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Fault Prediction for Power Transformer Using Optical Spectrum of Transformer Oil and Data Mining Analysis

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ABSTRACT Periodic preventive maintenance of power transformer should be conducted for its health monitoring and early fault detection. Transformer oil is a vital element where its contents and properties need to be monitored during the service life of a power transformer. This paper presents an optical spectroscopy measurement from 200 nm to 3300 nm to characterize the transformer oil, which were sampled from the main tanks and 'on-load tap changer' of power transformers. The correlation of the optical characteristics in the range of 2120 nm to 2220 nm to the Dissolved Gas Analysis results and Duval Triangle interpretation demonstrates that the low energy electrical discharges, high energy electrical discharges as well as the thermal faults rated at temperatures above 700°C in power transformers can be accurately predicted. For faster and accurate analysis of fault prediction, a data mining analytics tool was constructed using Rapid Miner server to analyze and verify the predictions for a total of 108 oil samples. For the optimization, continuous iterations were performed to determine the best absorbance-wavelength combination that can improve the accuracy of the prediction. The performance of the optical spectroscopy technique integrated with data analytic tool was analyzed and it was found that the technique contributes to a high accuracy of 98.1% in fault prediction. It is a cost-effective and quicker complementing approach to carry out pre-screening of the transformer oil in order to know the condition of the power transformers based on the transformer oil's optical characteristics.

INDEX TERMS Data mining, fault prediction, optical spectroscopy, power transformers, transformer oil.

I. INTRODUCTION

There are various power transformer condition monitoring techniques such as frequency response analysis [1]–[3], partial discharge analysis [4]–[8] and Dissolved Gas Analysis (DGA) [9], [10] that have been employed in determining the condition of power transformers. These techniques have benefited both manufacturers and operators in many ways, including obtaining information on the health of the power transformer, estimating the remaining service life, increasing plant availability and planning of maintenance schedules. Most power transformers are filled with petroleum-based insulating oil, which has excellent electrical insulating properties. Apart from acting as an insulating and cooling agent, transformer oil also can be used to determine the condition of the power transformer [11], [12]. This is due to the breaking of carbon-hydrogen (C-H) and carbon-carbon (C-C) bonds in the molecules of the oil when it is continuously subjected to electrical and thermal stresses during operation.

Degradation of transformer oil at low operating temperature has been recognized to produce extensive amounts of hydrogen (H_2) and methane (CH_4) gases along with trace amounts of ethane (C_2H_6) and ethylene (C_2H_4) gases. Thermal decomposition of cellulose paper also produces carbon dioxide (CO_2), water vapor, acetylene (C_2H_2) and carbon monoxide (CO) gases as a result of high temperature within

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the power transformer. A study of these dissolved gases alone would not reveal any faults occurring in the transformer oil. Conventionally, the ratio of fault gases produced are needed to diagnose the faults that commonly occur within the power transformers. These well-established ratios include Rogers's ratio, Doemenburg ratio, Duval triangle techniques and IEC ratio [13]–[15]. Duval triangle technique [16] is a common graphical approach which plots normalized coordinates of three types of gases, namely C_2H_4, CH_4 and C_2H_2, in a triangular coordinate system. Data points that fall into certain zones correspond to a certain type of fault. Using the Duval Triangle approach, external partial discharges (PDs) in the form of corona, low energy electrical discharges (D1), high energy electrical discharges (D2), thermal faults of temperatures below 300°C (T1), thermal faults at temperatures in between the range of 300°C and 700°C (T2), thermal faults at temperatures way above 700°C (T3), and combinations of electrical and thermal faults (DT) [17] can be identified.

However, the procedures involved from oil sampling to DGA test are tedious and has long results processing time. The measurement involved in DGA is a direct and destructive measurement. The emergence of optical spectroscopy offers great promise in the field of sensing, characterization and imaging. It is a direct, fast, non-invasive, and non-destructive analytical tool for qualitative and quantitative analysis in both research and industrial applications. For DGA applications, infrared (IR) spectroscopy [18], [19] has been used to determine the absorption properties of dissolved gases in transformer oil. Photo-acoustic spectroscopy has also been a popular choice for researchers [20]–[24] to determine the different types of dissolved gas in transformer oil at a certain wavelength. Raman [25], [26] and near-infrared (NIR) spectroscopy [27] have also demonstrated good progress in characterizing the optical absorption properties of dissolved gases in transformer oil. Although these techniques are excellent in characterizing the optical absorption properties of dissolved gases in transformer oil, there is a lack of further analysis and prediction involving these measurements. Determining the concentration of dissolved gases is not sufficient for power utilities to make any action plans for the respective power transformer.

