DEVELOPMENT OF MACHINE LEARNING-BASED ALGORITHM TO DETERMINE THE CONDITION IN TRANSFORMER OIL

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DEDICATION

For my beloved mother and father, Thank you for the support and sacrifices.

For my inspiring supervisor, Dr. Mohd Fairouz Bin Mohd Yousof.
Thank you for your encouragement for this research as well as for future undertakings.

For my friends, thank you for the support and suggestion

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ABSTRACT

One very popular and useful electric device in daily life is a transformer, and it is one of the greatest components of the power network system. The main fault of these transformers can purpose considerable damage. This not only disrupts other functions of the power supply, rather than caused very large losses. The interpretation of dissolved gas analysis (DGA) is used to detect incipient faults in transformer oil. This paper aims to develop a model for taking into consideration the results obtained from DGA to investigate the condition of transformer oil fault. Machine Learning (ML) algorithm have been utilized to detect the fault more accurate. Classification learning app used to train DGA data divided into three categories fault, Not determined (N/D) and stray gassing. Three different types of ML algorithm have achieved high accuracy of 93.0%, 95.4% and 97.7% support vector machine (SVM), Naïve Bayes algorithm (NB), K-nearest neighbour (KNN) respectively. Graphical User Interface (GUI) has overall the system by testing and verified with many different user data and performed a correct classification.

ABSTRAK

Salah satu alat elektrik yang sangat popular dan berguna dalam kehidupan seharian adalah pengubah dan ia adalah salah satu komponen sistem rangkaian kuasa yang paling hebat. Kesalahan utama pengubah ini boleh menyebabkan kerosakan yang besar. Ini bukan sahaja mengganggu fungsi bekalan elektrik yang lain, malah menyebabkan kerugian yang sangat besar. Tafsiran analisis gas terlarut (DGA) digunakan untuk mengesan kesalahan awal pada minyak pengubah. Makalah ini bertujuan untuk mengembangkan model untuk mempertimbangkan hasil yang diperoleh dari DGA, untuk menyelidiki keadaan kesalahan minyak pengubah. Algoritma Machine Learning (ML) telah digunakan untuk mengesan kesalahan dengan lebih tepat. Aplikasi pembelajaran klasifikasi yang digunakan untuk melatih data DGA dengan dibahagikan kepada tiga kategori kesalahan, Tidak ditentukan (N / D) dan sesat gas. Tiga jenis algoritma ML masing-masing telah mencapai ketepatan tinggi iaitu 93.0%, 95.4% dan 97.7% mesin vektor sokongan (SVM), algoritma Naïve Bayes (NB), K-tetangga terdekat (KNN). Antaramuka Pengguna Grafik (GUI) secara keseluruhan sistem dengan menguji dan mengesahkan dengan banyak data pengguna yang berbeza dan melakukan klasifikasi yang betul.

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LIST OF SYMBOLS AND ABBREVIATIONS

AUC	-	Area Under the ROC Curve
AC	-	Alternating Current
ANN	-	Artificial Neural Network
CH_4	-	Methane
$C2H_4$	-	Ethylene
C_2H_6	-	Ethane
C_2H_2	-	Acetylene
CO	-	Carbon monoxide
CO_2	-	Carbon dioxide
C	-	Hot Sport with paper Carbonization
DGA	-	Dissolved Gas Analysis
D1	-	Low Energy Electrical Discharge
D2	-	High Energy Electrical Discharge
DT	-	Indeterminate Thermal fault or Electrical Discharge
FPR	-	False Positive Rate
GUI	-	Guided User Interface
H_2	-	Hydrogen
K-NB	-	Kernel Naïve Bayes
KNN	-	K-Nearest Neighbor
ML	-	Machine Learning
N_2	-	Nitrogen
NB	-	Naïve Bayes
N/D	-	Not Determined
O	-	Overheating
O_2	-	Oxygen
PPM	-	Parts Per Million

PD	-	Partial Discharge
ROC	-	Receiver Operating Characteristics
S	-	Stray gas
SVM	-	Support Vector Machine
TNB	-	Tenaga Nasional Berhad
T1	-	Low Range Thermal Fault
T2	-	Medium Range Thermal Fault
T3	-	High Range Thermal Fault
TPR	-	True Positive Rate
TDCG	-	The Development Consulting Group

