



**Faculty of Engineering**

**A Single Perceptron Smart Sensor Technique for Pre-fault Monitoring  
System in an Indoor Substation**

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# A Single Perceptron Smart Sensor Technique for Pre-fault Monitoring System in an Indoor Substation

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A thesis submitted

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## DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

  
.....

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## ABSTRACT

Single Perceptron Smart Sensor (SPSS) is a new Ultra-High Frequency (UHF) sensor developed to significantly improve the pre-fault monitoring system for early detection, localization, and identification of the Corona and Arcs Electric Discharges (EDs) in an indoor substation. Corona and Arcs ED constitute a significant threat to electrical safety, the apparatus, and the stability of a power system due to the aging and material degradation in the power apparatus. Hence, an early preventive approach must be performed effectively for pre-fault threat detection. In this research, a novel pre-fault monitoring system utilizing SPSS is developed, embedding a novel Signal Identifier Technique for the Corona and Arcs ED detection, localization, and identification. The SPSS formation integrates a 2-element Linear Array Antenna with a Single Perceptron-Artificial Neural Network (SP-ANN). It detects and localizes the Corona and Arc ED signals based on the Direction of Arrival (DOA) angle. The SP-ANN utilizes a single-layer neuron with less complexity, speedy detection, and localization within seconds. The waveform-based signal feature extraction uses the Signal Identifier Technique for signal identification. Since the frequency range of the Corona and Arcs is undecidable, the accuracy of the pre-fault monitoring is tested for the Corona and Arcs ED at a sampling frequency of 300 MHz to 3 GHz. The SPSS has revealed an accuracy of 99.86% for signal identification with minimal computational complexity, thus giving another practical wireless technique for UHF signal interpretation.

**Keywords:** Single Perceptron-Artificial Neural Network, UHF Sensor, Corona discharge, Arcs discharge, Pre-fault monitoring

***Sebuah Sensor Pintar Perceptron Tunggal Teknik Untuk Sistem Pemantauan Pra-Kerusakan Dalam Sebuah Pencawang Dalam***

**ABSTRAK**

*Pengesan Pintar Perceptron Tunggal daripada Rangkaian Saraf Tiruan (SPSS) merupakan sebuah Pengesan Frekuensi Ultra Tinggi dihasilkan untuk meningkatkan keberkesanan sistem pra-pemantauan kerosakan bagi tujuan pengesanan, penyetempatan dan pengecaman isyarat Nyahcas Elektrik jenis Corona dan Arcs di dalam sesebuah Pencawang Dalam. Nyahcas Elektrik memberi ancaman yang besar terhadap keselamatan serta kestabilan perkakasan elektrik sistem kuasa di dalam sesebuah pencawang di mana ianya terhasil disebabkan oleh keusangan bahan pada perkakasan elektrik sistem kuasa. Ia boleh mempengaruhi kebolehpercayaan sesebuah peralatan voltan tinggi. Oleh yang demikian, tindakan pencegahan awalan perlu dirancang dengan berhati-hati dan pemantauan kerosakan harus dilaksanakan secara berkesan bagi mengesan ancaman awal kerosakan. Di dalam kajian ini, sebuah sistem pra-pemantauan yang baru telah dihasilkan menggunakan sebuah Pengesan Pintar Perceptron Tunggal daripada Rangkaian Saraf Tiruan serta menyematkan sebuah Teknik Pengecam Isyarat yang baru bagi pengesanan, penyetempatan dan pengecaman terhadap isyarat Nyahcas Elektrik jenis Corona dan Arcs. SPSS ini dihasilkan melalui gabungan sebuah Antenna Tatasusun Lelurus 2-elemen dengan Perceptron Tunggal-Rangkaian Saraf Tiruan (SP-ANN) untuk membentuk sebuah Pengesan Pintar Frekuensi Ultra Tinggi. Ianya berkebolehan untuk mengesan, menyetempat serta mengecam isyarat nyahcas elektrik jenis Corona dan Arcs berdasarkan Sudut Arah Ketibaan (DOA) isyarat. SP-ANN ini terdiri daripada satu lapisan neuron yang boleh mengurangkan kesukaran serta meningkatkan kepantasan proses pengesanan serta*

*penyetempatan isyarat dalam tempoh milisaat. Pengekstrakan ciri-ciri isyarat melalui bentuk gelombang isyarat dilaksanakan menggunakan Teknik Pengecam Isyarat. Memandangkan tiada penentuan yang khusus terhadap julat frekuensi bagi Nyahcas Elektrik jenis Corona dan Arcs, maka kejituan sistem pra-pemantauan ini telah diuji menggunakan sampel isyarat Nyahcas Elektrik jenis Corona dan Arcs berfrekuensi sekitar nilai 300 MHz hingga 3 GHz. SPSS telah menunjukkan tahap kejituan sebanyak 99.86% terhadap pengecaman isyarat menggunakan kekompleksan pengiraan yang minimum, dengan itu juga memberi satu teknik tanpa wayar yang praktikal untuk pentaksiran isyarat Frekuensi Ultra Tinggi.*

**Kata kunci:** *Perceptron tunggal-rangkaian saraf tiruan, pengesan frekuensi ultra tinggi, nyahcas elektrik corona, nyahcas elektrik arcs, pra-pemantauan kerosakan*

## TABLE OF CONTENTS

|                                                       | <b>Page</b> |
|-------------------------------------------------------|-------------|
| <b>DECLARATION</b>                                    | i           |
| <b>ACKNOWLEDGEMENT</b>                                | ii          |
| <b>ABSTRACT</b>                                       | iii         |
| <b><i>ABSTRAK</i></b>                                 | iv          |
| <b>TABLE OF CONTENTS</b>                              | vi          |
| <b>LIST OF TABLES</b>                                 | xi          |
| <b>LIST OF FIGURES</b>                                | xii         |
| <b>LIST OF ABBREVIATIONS</b>                          | xv          |
| <b>CHAPTER 1: INTRODUCTION</b>                        | 1           |
| 1.1 Background                                        | 1           |
| 1.2 Problem Statement                                 | 3           |
| 1.3 Objectives                                        | 5           |
| 1.4 Chapter Summary                                   | 5           |
| <b>CHAPTER 2: LITERATURE REVIEW</b>                   | 6           |
| 2.1 Overview                                          | 6           |
| 2.2 Power Substation and Monitoring System            | 6           |
| 2.2.1 Pre-fault Monitoring in Indoor Power Substation | 8           |
| 2.2.2 Corona and Arcs Electric Discharges             | 10          |

|                               |                                                                                                                                                  |    |
|-------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|----|
| 2.3                           | ED Signal Detection Techniques                                                                                                                   | 13 |
| 2.3.1                         | Array antenna for UWB wireless sensor                                                                                                            | 16 |
| 2.4                           | ED Signal Localization Techniques                                                                                                                | 21 |
| 2.4.1                         | Perceptron – Artificial Neural Network (P-ANN)                                                                                                   | 24 |
| 2.5                           | EDs Signal Identification                                                                                                                        | 28 |
| 2.6                           | Chapter Summary                                                                                                                                  | 32 |
| <b>CHAPTER 3: METHODOLOGY</b> |                                                                                                                                                  | 35 |
| 3.1                           | Overview                                                                                                                                         | 35 |
| 3.1.1                         | Framework of the Single Perceptron-ANN for Smart Sensor Formation                                                                                | 35 |
| 3.2                           | PART A: Investigate the most suitable $N$ -element array antenna as the SPSS model which has broad radiation and can adapt to the changes of DOA | 39 |
| 3.2.1                         | Linear Array Antenna Radiation Pattern for $N$ - elements Effect                                                                                 | 40 |
| 3.2.2                         | Inter-Element Spacing Effect on Linear Array Antenna                                                                                             | 41 |
| 3.2.3                         | Single Perceptron-ANN Effect on the $N$ -element Array Antenna                                                                                   | 42 |
| 3.3                           | PART B: Develop a novel SPSS, utilizing the SP-ANN Algorithm for ED_EMP signal detection and localization                                        | 44 |
| 3.3.1                         | SP-ANN Algorithm for Weight Optimization Tested $N$ -element Array Antenna                                                                       | 44 |
| 3.3.2                         | SPSS Formation Involving $N$ -element Array Arrangement                                                                                          | 49 |
| 3.3.3                         | SP-ANN Hyperparameters for the Fast Convergence Effect                                                                                           | 50 |

|                                          |                                                                                                                                                                   |           |
|------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| 3.3.4                                    | Simultaneous Signal Detection at Multiple DOA for 2-element Array Antenna                                                                                         | 51        |
| 3.3.5                                    | SP-ANN Algorithm for the Smart Simultaneous Signal Detection                                                                                                      | 57        |
| 3.3.6                                    | SPSS for Signal Electric Field Strength Tested on Multiple DOA                                                                                                    | 59        |
| 3.3.7                                    | SPSS Total Electric Fields ( $E_T$ ) and Radiated Power Intensity ( $P_i$ )                                                                                       | 61        |
| 3.4                                      | Part C: Evaluate the accuracy of the ED_EMP signal identification using the novel SP-Identifier Technique in waveform-based testing for Corona or Arc EDs samples | 63        |
| 3.4.1                                    | $E_P$ Model in Representing ED_EMP Tested at Multiple DOA                                                                                                         | 63        |
| 3.4.2                                    | Similarity of the ED_EMP Waveforms in Space and Time Domain                                                                                                       | 65        |
| 3.4.3                                    | Efficiency of the SP-Identifier Technique                                                                                                                         | 67        |
| 3.4.4                                    | Signal Identification for the SPSS Radiation Waveform                                                                                                             | 70        |
| 3.5                                      | Chapter Summary                                                                                                                                                   | 71        |
| <b>CHAPTER 4: RESULTS AND DISCUSSION</b> |                                                                                                                                                                   | <b>77</b> |
| 4.1                                      | Overview                                                                                                                                                          | 77        |
| 4.2                                      | Part A: Investigate the most suitable $N$ -element array antenna as the SPSS model which has broad radiation and can adapt to the changes of $\beta$              | 77        |
| 4.2.1                                    | Analysis of Linear Array Antenna for $N$ - elements Effect                                                                                                        | 78        |
| 4.2.2                                    | Analysis of Inter-Element Spacing Effect on Linear Array Antenna                                                                                                  | 81        |
| 4.2.3                                    | Analysis of the SP-ANN Effect on the $N$ -element Array Antenna                                                                                                   | 82        |

