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Investigating performance of transformer health index in machine learning application using dominant features

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Investigating performance of transformer health index in machine learning application using dominant features

Azlan Mohmad[1,2], M Ibrahim Shapiai[1], M Solehin Shamsudin [1,2], Mohd Azlan Abu[1] and Amirah Abd Hamid[1]

[1]Malaysia Japan International Institute of Technology (MJIIT), Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra, 54100 Kuala Lumpur
[2]Maju Integrated Engineers Sdn Bhd, T4-2-2, Tower 4 Level 2, Maju Link, Jalan Lingkaran Tengah II (MRR2), 57100, Bandar Tasik Selatan, Kuala Lumpur, Malaysia

E-mail: azlanm@mie-energy.com, md_ibrahim83@utm.my, solehin@mie-energy.com, mohdazlan.abu@utm.my

Abstract. Transformer Health Index (HI) has become a standard tool for performing transformer health evaluations. Due to economic constraints, the recently published paper focuses on developing various techniques to identify the most dominant features for transformer HI prediction. However, the fundamental problems concerning their input features remain unresolved since most suggested features contradict industry practice. In this paper, the primary objective is to investigate the performance of the transformer HI by developing and utilizing only dominant features following the industry recommendation. The investigated dominant features in this paper using 1) CO2/CO ratio and 2) the Incipient fault for detecting temperature abnormalities, and 3) the Dissipation Factor (DF) for detecting oil contamination. The performance validation is carried out using various machine learning (ML) classifiers. Also, the performance of the ML model is validated based on 10-fold type cross-validation to avoid biases in the experiment. As a result, the proposed Artificial Neural Network (ANN) network utilizing the investigated dominant features following the industry practice has produced the highest average accuracy of 80.09% than others ML techniques as a classifier. Hence, additional studies to complement the investigated dominant features may be considered for the subsequent investigation.

1. Introduction

Transformers are one of the most essential and costly components of any electrical network [1], and globally, the infrastructure for oil-type transformers is aging [2]. Maintenance and repair costs and the potential for transformers to be used beyond their limits worsen [3].

The transformer HI has become a widely accepted and approved technique for determining the overall condition of the transformer's [4]. As a result, it enables the industry to be more flexible in its maintenance programs [5]. However, although previous researched works have established and proposed various dominant features from various techniques, it is lacked in addressing industry

[1] azlanm@mie-energy.com

concerns. Therefore, it required additional evaluation with a practical component to attain the HI concept's full benefits [6].

2. Literature review

2.1. Related works

The first classical HI model was developed by [7], consisting of 24 input features. In [8], another additional three nos. of conditions criteria are introduced where the total overall considered input features are 27. Most researchers developed and improved classical techniques early, focusing less on establishing the dominant features.

ML-based HI model includes database-based classification and regression techniques. According to [9], the most common algorithm of ML used for transformer diagnosis is ANN. However, common classifiers such as Support Vector Machines (SVMs) and k-Nearest Neighbour (kNN) are used by previous researchers [10] [11]. Due to economic challenges, the researcher is re-focusing on establishing the dominant factor to develop a cost-effective model [12]. In [10], the adopted feature reduction technique showing an overall efficiency of 95.8%. Nine features are chosen, which consists of 1) Carbon Dioxide (CO2), 2) Acetylene (C2H2), 3) Ethane (C2H6), 4) Ethylene (C2H4), 5) Color, 6) Breakdown voltage (BDV), 7) Interfacial tension (IFT), 8) Moisture (H2O), and 9) Furan. While in [13], by utilizing the stepwise regression technique and ANN as the classifier, the results indicate 95% accuracy. From the study, six features are chosen, inclusive of 1) Furan, 2) Hydrogen (H2), 3) C2H6, 4) C2H2, 5) IFT, and 6) Acidity. Until today, no dominant features are accepted globally.

Certain suggested features proposed by [10] and [13] are inconsistent with the industry practice. For example, although the Furan test is a critical indicator of the quality of the paper insulation [14], it is not a standard or yearly inspection plan [15]. Instead, it is done on a case-by-case basis. Additionally, the IFT is classified under Group 2 as per IEC 60422 and is defined as an additional check, which can collect further details regarding the oil's condition and facilitate the oil's assessment for continued usage in operation. Therefore, as far as practicable, the dominating features should be considered within oil routine tests programs. Also, the choice of color as a dominant feature is disputed. According to IEC 60422, the color of insulating oil is not a critical property.