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CHAPTER 1

INTRODUCTION

1.1 Background of Project

The transformer is an extensive electrical system that converts a low-current and low-voltage electricity into high-current, high-voltage electricity with virtually no energy loss [1]. Failure of the transformer cannot be overlooked in any installation, and transformer failures may be caused by many reasons, such as deterioration of oil characteristics, overload, improper maintenance on oil level, and moisture that affects the life of the transformer insulation system and unbalanced load conditions. Therefore, the transformer custodian's great responsibility is to have a strict operation and maintenance system, which will ensure a long service life, trouble-free service, and low maintenance costs [2].

There are a large number of solid and liquid insulators as insulating materials in oil-filled power transformers. When a fault occurs inside the transformer, these insulators will be under electrical and thermal stresses. These stresses cause chemical analysis of insulation in oil-filled transformers. Some products of this chemical analysis are gases that can be dissolved in transformer oil [3]. In recent decades, studies have shown that dissolved gas is closely related to the type of fault in transformers oil, these gases are ethane (C_2H_6), ethylene (C_2H_4), methane (CH_4), ethyne (C_2H_2), hydrogen (H_2), carbon dioxide (CO_2) and carbon monoxide (CO). Therefore the transformer fault type can be achieved by quantity and type of gas produced [4]. The transformer oil acts as an information carrier from which the transformer can detect potential abnormal operating conditions. It can be achieved by performing the dissolved gas analysis (DGA). The analysis of dissolved gas is a well-known technique to detect early faults in transformers oil. The DGA includes taking a sample of oil from the service transformer of consideration, extracting the dissolved gasses from the oil sample, and quantitatively analyzing the characteristic faulty gas concentration through analysis techniques [5].

Stray gas is the gas produced in oil heated at a relatively low temperature (90 to 200°C), mainly methane, hydrogen or ethane. According to reports, transformers in service and transformers that have not yet been energized have stray outgassing [6]. This decomposition of oil is not accompanied by a decrease in oil quality in most cases. It is understandable that stray gassing makes asset managers worry about the increased risk of this ambiguity to the health of their assets and its impact on the effectiveness of asset insurance coverage [7].

In later days, numerous brilliant optimization calculations and machine learning calculations have been explored different areas, such as control transformers, since these strategies have fabulous blame conclusion execution. Control transformer blame diagnosis and other cutting-edge investigate are numerous. Within the conclusion fault of control transformers, a few machine learning and cleverly strategies are used to distinguish the condition of the transformer [8]. Using classifiers such as an artificial neural network (ANN), support vector machine (SVM), Naïve Bayes algorithm (NB), K-nearest neighbour (KNN) and many more. Those difference algorithms can be training and testing to perform a high efficiency of accuracy [9]. This project investigates case studies involving stray gassing activities, how material compatibility affects them, and the effects on monitoring conditions and classification of the DGA data using MATLAB and machine learning algorithms (SVM, KNN, NB).

1.2 Motivation of Research

DGA is the most fragile and effective technique for evaluating the well-being of oil-filled electrical equipment. Protection oils under abnormal electrical or thermal stress break down to release a small amount of gas. The subjective component of the exhaust gasses depends on the type of fault. It is conceivable by DGA to identify weaknesses such as overheating (pyrolysis), partial discharge (corona) and arcing in an amazing variety of oil-filled equipment. On Data from the investigation of dissolved gasses in protection, oil is cost-effective in the preventive maintenance program. Besides, it has

been shown that knowledge from DGA may provide advance warning of the development of faults instead of observing the advancement of the rate of blame.
The ability to screen broken down gasses in close-to-real-time transformers has been around for a long time and demonstrates its importance. Utilities do not persistently screen their simple transformer, where, in this case, it permanently means a few times a day, maybe reluctant to do so now for two reasons, taken toll and certainty, with perhaps the more significant reason to be certain.

Regularly, with rapid development and global creation, the DGA system should be developed by employing a more productive and rapid approach. To achieved the most excellent execution, this beautifully blamed conclusion structure must be designed to fit the typical characteristics of the neighbourhood transformers. In any case, nations with a comparable environment, transformer utilization and other criteria may discover this framework valuable and appropriate with minor alteration. Subsequently, this extends is persuaded by two components which are to create an intelligent diagnosis system conclusion framework to supplant remote master to spare maintenance cost and to foresee prior fault that empowers prudent measures to be attempted so as to play down the hazard of a transformer blast.