|       |                                                                                                                                                                   |     |
|-------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| 4.3   | Part B: Develop a novel SPSS, utilizing the SP-ANN Algorithm for ED_EMP signal detection and localization                                                         | 85  |
| 4.3.1 | Analysis of the SP-ANN Algorithm for Weight Optimization                                                                                                          | 86  |
| 4.3.2 | Analysis of the SPSS Formation Involving $N$ -element Array Arrangement                                                                                           | 89  |
| 4.3.3 | Analysis of the SP-ANN Hyperparameters for the Fast Convergence Effect                                                                                            | 94  |
| 4.3.4 | Analysis of Simultaneous Signal Detection at Multiple DOA for 2-element Array Antenna                                                                             | 98  |
| 4.3.5 | Analysis of SP-ANN Algorithm for the Smart Simultaneous Signal Detection                                                                                          | 102 |
| 4.3.6 | Analysis of the SPSS for Signal Electric Field Strength Tested on Multiple DOA                                                                                    | 104 |
| 4.3.7 | Analysis of the SPSS for the Total Electric Fields ( $E_T$ ) and Radiated Power Intensity ( $P_i$ ) at A Fixed DOA and Multiple Ranges of Signal Distance, $r$    | 108 |
| 4.4   | Part C: Evaluate the accuracy of the ED_EMP signal identification using the novel SP-Identifier Technique in waveform-based testing for Corona or Arc EDs samples | 112 |
| 4.4.1 | Analysis of the $E_P$ Model in Representing ED_EMP Tested at Multiple DOA                                                                                         | 112 |
| 4.4.2 | Analysis of Similarity of the ED_EMP Waveforms in Space and Time Domain                                                                                           | 115 |
| 4.4.3 | Analysis of the Efficiency of the SP-Identifier Technique                                                                                                         | 119 |
| 4.4.4 | Analysis of the Signal Identification for the SPSS Radiation Waveform                                                                                             | 122 |
| 4.5   | Chapter Summary                                                                                                                                                   | 128 |

|                                                  |      |
|--------------------------------------------------|------|
| <b>CHAPTER 5: CONCLUSION AND RECOMMENDATIONS</b> | 134  |
| 5.1 Conclusion                                   | 134  |
| 5.2 Contribution of Study                        | 137  |
| 5.3 Future Recommendations                       | 137  |
| <b>REFERENCES</b>                                | 138  |
| <b>APPENDICES</b>                                | 1822 |

## LIST OF TABLES

|                                                                                                           | <b>Page</b> |
|-----------------------------------------------------------------------------------------------------------|-------------|
| Table 2.1 Common insulation defect for Power Apparatus                                                    | 14          |
| Table 2.2 List of ED detection techniques emerged in recent year.                                         | 15          |
| Table 2.3 Comparison of ED localization method using the DOA method                                       | 23          |
| Table 2.4 ANN for PD signal recognition                                                                   | 27          |
| Table 2.5 Comparison of Performance for ED Detection, Localization and Recognition Methods and Techniques | 30          |
| Table 3.1 The Overall system specification                                                                | 37          |
| Table 3.2 The $E_P$ models for the SPSS Detection                                                         | 71          |
| Table 4.1 Magnitude of electric field strength measurement for ED activities                              | 110         |
| Table 4.2 Specification Table of SP-Identifier Technique                                                  | 123         |
| Table 4.3 Summary of the accuracy rate (%) of SP-Identifier Technique                                     | 126         |
| Table 4.4 Comparison of SP-Identifier accuracy rate (%) of different analysis methods                     | 126         |
| Table 4.5 The comparison of ED identification accuracy rate(%) for Single-source ED                       | 127         |
| Table 4.6 Based-Method Comparison for ED localization                                                     | 128         |

## LIST OF FIGURES

|                                                                                         | <b>Page</b> |
|-----------------------------------------------------------------------------------------|-------------|
| Figure 2.1 Percentage of insulation faults (Refaat et al., 2018)                        | 7           |
| Figure 2.2 The Sinc Function                                                            | 13          |
| Figure 2.3 The $N$ -element Linear Array Antenna (Hoole, 2001)                          | 18          |
| Figure 2.4 The 2-element Array Antennas (Hoole, 2001)                                   | 19          |
| Figure 2.5 The basic structure of a Single Perceptron ANN (Senthilkumar et al., 2018)   | 25          |
| Figure 3.1 Framework of Single Perceptron-ANN for Smart Sensor                          | 36          |
| Figure 3.2 The overall model of the pre-fault monitoring system in an indoor substation | 37          |
| Figure 3.3 Overall research activities for the pre-fault monitoring system              | 39          |
| Figure 3.4 Linear Array Antenna with $N$ -elements in the $z$ -axis (Hoole, 2001)       | 42          |
| Figure 3.5 The Smart sensor model with a 2-element array antenna                        | 43          |
| Figure 3.6 The SPSS Model with a 2-element array antenna                                | 45          |
| Figure 3.7 Flowchart of the SP-ANN Training Algorithm                                   | 48          |
| Figure 3.8 The 2-element SA Model                                                       | 51          |
| Figure 3.9 The SA nullifying the interference signal                                    | 52          |
| Figure 3.10 The SA maximizing the desired signal                                        | 53          |
| Figure 3.11 The SA scanning process at two possible Corona or Arc sources               | 53          |
| Figure 3.12 The wall-mounted SA to detect and localize the ED from a Transformer        | 55          |
| Figure 3.13 The flowchart of the SA model for signal nullifying and maximizing          | 56          |
| Figure 3.14 The flowchart of the SPSS for signal nullifying and maximizing              | 58          |
| Figure 3.15 The topology of the SPSS toward a Power Transformer                         | 60          |
| Figure 3.16 The SPSS configuration for signal detection                                 | 61          |

|             |                                                                                            |     |
|-------------|--------------------------------------------------------------------------------------------|-----|
| Figure 3.17 | An ED_EMP generated in time domain                                                         | 64  |
| Figure 3.18 | The framework for the Similarity Comparison for the ED_EMP                                 | 66  |
| Figure 3.19 | Framework of SP-Identifier Technique                                                       | 68  |
| Figure 3.20 | The framework for the Similarity Comparison for SPSS radiation                             | 69  |
| Figure 3.21 | SP-Identifier Technique using the DataTip Alignment Method                                 | 70  |
| Figure 4.1  | The AF radiation patterns with the varying array length.                                   | 79  |
| Figure 4.2  | The $f(\varphi)$ radiation patterns of the 2, 3, 4, 6, 8 and 10-element                    | 80  |
| Figure 4.3  | The $f(\varphi)$ radiation patterns at $\beta=15^\circ, 45^\circ, 65^\circ$ and $90^\circ$ | 81  |
| Figure 4.4  | The radiation patterns at samples of $d$ for the $N=2$                                     | 82  |
| Figure 4.5  | The $f(\varphi)$ patterns of $N$ -element at all initial $W=0.1+j0$                        | 83  |
| Figure 4.6  | The $f(\varphi)$ radiation patterns of $N$ -element at all initial $W=2.0+j0$              | 84  |
| Figure 4.7  | The $f(\varphi)$ radiation patterns of $N$ -element at the optimized weight                | 87  |
| Figure 4.8  | The $N=2$ for RP01 and RP02 at $\theta_d=45^\circ$                                         | 89  |
| Figure 4.9  | The $N=3$ for RP01, RP02 and RP03 at $\theta_d=45^\circ$                                   | 90  |
| Figure 4.10 | The $N=4$ for RP01, RP02, RP03 and RP04 at $\theta_d=45^\circ$                             | 91  |
| Figure 4.11 | The $N=6$ for RP01, RP02, RP03 and RP04 at $\theta_d=45^\circ$                             | 92  |
| Figure 4.12 | The $N=8$ for RP01, RP02, RP03 and RP04 at $\theta_d=45^\circ$                             | 93  |
| Figure 4.13 | Graph of the SP-ANN response at DOA= $45^\circ$ and $\eta=0.001$                           | 95  |
| Figure 4.14 | Graphs of the SP-ANN corresponded to $\eta=0.005$ and $\eta=0.01$                          | 96  |
| Figure 4.15 | Graphs of the SP-ANN responses at DOA= $45^\circ$ and $0.02 \leq \eta \leq 1.0$            | 97  |
| Figure 4.16 | The radiation patterns of maximized $\theta_d$                                             | 99  |
| Figure 4.17 | The radiation patterns of nullified $\theta_i$                                             | 100 |
| Figure 4.18 | The SA responded to a small gap of $5^\circ$                                               | 101 |
| Figure 4.19 | The SA plotted with initial weights                                                        | 102 |
| Figure 4.20 | The SA plotted with updated weights                                                        | 102 |
| Figure 4.21 | The $f(\varphi)$ at $\theta_d=65^\circ$                                                    | 103 |

