Classification of Degraded Polymer Insulator Using Support Vector Machine

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***Abstract*—The ability to monitor closely the surface degradation condition of polymer insulator will be really beneficial to the power utility company in order to ensure smooth and safe power transmitted to the consumer. If the level of degradation condition could be classified, then it could ease the maintenance team to take proper action as to avoid any undesirable event from happening. In this study, it has implemented the leakage current signal parameters data in the classification process of degraded field-aged insulator. These signal parameters are extracted from the Spectrogram. Prior to this analysis, the leakage current signal is captured during the testing method of inclined plane tracking. The physical evaluations such as arithmetical mean of surface roughness and static contact angle are also measured for the purpose of comparison of surface conditions. The Support Vector Machine is implemented in the machine learning test, in which the percentage of classification accuracy between degraded sample and the controlled sample is recorded. To validate the classification results obtained, the insulator sheds under test was going through the Spray Method to determine the criteria of hydrophobicity class in Table 1 of the IEC TS 62073:2016. By using the percentage of total harmonic distortion data, the consistency results of the classification accuracy percentage have been successfully determined the two significant classes and the transition class between them. However, there is an existence of insignificant classes if the root means squared leakage current data is implemented. Therefore, by implementing the appropriate leakage current signal parameter data, the degradation classification could be determined accurately.**

***Keywords*—classification of degradation, support vector machine, leakage current, total harmonic distortions, hydrophobicity class**

I. Introduction

The outdoor polymeric insulator has several advantages over a non-polymeric insulator in high voltage application which include the uniqueness of its hydrophobic properties [1], its ability to achieve lightweight reduction up to 90%, therefore make it easy to handle for installation process [2]. However, this composite type insulator are quite sensitive to the local environmental conditions either naturally affected by ultraviolet, corona, mist, fog, moisture etc. or the sources of manmade environmental pollution such as acid rain, industrial dust and gases, etc. [3]. The combination of multiple stresses from environment, mechanical and electrical on the surface of polymer insulators in its long term field service will have high effect on their degradation factors. These factors might rapidly accelerate the losses of its mechanical and electrical properties such as surface hydrophobicity loss, surface resistance loss and can promote to the surface leakage current [4], electrical discharge, surface erosion that mainly affected by dry band arcing over the surface of the insulator. All these chronological degradation footprints should be properly treat to reduce the risk of partial failure or completely shutdown of power delivery system [5].

In order to minimize the potential risk failure that might affected by the polymeric insulators degradation, numbers of research works in this area have been carried out among the researchers around the world. This includes the physical evaluation such as surface roughness [6] and hydrophobicity properties such as hydrophobicity classification [7], static contact angle measurement [8]. Related to the electrical properties, the analysis of leakage current (LC) is one of the common researches done to monitor the degradation of the insulator. Numerous techniques and LC features implemented such as LC time-frequency representation [9], root mean squared LC (Irms) [10], variation of LC pattern which analyzed through power frequency component and harmonic contents [11].

With regards to the several recent studies related to LC features analysis that could be expanded, this study is intended to further extend the research that has been carried out in [9]. It is conducted to implement the LC signal parameters data into the classification process of degraded field-aged insulator using Support Vector Machine (SVM). The magnitude of Irms and percentage of total harmonic distortions (% THD) are the extracted data obtained from the Spectrogram in the previous study. It is proposed to classify the insulator degradation level based on the estimated electrical features data, so that it will conveniently facilitate in determining the range of the hydrophobicity classes that established in the IEC TS 60237:2016 guideline [12]. The percentage of classification accuracy (% CA) is the result of SVM classification performance measured that is used to classify each of electrical features data between degraded sample and controlled sample.

To validate the classification results obtained, the validity test which implemented Spray Method as outline in [12] is

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conducted for each of the sample under test. Three main criteria that described the hydrophobicity class in the Table 1 of the IEC TS 60237:2016 are compared. The first criterion is the surface contact angle value measured. The second and third is regarding the form of discrete droplet of water and the percentage wetted area covered by water on the insulator surface respectively. The percentage of water covered at the wetted area is calculated using image processing vision-based inspection by HALCON 11 Software.

