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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.

Keywords— classification, partial discharge and ensemble neural network, phase resolution and amplitude bin sizes.

29 Abbreviations

30	NN	neural networks
31	SNN	single neural network
32	ENN	ensemble neural network
33	PR	phase resolution
34	AB	amplitude resolution
35	PD	partial discharge
36	HV	high voltage
37	CI	confidence intervals
38	ϕ-q-n	phase-amplitude-number
39	IEC	international electrotechnical commission
40	$H_n(\phi)$	pulse count distribution
41	$H_{qn}(\phi)$	mean pulse-height
42	$H_n(q)$	amplitude-number
43	DEM	dynamically weighted ensemble network
44	DAN	dynamically averaged network
45	<i>sk</i>	skewness
46	<i>ku</i>	kurtosis
47	<i>Q</i>	discharge factor
48	<i>cc</i>	cross-correlation
49	<i>mcc</i>	modified cross-correlation
50	μ_S	average recognition rates of the SNN
51	μ_E	mean of the recognition efficiencies of the ENN
52	σ_S	variance of the recognition efficiencies of the SNN
53	σ_E	variance of the recognition efficiencies of the ENN
54	SEM	standard error of the mean
55	σ_{SM}	SEM of the recognition efficiencies of the SNN
56	σ_{EM}	SEM of the recognition efficiencies of the ENN

57

58

59 1. Introduction

60

61 Partial discharge (PD) measurements have been a vital index for evaluating electrical
62 insulation degradation under high voltage (HV) electrical stress. It is important to understand
63 the extent of insulation damage and the nature of an insulation fault through PD measurement
64 for reliable insulation assessment. PD is an electrical discharge that occurs within a localised
65 position of the electrical insulation when the insulation starts to degade [1] . If PD is detected,
66 it is also essential to recognize the nature and extent of the insulation defect, since each
67 particular PD fault has a distinct footprint pattern of discharge behaviour [2,3,4,5]. Over the
68 years, several techniques have been investigated for use in PD pattern recognition. These
69 include the neural network (NN)[1,6,7,8,9], fuzzy logic controllers [10], data mining
70 approaches [11], support vector machines[12], hidden markov models [13] and adaptive

71 resonance theory [14]. Such research has recorded successful recognition performance with
72 recognition rates reaching as high as 90% for unseen PD fault examples. These successful rates
73 were achieved through several feature extraction techniques when applied to acquire training
74 and testing parameters for the pattern recognition tools. Statistical fingerprints from ϕ -q-n
75 (phase-amplitude-number) patterns have been the most widely applied measures [1,15] for
76 PD recognition because of their capability for well-defined PD pattern quantification.
77 However, due to the complex nature of PD, coupled with degradation consequences, these
78 statistical fingerprints may show different characteristics over different insulation degradation
79 periods [16].

80 To improve the reliability and uniqueness of statistical fingerprints in being able to identify
81 PD defects, Gulski and Krivda [1] made significant efforts by establishing 95% mean
82 confidence intervals (CI) for statistical features for classes of several artificially created two
83 electrode PD defects. The statistical mean error tolerances as obtained by Gulski and Krivda
84 were based on fixed PR and AB sizes of the ϕ -q-n patterns and were determined from a series
85 of measurements ranging from 4 to 23 separate ϕ -q-n patterns for the same type of PD fault.
86 In this context, the research question is posed in relation to evaluating the sensitivity of
87 statistical fingerprints for different ϕ -q-n PR and AB changes and how such variations in PR
88 and AB could potentially influence classification outcomes when pattern recognition tools are
89 applied. Moreover, further research is important because different measuring instruments
90 may have different resolution settings for the ϕ -q-n pattern assessment and thus training data
91 captured using a different set-up may vary from the actual measurement which may lead to
92 an unreliable classification outcome.

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

104 the statistical error bounds recognition rates of the SNN and ENN for different resolution
105 sizes.

106

107 **2. Experimental set-up and feature extraction**

108

109 **2.1 Artificially created PD faults**

110

111 To obtain the PD samples for investigation, four different fault geometries were fabricated in
112 a HV laboratory to simulate PD faults currently occurring in practice (see Fig. 1). These
113 comprise corona in air and oil, surface discharges in air and oil, single voids and an electrode
114 bounded cavity. The corona discharge model is a point-plane arrangement. A needle of length
115 3 cm and tip radius of approximately 10 μm is connected to the HV, while an electrode is of
116 60 mm in diameter is connected to the ground. The voids are of 0.6 mm diameter and 50 μm
117 thickness, created at the center of the middle layer of 7 poly-ethylene-terephthalate (PET)
118 samples. The surface discharge in air was simulated by placing a small brass ball of 55 mm
119 diameter on perspex of geometrical size 65 mm x 65 mm x 8 mm. The surface discharge in
120 oil is simulated by a pressboard embedded in a container with Castrol insulating oil [15]. A
121 needle was placed at a predetermined angle to the surface of the pressboard and 45 mm
122 distance from a block earth electrode, also placed on the pressboard surface[17]. Examples of
123 the ϕ -q-n patterns for several of the considered PD fault geometries are shown in Fig. 2. For
124 corona in air, the positive and negative ϕ -q-n patterns have been separated for improved
125 visibility of the positive corona discharges characterized by their small repetition rate.

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

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

135 Fig.2: Example of the ϕ -q-n patterns for the PD faults considered.

136

137 Table 1: PD fault types with the test voltages and corresponding ϕ -q-n samples.

138

139 **2.2 Experimental test arrangement**

140 The PD measurement process was performed in accordance with the IEC60270 PD
141 standard[19]. The PD detection system produces a power cycle which is used to synchronize
142 real time ϕ -q-n patterns and possess functions for automatic data logging these patterns at
143 different time periods as well as controlling changes in PR and AB sizes. This is important
144 for the work presented in this paper, as several experiments require longer stressing periods
145 and data is required to be captured and stored systematically over certain resolution size for
146 analysis. PD calibration was carried out for PD apparent charge determination.

147 **2.3 Choice of statistical fingerprints for PD analysis**

148

149 For ϕ -q-n evaluation, statistical fingerprints have been widely applied because of their
150 capability for well-defined pattern quantification [1,15]. In order to simplify the ϕ -q-n
151 analysis, statistical fingerprints are usually extracted from 2D plots derived from the ϕ -q-n
152 patterns. The key 2D distributions of interest are the pulse count $H_n(\phi)$, mean pulse-height
153 $H_{qn}(\phi)$ and amplitude number $H_n(q)$ plots. These plots are presented in both the positive (+)
154 and negative half power cycles (-).

155

156 Similar to other literature [4], this paper applies 15 statistical parameters that serve as input
157 fingerprints for training and testing both the ENN and SNN. These include the skewness (sk)
158 and kurtosis (ku) of the $H_{qn}(\phi)_+$, $H_{qn}(\phi)_-$, $H_n(q)_+$, $H_n(q)_-$, $H_n(\phi)_+$ and $H_n(\phi)_-$ distributions,
159 the cross-correlation (cc), discharge factor (Q) and modified cross-correlation (mcc).
160 Definitions of these statistical parameters are available in [1] and their mathematical
161 expressions are shown in Table 2. In this table, μ represents the mean value, σ is the standard
162 deviation, n represents the size of the data and P_j is the probability of the discrete values x_j
163 and y_j . Q^+_s and Q^-_s represent the sum of discharge magnitudes in the positive and negative
164 half cycles while N^+_s and N^-_s represent the number of discharges in the positive and negative
165 half power cycle.

