Localisation of Partial Discharge Sources using Radio Fingerprinting Technique

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Abstract—**Partial discharge (PD) is a well-known indicator of the failure of insulators in electrical plant. Operators are pushing toward lower operating cost and higher reliability and this stimulates a demand for a diagnostic system capable of accurately locating PD sources especially in ageing electricity substations. Existing techniques used for PD source localisation can be prohibitively expensive. In this paper, a cost-effective radio fingerprinting technique is proposed. This technique uses the Received Signal Strength (RSS) extracted from PD measurements gathered using RF sensors. The proposed technique models the complex spatial characteristics of the radio environment, and uses this model for accurate PD localisation. Two models were developed and compared: k-nearest neighbour and a feed-forward neural network which uses regression as a form of function approximation. The results demonstrate that the neural network produced superior performance as a result of its robustness against noise.**

Keywords – Partial discharge; localisation; fingerprinting.

I. Introduction

A significant cause of plant failure in electrical substations is attributable to insulation degradation [1], and this impacts both availability and operating expenditure. Insulation degradation may be due to the presence of bubbles, voids, foreign particles and other impurities inside the insulation medium [2]. Irrespective of the causal mechanism, insulation degradation gives rise to partial discharges (PD), which increase in severity as the deterioration progresses [3] [4] and this in turn further degrades the quality of the insulation as part of a vicious cycle of breakdown. These discharges are therefore symptoms of insulation breakdown. In this context, PD is defined as a localised dielectric breakdown in a portion of an electrical insulation between two conducting terminals. If PD can be detected early, preventative maintenance can be employed to: minimise the likelihood of outages caused by catastrophic failure of equipment, increase plant life, and minimise costs.

PD produces impulsive electromagnetic emissions in form of radio frequency (RF) energy. It also produces light, heat, acoustic emissions in audible or ultrasonic ranges and also chemical reactions [5]. Consequently, several methods have been developed to detect PD; these methods include acoustic detection [6], chemical detection [5], detection by electrical contact [7] and radio frequency sensing [8]. Radio frequency sensing is attractive in terms of cost and convenience but can only be effective for PD monitoring if PD source locations can be determined with sufficient accuracy.
We propose to deploy a matrix of low cost radio sensors in the form of a wireless sensor network using commercial off-the-shelf components. However, a trade-off exists between cost and complexity. The low cost of the proposed solution allows a monitoring system to be permanently deployed and thus continuously monitor the substation in real-time. In the proposed approach, sensor nodes emit an emulated PD signal in a specific (short) timeslot particular to that node. All other nodes monitor these emulated signals allowing a database to be constructed of the spatial propagation characteristics across the substation environment. It is this propagation database which, when suitably interpolated can be used to locate sources of PD.

The location of PD can be estimated using its measured Location Dependent Parameters (LDPs) [9]. Typical LDPs include the Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA) and/or received signal strength (RSS) [10].

ToA, TDoA and AoA based techniques have been successfully implemented for PD location estimation but require significant complexity and hence, cost [9] [11]. Specifically, with TDoA, accurate source localisation is only possible with tight synchronisation across all receivers, while AoA requires an array of antennas at the receiver and relies on direct Line Of Sight (LOS) path for accurate location estimation [12].

Conversely, an RSS-based technique presents itself as a cost-effective and low-complexity solution for the PD localisation problem [12] [13]. RSS measurement does not require any special hardware and demands only very loose synchronisation between the receivers. Theoretically, a well-known propagation model can be used to estimate the distance between the transmitting source and each receiver node. The distance difference could then be employed with

multilateration techniques to estimate the location of the PD source.
However, most practical radio environments are complex and are not well described by ready-made models in literature and hence large localisation errors would result [14]. This motivates an investigation into the possibility of localisation using RSS-based fingerprinting [14] to improve the accuracy of PD source localisation in electrical substation. The fingerprinting technique captures and utilises the patterns exhibited by the PD signals at different locations within the propagation environment to estimate the PD location. The experimental results show that the fingerprinting technique achieves acceptable accuracy.

The rest of this paper is organised as follows. Section 2, provides the formulation of the problem. Section 3 describes the RSS-based fingerprinting localisation scheme. Section 4 describes the experimental procedure, data preparation and visualisation. The results are presented and discussed in section 5 with conclusions in section 6.

