Power Transformer Paper Insulation Assessment based on Oil Measurement Data using SVM-Classifier

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Abstract: Oil immersed paper insulation condition is a crucial aspect of power transformer's life condition diagnostics. The measurements testing database collected over the years made it possible for researchers to implement classification analysis to in-service power transformer. In order to generate a reliable model, more studies related to machine learning implementation to power transformer assessment need to be done. In this article, the objective of the study is to develop reliable new approach in transformer oil-immersed paper insulation condition assessment based on SVM-classifier model using its oil measurements. The measurements data (dielectric characteristics, dissolved gas analysis, and furanic compounds) of 149 transformers with primary voltage of 150 kV had been gathered and analyzed. The algorithm employed for developing classification model is Support Vector Machine (SVM). The model had been trained and tested using different datasets. Several different models have been created and the best has been chosen, resulting in 90.63% accuracy in predicting the oil-immersed paper insulation condition. Further implementation was executed to classify oil-paper condition of 19 transformers which Furan data is not available. The classification results were combined, reviewed, and compared to conventional assessment methods and standards. The comparation confirmed that the model developed has the ability to do classification of current oil-paper condition for the transformer population observed, based on Dissolved Gasses and Dielectric Characteristics.

Keywords: Power Transformer, Condition Assessment, Oil Immersed Paper Insulation, Classification Analysis, Support Vector Machine, Dissolved Gas Analysis, Dielectric Characteristics, Furan.

1. Introduction

Oil-impregnated paper is commonly used insulation in power transformers. Evaluation of the degradation of transformer paper insulation in an oil-filled transformer is critical due to the importance of power transformer in the electrical supply chain. Figure 1 shows the sample of transformer used in the analysis. Whilst monitoring condition of oil insulation can be done easily, assessing the state of paper insulation is more difficult because the paper is wrapped around the conductors and cannot be sampled without taking the transformer out of service [1]. Different diagnostic methods using Dissolved Gas Analysis (DGA) and aging estimation from loading history has been used. The application of 2FAL (2-furaldehyde) as measurement of specific chemical indicator of the aging of paper insulation has received increased attention in the last 20 years [2].

The degradation of cellulose paper insulation in oil-filled power transformer is promoted by four agents of degradation, such as, exposure to elevated temperature, oxygen, acid, and moisture. The processes of degradation for this are thermal, oxidation, and hydrolysis. These degradations caused chain scission or depolymerization and decreasing the tensile strength of paper, yielding glucose. This glucose will further degrade to form furans and other chemical products such as water and gases. The advantage of furan assessment, is that furans are only generated when insulation paper degrades [2].

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Figure 1. A sample of 150 kV power transformer used in this study

Despite the fact that furan is the most accessible yet reliable transformer paper assessment, this measurement is not done periodically by the utility. In order to find out the current condition of paper insulation, it is needed another inexpensive approach. Machine learning algorithm can be employed to model the current transformer paper condition level. Several studies have been done to find out the possibility of this method. Furan were used employing Fuzzy Logic to do transformer remnant life prediction [3]. K-NN and Decision Tree based classification for prediction of transformer furan level [4]. ANFIS was used to predict the Degree of Polymerization and further do the expected life estimation of transformer in [5], and simple multiple regression model has also developed to be compared with ANFIS model in [6].

SVM is one of the commonly adopted machine learning algorithms for data classification [7] [8] [9] [10] [11]. SVM used to forecast electric load along with other algorithm such as Fuzzy Time Series and Global Harmony Search [12]. A computational model was developed to estimate mass concentration of boiler flue gas in [13]. Another study implemented SVM to classify the results of the simulation in defining synchronization capability limits of permanent-magnet motor [14]. In power transformer diagnosis, SVM was implemented for fault detection [15] [16] [17] [18] [19] and [20]. Several machine learning approaches were used in [21], SVM was utilized along with Decision Tree, ANN, KNN, and Naïve Bayes to assess transformer furan content. This publication comes out with relatively low accuracy on SVM classifier.