|             |                                                                                                       |     |
|-------------|-------------------------------------------------------------------------------------------------------|-----|
| Figure 4.22 | The $f(\varphi)$ at $\theta_i = 100^\circ$                                                            | 103 |
| Figure 4.23 | AF plotted at $\theta_d = 65^\circ$                                                                   | 103 |
| Figure 4.24 | AF plotted at $\theta_i = 100^\circ$                                                                  | 103 |
| Figure 4.25 | The DOA = $45^\circ$ and the $Y = -1.231$ dB without SP-ANN                                           | 105 |
| Figure 4.26 | The DOA = $45^\circ$ and the $Y = 20.2$ dB with SP-ANN                                                | 106 |
| Figure 4.27 | The DOA = $65^\circ$ and the $Y = 26.31$ dB with SP-ANN                                               | 106 |
| Figure 4.28 | The DOA = $290^\circ$ and the $Y = 25.02$ dB with SP-ANN                                              | 107 |
| Figure 4.29 | The overall $Y$ observed at the DOAs of $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$       | 107 |
| Figure 4.30 | The $E_T = 458$ V/m normalized at 26.61 dB                                                            | 109 |
| Figure 4.31 | The $P_i = 278.3$ V/m normalized at 24.44 dB                                                          | 109 |
| Figure 4.32 | The graph of $E_T$ and $P_i$ versus Receiving Distance, $r$                                           | 111 |
| Figure 4.33 | The $E_P$ models at subjected DOA = $45^\circ$ , $120^\circ$ , $225^\circ$ and $300^\circ$            | 113 |
| Figure 4.34 | The $E_P$ models in the space domain for DOA = $45^\circ$ , $120^\circ$ , $225^\circ$ and $300^\circ$ | 113 |
| Figure 4.35 | The accuracy comparison chart of the SPSS $E_P$ model and ZigBee Impulsive Noise model measurement    | 114 |
| Figure 4.36 | The $E_P$ plotted in the space and time-domain for DOA = $45^\circ$ and $225^\circ$                   | 116 |
| Figure 4.37 | The Magnitudes $Y_S$ and $Y_T$ at DOA = $45^\circ$                                                    | 117 |
| Figure 4.38 | The Magnitudes $Y_S$ and $Y_T$ at DOA = $225^\circ$                                                   | 117 |
| Figure 4.39 | The error analysis for similarity comparison                                                          | 118 |
| Figure 4.40 | Data Extraction Accuracy using MATLAB DataTip Alignment Method                                        | 119 |
| Figure 4.41 | SPSS Radiation Patterns in Space and Time domain at DOA = $45^\circ$                                  | 120 |
| Figure 4.42 | SPSS Radiation Patterns in Space and Time domain at DOA = $225^\circ$                                 | 121 |
| Figure 4.43 | The SPSS radiation patterns for $E_P = 1$ GHz                                                         | 124 |
| Figure 4.44 | The SPSS radiation patterns for $E_P = 2$ GHz                                                         | 124 |
| Figure 4.45 | The SPSS radiation patterns for $E_P = 0.5$ GHz                                                       | 125 |

## LIST OF ABBREVIATIONS

|              |                                                   |
|--------------|---------------------------------------------------|
| 1-D CNN      | One-Dimension CNN                                 |
| $\phi$ -OTDR | Phase-sensitive optical time-domain reflectometry |
| AF           | Array Factor                                      |
| AFN          | Normalized Array Factor                           |
| AI           | Artificial Intelligence                           |
| AIS          | Air Insulated Substation                          |
| ANN          | Artificial Neural Network                         |
| BP           | Back-Propagation                                  |
| BPNN         | Back-Propagation Neural Network                   |
| BP-PSO       | Back Propagation-Particle Swarm Optimization      |
| CNN          | Convolutional Neural Network                      |
| CT           | Current Transformer                               |
| DCNN         | Deep Convolutional Neural Network                 |
| DL           | Deep Learning                                     |
| DOA          | Direction of Angle                                |
| DT           | Decision Tree                                     |
| E            | Error                                             |
| ED           | Electric Discharge                                |
| ED_EMP       | Electric Discharge Electromagnetic Impulse        |
| EFT/B        | Anti-Jamming Electrical Fast Transient/Burst      |
| EHV          | Extra High Voltage                                |
| EM           | Electromagnetic                                   |
| EMG          | Electromyography                                  |

|       |                                          |
|-------|------------------------------------------|
| ENN   | Ensemble Neural Network                  |
| EP    | Electromagnetic Impulse                  |
| ET    | Total Electric Fields                    |
| FBG   | Fiber Bragg Grating                      |
| FCM   | Fuzzy C-means Clustering                 |
| FDAS  | Fiber-optic distributed acoustic sensing |
| FL    | Fuzzy Logic                              |
| GIS   | Gas Insulated Switchgear                 |
| HV    | High Voltage                             |
| Hz    | Hertz                                    |
| HFCT  | High Frequency Current Transformers      |
| IR    | Infrared                                 |
| IoT   | Internet of Thing                        |
| LMS   | Least Mean Square                        |
| LSTM  | Long Shot-Term Memory Network            |
| MAV   | Mean Average Value                       |
| MCNN  | MobileNets convolutional neural network  |
| MFCC  | Mel-frequency Cepstrum Coefficients      |
| ML    | Machine Learning                         |
| MLP   | Multilayer Perceptron                    |
| MNN   | Multilayer Neural Network                |
| NCDS  | Non-Contact Directional Sensor           |
| P-ANN | Perceptron-Artificial Neural Network     |
| PCA   | Principle Component Analysis             |
| PD    | Partial Discharge                        |

|        |                                                     |
|--------|-----------------------------------------------------|
| Pi     | Power Intensity Radiated                            |
| PNN    | Probabilistic Neural Network                        |
| PRPD   | Phase Resolved Partial Discharge                    |
| PS-FBG | Phase-Shifted Fiber Bragg Gratings                  |
| PSO    | Particle Swarm Optimization                         |
| PT     | Potential Transformers                              |
| RF     | Radio Frequency                                     |
| RFID   | Radio Frequency Identification                      |
| RP     | Radiation Pattern                                   |
| RIV    | Radio Interference Voltage                          |
| RSSI   | Received Signal Strength Index                      |
| SA     | Smart Antenna                                       |
| SP     | Single Perceptron                                   |
| SP-ANN | Single Perceptron Artificial Neural Network         |
| SPSS   | Single Perceptron Smart Sensor                      |
| SRC    | Sparse Representation Classifier                    |
| SS     | Smart Sensor                                        |
| STFT   | Short-Time Fourier Transform                        |
| SVM    | Support Vector Machine                              |
| T-SNE  | Analysist-distributed stochastic neighbor embedding |
| TDOA   | Time Different of Arrival                           |
| TEV    | Transient Earth Voltage                             |
| TOA    | Time of Arrival                                     |
| UHF    | Ultra-High Frequency                                |
| UHV    | Ultra-High Voltage                                  |

|      |                             |
|------|-----------------------------|
| UWB  | Ultra-Wide Band             |
| VSWR | Voltage Standing Wave Ratio |
| WSN  | Wireless Sensor Networks    |

# CHAPTER 1

## INTRODUCTION

### 1.1 Background

Over the years, many smart sensors have been developed to improve the detection, localization, and recognition techniques of Electromagnetic (EM) signals. Most of these sensors are engaged with the digital and wireless communication system and are highly implemented in the fault monitoring system in power substations. Recently, Ultra-High Frequency (UHF) sensors have been among the famous techniques for EM measurement, especially in power substations due to the congregation of High Voltage (HV) power apparatuses in the substations. Playing an essential role in the power systems, the transmission, generator, and distribution station substations perform important power generation, transmission, and distribution tasks. Therefore, substation fault monitoring must be conducted speedily, accurately, and effectively to maintain the performance and reliability of the system (Fauzi et al., 2018; Guozhi et al., 2019; Lv et al., 2017; Tang et al., 2021; Zhu et al., 2018; Wang et al., 2017).

For the past years, many researchers have successfully discovered methods to improve the fault monitoring system for conventional substations (Gaouda et al., 2018; Mas'ud et al., 2014; Robles et al., 2016; Sarkar et al., 2016; Sima et al., 2017; Tan et al., 2017; Yongxiang et al., 2017). However, there is still room for improvement since many conventional substations are now slowly being converted into digital substations (Froese, 2017). Note that going digital means digitizing the protection, measurement, and control units. Conventional sensors are replaced by modern digital sensors that allow direct digital communication to the process bus. Copper wires connected point-to-point to the Current

Transformers (CTs) or Potential Transformers (PTs) are replaced by electronic voltage/CTs and fiber optics cables to minimize the exposure to HV electricity and the risk of damage to the equipment. Nevertheless, having this key substation equipment digitized, including sensor data, communications, and sensor signal processing, the substation may still be exposed to the risk of potential hazards such as Electric Discharges (EDs). Therefore, pre-breakdown and pre-fault monitoring is still required to detect the existence of EDs in the substations, which may lead to a complete breakdown of the system (Gataullin, 2020; Kumbhar et al., 2017; Polyakov et al., 2018; Ryan, 2001).

