MACHINE LEARNING ALGORITHM TO DETERMINE STRAY GASSING IN TRANSFORMER OIL BASED ON DISSOLVED GASES

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Dedicated for my beloved parents
Haw Lian Aik
and
Tan Mee Mee
for their endless love and support throughout my life.

For my inspiring supervisor
Ir. Dr. Mohd Fairouz Bin Mohd Yousof
for your advice and encouragement for this research.

For my love one
Chan Mei Ting
for supporting me throughout my study.

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ABSTRACT

Transformer is part of the most important electrical equipment in the distribution power system network. However, transformer will exhibit faults under long operation which may often be confused with the stray gassing (SG) phenomenon. Nevertheless, this SG phenomenon is still being left out by many researchers and the root causes are yet being identified. The current SG test and interpretation methods used by the industries is also very inefficient and inaccurate, where the existing Duval Pentagon Method (DPM) interpretation method is proven with a low accuracy of only 58.7% to interpret stray gassing condition. Therefore, an accurate and fast interpretation tool is required to solve the dissolved gas analysis (DGA) interpretation and gassing pattern of transformer materials should be investigated to help in transformer root cause determination. This research work involves the use of ensemble-based machine learning (ML) algorithms to improve the interpretation accuracy of DPM. Three ML models are developed, and all the models are also showing promising results with more than 70.0% of interpretation accuracy to interpret three different transformer conditions. The random-under-sampler (RUS)boosted trees model is the best model with the interpretation accuracy of 81.2%. Besides, three different transformer materials, which are insulation paper, core metal, and gasket were experimented with uninhibited and inhibited transformer oil under heat to understand the gassing behaviour caused by the materials. The findings indicate that for uninhibited oil, the insulation paper effects the generation of hydrogen (H_2), carbon monoxide (CO) and carbon dioxide (CO_2) gases, the core metal effects generation of CO gases, and the gasket effects the generation of H_2, methane (CH_4), ethylene (C_2H_4), CO and CO_2 gases. For the inhibited oil, the insulation paper effects the generation of H_2 and CO_2 gases, the core metal effects the generation of H_2, CO and CO_2 gases, and the gasket effects the generation of H_2, C_2H_4, CO and CO_2 gases. This research contributes to the use of data resampling method to design ML models with high interpretation accuracy and also contributes to the findings of gassing characteristics for gasket material.

ABSTRAK

Alat pengubah elektrik adalah sebahagian daripada peralatan elektrik yang paling penting dalam rangkaian sistem pengagihan kuasa. Namun, alat pengubah elektrik akan mengalami kerosakan dalam jangka Panjang operasi dan sering dikelirukan dengan fenomena gas sesat (SG). Walau bagaimanapun, fenomena SG ini masih diabaikan oleh ramai penyelidik dan banyak lagi punca SG yang belum dikaji. Kaedah ujian SG yang digunakan oleh industri sekarang sangat tidak effisen dan tidak tepat, di mana tafsiran DPM telah dibuktikan dengan ketetapan serendah 58.7% sahaja. Oleh itu, satu alat tafsiran yang tepat dan pantas diperlukan untuk menyelesaikan masalah tafsiran DGA dan bahan alat pengubah elektrik perlu dikaji dari segi corak pengegasan untuk membantu dalam penentuan punca pengesasan. Kerja penyelidikan ini merangkumi penggunaan algoritma pembelakaran mesin berasaskan *ensemble* untuk meningkatkan ketepatan tafsiran kaedah DPM. Tiga model pembelajaran telah direka, dan kesemua model telah menghasilkan keputusan yang memuaskan dengan lebih daripada 70.0% ketepatan dalam pentafsiran keadaan alat pengubah elektrik. RUS *boosted tree model* merupakan model yang paling bagus dengan keseluruhan ketepatan pentafsiran sebanyak 81.2%. Tiga bahan alat pengubah eletrik yang berbeza (kertas penebat, logam teras dan gasket) telah dikaji dengan campuran minyak pengubah terhalang dan minyak pengubah tidak terhalang di bawah haba untuk memahami corak pengegasan yang berlaku. Pendapatan kajian menunjukkan dalam minyak pengubah tidak terhalang, kertas penebat menyebabkan pengegasan H_2, CO dan CO_2, logam teras menyebabkan pengegasan CO dan gasket menyebabkan pengegesan H_2, CH_4, C_2H_4, CO dan CO_2. Dalam minyak pengubah terhalang pula, kertas penebat menyebabkan pengegasan H_2 dan CO_2, logam teras menyebabkan pengegesan H_2, CO dan CO_2 dan gasket menyebabkan pengegasan H_2, C_2H_4, CO dan CO_2. Kerja penyelidikan ini menyumbang kepada penggunaan keadah pensampelan semula untuk mereka model pembelajaran yang boleh menghasilkan ketepatan pentafsiran yang tinggi dan juga kepada penemuan ciri penghasilan gas untuk bahan gasket.

