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Partial Discharge Localisation by Artificial Intelligence Classification

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Abstract- *Partial discharge monitoring is a commonly used engineering tool for condition assessment of high voltage assets. In air insulated substations, radiofrequency antennas can be used to detect and localise partial discharge sources. For accurate partial discharge diagnosis, it is important that defect localisation is as accurate as possible. This paper proposes a neural network classification-based approach for localisation using radiofrequency measurements from multiple antennas. The proposed method relies on a ray tracing-based simulation of radiofrequency propagation to train the neural network. This approach is evaluated against a benchmark approach from a conventional received signal strength spatial localisation method. A hypothetical scenario with five possible partial discharge sources is utilised for the generation of test and evaluation data. An accuracy of 67% was achieved by the benchmark method, compared to 93% with the proposed method. This result indicates that the new approach could improve localisation of partial discharges in air insulated substations.*

I. BACKGROUND

Partial discharge (PD) radiofrequency (RF) measurements are commonly used for monitoring high voltage (HV) assets such as circuit breakers, busbars and insulators [1]. PD is a phenomenon which can occur from the breakdown of HV insulation and is, therefore, an indication of asset health [1]. This is why RF PD monitoring is a commonly used metric for condition monitoring of HV equipment. This paper focuses on the application of RF PD monitoring within air-insulated substation (AIS). Accurate localisation of PD is crucial in identifying the source of the deteriorating HV hardware and for the use of RF measurements in AIS PD monitoring.

A method of localising PD in AIS is through RF sensors and localisation algorithms [2, 3]. Conventional techniques often employ the time difference of arrival (TDOA) localisation technique [2, 3, 4]. However, this method requires high sampling rate data acquisition to correctly determine arrival time, typically in the order of 1 to 10 GS/s [3]. An alternative method which does not require such high sampling rates, as noted in the review paper by Upton et al. [3], are received signal strength (RSS) based methods. Further research demonstrates the use of neural networks to further improve localisation accuracy when using RSS based techniques [5].

II. OVERVIEW

This paper employs two RSS-based PD localisation methods. The first method is based on the propagation loss equation and will be used as a benchmark as it follows a conventional methodology. This benchmark method produces a spatial coordinate, after which an algorithm selects the nearest HV

equipment to that position. The second method is a new localisation method utilising artificial intelligence (AI) and the performance of which is compared with the benchmark method. The proposed method localises the PD source directly to the relevant HV equipment, thereby bypassing the intermediate step of determining spatial coordinates.

Both localisation methods operate on RSS measurements. To obtain the experimental data, a study was carried out in our HV laboratory. The environment in the laboratory was free of obstructions between antenna and PD sources. Five spatial coordinates were selected as potential PD source sites. These five points emulate the positions of five HV assets which are to be monitored. Three antennas were used for RF monitoring.

In addition to the experimental measurements, training data for the neural network used in the proposed method was generated through a ray-tracing simulation of a virtual environment replicating the laboratory setup.

III. PARTIAL DISCHARGE RSS DATA

Several methods exist for localising PD sources, and the choice of technique typically depends on the sensing hardware available. This paper focuses on approaches that utilise RSS, where RSS is derived from the peak amplitude of the detected PD signal.

To support the development and evaluation of the localisation methods, RSS data was obtained from two sources under the same environment and antenna configuration. An empirical dataset, collected at the HV laboratory at Cardiff University, was used to evaluate both the benchmark and proposed localisation methods. In addition, a simulated dataset was generated through a ray tracing simulation that replicates this laboratory scenario, as described by Williams et al. [6]. This dataset was used exclusively to train the neural network employed in the proposed method.

A. Empirical Data Procedure

Four monopole UHF antennas were used in conjunction with a 2 GS/s oscilloscope, with the trigger threshold set above the environmental noise floor to ensure reliable detection of PD events.

RSS was computed from the peak amplitude of each captured waveform. The received signal strength in dBm was then obtained using the standard power conversion expression based on a 50 Ω termination. For every detected PD event, the RSS value recorded at each antenna position was stored to form the empirical dataset.