Furthermore, there is no direct correlation between a change in the color of the insulating liquid and a specific problem. Finally, IEC 60422 indicated that a high BDV does not always represent the absence of all pollutants. Instead, the BDV is showing the mineral oil capacity to withstand electrical stress. In addition, IEEE C57.104 specifies that, except in rare situations, there should be no correlation factor between a BDV and transformer failure.

Instead of relying on various algorithm techniques for feature selection, this study suggests developing and performing a systematic study of the HI dominating feature while considering IEC and IEEE, as both standards have been globally accepted in the industry. Hence, the full potential of HI can be further explored by the industry.

2.2. Dominant Features Based on Industry Practises

Theoretically, the defined dominant features for the development of HI models should correlate with degradation factors that collectively lead to the transformer's loss of life. The term "loss-of-life," as defined in IEEE C57.91, refers to the "loss-of-insulation life. Also, as per IEEE C57.91, the temperature is the only driving parameter that leads to the aging or deterioration of transformer insulation. Therefore, the dominant features established for this study are monitoring the transformer temperature abnormality by manipulating data from the Dissolved Gas Analysis (DGA) and assessing the transformer oil contamination.

The IEEE C57.104 describes a fundamental correlation whereby the relative gas concentration produced in mineral oil is governed by the type of fault and is proportional to the energy level and temperature at the fault location. Hence, for this study, instead of proposing various combinations of gases [10] [12], the type of incipient fault is considered as it is proportional to the temperature of the fault location. On the other hand, IEC 60599 stated that the CO2 and CO emissions from paper insulation increase rapidly with the temperature. Therefore, high CO values (>10,000 ppm) and high CO2/CO ratio, which is more than ten, indicate transformer overheating problems due to paper or oil oxidation. While the CO2/CO ratio, which is less than three, indicates probable paper involvement in fault. Hence, both incipient fault and CO2/CO having the capability in detecting temperature abnormality.

According to IEC 60422, oil contamination tests are determined either by acidity, DF, or IFT. The tests are intercorrelated and have the same information. Based on IEC 60422, DF is very sensitive to soluble polar contaminants, aging products, or colloids in the oil. Thus, changes in concentration level may be monitored using these criteria, even when contamination is so tiny as to be chemically undetectable.

Based on the provided background, the 1) incipient fault, 2) CO2/CO ratio, and 3) DF should be considered dominant features for the HI development. As a result, the proposed dominant features are more robust and practical for industrial applications as the features are in line with industry code and standards. With this consideration, the potential of the transformer HI can be further explored and accepted by the industry. Finally, the performance of the HI is to be investigated by utilizing various ML classifiers as described in Section 3.0.

3. Researched Methodology

3.1. Framework

For this researched paper, the proposed overall researched methodology is given in the block diagram shown in Figure 1.

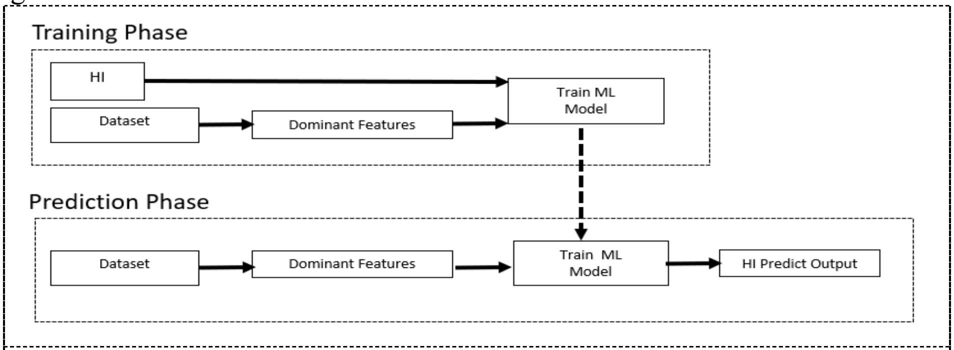


Figure 1. Framework for ML

3.2. Dataset Preparation

The oil sample dataset, including the input features and transformer HI categories, is extracted from [12]. The extracted dataset consists of 730 nos. of oil samples for transformer rated at 66/11kV transformers with ratings ranging between 12.5MVA to 40MVA. The same dataset is also utilized in [13]. The dataset consists of 14 nos. of input features, and the HI is categorized into five categories. There are 1) Very Good, 2) Good, 3) Fair, 4) Poor, and 5) Very Poor.

For the input features, it consist of 1) H2, 2) CH4, 3) C2H6, 4) C2H4, 5) C2H2, 6) CO, 7) CO2, 8) H20, 9) Acidity, 10) BDV, 11) DF, 12) Color,13) IFT and 14) Furan. The summary for the dataset distribution is tabulated in Table 1.