Many approaches to fault detection in substation monitoring have been reported, with simulation results suggesting effective detection, localization, and recognition of the substation faults caused especially by Dielectric Breakdown (Arias et al., 2018; Christina et al., 2018; Moreira et al., 2020; Srisongkram et al., 2019). However, it is still a major issue in power systems, originating mostly in insulation degradation, thus producing EDs such as Corona and Arc discharges. The application of sensors from the groups of Photodetector and Ultraviolet sensors is still preferred by some researchers to get a rapid diagnosis and prognosis of the causes of faults, which enables appropriate measures to be taken. The common sensors used for fault detection are Acoustic Emission, Radio Interference Voltage (RIV) Measurement, Infrared (IR) Thermography, Electric Field Measurement, Visual Observation, and Ultraviolet Camera. However, these sensors depend on the visibility of the light emitted by EDs and the use of the EM spectrum, which is limited to  $10^{14}$  Hz (100 THz) (P. R. Hoole et al., 2013). Currently, sensors such as array antennas and UHF sensors have been used to replace the conventional sensors in detecting and localizing the ED to improve the efficiency of substation fault monitoring (Azam et al., 2022; Ghanakota et al., 2022; Nobrega et al., 2019; Rhamdhani et al., 2022; Uwiringiyimana et al., 2021; Wu et al., 2022;

Xavier et al., 2021; Yadam et al., 2021, 2022; Zhu et al., 2019). In general, an ED in a substation indicates the presence of cracks, voids, or other insulation degradation within the electrical equipment. It can lead to equipment failure, serious accidents, and electric breakdown of the power distribution system (Mohan et al., 2019; Shahsavarian et al., 2020; Tsyokhla et al., 2019a; Zamudio-Ramirez et al., 2019; Zhang et al., 2019). When an open circuit occurs at a conventional CT, for example, the inductive circuit can produce hazardous conditions. HV on the secondary load (depending on the load) may develop and lead to ED in the form of flashovers and arcing, which put the substation or personnel at great risk, and the stability of electrical equipment could be disturbed. The most common EDs are Electric Corona Discharge and Electric Spark/Arc, which can be detected not only on the overhead HV power transmission lines but also frequently inside substations that consist of substation equipment like transformers, circuit breakers, and switches. Moreover, the ED measurement techniques rely on the different physical activities of the ED. Many factors affect the ED activities, such as environmental temperature, humidity, voltage, and load. Therefore, the ED frequency spectrums also vary depending on different environmental conditions. Based on the antenna characteristics and background noise for the detection, the frequency spectrums of the ED, such as Corona and Arc, are widely distributed across a range of 300 MHz – 3 GHz with various types (Affendi et al., 2020; Bruzzzone, 2021; Chai et al., 2018; Dukanac, 2018; Hamdani et al., 2018; Laksono et al., 2020; Li et al., 2018; Thiviyathan et al., 2022).

## **1.2 Problem Statement**

In the past, researchers have successfully developed high-performance and ultra-modern techniques to provide a better way for HV equipment insulation condition monitoring systems. However, these techniques do not include a pre-monitoring system for

the entire substation environment at a time. Mostly, the monitoring system focuses on individual equipment such as transformers, Gas Insulated Switchgear (GIS), or transmission cables, and frequently, the insulation condition is only realized when the damage has already long occurred on the equipment due to lack of pre-monitoring action. Although the designed systems include high performance, efficient, and smart characteristics for insulation condition monitoring of ED detection, localization, and recognition, there are constraints in the implementation. This is due to the extensive data and memory system required for smart signal recognition. Hence, multiple applications of sensors are required to improve signal detection and localization from multi-ED sources concurrently. Furthermore, the implementation requires high costs for new upgrading works and installation to replace the existing monitoring system.

The smart signal recognition technique requires an extensive data system, such as data storage and memory for the dataset libraries, to support recognition methods for multiple ED sources. When the processed sample data does not match any of the datasets in the data libraries system, the recognition is considered to fail. This is the drawback of the modern signal recognition. Hence, conventional methods and techniques are still preferable. However, a conventional periodic manual checking system is time-consuming and is less practical, especially for substations in rural areas. Based on the limitations, a novel pre-fault monitoring system utilizing a wireless smart sensor called a Single Perceptron Smart Sensor (SPSS) is developed to detect and localize the early formation of Corona or Arcs ED signals based on its single source direction of arrival angle (DOA), embedding a novel SP-Identifier Technique for Corona or Arcs ED signal identification.

### 1.3 Objectives

The main goal is to demonstrate the ability of the developed SPSS to detect, localize, and identify the EM Ultra-High Frequency (UHF) impulse signal of Corona or Arc discharges for pre-fault monitoring in an indoor substation. It can be achieved based on the following specific objectives.

- i. To investigate the most suitable  $N$ -element array antenna as the SPSS model, which has broad radiation and adapts to the changes of the propagation phase.
- ii. To develop a novel SPSS utilizing the Single Perceptron-Artificial Neural Network (SP-ANN) Algorithm for ED\_EMP signal detection and localization.
- iii. To evaluate the accuracy of the ED\_EMP signal identification using the novel SP-Identifier Technique in waveform-based testing for Corona or Arc EDs samples.

### 1.4 Chapter Summary

This chapter gives an overview of the effect of ED and its impacts on the monitoring system in power substations, enlisting reviews on recently developed techniques and methods for ED measurement. The study background, problem statement, and objectives are presented. The main contribution of this research is to develop a pre-fault monitoring system utilizing a smart UHF sensor, the SPSS, and a Signal Identifier Technique to enhance the performance for the detection, localization, and identification of the UHF EM Signal, mainly Corona and Arc discharges, thus, improving the pre-fault monitoring system in an indoor substation.

## **CHAPTER 2**

### **LITERATURE REVIEW**

#### **2.1 Overview**

This chapter consists of four main parts. The first part reviews the power substation, relating to the breakdown and monitoring system in general. Here, the fundamentals of Corona and Arcs Electric Discharges (EDs) formation and how they influence the performance of a power substation are also discussed. Part two reviews the ED detection measurement techniques relating to the elementary principles of an array antenna as a sensor. Part three involves the ED signal localization, utilizing a Perceptron-Artificial Neural Network (P-ANN) for the soft-computing techniques. The last part studies the EDs signal recognition, involving the signal identification techniques and how these methods relate to the complexity of the system.

#### **2.2 Power Substation and Monitoring System**

A power substation consists of an electrical apparatus involving electrical and mechanical activities for power generation, transmission, and distribution. There are several types of substations based on the application, such as Transmission and Distribution Substations, High Voltage (HV), Extra High Voltage (EHV) and Ultra High Voltage (UHV) substations, indoor and outdoor substations, and the latest digital substations. However, these substations congregate the common major electrical equipment. This includes electrical power transformers, conductors, insulators, isolators, bus bars, lightning arresters, circuit breakers, and relays, including underground cables. In many cases, the causes and the threats of substation breakdown are mostly discovered in this major electrical equipment. The abnormal activities that occur in the equipment are due to its degradation and generate groups

of EDs from Partial Discharge (PD). About 85% of equipment failures are related to PD (Refaat et al., 2018), and Figure 2.1 displays the summary of the faults relating to material insulation. About 95% of the breakdown was attributed to switchgear bus insulation failure.

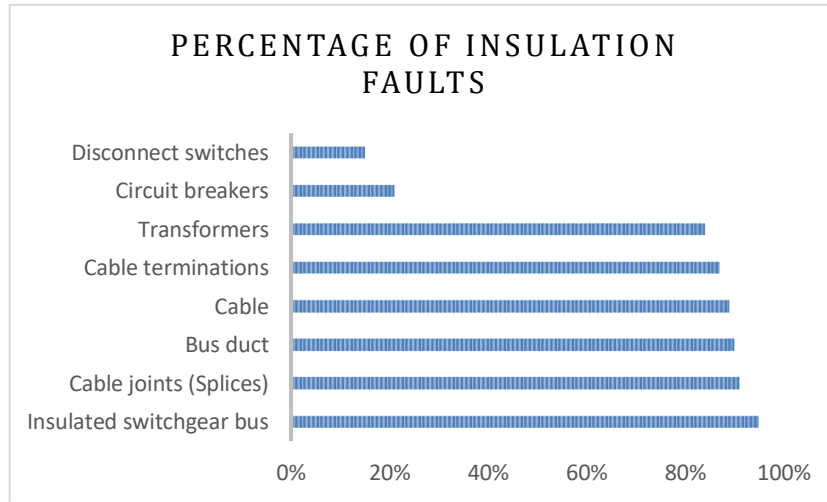


**Figure 2.1:** Percentage of insulation faults (Refaat et al., 2018)

Generally, when the PD occurs in the substation, it indicates the presence of cracks, voids, and insulation degradation within the electrical equipment, which can lead to equipment failure, serious accidents, and electric breakdown in the power substation (Hoole et al., 2013). For example, when an open circuit occurs at the Current Transformer (CT), the inductive circuit can create hazards where the HV condition on the load develops and produces the ED in the form of flashovers and arcing, thus leading to equipment failure. The most common EDs are Corona and Arc discharges. The formation of the Corona and Arc discharge phenomena is described in Section 2.2.2. These types of EDs generate small sparks within the dielectric insulation of the power apparatus. Although they do not cause an immediate breakdown, as time goes on, sparks may degrade the insulation performance with the chemical reaction of the insulator material. Therefore, early warning with pre-fault monitoring is essential for early ED detection.