Artificial PD signals were generated using a piezoelectric device. Although the resulting RF emissions likely exhibit higher amplitudes than those typically produced by HV equipment, the associated frequency spectra are comparable to those seen in literature [7]. If multiple PD events were to occur simultaneously in different locations, errors would be introduced in localisation as the system would not account for this scenario. Each PD recorded event is a 5-microsecond sample. This suggests that PD events must occur at an interval greater than this for successful use of the localisation method.

This is considered acceptable because practical PD measurement systems in AIS commonly employ low-noise amplifiers and band-pass filters, which could lead to received waveforms of similar magnitude and spectral characteristics, such as the device developed by Saeed et al. [8]. An example waveform from the piezoelectric sparking device used in the experiment is shown in Fig. 1.

The experiment was carried out in the HV laboratory at Cardiff University. Five hypothetical positions of HV assets were selected for the study. There were no physical obstructions in the environment between the antennas and hypothetical PD positions. Artificial PD was generated three times at each of the five positions to emulate the RF emission of PD at those positions. Replicating a scenario where HV assets are being monitored and localisation of the RF signals is required. The top view layout of this scenario can be seen in Fig. 2.

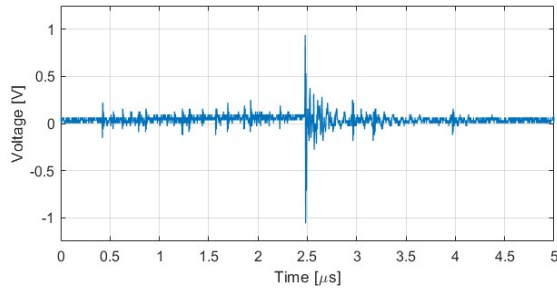


Figure 1: Artificial partial discharge from sparking device measured at 10cm from source with a monopole antenna at 2GS/s.

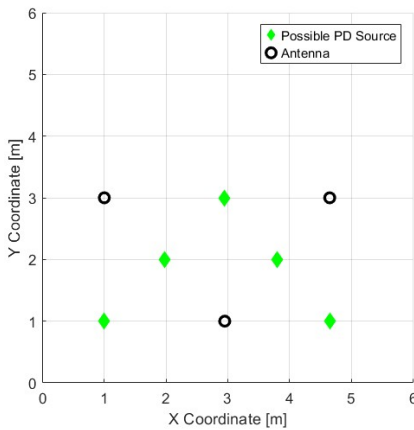


Figure 2: Top view layout of the 3-antenna and 5 hypothetical PD source scenario.

B. Simulated Data Procedure

The RF propagation and PD emission simulations used in this study are based on the framework presented by Williams et al. [6]. The key feature of this simulation is the ray tracing methodology employed to calculate the RSS at multiple antennas from a specified PD source.

The simulation requires a 3D CAD model of the environment in which PD is to be simulated. A free space path loss model was used in this study, given the obstruction free setup used in the measuring of empirical data. The placement of the antennas can be implemented by defining the spatial coordinate of their position. Similarly, PD is simulated as an RF transmitter, the position of which is defined as a range of spatial coordinates corresponding to each possible source of PD. A single transmission frequency of 300 MHz is used in the propagation methodology which is unlike the wideband signals seen in measured PD. However, no significant differences in localisation results were identified when changing the simulation frequency along the typical PD wideband frequency range of 100 - 1000 MHz.

Noise is added to the calculated RSS to create a database of possible received measurements. The noise is defined from a dataset manually created from real measurements. These measurements are taken by placing 3 antennas in parallel, as close as possible to each other. Artificial PD is, then, generated at varying distances perpendicular to the antenna array, and the RSS is measured at each antenna.

The pairwise differences of RSS for each artificial PD measurement set are calculated, and this provides a profile of measurement differences, as can be seen in Fig. 3. This distribution of measured differences is added to the simulated RSS as this is the expected characteristics of the measurement system being used.

