of levels may vary contingent upon the design of the model.

The output of the network is given by:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 \, \partial \left(\sum_{i=1}^{n_i} w_{ij}^1 \, x_i^0(t) + w_{k0}^1 x_0^1 \right) \quad (1)$$

for $1 \leq j \leq n_h$ and $1 \leq k \leq m$

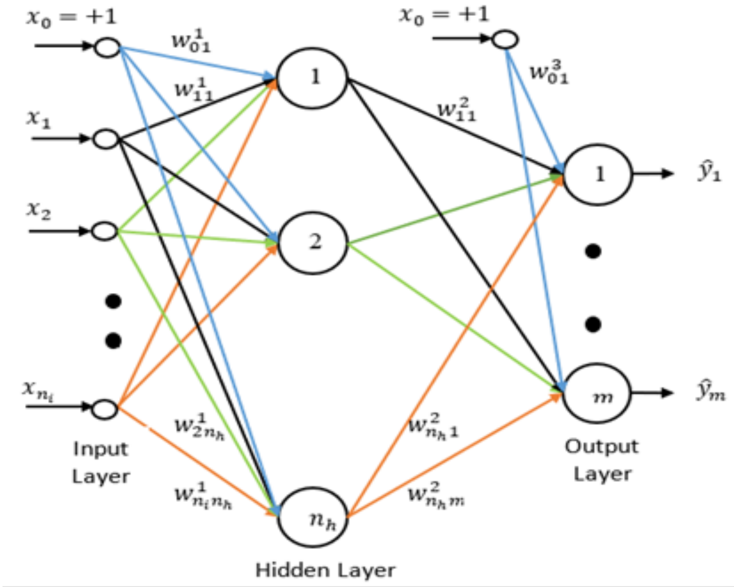

Fig. 4. MLP architecture with one hidden node

with the Logsig and Purelin activation functions. The Logsig activation function is coupled to a bipolar sigmoid and ranges from 0 to +1. As the reference, Figure 5 shows the Logsig function for the MLP network. The threshold must be configurable at any point between 0 and +1.

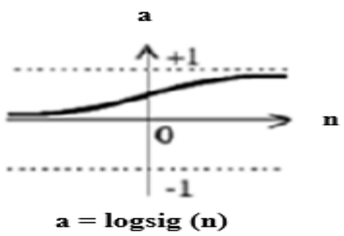

Fig. 5. Logsig activation function

The Tansig activation function is associated with a bipolar sigmoid. The output of the Tansig function is range from -1 to + 1. Figure 6 shows the Tansig function for MLP network activation. The threshold must be ranging at any point ranging between -1 to +1.

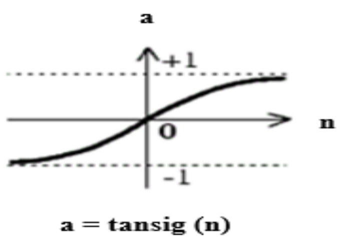

Fig. 6. Tansig activation function

4. Result and Discussion

The implementation of the KGM will be undertaken, and the primary objective of this research is to determine the most efficient approach to attaining it. The objective of the research is to evaluate and contrast the effectiveness of different training algorithms with respect to the morphology of the parameters under discussion. To assess the efficiency of the network, parameters such as accuracy and MSE are employed. Furthermore, this research will explore alternative approaches to diagnosing

DGA. The anticipated output values are presented in Table II, representing the accuracy and MSE of the MLP classifier, expressed as percentages.

Table 2
The performance of MLP with different training algorithm and activation function

Training algorithm	Accuracy	MSE
BP with Logsig	76.02%	0.88
BP with Tansig	82.67%	0.85
LM with Logsig	89.38%	0.71
BR with logsig	90.89%	0.47
LM with Tansig	91.25%	0.33
BR with Tansig	93.47%	0.26

The results presented in Table II provide valuable insights into the strengths and weaknesses of different classifiers in relation to the task. The MLP classifier emerges as the most suitable option for this specific classification challenge due to its notable precision and minimal MSE, rendering it a feasible alternative. The MLP classifier has been selected for further analysis based on its superior performance, as indicated in Table II. Three distinct training methods, namely BP, LM, and BR, have been utilised to train the MLP network. The MLP network is activated with Logsig and Tansig activation functions. As depicted in table above, it is evident that each training procedure has the potential to generate distinct prediction results. The results from using the three training methodologies and two activation functions with the MLP classifier in addition to the corresponding prediction outputs. The performance of predictions can yield performance measures such as accuracy and MSE. Due to the diverse optimisation approaches, convergence behaviours, and capabilities of different training algorithms in handling complex data patterns, it is anticipated that there will be variations in the prediction outcomes. LM and BR are widely recognised as advanced optimisation methods that are highly effective in dealing with non-linear issue. On the other hand, BP is a well-established, commonly employed algorithm.

The findings indicate that the BR algorithm with Tansig activation function has superior performance, achieving a prediction accuracy of 93.47% and a MSE of 0.26. The BR training approach has superior performance compared to the other training methods in terms of prediction high accuracy and exhibits a lower MSE. The LM algorithm with Tansig activation function, which is ranked second in terms of performance, demonstrates an accuracy of 91.25% and a MSE of 0.33. Although LM exhibits significantly inferior performance compared to BR, it nevertheless demonstrates comparable accuracy and MSE values. In contrast, the performance of the BP algorithm appears to be inferior to that of the BR and LM algorithms. The backpropagation algorithm (BP) achieves an accuracy of 82.67% and a MSE of 0.85 with Tansig activation function and 76.02% and a MSE of 0.88 with Logsig activation function. The observed decrease in prediction accuracy and increase in MSE may suggest that the BP algorithm may not be well-suited for the specific task or dataset under evaluation. Based on the results presented in Table II, it can be concluded that the BR algorithm with Tansig activation function emerges as the most favourable choice for training the MLP network. This determination is based on its superior performance in terms of accuracy, which is the highest among the evaluated options, as well as its ability to minimise the MSE, which is the lowest observed. The selection of the training method significantly impacts the performance of the MLP classifier. Based on the results obtained, it can be inferred that BR is a more suitable choice for the given task compared to LM and BP. On top of that, Tansig activation function is capable of giving better performance than Logsig activation function.

5. Conclusion

The objective of this study is to assess the precision, applicability, and reliability of classifiers in forecasting the health indices of power transformers. Gaining a comprehensive comprehension of the functioning mechanisms of these networks facilitates the advancement of more precise and reliable techniques for assessing the condition of transformers. Consequently, this leads to the formulation of improved maintenance strategies, increased reliability, and enhanced performance of power systems. This study proposes a novel approach to enhance the diagnostic precision of transformer failures through the utilisation of a MLP network classifier in the domain of DGA. The present approach utilises the MLP network to evaluate the performance of power transformers in terms of their health index. The classifier used six primary concentrations of flammable dissolved gases as input for determining the type of transformer failure. These gases included hydrogen, ethane, methane, carbon monoxide, ethylene, and acetylene. The MLP neural network, trained using the BR training algorithm and Tansig activation function, achieved a maximum accuracy percentage of 93.47% and a MSE value of 0.26.

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