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ONLINE PARTIAL DISCHARGE MEASUREMENT FOR CONDITION-BASED MAINTENANCE OF HV POWER CABLES IN RAILWAY INFRASTRUCTURE

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Abstract Partial discharge (PD) measurement as one of well-known method to evaluate the condition of high voltage (HV) power cables has been studied over many decades. Cable insulation failure could result in a power outage, which could then cause a loss of service in the transportation system and even dangerous events like fire accidents. It is of a great interest to railway infrastructure operators to monitor and identify the cable faults before any possible accident occurs. The paper focuses on the diagnostic problem to detect the HV cable fault based on the Phase Resolved Partial Discharge (PRPD) patterns. Classification models, such as Random Forest and Convolutional Neural Network, are considered to classify the pattern of PRPD based on the mostly occurring PD types in HV cables, such as corona, surface, and void patterns. Experiments are performed and the PRPD data from the experiments are collected. The optimal model is applied in the online monitoring program which will be used continuously to evaluate the cable condition and arrange the optimal schedule for maintenance. According to the analysis, both algorithm perform well in the PRPD pattern categorization, with accuracy up to 83.45%. This indicates that due to the more effective behavior, PD assessment with PD sensors is preferable.

Keywords: Condition-based maintenance, Partial discharge, Fault detection, High voltage cable

1. Introduction

High voltage power cables are one of the main components in the power supply and distribution system. Cable insulation breakdown could lead to a power loss which may lead to a production loss in manufacturing system, service loss in transportation system, and it also could lead to a harmful event, such as fire accidents. Thus, like any other complex or vital systems, it is important to perform a maintenance and monitoring of high voltage (HV) cable condition to reduce, or possibly avoid, such unwanted events.

CIGRE 279 is one of international standard related to HV cables and it includes the maintenance strategies for HV cables and accessories [1]. Based on CIGRE 279, the main reasons for performing maintenance on HV cables are to avoid failures, to avoid environmental damage, to avoid a more expensive maintenance later, to extend the life of the equipment, to avoid the harmful situations, to repair the failed components, and to avoid legal and financial penalties. CIGRE 279 summarizes the failure modes of HV cables, the probability of occurrence, the diagnostic indicator, and the related maintenance/preventive actions. Electric wires may now be characterized and evaluated in advance using partial discharge (PD) detection and analysis[2], [3]. It is showed that one of potential maintenance/preventive action is a partial discharge (PD) measurement since it can be performed both online or offline depends on the test equipment and it covers more than half of the cable failure modes.

Based on IEC 60270, the definition of partial discharge (PD) is a localized electrical discharge that only partially bridges the insulation between conductors, and which can or cannot occur adjacent to a conductor [4]. The standard also includes the guidance on how to measure the partial discharge in HV cables. All cable manufacturers perform PD measurement test during the cable quality control process to determine whether the cable has passed the allowable PD level. The power distributor companies perform periodic maintenance

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actions which include a PD measurement to determine whether the cable has no faults which lead to more harmful events.

Many studies on PD measurement to identify whether the cable is in good condition or whether one is in a bad condition and needs further maintenance, such as a cable replacement. Not only to identify the condition of HV cables, but PD measurement is also used to identify the condition of other electrical equipment in power supply and distribution system, such as, transformers, rotating machines, medium voltage (MV) cables, gas insulated switchgear (GIS) [5], [6]. Through PD measurement, PD pattern can be obtained and based on the PD pattern, the type of PD occurring in the cable can be identified and the suitable action can be performed. Studies on PD classification methods can be referred in [7], [8].

One of widely used methods is Phase Resolved Partial Discharge (PRPD) pattern classification. PRPD data pattern shows the PD pulse quantity, the phase angle in which the PD occurs, and the rates of occurrence of the corresponding PD within a predefined time interval. PD detection methods and categorization in cables have been the subject of several publications published in the literature before the present study[9], [10]. Random Forest (RF)-based feature-selection algorithm was proposed to identify the PD pattern in [11]–[13]. The study compared the proposed algorithm to the BPNN and SVM and showed that the proposed algorithm outperforms those methods in classifying the PD pattern[14], [15]. As sensor technology and IoT improves significantly, sensors have been used to monitor the PD data and the automation of PRPD data collection, which is considered big data, became possible and make the PD classification more accurate through deep learning. Although there has been significant advancement in condition online monitoring and evaluation in terms of measurement techniques, measurement accuracy, and fault location, there are still a number of issues that need to be addressed through additional research, including the dependability of the long-term operation of sensors, their accuracy, sensitivity, and interference-resistance, the efficiency of data acquisition and transmission, and the accuracy of fault location techniques[16]. However, depending on the precise combination of existing feature extraction techniques and classification approaches, the PD recognition execution varies extensively. Deep learning methods have been studied for PD classification based on PRPD data pattern[17], [18]. Long short-term memory (LSTM) has been proposed in the classification of PD pattern in GIS where the data is measured with ultra-high frequency (UHF) sensor[19]. Autoencoder (AE) was considered also in the classification of PD pattern in GIS[20]. CNN has been considered in the PD classification in HV switchgears, GISs, and transformers[21]–[24]. The improvement model of deep learning such as CNN will boost observational precision of PD conditions. The results show that the suggested model's accuracy is better than the existing models[25].

