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Statistical error tolerances of partial discharge recognition rates

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***Abstract*— This paper compares the statistical error tolerances of the single neural network (SNN) and the ensemble neural network (ENN) recognition efficiencies, when both the SNN and ENN are applied to recognize partial discharge (PD) patterns. Statistical fingerprints from the phased and amplitude resolved patterns of PDs, have been applied for training and testing the SNN and the ENN. Statistical mean and variances of the SNN and ENN recognition rates were compared and evaluated over several iterations in order to obtain an acceptable value. The results show that the ENN is generally more robust and often provides an improved recognition rate with the higher mean value and lower variance when compared with the SNN. The result implies that it is possible to determine the accurate statistical error tolerances for the SNN and ENN recognition probability for correct diagnosis of PD fault.**

Keywords— Partial discharge; Single neural network; Ensemble neural network.

I. INTRODUCTION

Partial discharge (PD) is a well known electrical discharge phenomenon that occurs within the high voltage insulation system. It occurs as a result of sustained high electric field stress. In recent times, the pursued goal has been identifying a robust technique for classifying PD patterns using several pattern recognition techniques. Among these techniques, the neural network (NN) was widely applied, due to its ability to learn well from few training examples [1, 2, 8]. Over the last few years, the author of this paper has been trying in successive stages to determine an improved PD pattern recognition technique using the ensemble neural networks (ENN) [2, 3]. An ENN is a model that trains many NN topologies and combines their output predictions [3]. From the literature [2], statistical confidence limits of recognition rates of the ENN have been determined and the results were compared with the widely applied single neural network (SNN). However, these results were based on training and testing of the ENN and SNN based on a small dataset. In order to improve the situation, this paper determines a more reliable ENN and SNN statistical recognition rates using relatively large dataset.

To discriminate PDs, statistical features from φ-q-n (phase-amplitude-number) patterns were widely applied as training and testing fingerprints for several NN models. Gulski [1] obtained high recognition rates for PD patterns results using 15 statistical fingerprints as training and testing set for several NN models. Following Gulski, this paper applies statistical features from the φ-q-n patterns to train and test both the ENN and SNN. The φ-q-n patterns were obtained over a lengthy time period, at the level of initial insulation degradation. The overall focus of this paper is to determine a robust technique that can effectively discriminate and recognize PD patterns and can serve as a practical tool for diagnosing complex PD phenomenon.

II. PD MEASUREMENT PROCESS

The PD measurement process follows the IEC 60270 PD standard [4]. The high voltage (HV) A.C system comprises of a HV transformer, an AC measurement capacitor, a PD measurement capacitor, an over voltage protection, a current/ voltage regulating devices and a PD detection circuit. In this Investigation, a power frequency of 50Hz is used in all the experiments. Fig. 1 shows the general HV set-up showing the HV transformer, two capacitors, a sample test-cell. An earth rod was applied to discharge the HV system as necessary.

The PD measurement software as developed by the HV laboratory of Glasgow Caledonian University measures the apparent charge associated with the PD and generates the φ-q-n patterns over longer stressing period. Four PD faults are simulated. These include voids in polyethylene-terephthalate (PET) insulation, electrode bounded cavity, surface discharge in air and surface discharge in oil.

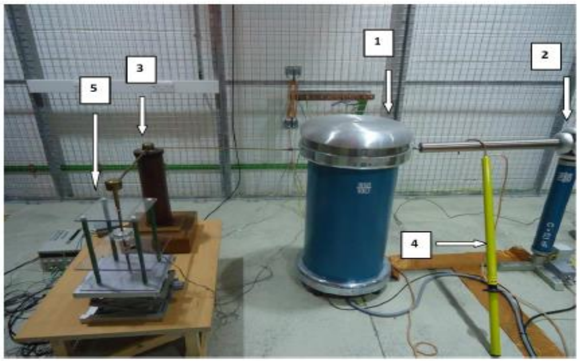

Fig. 1: Photo of the HV system; (1) HV transformer (2), AC capacitor, (3) PD measurement capacitor, (4) Earth rod, (5) Test cell.

Surface discharge in air was investigated by placing a small brass ball of 55mm diameter on Perspex insulation as shown in Fig.2a. Discharges occur as a result of electric field enhancement at the ball-perspex contact and extended beyond the contact point of the electrode and perspex. The inception voltage is approximately 4.2kV and the experiment was conducted at approximately 5kV (i.e. 20% above the inception voltage). The Perspex was stressed for 4 hours and the φ-q-n patterns captured continuously over this period.