II. PROBLEM FORMULATION

The problem of PD localisation considers sources of unknown PD location radiating electromagnetic (EM) signals from defective insulation systems. These EM signals propagate away from the source and are measured using receivers placed in the vicinity of the discharge site as illustrated in Figure 1. The area used for the experiment is modelled as a finite location space $L = \{l_1, ..., l_n\}$ of n discrete locations. The location space is taken as a set of physical locations with x and y coordinates:

$$L = \{l_1 = (x_1, y_1), ..., l_n = (x_n, y_n)\} \quad (1)$$

where (x_i, y_i), $1 \le i \le n$, represents the location of a PD source.
Suppose there are m reference antennas (sensor nodes) placed in the environment, the received signal strength (RSS) vector received at a reference antenna k can be denoted as;

$$R_k = (r_{k1}, ..., r_{kn}), \quad (2)$$

where r_{kj}, $1 \le k \le m$, $1 \le j \le n$, represents the RSS value received by the k^{th} reference antenna from the j^{th} PD source and n is the number of PD sources in the location space. The aim is to estimate the location of the PD source (x_i, y_i) in the location space L, given the set of RSS vectors R_k, $1 \le k \le m$ received at reference antennas. Both the antennas and the PD sources are assumed to be stationary during measurement.

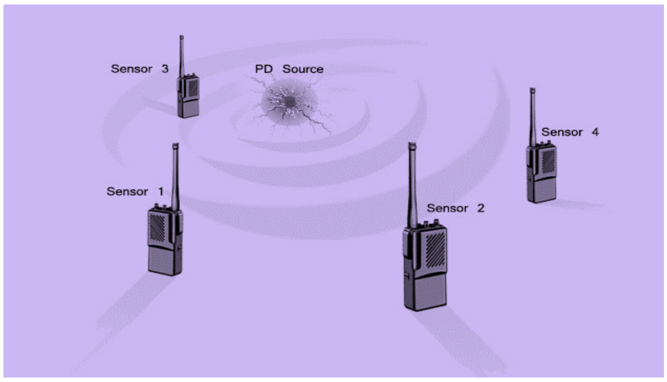

Figure 1 RF measurement of PD signals

III. RSS-BASED FINGERPRINTING

The fingerprinting technique is one of the most viable methods for RSS-based location estimation due to its ability to adapt to the variation of indoor and challenging propagation environments [15]. It is normally executed in two phases; the training phase and the estimation phase [14] [16]. In the training phase, the aim is to construct a training database (radio map) that stored pre-recorded RSS from receivers at reference points. The database is built on the assumption that each point within the environment has a unique RF characteristic. In the estimation phase, the PD source location is estimated by comparing the real-time RSS against the records in the radio map through statistical learning methods. The basic structure of the fingerprinting system is as shown in Figure 2.
The location fingerprint $[(x_i, y_i), (R_1, R_2, ...R_m)]$ is created using the reference points (x_i, y_i) and RSS of the PD signals obtained from the corresponding reference point.
Mathematically, the fingerprinting training database can be expressed as:

$$D = (R_1, X_1), (R_2, X_2), ..., (R_N, X_N) \quad (3)$$

where R_k represent the fingerprint from the k^{th} antennas and X_n represent the position of PD given by $X_n = [x_i, y_i]$. N denotes the size of the fingerprinting database.

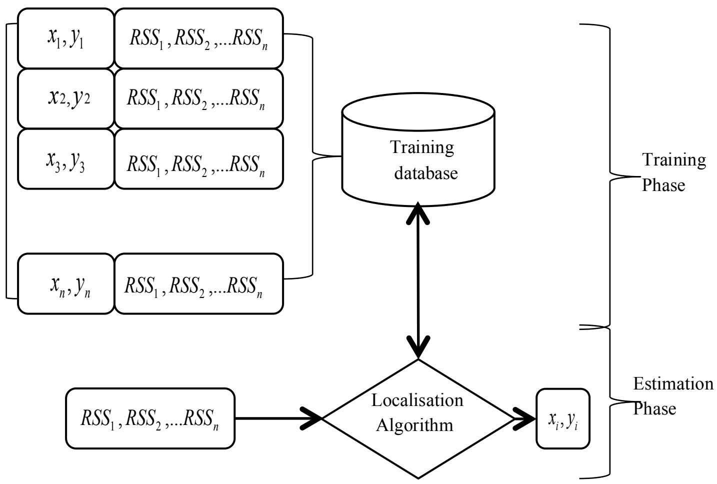

Figure 2 Basic structure of fingerprinting system

The radio map contains all such vectors for a grid of locations within the environment used. There are several techniques that can be used to train the database and estimate the location of the source; these include distance dependent algorithms, such as K nearest neighbour [14] and pattern matching algorithms using Neural Networks [17].