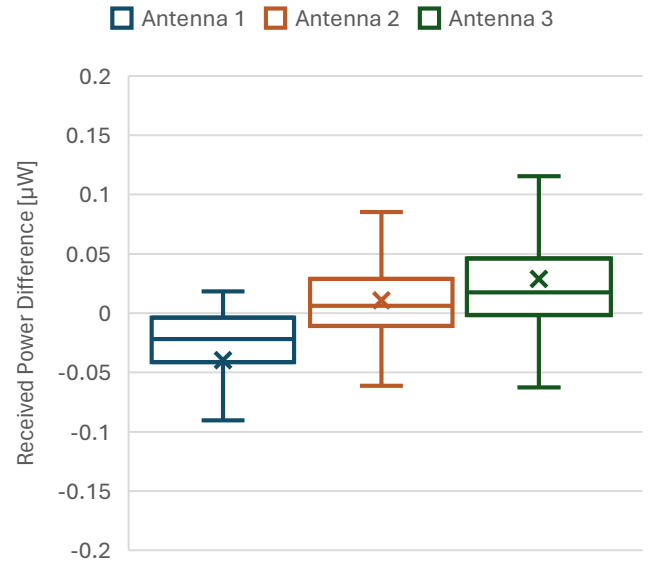


Figure 3: Example noise profile, generated for RF simulation, for a 3-antenna setup.

IV. LOCALISATION METHODS

Typically, PD localisation methods localise to a spatial coordinate. Therefore, the benchmark method will be based on a conventional approach which utilises RSS based localisation to spatial coordinates. The proposed new method described in this paper localises directly to potential PD sources which, in this case, are the HV equipment.

A. Benchmark Spatial Coordinate Localisation

To provide a baseline for performance comparison, a benchmark localisation approach based on RSS measurements is implemented. This method follows RSS based localisation techniques that estimate the spatial coordinates of a PD source using measurements acquired from multiple spatially distributed antennas, similar to the approaches reported in [3, 8].

In the benchmark system, RSS measurements from each antenna are processed to estimate the 2D spatial coordinates of the PD source within the monitored environment. Once the source location is estimated, the nearest HV asset is identified by computing the Euclidean distance between the estimated PD coordinates and the known positions of all equipment stored in a database. The asset with the minimum distance to the estimated location is then assigned as the most probable PD source.

This two-stage process of spatial localisation followed by nearest-neighbour equipment identification provides a direct and interpretable benchmark against which the proposed method can be evaluated. An example execution of the benchmark algorithm is illustrated in Fig. 4. In this scenario, a PD event is localised to coordinates (4.41, 1.68), and the nearest asset in position (3.80, 2.00) is subsequently identified as the PD source. As the PD signal was artificially generated at coordinates (3.80, 2.00), this result corresponds to a correct source identification in this instance.

Rather than evaluating performance solely in terms of spatial localisation error in meters distance from the true source, the benchmark is assessed using the success rate of correctly identifying the originating HV asset. This metric aligns more closely with the practical requirements of condition monitoring

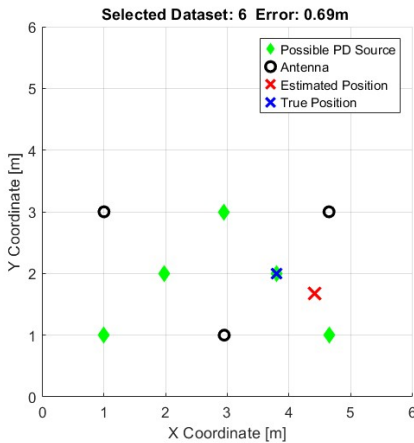


Figure 4: Conventional method of localisation result. Estimated position (4.41, 1.68) is 0.69 m from true position (3.80, 2.00).

in AIS, where accurate identification of the deteriorating component is of greater operational significance than precise spatial coordinate estimation.

B. Classification Localisation Method

An alternative method is to localise PD to HV equipment through AI classification methods. The justification for this approach is that the purpose of localising PD is for condition monitoring of equipment. Therefore, the goal is to correctly identify the equipment which the RF PD signal emanates from, not necessarily the exact spatial coordinate.

This methodology consists of the following stages. First, potential sources of PD are identified, these being the HV assets within the substation that require monitoring. Next, a 3D model of the AIS environment is developed. The spatial coordinates of the RF antennas are then defined within the simulated environment to accurately replicate the real-world sensor deployment. RF emissions associated with PD activity are subsequently simulated for each identified HV asset, and the resulting RSS are recorded for each antenna location.

The simulated measurements are used to construct a database capturing the RSS at each antenna for each PD. This database is employed to train a fully connected feed forward neural network using scaled conjugate gradient backpropagation, where the classes correspond to the HV assets. Finally, the trained model is validated using real-world, experimentally acquired data to assess its localisation and classification performance.