For single void, an experiment was carried out using a set of samples containing a cylindrical void in PET, as shown in Fig. 2b. Nine PET layers were created for the experiment and the void was located at the middle of the PET layers. The inception voltage was 2.82kV and measurements were taken at 3.6kV. PD data were captured from the start of the experiment, up to 7 hours of stressing period.

Discharges from electrode bounded cavity were investigated by creating a 10mm diameter cavity at the topmost PET layer adjacent to the HV electrode. This is to ensure that the void has an electrode surface at one side and the PET surface on the opposite side. Similar to the single void experiment, nine PET layers were used, including the one possessing the void (see Fig. 2c). For this experiment, a voltage of 3.6kV was applied and then *φ-q-n* patterns captured at 15mins intervals throughout the 7-hour degradation period.

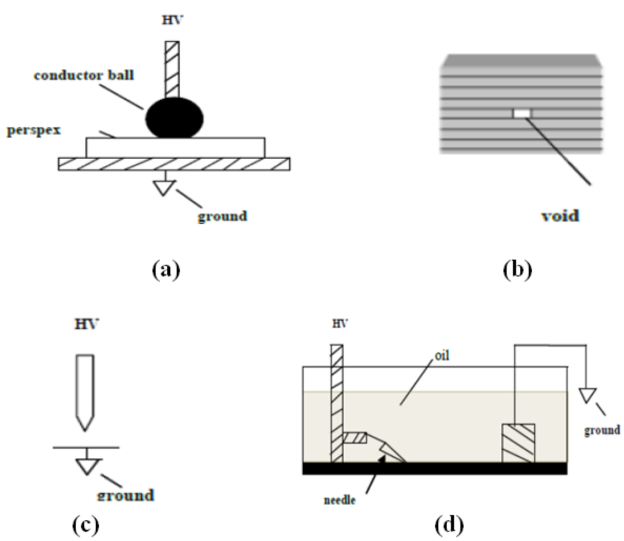

Fig. 2:Simulated PD faults: a) surface discharges in air; b) 0.6mm single void; c) corona in air, and d) surface discharge in oil.

Surface discharge along an oil-pressboard interface was investigated by means of an experimental test cell as shown in Fig. 2d. A section of pressboard was embedded in a container with Castrol insulating oil. A needle was placed at a predetermined angle to the pressboard surface and certain distance from a block earth electrode, also placed on the pressboard surface. The needle was of length 30mm and has a tip radius of 10μm. Point to earth gap distance of 25mm was considered.

III. The Ensemble Neural Network

An ENN is a well known technique for training a number of SNN models and aggregating their component predictions. The inspiration for this technique is based on the fact that by aggregating the outcomes of a number of trained SNNs, the generalization performance of the SNN might be enhanced. It has been shown in the literature [6] that this is only possible if the components SNNs forming the ensemble are simultaneously diverse and accurate. Among several techniques for training the SNNs in the ensemble, bagging(bootstrapping) has been widely applied. In bagging, a number of training fingerprints are generated by bootstrap resampling of the original dataset. In this case, several training fingerprints are repeated while others are simply eliminated. One merit of the bagging process is that it helps prevent over fitting common to NNs, and also provides accurate values of bias and variance [7]. Therefore, this paper applies the bagging technique to choose fingerprints from the original input parameters that serves as input to the constituent SNNs in the ensemble. The ENN prediction was determined by combining the component SNN outputs in the ensemble, using the dynamically weighted averaging of the networks [3].

IV. Statistical Fingerprints For The SNN And ENN

This paper uses 15 statistical fingerprints as input and output parameters to the SNN and ENN. Statistical parameters of interest comprise the skewness (*sk*), kurtosis (*ku*), discharge factor, cross-correlation (*cc*) and modified cross-correlation (*mcc*), obtained from the two-dimensional derived plots of the φ-q-n patterns, i.e. *Hn(φ)+, Hn(φ)-*, *Hn(q)+*, *Hn(q)-*, *Hqn(φ)+, Hqn(φ)-* plots. The definition of the 2D distributions for evaluating the SNN and ENN is shown in Table 1.

