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HEALTH INDEX OF TRANSFORMER'S MONITORING USING ARTIFICIAL INTELLIGENT

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ABSTRACT

Dissolve Gas Analysis (DGA) for transformers is used to differentiate between a transformer in good condition or the one which needs to schedule for maintenance. The main goal of DGA is to identify more precisely problems caused by the various gas formations in the transformer and encountered. Key Gas Method (KGM) analysis is one of the DGA's techniques often used. KGM is used in forecasting the health index of the transformer based on formational of gases in transformer. KGM's classified the transformer health index in several conditions, which are Condition 1, Condition 2, Condition 3, or Condition 4. The multilayer perceptron (MLP) network outperforms K-Nearest Neighbourhood (KNN), Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) classifiers with 90.02 % on accuracy. On the other hand, Bayesian Regularization (BR) training algorithm gives the best accuracy results among Levenberg Marquardt and Backpropagation training algorithms with 95.10 % on accuracy.

1.0 INTRODUCTION

Transformers are crucial in a substation's power system. However, they require regular maintenance to prevent malfunctions and power outages, which can lead to significant financial losses and hazardous environments [1-2]. Power transformers, operating near their maximum capacity due to increasing load demands, are prone to failure. This study focuses on using neural networks for transformer health monitoring to strike a balance between maintenance expenses, capital expenditures, and safety [3]. Transformers experience thermal and electrical stress, with the latter causing voltage irregularities, hot patches, and potential cable failures. Various diagnostic methods exist, such as numerical analysis, leak factor calculation, Park's vector approach, ANNs, and high-frequency analysis. A study by Reddy and Kumar proposes a field-based and precise method using double Fourier Series modelling to detect transformer faults [4]. However, the approach's limitations, such as requiring extensive data and complex mathematical calculations, restrict its widespread use. ANNs, with nodes resembling biological neurons and interconnecting links, can process input data, perform operations, and yield node values, making them effective for monitoring transformer health [5]. Choosing an appropriate diagnostic method is vital in identifying transformer defects and maintain operational efficiency, safety, and cost-effectiveness quickly and efficiently.

There is a method that is often used in determining the transformer health index. This method is the method that has been used by one of Malaysia power provider which is by recording the amount of gas found in the transformer oil. The oil will be taken to the laboratory to calculate and analyse the amount of TDCG and then determine the type of condition of the transformer whether it is condition one (1), two (2), three (3) or four (4). The DGA method is commonly used to detect early faults and evaluate the condition of power transformers. However, there are still some important issues that require further investigation to enable utilities to reliably diagnose transformer issues [6-7]. Firstly, not all combinations

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of gas ratios from measurements can be accurately classified into specific fault types in different DGA interpretation schemes, which may result in inconsistent diagnostic results when using different interpretation methods [8-9]. Secondly, certain DGA methods may not be able to diagnose certain faults, while other interpretation schemes can identify potential faults in transformers. Lastly, existing DGA interpretation schemes are mainly based on statistical analysis and expert knowledge and may not fully explore the relationship between gas concentrations and different fault types. Therefore, more advanced interpretation techniques such as expert systems, ANNs, and fuzzy logic are required to determine the correlation between dissolved gases and the insulation conditions of transformers [6].

2.0 LITERATURE REVIEW

An electrical power system is a network of electrical devices used to provide, transmit, and utilize electric power is referred to as an electric power system. An electric grid is a method for distributing electricity to buildings and businesses over a wide area. The supply of electrical power system is completed through a generation source (such as a power plant), the transfer is accomplished through a transmission and distribution system, and the consumption can be accomplished through either residential or industrial uses, such as running large motors or powering your home's lights and air conditioner. The electrical grid, which supplies energy to businesses and residences over a wide area, is an illustration of a power system. There six main components in electrical power system which is power plant that generate an electricity, transformer which is step up and step down the voltages, transmission line to convey the power, substations where the voltage is reduced to transport electricity over distribution lines, distribution lines and distribution transformers used for that decrease the voltage to the required level for consumer goods. Inspection of transformers is crucial as the insulation may degrade, leading to mechanical issues and potential short circuits between conductors. Dissolved Gas Analysis (DGA) is a widely used method to assess transformer condition, detecting faults by analysing gases dissolved in the transformer oil [7]. DGA is effective in identifying around 70 % of common transformer issues and excels in interpreting gas levels for anomaly detection. It can identify problems such as partial discharge, thermal issues, and arching. The presence of specific gases in the transformer indicates the formation of problems. Overall, DGA is a valuable technique for diagnosing and monitoring transformer health. There are six types of faults that are shown in Table 1 [8].