166

167 Table 2: Mathematical expressions of statistical fingerprints

168

169 **3. Description of the ENN algorithm**

170

171 An ENN is a learning model comprising a limited number of NNs trained for the same task
 172 [20]. The ENN can enhance the generalization performance of the SNN by simply training a
 173 number of SNNs and combining their output predictions. Diverse types of ENN architectures
 174 have evolved. These include the simplest ENN, The Naive classifier technique, the
 175 generalised ENN and the dynamically weighted ensemble method (DEM) [21]. The latter
 176 determines the neural network weight at any time the network is estimated and provides the
 177 best performance at any instant [21]. The weight is proportional to the certainty of the
 178 individual NN prediction and this certainty evaluates how close the output is to any known
 179 target value. The prediction of the NN can be regarded to be a probability of any occurrence.
 180 For example, assume that $b = f(a)$ is the output of the network and a represents the input
 181 variables. If b approaches unity, it is more certain that it belongs to a certain class. When b is
 182 close to 0, it is certain that this instance is not in that particular class. The certainty of the NN
 183 is computed as follows[10],

$$184 \quad c(b) = \begin{cases} b & \text{if } b \geq 0.5 \\ 1-b & \text{otherwise} \end{cases} \quad (1)$$

185 The prediction of the Dynamically Averaged Network (DAN) can be computed as follows:

$$186 \quad f_{DAN} = \sum_{j=1}^n w_j f_j(a) \quad (2)$$

187
188
189

190 where the weights w_i are defined based on

$$191 \quad w_j = \frac{c(f_j(a))}{\sum_{j=1}^n c(f_j(a))}. \quad (3)$$

192
193
194

195 Figure 3 shows the proposed ENN model for recognition of the PD patterns. The ENN
 196 developed in this work comprises several SNN architectures having the same configuration
 197 but with different initial parameters. To obtain accurate values of bias and variance [22], the
 198 ENN model is trained from bootstrapped resample data. Bootstrap resampling is a criterion
 199 employed at the instance when the input fingerprints for the NN are limited. It is
 200 implemented so as to have a number of resampled datasets that can be applied as input (i.e.
 201 training) fingerprints for several NNs. With this strategy, the resampled datasets have the
 202 same dimension as the original dataset in such a way that some samples are replicated while
 203 others are discarded. Bootstrap resampling provides an accurate value of the variance and

204 bias of the NN. This technique has been successfully applied to the ENN of various
205 categories of data in the medical and engineering related fields and has demonstrated
206 improved results [20,21,22].

207 Fig.3: The ENN model.

208 Among the various ENN data aggregation techniques, the dynamically weighted ensemble
209 has been shown to outperform others in different application scenarios, e.g. in Ref [23], and
210 therefore as a consequence this paper applies the same techniques to evaluate the SNN
211 outputs in the ensemble. Six SNNs are applied in this work in order to have a reasonable
212 number of diverse models to improve the generalization.

213

214

215

216 **4 PD faults analysis**

217 This section presents the results of statistical fingerprint classification sensitivity to different
218 PR and AB resolution sizes of the $H_{qn}(\varphi)_+$, $H_{qn}(\varphi)_-$, $H_n(q)_+$, $H_n(q)_-$, $H_n(\varphi)_+$ and $H_n(\varphi)_-$
219 distributions. In evaluating fingerprints for variable PR the $H_n(q)$ distributions have not been
220 considered because they do not demonstrate any statistical variation. This is expected because
221 PR change only affect the phase bins not the amplitude bins. Similarly when evaluating AB,
222 the $H_n(\varphi)$ statistics have not been considered. Additionally, the sensitivity of Q , cc and mcc
223 were not considered, because they are found to be insensitive to different resolution sizes. For
224 Q , the mean discharge level is undoubtedly the same for any φ - q - n resolution changes, while
225 for cc the correlation of the positive and the negative half power cycles remain unchanged for
226 φ - q - n resolution variations.

227

228 As an example, the influence of the change in PR and AB sizes on phase and amplitude
229 resolved patterns for surface discharge in air is shown in Fig.4. The φ - q - n patterns were
230 initially captured at 1° PR and 100 AB. Then, two approaches were implemented for data
231 transformation. First, φ - q - n fingerprints were captured at 1° PR and 100 AB over the 360°
232 cycle and transformed to 3° , 6° , 9° , 12° and 15° PR, keeping the AB size constant. Second,
233 based on the transformation of the φ - q - n fingerprint in the first strategy, samples having 6°
234 PR and 100AB are further transformed to 50 AB and 25 AB, keeping the PR size constant.
235 The plots visually show that as the resolution is varied from 1° to 15° or 100 AB to 25 AB,
236 discharge numbers for each PR or AB vary resulting in potentially different statistical

237 variability of the ϕ -q-n patterns. For reliable statistical evaluation, 95% CI for different PR
238 and AB sizes were obtained over large ϕ -q-n samples as summarised in Table 1. As an
239 example, the 95% statistical CIs for air surface discharges and the dielectric bounded void are
240 presented in the Appendix for different PR and AB sizes.

241

242 There are three essential deductions:

243

244 1) The sk and ku mean values and CIs of $H_n(q)$ are more sensitive to different PR sizes than
245 AB sizes when compared to that of the sk and ku of other distributions, e.g. $H_n(\phi)$ and
246 $H_{qn}(\phi)$. This is attributed to the $H_n(q)$ distributions becoming increasingly peaked as the AB
247 sizes are reduced.

248 2) The sk and ku mean values and CIs of the $H_{qn}(\phi)$ appear to show higher sensitivity levels
249 to different PR sizes than AB. As the PR increases, PD patterns become flatter across the
250 phase dimension resulting in statistical changes.

251 3) The cc is sensitive to different PR and AB sizes, but no defined variation trend is visible
252 across the various geometries considered. This is due to several factors affecting the cc which
253 varies from one PD fault to the other e.g. the discharge amplitude distribution, flatness and
254 peakedness of the distribution.

255

256 Fig. 4: Processed surface discharge in air patterns.

257

258 **5. Application of the ENN to discriminate different PD ϕ -q-n resolutions**

259

260 **5.1 SNN and ENN training and testing approaches**

261 To evaluate the robustness of the SNN and ENN in classifying and discriminating the
262 statistical variations for different PR or AB sizes of the ϕ -q-n patterns, two strategies were
263 implemented:

264 1) Firstly, both the SNN and ENN were trained with the 6° PR, 100 AB captured ϕ -q-n
265 fingerprints and then tested with the same data, but using 3° , 12° and 15° PR and 100
266 AB. This was to determine the robustness of the SNN and ENN in capturing statistical
267 variations arising from different PR size of the ϕ -q-n patterns.