Figs. 3-6 show the mean statistical parameters for each PD fault, which were applied as inputs in order to evaluate the performance of both the SNN and ENN. It is obvious that there exists statistical variability between the PD patterns considered. The *sk* and *ku* appears to show higher variability and distinction between the PD patterns compared to the other statistical measures, because their high variance statistic. Additionally, the *ku* of *Hn(q)* distributions consistently demonstrate higher values and distinction when compared to the other parameters. This is due to the highly peaked nature of

Table 1: 2D derived plots from the φ-q-n patterns

Distribution	Description
$H_n(\varphi)+$	Pulse-count distribution (+ve half cycle) in phase
$H_n(\varphi)-$	Pulse-count distribution (-ve half cycle) in phase
$H_{qn}(\varphi)+$	Mean pulse-height distribution (+ve half cycle) in phase
$H_{qn}(\varphi)-$	Mean pulse-height distribution (-ve half cycle) in phase
$H_n(q)-$	Pulse amplitude distribution (+ve half cycle) in amplitude
$H_n(q)-$	Pulse amplitude distribution (-ve half cycle) in amplitude

the Hn(q) plots, especially at the lower amplitudes [3], making them suitable for statistical discrimination of PD faults.

V. Results And Discussion

It is widely known that the SNN gives a different performance assessment with different initial states [5]. To analyze these variations, this paper compares the mean and variance of the recognition efficiencies for both the SNN and ENN, when applied to discriminate between the void, surface discharges in air, surface discharge in oil and corona in air. The statistical measures of mean and variance permits the determination of the statistical error tolerances for the SNN and ENN recognition rates for PD fault geometries. To simplify this analysis, relevant statistical abbreviations for the statistical indicators were considered and described in Table 2. N represents the number of simulation iterations. For effective evaluation of the mean and variance recognition efficiencies of the SNN and ENN, 100 iterations were considered. This is desirable in order to obtain high degree precision on the SNN and ENN recognition efficiencies. Previously [2], the ENN has demonstrated an improved performance assessment when compared with the SNN, but this result was based on limited data. For reliability and better discrimination of PD geometries, this paper applies relatively large data set of PD faults for the SNN and ENN evaluation.

Both the SNN and ENN were evaluated using statistical fingerprints of the void, surface discharges in air, surface discharge in oil and corona in air. Each set of fingerprints composed of a matrix (140 x 17). The first 15 columns were taken as the input fingerprints, while the last 2 represent the output data. The input fingerprints were the PD statistical features in Fig. 4 while the output parameters for the 4 PD fault types were [0 1], [1 0], [0 0] and [1 1]. For each PD fault geometry, out of the 140 input row vectors, 40 were selected as the testing fingerprints for the developed SNN and ENN. For the ENN, six networks having the same arrangement, and then trained and tested from the 140 input row vectors of bootstrapped resample data. In choosing the best SNN arrangement for the ensemble, the hidden layer, learning and momentum rates were adjusted and the best parameters are selected for comparison and these were applied as the configurations for the ENN. One hidden layer with 20 neurons were chosen, having learning and momentum rates of 0.06 and 0.9 respectively. Relevant abbreviations applied in this paper are presented in Table 2.

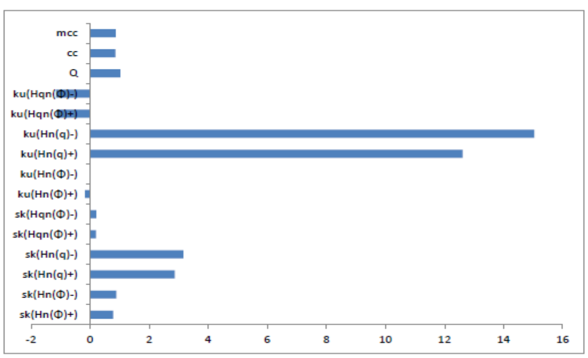

Fig. 3: Average values of statistical parameters for single void.

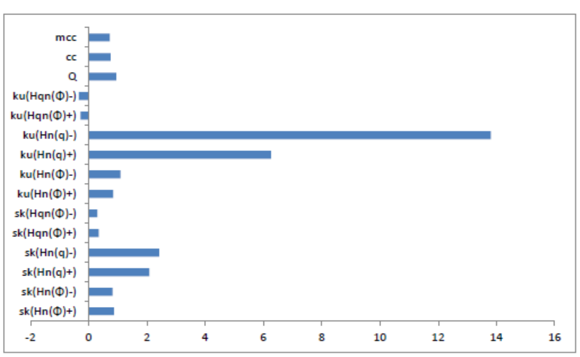

Fig. 4: Average values of statistical parameters for surface discharge in air.