Table 1. Summary on Transformer Data Per HI Categories

HI Code	HI Status	Nos of Transformer
1	Very Good	482
2	Good	60

3	Fair	111
4	Poor	66
5	Very Poor	11

3.3. Identification of Dominant Features
CO2/CO and DF features are manipulated directly from the dataset. For the incipient fault features, the Duval triangle one method is utilized. This method has been used and is recognized by IEC and IEEE standards. Analysis from the incipient fault is coded according to the categories, 1) Fault Code 0 for PD, 2) Fault Code 1 for T1, 3) Fault Code 2 for T2, 4) Fault Code 3 for T3, 5) Fault Code 4 for DT, 6) Fault Code 5 for D1 and 7) Fault Code 6 for D2. The fault code is assigned based on the severity of the fault level, which is in proportion to the temperature level. For example, fault code 6 represents the highest temperature level.

3.4. Experimental Setup
As defined in Section 2.0, it is suggested to uses various ML for predicting and developing the HI model for performance comparison. For this study, the classifiers are 1) ANN, 2) SVM, 3) kNN, and 4) LDA. Refer to Table 2 for a summary of the ML parameter setup-up.

Table 2. Summary on ML Network Setup

No	Classifier	Parameter
1	ANN	Hidden Layer = 2, Number of Hidden Nodes = 200, Epoch = 200, Normalization = MinMaxScaler
2	SVM	Regularization = 12 norm, Loss = Square hinge
3	kNN	Number of Neighbour = 7, distance = Minkoswki
4	LDA	Not applicable

3.5. Training and Testing of the ML models
Supervised learning is adopted as the input features are provided with the transformer HI prediction. 70% is set as training from the available dataset, and the remaining 30% is set for testing purposes. Testing parameter of 30% is selected due to the limited data distribution, especially for the "Very Poor." In [10], although 65% is considered for training and 35% for testing, fewer transformer HI categories are considered. Hence, having better data distribution.

The cross-validation technique is implemented to diagnose overfitting. Cross-validation is an ML model evaluation technique that encompasses training multiple machine learning models on subsets of the available input data and assessing them on the complementary subset. Therefore, a 10-Fold cross-validation technique is implemented similar to selection in [11]. For the 10-fold validation technique, the procedure is reproduced numerous times with various splits of the sample results into 10-parts.

3.6. Performance Evaluation of the ML models

Evaluating the ML model is a critical step. For this study, classification accuracy is executed to evaluate the ML performance. Classification accuracy is a ratio of the number of correct predictions to the total numbers of input samples.

4. Result & Discussion

4.1. Result
Reference shall be made to Table 3 on the experimental result. The benchmark result is extracted from the same dataset as published in [12]. The obtained benchmark results for reduced features is 95%. From Table 3, the maximum average accuracy of 80.09% is obtained from the ANN ML model by

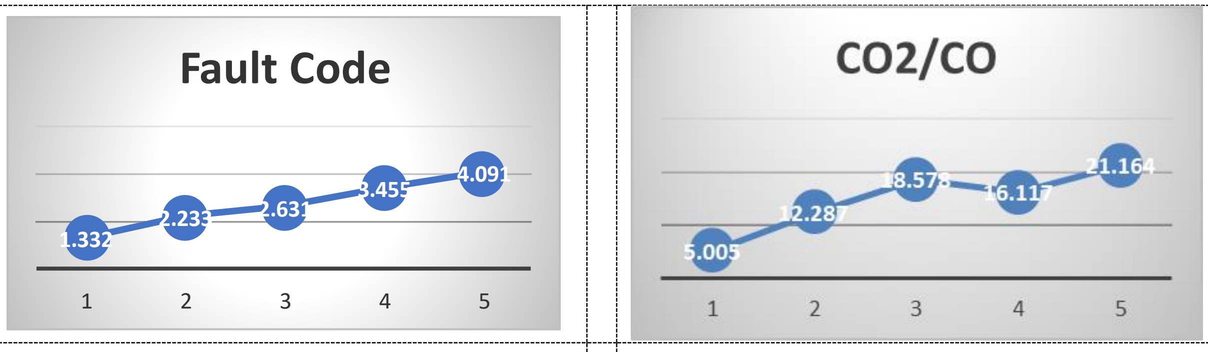
utilizing dominant features following the industry practice. On the other hand, the lowest average accuracy of 74.80% is obtained from the kNN model.