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LIST OF SYMBOLS AND ABBREVIATIONS

d_j	-	Disjoint
Log_{10}	-	Logarithm with base 10
x_j	-	Attribute
x_j,j	-	Fixed attributes set of j
%	-	Percentage
Є	-	Epsilon
℃	-	Degree Celsius
∑	-	Summation
≠	-	Unequal
AI	-	Artificial intelligence
AID	-	Automatic interaction and detection
ANN	-	Artificial neural network
CART	-	Classification and regression tree
CH_4	-	Methane
C_2H_2	-	Acetylene
C_2H_4	-	Ethylene
C_2H_6	-	Ethane
CO	-	Carbon monoxide
CO_2	-	Carbon dioxide
D	-	Dataset
DBPC	-	2, 6-ditertiary-buthyl para-cresol
DGA	-	Dissolved gas analysis
DPM	-	Duval pentagon method
DRM	-	Dornenburg ratio method
DTM	-	Duval triangle method
FNR	-	False Negative Rate
GC	-	Gas chromatograph

GUI	-	Graphical User Interface
H_2	-	Hydrogen
IEC	-	International Electrotechnical Commission
IEEE	-	Institute of Electrical and Electronics Engineers
IPSO	-	Improved particle swarm optimization
KNN	-	K-nearest neighbors
O_2		Oxygen
LSTM	-	Long short-term memory
mL	-	Milli Litre
OLTC	-	On load tap changer
ppm	-	Parts per million
PSO	-	Particle swarm optimization
RF	-	Random Forest
RRM	-	Rogers ratio method
RUS	-	Random under sampler
S	-	Set
SG	-	Stray gassing
SMOTE	-	Synthetic Minority Oversampling Technic
SVM	-	Support vector machine
TNBR	-	Tenaga Nasional Berhad-Research
TPR	-	True Positive Rate

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CHAPTER 1

INTRODUCTION

1.1 Project Background

A transformer is a static electrical component with no moving parts that are used for stepping up or down or isolating one circuit from another. The transformer voltage can be stepped up during long-distance transmission and stepped down for commercial or industrial use with very low losses [1]. Due to this functionality, the transformer becomes one of the most important pieces of equipment in an electrical system. Although there is an emergence of dry-type transformers in this generation, but oil-immersed transformers still hold the majority among the transformer type used in our country due to the long-lasting characteristic which can be maintained and repaired when necessary. Fuji Electric claims that the life expectancy of an oil-filled transformer is about 30 years [2]. However, the transformers might still begin to generate failure signals during the servicing period if proper maintenances are not provided. This situation might further lead to huge financial losses and at the same time cause damages and shorten the servicing lifetime of the transformers. A statistical assessment [3] shows that most of the failures in the transformer are related to insulation, where 33.9% are located at the tap changer and 32.1% are located at the winding. These failures should be able to be detected earlier if proper maintenance action is conducted, which can extend the servicing period of the transformers. Unfortunately, due to the lack of proper maintenance, 35.7% of the transformers were scrapped due to the incapable of repairing when failures occur [3].