Determining end-of-life of operating power transformer is a challenging thing. By combining analytical, inspection, and testing methods together, we can obtain a complete picture of the condition of units in service [22].

This article implemented classification analysis using SVM as an additional insight to help utilities assess transformer oil-impregnated paper insulation condition by using transformer oil measurements data. The main issues of developing SVM model classification analysis were discussed, which are: data preparation; feature selection; and model validation. Different models had been developed to find the best model to meet accuracy level intended. The proposed model then compared to conventional methods and standards to validate the classification result.

2. Methodology

Classification is the problem of identifying data, in this case is transformer oil-paper condition to the known category. This section presents the step by step methodology of SVM classifier model development. The attributes observed, guidelines of 2FAL assessment, model development flowchart, preprocessing and outlier elimination, and SVM classifier algorithm are presented in this section.

A. Sample

Measurements data (dissolved gases, oil dielectric characteristics, and furan) of 149 inservice transformers had been gathered. Figure 1 shows one of the transformers observed in this study. All of the measurements data are from 3 phase power transformers with 150 kV primary voltage, and operating life of 3 up to 44 years.

B. Attributes Observed

In this article, the authors gathered measurements data consisting of dissolved gases, dielectric characteristics, and furanic compounds.

- Dissolved Gas Analysis

DGA of insulating oil is universally used and considered as an important indicator of transformer's overall condition all over the world [23]. The dissolved gasses were measured and interpreted based on [24], consists of Hydrogen (H₂), Methane (CH₄), Carbon Monoxide (CO), Carbon Dioxide (CO₂), Ethylene (C₂H₄), Ethane (C₂H₆), Acetylene (C2H2) and Total Dissolved Combustible Gas (TDCG).

- Dielectric Characteristics

Characteristics of transformer oil insulation were measured and interpreted based on [25], consists of Breakdown Voltage in kV (IEC 60156), Water Content in ppm (IEC 60814), Acidity in mg KOH/g (IEC 62021), Interfacial Tension in dyne/cm (ASTM D971), and Color Scale (ISO 2049).

- Furanic Compounds

Furans are part of the degradation products of cellulose insulation paper in transformers, and they are partially soluble in the insulation fluid [2]. Most often, five furanic compounds measured are 2-furaldehyde (2FAL), 5-methyl-2-furaldehyde (5M2F), 5-hydroxymethyl-2-furaldehyde (5H2F), 2-acetyl furan (2ACF), and 2-furfurol (2FOL). 2FAL is considered as the main compound among these furanic compounds because of its higher generation rate and stability inside a transformer [26]. 2FAL is usually correlated to Degree of Polymerization (DP). Paper with initial DP value of approximately 1000 is expected to last the lifetime of the transformer (25-30 years), but a DP of 150-250 is regarded to be the end of life criterion for the transformer insulation because the paper is also at risk of mechanical failure [27].

C. Analysis Methods

2FAL is the most accessible measurement for assessing insulation paper of power transformer, however, 2FAL is not a routine test. This subsection discussed the methods of assessing oil-immersed paper in power transformer when there are furan measurements and using SVM-classifier when no furan measurement is available.

Table 1. Ouldelines for On minersed insulation raper Degradati							
	2FAL (ppm)	DP Value	Oil-Paper Health Category				
	0-0.1	1200-700	Healthy Insulation				
	0.1-1	700-450	Moderate Deterioration				
	1-10	450-250	Extensive Deterioration				
	>10	<250	End of Life Criteria				

Table 1. Guidelines for Oil Immersed Insulation Paper Degradation

Determining Oil-Paper Condition based on Measurement Data Table 1 shows the guidelines used for assessing the significance of 2FAL measurement, as used by several publications [28] [3] [29]. The correlation between 2FAL and Degree of Polymerization with its extent of degradation is shown. Measurement data of 2FAL falls into categories in Table 1, 'Healthy', 'Moderate', 'Extensive', and 'End of Life'. When degree of polymerization of transformer paper reaches the value of 250 or lower, the paper considered to lost its mechanical strength and transformer has reached its end of life. Table

Table 2. Number of data each category						
Category	No. of Transformers	Percentage				
Healthy						
Insulation	67	48 %				
Moderate						
Deterioration	54	40 %				
Extensive						
Deterioration	16	12 %				

2 and Figure 2 show the number of transformers measurement data that falls into each category.



