Comprehensive evaluation and detection of partial discharge in WBG motor drive using DBSCAN based feature extraction

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2023 IEEE Energy Conversion Congress and Exposition (ECCE) | 979-8-3503-1644-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ECCE53617.2023.10362669

***Abstract*—The emergence of Wide Band Gap (WBG) technology has significantly enhanced the efficiency and power density of motor drives. As a result, WBG motor drives have widely been adopted in aircraft and transportation applications, particularly in More Electric Aircraft (MEA) systems. However, the reliability of the WBG high-power drive system is still a major concern. The reliability of medium and high-voltage motor drives sees an increased insulation degradation due to a more intense partial discharge (PD) exposure. Hence, PD condition monitoring, detection, and analysis are valuable for reliable operation and timely maintenance. This paper deals with PD detection at various voltage levels, dV/dt, and waveform shapes. This paper provides robust detection and analysis of PD events deriving the key relationship between PD probability and factors impacting PD events. This paper provides novel PD detection based on pattern recognition which is adaptable to varying voltage and frequency of supply. This algorithm can help the computation of charge per PD event as well as PD probability.**

***Index Terms*—Partial discharge, detection algorithm, DBSCAN feature extraction, PD detection setup**

I. Introduction

Rapid electrification of the transportation and aircraft industry in recent years has led to demand for high power density and efficiency in power electronics motor drives. Recent studies show that motor drive insulation failure due to voltage stress, higher dV/dt, aging, and degradation is the main reason behind the reduced reliability and lifetime of high voltage motor drives [1]. Moreover, 85% of the failures in high and medium voltage equipment can be owed to partial discharge events [2], [3]. Standards (IEC 60034-18-41 and IEC 60034-18-42) define Partial discharge inception voltage (PDIV) as the voltage level beyond which a PD event occurs. For assessment of the reliability of the systems, standards are also using the Repetitive Partial Discharge Inception Voltage. (RPDIV) is the minimum peak-to-peak voltage that gives rise to at least five PD events in every ten voltage impulses [4] as defined by IEC 61934. Hence, PD-based condition monitoring will play a vital role in the maintenance of electrical motor drives. PD condition monitoring/detection is a non-trivial task as PD in power electronic systems is a high-frequency phenomenon. This poses challenges like high-frequency sensing, big data analysis, and interpreting PD patterns [5]. Normal PD monitoring includes the following steps as suggested in [6].

1) PD signal/event collection
2) PD signal data feature extraction
3) PD event classification or clustering
4) Interpret PD event characteristics

1) PD signal detection techniques: PD sensing methods can be divided into mainly electrical, acoustic, and chemical detection techniques [6]. There are other obsolete methods like light and temperature detection techniques. They are no longer used due to incompatibility with the high-frequency nature of PD events, especially in wide band gap (WBG) systems. Some of the state-of-the-art electrical sensors for detecting PD electromagnetic waves (300 MHz to 3 GHz) are Ultrahigh frequency (UHF) sensors or UHF antennas [7], high-frequency current transformer (HFCT) sensors (3 MHz to 3 MHz) [8], E-field and H-field probe. Additionally, acoustic sensors have the capability to identify sound waves produced by partial discharge within both the sonic and ultrasonic frequency ranges. Acoustic sensors have advantages: easy installation, immune to electromagnetic interference, cost-effective, and effective in localizing PD sources [6]. Lastly, chemical detection is typically invasive and primarily applied to oil-filled components, such as transformers, restricting its usage in other equipment [9]. Moreover, it lacks the ability to reveal the specific location of partial discharge (PD) occurrences. This data serves as an important indicator for PD detection.