One of the best diagnostic methods for oil-immersed transformers is the DGA. DGA is a widely used technique to estimate the condition of oil-immersed transformers. The measurement of the level and the changes of combustible gases in insulating oil, which include methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO), carbon dioxide (CO_2), and hydrogen (H_2) is a trustworthy diagnostic tool which can be used as an indicator of undesirable events occurring inside the transformer. Faults happening inside the transformers such as hot spots, electrical arcing, or partial discharge can be predicted based on the increment of the combustible gases in the transformer oil. Therefore, the identification of these gases being generated by a particular unit can provide useful information for a condition-based maintenance program [4].

Many interpretation methods for DGA had been researched to be used as handy tools for analysing the condition of the oil-insulated equipment. Some examples of the widely used interpretation methods are Key Gas Method, Dornenburg ratio method (DRM), Rogers ratio method (RRM) [5], IEC gas ratio method, Duval triangle method (DTM) and DPM [6]. In the early stage, the interpretation methods such as the Key Gas Method, DRM and RRM mainly focus on the basic transformer faults, such as partial discharge (PD), thermal fault, or arcing fault. This is due to less research had been conducted on the SG characteristic of oil-insulated equipment. The percentage reliability of the interpretation methods is also varied and comparably low. Besides, external factors such as differences in the rated voltage level of transformers will also affect the reliability of these interpretation methods [7]. Later, with more concerns being rose against the stray gassing event in the oil-insulated equipment, the DTM method was updated in 2008 with 2 new Triangle, named Duval Triangle 4 and 5 to be used for the low-temperature faults which covers the stray gassing event. The DPM was also introduced in 2014 by Duval, M. to deal with this gassing characteristic, six basic transformer faults, and stray gassing in mineral oil. This method proved to be accurate in predictions and consistent for various types of transformers, as shown in [8].

The emergence of machine learning as the ideal tool to carry out the intelligent monitoring and analysis system provides the possibility for the DGA interpretation accuracy to be further enhanced. Through the use of various machine learning algorithms, the accuracy of various interpretation methods was shown to be improved, such as in [9] [10]. Many different ML algorithms had also been implemented, such as the artificial neural networks (ANN), k-nearest neighbour (KNN), support vector machine (SVM), decision tree, and even deep learning algorithms to improve the prediction accuracy of different interpretation methods [11].

1.2 Problem Statement

In recent years, it was found that certain gases formed and dissolved in insulating oil are not due to incipient faults in the transformers. Based on the initial investigation and assessment conducted, no abnormalities were found in the transformer. In addition, the loading pattern of these transformers were relatively low compared to its design rating capacity and no defects in the external cooling system were found. One of the possible causes of the formation of these combustible gases was due to SG phenomenon which is a natural event [12]. According to statistics on the power transformer population installed at Tenaga Nasional Berhad (TNB) transmission and distribution substation, on average 600 transformers were found to have high combustible gases over the last three years [13]. Without an accurate diagnostic assessment, field engineers may take unnecessary maintenance action and later increase the operation maintenance cost. One of the examples is that the increment of H_2 gas in the transformers is often mistakenly attributed to corona partial discharge [14]. Thus, a method of interpretation for stray gassing is required to identify this stray gassing phenomenon.

The SG test is the most reliable method used by industries to identify the SG phenomenon accurately. However, this method of testing as stated in the ATSM D7150 standard [15] and CIGRE Technical Brochure #771 [16] required a very long heating time of up to 164 hours to obtain the SG result, which turn out to be very inefficient. Therefore, DGA interpretation methods gain the advantage to be able to interpret the transformers' condition based on the DGA result in a short time. Among the DGA interpretation methods, the Duval Triangle Method (DTM) and DPM are the most used interpretation tools which cover the SG identification. However, a study by Kim, S. et al. [17] showed that the Duval triangle 4, Duval triangle 5, and Duval pentagon were only capable of identifying 67.4%, 45.7%, and 58.7% of the SG phenomenon accurately. The low percentage of interpretation accuracy does not allow the interpretation tool to be utilised as a reliable alternative for identifying the SG of transformer oils. Therefore, the problems above rise the concern of the need for an interpretation method that must be accurate and fast when making the interpretation of the SG phenomenon.