II. EXPERIMENTAL DESCRIPTIONS

A. Test Material

The testing materials deployed are the 12-year field-aged surge arrester's housing insulator obtained from the Malaysian national power company, Tenaga Nasional Berhad (TNB). Originally, these field-aged insulator were removed from the transmission main intake at Plentong power substation located along the coast in the state of Johor, Malaysia. The ethylene propylene diene monomer (EPDM) silicone rubber insulator in the polyvinyl nitrate (PVN) polymer station class surge arrester (SA) is used for testing [13].

B. Sample Preparation

The details of degraded samples and controlled samples preparation procedures can be referred to [6], however only the 12-year field-aged insulator is considered in this study. The data of the LC features from Inclined Plane Tracking (IPT) Test that have been applied in this classification of degradation study are obtained from the samples' name as following details. The controlled samples are named as CS-x, and various degraded test samples are named as TS-x, where the x= 1, 2, .., n is the number of particular sample.

C. Surface Roughness Test

The surface of insulator physical tests are carried out prior to the electrical stress test as to estimate the degradation level through non-destructive evaluation on the samples surface. The details of surface roughness testing can be referred to [6].

D. Electrical Stress Test

The electrical stress test within the IPT Test was carried out based on the BS EN 60587 [14]. The Method 1 test is applied, whereby a 3.5 kV constant AC voltage is continuously supplied to simulate continuous tracking voltage for 60 minutes of testing period for each of tested location involved [9].

E. Machine Learning Test of SVM Classifier

Prior to machine learning test (MLT), the electrical features for each location tested which are the average Irms in a minute for 1 hour testing period is prepared. Similarly, it goes to the average of % THD. This means that for each of location tested, there are about 60 data of average Irms and 60 data of average % THD are extracted from the LC signal by using the Spectrogram that is analyzed in MATLAB Program.

The SVM classifier program applied in this study is a simple machine learning algorithm that adopted from Machine Learning Toolbox in MathWork File Exchange [15]. The default setting of the program is maintained with the radial basis function as the kernel trick that suited to the nature of non-stationary data. Although in general *k* remains an unfixed parameter, the *k*=10 is commonly used for k-fold cross-validation value [16]. The process flow of SVM machine learning test that has been conducted is shown in Fig. 1.

In this supervised learning, the 4 data sets of labeled data have been classified as a good condition of insulator surface, whereas the 8 data sets of unlabeled data have unknown class of the insulator surface degradation level. Hence, the labeled data set is used as the basis for predicting the classification of other unlabeled data through the use of SVM machine learning test algorithm.

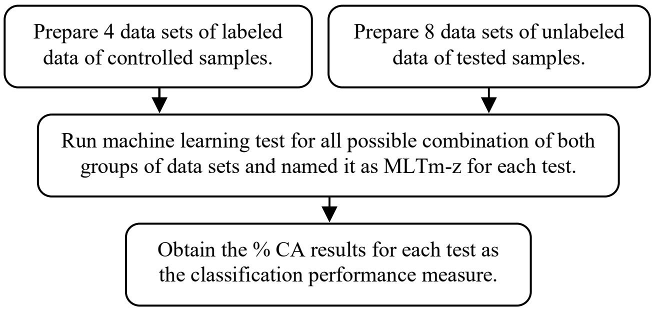

Fig. 1. Process flow of SVM machine learning test.

In total there are 64 MLT that have been run. Half of the tests were the implementation of Irms data and the others for % THD. To ease the test number identification, the test is named as MLTm-z, where m=1,2,3,…n is the number of possible combination of both group data sets, whereas the z=1 for % THD data and z=4 for Irms data.

The % CA is obtained from each of the MLT and the calculation inside the program algorithm can be explained with the aid of Confusion Matrix as shown in Fig. 2.

True Positive (TP) Reality data : CS-1 SVM predict data : CS-1 Number of TP data (*p*) : 60	**False Negative (FN)** Reality data : CS-1 SVM predict data : TS-1 Number of FN data (*q*) : 0
False Positive (FP) Reality data : TS-1 SVM predict data : CS-1 Number of FP data (*r*) : 57	**True Negative (TN)** Reality data : TS-1 SVM predict data : TS-1 Number of TN data (*s*) : 3

Fig. 2. Description of each cell in the confusion matrix of MLT1-1.