268

269 2) Secondly, the first strategy was repeated except that the testing was carried out with
270 25AB and 50AB ϕ -q-n data but all at 6° PR. This aims at determining whether the
271 SNN and ENN can still capture statistical variations that may arise from a different
272 AB resolution of the ϕ -q-n patterns.

273
274

275 **5.2 Statistical merit indicators for comparing the SNN and ENN** 276 **recognition rates**

277 As stated in the literature [22], the major weakness of the SNN lies with its various
278 performance evaluation, when trained with several initial conditions (i.e. weights and biases).
279 To improve the situation, this paper applied statistical measures such as the average, variance
280 and standard error of the mean (SEM) for the SNN and ENN comparison[15].To obtain a
281 certain degree of precision on the classification outcomes and as used in a previous paper,
282 100 iterations were chosen for all statistical determinations[15]. This aims at developing and
283 comparing statistical error bound recognition efficiencies of the SNN and ENN for the various
284 ϕ -q-n resolution sizes.

285 **5.3 Results and discussion**

286 Similar to previous research work [1,15,24],statistical measures extracted from ϕ -q-n
287 fingerprints at different resolution dimensions form the input fingerprints for SNN and ENN
288 evaluation. To classify and discriminate these extracted statistical features, as a case study,
289 this paper considered surface discharge in air patterns as the training set, while testing was
290 carried out with the same surface discharge data and other PD faults of different PR and AB
291 dimensions. Six generated ϕ -q-n datasets, Data 1 through to Data 6 are shown in Table 3.

292

293 Table 3: Samples of training and testing data for the SNN and ENN

294

295 Both the SNN and ENN were evaluated using statistical data of **Data 1, Data 2, Data 3, Data**
296 **4, Data 5** and **Data 6**. Each set of fingerprints was composed of a matrix of size 28 rows x 17
297 columns. The first 15 columns were considered to be the input data, while the remaining 2
298 were the output fingerprints. The input fingerprints into the SNN and ENN are the PD
299 samples shown in Table 3, while the output parameters for the PD sample fault are chosen to
300 be [0 1], [1 0], [0 0] and [1 1]. For each PD fault data matrix, 8 rows out of 28 were selected
301 as the testing fingerprints for the SNN and ENN. The ENN configuration is composed of six
302 networks with the same structure trained and tested from the 28 row vectors of bootstrapped

303 resampled data. In order to choose the best SNN set-up for the ensemble, the hidden layer,
304 learning and momentum rates were adjusted and optimum parameters chosen for comparison
305 with the SNN with these forming the configurations for the ENN. One hidden layer with 25
306 neurons was selected, having momentum and learning rates of 0.9 and 0.06 respectively.

307

308 Figs. 5, 6, 7 and 8 show the classification performance of the SNN and ENN when **Data 1** is
309 used for training and then testing undertaken with **Data 1, Data 2, Data 3 and Data 4**
310 respectively. Similarly, Figs. 9 and 10 demonstrate the classification result of the SNN and
311 ENN when **Data 1** is used for training and then testing undertaking with **Data 5 and Data 6**.
312 From these figures, the following information have been deduced:

313

314 1) When either the SNN or ENN is trained and tested with the same PD fault having the
315 same PR and AB size of the ϕ -q-n patterns, the ENN shows improved recognition
316 performance over the SNN (see Fig.5). It is obvious that μ_E , σ_E and σ_{EM} shows higher
317 recognition values than that of μ_S , σ_S and σ_{SM} . For the SNN and ENN trained with one
318 PD fault and test with another, the ENN does not always produce an improved
319 recognition performance over the SNN. This is clearly demonstrated by the σ_E and σ_{EM}
320 having identical recognition intervals to σ_S and σ_{SM} , but still μ_E is greater than μ_S ,
321 showing that on average the ENN has an improved recognition result in comparison to
322 the SNN.

323

324 2) For the SNN and ENN trained with surface discharge in air data of one resolution size
325 and then tested with the same data having different resolution sizes (Figs. 6-10), the
326 ENN and SNN both appear to show higher average recognition probability compared to
327 the other PD faults. However, the ENN appears to be better in this case as its variance
328 intervals are always higher than any other tested PD faults (σ_E and σ_{EM} shows higher
329 recognition values than that of the σ_S and σ_{SM}), indicating the ENN's improved
330 capability to recognize closely similar PD statistical fingerprints. This result implies
331 that even with a change in resolution sizes, it is possible to determine closely similar
332 PD fault scenarios using the SNN and the ENN.

333

334 3) To examine the capabilities of the SNN and ENN in relation to two PR sizes of the ϕ -q-
335 n patterns Figs. 5-8 were evaluated. The most visible change is between Figs. 5 and 8
336 i.e. when the resolution size is changed from 6° to 15° , whilst there is insignificant
337 change in the SNN and ENN recognition capabilities when the resolution size is

338 changed from 6° to 12° or from 6° to 3°. There is basically very little decrease in the
339 values of μ_S and μ_E that can be statistically quantified. Comparing Figs. 5 and 8 shows
340 that there is a slight decrease in the values of μ_S and μ_E in Fig.8 compared to that of
341 Fig.5, which appears not to be statistically significant. Generally, there is rise in the
342 values of μ_S , μ_E , σ_E , σ_S , σ_{EM} and σ_{SM} for untrained PD faults in Fig.8 when compared to
343 these parameters in Fig. 5, but the ENN parameters clearly show a rise in the statistical
344 indicators compared to the SNN. This result implies that the ENN appears to be more
345 sensitive in discriminating the 2 PRs of the ϕ -q-n patterns, however there exists little
346 variation in the 2 PR ϕ -q-n patterns applied for training and testing both the ENN and
347 SNN.

348

349 4) To examine the performance of the SNN and ENN in capturing two AB sizes of the ϕ -
350 q-n patterns, Figs. 9, 10 and 5 were compared. Generally, lower values of μ_S and μ_E are
351 visible for surface discharge in air (when compared to training and testing surface
352 discharge in air at the same resolutions or 2 PRs of the ϕ -q-n patterns i.e. Figs. 5-8).
353 The change appears to be more visible in the SNN and ENN recognition rates when the
354 AB resolution size is changed from 100AB to 25AB rather than 50AB. For both
355 changes there is at least a 5% reduction in the recognition rates of the SNN and ENN
356 for surface discharge in air. However, when the resolution size is changed from 100AB
357 to 25AB it is obvious that σ_E , σ_S , σ_{EM} , σ_{SM} values of Fig. 10 appear to be higher than
358 those of Fig. 5 and Fig. 9. This shows a much wider correlation exists of the testing
359 data with the training data. Comparing Fig. 10 and Fig. 5 shows that the ENN has
360 higher sensitivity in statistical operator variations compared to the SNN. This results
361 implies that there exists significant variations between the training and testing data
362 caused by the change in the AB size of the ϕ -q-n patterns.

363

364 Fig. 5. Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with
365 surface discharge in air 6° PR and 100 AB and tested with the same surface discharge and 3
366 other PD faults but at 6° PR and 100 AB. (μ_S and μ_E values are the centre of variances of
367 SNN and ENN).