There are many ED detection techniques accessible, such as the application of sensors from the category of Photodetector and Ultraviolet. These sensors are still preferred in providing a rapid indication of the causes of faults and allowing significant actions to be taken. The common sensors mostly used for fault detection are Acoustic Emission, Radio Interference Voltage (RIV), Measurement, Infrared (IR) Thermography, Electric-Field Measurement, Visual Observation, and Ultraviolet Camera. Most of these sensors are contact-type sensors designed for specific diagnoses or apparatuses that must be attached to the equipment for monitoring purposes. Besides these sensors, other ED detection and localization techniques may use an antenna as a non-contact type of sensor. It focuses on the Electromagnetic (EM) frequency spectrum, specifically the Ultra-High Frequency (UHF) EM signals, depending on the application and its placement. This technique is known as the UHF measurement technique to detect and localize EDs. It is efficient for ED detection that occurs on non-metal shielded apparatus when the EM wave leaks into the space in the substation.

### **2.2.1 Pre-fault Monitoring in Indoor Power Substations**

An indoor power substation is a structure that transforms high-voltage electricity from the power grid into lower voltage levels appropriate for use in residences and commercial buildings. Transformers, circuit breakers, cables, and switchgear are common apparatuses in indoor power substations. They are a vital component of the power grid infrastructure and play a significant role in electrical electricity distribution. Many power interruptions and equipment failures happened due to the insulation system of this power apparatus (Fofana et al., 2016; Islam et al., 2018; Montanari et al., 2019; Murugan et al., 2015). EDs generated from the insulation degradation have a negative effect on the power apparatus, leading to equipment breakdown. To avoid these issues and preserve the

dependability of power systems, EDs should be detected early (Samaitis et al., 2021). Traditional monitoring methods, such as periodic manual monitoring systems, are time-consuming and have low accuracy (Ranvir et al., 2015), and some rural substations require even more time to take action. Therefore, to date, monitoring approaches offer both online and offline monitoring of EDs.

Online monitoring provides real-time detection of EDs (Kong et al., 2020; Luo et al., 2017; Tsyokhla et al., 2019), while offline methods require manual intervention and frequently provide more precise values for equipment evaluation during maintenance or inspection (Arumugam et al., 2018; De Faria et al., 2015; Hussain et al., 2020). When compared to offline approaches, online monitoring systems are mostly used as they can detect EDs instantly as well as provide ongoing monitoring and prompt instant alert of any abnormal activities from the apparatus (Abdullah et al., 2018; Singsathien et al., 2017; Zhang et al., 2016). Pre-fault monitoring is a crucial instrument for contemporary power systems that demand high levels of reliability. It also helps to pre-define any abnormal activities of power apparatus, hence reducing breakdown, enhancing safety, and lowering costs by warning operators of probable equipment faults before they happen (Khan et al., 2019; Qiu et al., 2018; Ullah et al., 2017; Wu et al., 2020). Wireless monitoring sensors offer an alternative for HV equipment in substations and provide good prospective applications in wide-area monitoring (Harid et al., 2016). In this research, the pre-fault monitoring system is defined as the development of an early monitoring system comprising three components: ED detection, ED localization, and ED identification.

### 2.2.2 Corona and Arcs Electric Discharges

In general, when the crack occurs within insulation for an instant, the electrical field in a medium (usually air) reaches the optimum point of the dielectric strength, causing the dielectric breakdown (Subramaniam et al., 2021), the dielectric collapses and the Corona is formed. However, since the medium distributes the charges rapidly, the Corona lasts only about seconds (Zhang et al., 2021). If the Corona persists longer, then this long-lasting Corona will be known as Electric Arc. On the other hand, if the electrical field is insufficient to sustain the Corona, then the Corona phenomenon ends, and the spark develops. Corona and Arc discharges can cause power loss, audible noise, complete system breakdown, transformer fire, rapid aging of HV substation apparatus, interference with navigation and communications, purple glow, and computer interference. Therefore, techniques and methods have been developed, considering the ED as the tool for detecting, localizing, and classifying ED activities to diagnose their severity.

A multitude of successful approaches has appeared in improving the efficiency of the A multitude of successful approaches have appeared to improve the efficiency of the techniques and methods. These approaches involved empirical simulations and comprehensive evaluations to study and interpret the EDs in the UHF EM signals. The EDs occur in many ranges of UHF impulsive signals depending on the source of the degradation. In many works, the measurement of the impulse signal takes place in various environments and frequency bands. HV equipment can generate high-energy impulsive noise; the higher the voltage, the more significant the impulse becomes (Mei et al., 2020; Xiao et al., 2007). Reviews revealed that the ED emits UHF ranging from 300 MHz to 3 GHz (Gohil et al., 2018; Wu et al., 2015; Yaacob et al., 2013). In some cases, the Corona discharge exhibits a higher frequency range compared with Arc discharge and vice versa. The early stage of these

discharges can be detected using an ultrasonic listening device at the ultrasonic frequency range of 20 KHz to 100 KHz (Dewi et al., 2017). Other studies claimed that in the ED Electromagnetic Impulse (ED\_EMP) generated at a closed switchboard, the peak frequency for series Arc discharge is between 100 MHz and 160 MHz. In contrast, Corona discharge is given between 40 MHz and 80 MHz, depending on the defects. Both of these discharges shared a common frequency in the range of 150 KHz to 10 MHz (Kil et al., 2010; Park et al., 2012).

A study involving the HV insulator monitoring using the Radio Frequency (RF) sensing method demonstrated that the transition from Corona discharge to dry-band Arc discharge can be identified. The average detected voltage spectral density was higher for dry-band Arc discharges at 800 MHz – 900 MHz, while Corona discharge exhibited stronger levels in the 1.25 GHz – 1.4 GHz (Fernando et al., 2012). The ED in the 300 MHz – 3 GHz band is preferable for UHF detection or sensing methods due to its lower noise level compared to lower frequency bands (Cai et al., 2014). Every Corona and Arc event depends on the nature of the generation mechanism and where the severity occurred. Research indicates that detecting PD signals in an excessively noisy environment can enhance the detection of PDs in a low-air-pressure environment (Nasr et al., 2021). Based on these findings, an ultimate frequency range for the Corona and Arc discharges is undecidable and does not have appreciable energy at UHF frequencies (Nobrega et al., 2019).

The EDs exhibit different characteristics and are influenced by different faults (Verginadis et al., 2021). Therefore, this research uses a UHF frequency spectrum between 300 MHz to 3 GHz as the sampling frequency range for the ED\_EMP signal to represent the EDs of the Corona and Arcs. A UHF measurement technique employing a UHF sensor is

proposed to smartly detect, localize, and identify the ED\_EMP or any abnormal electrical activities in the event of Corona or Arc phenomena in an open space of an indoor substation. This technique has the potential to compensate for the shortcomings of the conventional method (Azirani et al., 2021). The UHF sensors are designed specifically for each power equipment to face the difficulties in identifying the fault and location of PD (Roslizan et al., 2020). There are issues raised against the application of UHF sensors in PD detection methods regarding accuracy. The UHF sensors are considered imperfect immunity against external noises (Jahangir et al., 2017).

A substation has a noisy environment, generally polluted background noises mainly from the communication system. Therefore, the detected signals may be incorrect for the monitoring information due to these interference signals. However, PD activities emit impulse signals (Au et al., 2015; Kumar et al., 2007; Sacuto et al., 2016; Xiong et al., 2017), while communication signals or white noise events are continuous signals. Therefore, it is possible to distinguish them. Even in the aircraft system, the spectrum of discharges occurring at atmospheric pressure is up to 350 MHz, while the spectrum of the noise-induced switching does not exceed 150 MHz (Abadie et al., 2016). The communication signals are continuous analog signals, while PD signals are the pulses confined in nanoseconds. Since the PD activity is related to the discharge amplitude and location, PD localization can also be achieved. The location information can provide targeted guidance for further maintenance work (Judd et al., 2005). In this research, the Corona and Arc discharge impulse signals are represented as the ED\_EMP. This signal is an impulsive sinusoidal signal with a very short rising time that lasts for nanoseconds and is modeled as a Sinc Function (Seo et al., 2015a). It is a desirable property in a pulse, as it helps avoid intersymbol interference, a major cause of degradation in digital transmission systems (Grami, 2016). Figure 2.2 illustrates the Sinc

Function of an ED\_EMP written as  $E_P$  for simulation purposes, and generally, Equation 2.1 is the Sinc Function (Seo et al., 2015).

