# Insipient Insulation Fault Detection Using Phase-Resolved Partial Discharge Pattern Matching

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***Abstract*— The phenomenon of partial discharge in high-voltage equipment poses a significant threat to system reliability, emphasizing the importance of early fault detection and detailed analysis. This paper presents CosNet, a deep learning model developed to identify pertinent features in 2D images of Phase-Resolved Partial Discharge (PRPD) patterns and established templates. Subsequently, these features are evaluated using a cosine similarity function to assess the similarity between specific PRPD pulse patterns and these templates. Our study indicates that PRPD patterns resulting from slot defects in stator motors frequently manifest themselves in a triangular shape. The success of our proposed method sheds light on the potential to standardize partial discharge analysis using artificial intelligence, which could replace the hazardous and time-consuming task of amassing large datasets.**

***Keywords*— condition monitoring, electrical insulation, partial discharge, image processing, pattern recognition**

## I. Introduction

Electrical equipment constitutes invaluable assets that must be protected and maintained, with their primary role being the consistent provision of electricity to support the essential functions of our daily lives. Yet, over time and with continuous use, complications begin to emerge. One of the primary culprits of equipment malfunctions in power facilities is insulation issues. The initial sign of insulation degradation is the emergence of partial discharge (PD), a phenomenon that can often go undetected. Continuous operation can intensify this problem, accelerating the ageing of the equipment aging and eventually leading to complete failure [1]. Hence, it is vital to detect PD and report on insulation condition. Taking timely action can prevent this issue from escalating, averting serious repercussions.

Defects in insulation can arise from various sources. Manufacturing imperfections might introduce tiny gaps while handling during delivery or installation might lead to mechanical damage. Operational wear, such as physical harm to the electrical apparatus, or natural aging can erode the resilience of the insulating material [2]. These defects can instigate various forms of PD as illustrated in Fig. 1. Examples include internal discharges within voids of solid or liquid insulators, surface discharges on the insulator's external layer, corona discharges stemming from uneven electric fields at electrode tips, or treeing caused by continuous discharge effects in solid insulating materials.

PD detection is carried out using sensors such as Ultra High Frequency (UHF) couplers, High-Frequency current Transformers (HFCTs), Piezoelectric Transducers, and Transient Earth Voltage (TEV) detectors. The acquired signals are often displayed in Phase-Resolved Partial Discharge (PRPD) plots to aid with analysis. The PRPD data are obtained based on voltage waveform where the phase angle of the applied voltage is divided into definite number of segments, and the voltage is kept at a persistent level [3]. Each of the PD signals are captured using a PD detector and pulses are quantified based on the phase angle ($\varphi$), magnitude of charge ($q$), and the number of PD events ($n$) over a specific period. The measurements known as a $\varphi - q - n$ when displayed on a plot with the power frequency sinewave form a PRPD pattern.

Significant effort has been put into making the analysis of PD faster and easier using advanced computation techniques. These include the use of Gray-Level Co-occurrence Matrix (GLCM) features along with Support Vector Machine (SVM) [4] and HOG features [5]. However, the use of intricate descriptive feature extraction techniques involves complicated mathematical procedures. Lately, deep learning, such as Convolutional Neural Networks (CNN), have been embraced to improve feature extraction efficiency. The effectiveness of CNNs has been proven in various sectors like health [6], and security [7] in addition to condition monitoring where CNNs

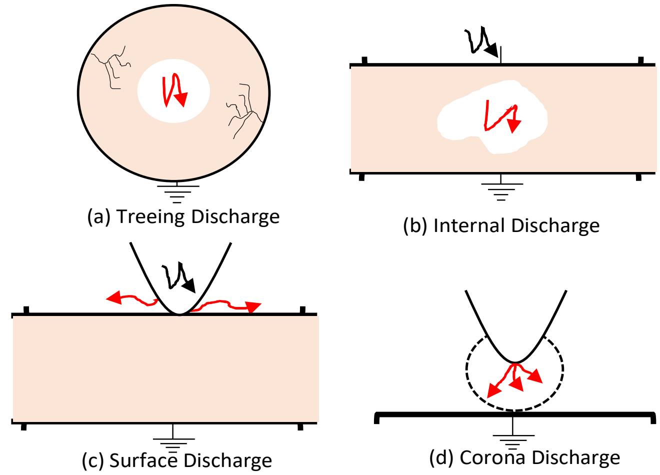


Fig. 1. Four typical partial discharge types.

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have been applied with promising results. Nevertheless, the substantial computational requirements associated with deep-learning techniques present challenges within industrial settings where computational resources may be limited. This underscores the ongoing need for research in methods for recognizing PRPD patterns.

