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Transformer Health Index Monitoring using Artificial Neural Network

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ABSTRACT

Dissolved Gas Analysis (DGA) is an effective method for detecting power transformer faults due to its high sensitivity to minor electrical faults. This study employs DGA, specifically the Doernenburg Ratio Method (DRM), to classify transformer faults and predict transformer health, categorizing it into one of four conditions. The analysis leverages Multilayer Perceptron (MLP) neural networks for decision-making, comparing various DGA methods to identify the most appropriate one and resolving conflicts in the Doernenburg ratios. Different MLP network architectures are evaluated by analysing two output data types and three hidden layer types. The models are trained and tested using experimental data from Malaysia's power provider company. The results suggest that MLP network ratios combination offers high accuracy and generalizes better compared to other models and is practically applicable for automated power transformer diagnosis. The classification accuracies of the MLP network classifier are compared with Fuzzy Logic (FL), Radial Basis Function (RBF), K-Nearest Neighbour (KNN), and Probabilistic Neural Network (PNN) classifiers. Findings indicate that the proposed preprocessing approach significantly improves diagnosis accuracies for power transformer fault classification.

1. Introduction

1.1 Theoretical Background

Power transformers are important parts of the power system in substations. They need regular maintenance to avoid breakdowns and power outages, which can be costly and dangerous [1-2]. Transformers often operate close to their maximum capacity because of growing power demands, which makes them prone to failure. This study looks at using neural networks to monitor transformer health to balance maintenance costs, capital spending, and safety [3]. Transformers face thermal and electrical stress, with electrical stress causing voltage issues and possible cable failures. The reliability of a power system relies heavily on the condition of its power transformers. Being one of the most crucial and expensive parts, a transformer's failure can lead to power outages. Early detection of

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trallowmer problems allows for preventative maintenance, reducing the risk of failures and service interruptions [2]. Traditional devices like Buchholz relays or differential relays monitor transformers, but they only react to severe issues requiring equipment shutdowns. Early fault detection techniques are valuable to prevent outages [3].

DGA is a very useful tool for early fault detection. It regularly checks the insulation oil in transformers to measure gas levels caused by the breakdown of insulating materials. Methods like the Doernenburg ratios analyse these gas levels to identify faults [4-5]. Artificial Intelligence (AI) methods, including Artificial Neural Networks (ANNs), have been applied to DGA data for improved transformer fault diagnosis. ANNs can handle complex problems with multilayered networks [5,8]. The RBF network is often used for pattern recognition and fault diagnosis. Moravej *et al*., [9] applied RBF network to transform differential relaying [9]. Additionally, integrated neural fuzzy approaches for transformer fault diagnosis using DGA have been developed. These methods use competitive learning and fuzzy logic models to handle noisy input data effectively [10]. The backpropagation (BP) neural network is another advanced tool for fault diagnosis, extensively used in transformer fault detection [11-12].

A common method to determine the transformer health index is used by power provider company in Malaysia. This method involves recording the amount of gas found in the transformer oil, which is then analysed in a laboratory to calculate the Total Dissolved Combustible Gas (TDCG) and determine the transformer's condition (1 to 4). The DGA method is widely used to detect early faults and assess the condition of power transformers. However, there are still several important issues that need further investigation to enable reliable transformer diagnostics [6-7]. Firstly, not all gas ratio combinations from measurements can be accurately classified into specific fault types using different DGA interpretation schemes. This may result in inconsistent diagnostic results when different interpretation methods are used [8-9]. Secondly, certain DGA methods may not be able to diagnose specific faults, while others can. On top of that, the research tries to utilize artificial intelligence (AI) techniques for monitoring the health index of power transformers based on DRM. The performance of hierarchical neural networks in assessing the health index of power transformers based on DRM technique will be measured and compared against other diagnostic methods.

2. Literature Review

2.1 Electrical Power System

An electrical power system is a network designed to generate, transmit, and use electric power. Essentially, an electric grid is how electricity is distributed to homes and businesses over a wide area. This process starts at a power plant, where electricity is generated. The electricity is then transferred through a system of transmission and distribution lines, eventually reaching residential and industrial consumers. This could involve running large motors or powering household appliances like lights and air conditioners. The electrical grid, which supplies energy across a wide area, is a great example of a power system. There are six main components in this system: power plants that generate electricity, transformers that step up and step-down voltages, transmission lines that carry electricity over long distances, substations where voltage is reduced for distribution, distribution lines that transport electricity to consumers, and distribution transformers that lower the voltage to levels suitable for consumer use.