2) PD signal feature extraction: In order to capitalize on above mentioned high-frequency sensing methods, accurate feature extraction and data analysis will be key. State-of-the-art literature has suggested automated [10] as well as hand-crafted feature extraction [1]. Clustering, classification, principle component analysis (PCA), and deep learning-based feature extraction have been frequently used as suggested in [9]. The key challenge is that all this feature extraction is PD event specific. For instance, if the type of excitation to DUT is changed, the PD pattern changes. This causes inaccuracy in analysis. Moreover, features extraction needs to be a hybrid approach to ensure compatibility with various types of PD events, as suggested in IEC 60270; also, it should extract as much information from the data as possible.

3) PD data analysis: According to IEC 60270, Phase-resolved PD (PRPD) and phase-resolved pulse sequence (PRPS) are two forms of presenting the pattern of PD in a time domain and frequency domain, respectively [11]. PRPD and PRPS can be derived from any of the above-mentioned detection philosophies. [12] suggests the identification of PD using a support vector machine into two types, namely type 1 and type 2. Whereas, [6] suggest analyzing PD event using the frequency of occurrence and the PDIV requirements using a decision learning tree. The data analysis algorithm depends on the application and type of DUT for PD detection. PD data analysis can be divided into phase delay analysis and time event-based analysis as suggested in [12].

PD condition monitoring system requires high sensing accuracy, sensitivity, and robustness, making it a non-trivial task. Traditionally, PD detection methods have used hand-crafted features extracted or statistical feature extraction techniques. PD feature extraction can be threshold-based, statistical, time, frequency features, etc. Recent advancement in PD detection algorithm utilizes clustering (K-means, DBSCAN, etc.), classification (logistic regression, decision tree, random forest, gradient-boosted tree, etc.), and deep learning approaches (convolutional neural networks, long short-term memory networks, generative adversarial networks, etc.) on extracted feature for PD event detection. However, they cannot detect the start and stop timing of PD events. Moreover, features hand-crafted or deep learning based are case specific targeted at one specific supply condition (Sine Wave, Bipolar, Unipolar pulse). Additionally, the peak Detection based approach is inaccurate due to Low SNR/ Low magnitude PD. Additionally, the impact of varying voltage, dV/dt, and frequency on PD patterns is not explored in great detail in the literature.

The main objectives of the paper are a) Sensing PD using H-field, E-filed sensors, and a novel resistance-based sensing method. b) DBSCAN-based adaptable feature extraction for PD detection under varying voltage levels, dV/dt, and wave shape at STP c) Accurate and robust detection of PD using pattern recognition. d) Lastly, evaluation of the frequency of PD occurrence, the average charge per PD event, and PD probability for varying operating conditions. It shall be noted that all tests were conducted at STP.

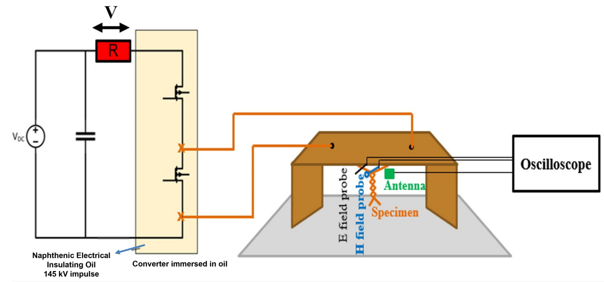

Fig. 1. PD detection sensing schematic

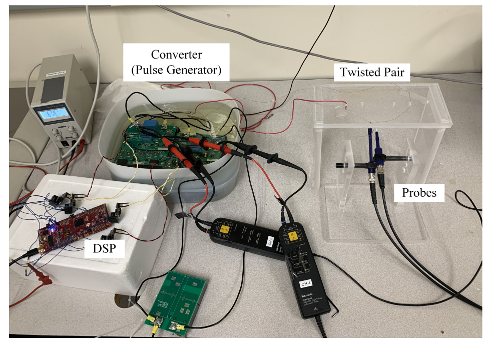

Fig. 2. PD detection test setup

II. Proposed PD-based Condition Monitoring

In order to overcome above mentioned challenges, this paper provides a case adaptive two-stage pattern recognition-based PD detection algorithm, which is supply-adaptive, peak, and time-dependent. This allows the user to detect the number of PD events, their start and stop instances, charge enclosed per PD event. This helps in developing an empirical relationship between PD events with dV/dt, type of supply, voltage level, supply pulse width, etc. The PD event data acquisition needs to be noise immune for accurate analysis of PD detection.