368 Fig. 6. Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with
369 surface discharge in air 6° PR and 100 AB and tested with the same surface discharge and 3
370 other PD faults but at 3° PR and 100 AB μ_S and μ_E values are the centre of variances of
371 SNN and ENN).

372 Fig. 7. Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with
373 surface discharge in air 6° PR and 100 AB and tested with the same surface discharge and 3

374 other PD faults but at 12° PR and 100 AB (μ_S and μ_E values are the centre of variances of
375 SNN and ENN).

376 Fig. 8 Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with surface
377 discharge in air 6° PR and 100 AB and tested with the same surface discharge and 3 other PD
378 faults but at 15° PR and 100 AB (μ_S and μ_E values are the centre of variances of SNN and
379 ENN).

380 Fig. 9 Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with surface
381 discharge in air 6° PR and 100 AB and tested with the same surface discharge and 3 other PD
382 faults but at 6° PR and 50 AB (μ_S and μ_E values are the centre of variances of SNN and
383 ENN).

384 Fig. 10 Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with
385 surface discharge in air 6° PR and 100 AB and tested with the same surface discharge and 3
386 other PD faults but at 6° PR and 25 AB (μ_S and μ_E values are the centre of variances of SNN
387 and ENN).

388 **6. Conclusions**

389 For the majority of the PD sources considered, statistical mean CI variations exist for
390 different PR and AB sizes. This has been shown to be most significant in the $H_n(q)^+$ and
391 $H_{qn}(\varphi)^-$ plots but less significant in the $H_n(\varphi)$ plots. Both the SNN and ENN capabilities have
392 been tested for recognizing and discriminating resolution sizes of the φ -q-n patterns and the
393 results clearly show that they can detect slight changes in resolution sizes of these patterns.
394 Additionally, the results shows that the ENN, being more capable, is more sensitive in
395 capturing several resolution changes. These results imply that for practical PD recognition
396 applications, care has to be taken not to simply train SNN or ENN with any PD φ -q-n
397 resolution data and test with another φ -q-n resolution data and expect to obtain reliable
398 results. Furthermore, since different measuring instruments may have different settings for
399 the φ -q-n patterns which are captured and stored for analysis, it is important that certain φ -q-n
400 PR and AB sizes be maintained for consistency of recognition, otherwise unreliable
401 predictions may be incurred.

402

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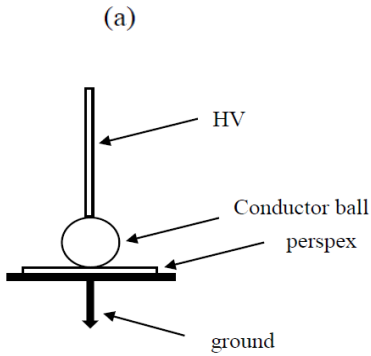
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514 **Figures**

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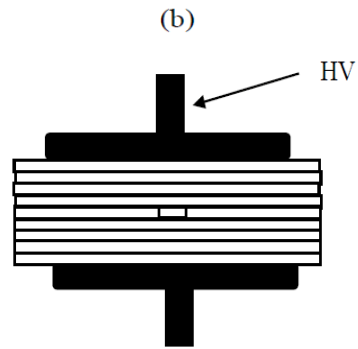
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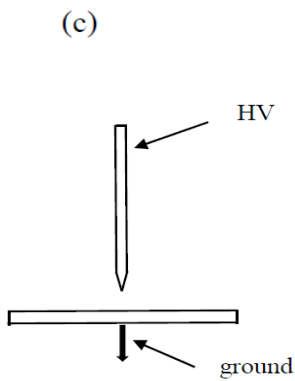
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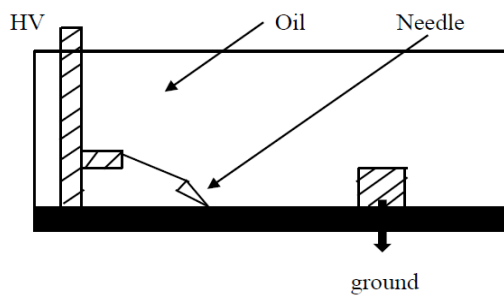
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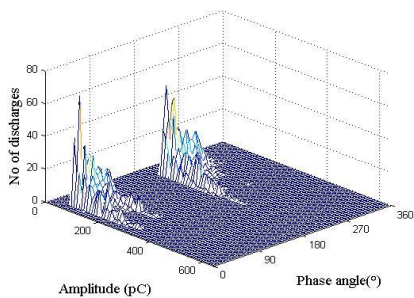
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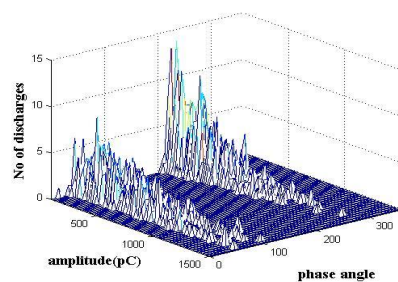


527 Fig. 1: Simulated PD faults a) surface discharge in air b) single void in PET c) corona in air d) surface
528 discharges in oi

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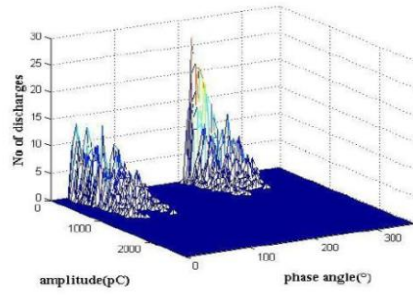


(a) Single void

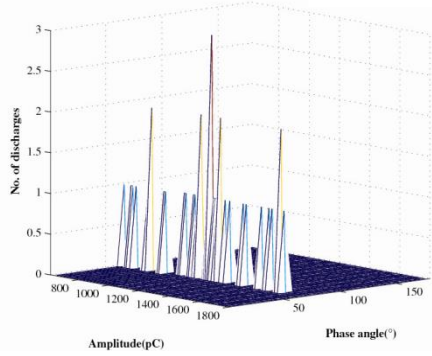


(b) surface discharge in air

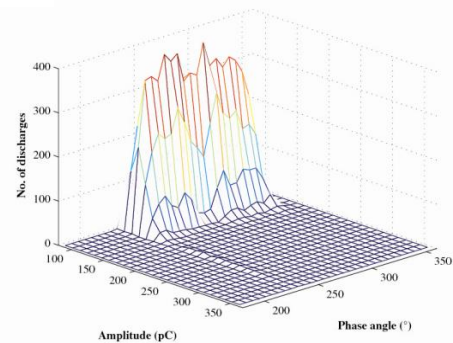
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(c) surface discharge in oil



