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An investigative study into the sensitivity of different partial discharge φ-q-n pattern resolution sizes on statistical neural network pattern classification

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ABSTRACT

This paper investigates the sensitivity of statistical fingerprints to different phase resolution (PR) and amplitude bins (AB) sizes of partial discharge (PD) φ-q-n (phase-amplitude-number) patterns. In particular, this paper compares the capability of the ensemble neural network (ENN) and the single neural network (SNN) in recognizing and distinguishing different resolution sizes of φ-q-n discharge patterns. The training fingerprints for both the SNN and ENN comprise statistical fingerprints from different φ-q-n measurements. The result shows that there exists statistical distinction for different PR and AB sizes on some of the statistical fingerprints. Additionally, the ENN and SNN outputs change depending on training and testing with different PR and AB sizes. Furthermore, the ENN appears to be more sensitive in recognizing and discriminating the resolution changes when compared with the SNN. Finally, the results are assessed for practical implementation in the power industry and benefits to practitioners in the field are highlighted.

1. Introduction

Partial discharge (PD) measurements have been a vital index for evaluating electrical insulation degradation under high voltage (HV) electrical stress. It is important to understand the extent of insulation damage and the nature of an insulation fault through PD measurement for reliable insulation assessment. PD is an electrical discharge that occurs within a localised position of the electrical insulation when the insulation starts to degrade [1]. If PD is detected, it is also essential to recognize the nature and extent of the insulation defect, since each particular PD fault has a distinct footprint pattern of discharge behaviour [2–5]. Over the years, several techniques have been investigated for use in PD pattern recognition. These include the neural network (NN) [1,6–9], fuzzy logic controllers [10], data mining approaches [11], support vector machines [12], hidden markov models [13] and adaptive resonance theory [14]. Such research has recorded successful recognition performance with recognition rates reaching as high as 90% for unseen PD fault examples. The successful rates are achieved through several feature extraction techniques when applied to acquire training and testing parameters for the pattern recognition tools. Statistical fingerprints from φ-q-n (phase-amplitude-number) patterns have been the most widely applied measures [1,15] for PD recognition because of their capability for well-defined PD pattern quantification. However, due to the complex nature of PD, coupled with degradation consequences, these statistical fingerprints may show different characteristics over different insulation degradation periods [16].

To improve the reliability and uniqueness of statistical fingerprints in being able to identify PD defects, Gulski and Krivda [1] made significant efforts by establishing 95% mean confidence intervals (CI) for statistical features for classes of several artificially created two electrode PD defects. The statistical mean error

Abbreviations: NN, neural networks; SNN, single neural network; ENN, ensemble neural network; PR, phase resolution; AB, amplitude resolution; PD, partial discharge; HV, high voltage; CI, confidence intervals; φ-q-n, phase-amplitude-number; IEC, international electrotechnical commission; $H_n(\varphi)$, pulse count distribution; $H_{qn}(\varphi)$, mean pulse-height; $H_n(q)$, amplitude-number; DEM, dynamically weighted ensemble network; DAN, dynamically averaged network; *sk*, skewness; *ku*, kurtosis; *Q*, discharge factor; *cc*, cross-correlation; *mcc*, modified cross-correlation; μ_S, average recognition rates of the SNN; μ_E, mean of the recognition efficiencies of the ENN; σ_S, variance of the recognition efficiencies of the SNN; σ_E, variance of the recognition efficiencies of the ENN; SEM, standard error of the mean; σ_{SM}, SEM of the recognition efficiencies of the SNN; σ_{EM}, SEM of the recognition efficiencies of the ENN.

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tolerances as obtained by Gulski and Krivda were based on fixed PR and AB sizes of the *φ-q-n* patterns and were determined from a series of measurements ranging from 4 to 23 separate *φ-q-n* patterns for the same type of PD fault. In this context, the research question is posed in relation to evaluating the sensitivity of statistical fingerprints for different *φ-q-n* PR and AB changes and how such variations in PR and AB could potentially influence classification outcomes when pattern recognition tools are applied. Moreover, further research is important because different measuring instruments may have different resolution settings for the *φ-q-n* pattern assessment and thus training data captured using a different set-up may vary from the actual measurement which may lead to an unreliable classification outcome.

In an attempt to address these situations, this paper aims at determining the sensitivity of statistical fingerprints as a function of PR and AB sizes of the *φ-q-n* patterns. For each statistical fingerprint defining a particular PD defect, statistical 95% mean error tolerances for different resolution sizes are compared, quantified and evaluated. To achieve this, a number of *φ-q-n* samples (ranging from 40 to 215) for different PD fault scenarios are considered. This is used to quantify the statistical behaviour as a function of PR or AB and provide potentially an improved classification tool since large datasets of the same PD sources are considered. Due to the success of the ensemble neural network (ENN) in classifying PD patterns [15], this paper extensively compares the ENN's capability with the single neural network (SNN) in classifying and discriminating different resolution sizes of the *φ-q-n* patterns over several statistical merit indicators. This is important to determine and compare the statistical error bounds recognition rates of the SNN and ENN for different resolution sizes.