2.2 Dissolved Gas Analysis (DGA)

Inspecting transformers is essential since insulation can degrade, leading to mechanical problems and possible short circuits between conductors. The DGA is a widely used technique to evaluate transformer condition by detecting faults through the analysis of gases dissolved in transformer oil [7,13]. DGA effectively identifies approximately 70% of common transformer issues, excelling at interpreting gas levels to spot anomalies. It can detect issues like partial discharge, thermal problems, and arcing. Specific gases in the transformer oil indicate the development of issues. Overall, DGA is a valuable tool for diagnosing and monitoring transformer health. There are six types of faults listed in Table 1 [13].

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 ℃ (T1)	Overloading or blocked oil ducts
Thermal faults of temperatures between 300 and 700℃ (T2)	Defective contacts and welds
Thermal faults of temperatures >700℃ (T3)	Large circulating currents in tank and core

Traditional methods for analysing transformer oil can be time-consuming and prone to inaccuracies, resulting in delayed fault detection and potential catastrophic failures. Errors in sampling and storage further contribute to inaccuracies and unclear diagnoses. To address these challenges, online monitoring DGA employs methods such as the DRM, KGM, Rogers Ratios Method (RRM), and Duval Triangle method. Online monitoring offers a more efficient and reliable way to identify faults, reducing the risk of transformer failures and minimizing the time between fault occurrence and diagnosis. By using online DGA, the need for manual sampling and laboratory testing is eliminated, ensuring immediate fault detection and enabling timely actions to prevent further transformer damage. This approach allows for continuous monitoring through internet-based systems, enabling real-time detection of changes in gas concentrations.

2.3 Doernenburg Ratio Method (DRM)

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"). This 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 transformer’s industry since this method is the most fundamental method for determining transformer health index.
The gases that are involved in KGM are as follows:

- Hydrogen (H2)
- Methane (CH4)
- Acetylene (C2H2)
- Ethylene (C2H4)
- Ethane (C2H6)
- Carbon Monoxide (CO)

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

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. The status of the transformer based on Condition Based Maintenance (CBM), Asset management department of a power provider company 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.

2.4 Artificial Neural Network (ANN)

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

3. Methodology

3.1 Acquire Transformer's Data from Database and Apply KGM

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 gases in Table 3.

Table 3
Dissolve key gas concentration limit

No.	Hydrogen (H2)	Oxygen (O2)	Nitrogen (N2)	Methane (CH4)	Carbon Monoxide (CO)	Carbon Monoxide (CO2)	Ethylene (C2H4)	Ethane (C2H6)	Acetylene (C2H2)	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
9	13655	1614	53211	1264	317	2332	2947	411	9848	4
10	1056	1516	61429	86	145	860	117	14	979	3

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.

Table 4
Dissolve key gas concentration limit

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

3.2 Create an ANN

Once the data has been examined, the process of choosing activation functions, establishing the connections between the neurons, and deciding on the number and size of layers will be made. After that, the network's weights and biases at random will be initialized. An optimization approach such as backpropagation is used to update the weights and biases after feeding the network training data, computing the output, comparing it to the intended output, and updating the weights and biases. Lastly, check the accuracy to see if it matches the output.

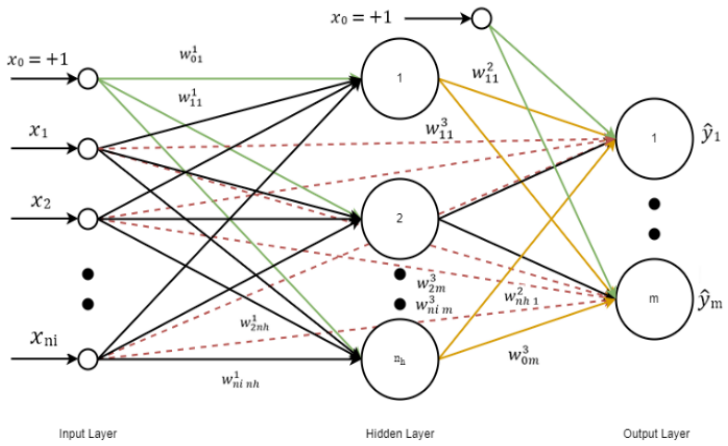


Fig. 1. MLP architecture with one hidden layer

To create a successful neural network model, much thought should be given to the network architecture, training parameters, and regularization methods throughout the process. The process through which data travels in MLP network from the input to the output layer (forward) is known as feedforward. Between the input and output layers, MLP may have one or more layers.