For an example, the % CA of MLT1-1 in Fig. 2 is calculated. The distribution of 120 data with the combination of 60 data % THD of each CS-1 and TS-1 can be seen at each cell of the confusion matrix. Then, by applying the formula as in (1), the % CA of MLT1-1 can be obtained as 52.5 %.

$$\% CA = [(p + s) / (p + q + r + s)] \times 100 \% \quad (1)$$

F. Validity Test

The Spray Method based on the IEC TS 60237:2016 guideline [12] is carried out for each of the 12 tested samples. The static contact angle testing is conducted using the Phoenix Mini Contact Angle Analyzer Model manufactured by Surface Electro Optics (SEO™) [17]. This analyzer has implemented the static contact angle, whereby each of single droplets of distilled water having about 1.0 mS/m is placed on the different surface of the insulator samples with micro-syringe. Combination of a charge-coupled device camera and Surfaceware Software, a digital image is automatically analysed the average of left and right of the contact angles.

The percentage of wetted area covered is one of the criteria, and the HALCON 11 Software is required for this purpose. This vision-based inspection of industrial product has been utilized in [18] to detect a class of defects in gluing application. Minor modification is done to suit with the image recognition of wetted area by adding on a second layer of filtering process. Fig. 3 shows the process flow of this application.

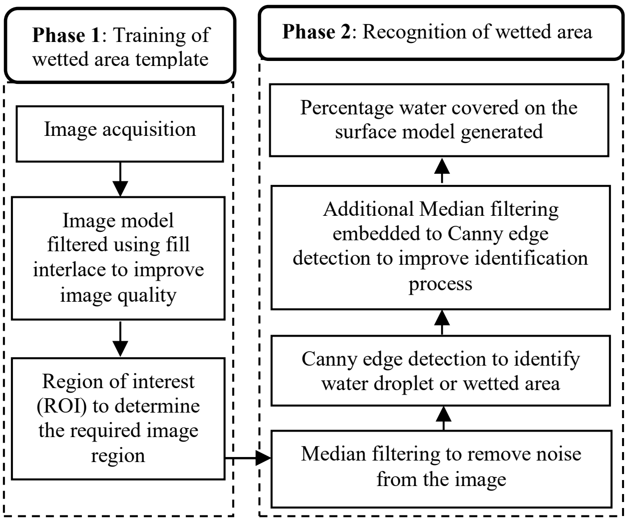

Fig. 3. Process flow of HALCON 11 image processing software.

There are two phases involved including the training of a template and recognition of wetted area. By implying the sequential process from image acquisition, setting the region of interest (ROI), undergo several image filtering and recognition process, this algorithm successfully calculate the percentage of water covered. It is gathered around the ROI by comparing pixels between object and the background. Object means that water is covered at the material surface, whereas the background will be otherwise.

III. RESULTS AND DISCUSSION

A. Results of Surface Roughness Test

As for the reference data, the values of surface roughness among the controlled samples, CS-1 to CS-4 are the smallest compared to others which the measured values between 0.925 µm and 1.238 µm. However, the test samples TS-5 to TS-8 depicted the roughest surface with the readings in the range of 3.810 µm to 10.254 µm. Observation on the TS-1 to TS-4 indicates that each of the sample still have good hydrophobicity property and the surface roughness value range between 1.243 µm to 2.028 µm in which it is still consider a bit higher than the controlled samples.

B. Percentage Classification Accuracy Results

Fig. 4 and Fig. 5 depict the bar charts of % CA of MLT results for the 32 possibilities combinations of 8 samples test with 4 controlled samples. These results have implemented the % THD and Irms as electrical features data respectively.

The results of % CA in Fig. 4 have indicated significantly the % THD data have the ability to classify the samples tested into 3 potential hydrophobicity classes which named as HC-A (around 50 %), HC-B (around 75 %) and HC-C (around 100 %). Thus, the results of Spray Method in validity test as in TABLE I determined the specific hydrophobicity class (HC) for each of them.

These findings have proved that the % THD plays a very important role in influencing the degree of degradation of insulator surface. The odd harmonic component especially the 3rd harmonic is the dominant harmonic number that is increased with the increment of the degradation [19], [20].

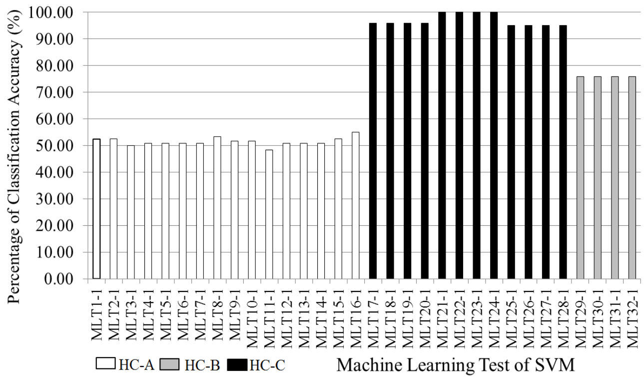

Fig. 4. The % CA of MLT results with %THD data implemented.