Figure 2. Percentage of number of transformers in each Category

- Support Vector Machine Classifier

Support Vector Machine (SVM) is a promising algorithm in learning theory [30], especially for classification problems. The classic SVM was introduced with polynomial kernels by Boser et al. in [31], and with general kernels by Cortes and Vapnik in [32]. Among other linear programming, SVM is important because of its linearity and flexibility for large data setting [33]. SVM is a powerful supervised learning algorithm, which has been successfully applied in various classification and regression problem. SVM is known to be efficient, particularly in large classification problems, because the training of the classified vectors does not have a distinct influence on the performance of SVM. Therefore, SVM has the required potential to handle very large feature spaces. Also, SVM-based classifiers are claimed to have good generalization properties compared with conventional classifiers, because in training the SVM classifier, the structural misclassification risk is to be minimized, whereas traditional classifiers are usually trained so that empirical risk is minimized [18].

In the beginning, SVM was proposed to do binary classification. Therefore, for multiclass problem, traditional SVM needs to be extended. Various different binary classification methods are implemented for the purpose of multi-category classification, such as 'one-against-all' and 'one-against-one' [34]. Multiclass SVM do data classification by learning to find the best hyperplane separating data points of one class from the other.

D. Classification Model Flowchart

Figure 3 shows the process of developing classification analysis in this study. First, transformer oil measurements data were accessed and explored. These data including of Transformer Profile (voltage and operating time), Dissolved Gasses (H₂, CH₄, C₂H₂, C₂H₆, C₂H₄, CO, and CO₂), Dielectric Characteristics (BDV, Water Content, Acidity, IFT, and Color Scale), and Furanic Compound. Then, the data from different sources was composed to the same format. The outliers were eliminated using one-class SVM. The inliers data was separated to training and testing datasets.



Figure 3. Classification model development flowchart

This study compared the classification accuracy of both linear and quadratic SVM classifier. The three classifications shown in Table 1, 'Healthy', Moderate', and 'Extensive' were the target category for SVM classifier. 'End of life' category was not included in this discussion due to no transformer measurement data collected was included in that category.

3. Results and Discussion

This section presents the results of SVM model development in classification analysis of transformer paper insulation condition. In this section, the data preparation, classification result, and model validation are presented.

A. Data Preprocessing

Measurement data gathered to develop classification model consist of dielectric characteristics and dissolved gasses with total 15 attributes. Before developing the model, the attributes are ranked by Analysis of variance (ANOVA) and chi-squared criteria:

• ANOVA) the difference between average values of the feature in different classes, in order to find out if an attribute is significant for model development.

Steps for ANOVA calculations [37].

-P ^D .		
а.	Calculate the correction factor using equation 1.	
	$CF = \frac{(\sum x)^2}{N}$	(1)
b.	Calculate the sum of squares total value (SS Total) using equation 2.	
	$SS Total = \sum x^2 - CF$	(2)
с.	Equation 3 to calculate the SS Group value.	
	$SS\ Group = \sum \frac{(\sum x)^2}{n} - CF$	(3)
d.	Equation 4 to do calculation of the SS error value.	
	$SS \ Error = SS \ Total - SS \ Group$	(4)
e.	Calculate MS group value using equation 5.	
	$MS\ Group = \frac{SS\ Group}{df\ Group}$	(5)
f.	Calculate MS error value using equation 6.	
	$MS \ Error = \frac{SS \ Error}{df \ Error}$	(6)
g.	Equation 7 to calculate Variance Ratio (V.R.)	
	$V.R. = \frac{MS Group}{MS Error}$	(7)
Ch	i squared: dependence between the feature and the class as measure by the chi	callar

• Chi-squared: dependence between the feature and the class as measure by the chi-square statistic, the calculation is done using equation 8.

$$x^{2} = \sum_{i=1}^{n} \frac{(O_{i} - E_{i})^{2}}{E_{i}}$$
(8)

 $x^2 =$ Pearson's cumulative test statistic

 O_i = the number of observations of type *i*.