A. Proposed PD Detection Methodology

The detection method depends on a multi-sensor PD measurement approach as suggested in Fig. 1 and Fig. 2. This paper employs a two-stage PD detection approach as suggested in Fig. 3 and Fig. 4. The major component of the PD detection flowchart is as follows:

- Data Acquisition: Proposed methodology utilizes sensor data from E-field, H-field, and voltage sensor as suggested in Fig. 2. The data is varied in terms of voltage level, type of voltage waveform, and duty of supply voltage.
- Signature Extraction: The proposed methodology uses density-based spatial clustering of applications with noise (DBSCAN) clustering for signature extraction. It is notable that DBSCAN can help users to overcome the disadvantages of threshold-based signature extraction.
- Post-Processing: Start, stop time of PD event and triangular charge computation are later extracted from the signature extraction for deriving features for PD events.
- Supervised data: These features are now assigned labels such as PD event, noise, and signal.

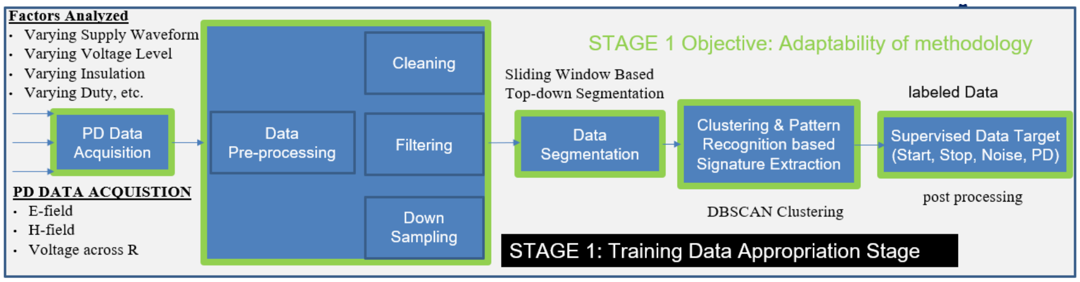

Fig. 3. Stage 1: Training Data Appropriation Stage

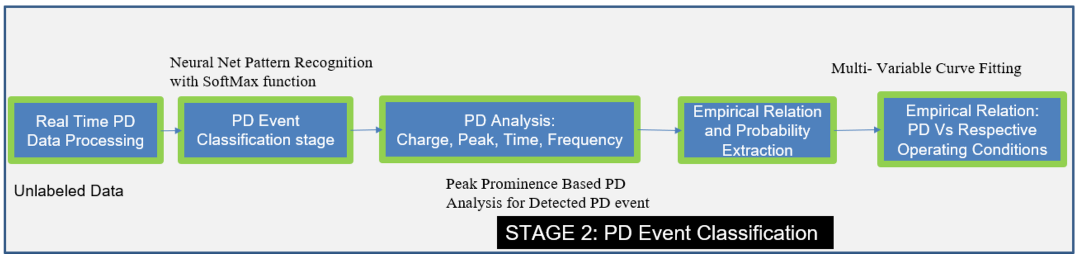

Fig. 4. Stage 2: Pattern Recognition-based PD Detection

- Classification: This paper implements neural network pattern recognition using the softmax function for PD event detection
- Analytic: The PD event goes to post-processing analysis for the derivation of charge enclosed, impact assessment of given PD event. Lastly, an empirical relationship between PD probability and operating conditions is derived.

B. Experimental Setup: PD Sensing

Fig. 2 shows the schematic and test setup developed for accurate comparison of PD intensity in twisted pairs for different voltage waveforms (unipolar, bipolar up to 20 kHz).