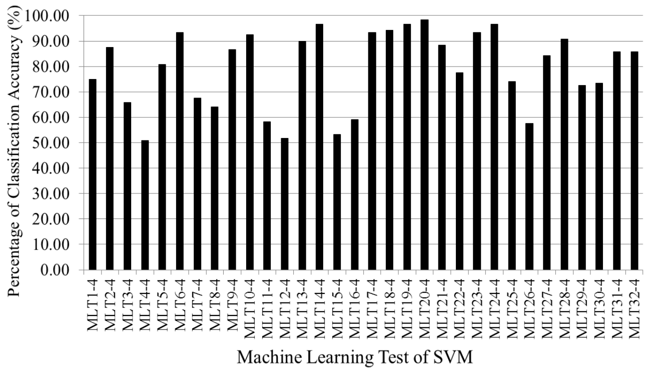

Fig. 5. The % CA of MLT results with I_{rms} data implemented.

However the results in Fig. 5 have shown insignificant distribution of % CA in overall MLT. Therefore Irms data have insufficient capability to classify the samples tested. These results have also been acknowledged by several researchers indicating that the LC magnitude and peak value are no longer a good tools for insulator surface performance indicator [21], [22].

C. Validity Test Results

TABLE I shows the results of the Spray Method that has described the criteria of discrete water droplets are only formed on the surface for the contact angle value which is greater than 60°. However for the samples with contact angle of 0°, in which they correspond to the roughest hydrophilic surfaces, the percentage of wetted area have been processed and calculated by HALCON 11 Software.

TABLE I. RESULTS OF THE SPRAY METHOD AND HALCON 11SOFTWARE

Name of sample	Wetted area covered (%)	IEC TS 62073:2016 Guideline		
		Descriptions of water droplet and wetted area	*Contact angle (°)*	*Hydrophobicity Class (HC)*
TS-1	-	Only discrete droplets are formed	96.31 > 60	HC-A= HC1
TS-2	-		104.71 > 60	HC-A= HC1
TS-3	-		114.25 > 60	HC-A= HC1
TS-4	-		114.88 > 60	HC-A= HC1
TS-5	92.73%	90% <wet<100%	0	HC-C= HC6
TS-6	97.70%	90% <wet<100%	0	HC-C= HC6
TS-7	90.28%	90% <wet<100%	0	HC-C= HC6
TS-8	86.20%	10% <wet<90%	0	HC-B= HC5

The percentage of wetted area covered shows that the TS-8 tested sample which potentially recognized as HC-B class has been classified in the HC5, whereas TS-5 to TS-7 recognized as potential class of HC-C are classified in the HC6. The others are recognized as potentially class of HC-A and have been classified in the HC1 due to their contact angle value greater than 60° and their water droplets characteristic observed as only discrete water droplets is formed on the surface .

IV. CONCLUSION

By using the %THD data in MLT, the consistency of the % CA results have been successfully classified the EPDM polymer type insulator under test into two significant classes which are HC1 and HC6. Meanwhile, the HC5 is the transition class between them. This is validated by the correlation results of description criteria in the IEC TS60237:2016 guideline. However, for Irms data that is implemented in the MLT, there is an existence of inconsistency of % CA distribution although it is tested in a same group of samples. So, Irms itself could not be solely used as an electrical feature to indicate the degradation level of polymer insulators. Therefore, by implementing an appropriate LC signal parameter data, the degradation classification could be determined accurately. By monitoring the % CA that has implemented % THD, it will be able to estimate the hydrophobicity class and facilitate the recognition process of degraded insulator that are required in any routine maintenance or some precaution action that needs to be carried out.

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REFERENCES

[1] Y. Xiong, S. M. Rowland, J. Robertson, and R. J. Day, "Surface analysis of asymmetrically aged 400 kV silicone rubber composite insulators," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 15, no. 3, pp. 763–770, 2008.