 $E_i = N_{pi}$ = the expected (theoretical) frequency of type *i*, asserted by the null hypothesis that the fraction of type *i* in the population is p_i

n= the number of cells in the table.

Table 3 shows the rank of attributes based on ANOVA and chi-squared. Color has the highest ANOVA and chi-square, followed by IFT, CO, CO2, accumulation of CO+CO2, TDCG, acidity, and other attributes. This rank is then used for attributes selection in SVM model development.

Table 3. Rank of attributes based on ANOVA and chi-squared							
Rank	Attributes	ANOVA	Chi-squared				
1	Color	44.16	36.72				
2	IFT	19.87	19.95				
3	CO	15.04	17.87				
4	CO_2	11.63	16.79				
5	$CO+CO_2$	13.92	15.42				
6	TDCG	1.24	9.09				
7	Acidity	9.82	8.24				
8	C_2H_2	0.15	4.52				
Rank	Attributes	ANOVA	Chi-squared				
9	H_2	0.56	3.68				
10	Water Content	1.17	2.87				
11	C_2H_6	0.63	2.66				
12	C2H4	0.50	2.36				
13	CO2/CO	1.20	1.27				
14	Breakdown Voltage	0.20	0.76				
15	CH ₄	0.01	0.32				

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B. Data Reduction: Eliminating Outliers

As much as 149 transformer measurements data collected, were analyzed under Orange Data Mining Program to find the outliers using one-class SVM with non-linear kernel (RBF). This is an unsupervised learning algorithm that learns a decision function for novelty detection. It classifies new data as similar or different to the training set [38]. The inliers data from this process (102 data) were used as SVM model development and validation.

C. Dataset Preparation

The inliers data resulted from outlier elimination then divided into two datasets. of 150 kV transformer testing measurements were collected. These data consist of three paper condition categories as shown in Table 2 and Figure 2. There are 54 transformers in 'Healthy' category, 39 transformers in 'Moderate' category, and 9 transformers in 'Extensive' category.

The measurements data then divided into two datasets, with 70 transformers in training datasets and 32 transformers in testing datasets. The configuration of training and testing data is shown in Table 4.

Table 4. Training and testing data separation						
Datasets	Category	Number of Transformers				
T	Healthy	37				
(70 Transformers)	Moderate	27				
(70 Transformers)	Extensive	6				
Testing	Healthy	17				
(22 Transformers)	Moderate	12				
(32 Transformers)	Extensive	3				

D. SVM Classification Model Development

Three categories of transformer paper degradation level, 'Healthy', 'Moderate', and 'Extensive' were used as target class. The attributes included were dissolved gasses and dielectric characteristics, with the total of 15. The attributes selection is shown in Table 5. The attributes selection is based on the rank discussed in subsection 3.1.

No. of Attributes		0	-		-	
Parameters	15	8	7	6	5	4
H ₂	0	Х	х	х	Х	х
CH ₄	0	х	х	х	х	х
C_2H_4	0	х	х	х	х	х
C_2H_6	0	х	х	х	х	х
C_2H_2	0	0	0	х	х	х
TDCG	0	0	0	0	х	х
Water	0	х	х	х	х	х
BDV	0	х	х	х	х	х
CO	0	0	0	0	0	0
CO_2	0	0	0	0	0	0
CO+CO ₂	0	0	х	х	х	х
CO ₂ /CO	0	х	х	х	х	х
Acidity	0	0	0	0	0	х
IFT	0	0	0	0	0	0
Color	0	0	0	0	0	0

Table 5. Attributes Selection	on
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Table 6 shows 12 models created using Linear and Quadratic SVM. Training and testing datasets were used to evaluate the model, with respective accuracy. The best-chosen model was number 12, with attributes of CO, CO₂, IFT, and Color. This model was able to do classification of testing dataset with 90.63% accuracy.