Thus, this paper proposes to categorize the fault condition directly based on the absorbance spectrum of the transformer oil measured in the ultraviolet-visible-near infrared (UV-Vis-NIR) region without determining the concentrations of the fault gases. While preliminary studies have been carried out in [28], this work provides a detailed analysis of the specific optical properties with the established fault characteristics based on Duval Triangle. The correlation between the optical spectra in the region of 2140-2220 nm and the fault conditions are discussed. This work also proposes a procedure to incorporate data from the optical spectra of transformer oil into the Rapid Miner analysis tool for fault prediction in power transformer. The data mining analytic tool used in this study would provide a faster and cost-effective analysis to determine the absorbance threshold value as well as the range of the wavelength to categorize and predict the fault condition based on the absorbance spectrum of transformer oils.

II. EXPERIMENTAL DETAILS

A total of 108 transformer oil samples were obtained from multiple in-service power transformers with various life spans. Transformer oil samples collected in this study were sampled from the main tank and the OLTC tank of power transformers. DGA was performed for all samples using gas chromatography, which complies with the International Electrotechnical Commission (IEC) 60567 standard. The findings of the DGA have been further evaluated using the Duval triangle method. There are two categories of Duval triangle, first category is for the main tank and the second category is for the OLTC tank. Nonetheless, all the samples are evaluated using the stated Duval triangle method for the main tank. This is due to the difficulty in obtaining oil samples from the main tank with D1 and D2, which mostly arises in the OLTC [29], [30]. Thus, OLTC oil samples were chosen and employed to reflect oil samples from the main tank with D2 and D1 types of fault. It is worth noting that the discharge and high temperature thermal faults, which are categorized in D1, D2 and T3, are the most severe faults compared to that of PDs, T1, T2 and DT. Therefore, this study focuses on the fault prediction for D1, D2 and T3, and categorized other faults as Others (O).

III. OPTICAL SPECTROSCOPY MEASUREMENT

The Agilent Cary5000 spectrophotometer was used to conduct optical spectroscopy measurement. The UV-Vis-NIR light was transmitted through 1 cm path-length cuvettes comprising the sampled transformer oil and the reference oil sequentially, and the respective optical transmittance was recorded. The absorbance values were then calculated according to the Beer-lambert Law as shown in (1).

$$Absorbance = -log_{10}(\frac{S-B}{R-B}) \tag{1}$$

where S is the transmittance of light transmitted through the sampled transformer oil, R is the transmittance of light transmitted through the reference oil, and B is the baseline measured by the instrument.

The transformer oil samples were evaluated in the range of 200-3300 nm. The correlation between the absorbance spectrum derived from the optical analysis of the transformer oil samples and their respective fault condition has been studied. Fig. 1 demonstrates the optical absorbance spectra of several transformer oil samples under various fault conditions at the 2120-2220 nm region, and Table 1 shows their respective fault condition. Samples obtained from main tank were labeled as A1 to A10 while the samples obtained from OLTC tank were labeled as B1 to B11.

Based on Fig. 1, it can be observed that samples with D2 and D1 fault conditions exhibit a peak absorbance approximately at 2172 nm. Most samples with D2 fault condition show higher absorbance value compared to samples with

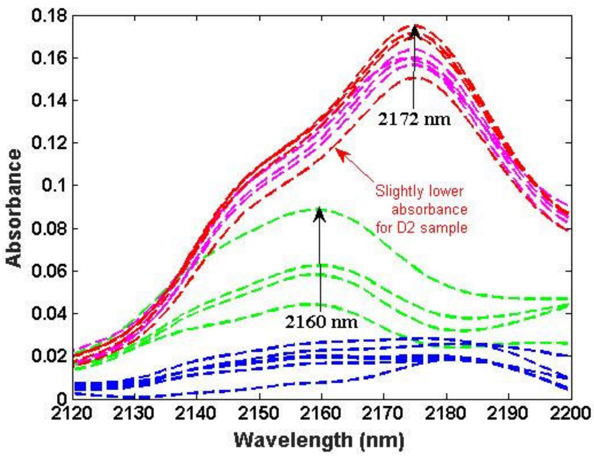

FIGURE 1. Absorbance spectrum of transformer oil samples with D2 (red), D1 (Pink), T3 (Green) and other (Blue) condition at the 2120-2220 nm region.