The voltage pulses are generated using two CREE CRD8FF-1217P SiC-based half bridge boards, which are immersed in oil to prevent background PDs. For detecting PD, the UHF detection method is employed comprising of the following sensing technique.

1) H-field probe
2) E-field probe
3) Dipole antenna
4) Voltage across resistor R as suggested in Fig. 1.

All these are placed near the twisted pair. For holding the probes/antenna and the twisted pair, an acrylic-based sample and probe fixture are developed. The probe fixture has slots for adjusting the probe height and depth and can be locked in place. Similarly, the sample fixture has equally spaced holes on top to ensure the center alignment of the sample. Lastly, to measure the PD intensity, a resistor R is connected in series with the twisted pairs, and its voltage v_R is measured on the scope. The PD intensity in terms of charge Q is then determined by integrating the resistor current v_R/R at time instants where the UHF probes detect PD events as suggested in (1).

$$Q_{PD} = \int i(t)dt = \int \frac{V(t)}{R} \tag{1}$$

It was observed experimentally that PD events were detected that H-field, as well as E-field sensors, were efficiently able to pick up the PD events as shown in Fig. 5 and Fig. 6. However, it can be easily seen that pattern between switching noise, and PD event using H-field and E-field is not unique. Hence the detection algorithm has to be based on threshold values. The detection would be easier with the E-field probe as signal noise and PD can be easily distinguished, unlike the H-field probe.

On the other hand, PD detection with voltage across resistance shows variation in signal pattern as well as magnitude. Moreover, it makes PD detection a lower frequency phenomenon as PD charges discharge with a larger time constant as compared to H-field and E-field probes. It helps PD signal post-processing for feature extraction. Lastly, PD detection using R can be used to analyze the charge enclosed in each PD event. It can be used in conjunction with PDIV, magnitude threshold, and PRPS.

C. PD detection: Proposed feature extraction

Feature extraction is essential in PD detection as raw data often contains an overwhelming amount of information, not all of which is relevant to the task. By extracting pertinent features, the data becomes more manageable and suitable for analysis. Moreover, feature extraction reveals meaningful patterns and relationships, enabling machine learning models to learn effectively and generalize well.

In PD detection, common features like amplitude, frequency, pulse width, phase, and statistical properties of waveforms play a vital role. These features capture various PD

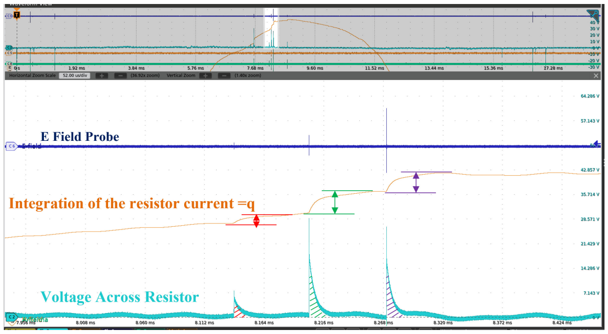

Fig. 5. Charge approximation for voltage across resistor method

characteristics and aid in distinguishing between normal and PD events. Additionally, tailoring feature extraction to specific PD sources or insulation materials enhances the model's sensitivity and accuracy, adapting it to different scenarios. The overall benefit of feature extraction is improved PD detection accuracy, facilitating effective condition monitoring and maintenance in electrical systems. Feature extraction for PD detection has to have the following features:-

1) Feature should be able to detect PD signal variation under varying voltage levels, wave shape, and dV/dt.
2) Features must be able to deal with SNR carefully, not eliminating PD signals during the filtering process
3) Features must ensure that data segmentation doesn't avoid PD events. Hence, sliding window segmentation is popular for feature extraction.

It was observed that threshold-based clustering and outlier detection is not a good solution, especially with H-field and E-field data set. For instance, K-mean or K-medoid clustering is not the best. The proposed feature extraction uses density-based clustering. DBSCAN is a density-based clustering algorithm that groups data points based on their proximity and density. It does not require specifying the number of clusters beforehand, and it can identify noise points as well. DBSCAN is well-suited for datasets with varying cluster shapes and densities, and it is effective in discovering clusters of arbitrary shapes. The data used for DBSCAN was pre-processed using savitzky-golay filtering [13].