Table 0. Accuracy of different SVM models									
No.	Training	Testing	Туре	No. of					
	Accuracy	Ассигасу		reatures					
1	85.71	81.25	Linear	15					
2	94.29	75.00	Quadratic	15					
3	82.86	81.25	Linear	8					
4	92.86	78.13	Quadratic	8					
5	82.86	81.25	Linear	7					
6	92.86	78.13	Quadratic	7					
7	80.00	84.38	Linear	6					
8	91.43	71.88	Quadratic	6					
9	80.00	84.38	Linear	5					
10	85.71	71.88	Quadratic	5					
11	80.00	81.25	Linear	4					
12	87.14	90.63	Quadratic	4					

Table 6. A	Accuracy	of different	SVM	models
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E. Performance of the model

The ability of selected model to do classification of new data was examined. Performance validation of the proposed model (based on 70 transformer data) to classify new data was performed using 32 transformers testing dataset. Figure 4 shows confusion table of selected model, after checked using dissolved gases and oil characteristics measurement data of independent testing dataset.

SS	Healthy	94.12 16	5.88 1	0 0		94.12%	5.88%
ue Cla	Moderate	8.33 1	91.67 11	0 0		91.67%	8.33%
Tr	Extensive	0 0	33.33 1	66.67 2		66.67%	33.3%
		Healthy	Moderate	Extensive		True Positive	False Negative
Predicted Class							-

Figure 4. Confusion table of proposed model tested using independent testing dataset

As much as 94.12% Healthy transformers were correctly classified, while only one misclassified as Moderate. Moderate transformers were classified correctly for 91.67%, only one misclassified as Healthy. While 1 out of three Extensive transformers were misclassified as Moderate.

Overall, the result shows that the model developed is prospective to be used in classifying different transformer measurements data with 29 correctly classified transformers out of 32 transformers data.

F. Application of the Developed Model to in-service Transformer Lacking Furan Measurement Data

The previous subsection has reported the performance of proposed model. SVM model developed has the accuracy of 90.63% in classifying transformer oil-paper condition to three classes: Healthy; Moderate; and Extensive. This section describes the application of proposed model in assessing in-service high voltage transformer. As much as 19 distinct transformers data with no furan measurements were observed to do classification of the oil-paper insulation condition using proposed SVM-classifier model, and the results are shown in Table 7.

Table 7 shows the classification results of 19 transformers. As much as 8 transformers classified as Healthy Transformers, 6 transformers as Moderate Ageing, and 5 transformers as Extensive Ageing. This classification results were validated using conventional methods, such as ratio of CO2/CO, level of CO and CO2 respectively, and limit of each oil-characteristics. Based on SVM model developed, the category of oil-paper insulation is predicted. "H" is for Healthy Transformer, "M" is for Moderate Ageing, and "E" is for Extensive Ageing. Green-colored cells show transformers with Healthy class, blue-colored cells show moderate-class transformers, and yellow is transformers with extensive condition. Red-colored cells show parameters in oil which exceeding limits shown in Table 8.