1.3 Problem Statement

Transformer failure usually results in a widespread network outage. The replacement of a power transformer is costly. Units can cost up to $1 million, and long lead times are common. It is, therefore, necessary for any electricity company to manage such assets effectively. Only oil suppliers have recently carried out stray gasification checks on oil batches prior to shipment. Increased stray gasification operation reports in relatively new transformers (less than five years in service), OEM transformers (original equipment manufacturers) and end-users began the in-house test. The main instrument in the electrical network is known as the power transformer. More than 1,000 power transformers in Malaysia that TNB (Tenaga Nasional Berhad) are in operation. Prevention techniques for early detection of transformer faults to prevent the introduction of damage. Hence, there is a need for DGA (Dissolved gas analysis) to have been implemented over the years where required maintenance can be conducted by TNB maintenance teams. Operating experience and study. However, indicate that the dissolved gas can also be produced at a lower temperature in the insulating oil transformer without any fault transformer or specific anomalies. Thus, many methods to test insulating oil and its ability to form this "stray gas" have been developed. In order to defeat such a high cost in the interpretation of the test result, MATLAB software with machine learning algorithms will be built to explicate this problem.

1.4 Project Objective

The aims of the project are as follows:

1. To investigate the effect of interaction between transformer oil and other transformer materials on the dissolved gasses.
2. To design a method for detecting faults gassing of transformer oil using the machine learning algorithm.
3. To develop a computer-guided user interface (GUI) of the designed detection method.

1.5 Project Scope

1. Dissolved gasses investigated in this project are hydrogen (H_2), oxygen (O_2), nitrogen (N), carbon monoxide (CO), carbon dioxide (CO_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4) and ethane (C_2H_6).
2. This project will investigate the gasses in transformer oil using Dissolved gas analysis (DGA) method to test the gasses, and use to analysis the gasses.
3. Dissolved gas analysis (DGA) data will be collected from oil samples of real transformers from TNB (Tenaga Nasional Berhad).
4. The Duval triangle method will be able to analysis oil gasses.
5. Transformer materials that will be investigated are dotted diamond paper, metal plate, coated metal plate and core metal.
6. The analysis will be performed using machine learning algorithms by using MATLAB software.

1.6 Thesis Organization

This report consists of five main chapters from chapter one until chapter five. For chapter one, it gives the basic idea of the project, the addressing of the problem that is to be solved and the objective of the project, which is usually a solution to the mentioned problem. In the second chapter, past research paper that is related is used as a reference. The highlight is to study the techniques used to be implemented to a project and decide on what method is suitable. The third chapter emphasizes on highlighting all the techniques that had been agreed to be used in this project. It explains all the process flow throughout the process of getting the desired output. For the following fourth chapter, the results of the project, as well as the simulation, are shown, and another process is being discussed in the chapter. Lastly, for the final chapter, conclusions are made based on the project that has been developed as well as mentions of future works and upgraded that could be done.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The transformer is one of the most useful appliances ever. Transformers can increase or decrease the voltage or current in an alternating current (AC) network, circuits can be disconnected from each other, and can increase or decrease the exact value of capacitors, inductors or resistors [10]. In expansion, transformers empower us to transmit power over long distances and circulate securely in industrial facilities and homes.

The cost of transformers is high as a case of the transformers within the extend 75-500 MVA cost almost from $2 to $7.5 million within the United States. This is taken a toll without transportation, charges and other variable costs [11]. The disappointment of one transformer leads to the loss of the price of one transformer or the interference of the energy supply to buyers. In this manner, observing transformer oil could be an adjust strategy and is valuable for identifying the cause of transformer damage [12].

2.2 Power Transformer

A transformer may be a four-terminal device that converts the AC input voltage to a lower or higher AC yield voltage. It changes over the voltage from one particular circuit to another without changing the frequency, notwithstanding of the voltage level. The transformer is basically composed of three parts: the essential winding serves as the input, the auxiliary winding serves as the output, and the iron core is utilized to improve the produced magnetic field [13]. Transformers have no inner moving parts and exchange energy from one circuit to another through electromagnetic acceptance. External cooling may incorporate heat exchangers, radiators, oil and fans pumps. Transformers are ordinarily utilized since the voltage must be changed. A power transformer is characterized as a transformer with an evaluated power of 500 kVA and more prominent (an ordinary control transformer is shown in Figure 2.1).