V. RESULTS

To evaluate the performance of the neural network approach, three artificial PDs were generated successively at five separate locations, as described in Section III-A.

Using the benchmark localisation methodology described in Section IV-A, an overall correct localisation accuracy of 67% was achieved, i.e., in 67% of cases, the correct PD source was identified. When modifying the criteria to include the 2 nearest potential PD sources as a correct identification, this accuracy increased to 73%. The first stage spatial localisation of this methodology achieved an error of 0.93m.

In contrast, the proposed neural network-based method achieved a PD source identification accuracy of 93%,

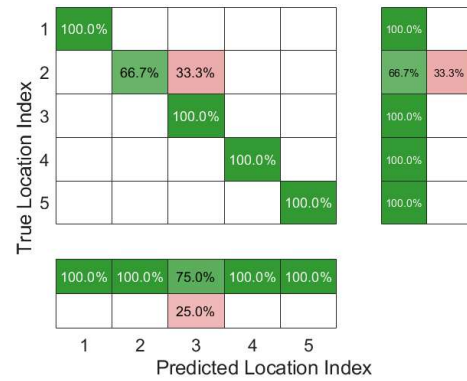


Figure 5: Confusion matrix of neural network test result on empirical data.

corresponding to a single misclassification out of the fifteen test cases. The confusion matrix for the neural network classifier is shown in Fig. 5, where the lone incorrect classification can be observed.

The incorrect classification by the neural network approach was correctly identified by the benchmark method and is the case depicted in Fig. 4. In the first stage of spatial coordinate localisation in the benchmark method, this PD event was localised to (4.41, 1.68) which is 0.69m from the correct source and 0.72 m for the second nearest potential source.

VI. DISCUSSION

For the neural network approach, simulation for data generation and training of a neural network is required, whereas for the benchmark used, this is not the case. The benchmark method can be used immediately in any scenario upon placing antennas. For the neural network method, the scenario needs to be modelled. CAD made drawings can be seen used in other RF simulations of PD transmission [6].

As the environment was free of obstructions, this does not make full use of the ray tracing methodology and only considers free space path loss.

Despite this limitation of the study, the use of ray tracing simulation data has been demonstrated for the training of a neural network for classification and its use in localising PD sources in a hypothetical scenario. Test results show a clear improvement from 67% to 93% accuracy, when using the neural network approach in this scenario.

The 0.93m spatial localisation error from the first stage of the benchmark method is comparable to the localisation errors seen in literature where RSS based localisation is utilised [8, 9, 10]. An RSS-based method is used as a benchmark due to having the same hardware requirements, as opposed to other techniques such as TDOA.

The PD event that was incorrectly localised by the neural network method was correctly identified by the benchmark method. However, it is worth noting that, in the first stage of the benchmark localisation process, the estimated spatial coordinate of the PD event was (4.41, 1.68). This location lies 0.69 m from the correctly identified source and 0.72 m from the second nearest potential source. The proximity of these distances indicates that the RF RSS measured at the antennas for this event exhibit strong similarity to those associated with both potential sources. Consequently, the first stage of the benchmark method effectively localises the PD event to a position nearly equidistant between the two assets, highlighting the inherent ambiguity in the measured signals for this case and explaining the misclassification observed in the neural network output.

VII. CONCLUSION

This paper presented a neural network-based approach for the localisation of PD sources in AIS. Unlike conventional localisation techniques that estimate spatial coordinates, the proposed method directly identifies the probable PD source. The neural network is trained using a database of simulated RF RSS measurements generated through a ray tracing-based simulation of the substation environment, including PD source

and antenna locations. When evaluated using empirical measurement data, the proposed method achieved a PD source identification accuracy of 93%, outperforming a conventional RSS-based benchmark approach, which achieved an accuracy of 67%. These results indicate that the proposed approach could provide an effective alternative for PD localisation in AIS condition monitoring and warrants further investigation and validation.

VIII. FUTURE WORK

In future studies, the full capability of the simulation should be evaluated. This should be done by repeating the experiment in a complex environment with obstructions similar to an AIS or, preferably, at an AIS itself. This would allow for further comparison of the proposed method with existing methods and explore potential improvements in the method such as accounting for simultaneous PD events, which can occur in AIS.

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