	H2 (ppm)	CH4 (ppm)	C2H4 (ppm)	C2H6 (ppm)	C2H2 (ppm)	CO (ppm)	CO2 (ppm)	CO+CO2 (ppm)	C02/C0	TDCG(ppm)	Water Content	BDV (kV)	Acidity (mgKOH/g)	Interfacial Tension (dyne/cm)	Color Scale	Age	Predicted Class
1	302.3	136.6	115	0	0	364.9	2950.8	3315.7	8.09	918.8	5.85	55.6	0	30.4	0.5	2	Η
2	184	145.1	145.8	0	0	391.8	3536.1	3927.9	9.03	866.7	5.05	88.2	0	32.2	0.6	3	Η
3	0	104.52	12.5	212.27	0	396.27	2923.05	3319.32	7.38	725.56	2.17	78.8	0.15	31.1	0.9	4	Η
4	140.1	0	126.77	171.1	0	285.43	2375.51	2660.94	8.32	723.4	2.89	82.5	0.01	33.5	0.5	5	Η
5	0	0	0	0	0	215.03	1651.9	1866.93	7.68	215.03	3.88	64	0.02	48.3	1.3	9	Η
6	177.47	10.95	146.38	146.38	0	869.92	3369.92	4239.84	3.87	1351.09	6.0	94.5	0.01	32	0	10	Η
7	0	109.97	14.36	174.82	0	661.42	3071.63	3733.05	4.64	960.57	3.72	76.8	0.26	21.7	4.7	13	Μ
8	0	104.86	0	185.31	0	585.29	1723.77	2309.06	2.95	875.46	3.66	80	0.18	15	4.8	13	Μ
9	0	0	44	0	0	345	4747	5092	13.76	389	22.27	80	0.01	27.6	0.8	13	Η
10	32.3	122.37	51.61	194.29	14.27	793.48	522.08	1315.56	0.66	1208.32	6.57	87.4	0.3	16.4	4.9	15	Μ
11	1400.1	251.21	37.73	184.14	65.66	195.4	219.59	414.99	1.12	2134.24	3.1	51.7	0.48	18.5	3.6	16	Μ
12	0	348	32	516.7	0	774	817	1591	1.06	1670.7	4.39	60	0.11	26.5	1.4	18	Η
13	65.31	0.26	11.99	8.31	15	569.26	9144.41	9713.67	16.06	670.12	20.96	46.3	0.02	19.5	3.7	18	Е
14	0	0	0	0	0	1069.65	8511.14	9580.79	7.96	1069.65	2.86	80	0.04	10.9	4.7	18	Е
15	0	124.44	60.52	269.21	0	561.28	3416.53	3977.81	6.09	1015.45	3.98	80	0.16	14.6	4.6	20	Μ
16	0	57.24	0	24.69	0	882.24	3228.12	4110.36	3.66	964.17	4.93	80	0.21	11.3	6.7	22	Е
17	0	0	29	0	0	1518	942	2460	0.62	1547	4.38	74.1	0.11	25.2	2.9	26	Μ
18	91.46	1.35	4.96	3.39	3.52	1106.21	6690.26	7796.47	6.05	1210.89	36.89	50.8	0.16	16.8	4.1	28	Е
19	0	7	42	5	3	1398	17977	19375	12.86	1455	41.46	57.2	0.06	22.6	3.3	30	Е

Table 7. Assessment of 19 units of 150 kV Power Transformerswithout Furan measurements data.



Figure 5. Principal layout of key-gases characteristic [39], CO and CO2 is the main gas indicator of overheating of cellulose in transformer oil.

Out of dissolved gases parameters, CO and CO_2 both are caused by overheating of cellulose shown by Figure 5. Since the focus on this study is the condition of oil-immersed paper insulation in transformer, only these two gases were considered correlated. This also proved by attributes rank in Table 3.

The polymeric chains of solid cellulosic insulation (paper, pressboard, wood blocks) contain a large number of anhydroglucose rings, and weak C-O molecular bonds and glycosidic bonds which are thermally less stable than the hydrocarbon bonds in oil, and which decompose at lower temperatures. Significant rates of polymer chain scission occur at temperatures higher than 105 °C, with complete decomposition and carbonization above 300 °C [27].

EPRI Guidelines for the fife e	lions [40]	
Category	CO2 (ppm)	CO (ppm)
Condition 1 Normal	0-2500	0-350
Condition 2 Modest Concern	2400-4000	351-570
Condition 3 Major Concern	4001-10000	571-1400
Condition 4 Imminent Risk	>10000	>1400

Table 8. Significance level of CO and CO2 dissolved in Transformer Oil Insulation based on

Ratio of CO_2/CO based on IEC60599 [24] is an indicator of the thermal decomposition of cellulose. As the magnitude of CO increases, the ratio of CO_2/CO decreases. This may indicate an abnormality that is degrading cellulosic insulation [41]. With ratio of CO_2/CO less than 3, it is generally considered as indication of paper fault with some degree of carbonization [24].