A. *K-nearest neighbour localisation algorithm*

K-nearest neighbour (K-NN) is one of the simplest supervised learning algorithms used for location estimation. It estimates the location of a target based on a similarity measure in the signal space. In this paper, the Euclidean distance [14] is used as a similarity measure to determine the K-nearest neighbours of the target. The Euclidean distance is calculated as

$$ED = \sqrt{\sum_{k=1}^{m} (r_{kt} - r_{kj})^2} \quad (4)$$

where r_{kt} is the RSS value from PD of interest observed at k reference antenna and r_{kj} is the RSS value recorded in the radio map.

In order to estimate the location of PD, the algorithm computes the distance in signal space between the PD measurement and the recorded data, and returns the K neighbours closest to that PD source. The estimated location of the PD is the average the K-nearest neighbours.

The value of the parameter k is determined by the empirical rule [18] $k = \sqrt{N_T}$, where N_T is the number of samples for which their locations are to be estimated.

B. *Neural network localisation algorithm*

Another approach is to use a feed forward neural network [17] for location fingerprinting. This approach can be regarded as a function approximation problem consisting of a nonlinear mapping of the PD received signal strength input onto the dual output variables representing the location coordinates of the PD source.

The multi-layered perceptron (MLP) [13] model has been used. The network consists of an input layer, a hidden layer and an output layer as shown in Figure 3. A sigmoidal activation function was used in the hidden layer to provide robustness against extreme values and a linear activation function in the input and output layers.

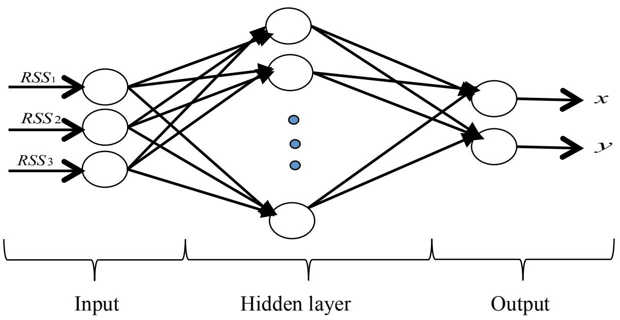

Figure 3 Basic model of localisation neural network

During the learning phase, the neural network is trained to form a set of fingerprints (RSS values) as a function of PD location. Each sample is presented to the inputs and the error between the network outputs and the desired outputs is obtained. The neuron weights are then adjusted to minimise error. The input values can be regarded as the vector sum of the true input value and random noise. As long as the noise has zero mean, the weight updates due to the noise component will cancel out with a sufficient number of samples. This noise immunity makes neural networks attractive for these applications. In the testing phase the unseen RSS values of PD collected from other locations are applied to the input of the neural network. The output of the neural network gives the estimated location of the PD.

In this paper, all the fingerprints formed from the PD data collected by three antennas have been applied to the input of the neural network. During the training process, K-fold cross-validation is used to determine the optimal configuration of the neural network. In k-fold cross-validation the original training data is randomly divided into k equal size sub sets (the folds). In each case, one of the k subsets is used as validation data and the remaining are used for training. The cross-validation process is repeated k times and the average of the k results from the folds gives the test accuracy of that particular network. In this work, a 10-fold cross validation is used. From all the networks tested by cross validation the feedforward 3-4-2 structure of the neural network with four neurons in the hidden layer has the best accuracy. The Bayesian Regularisation (BR) learning algorithm is used to train the network which maximises generalisation. The training of the network is done off-line using the database created by the emulated PD events. The unseen PD data are then presented to the network. The neural network uses the knowledge acquired during training to provide interpolated values for the coordinates of the unseen data.