[2] R. Tripathi, G. Grzybowski, and R. Ward, "Electrical degradation of 15 kv composite insulator under accelerated aging conditions," in *2013 IEEE Electrical Insulation Conference, EIC 2013*, 2013, pp. 404–408.

[3] A. R. Verma and B. S. Reddy, "Interpretation of surface degradation on polymeric insulators," *Eng. Fail. Anal.*, vol. 95, no. June 2018, pp. 214–225, 2019.

[4] A. A. Salem *et al.*, "Proposal of A Dynamic Numerical Approach in Predicting Flashover Critical Voltage," *Int. J. Power Electron. Drive Syst.*, vol. 10, no. 1, pp. 51–58, 2019.

[5] G. Haddad, K. L. Wong, and P. Petersen, "Evaluation of the Aging Process of Composite Insulator based on Surface Charaterisation Techniques and Electrical Method," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 23, no. 1, pp. 311–318, 2016.

[6] A. Din, M. A. M. Piah, A. R. Abdullah, and N. F. Kasri, "Surface roughness condition of field-aged polymer insulators at different installation area," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 15, no. 2, pp. 600–608, 2019.

[7] Israrullah et al., "Accelerated Multi Stress Aging and Life Estimation of Polymeric Insulators," in *17th International Bhurban Conference on Applied Sciences & Technology (IBCAST)*, 2020, pp. 55–61.

[8] R. Ullah and M. Akbar, "Lifetime Estimation based on Surface Degradation and Characterization of HTV Silicone-Rubber based Composites for HVAC and HVDC Transmission," *CSEE J. POWER ENERGY Syst.*, pp. 1–8, 2019.

[9] A. Din, M. A. M. Piah, A. R. Abdullah, N. Norddin, and F. S. Abdullah, "Leakage current signal parameter of various surface roughness conditions of field-aged polymer insulators," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 20, no. 2, pp. 638–645, 2020.

[10] W. Song *et al.*, "Aging characterization of high temperature vulcanized silicone rubber housing material used for outdoor insulation," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 22, no. 2, pp. 961–969, 2015.

[11] A. R. Verma and B. S. Reddy, "Leakage Current Patterns Observed in Polymeric Insulators Rotating Subjected to Wheel and Dip Test," *ICHVE 2018 - 2018 IEEE Int. Conf. High Volt. Eng. Appl.*, pp. 23–26, 2019.

[12] (International Electrotechnical Commission), "TECHNICAL Guidance on the measurement of hydrophobicity of insulator surfaces." pp. 1–24, 2016.

[13] "PVN Polymer Station Class Arresters," *Hi-Tension News*, no. 1051, pp. 1–4, 1993.

[14] "Electrical insulating materials used under severe ambient conditions — Test methods for evaluating resistance to tracking and erosion (BS EN 60587:2007)," vol. 3. pp. 1–14, 2007.

[15] J. Too, "Simple Machine Learning Algorithms for Classification Version 1.0.4," vol. 4, no. May. p. 71461, 2019.

[16] McLachlan, *Analyzing microarray gene expression data*. Wiley, 2004.

[17] "Sessile Drop Method (Static Contact Angle)," *SEO- Surface Electro Optics*. .

[18] M. H. Harun, M. F. Yaakub, A. F. Z. Abidin, A. H. Azahar, M. S. M. Aras, and M. B. N. Shah, "The investigation on defect recognition system using gaussian smoothing and template matching approach," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 18, no. 2, pp. 812–820, 2020.

[19] Rachmawati, M. Wakhidin, and Suwarno, "Study on Leakage Current Characteristics and Electrical Equivalent Circuit Properties of Aged Polymer Insulator under Artificial Environmental Condition," in *The 4th IEEE Conference on Power Engineering and Renewable Energy (ICPERE)*, 2018, p. 6.

[20] M. K. Moghadam, M. Taheri, S. Gharazi, M. Keramati, M. Bahrami, and N. Riahi, "A study of composite insulator aging using the tracking wheel test," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 23, no. 3, pp. 1805–1811, 2016.

[21] A. H. El-hag, "Leakage current characterization for estimating the conditions of non-ceramic insulators ' surfaces," *Electr. Power Syst. Res.*, vol. 77, pp. 379–384, 2007.

[22] D. Pylarinos, E. Thalassinakis, and P. Str, "Investigation and Classification of Field Leakage Current Waveforms," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 19, no. 6, pp. 2111–2118, 2012.