According to [25], transformers 150 kV observed in this study is in Category B, which are power transformers with nominal system voltage above 72.5 kV and up to and including 170 kV. Table 9 shows recommended limits for mineral insulating oils dielectric characteristics. These limits are also used as confirmation of the results.

 Table 9. Application and interpretation of dielectric characteristics tests

 Property
 Recommended action limits

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Property	Recommended action mints		
	Good	Fair	Poor
Breakdown voltage (kV)	>50	40 to 50	<40
Water content (ppm)	<20	20 to 30	>30
Acidity (mgKOH/g)	< 0.1	0.1 to 0.2	>0.2
IFT (dyne/cm)	>25	20 to 55	<20
Color Scale			>3.5

Transformers number 18 and 19 (TRF #18 and #19), which are two of the oldest transformers in these population, classified as **E** (Extensive Ageing). TRF #19 shows CO₂/CO ratio of 12.86. Ratio more than 10 is an indication of thermal fault in the paper insulation on temperature less than 150°C, this temperature gives effect to the paper ageing in the long term. TRF #13 also shows ratio higher than 10, with high level of CO and CO₂, this also mean TRF #13 is also undergoing long term ageing in temperature less than 150°C. Both TRF #18 and #19, along with other extensive-classified transformer have high level of CO and CO₂, exceeding major concern level of CO and CO₂ concentration in oil shown in Table 8. Besides CO and CO₂, most of other oil properties of these transformer are at poor condition, such as low interfacial tension and dark oil color. Even, TRF #18 and #19 have very high water content, which are up to 36.89 and 41.46 ppm respectively.

At the early stage, TRF #1 to TRF #6, which have operating life of 10 years or less, classified as healthy. From oil characteristics point of view, almost all healthy-classified transformers have relatively good oil parameters. This is in line with study in [42], that the ageing process happens during the life of transformer, decrease the condition of the transformer and changes certain parameters in oil insulation.

From the training accuracy (70 transformers), then validated with testing dataset (32 transformers), followed by implementation to 19 transformers with no furan data, verified by comparing the result to conventional assessment methods and standards, the developed SVM model can successfully classify transformer oil-paper condition using no furan measurement.

The proposed model also able to recognize the decreasing trend of transformer oil-immersed paper insulation condition as the operating time increasing.

4. Conclusions

Classification analysis of in-service 150 kV Power Transformers insulation condition using Support Vector Machine (SVM) is presented in this article. As much as 149 150 kV power transformer measurements data (Dielectric Characteristics, Dissolved Gases, and Furan) were accessed and explored. The outliers were eliminated using one-class SVM. The inliers data was separated to training and testing datasets. Attributes selection were done by implementing ANOVA and Chi-Squared, resulting in CO, CO₂, IFT, and Color. As much as 70 transformers were used to develop and train the model, while 32 distinct transformers were used as testing data.

The proposed method is able to recognize different category of transformer oil-immersed paper insulation condition based on the dissolved gasses and dielectric characteristics measurement data. For training and testing, the measurements data have been divided into two separate datasets. After selecting the best features and comparing with different models, the best-performed model has been chosen, resulting in total 90.63% accuracy in distinguishing the oil-immersed paper insulation condition into three categories: Healthy; Moderate; and Extensive (29 correct classification out of 32 transformers). Further implementation was executed to classify oil-paper condition of 19 Transformers with no Furan data available. The result then verified and compared to conventional assessment methods and standards, confirming that the model developed has the ability to do classification of current oil-paper condition based on Dissolved Gasses and Dielectric Characteristics.

This paper has demonstrated that the model proposed has the ability to do prediction of current insulation paper condition category and has the practicality to be additional insights in transformer condition monitoring.

5. References

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