III. Investigating PD Events: Pattern Recognition and Insights

The proposed methodology deals with PD detection at various voltage levels, dV/dt, and waveform shapes. The data was collected using unipolar and bipolar square pulses at 60Hz up to 20kHz. The voltage across R At the same time, various sensor data were used for PD detection. This brings forth the challenge of multiple-feature extraction.

A. Impact of varying voltage waveform

The voltage waveforms were varied in terms of shape and frequency. The key variations were as follows:-

- Unipolar square pulse: The voltages were varied from 700V to 1.1 kV, and the frequency was varied were 60 Hz, 2 kHz, and 60 kHz.
- Bipolar square pulse: The voltages were varied from 700V to 1.1 kV, and the frequency was varied were 60 Hz, 2 kHz, and 60 kHz.
- Sine wave: The voltages were varied from 700V to 1.1 kV; frequency was 60 Hz.

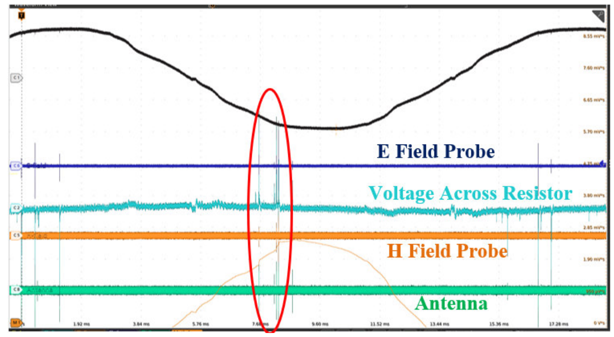

Fig. 6. Sine wave voltage excitation

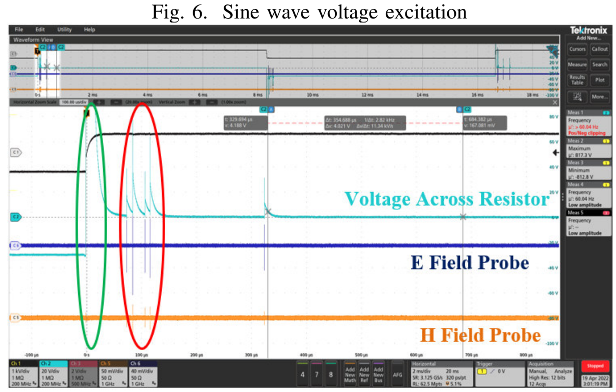

Fig. 7. Bipolar voltage excitation

The PD signatures varied significantly with wave shape. It was observed that for the same voltage level, less PD was observed in unipolar as compared to bipolar pulses. At the same time, the PD signatures changed in terms of H-field and E-filed peaks. Also, the voltage across the resistor varies significantly, as suggested in Fig. 6 and Fig. 7. Bipolar voltage PD tests at a 2kHz switching frequency In the same voltage level that unipolar voltage did not generate PD, bipolar voltage is causing PD events

B. Impact of varying frequency

Frequency of excitation with similar voltage level and dV/dt impact strength and pattern of PD event signals. Fig. 8 and Fig. 9 suggest that with increased frequency and the same voltage level, the PD event pattern changes. It is observed PD occurs mostly at switching transient at higher frequencies. At the same time, PD events were also observed at stable regions in low-frequency square pulse.