Figure 2.1: Power transformer [13]

The power transformer is one of the vital components of the power system, and it can be portrayed as a transformer for transmitting power between distinctive parts of the circuit between the generator and the main circuit of the control distribution framework. Any fault or blunder within the power transformer may cause the power supply to be hindered.

Transformer internal issues are categorized into electrical or thermal where each fault advances specific characteristic gases and produces energy from low levels to high levels of supported arcing. A partial discharge which produces CH_4 and H_2 may be a low-level energy fault, though arcing that's able of creating all gases counting C_2H_2 as a high-level energy fault [14]. The different deficiencies and their characteristic gases they deliver are illustrated in Figure 2.2.

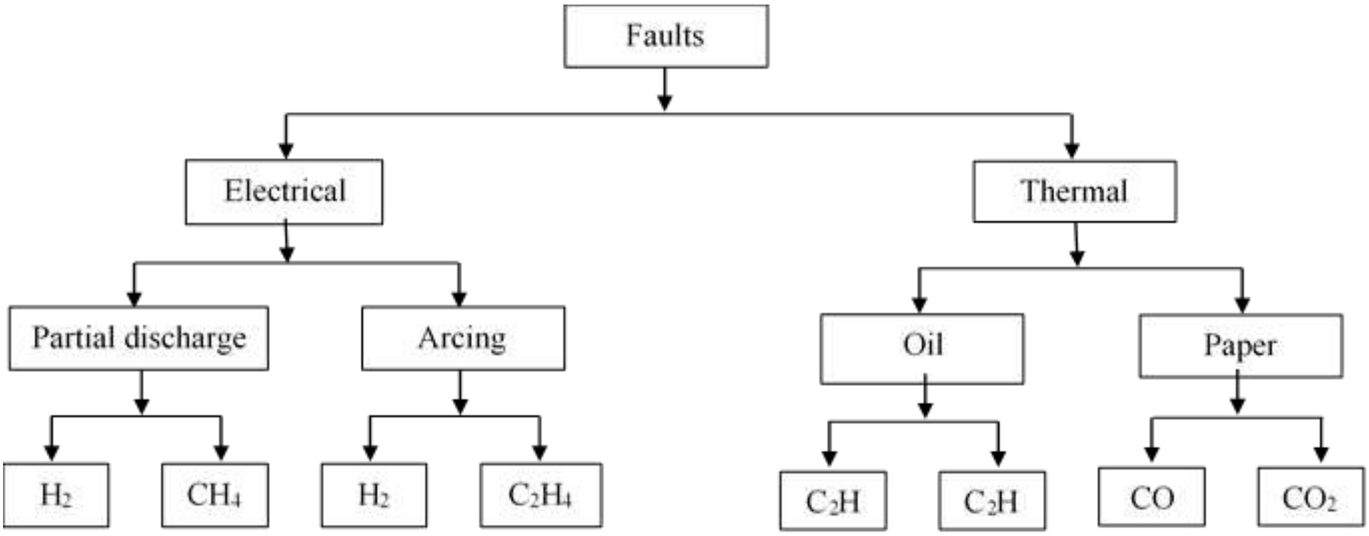

Figure 2. 2: Faults Types and Associated Gases [15]