TABLE 1. Duval fault condition based on dissolved gas limits.

Samples obtained from Main Tank	Type of Fault from Duval Analysis	Samples obtained from OLTC	Type of Fault from Duval Analysis
A1	O	B1	D1
A2	T3	B2	D1
A3	T3	B3	D2
A4	O	B4	D1
A5	O	B5	D1
A6	O	B6	D2
A7	T3	B7	D2
A8	O	B8	D2
A9	O	B9	D2
A10	T3	B10	D1
		B11	D1

* O = other faults / normal

D1 fault condition. However, it can be seen that one of the samples with D2 fault condition (indicated by red arrow in Fig. 1) shows a lower absorbance compared to the samples with D1 fault condition. This could suggest that the sample is just approaching to D2 fault condition from D1 fault condition.

An absorbance peak at 2160 nm can also be observed and this peak is produced by samples with T3 fault condition. Their overall absorbance is approximately twice as low as the absorbance for samples with D2 and D1 faults. Finally, there are a few oil samples with very poor absorbance within the wavelength range. These are the samples with other conditions.

Based on the results obtained, if the sample exhibits a peak absorbance at 2172 nm with absorbance value of 0.16 approximately, the power transformer is in critical condition of D1 or D2, and immediate action is required to resolve the problem. If the sample exhibits a peak absorbance at 2160 nm with absorbance value of 0.06 approximately, the power transformer is categorized as T3 fault condition and constant monitoring of power transformer is recommended. If the sample does not exhibit any significant absorbance peak in the 2120-2220 nm range, the power transformer is in non-critical condition. Optical characterization of transformer oil in the range of 2120-2220 nm would allow the maintenance team to estimate the health of the power transformer and make appropriate decision on its maintenance and service schedule.

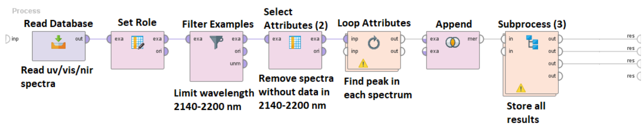

FIGURE 2. Algorithm that extract spectrum files and store into database.

To statistically validate the trend observed on the optical absorbance spectra, a total of 87 additional samples were collected, and their optical spectra were obtained for data mining analysis. Due to the large number of samples tested daily for power utilities, simple visualization on the optical absorbance spectra of the samples for fault prediction would be tedious. Thus, a data mining tool was proposed to determine the criteria or threshold for optical spectra of transformer oil samples for different fault conditions.

IV. DATA MINING ANALYTIC TOOL

Rapid Miner is a data mining analytic tool which is used to analyze data and support various techniques of data mining. A transformer oil sample search tool was constructed by using Rapid Miner server as shown in Fig. 2. The Rapid Miner was used to extract the optical spectra files and store into the database It is a web-based tool that searches for optical spectrum of transformer oil sample that meet the search criteria within the research constraint and helps to identify the accuracy of this monitoring method when it is applied on other optical spectrum of transformer oil.

A continuous iteration process that searches for the best optical absorbance-wavelength combination was then carried out for further optimization. The algorithm prioritized the accuracy for fault prediction instead of normal condition prediction as the former is the more crucial criteria. The flowchart of the overall process is illustrated in Fig. 3. Firstly, the optical spectrum data measured using the spectrophotometer was extracted from each file and uploaded into the system to store all the spectra into a database to begin the data processing using the algorithm as shown in Fig. 4. In the algorithm, each spectrum file was read and the column label was generated based on the file name of the spectrum file, which is the sample ID of the measured sample. The spectrum was then joined into the existing table and store in the memory. At the end of the main algorithm as shown in Fig. 2, all the sample absorbance spectra were stored in a table as shown in Table 2.