(d) +ve corona in air



(e) -ve corona in air

Fig. 2: Example of the ϕ -q-n patterns for the PD faults considered

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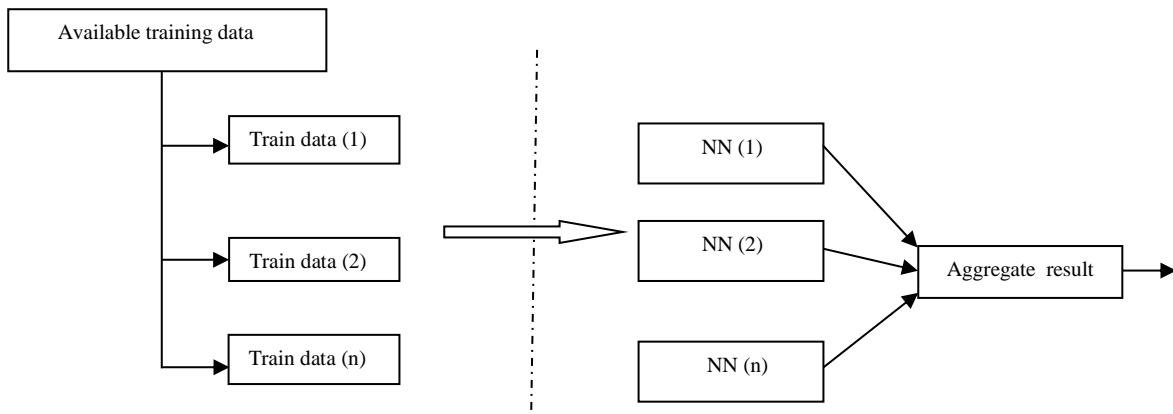
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Fig. 3: The ENN model[10]

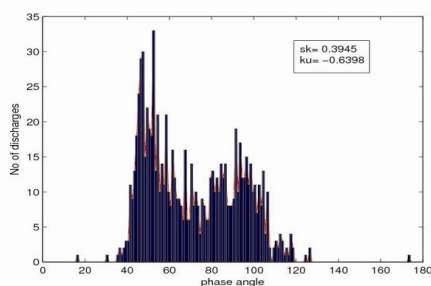
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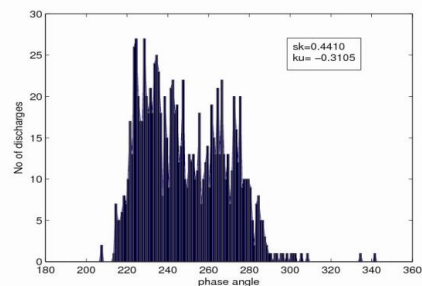
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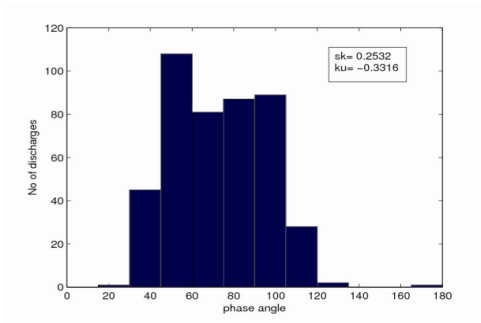


$H_n(\phi)^+$ at 1°PR and 100 AB



$H_n(\phi)^-$ at 1°PR and 100 AB

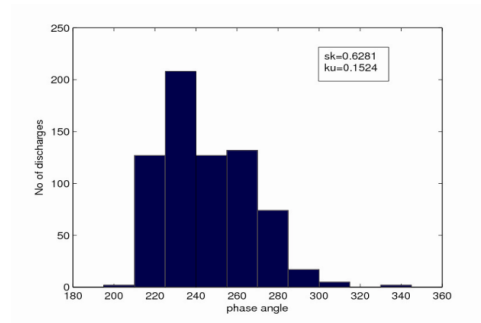
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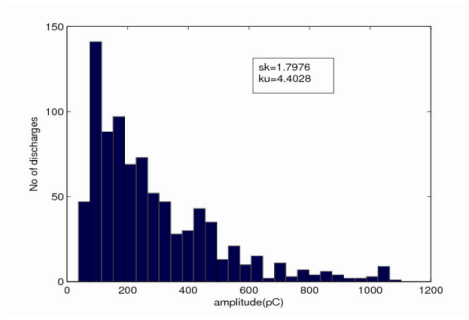
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$H_n(\varphi)+$ at $15^\circ PR$ and $100 AB$



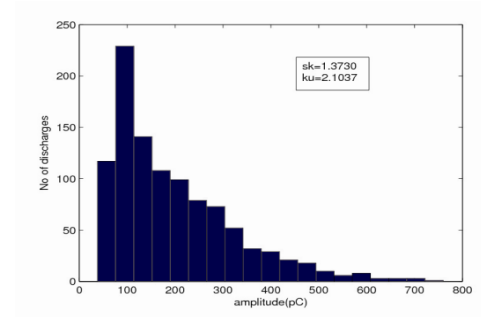
$H_n(\varphi)-$ at $15^\circ PR$ and $100 AB$



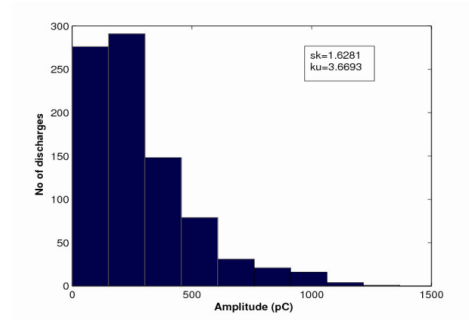
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$H_n(q)-$ at $6^\circ PR$ and $100 AB$



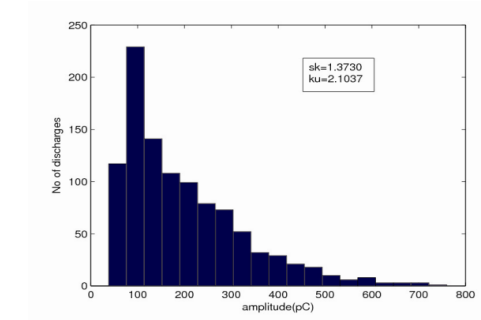
$H_n(q)-$ at $6^\circ PR$ and $100 AB$



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$H_n(q)+$ at $6^\circ PR$ and $25 AB$



$H_n(q)+$ at $6^\circ PR$ and $25 AB$

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Fig. 4: Processed surface discharge in air patterns.