ML had been utilised as one of the effective ways to improve the DGA interpretation methods. However, works involving the use of ML to improve the DGA interpretation were mostly focused only on the transformer faults, whereby the SG phenomenon was excluded. This was shown in the study by Rao, U. M. et al. [18] where the SG condition was purposely excluded when building the ML classification model to prevent the SG data from interrupting and confusing the fault classification. Another study by Saravanan, D. et al. [10] also classified only the transformer faults by using the SVM and multilayer ANN and did not include the SG phenomenon. Thus, there is a need to have a ML model which can classify both transformer faults and SG conditions to be more practical when used to interpret actual transformer conditions based on the DGA.

Besides identifying the condition of oil-immersed transformers, whenever faults or SG activities were found within the transformers, it is also important to identify the root cause for the generation of specific gases, which can help the site engineers to decide the necessity to solve the gassing phenomenon and also to reduce the time taken for checking and repairing the transformers. Therefore, studies had been done to identify various root causes for the transformer gassing phenomenon. A study by I. Atanasova-Hohlein [19] investigated the root cause for the gassing characteristic of transformer oil due to the influence of copper material. Another study by Gao, S. H. et al. [20] had investigated the benzotriazole metal passivator (BTA) as the root cause of abnormal dissolved gases generation, especially CO, $\mathrm{CO_2}$ and $\mathrm{H_2}$ in the transformer oil. However, as there are still many other transformer materials that were not being investigated, it is crucial to experiment with those transformer materials to understand about the gassing effect caused by those materials.

The problems stated above contributed to the idea in this research work to develop an analysing tool for the transformer conditions which is fast and accurate using a ML algorithm. The tool developed was able to differentiate whether the transformer is in normal condition, build-up of stray gases, or faulty condition. Moreover, the tool was also able to determine the root cause of gases formation in the transformer and the possible formation of stray gases based on the outcome of the laboratory findings on three different transformer materials, which are insulation paper, transformer ferrite core and gasket. Thus, cost savings in the operation and maintenance of the transformer could be achieved, due to avoidance of unnecessary maintenance action taken.

1.3 Objectives

The aims of the project are as follows:

i. To analyse the transformer oil based on the Duval pentagon interpretation method and determine the gassing characteristic of the dissolved gases.
ii. To develop a machine learning model with MATLAB classification learner app by the ensemble-based algorithm for the interpretation of transformer conditions from the dissolved gases.
iii. To analyse the performance of the developed machine learning model in terms of percentage of accuracy to interpret actual transformer conditions.

1.4 Project Scopes/ Limitations

The scopes of the project are as follows:

i. Dissolved gases investigated in this project included CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2, and H_2.
ii. DGA method was used to identify the gases in the transformer oil.
iii. DGA data were collected from oil samples of real transformers from local power utilities.
iv. Transformers were rated 33kV and below, 3-phase, and oil samples were collected from the main tank of transformers.
v. The gas data were analysed by using DPM.
vi. Transformer materials that were investigated include transformer ferrite core, winding paper insulation, and main tank gasket seal.
vii. Transformer oil used were Hyrax Hypertrans HR Inhibited Transformer Oil, and Hyrax Hypertrans Uninhibited Transformer Oil.
viii. Temperature for the stray gassing experiment was set at 60˚C, 80˚C, and 100˚C.
ix. Ensemble-based algorithms, which are boosted trees, RUS boosted trees, and subspace KNN were used to develop the machine learning models to perform analysis of transformer's conditions based on DGA.

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APPENDIX D

VITA

The author was born on 19 January 1995 in Penang, Malaysia. He went to S.M.J.K. Chung Ling for his secondary school. He then enrolled to Universiti Tun Hussein Onn Malaysia (UTHM) in 2015 and graduated with bachelor's degree in electrical engineering with honours in 2019. After graduation, he worked in Promserv Engineering Sdn. Bhd. as an electrical field engineer for 2 years. In 2021, he enrolled at UTHM for Master of Electrical Engineering.