The spectra data in the database were then further processed by the peak-finding algorithm as shown in Fig. 5. In the algorithm, the wavelength was set to 2140-2200 nm and each spectrum was pre-processed using moving average. Moving average algorithm was developed to smooth out any

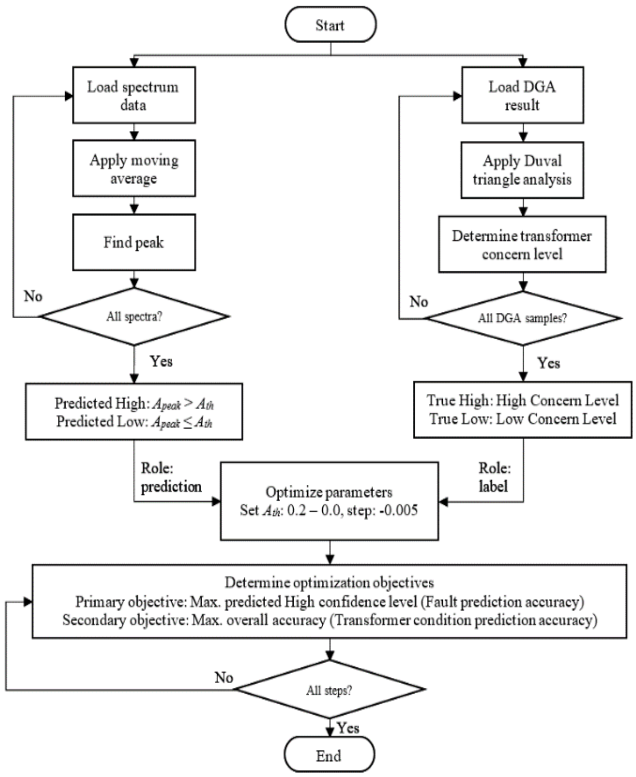

FIGURE 3. Flowchart of the overall process.

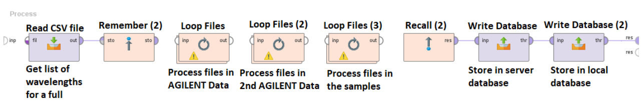

FIGURE 4. Sub-algorithm that process each spectrum file.

TABLE 2. Examples of the sample spectra stored in the database.

Wave length (nm)	Absorbance					
	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
2200	0.0039	0.0092	0.0044	0.0037	0.0393	0.0096
2199	0.0051	0.0105	0.0057	0.0050	0.0395	0.0101
2198	0.0063	0.0118	0.0068	0.0062	0.0397	0.0107
2197	0.0075	0.0132	0.0080	0.0074	0.0400	0.0112
2196	0.0087	0.0146	0.0093	0.0087	0.0402	0.0118
2195	0.0098	0.0158	0.0103	0.0098	0.0405	0.0124
2194	0.0109	0.0172	0.0115	0.0111	0.0408	0.0130

short-term fluctuations from the raw spectrum data and can be defined as:

$$A_{avr}\left(\lambda_n\right) = \frac{1}{3}\sum_{m=n-1}^{n+1} A\left(\lambda_m\right) \tag{2}$$

where $A_{avr}(\lambda)$ is the absorbance after moving average at wavelength λ, $A(\lambda)$ is the absorbance data at wavelength λ and λ_n is the discrete values of wavelength. Table 3 shows the sample data to illustrate the calculation.

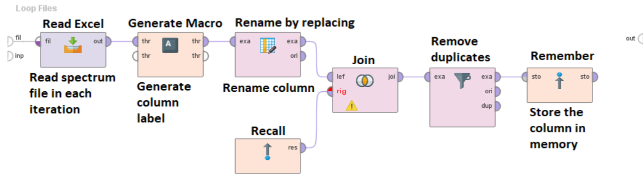

FIGURE 5. Algorithm that processes the spectra and finds the peak absorbance value with its corresponding wavelength.

TABLE 3. Sample data to illustrate the calculation of the moving average.

n	Wavelength, λ_n	Sample 1, $A_1(\lambda_n)$	Sample 1, moving averaged, $A_{avr1}(\lambda_n)$
1	2200	0.003908	-
2	2199	0.005117	0.005103
3	2198	0.006283	0.006292
4	2197	0.007477	0.007476
⋮	⋮	⋮	⋮
59	2142	0.012237	0.012221
60	2141	0.011943	0.011913
61	2140	0.011558	-

Below are the examples of the calculation for moving average by using (2) and the sample data in Table 3.