Table 1. Type of fault

Type of fault	Description
Partial discharges of the corona-type (PD)	Discharges in gas bubble or voids trapped in paper
Discharges of low energy (D1)	Low energy arcing, inducing surface tracking of paper & carbon particles in oil
Discharges of high energy (D2)	High energy arcing or flashovers
Thermal faults of temperatures <300 °C (T1)	Overloading or blocked oil ducts
Thermal faults of temperatures between 300 and 700°C (T2)	Defective contacts and welds
Thermal faults of temperatures >700°C (T3)	Large circulating currents in tank and core

Conventional testing methods for transformer oil analysis can be time-consuming and prone to inaccuracies, leading to delayed fault identification and potential catastrophic failures. Human errors in sampling and storage further contribute to inaccuracies and ambiguous diagnoses. To overcome these challenges, online monitoring DGA has Doernenburg Ratios Method (DRM), KGM, Rogers Ratios Method (RRM), and Duval Triangle Method are employed in DGA [9-10]. Online monitoring provides a more efficient and reliable means of identifying faults, reducing the risk of transformer failures, and minimizing the time between fault occurrence and diagnosis. By adopting online DGA, the need for manual sampling and laboratory testing is eliminated, ensuring prompt fault detection, and enabling timely actions to save the transformer from further damage been developed. This approach enables continuous monitoring through internet-based systems, allowing for real-time detection of changes in gas concentrations.

Key gas method, which is thought of as a TDCG modification. It enables a rough estimation of potential fault types that are empirically identified from a transformer's particular gas profile. This approach also emphasizes the gas that makes up the majority of TDCG (sometimes known as the "key" gas") [11]. This

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approach is helpful for benchmarking in the normal range as well as for validating diagnoses in the warning range. This method's strong propensity for producing ambiguous outcomes is another drawback. If applying the given values in accordance with the standard, all gases will be high but inadequate to signal a fault if a serious fault includes the paper insulation. KGM is the most common method that have been used in TNB because this method is the most fundamental method for determining transformer health index. The gasses that involved in KGM are Hydrogen (H_2), Methane (CH_4), Acetylene (C_2H_2), Ethylene (C_2H_4), Ethane (C_2H_6) and Carbon Monoxide (CO). TDCG can be calculated when the concentrations of the dissolved flammable gases are added up to determine the total dissolved combustible gas. Since carbon monoxide typically makes up a significant portion of TDCG, its utility for fault identification and diagnosis is not substantial. It indicates the condition level of the transformer shown in Table 2 [12].

Table 2. Dissolve key gas concentration limit

Status	Dissolved key gas concentration limit [μL/L(ppm) ^{3}]							
	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDCG
Condition 1	100	120	1	50	65	350	2500	720
Condition 2	101-700	121-400	2-9	51-100	66-100	351-570	2500-4000	21-1920
Condition 3	701-1800	401-1000	10-35	101-200	101-150	571-1400	4001-10000	1921-4630
Condition 4	>1800	>1000	>35	>200	>150	>1400	>10000	>4630

The status of the transformer based on Condition Based Maintenance (CBM), Asset management department, TNB indicates that:

a) Condition 1 – No fault detected, can be used.
b) Condition 2 – Fair condition, with a possibility of a fault present, can still be used.
c) Condition 3 – Poor condition. There is fault detected, requires maintenance within 6 months.
d) Condition 4 – Bad condition. There is a serious fault detected and requires maintenance within 3 months.

Artificial neural networks (ANNs) mimic the functioning of the human brain. With billions of neurons communicating through electrochemical impulses, the brain's structure and connections determine its performance. Neurons consist of components such as dendrites, soma (cell body), axon, and synapses. Dendrites receive signals, the soma processes information, and the axon transmits signals to other neurons at synapses. ANNs replicate biological neural networks using synthetic nodes connected by weighted connections. The nodes have transfer functions, which are the inputs, hidden layers, and output nodes. The connections between nodes represent the mathematical model of artificial neurons, encoding information in the network. ANNs excel at fitting complex nonlinear models without prior specification, making them valuable for data modelling. They make decisions based on the weighted inputs, accounting for bias and processing the sum through a transfer function. The output represents the analysed information. The flexibility and ability to learn from data are advantages of neural networks, as they can make decisions without requiring explicit programming [13].