IV. EXPERIMENTAL PROCEDURE

In order to assess the viability of deploying a matrix of sensors in an electrical substation for PD monitoring, a measurement campaign was carried out in a laboratory which is a 19.20 m x 8.40 m rectangular space at the University of Strathclyde, Glasgow. The laboratory contained a great deal of clutter including metallic objects which gives rise to a complex multipath-rich radio environment. Although the radio environment in the lab cannot be expected to approximate that within an electrical substation, it is sufficiently complex to enable evaluation of the finger printing techniques being investigated. Figure 4 shows the measurement space and geometry. A 1 m x 1 m grid map of 152 points was constructed in the floor of the laboratory. Pulse emulated PDs were generated at the predefined grid points (black dots) using a picosecond pulse generator. The pulse duration was 10 ps and the pulse repetition frequency was 100 kHz. Three omnidirectional antennas (173 MHz) were deployed in the laboratory at predefined locations as shown in Figure 4 to capture the PD signals.

Figure 5 shows a sample of the recorded signal trace. The PD source was attached to a 70 ~ 1000 MHz omnidirectional antenna which was made movable from one grid point to another. It is assumed there were no changes in the experimentation environment between measurements.

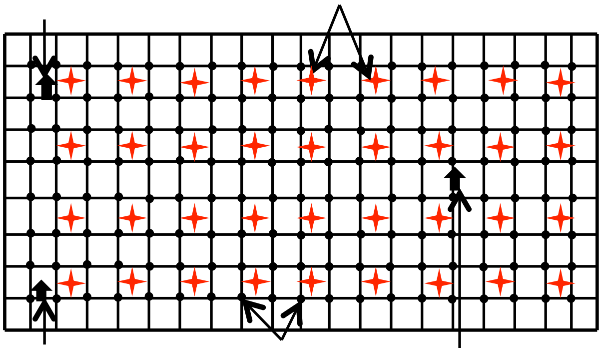

Figure 4 Layout Grid for Measurement Campaign

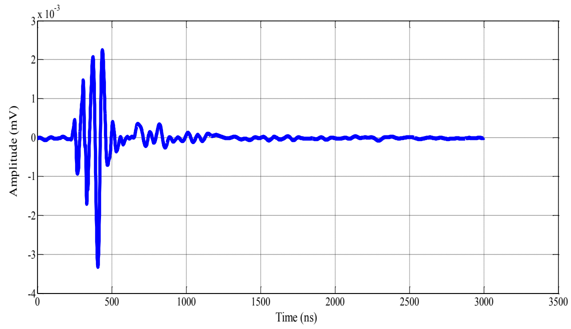

Figure 5 Pulse signal

During the calibration phase, 20 PD measurements were collected at each of the 152 grid points bringing the total calibration data collected from the three receive antennas to 9120. For test dataset, PD data was collected at 36 spatially uniform inter-grid locations (red crosses). These signals were captured and recorded using a multichannel 40 GS/s digital oscilloscope. The oscilloscope analogue bandwidth is 9 GHz. The PD data acquired from measurement were sampled at 2 GS/s. This sampling rate allows the signals to be captured with high resolution.

A. *Data preparation and visualisation*

The PD parameter used in this work is received signal energy (RSE). The calculated average values of energies of the 20 received PD pulses at each grid point and inter-grid point forms the training and testing data set respectively. This brings the total number of training and test data to 456 and 108 respectively. Figure 6 shows the RSE pattern at various points in the radio environment for each of the three antennas. The figures reveal the complexity of the radio environment, which does not fit any well-known propagation model. The complexity of the signal attenuation with distance is a result of noise and multipath distortions/shadowing.