3.3 Compare ANN with Other Classifiers

Neural network performance will be compared with other classifiers such as Support Vector Machine (SVM), KNN, and Linear Discrimination Analysis (LDA). A neural network's performance against other classifiers can be compared to help determine which model is most suitable for a given task. We can select the classifier that offers the best balance between accuracy, computational complexity, interpretability, and other important variables based on the evaluation findings.

3.4 Configuration of Hierarchical MLP

A hierarchical neural network is structured in a hierarchical manner, where lower-level layers capture basic patterns and higher-level layers learn more complex representations from the outputs of the lower layers. This arrangement allows the network to construct a hierarchy of features, enabling effective processing of complex data. Hierarchical neural networks excel in tasks involving image and speech recognition, natural language processing, and other domains with data that exhibits hierarchical relationships or structures. They are capable of handling data with multiple levels of abstraction and capturing dependencies between different features or variables, facilitating information extraction from complex datasets.

Table 5
ANN prediction using hierarchical factor

Factor	Description
1	Conditions 1, 2, 3 & 4
2	Condition 1 & 2 and Condition 3 & 4
3	Condition 1 & 3 and Condition 2 & 4
4	Condition 1 & 4 and Condition 2 & 3

ANN could employ a lot of techniques to do predictions. In this research, the arrangement of input and target data tabulated are assorted in a hierarchical order. There are four (4) conditions

needed to commence prediction and four (4) factors or configurations suggested for this research. On top of that, the research tries to reduce the network calculation by suggesting the factor of ANN. By increasing factors within the ANN would significantly reduce computational demands of the ANN, allowing easier computing of the transformer's health. Furthermore, the hierarchical network outperformed the traditional network and enabled us to determine the qualitative relevance of certain of the input parameters; the behaviour of the traditional network could not even be qualitatively examined [13].

3.5 GUI Layout

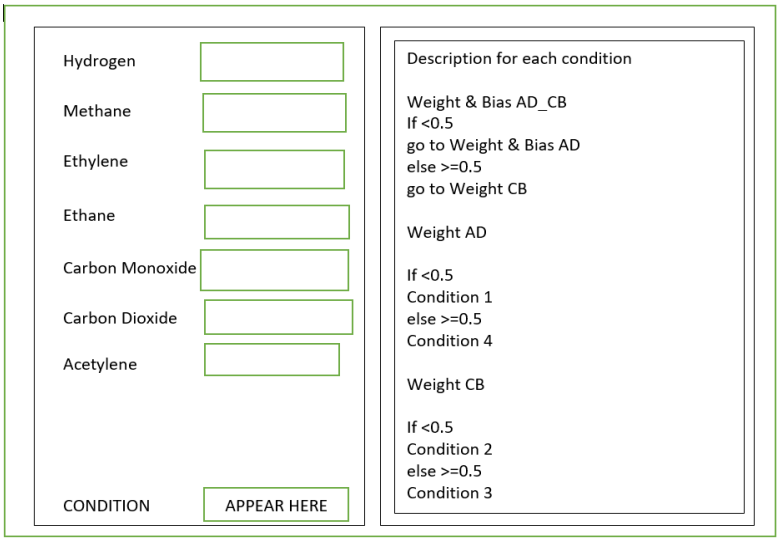


Fig. 2. GUI layout

The GUI of transformer health index monitoring will be designed by using MATLAB software. There are seven types of gases that will be the input of the GUI, which is hydrogen, methane, ethylene, ethane, carbon monoxide and carbon dioxide and acetylene. The gas number in ppm will be entered and the result of transformer health condition index decision will be shown in Table 3.