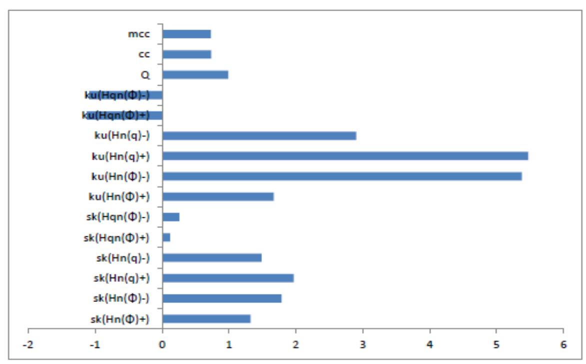

Fig. 5: Average values of statistical parameters for electrode bounded cavity.

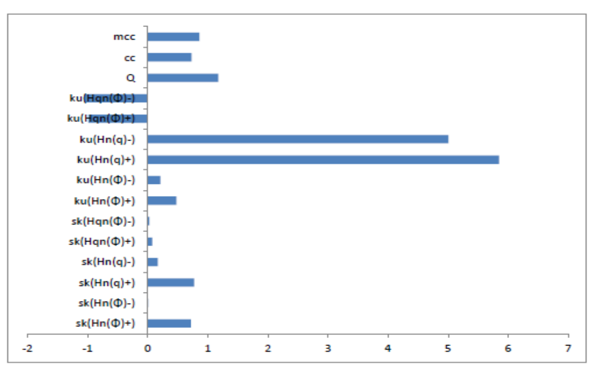

Fig. 6: Average values of statistical parameters for surface discharge in oil.

Table 2: Description of Abbreviations of mean and variance used.

Abbreviation equation	Description
$\mu_S = \frac{1}{N}\sum_{i=1}^{N} X_{iS}$	mean of the recognition rates of the SNN, where X_{is} are the individual recognition result;
$\mu_E = \frac{1}{N}\sum_{i=1}^{N} X_{iE}$	mean of the recognition rates of the ENN, where X_{iE} are the individual ENN recognition result;
$\sigma_S = \frac{1}{N}\sum_{i=1}^{N}(X_{iS} - \mu_S)^2$	Variance of the recognition rates of the ENN, where X_{is} are the individual ENN recognition result;
$\sigma_E = \frac{1}{N}\sum_{i=1}^{N}(X_{iE} - \mu_E)^2$	mean of the recognition rates of the ENN, where X_{iE} are the individual ENN recognition result

In order to investigate the effectiveness of the SNN and ENN in recognizing different PD faults, the approach employed is as follows: Training both the SNN and ENN with PD fingerprints of one geometry and then testing with the fingerprints of the other PD faults geometries.Similar permutation is applied to the other PD fault samples.

Figs. 7-10 show plots of the mean values, variances (i.e. µS, µE, σS, σE) of the recognition efficiencies of the SNN and ENN, when they trained with any of the PD fault samples (void, surface discharges in air, surface discharge in oil and corona in air) and then tested with all the PD fault φ-q-n samples taken independently from the 4 PD samples. The results show that for the ENN and SNN trained and tested with PD φ-q-n fingerprints of same PD geometry fingerprints, µE, always demonstrate higher mean recognition rate and better (i.e. lower) recognition rate statistical error limits when compared with µS, σS. For the SNN and ENN trained and tested with different PD datasets, their confidence limits clearly show that the ENN does not always produce an improved result over the SNN. This clearly indicates that there are some instances when the SNN might outperform the ENN at certain initial weights and biases. This investigation may be applied as a means of recognition if different biases and weights are used to obtain a number of SNN and ENN outputs. It is clear from this result that the ENN appears to be generally more robust when compared with SNN in discriminating PD patterns. However, this has to be verified with more complex PD statistical fingerprints. Compared to the literature [2], this result shows lower statistical error tolerance due to the relatively large PD fingerprints applied for the SNN and ENN evaluation.

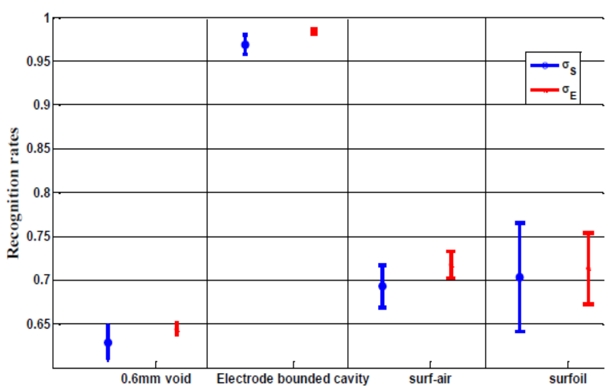

Fig. 7. Plot of σ_S, σ_E , when both SNN and ENN are trained with electrode bounded cavity and then tested with all 4 PD faults. . (μ_E and μ_S are the mean values of the variance intervals of the ENN and SNN respectively).