In this study, an innovative method for segmenting and extracting PD patterns from complex PRPD images is introduced. The process begins by identifying regions of interest and key characteristics within the data, crucial for PD analysis, which are then fed into an advanced deep-learning algorithm. The capability of deep-learning models to discern meaningful patterns from limited PRPD samples is demonstrated, challenging the traditional requirement for extensive datasets in complex tasks like PD analysis. The unique approach utilizes a cosine similarity function as the output layer of the deep-learning model, enabling the matching of a single processed PRPD image with a pre-defined template. This method not only provides insightful PD interpretations but also represents a novel asset-based PD recognition approach in condition monitoring. By identifying fault types through PRPD pattern characteristics and employing pre-defined templates, the method circumvents the need for large-scale data collection, marking a significant advancement in the field.

## II. Image-Pre-processing

Before attempting pattern recognition, it is essential to implement pre-processing methods to either reduce the imperfections or improve the quality of the PRPD images. The methods utilized in this study for PRPD image pre-processing are described in the following sections.

### A. Noise Reduction

Noise reduction is achieved using Bilateral Filtering (BF). This method operates by considering both the geometric proximity and photometric similarity of pixels within a local window to determine the value of a specific pixel. This approach ensures that noise is effectively smoothed out, while maintaining the sharpness of edges. The calculation for BF can be applied to any pixel located at position $X$, using (1):

$$I(X)=\frac{1}{C}\sum_{y\in\mathbb{N}(X)} e^{\frac{-\|y-x\|^2}{2\sigma_d^2}}\cdot e^{\frac{-\|I(y)-I(x)\|^2}{2\sigma_r^2}}\cdot I(y) \tag{1}$$

The parameters $\sigma_d$ *and* $\sigma_r$ in this context are utilized to control the trade-off between the spatial and intensity domains respectively. Here, $\mathbb{N}(X)$ refers to a spatial local window of position $X$, while $C$ stands for the normalization constant. The value of constant $C$ is obtained by (2):

$$C=\sum_{y\in\mathbb{N}(X)} e^{\frac{-\|y-x\|^2}{2\sigma_d^2}}\cdot e^{\frac{-\|I(y)-I(x)\|^2}{2\sigma_r^2}} \tag{2}$$

The values assigned to the two parameters, $\sigma_d$ *and* $\sigma_r$, are instrumental in determining the final quality of the denoised output. Determining the optimal values for these parameters often involves a process of trial and error.

### B. Illumination Enhancement

Histogram equalization (HE) is a method used to improve the quality of digital images by redistributing pixel values across a specified gray range. Sometimes referred to as histogram flattening, this nonlinear stretching technique ensures that pixel values are roughly equalized within the range, leading to a more uniform distribution of gray levels. The resulting effect is an image that appears flatter and clearer. The underlying principle of HE is to distribute the gray levels evenly, which often enhances the overall contrast and clarity of the image.

### C. Contrast Enhancement

To further boost the contrast of images, the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique was used. It ensures better contrast without compromising the quality of the image. $\beta$ represents the limit value (clip limit) which signifies the highest permissible histogram height, and can be established through (3):

$$\beta=\frac{M}{N}\left[1+\frac{a}{100}\left(S_{\max}+1\right)\right] \tag{3}$$

$N$ represents the grayscale value (typically set at 256), $M$ refers to the region size, $\alpha$ signifies the clip factor indicating the addition of a histogram with a value ranging from 1 to 100 [8], and $S_{max}$ is the maximum permissible slope. The PRPD images were sectioned into $8 \times 8$ sized areas, and the clip limit was set to 3.

### D. Image Segmentation

The k-means clustering algorithm was used to partition a PRPD image into a specific number of groups, where a region of interest was selected [9]. Using the k-means algorithm involves two distinct stages. In the first stage, the $k$ centroid is calculated, and in the second stage, each point that has a closest centroid from the respective data point is selected. Euclidean distance is one of the common methods used to define the closest centroid. The k-means clustering is an iterative method that for each grouping, the new centroid of each cluster will be recalculated, and the Euclidean distance will also be calculated between each centre and each data point and assign the point to the cluster with the shortest Euclidean distance. An image with dimensions $x \times y$ can be partitioned into $k$ number of clusters. If $p(x, y)$ are the image pixels to be clustered, and $c_k$ is the centre of the cluster, the steps for implementing the k-means clustering algorithm are the following:

i. Set the number of clusters $k$ and centre.
ii. Calculate $d$ (Euclidean distance) between the centre and each pixel of the input image.
iii. Assign all pixels to the closest centre based on $d$.
iv. Recalculate the new position of the centre.
v. Iterate until the error value is satisfied.
vi. Reshape the cluster pixels into an image.