C. Impact of voltage level

The partial discharge (PD) event generates a near-field electromagnetic emission dominated by the electric field (high voltage, low current emission), which is captured by the probes. When PD occurs in an air environment, it emits an

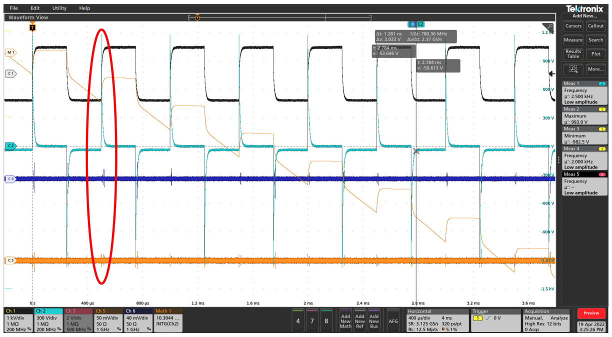

Fig. 8. 20kHz Bipolar voltage excitation across specimen

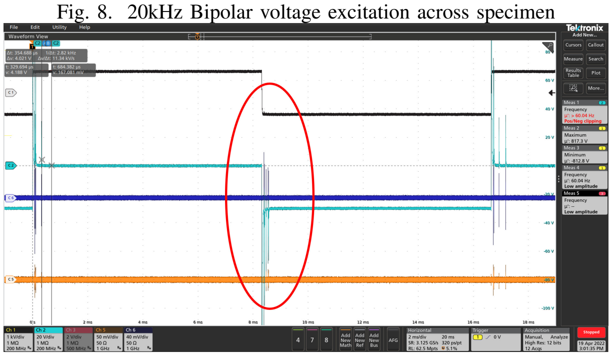

Fig. 9. 2kHz Bipolar voltage excitation across specimen

electromagnetic wave with a frequency of around 300 MHz. Following the near-field boundary criteria (D=/2), the probes are positioned within a boundary distance of 15.9 cm to ensure consistent results for different test voltages.

In Fig. 11, we observe the PD pulse detected by the probes, showing a frequency of 336 MHz. Moving on to Fig. 10-11, we present the PD test results for a 20 kHz unipolar square wave. Notably, the first PDIV is observed at 750 V. Increasing the voltage level from 750 V to 800 V leads to higher PD amplitudes and an increased number of pulses with PD events, indicating a noticeable effect of the voltage level on PD occurrence.

This suggests that higher voltage levels can result in reflected waves with significant amplitude, leading to insulation deterioration and potential damage over time. Understanding and monitoring PD occurrence at different voltage levels is crucial for ensuring the reliability and longevity of electrical insulation systems.

D. Experimental validation: PD detection

PD events are experimentally observed using H-field, E-field, and voltage sensors across R, as depicted in Fig. 2 and Fig. 1. Additionally, Fig. 12 illustrates the PD width and the number of PD events using V_R.

For the computation of charge enclosed in each PD event, a triangular approximation of integral current, as suggested in Fig. 13, was employed. It is worth noting that threshold-based PD detection methods [6] lack the ability to provide information about the start and stop of PD events and the charge per PD event. These methods only detect PD events and compute the number of occurrences.

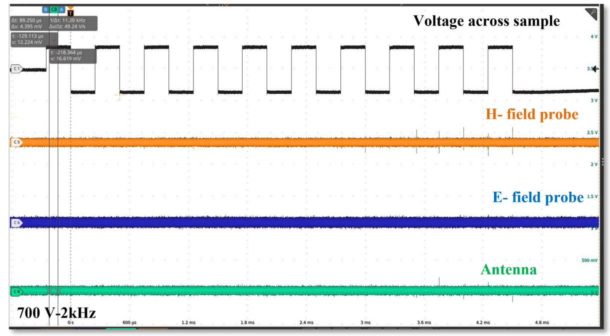

Fig. 10. PD test results at 700V.

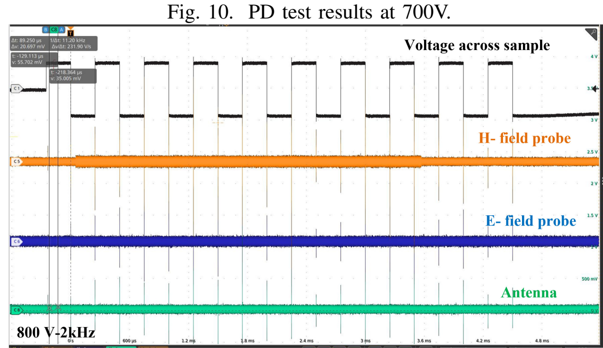

Fig. 11. PD test results at 800V.