$$\begin{aligned}
A_{avr1}\left(\lambda_2\right) &= \frac{1}{3}\sum_{m=2-1}^{2+1} A_1\left(\lambda_m\right)\\
&= \frac{1}{3}\left[A_1\left(\lambda_1\right) + A_1\left(\lambda_2\right) + A_1\left(\lambda_3\right)\right]\\
&= \frac{1}{3}\left[0.003908 + 0.005117 + 0.006283\right]\\
&= 0.005103\\
A_{avr1}\left(\lambda_3\right) &= \frac{1}{3}\sum_{m=3-1}^{3+1} A_1\left(\lambda_m\right)\\
&= \frac{1}{3}\left[A_1\left(\lambda_2\right) + A_1\left(\lambda_3\right) + A_1\left(\lambda_4\right)\right]\\
&= \frac{1}{3}\left[0.005117 + 0.006283 + 0.007477\right]\\
&= 0.006292\\
&\vdots\\
A_{avr1}\left(\lambda_{60}\right) &= \frac{1}{3}\sum_{m=60-1}^{60+1} A_1\left(\lambda_m\right)\\
&= \frac{1}{3}\left[A_1\left(\lambda_{59}\right) + A_1\left(\lambda_{60}\right) + A_1\left(\lambda_{61}\right)\right]\\
&= \frac{1}{3}\left[0.012237 + 0.011943 + 0.011558\right]\\
&= 0.011913
\end{aligned}$$

The peak absorbance in the wavelength range was found by calculating the gradient of the absorbance spectrum and then identifying the change of sign of the gradient. For the spectrum with multiple absorbance peaks, the global maximum or minimum peak was chosen. The output of the algorithm in Fig. 5 is shown in Table 4. These records of the peak absorbance values were used in the analytics.

TABLE 4. Examples of peak absorbance and its corresponding wavelength obtained using the Algorithm.

Examples	Wavelength (nm)	Peak absorbance
Example A	2180	0.018420843
Example B	2176	0.028496211
Example C	2161	0.019589229
Example D	2177	0.020315897
Example E	2185	0.042132198
Example F	2182	0.018903206

TABLE 5. Mapping of duval triangle analysis results into high/low transformer concern level.

Duval triangle analysis	True High/Low
T3: Thermal fault, T > 700°C	High
D1: Discharges of low energy	
D2: Discharges of high energy	
Normal	Low
T1: Thermal fault, T < 300°C	
T2: Thermal fault, 300°C < T < 700°C	
PD: Corona partial discharges	
DT: Discharges + Thermal fault	
C: Hot spots with carbonization of paper, T > 300°C	
O: Overheating, T < 250°C	
S: Stray gassing of transformer oil	

TABLE 6. Summary of the prediction accuracy on duval triangle analysis results using UV/Vis/Nir spectra analytics.

	True High	True Low	Class Precision
Predicted High	16/18	36/90	30.77%
Predicted Low	2/18	54/90	96.43%
Class Recall	88.89%	60.00%	

TABLE 7. Iterations of optimization Algorithm.

Iteration	Absorbance threshold	Overall accuracy	Predicted High confidence level
1	0.200	0.870	0.222
2	0.195	0.870	0.222
3	0.190	0.870	0.222
4	0.185	0.870	0.222
5	0.180	0.870	0.222
6	0.175	0.870	0.222
7	0.170	0.870	0.278
8	0.165	0.870	0.278
9	0.160	0.861	0.278
10	0.155	0.861	0.278
11	0.150	0.861	0.278
12	0.145	0.861	0.278
13	0.140	0.861	0.278
14	0.135	0.852	0.278
15	0.130	0.852	0.333
16	0.125	0.843	0.333
17	0.120	0.843	0.444
18	0.115	0.833	0.500
19	0.110	0.824	0.500
20	0.105	0.833	0.556
21	0.100	0.824	0.556
22	0.095	0.815	0.556
23	0.090	0.815	0.556
24	0.085	0.806	0.556
25	0.080	0.796	0.556
26	0.075	0.769	0.556
27	0.070	0.750	0.556
28	0.065	0.750	0.556
29	0.060	0.722	0.556
30	0.055	0.722	0.611
31	0.050	0.713	0.667
32	0.045	0.722	0.722
33	0.040	0.694	0.722
34	0.035	0.694	0.778
35	0.030	0.704	0.833
36	0.025	0.676	0.833
37	0.020	0.648	0.889
38	0.015	0.565	0.889
39	0.010	0.519	0.889
40	0.005	0.481	0.889
41	0.000	0.463	0.889

V. RESULTS AND DISCUSSION

Based on the analytical results of DGA, the Duval triangle analysis was performed on all the results to assess the condition of the power transformer. Several results can be obtained from the Duval triangle analysis, however for this study, the Duval triangle analysis were simplified and the results were mapped into High/Low transformer concern level as shown in Table 5.