Table 3. Result Summary in Percentage

	Average Accuracy	Min Accuracy	Max Accuracy	Standard Deviation
Al Qudsi (Feature Reduction) – Base Case	95	-	-	-
ANN	80.09	76.71	82.19	1.80
SVM	78.31	74.42	79.91	1.62
kNN	74.80	71.23	71.26	1.56
LDA	77.63	73.52	82.19	2.47

4.2. Analysis & Discussion

Before discussing the obtained result, it is crucial to analyze the provided dataset. The aim is to have some knowledge and background of the dataset for each transformer category. By utilizing CO2/CO and incipient faults, the trending patent for 730 nos. of the transformer can be determined mainly on validating the over-temperature driving factor as stated in Section 2.2. Refer to Figure 2 on the obtained patents trending for CO2/CO and incipient fault. The patent trending is established by utilizing mean data. Also, Figure 3 shows a boxplot for the DF and categories.



(a) (b)

Figure 2. HI Class Trending (a) Incipient Fault and Categories and (b) CO2/CO and Categories

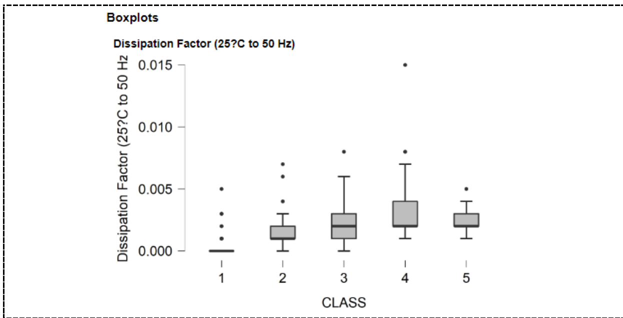


Figure 3. Boxplot between DF and Categories

Figure 2a shows an increment in the severity of incipient fault patent against HI categories, translated to transformer experience over-temperature issues. For example, the transformer under the "Very Poor" categories experience severe fault compared to others. In addition, the transformer over-temperature conditions may occur due to the increment of transformer loading and may not be distinguished by the incipient fault features. Hence, the CO2/CO complement the incipient fault features. However, based on Figure 2b, there is a tendency for the CO2/CO ratio patent to misclassify, especially for transformer under categories "Fair" and "Poor" as the patent is almost similar, making it difficult to differentiate.

For the OQA features, DF is considered as the features are sensitive to oil contamination. The contaminated oil may affect the transformer oil circulation and heat transfer inside the transformer. Therefore, the DF boxplot shown in Figure 3 shows minimum outliers and may provide greater accuracy for the ML modeling.

Based on Table 3, the benchmark result from [12] shows the highest accuracy (95%) compared with the developed features following industry standards. However, the highlighted accuracy may be considered a bias setup as the proposed experiment does not evaluate cross-validation on reported findings. Hence, overfitting or the tendency of a pattern to generalize is not able to analyze. The final selected features in [12] consist of 1) Furan, 2) IFT, 3) H2, 4) C2H6, 5) C2H2, and 6) Acidity. As described in Section 2.2, Furan and IFT lead to late prediction as the tests do not fall under routine tests. Also, Acidity and IFT are intercorrelated and creating redundant features as both features having the same knowledge.

Unfortunately, although 1) CO2/CO, 2) Incipient fault, and 3) DF show strong patent trends in classifying the transformer HI (Refer Figure 2a, 2b & 3), the ML models only show the maximum average accuracy of 80.09% via the ANN model. As described in Section 2.0, both 1) CO2/CO and 2) Incipient fault is selected for monitoring temperature abnormalities, and only one feature is selected from the oil quality assessment. Hence, the selection of DF may not be sufficient and require additional knowledge from others oil quality analyses to predict the HI accurately. Hence, consideration may be required for additional features from the OQA. However, the selected features shall be extracted from the routine test activity as practice in the industry as far as possible. Also, previously, the investigation focuses more on selecting dominant features and less consideration on the technique. Hence, an improvement on the technique is to be further explored.

5. Conclusion

While most researchers have demonstrated the capabilities of numerous HI computing approaches, the fundamental problems concerning their input features remain unresolved. Therefore, for the HI model to be practiced in industry applications, following industry practice is needed.

However, the identified dominant features, 1) CO2/CO, 2) Incipient Fault, and 3) DF, obtained a maximum average accuracy of only 80.09% with the ANN classifier while the lowest recorded average accuracy is 74.80% with utilizing the kNN as a classifier. While the achieved performance is not superior to the features of the base case [12], the developed model perfectly describes current industrial practice. It demonstrates that the transformer HI model is still in development, but that answers a research gap. Until today, no defined recommendations or standards, either IEC or IEEE, are established to assess the transformer's overall conditions using available maintenance data.

It can be concluded that for the HI to practice in real-life application, selecting dominant features following industry practice and improving technique is equally important and requires further exploration.

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