In contrast, the proposed method utilizes triangular approximation along with filtering to estimate charge computation, start and stop times of PD events, and the number of PD events for various operating conditions. The pattern recognition used for H-field and E-field sensors was DBSCAN and a neural net based on the softmax function was used. The accuracy of pattern recognition is analyzed using a confusion matrix as suggested in Fig. 14. It shall be noted that E-field and H-field sensor data are impacted by SNR ratio as well as filter coefficient during post-processing. The pattern hence is bound to miss PD events with lower magnitude glitches. This has been compensated using diligent consideration and a multiple-sensor approach.

The pattern recognition-based PD event detection technique can be leveraged to establish relationships between various factors influencing PD events. Table I offers a comprehensive analysis of crucial parameters, such as the number of PD events, RPDIV (Repetitive Partial Discharge Inception Voltage), PD probability, and average charge per PD event, across different source waveforms.

It is important to note that the data analyzed in Table I was collected without the use of pressure or temperature chambers. Consequently, the impact of temperature, pressure, and humidity on PD events has not been taken into account. Additionally, the twisted wires employed in the experiments were non-insulated, leading to the exclusion of any considerations related to insulation thickness.

The main objective of this research is to present a methodology for enhanced PD detection, which can be utilized as an online algorithm in conjunction with experimentation. By doing so, empirical expressions can be derived to establish correlations between PD occurrences and factors influencing PD events. Table. I attempts to investigate voltage waveform and frequency. It was observed that unipolar voltage saw a lower charge per PD event as compared to bipolar and sine wave excitation. At the same time can also be observed when the frequency lowered, overall PD probability increased for square wave pulses, whereas an inverse trend was observed for sine wave. In summary, the study employs pattern recognition for efficient PD event detection and offers a comprehensive analysis of key PD parameters. Although certain environmental and material factors were not considered in the current analysis, the research lays the groundwork for further exploration and development of a robust PD detection approach, ultimately facilitating the derivation of empirical relationships between PD and its influencing factors.

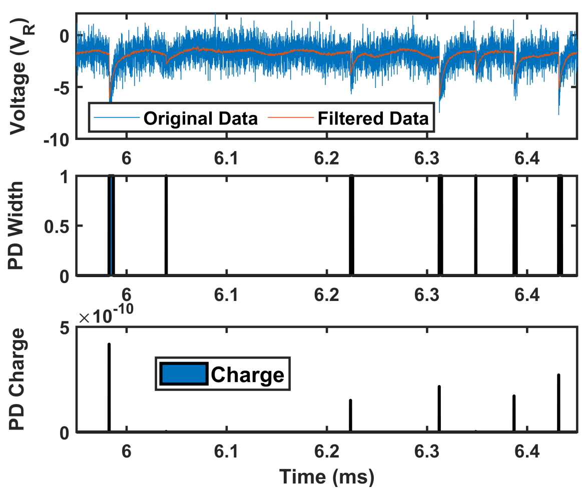

Fig. 12. PRPD detection using two-stage pattern recognition

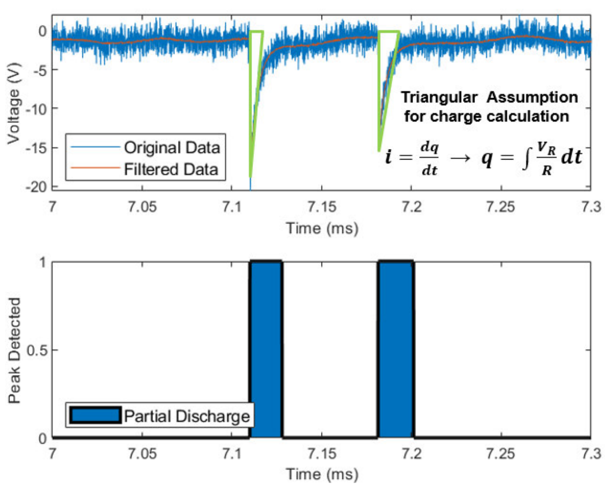

Fig. 13. Charge Computation per PD event

Table. I shows an analysis of a number of PD events, RPDIV, PD probability, and average charge per PD event for varying source waveforms.