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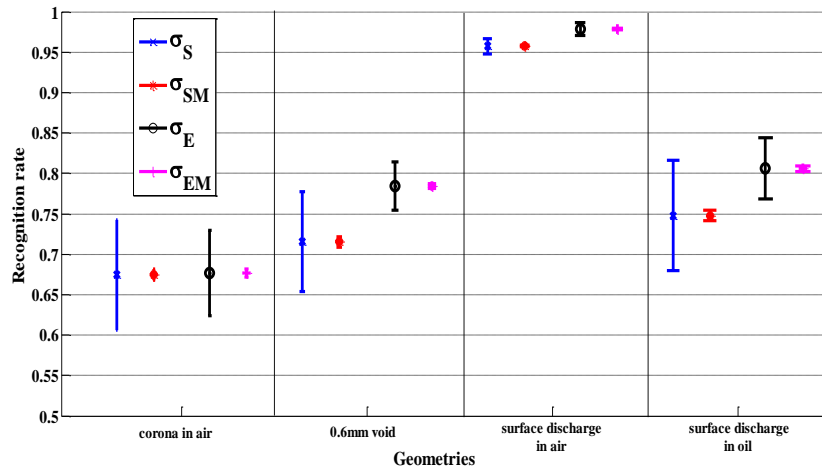
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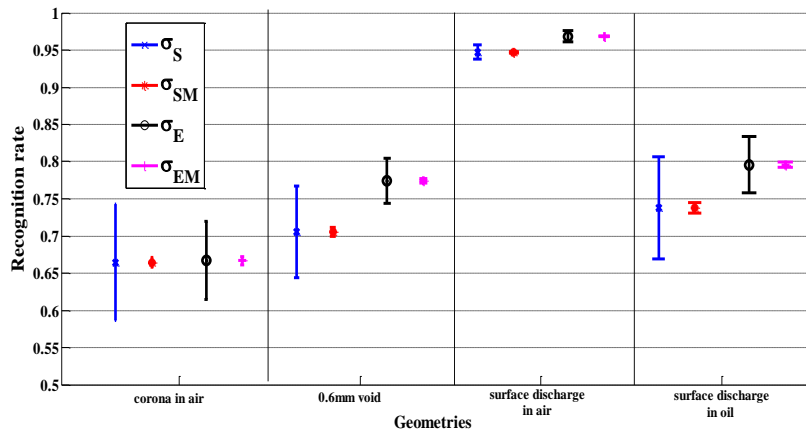
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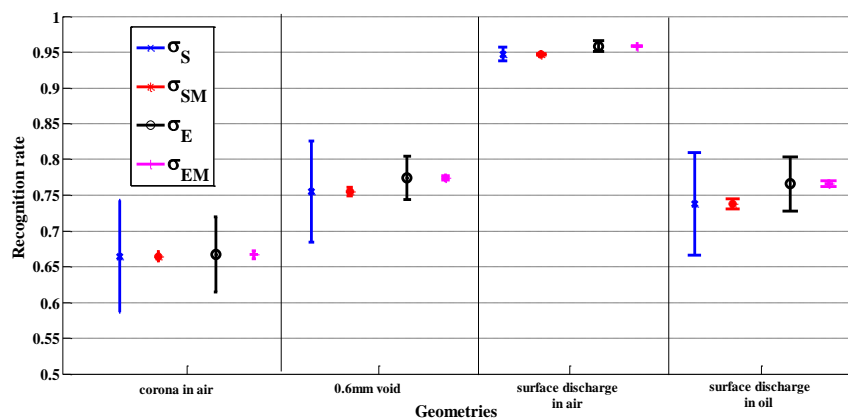
567 Fig. 5. Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with surface discharge in air 6°
 568 PR and 100 AB and tested with the same surface discharge and 3 other PD faults but at 6° PR and 100 AB. (μ_S
 569 and μ_E values are the centre of variances of SNN and ENN)



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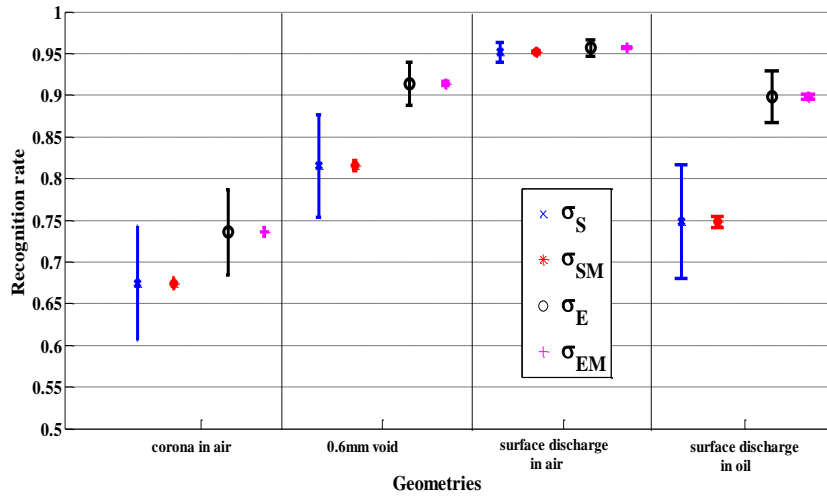
571 Fig. 6. Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with surface discharge in air 6°
 572 PR and 100 AB and tested with the same surface discharge and 3 other PD faults but at 3° PR and 100 AB μ_S
 573 and μ_E values are the centre of variances of SNN and ENN)

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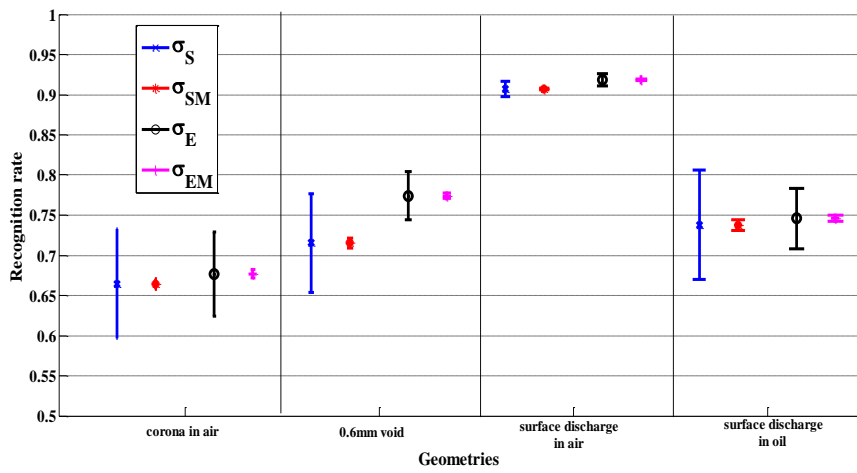
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576 Fig. 7. Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with surface discharge in air 6°
 577 PR and 100 AB and tested with the same surface discharge and 3 other PD faults but at 12° PR and 100 AB (μ_S
 578 and μ_E values are the centre of variances of SNN and ENN)



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580 Fig. 8 Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with surface discharge in air 6°
 581 PR and 100 AB and tested with the same surface discharge and 3 other PD faults but at 15° PR and 100 AB (μ_S
 582 and μ_E values are the centre of variances of SNN and ENN)

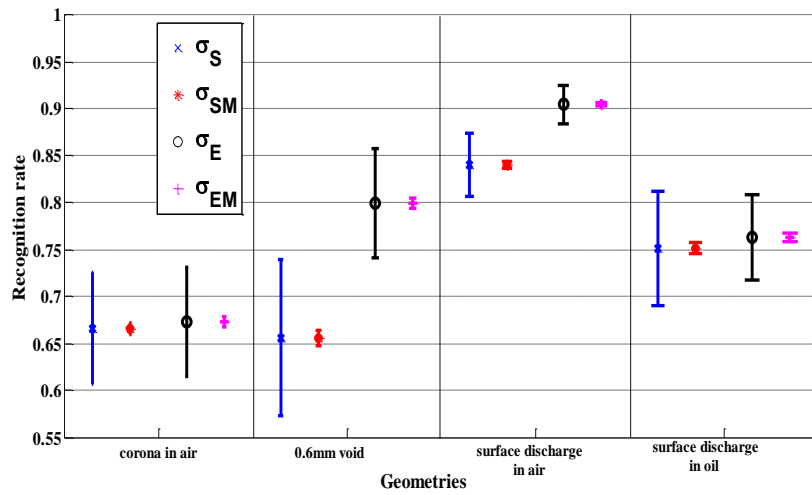


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584 Fig. 9 Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with surface discharge in air 6°
 585 PR and 100 AB and tested with the same surface discharge and 3 other PD faults but at 6° PR and 50 AB (μ_S
 586 and μ_E values are the centre of variances of SNN and ENN)