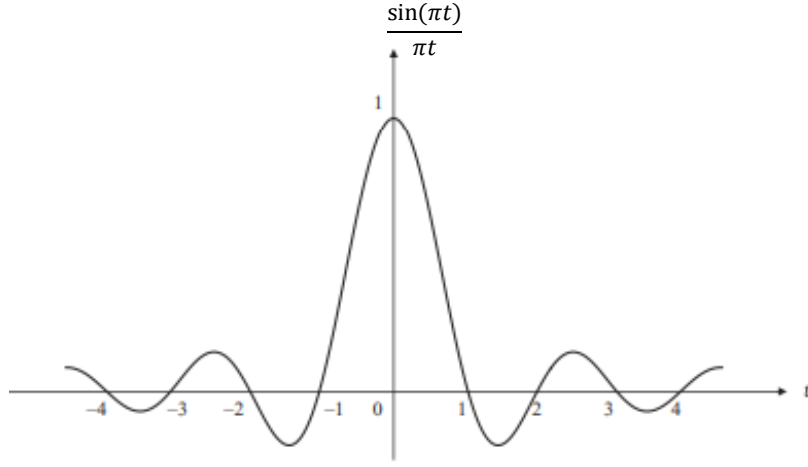


**Figure 2.2:** The Sinc Function

$$f(t) = \frac{\sin(\pi t)}{\pi t} = \text{sinc}(\pi t) \quad \text{Equation 2.1}$$

$$E_P(t) = \frac{\sin(2\pi f t)}{2\pi f t} = \text{sinc}(2\pi f t) \quad \text{Equation 2.2}$$

Equation 2.2 (Seo et al., 2015) is the general equation of the individual event of  $E_P$  represented by a normalized Sinc Function for the parameter  $f$  at various frequencies. This  $E_P$  becomes the desired signal, representing the ED\_EMP that occurred in the indoor substation.

### 2.3 ED Signal Detection Techniques

The initial stage in ED diagnostics is ED detection to ensure accurate and reliable ED signals are obtained before utilizing any procedures for ED signal localization and ED signal recognition. Table 2.1 presents a list of common insulation faults that ED diagnostic can identify for various types of power apparatus. The faults and cavities usually come along with EDs such as Corona, Surface, Void, and Arcs discharge.

**Table 2.1:** Common insulation defect for Power Apparatus

| Author/Year                | Equipment                | Electric Discharge                                  | Type of Defect                                                                            |
|----------------------------|--------------------------|-----------------------------------------------------|-------------------------------------------------------------------------------------------|
| (Chai et al., 2018)        | Transformer              | Corona discharge                                    | - Sphere cavity, Surface cavity and cylinder cavity                                       |
| (Darabad et al., 2012)     | Transformer              | Corona discharge                                    | - Surface cavity and cylinder cavity                                                      |
| (Ganeshan et al., 2017);   | Transformer              | Corona discharge                                    | - Degradation on point metal/pressboard/oil triple point                                  |
| (Zhang et al., 2016)       | Bushing                  | Corona discharge, Surface discharge                 | - Bushing top cap, poor bushing taps joint, oil-side porcelain and grading ring cavities. |
| (Cheng et al., 2021)       | Bushing                  | Corona discharge, Surface discharge                 | - Bushing tap connection                                                                  |
| (Abdullah et al., 2018)    | Cable                    | Corona discharge                                    | - Internal cavity and Surface cavity,                                                     |
| (Singsathien et al., 2017) | Cable                    | Corona discharge                                    | - Cable joint and cable end cavities                                                      |
| (Song et al., 2018)        | Gas Insulated Switchgear | Corona discharge, Void discharge, Surface discharge | - Basin insulator and busbar support insulator cavities,                                  |
| (Rao et al., 2019)         | Gas Insulated Switchgear | Corona discharge, Void discharge, Surface discharge | - Defective Epoxy insulators, and Floating particles                                      |
| (Broderick et al., 2018)   | Bus Duct                 | Arcs discharge                                      | - Bus Duct insulation.                                                                    |

ED detection can be classified into conventional and unconventional methods. The conventional method uses the standard of IEC60270 for measurement of apparent charge displacement,  $q$  expressed in pico-Coulombs (pC). This measurement technique gives good sensitivity to defects. However, it is unsuitable for online PD monitoring as it requires a shielded environment (Desai et al., 2018). Conventional measurement techniques are costly since they utilize high power consumption or require offline settings or installation (Upton et al., 2018). Therefore, the unconventional method takes place for measurement involving high frequency, such as UHF sensors (El-Faraskoury et al., 2012; Götz et al., 2020). In recent years, for the detection of EM pulse, many ED detection techniques have focused on unconventional methods, specifically the UHF sensors. Table 2.2 presents a list of ED detection techniques that have emerged in recent years. Among the techniques are Artificial

Neural Network (ANN), Machine Learning (ML) and Deep Learning (DL), UHF Detection, Optical Sensing Techniques, Wireless Sensor Networks (WSN), and other non-contact sensors.

**Table 2.2:** List of ED detection techniques emerged in recent years

| Author/Year                | Equipment/<br>Targeted<br>Area                 | Detection<br>methods<br>/techniques                     | System                                                                                                           | Measurement<br>Type                                                           |
|----------------------------|------------------------------------------------|---------------------------------------------------------|------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| (Samaitis et al., 2021)    | Connectors for bushing insulator.              | L-shape array antenna                                   | - Antenna for Detection, ML for Localization and DL for Classification                                           | Artificial Neural network (ANN), Machine Learning (ML) and Deep Learning (DL) |
| (Peng et al., 2019)        | HV cables                                      | Not available                                           | - Convolution Neural Network-DL for pattern recognition                                                          |                                                                               |
| (De Oliveira et al., 2017) | Stator bars                                    | Not available                                           | - Artificial Neural Network (ANN)-ML and DL for classification                                                   |                                                                               |
| (Zhu et al., 2016)         | Air Insulated Substation (AIS)                 | UHF array antenna                                       | - Long Shot-Term Memory Network (LSTM)-CNN-DL for classification                                                 |                                                                               |
| (Meitei et al., 2021)      | Transformer                                    | Optical Fiber Bragg Grating (FBG) Sensor                | - easily placed inside the tank, small size, and free from EM Interference                                       | Optical Sensing Techniques                                                    |
| (Ma et al., 2019)          | Gas Insulated Switchgear                       | Fiber Optic Sensor                                      | - Acoustic Emission PD detection method to detect small defect.                                                  |                                                                               |
| (Ma et al., 2018)          | Transformer                                    | Phase-shifted fiber Bragg gratings                      | - PS-FBG for PD detection and time division multiplexing for localization                                        |                                                                               |
| (Wu et al., 2021)          | Gas Insulated Switchgear (GIS) and Transformer | Fluorescent Optical Fiber Sensor                        | - PD detection is based on the amplitude of the impulse voltage applied to the conductor of GIS and Transformer. |                                                                               |
| (Zhu et al., 2016)         | Air Insulated Substation (AIS)                 | Antenna array double-cone structure                     | - use probability-based localization algorithm to estimate PD position                                           | Ultra-High Frequency (UHF) Detection                                          |
| (Chai et al., 2018)        | Transformer                                    | Microstrip-fed planar elliptical monopole array antenna | - UWB frequency response offers a more effective for PD recognition                                              |                                                                               |
| (Sarkar et al., 2014)      | Transformer                                    | Microstrip patch array antenna                          | - Non-contact PD detection, cost effective online monitoring                                                     |                                                                               |

**Table 2.2** continued

|                       |                                    |                                       |                                                                                                                  |                                |
|-----------------------|------------------------------------|---------------------------------------|------------------------------------------------------------------------------------------------------------------|--------------------------------|
| (Zhang et al., 2018)  | Switchgear                         | Transient earth Voltage (TEV) WSN     | - reduce the fault rate, improve operation and maintenance level                                                 | Wireless Sensor Networks (WSN) |
| (Upton et al., 2018)  | Indoor substation                  | Radiometric WSN system                | - WSN uses received signal strength of the EM wave from a PD source                                              |                                |
| (Zhuang et al., 2019) | Switchgear cabinet and power cable | WSN based on IoT                      | - insulation condition monitoring for the distribution grid.                                                     |                                |
| (Sack et al., 2010)   | HV Conductor                       | Non-contact directional sensor (NCDS) | - for the determination of travelling wave direction along conductors                                            | Other non-contact sensor       |
| (Ivanov et al., 2021) | Switchgear                         | Electromagnetic and acoustic sensors  | - diagnostics of the state of HV insulators under operating voltage                                              |                                |
| (Shen et al., 2020)   | HV equipment                       | Solar-blind UV sensor                 | - PD detection system, based on the UV Pulse Method, which is of high precision and can reflect early discharge. |                                |

Modern techniques utilize ANN, ML, or DL as an approach to smart detection, hence making the monitoring system more efficient. As observed from the table, array antennas are among the selected antenna types depending on the types of detection and application. Some array antennas are designed for specific criteria such as frequency, bandwidth, physical size, and directivity. With antenna arrays, an omnidirectional or directive antenna, for instance, can also be assembled from individual elements of several elements arranged in a specific geometric configuration (Mikki et al., 2018; Noordin et al., 2011).

### 2.3.1 Array antenna for UWB wireless sensor

Various localization systems based on Ultra-Wideband (UWB), WSN, and ultrasound, to name a few, have been developed in regard to many established location-aware wireless applications, such as mobile and coordinated communication systems (Zhuoling et al., 2015). In this research, a small Linear Array Antenna is used to develop the

UWB wireless sensor as a model for Single Perceptron Smart Sensor (SPSS) implementation in an indoor environment. UWB signals are a desirable option for indoor localization since their application provides reliable performance in heavy multipath environments (Monica et al., 2019; Monica et al., 2014; Ridolfi et al., 2018). A small-size Linear Array Antenna is selected since using a small number of array elements reduces the costs and complexity of the system (Karmakar, 2021; Siakavara, 2010). The UWB array antennas are preferred due to their wide coverage and less complexity (Lakrit et al., 2021), and it has an excellent transient response in the UHF working band (Zhang et al., 2014). The signal captured from a broader detection range provides more information. Thus, higher accuracy of ED detection can be achieved when applied in conjunction with the frequency spectrum analysis (Yang et al., 2021). Furthermore, an array antenna lined with a single axis can scan through 360° azimuth, reducing the number of antennas required for a multicell system (Ndifon et al., 2018).