## III. PRPD Pattern Recognition Methodology

When partial discharges are recorded and presented a PRPD form, well-defined representations are produced. Processing these directly can have several advantages compared to other approaches that attempt to analyse individual PD pulses. In this study, phase-resolved plots of partial discharges in the form of images are processed by firstly isolating individual PRPD patterns, and then cosine similarity is employed to assess the degree of resemblance between each pulse pattern and predefined shape templates (Fig. 2). The templates are themselves created by phase-resolved plots specified in international standards and related literature, such as CIGRE brochures, where these are used as guidelines for the interpretation PD measurements.

### A. Cosine Similarity

Cosine similarity (CS) is a mathematical measure that calculates the cosine of the angle between two non-zero vectors in an inner dot product space. The similarity $S$ is computed using (4) where $a$ and $b$ are the two given vectors and $\theta$ is an angle between them:

$$S = \cos\theta = \frac{a \cdot b}{\|a\| \cdot \|b\|} = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^{\,2}}\sqrt{\sum_{i=1}^{n} b_i^{\,2}}} \tag{4}$$

CS is computed to find the shortest distance between each PRPD pattern and each of the pre-defined shape templates:

$$CS_{shortest} = \min\left[ dist\left( PRPD_{pattern}, Template_{image} \right) \right] \tag{5}$$

To measure the dissimilarity between the pattern and template, the Cosine Distance can be calculated which provides a score ranging from 0 to 1. A higher score indicates greater dissimilarity between the two vectors, while a lower score indicates greater similarity.

### B. CosNet

Deep learning models are inherently data-hungry algorithms, necessitating a substantial amount of data for effective learning and performance on new tasks. This characteristic has led to the requirement for high-powered computing hardware during training, which can result in significant financial expenses, making their deployment in industries challenging.

To address the limitations, an innovative image processing and recognition model, the CosNet (Fig. 3), was developed for PD analysis. It integrates k-means segmentation into the pipeline framework, with a cosine similarity function as the output layer. This approach leverages the benefits of both transfer learning and specialized feature segmentation to enhance efficiency and accuracy in the recognition of PRPD patterns. The k-means algorithm is integrated into the pipeline as preprocessing before feeding the centroids into the pretrained ResNet50 CNN, which is a very large neural network with 50 convolutional layers featuring skip connections in the network that allow efficient feature reuse.

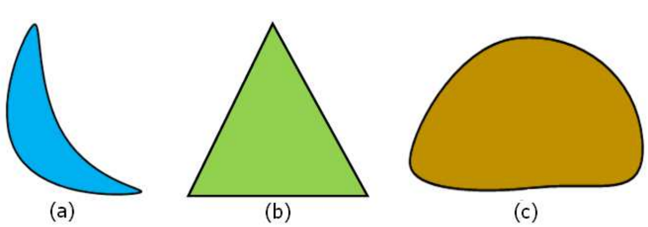


Fig. 2. Predefined PRPD pattern shape templates: (a) crescent, (b) triangular, (c) semicircular

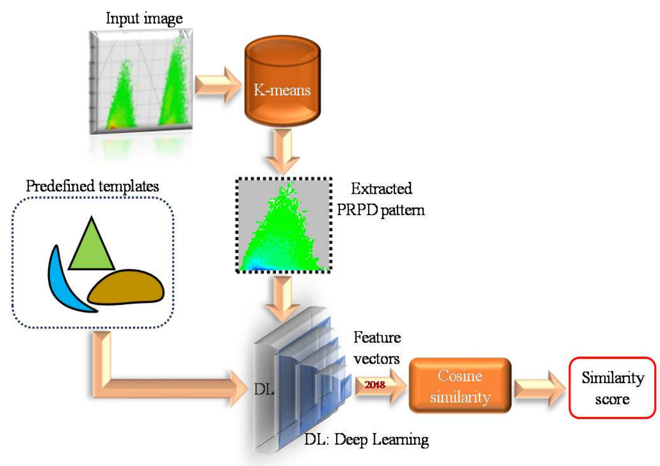


Fig. 3. Schematic representation of CosNet image processing and recognition model for automated PRPD pattern analysis.

## IV. Model Validation

To investigate the capabilities of the new *CosNet* PRPD image processing and recognition model, a series of experiments was undertaken using images from existing literature where the types of defects had already been determined through manual PRPD pattern analysis. Two examples are presented together with the associated metrics.

The first experiment (E1) involves slot defect analysis in a 10 KV motor where a defect was intentionally introduced by abrasion on the insulation surface [10]. PD measurements were performed at temperatures of 20 ℃ and 80 ℃ and the data presented in the form of PRPD plots (Fig. 4(a)). In the second experiment (E2), an additional stator with slot defects is examined. Specifically, internal discharges of a stator core slot obtained at voltage levels spanning from 3-10 kV [11] were recorded in the form of PRPD plots (Fig. 4(b)). The successful segmentation of the patterns in each case is clearly presented, with contour lines delineating each pattern for clarity.