2. Experimental set-up and feature extraction

2.1. Artificially created PD faults

To obtain the PD samples for investigation, four different fault geometries were fabricated in a HV laboratory to simulate PD faults currently occurring in practice (see Fig. 1). These comprise corona in air and oil, surface discharges in air and oil, single voids and an electrode bounded cavity. The corona discharge model is a point-plane arrangement. A needle of length 3 cm and tip radius of approximately 10 μm is connected to the HV, while an electrode is of 60 mm in diameter is connected to the ground. The voids are of 0.6 mm diameter and 50 μm thickness, created at the centre of the middle layer of 7 poly-ethylene-terephthalate (PET) samples. The surface discharge in air was simulated by placing a small brass ball of 55 mm diameter on perspex of geometrical size 65 mm × 65 mm × 8 mm. The surface discharge in oil is simulated by a pressboard embedded in a container with Castrol insulating oil [15]. A needle was placed at a predetermined angle to the surface of the pressboard and 45 mm distance from a block earth electrode, also placed on the pressboard surface [17]. Examples of the *φ-q-n* patterns for several of the considered PD fault geometries are shown in Fig. 2. For corona in air, the positive and negative *φ-q-n* patterns have been separated for improved visibility of the positive corona discharges characterized by their small repetition rate.

The experimental conditions and test *φ-q-n* samples generated for each PD fault type is shown in Table 1. For each fault, relatively large *φ-q-n* samples were generated so as to determine reliable 95% mean CI limits for improved evaluation by the SNN and ENN. For corona in air, measurements were taken at several voltages over two gap distances of 5 mm and 10 mm because of the discharge behaviour of the positive corona discharge which have low repetition rate and higher amplitude [18]. They are then combined to form the *φ-q-n* corona set for SNN and ENN evaluation.

2.2. Experimental test arrangement

The PD measurement process was performed in accordance with the IEC60270 PD standard [19]. The PD detection system produces a power cycle which is used to synchronize real time *φ-q-n* patterns and possess functions for automatic data logging these patterns at different time periods as well as controlling changes in PR and AB sizes. This is important for the work presented in this

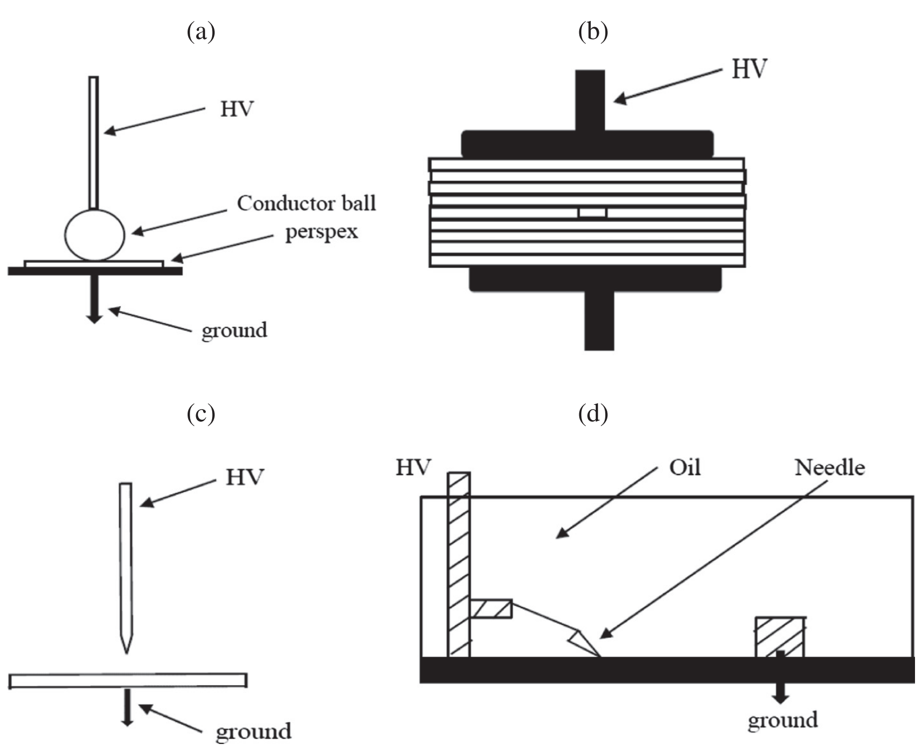

Fig. 1. Simulated PD faults (a) surface discharge in air, (b) single void in PET, (c) corona in air and (d) surface discharges in oil.