According to (Roslizan et al., 2020), a small antenna is proven to have the highest sensitivity for PD activities compared to bigger antennas. The smaller size array antenna is subjected to the selection of the number of an array element ( $N$ ) to avoid complexity during the signal processing (Bodhe et al., 2014; Uthansakul et al., 2004). The smallest array antenna is the single-element antenna. It has a relatively wide Radiation Pattern (RP), which fulfills the requirement of this research work. However, a single-element antenna has a low directivity or gain and is unsuitable for long-distance communication. Therefore, an antenna with high directivity is the most preferable and often required for far-field detection. Such antennas can be constructed by modifying the dimension of the radiating aperture to the maximum size, which is greater than the wavelength,  $\lambda$ . Still, such an approach may lead to multiple side lobes of the RPs. Thus, fabrication of the antenna may be difficult due to the

size of the antenna. Therefore, to overcome these problems, the array antenna is preferable. An array antenna is a configuration of multiple identical antenna elements arranged and interconnected in space to obtain a directional RP. Arrays are built using small elementary antennas to achieve the same performance as a single large antenna, and they can be designed and constructed in many geometric configurations. The most elementary configuration form is a Linear Array Antenna with some antennas aligned in a straight line. An  $N$ -element Linear Array Antenna with uniform amplitude and element spacing distance,  $d$ , is considered and oriented along the  $x$ -axis, as illustrated in Figure 2.3. The current,  $I$  that flows at each element ( $n = 0, 1, 2, 3 \dots, N-1$ ) is assumed to have the same magnitude and current phase angles of  $n\delta$  ( $0, \delta, 2\delta, 3\delta \dots, (N-1)\delta$ ).

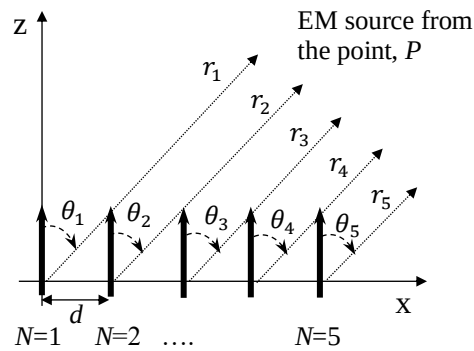


**Figure 2.3:** The  $N$ -element Linear Array Antenna (Hoole, 2001)

The fundamental study is necessary to understand the elementary concept of the array antenna and the effect of the array length ( $N$ -element) when incorporated with an ANN algorithm. Maxwell's Equations are used to describe the propagation of EM fields by investigating how the EM components, electric field intensity ( $E$ ) and magnetic field intensity ( $H$ ), interact and propagate to objects and are visualized in the antenna RPs (Hoole, 2001).

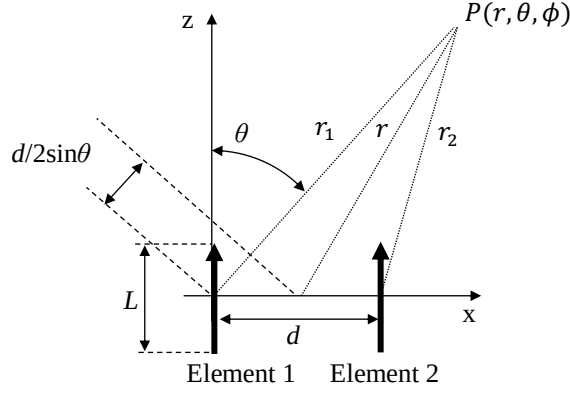


**Figure 2.4:** The 2-element Array Antennas (Hoole, 2001)

Two infinitesimal antennas are considered and used to form the 2-element array antenna, as displayed in Figure 2.4. Note that the  $I$  flow through each element and has a phase angle,  $\delta$ . The phase shift is obtained from the same source at a point,  $P$ , for both elements so that the same magnitude of  $I$  flows through both antennas. By assuming  $r_1, r_2 \gg d$ ,  $\theta_1 \approx \theta_2 \approx \theta$  and considering the large distances,  $r_1 = r_2 = r$  source signals from the far-field zone at  $P$  are observed where  $\phi = 0$ . Therefore, the resultant fields (Hoole, 2001) at  $P$  are given as follows.

$$E_\theta = u_\theta j\eta \frac{kIL}{4\pi} \left[ \frac{e^{-j(kr_1 + \delta/2)} \sin \theta_1}{r_1} + \frac{e^{-j(kr_2 - \delta/2)} \sin \theta_2}{r_2} \right] \quad \text{Equation 2.3}$$

where  $L$  is the length of this infinitesimal conductor,  $\eta$  is wave impedance in free space ( $\eta = 120\pi \Omega$ ), and the permeability of free space,  $\mu = 4\pi \times 10^{-7} \text{H/m}$ . There is not much difference in the amplitude of resultant fields due to the large  $r$ . However, large changes in the phase of the resultant fields may occur due to the small difference between the distance,  $r$  (expressed in the exponential form), and the high-frequency signal. The phase of the

electric fields radiated by these two elements may significantly affect the magnitude of the resultant fields. The resultant field (Hoole, 2001) is given as follows.

$$E_{\theta} = u_{\theta} j \eta \frac{k I L e^{-j k r} \sin \theta}{4 \pi r} \left[ 2 \cos \left( \frac{k d \sin \theta + \delta}{2} \right) \right] \quad \text{Equation 2.4}$$

where the Array Factor (AF) of this 2-element array antenna (Hoole, 2001) is given as,

$$\text{AF} = 2 \cos \left( \frac{k d \sin \theta + \delta}{2} \right) \quad \text{Equation 2.5}$$

The AF is dependent on the distance between  $d$  and  $\delta$ . The transmitted power radiated by an antenna is given by Poynting Vector,  $P = E \times H$ . The power flow is perpendicular to the  $E$  and  $H$  planes; hence, the Power Intensity Radiated ( $P_i$ ) for far-field (Hoole, 2001) is derived as:

$$P_i = \frac{1}{2\eta} |E_{\theta}^2| \text{ W/m}^2 \quad \text{Equation 2.6}$$

In most analyses, signals are assumed to be sinusoidal signals in the term of time-domain, and therefore, in the phasor domain analysis, it is represented by the time domain,  $e^{j\omega t}$ . The complete phasor domain equation is normally written as  $E_0 e^{-jkR} e^{j\omega t}$  for imaginary terms and  $E_0 \cos(\omega t - kR)$  for a real term, where  $R$  is the radial distance,  $k$  is the wave number, ( $k = \omega/c = \omega/\sqrt{\mu_0 \epsilon_0}$ ) where  $\omega$  is the radian signal frequency,  $\mu_0$  is the permeability of free space ( $\mu_0 = 4\pi \times 10^{-7} \text{ H/m}$ ),  $\epsilon_0$  is the permittivity of free space ( $\epsilon_0 = 8.854 \times 10^{-12} \text{ F/m}$ ),  $c$  is the velocity of light ( $c = 2.998 \times 10^8 \text{ m/s}$ ) and  $\eta$  is wave impedance in free space ( $\eta = 120\pi \Omega$ ). Therefore, these parameters are needed for most of the ED signal analysis in Chapter 3.

## 2.4 ED Signal Localization Techniques

Finding the weak insulation region requires precise ED source localization. Due to this, the accurate and speedy localization technique has become the focus of ED diagnosis for power apparatus. Conducting a diagnostic test with proper ED source localization and identifying the ED source type in the power system is vital for preventing breakdown, resulting in the risk of safety and stability of the power system. Proper ED localization will enable the planning of maintenance procedures for power equipment (Benzing et al., 2012; Cai et al., 2020; Gao et al., 2018; Kong et al., 2020; Zhu et al., 2016). There are many significant methods for ED localization. However, the application and implementation depend on the nature of faults. Therefore, when it comes to accuracy, different measurement methods have advantages in various applications for power equipment. Different types of ED provide an early diagnosis of the severity of a damaged spot where ED is happening. Wireless RF signal-based indoor localization methods mainly include conventional methods such as Fingerprint- Received Signal Strength Index (RSSI), Time of Arrival (TOA), Time Difference of Arrival (TDOA), and Direction of Angle (DOA).