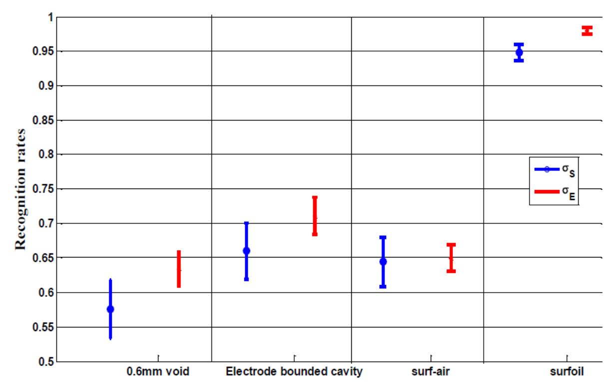

Fig. 9. Plot of σ_S, σ_E when both SNN and ENN are trained with surface discharge in oil and then tested with all 4 PD faults (μ_E and μ_S are the mean values of the variance intervals of the ENN and SNN respectively).

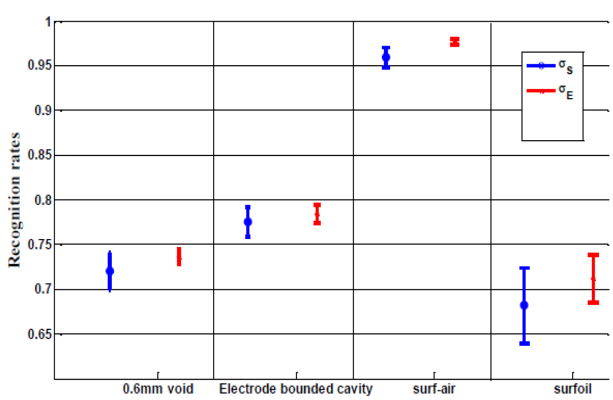

Fig. 8. Plot of σ_S, σ_E when both SNN and ENN are trained with surface discharge in air and then tested with all 4 PD faults. (μ_E and μ_S are the mean values of the variance intervals of the ENN and SNN respectively).

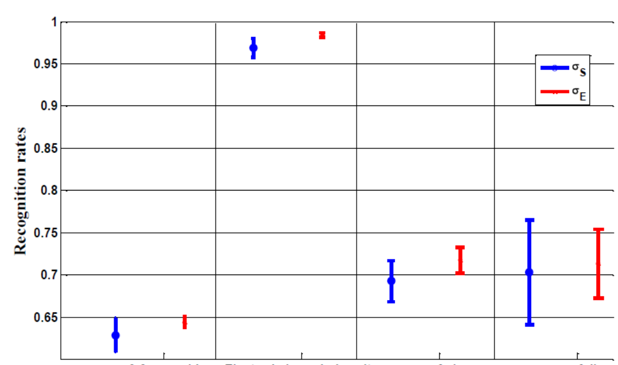

Fig. 10. Plot of σ_S, σ_E when both SNN and ENN are trained with 0.6mm void and then tested with all 4 PD faults. (μ_E and μ_S are the mean values of the variance intervals of the ENN and SNN respectively)

VI. CONCLUSION

In this paper, statistical error tolerances of partial discharge recognition rates using the SNN and ENN have been determined. Statistical data obtained from the φ-q-n patterns were applied in training both the SNN and ENN. In comparison to the SNN, the ENN has shown improved recognition performance in discriminating a number of PD fault samples using the same training and testing fingerprints. The ENN consistently shows higher average recognition rate and lower statistical error over the SNN for repeated iterations. The result obviously indicates the ENN can be a potential tool for practical PD recognition applications. This result implies that it is possible to know the statistical error tolerances of PD recognition rates using the NN tools that can provide reliable interpretation of PD fault cases within any High voltage set-up. Future work concentrates on determining the robustness of the ENN is discriminating different noise sources in partial discharge patterns. In order to avoid lengthy simulations, there is also need to investigate the optimum weights of SNN and ENN topologies for PD classification.

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