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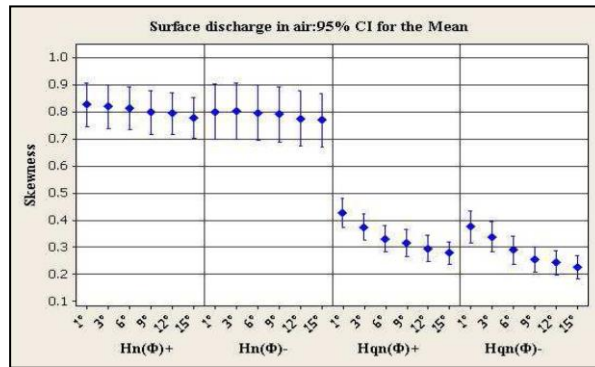


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590 Fig. 10 Plot of μ_S , μ_E , σ_S , σ_E , σ_{SM} and σ_{EM} when both SNN and ENN are trained with surface discharge in air
 591 6° PR and 100 AB and tested with the same surface discharge and 3 other PD faults but at 6° PR and 25 AB (μ_S
 592 and μ_E values are the centre of variances of SNN and ENN)

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APPENDIX: The 95% CI of statistical fingerprints with different PR and AB sizes



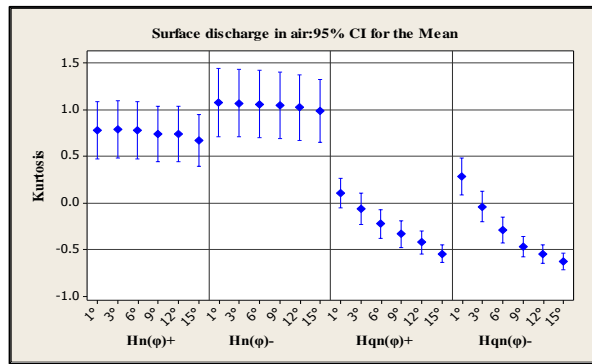
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a) *sk* of the 1°, 3°, 6°, 9°, 12° and 15° PR for the $H_n(\varphi)$ and $H_{qn}(\varphi)$ plots at 100 AB

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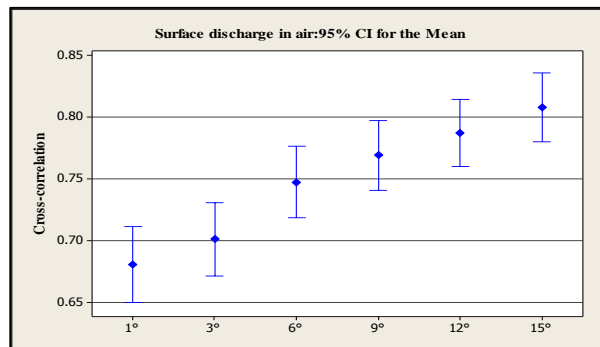
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b) *ku* of 1°, 3°, 6°, 9°, 12° and 15° for the $H_n(\varphi)$ and $H_{qn}(\varphi)$ plots at 100 AB

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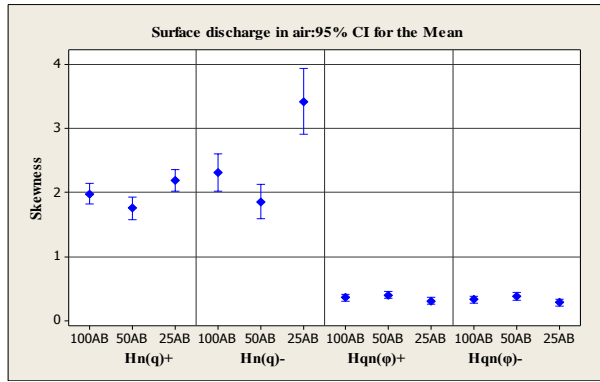
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c) *cc* of 1°, 3°, 6°, 9°, 12° and 15° PR for the $H_n(\varphi)$ and $H_{qn}(\varphi)$ plots at 100 AB

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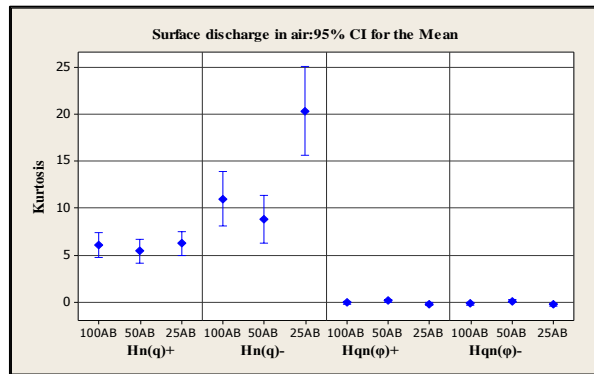
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d) *sk* of the 100AB, 50AB and 25AB PR for $H_n(q)$ and $H_{qn}(\varphi)$ plots at 6° PR

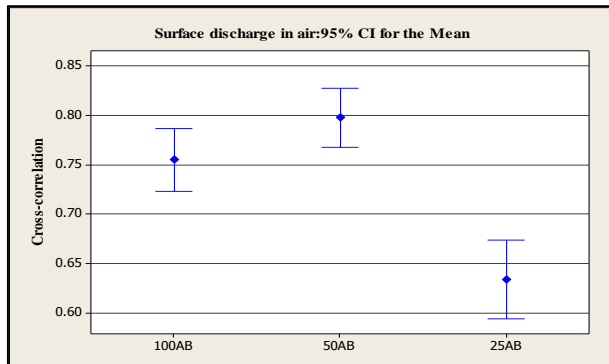
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e) *ku* of the 100AB, 50AB and 25AB PR for $H_n(q)$ and $H_{qn}(\varphi)$ plots at 6° PR

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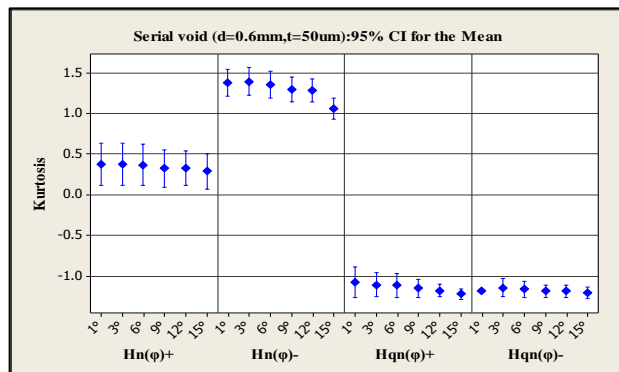
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f) *cc* of 100AB, 50AB and 25AB data all at 6° PR.