2.2.1 Power Transformer Main Structure and Appearance

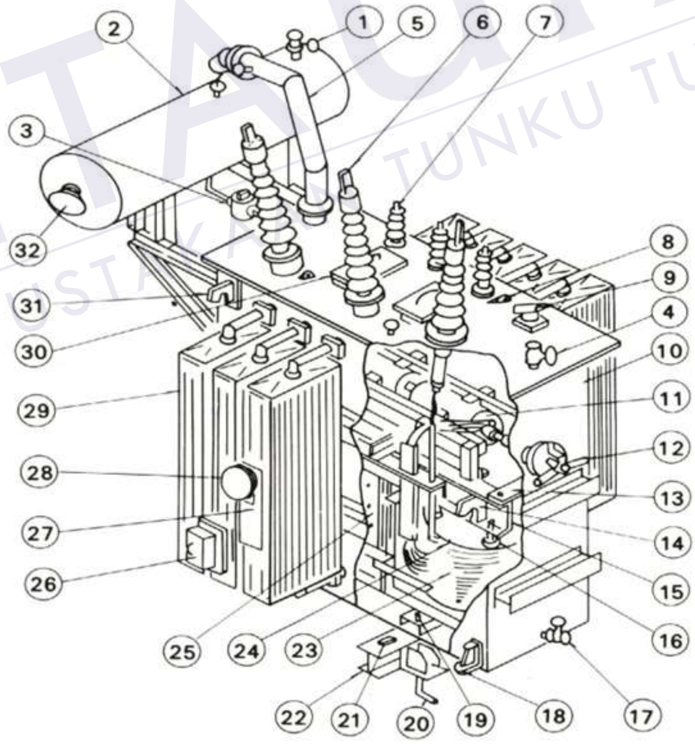

Figure 2. 3: Components of Transformer

Table 2. 1: Components' name of power transformer

No	Components' name	No	Components' name	No	Components' name	No	Components' name
1	Oil filter valve	9	B C T Terminal	17	Oil drain valve	25	Core
2	Conservator	10	Tank	18	Jacking boss	26	Terminal box for protective devices
3	Buchholz relay	11	De-energized tap changer	19	Stopper	27	Rating plate
4	Oil filter valve	12	Tap changer handle	20	Foundation bolt	28	Dial thermometer
5	Pressure-relief vent	13	Fastener for coil and core	21	Grounding terminal	29	Radiator
6	High-voltage bushing	14	Lifting hook for coil and core	22	Skid base	30	Manhole
7	Low-voltage bushing	15	End frame	23	Coil	31	Lifting hook
8	Suspension lug	16	Coil pressure bolt	24	Coil pressure plate	32	Dial type oil level gauge

2.3 Transformer Oil

Transformer oil (called as insulating oil) could be an extraordinary sort of oil that has fabulous electrical cover properties and is steady at high temperatures. In oil-filled power transformers, transformer oil is used to cover, prevent arcing and corona release, and dissipate heat from the transformer (that is, as a coolant). In addition, transformer oil is used to protect the transformer's iron core and windings since they are completely submerged within the oil. Its ability to resist oxidation of cellulose paper insulation materials is another imperative feature of insulating oil [16]. In the atmosphere, transformer oil serves as a block between oxygen and cellulose, preventing direct contact, thus reducing oxidation. The amount of transformer oil is usually measured using MOG (Electromagnetic Oil Level Gauge).

There are two typically two kinds of transformer oil used in transformers, which are mineral and manufactured oil. The transformer description and contrast will appear in Table 2.2.

Table 2. 2: Classification of Transformer Oil [17]

Transformer Oil		
Mineral Oil (Petroleum product)		**Synthetic Oil** (chemical products)
Paraffinic Oil	**Naphthenic Oil**	**Silicon Oil**
• The oxidation rate of paraffin oil is lower than that of naphtha oil, but the oxidation product of sludge at the bottom of the tank is inert and precipitated, interfering with the transformer's cooling system. • It has high pouring point due to the wax content. • In India, it is commonly used because of its cheap and readily available.	• Naphtha oil is easier to oxidize than paraffin, but the product of oxidation, such as naphtha oil sludge, is much more soluble than paraffin oil. • As a result, the bottom of the transformer would not precipitate the sludge of naphtha-based gasoline. • Therefore, the convection circulation of the oil is not obstructed and does not interfere with the transformer cooling.	• Generally, these are chemical products, such as Silicon Oil. Those are all Fireproof, so used only for a fire-prone environment. • Lower heat dissipation and high moisture absorption capacity. • High cost than mineral oil.

Mineral insulating oil experience oxidative corruption process within the presence of oxygen to make sludge and acid. To anticipate these forms, an oxidation inhibitor is utilized for interrupting the process of oxidation and subsequently minimize oil deterioration and extend the working life of the transformer oil. Depending on the nearness of oxidation inhibitor, mineral insulating is categorized as 1. Uninhibited oil 2. Inhibited oil [18].

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