3.0 RESEARCH METHODOLOGY

By integrating Key Gas Method (KGM) within the system, the data obtained from the transformer would be sorted, in accordance with the condition displayed in Table 3. The conditions within the table mentioned are based on the Total Dissolved Concentration Gases (TDCG), calculated through the summation of all the listed gasses in Table 4.

Table 3. Data from TNBR

No.	H_2	O_2	N_2	CH_4	CO	CO_2	C_2H_4	C_2H_6	C_2H_2	Condition
1	580	208	72745	187	67	711	209	283	1235	3
2	392	1226	69081	80	62	811	44	288	196	2
3	5815	1276	58472	822	791	1302	775	1125	3223	4
4	88	9499	51376	11	528	6394	19	10	25	1
5	90	5719	50612	14	586	7422	16	9	30	2
6	82	9359	61758	9	573	6746	8	7	10	1
7	5502	146	60133	274	148	1047	267	69	2506	4
8	9403	1141	56528	703	209	1356	1038	136	4175	4

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No.	H_2	O_2	N_2	CH_4	CO	CO_2	C_2H_4	C_2H_6	C_2H_2	Condition
9	13655	1614	53211	1264	317	2332	2947	411	9848	4
10	1056	1516	61429	86	145	860	117	14	979	3

* Hydrogen=H_2, Oxygen=O_2, Nitrogen=N_2, Methane=CH_4, Carbon Monoxide=CO, Carbon Dioxide=CO_2, Ethylene=C_2H_4, Ethane=C_2H_6, Acetylene=C_2H_2

Table 4. TDCG concentration limit

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

The data will be categorized into four (4) types of conditions based on TCDG limit concentration as shown in Table 4. By using TCDG as a reference, this will be easier to know the output data to observe the transformer's health by type of conditions. There are four (4) types of conditions which is "Condition 1", in which there is no fault detected and it could be used accordingly. Secondly, "Condition 2" which is within fair condition, with the possibility of some miniscule fault, yet still usable. For "Condition 3", the transformer is already in poor condition because there is fault detected, requiring and need repair or maintenance within six (6) months. Lastly, "Condition 4" is the transformer's health being in a critical condition because there is serious fault detected and urgent repair services are required within three (3) months or as soon as possible.

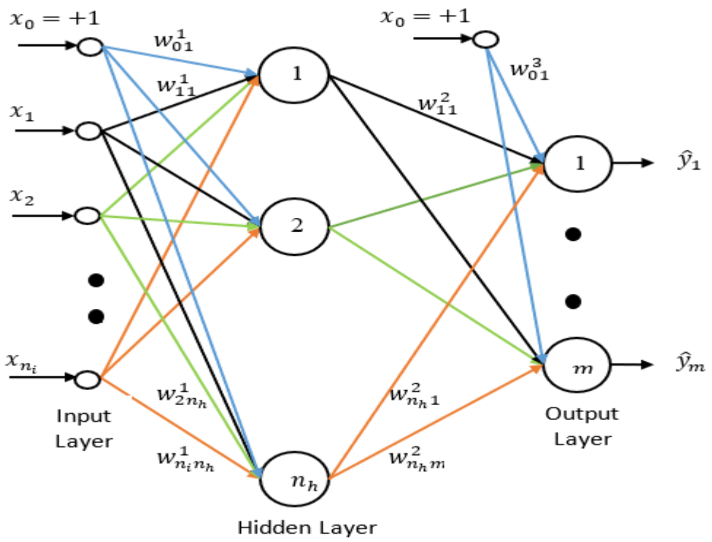

Figure 6. MLP architecture with one hidden layer

Neural network performance will be compared among training algorithm which are Bayesian Regularization (BR), Levenberg Marquardt (LM) and Backpropagation (BP). A neural network's performance against other training algorithm can be compared to help determine which model is most suitable for a given task. The research needs to select the classifier that offers the best balance between accuracy, computational complexity, interpretability, and other important variables based on the evaluation findings.