In this paper, we considered a PRPD data pattern classification to identify the condition of the HV cables distributing the power the for the railway infrastructures. The organization of the paper is as follows. Section 2 gives a brief explanation about PD in HV cables and the PRPD pattern. Section 3 shows the data used in the analysis and the considered methods for the PRPD pattern classification. Section 4 shows the analytical results and Section 5 concludes the study.

2. PD in HV Power Cables in Railway Infrastructure

PD is defined as a localized electrical discharge that only partially bridges the insulation between conductors, and which can or cannot occur adjacent to a conductor [4]. Based on CIGRE 279, the maintenance/preventive action, including PD measurement, to identify the condition of HV cables and the accessories can be summarized in Table 1. Although, periodic/visual inspection can cover most failure modes of the cable and accessories, since the periodic/visual inspection is costly in term of maintenance budget, time, and technician allocation. It is better to perform PD measurement through PD sensors due to the more efficient behavior.

Based on the location of occurrence, PD can be classified into two types: internal PD and external PD. Internal PD occurs inside the power cable, while external PD occurs outside the cable, such as around cable accessories (joint and termination). Example of internal PDs are PDs occurs in cable void and PDs from treeing inside cable. Example of external PDs are corona PD, which generally occurs from a sharp

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electrode into the gas and surface PD, which occurs in the surface of joint area. Studies showed that each PD type has unique pattern.

Table 1. Diagnostic tool for Extruded Cables based on CIGRE 279 [26]

Tool	Number of failure modes which can be identified			Total
	Cable	Joint	Termination	
Periodic/visual inspection	2	1	7	13
Serving test	2	0	0	2
Tanδ measurement	1	0	0	1
Temperature measurement	2	0	0	2
PD measurement	2	5	4	11
Chemical and physical analysis	0	0	2	2
X-Ray	1	2	1	4

PRPD analysis is one of methods to evaluate and help on identifying the PD pattern. Briefly explained, PRPD analysis is a tool able to show the pattern of PD measured within a certain time interval. PRPD analysis output is a PRPD plot showing the PD pulse counts with a certain magnitude in a certain phase angle. The plot is usually a 2-dimension graph with a color representation of the PD pulse counts as seen in Figure 1.

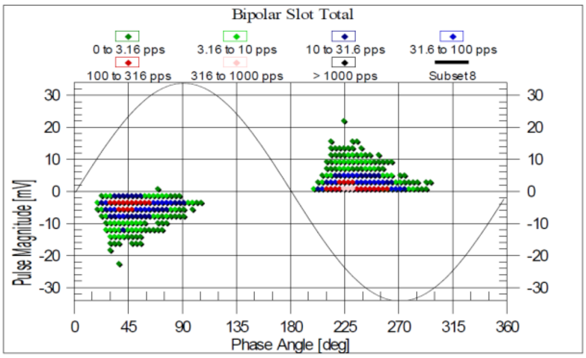

Fig. 1 PRPD plot illustration sample

3. Methods

We designed and performed an experiment to simulate the PD occurrence in the HV cables. We simulate three kinds of PD occurrence based on the PD types, such as void PD, corona PD, and surface PD. PD test materials for those three PD types are used in the experiment and three locations of the test material, such as the transformer, joint box, and the cable endpoint (termination), are considered as the experiment treatment. Since the cable is a 3-phase HV cable, we also consider the three phase-locations as the treatments. Overall, we have 3x3x3 (27) experiment scenarios. Due to the experiment duration limitation, we only considered two repetitions for each scenario and the PD measurement was performed for 5 minutes for each scenario.

Fig. 2 PD Simulation Experiment

Table 2. Experiment Features

No	PD test material	PD location	Cable phase-location
1	Corona PD	Transformer	Phase A
2	Surface PD	Joint box	Phase B
3	Void PD	Termination	Phase C

PRPD plot and the corresponding 2-dimension dataset for each experiment scenario are collected and used as the inputs in the model, while the PD types (corona, surface, and void PD) are used as the target values. Convolutional Neural Network (CNN) and Random Forest (RF) are considered in the classification model. Why consider this two approach since this two deep learning and machine learning approach.