TABLE I
PD DETECTION VS. VARYING VOLTAGE AND FREQUENCY

Waveform	Frequency @ 20 kHz			
	No. of PD Events per Cycle @800V	RPDIV (kV)	PD Probability Over 100 Cycle @800V	Average Charge Per PD (PU) @800V
Sine Wave	18	0.59	0.86	4.6
Unipolar Pulse	4	0.82	0.27	0.9
Bipolar Pulse	34	0.5	0.88	5.8
Waveform	**Frequency @ 60 Hz**			
	No. of PD Events per Cycle @800V	RPDIV (kV)	PD Probability Over 100 Cycle @800V	Average Charge Per PD (PU) @800V
Sine Wave	59	0.78	0.71	28
Unipolar Pulse	18	0.9	0.36	7.6
Bipolar Pulse	112	0.72	0.82	13.7

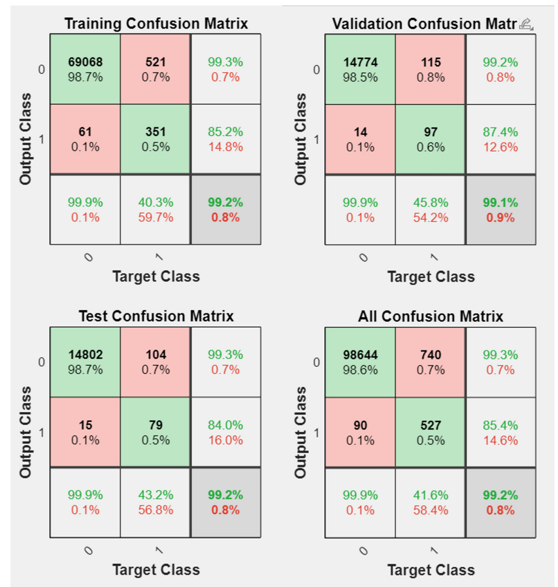

Fig. 14. DBSCAN and SoftMax Neural Net based Pattern Recognition: confusion matrix

IV. CONCLUSION

This paper focuses on the detection of partial discharge (PD) in a twisted wire pair using electromagnetic radiation. The analysis performed in this study delves into the impact of varying voltage, dV/dt, and frequency on PD events. Moreover, the paper introduces a novel PD detection method based on pattern recognition, which can adapt to different voltage and frequency levels of the power supply. This algorithm facilitates the computation of charge per PD event and PD probability. The pattern recognition technique employed in this research is a hybrid of machine learning and manual/approximate approaches. Specifically, the algorithm uses DBSCAN and neural network-based pattern recognition for E-field, H-field, and antenna sensors while employing triangular approximation for PD detection using voltage across resistance.

In summary, the research employs a combination of multiple sensor types and sophisticated computational methods to thoroughly investigate PD events. This approach provides valuable insights into the behavior of PD under various operating conditions. Additionally, the paper aims to derive statistical PD probability, RPDIV, and charge per PD event for different voltage excitations.

The proposed approach significantly enhances the understanding of PD behavior, encompassing charge computation, temporal aspects, and statistical measures. This valuable information contributes to more reliable condition monitoring and facilitates efficient maintenance of electrical insulation systems.

ACKNOWLEDGMENT

The authors would like to acknowledge the National Science Foundation (NSF Award No. 1846917) and Federal Aviation Administration (FAA Award No. 692M15-20-C00010) for lending financial support for this work.

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