Table I shows the similarity scores and Fig. 5 presents the results of the PRPD image processing diagrammatically. The CosNet model in consistently and reliably able to identify slot discharge defects from PRPD images, matching them to the triangular pattern with a high similarity score. Except for pattern E1P1, the difference between the best match and the second-best match is greater the 15%, a testament to the ability of the model to confidently decide regarding the similarity of the patterns with the appropriate template indicative of a slot discharge defect. Additionally, Table 1 shows the time taken to compute the match percentages. In all cases this is a fraction of a second.

## V. Conclusion

For the purposes of recognizing, extracting, and processing PRPD patterns from two-dimensional plots automatically to identify specific defect types affecting electrical equipment, a

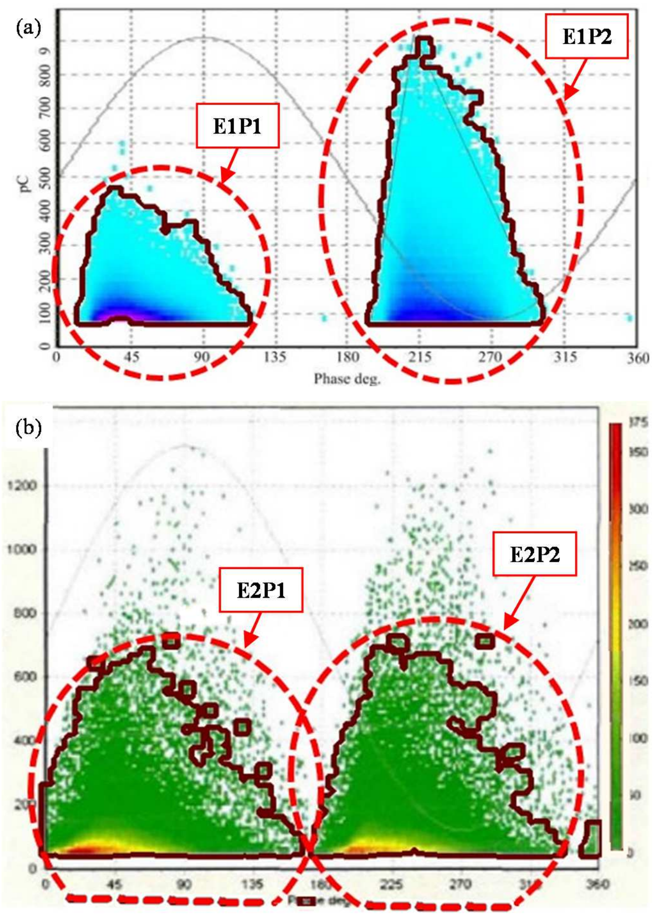


Fig. 4. PRPD plots of stator slot discharges: (a) from E1 dataset and (b) from E2 dataset.

new methodology was developed and validated. In summary, the new solution is:

i. **Monitoring equipment agnostic.** It is not tied to equipment supplied by a specific manufacturer and can be used with monitoring systems that are already in use.

ii. **Fast and efficient.** Analyzing a PRPD pattern and reporting the similarity score indicating the type of defect takes less than a second. and does not require training that relies on extensive data sets.

iii. **Flexible.** The model can be adapted to include any number of templates of known defects and can be employed as narrowly or as widely as deemed necessary.

TABLE I

IDENTIFICATION OF STATOR SLOT DISCHARGE PATTERN USING COSNET

| Pattern | Match (%) | | | Time (s) |
|---|---|---|---|---|
| | Triangular | Semi-Circular | Crescent | |
| E1P1 | 78.06 | 67.55 | 72.59 | 0.2329 |
| E1P2 | 72.54 | 57.35 | 57.76 | 0.2450 |
| E2P1 | 89.42 | 55.05 | 54.96 | 0.1796 |
| E2P2 | 80.50 | 53.46 | 51.28 | 0.1570 |

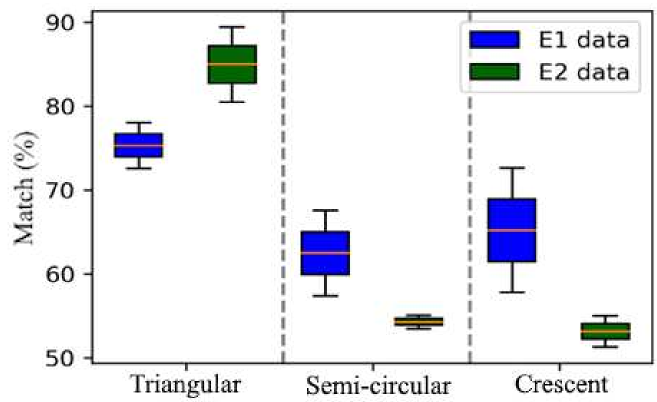


Fig. 5. Diagrammatic presentation of the PRPD pattern recognition results for E1 and E2 showing consistently strong match to the triangular pattern.

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