4.0 RESULTS AND DISCUSSIONS

The objective of this study is to discover the optimal procedure for carrying out the KGM. The best factor morphology's performance with each training algorithm will be compared as part of the research and the best method will be an GUI of transformer health index monitoring by using MATLAB. The network's performance is based on accuracy and MSE, which will be tested further using additional DGA diagnosis techniques. The result shows a comparison of result between neural network with other classifier such as KNN, SVM and discrimination in percentage.

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Table 6. Classifier performances

Classifier	Accuracy (%)	MSE
KNN	88.32	0.25
MLP	90.02	0.17
LDA	72.35	1.37
SVM	86.47	0.32

This study entails the comparison of four independent classifiers to assess the precision of the transformer health index. Among the classifiers under consideration, the MLP has the most noteworthy accuracy level of 90.02 %, achieved by the iterative optimisation of weights and biases. Furthermore, it demonstrates a commendable capacity to reduce the discrepancy between predicted and desired results, as evidenced by its MSE score of 0.25. The last algorithm to be discussed is the KNN classifier, which exhibits the second highest level of performance, achieving an accuracy rate of 88.32 % and a MSE value of 0.25. This performance displays its proficiency in estimating the health index of the transformer. In contrast, the SVM classifier demonstrates an accuracy rate of 86.47 % and a MSE value of 0.32.

Although the SVM does not outperform the two leading classifiers, it nevertheless exhibits a commendable degree of accuracy when it comes to forecasting the health index of transformers. In conclusion, the LDA classifier demonstrates the lowest level of accuracy, with a recorded accuracy rate of 72.35 %. Furthermore, it has a larger MSE value of 1.37, suggesting a more significant discrepancy between the predicted and desired results in comparison to the remaining classifiers. In conclusion, the research findings indicate that the MLP has superior performance in terms of accuracy and MSE reduction. It is followed by the KNN and SVM models. On the other hand, LDA exhibits worse accuracy and MSE performance when evaluating the health index of the transformer.

Table 7. Results of training algorithm based MLP Network

Training algorithm	Accuracy (%)	MSE
BP	81.27	1.19
LM	92.19	0.15
BR	95.10	0.09

On the other hand, the MLP network has been selected for a comprehensive examination, which entails the use of various training methods, including BP, LM and BR. Significantly, the BR training algorithm stands out as the highest performing method among the three, demonstrating an impressive accuracy rate of 95.10 % and a low MSE value of 0.09. The result highlights the effectiveness of the BR algorithm in enhancing the forecasting capabilities of the MLP network for the transformer health index. The subsequent section presents the LM training method, which exhibits the second-highest level of performance in this examination. The achieved accuracy level is 92.19 %, accompanied by a MSE value of 0.15. The statement highlights the efficacy of the LM algorithm in improving the accuracy and precision of the MLP network for forecasting the health index of transformers.

On the other hand, it can be observed that the BP training algorithm produces the least desirable outcomes when compared to the other two methods. The achieved accuracy rate is 81.27 %, accompanied by a higher MSE of 1.19. Although the MLP network's performance with this training strategy is not as impressive as that of the BR and LM algorithms, it nevertheless offers valuable insights for study. In conclusion, the analysis demonstrates that the BR training algorithm emerges as the most optimal selection for enhancing the accuracy of the MLP network and reducing the MSE, with the LM method ranking second in effectiveness. On the other hand, the BP method demonstrates relatively inferior performance in terms of accuracy and MSE for predicting the health index of transformers.

5.0 CONCLUSIONS

The study aims to monitor the health index of power transformers using artificial intelligence and analyse the condition of transformers based on the analysis of six gases. The key gas method is employed to determine the transformer's condition, and the data is then trained using a neural network to assess accuracy. The objective is to enhance monitoring and assessment of transformer health by applying artificial intelligence techniques such as machine learning and data-driven models. This enables the identification and diagnosis of potential faults or anomalies in power transformers, leading to proactive maintenance, reduced downtime, and improved performance of power systems. The study successfully

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achieves its objectives by obtaining accurate outputs through training and demonstrating the performance of neural networks in determining transformer health. The study explores the reliability, generalizability, and accuracy of hierarchical neural networks in predicting the health index of power transformers, which can facilitate the development of more precise and reliable methods for assessing transformer health and improving maintenance plans. The research also introduces a novel DGA method using a neural network classifier to enhance the diagnostic precision of transformer failures. The study compares the performance of different classifiers, with the neural network achieving the highest accuracy.

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