4. Results and Discussion

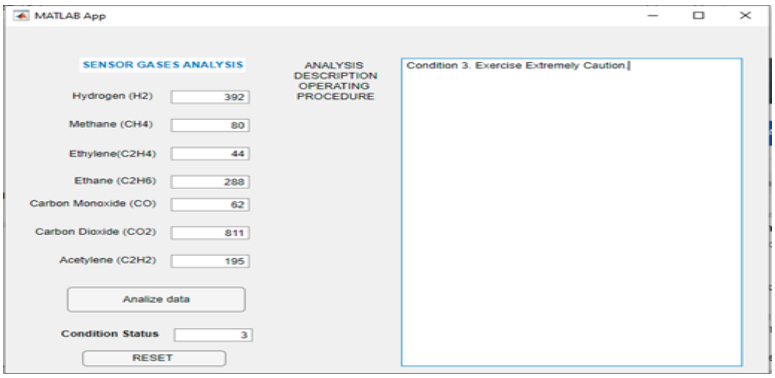
The objective of this study is to discover the optimal procedure for carrying out KGM. The best factor in morphology's performance with each training algorithm will be compared as part of the research and the best method will be a GUI of transformer health index monitoring by using MATLAB. The network's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

Table 6
Classifier performances

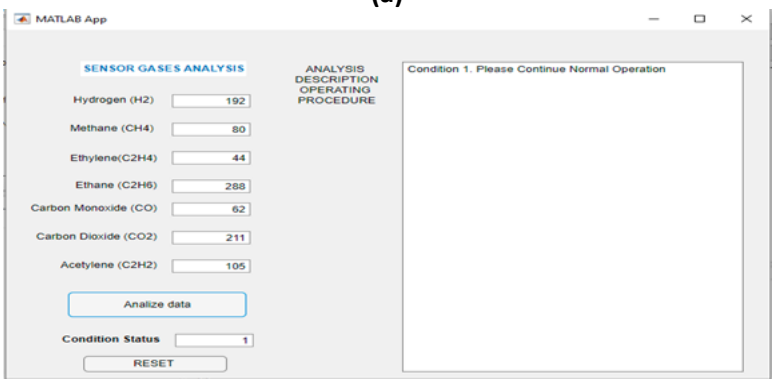
Classifier	Result
KNN	88.32%
MLP (LM)	89.32%
LDA	72.38%
SVM	86.47%

Table 7
Results of four factors using MLP network

Training algorithm	Factor 1	Factor 2	Factor 3	Factor 4
BP	76.01%	90.05%	89.52%	92.02%
BR	89.63%	93.34%	91.73%	95.16%
LM	89.32%	92.47%	90.26%	93.12%



(a)



(b)

Fig. 3. Interface of GUI output

The study compares four classifiers (KNN, neural network, linear discrimination, and SVM) to assess the accuracy of transformer health index. The KNN algorithm determines the class or value of a data point based on its closest neighbours in the feature space. The ANN, trained by adjusting weights and biases, achieved the highest accuracy of 90.0% by reducing the discrepancy between expected and desired outputs. Linear discrimination, using linear decision boundaries, yields the lowest accuracy of 72% due to limited expressiveness for complex, nonlinear data distributions. SVM locates an optimal hyperplane to separate classes and achieve 86.4% accuracy.

The neural network is the preferred classifier due to its ability to generalize, handle complex relationships, and learn from unstructured data. Factors 1, 2, 3, and 4 are used to train the data, with factor 4 demonstrating the best results in training the transformer health index. The hierarchical merging of distinct datasets enhances the network's ability to manage fluctuations, identify relevant features, and make accurate predictions. The chosen factor is then used to develop a GUI interface in MATLAB as shown in Figure 3 (a) and (b) enabling engineers to make efficient decisions about transformer's health conditions, saving time and leveraging artificial intelligence for monitoring. In practice, this interface can be used in labs to aid engineers in assessing transformer health, streamlining the monitoring process using artificial intelligence.

5. Conclusion and Recommendations

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 achieves its objectives by obtaining accurate outputs through training and demonstrating the performance of hierarchical 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.

For future recommendations, the amount of data of transformers will be increased to produce more balanced implementation of the system. A neural network may perform better when the data is balanced, particularly when doing classification tasks. The neural network may learn from a more complete set of instances for each class when the classes in the dataset are balanced, as they have equal representation. This helps the network avoid bias towards any class and enhances its capacity for generalization and precise prediction. Next, the usage of another classifier to get more accurate data. In addition to neural networks, using several classifiers can help to increase the precision of data analysis. Although powerful and adaptable, neural networks may not always be the best option for a given dataset or task. Employing a broad collection of classifiers enables a thorough examination and comparison of findings, as each classifier has its own benefits and shortcomings of their own.

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