A peak absorbance threshold was defined to generate predicted High/Low transformer concern level based on the peak absorbance values, where the values lower than the threshold was set as Low and those higher was set as High. A summary of the prediction accuracy on Duval triangle analysis results using the UV-Vis-NIR spectra analytics with the optimum absorbance threshold is shown in Table 6.

The optimum threshold is obtained, as absorbance value is equal to 0.02 where the confidence level for predicted High value is the highest. Table 6 indicates that 16 out of 18 samples were predicted correctly, which gives 88.89% accuracy in the detection. 2 samples, or 11.11% were predicted wrongly since the algorithm predicted the samples to be Low while they were predicted high using DGA and Duval Triangle Analysis. Meanwhile, in term of prediction for the true Low, 60% of the samples were predicted correctly. The value of the overall accuracy and confidence level for predicted High is shown in Table 7.

Table 8 shows a number of random results out of 108 samples of the prediction on Duval triangle analysis results using UV-Vis-NIR spectra. From all the samples, it gives 64.8% correct diagnosis (True High, Predicted High and True Low, Predicted Low) and 33.3% are overestimating (True Low, Predicted High) which sum up to 98.1% accuracy in detection of critical oil samples with only 1.90% underestimation (True High, Predicted Low) of the samples. Therefore, by using optical spectrum of transformer oil and data mining analysis, the proposed alternative method in this study is a cost-effective and time-saving which can be used as a

TABLE 8. Results of the prediction on duval triangle analysis results using UV/Vis/Nir spectra analytics.

Sample ID	Conventional technique via DGA					Optical spectrum with Rapid Miner analysis		*Estimation
	CH_4	C_2H_4	C_2H_2	Duval triangle analysis result	True High/Low	Peak Absorbance	Predicted High/Low	
Sample 1	8	92	0	T3: Thermal fault, T > 700ºC	High	0.527	High	OK
Sample 2	11	189	0	T3: Thermal fault, T > 700°C	High	0.321	High	OK
Sample 3	5	8	12	D2: Discharges of high energy	High	0.222	High	OK
Sample 10	4	2	3	D1: Discharges of low energy	High	0.133	High	OK
Sample 12	4	3	3	D2: Discharges of high energy	High	0.125	High	OK
Sample 15	144	29	0	T1: Thermal fault, T < 300°C	Low	0.121	High	Ov
Sample17	110	23	0	S: Stray gassing of transformer oil	Low	0119	High	Ov
Sample 28	15	58	23	DT: Discharges + Thermal fault	Low	0.072	High	Ov
Sample 7	6	5	0	Normal	Low	0.161	High	Ov
Sample 103	4	78	0	T3: Thermal fault T > 700ºC	High	0.099	Low	Ud

*Ud= Underestimation; Ov=Overestimation; OK= Correct estimation

complementing tool to predict fault within power transformer with high accuracy.

VI. CONCLUSION

This research focuses on the optical characterization of transformer oil in relation to the fault conditions based on DGA results and Duval's triangle interpretation. The findings indicate that samples with D2 and D1 fault conditions exhibit high optical absorbance peaks near 2172 nm. On the other hand, an absorbance peak near 2160 nm indicates T3 fault condition in the power transformer. Additionally, the data mining analytic tool used in this study also provides a quick complementing analysis to determine the absorbance threshold value as well as the range of the detection wavelength, for the categorization of power transformer conditions based on optical spectrum of transformer oil. The performance of the optical spectroscopy technique integrated with data analytic tool was analyzed and it was found that the technique contributes to a high accuracy of 98.1% in fault prediction. The optical characterization of transformer oil in the NIR region is undoubtedly a more cost-effective and faster alternative to distinguish T3, D2 and D1 faults from less severe faults in power transformers. It is evident that optical spectroscopy integrated with data analytics tool is a reliable technique to complement the existing comprehensive transformer oil testing method. It minimizes the frequency of routine DGA test and interpretation using the Duval Triangle.

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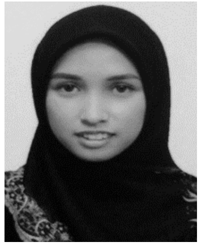

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