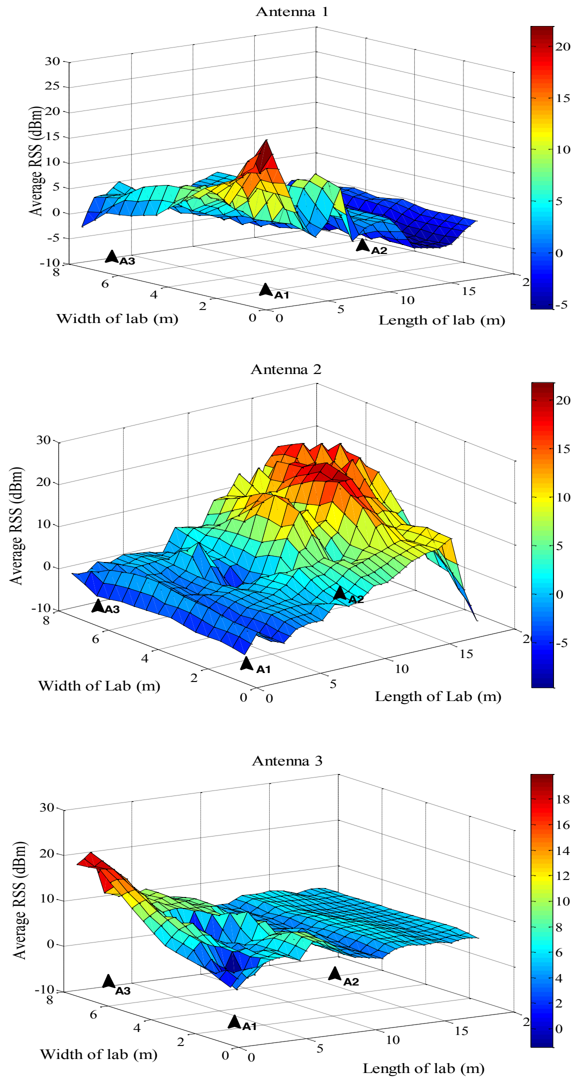

Figure 6 Variation of RSS in propagation environment for antenna1, 2 & 3

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section provides an empirical evaluation of the performance of the fingerprinting based localisation techniques described in Section 3. The average RSE used here is the test data taken from 36 spatially uniform locations (Figure 4). The performance of the localisation techniques is evaluated based on statistical error metrics. The localisation error is taken to be the Euclidean distance between the estimated location and the true location of the PD source. The cumulative density function (CDF) of the distance error is used to describe the performance of the algorithms. This is chosen because it shows how consistent the algorithms work or perform and it captures both the accuracy and precision of the algorithms.

Figure 7 shows the CDF of the localisation error for the K-nearest neighbour and neural network fingerprinting techniques. The k-NN algorithm achieves a precision of 80 % of locations with an error less than 3 m. The maximum error for k-NN is 6.37 m for 3 % of the cases.

On the other hand, the neural network algorithm achieves more than 85 % of locations with an error less than 3 m. The maximum localisation error is 4.18 m for 3 % of the cases.

Table 1 gives a summary of the error measures for both k-NN and neural network fingerprinting algorithms. The 95 % confidence interval (CI) is computed assuming a normal distribution of the errors. 95 % CI indicates the probability that the true value of the parameter (mean or standard deviation) of the localisation error lies in the confidence range. From the result shown in Table 1, we are 95 % confident that the value of the mean error for k-NN and neural network algorithms lie in the range 1.16 to 2.28 m and 1.31 to 2.04 m respectively. It can be seen that both algorithms are practically feasible with mean localisation error of less than 2 m. However, the neural network is more robust due to its lower error standard deviation.

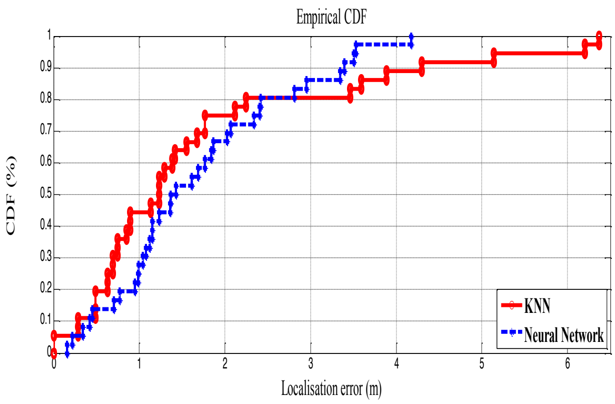

Figure 7 CDF of localisation error for fingerprinting techniques

Table 1 Summary of error measures for the models

Parameter	Model	95% Confidence Interval		
		Lower boundary (m)	Upper boundary (m)	Mean & Standard deviation values (m)
Mean	K-NN	1.16	2.28	1.72
	Neural Network	1.33	2.04	1.68
Standard Deviation	K-NN	1.35	2.16	1.66
	Neural Network	0.85	1.36	1.05

VI. CONCLUSIONS

An implementation of an RSS-based fingerprinting technique for PD source localization has been described. The proposed technique is based on the construction of a fingerprinting database of RSS extracted from PD measurement. The k-nearest neighbour and neural network algorithms are used to construct the database and locate the PD sources. The performance of the fingerprinting technique based on k-nearest neighbour and neural network has been evaluated using empirical test data. The results (average localisation error less than 2 m) demonstrate that fingerprinting localisation is practical for a PD detection and localisation systems. Neural networks can yield superior performance as a result of their robustness in the presence of noise.

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