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Fig. A1: The mean values and 95% CI of the mean for surface discharge in air

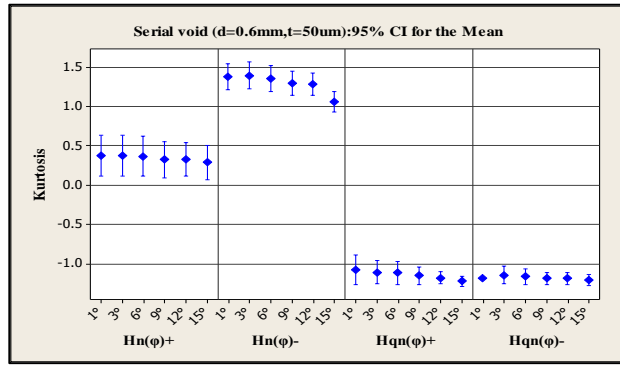
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a) *sk* of the 1° , 3° , 6° , 9° , 12° and 15° PR for the $H_n(\varphi)$ and $H_{qn}(\varphi)$ plots at 100 AB

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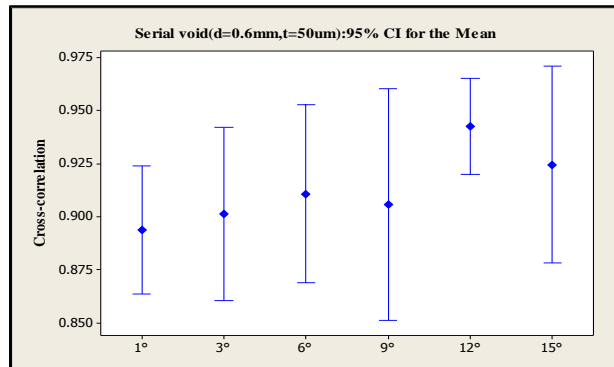


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b) ku of the 1°, 3°, 6°, 9°, 12° and 15° PR for the $H_n(\varphi)$ and $H_{qn}(\varphi)$ plots at 100 AB

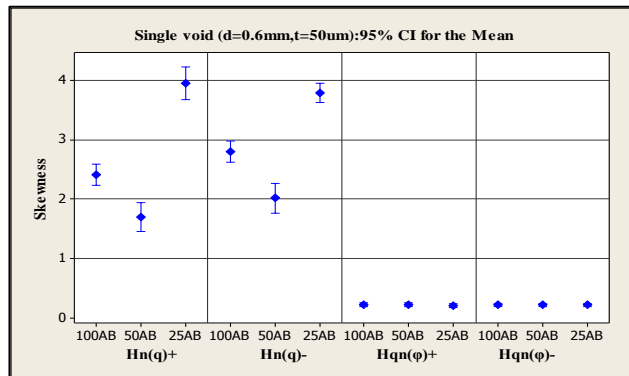


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c) cc of 1°, 3°, 6°, 9°, 12° and 15° PR for the $H_n(\varphi)$ and $H_{qn}(\varphi)$ plots at 100 AB



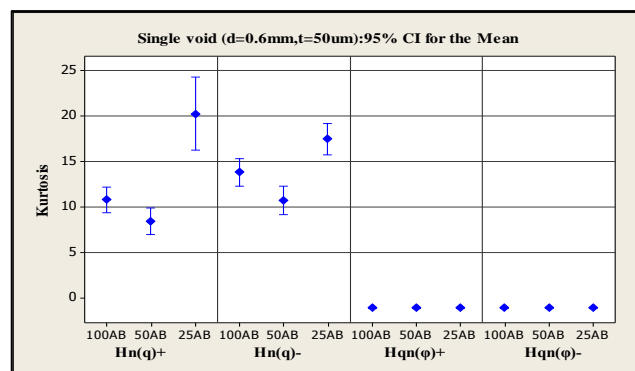
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d) sk of the 100AB, 50AB and 25AB PR for $H_n(q)$ and $H_{qn}(\varphi)$ plots at 6° PR

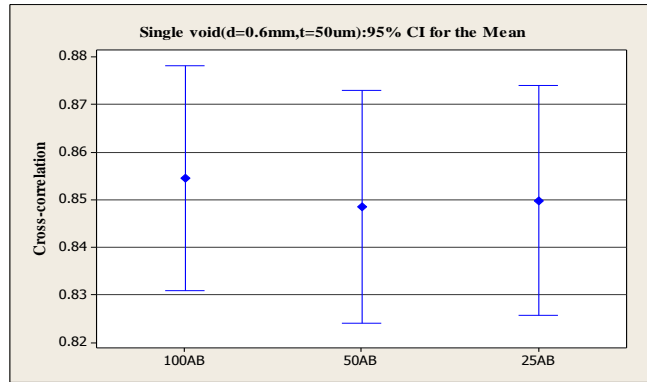


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e) sk of the 100AB, 50AB and 25AB PR for $H_n(q)$ and $H_{qn}(\varphi)$ plots at 6° PR



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f) *cc* of 100AB, 50AB and 25AB data all at 6° PR.

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Fig. A2: The mean values and 95% CI of the mean for single void in PET

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Tables:

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Table 1: PD fault types with the test voltages and corresponding ϕ -q-n samples.

PD fault type	Test voltage	ϕ -q-n samples generated
Corona in air	1.5 kV, 1.9 kV, 2 kV and 2.2 kV for the 5 mm gap and 1.7 kV, 1.9 kV, 2.3 kV and 2.8 kV for the 10 mm gap distance	42
Surface discharge in air	5 kV	148
Surface discharge in oil	18.5 kV	90
Void in the insulation	2.7 kV	169

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Table 2: Mathematical expressions of statistical fingerprints

Statistical operator	Mathematical equation
Skewness	$sk = \frac{\sum (x_j - \mu)^3 P_j}{\sigma^3}$
Kurtosis	$ku = \frac{\sum (x_j - \mu)^4 P_j}{\sigma^4}$
Discharge Factor	$Q = \frac{Q_s^- / N_s^-}{Q_s^+ / N_s^+}$
Cross-correlation	$cc = \frac{\sum x_j y_j - \frac{\sum x_j \sum y_j}{n}}{\sqrt{\left[\sum x_j^2 - \frac{(\sum x_j)^2}{n} \right] \left[\sum y_j^2 - \frac{(\sum y_j)^2}{n} \right]}}$

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Table 3: Samples of training and testing data for the SNN and ENN

Samples	Description
Data 1	surface discharge in air ϕ -q-n data at 6° PR and 100 AB
Data 2	surface discharge in air and 3 other PD faults ϕ -q-n data, all at 3° PR and 100AB
Data 3	surface discharge in air and 3 other PD faults ϕ -q-n data, all at 12° PR and 100AB
Data 4	surface discharge in air and 3 other PD faults ϕ -q-n data, all at 15° PR and 100AB
Data 5	surface discharge in air and 3 other PD faults ϕ -q-n data, all at 6° PR and 50 AB.
Data 6	surface discharge in air and 3 other PD faults ϕ -q-n data, all at 6° PR and 25 AB.

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