3. Results

The following is a recap of data on OEE values Based on PRPD plots measured from the experiments, visually we can confirm that there exist difference PD patterns for the considered PD types (see Figure 3). Also, we can also confirm that the phase location difference only affects the location of the PD phase angle in PRPD plot but has similar pattern (see Figure 4).

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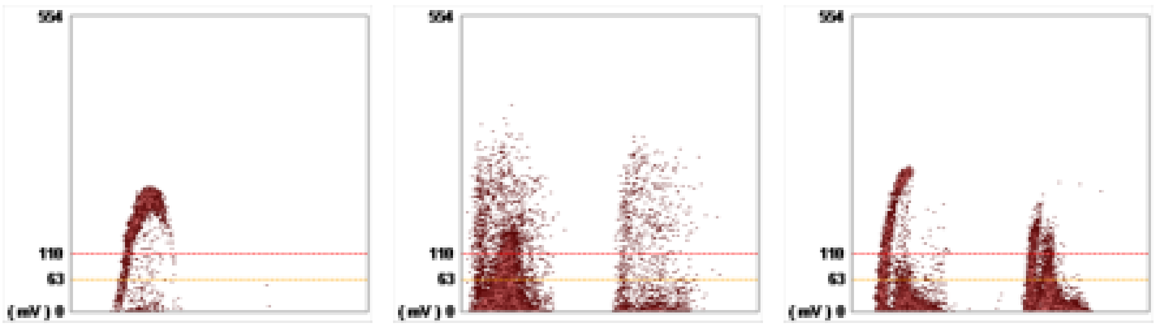
Also, it shows a difference in the PD magnitude, which may be resulted from the distance difference to the sensor location.

Using these PRPD plot images as the input in CNN resulting in the overall classification accuracy 83.45% within 30 epochs. While RF results in the per-group classification accuracy as shown in Table 3 and the overall classification accuracy is 83.09%. These numbers show that CNN and RF performs similarly in this specific study and should not be applied for the PD pattern classification problem in general, since the data is not a real data from the field but simulated from the experiment.

4. Conclusions

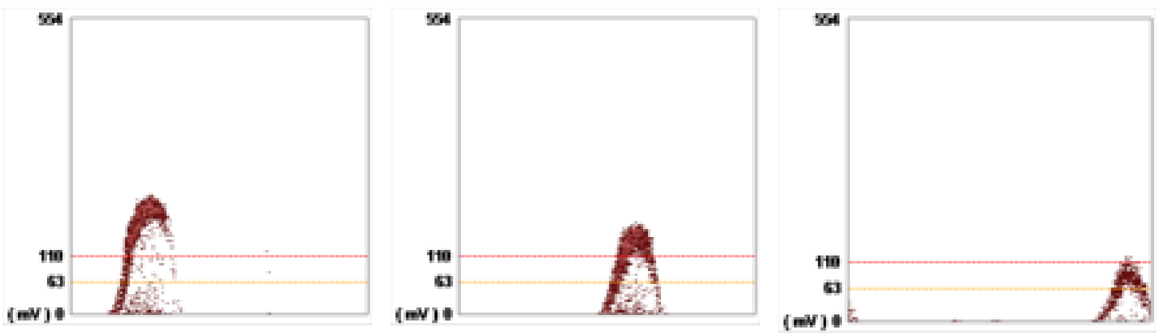
The paper studied the PD pattern classification problem in HV power cables. The PD data is collected from experiments with PD test materials. There were 27 different test scenarios, where the treatments are the PD type test material (corona PD, surface PD, void PD), PD location (transformer, joint box, and cable phase-location (A, B, C) and the repetition number is two per scenario due to the experiment time limit. PRPD plot and the PRPD dataset are collected and used as the input in the classification model (CNN and RF). The analysis showed that CNN and RF perform well in the PRPD pattern classification, where the overall accuracy for CNN is 83.45% and that of RF is 83.09%.

For further studies, many studies can be done. We can consider the real case data as the input in the analysis because the real case data has noise which occurs from the external factors such as environment. Another study is to consider the variable of time to show the deteriorating process, which can be further used in the remaining lifetime prediction for the HV cables and will be an essential information in the maintenance scheduling problem for the HV cables.



(a) (b) (c)

Fig. 3 PRPD plot samples for three different PD types. (a) corona PD, (b) surface PD, and (c) void PD



(a) (b) (c)

Fig. 4 PRPD plot samples for different phase location. (a) termination, (b) joint box, and (c) transformer

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Table 3 RF Accuracy

Corona PD	Surface PD	Void PD
0.8841	0.7681	0.8406

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