RSSI requires a fingerprint map by a site survey before the PD localization (Chen et al., 2018; Han et al., 2020; Shu et al., 2016), thus, putting the substation at risk of service (Robles et al., 2018). TDOA is generally used for the spatial position of the PD source. However, this method requires at least four sensors to establish the non-linear location equations, and solving the equations will determine the ED source location (Ning et al., 2021; Zeng et al., 2015). TOA method determines the distance between the target and the sensor by measuring the time required for the signal to travel (Li et al., 2016; Wang et al., 2014; Zou et al., 2020). The implementation complexity and cost of DOA are lower than that of a fingerprint as it could eliminate the time-consuming task of developing and updating

the fingerprint database (Xin et al., 2020). In recent years, many smart localization techniques have been developed and categorized as unconventional localization techniques. It utilizes ML such as Fuzzy Logic (FL), Support Vector Machine (SVM), Ensemble Model-Decision Tree (DT) and Random Forest (RF), and Neural Network (NN)-DL technique, which is also a subset of ML techniques and many others. Employing ML and DL incorporating conventional localization techniques into the condition monitoring system has demonstrated encouraging results in comparison to conventional techniques alone. TOA and TDOA are frequently mentioned as alternatives when comparing DOA localization techniques to other localization systems. Hence, DOA, TOA, and TDOA techniques are compared here. When exact time synchronization is given, TOA can provide high accuracy in source localization (Jia et al., 2019; Mekonnen et al., 2015; Sun et al., 2013). It works well when specific distance measurements are vital, such as determining ED sources within a power grid system. TDOA is a multiple sensors system and works well for localization or monitoring applications when numerous sensors are widely scattered in a wide-area space (Cao et al., 2020; Dalveren et al., 2017; Qin et al., 2016). However, increasing the sensors may not consistently yield a better algorithm behavior in terms of minimizing the mean square error (Sanchez et al., 2018). In some cases, the combination of TDOA, TOA, and DOA approach, known as a hybrid approach, is used to leverage the strengths of each method. This approach improves the accuracy in complex ED localization situations. Regardless, a complete modern monitoring system should include detection techniques, smart signal localization, and identification techniques. It allows faster decisions about the best possible course of action, such as load shedding, power system islanding conditions, and generator switching (Jiang et al., 2014). In this research, the DOA is selected for the localization of ED sources due to its low complexity and cost efficiency. The Linear Array

Antenna is integrated with a single perceptron NN to produce a smart localization system based on DOA. The direction measured by a Linear Array Antenna is regarded as the location of the ED source. Fast rise times of ED pulses result in a wide Electromagnetic (EM) spectrum (Cadilhon et al., 2010; Ghosh et al., 2020; Wang et al., 2020); thus, this research focuses on DOA of wideband signals. Understanding the DOA of ED sources can also help to optimize the placement of sensors for ED monitoring (Saravanakumar et al., 2018). This suggests that the sensor is positioned to provide broad coverage for the equipment and detect ED occurrences from various angles. Therefore, the recommendation for the sensor placement is studied in Chapter 3.

**Table 2.3:** Comparison of ED localization method using the DOA method

| Author/Year            | Methods/Techniques of Localization | Sensor type                       | Error of localization | ED Source          |
|------------------------|------------------------------------|-----------------------------------|-----------------------|--------------------|
| (Wu et al., 2020)      | DOA method                         | Monopole array sensor             | 3.5°                  | 1.1 GHz            |
| (Zhou et al., 2018)    | DOA Method                         | 4 x 4 UHF array sensor            | 4°                    | 300M-1.5GHz        |
| (Yongfen et al., 2015) | DOA Method                         | 16 x16 UHF array sensor           | 2°                    | 50 KHz and 150 KHz |
| (Han et al., 2020)     | DOA Method                         | UHF array sensor                  | <6°                   | 300 MHz-1.5GHz     |
| (Xu et al., 2022)      | DOA Method                         | Spiral antenna circular array     | 3.39°                 | 1.5 GHz and 2 GHz  |
| (Liu et al., 2017)     | DOA Method                         | 4-elements uniform circular array | <5°                   | 300 MHz - 1.5GHz   |

DOA method is preferable in this research as it is a simpler system and does not require highly accurate time synchronization among sensors. Furthermore, DOA can be used for single-sensor source localization or resource-constrained applications (Razzaque et al., 2013), which meet the requirements of this research work. Table 2.3 provides the comparison of ED localization for a multirange of ED sources. The comparison focused on the numerical difference of localization error measured in degree. All of the based-method

ED localization is reviewed for UHF frequency, ranging between 300 MHz – 1.5 GHz to an ultrasonic frequency range of 50 KHz- 50KHz, and relatively, the ED localization error falls between 2° to 6°. Since ED signals are random in nature, they may exhibit various amplitudes, shapes, and other features. Therefore, the ultimate decision regarding ED localization depends on the specific characteristics of the power apparatus being monitored. Selecting the right approach ensures the accuracy of ED diagnosis.

#### **2.4.1 Perceptron – Artificial Neural Network (P-ANN)**

A Smart Antenna (SA) is an antenna that can perform an adaptive beamform to dynamically scan and adjust its RP to optimize some characteristics of the signal received. During the scanning process, the main beamform is electronically steered for different values of beam steering angle or direction that can be varied in small discrete steps. Then, the beamform is optimized to achieve maximum reception in the desired direction. In contrast, signals from other directions are rejected, hence overcoming the drawback of a conventional antenna that cannot reject interference. This sensing technique provides reliable information in the communication system as it can cut off any unwanted signals while maximizing the beamform towards the desired user. The vital part of this technique is the signal processing unit. The capability of a smart signal processing technique, when combined with an antenna, makes it a significant smart sensing system for an antenna. Although the technology is not new, researchers still discover and enhance new techniques and methods to improve the efficiency of the sensing system. In recent years, researchers have adopted Artificial Intelligence (AI) in developing methods and techniques for a smart UHF sensor. Soft computing techniques such as ANN are employed in adaptation to the digital era to improve efficiency and safety, especially in power substations. ANN takes place in many applications as it has fast convergence features, low memory, and adaptation to complex changes

(Senthilkumar et al., 2018). ANN adopts the analogy of biological neuron networks. It is a computer model of the human brain with a fast response to computational tasks such as identification, estimation, optimization, and many more data processing tasks. The data processing involves the ANN training set to achieve the desired outcomes. Figure 2.5 illustrates the basic structure of a Single Perceptron (SP) (or neuron) of the ANN. It consists of numerical input data ( $X_1, X_2, \dots, X_n$ ), a weight ( $W_1, W_2, \dots, W_n$ ) and a bias ( $b$ ), a weighted sum, an activation function, and a numerical output data ( $Y$ ).

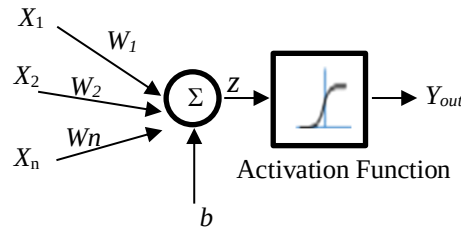


**Figure 2.5:** The basic structure of a Single Perceptron ANN (Senthilkumar et al., 2018)

For this model of ANN, Equation 2.7 is the net input function ( $z$ ) or can be generalized as in Equation 2.8. Meanwhile, Equation 2.9 is the final output,  $Y_{out}$ , obtained by multiplying the net input function with an activation function ( $F$ ).

$$z = b + (X_1W_1 + X_2W_2 + \dots + X_nW_n) \quad \text{Equation 2.7}$$

$$z = b + \sum_{k=1}^n W_k X_k \quad \text{Equation 2.8}$$

$$Y_{out} = zF \quad \text{Equation 2.9}$$

The weights are the coefficients initialized at the origination of each training. For each training set, the error estimation is computed between the desired and actual outputs.

Then, the error is used to adjust the weight. The training is repeated until the error on the entire training set is less than the specified limit or continues until reaching the maximum number of iterations. This whole training set is referred to as the perceptron algorithm, where the learning algorithm automatically updates the weight coefficients to the optimum value. Different NN applications may apply different types of activation functions. In this research, the smart sensor is computed with a non-linear sigmoid activation function to reduce the complexity and minimize time delay processing in achieving the desired output. The hyperparameters, the learning rate or step size, and the bias control the effect of the weights updating and the convergence rate of a perceptron. Therefore, selecting the initial values for these hyperparameters is crucial. The algorithm results may fluctuate dramatically under the different configurations of hyperparameters (Zhang et al., 2019). Another characteristic of a perceptron that can be highlighted in this research is signal amplification. Perceptron amplifies the signal naturally due to the weight factor multiplied to each input of the perceptron, thus giving the advantage to a system where an extra unit of the signal amplifier is unnecessary to accomplish signal processing. In ANN, the input signals are processed mathematically by multiplying each input signal by a weight,  $W$ , and a bias,  $b$ . At that point, sum up the input signals and place them at the output as a transfer function that will yield the final output signals. On account of the human brain, the final output signals might activate signs in the muscles, for example, to move the human body for activity. For the SAs, the final output signals might divert the beamform toward the desired users. This research introduces a new adaptive beamforming algorithm by implementing a Single Perceptron Artificial Neural Network (SP-ANN) to electronically smart beamform a Linear Array Antenna. An SP-ANN for linear array beamforming is a fast and accurate method, requiring little computational power or time compared to the more commonly used multilayer

perceptron (MLP) for beam forming (Senthilkumar et al., 2016). This algorithm successfully optimized the weights of the perceptron better than the Least Mean Square (LMS) method (Senthilkumar et al., 2016, 2018). The SP-ANN technique operates based on the DOA to detect and localize the ED EM in the microwave frequency spectrum for Corona and Arc discharges in an indoor substation. For this, a single perceptron is utilized to perform the beam steering smartly for the ED signal localization technique. Many research works have employed ANN-based systems to recognize PD signals, such as Multilayer Perceptron (MLP), as summarized in Table 2.4. However, few use the ANN-based system to perform beam steering in signal localization techniques.

**Table 2.4:** ANN for PD signal recognition

| Author/Year             | Technique                  | Application    | Accuracy | Equipment         |
|-------------------------|----------------------------|----------------|----------|-------------------|
| (Palhares et al., 2018) | 5-layer neurons for MLP    | PD recognition | 73.67%   | Power Transformer |
| (Guzmán et al., 2017)   | 3-layer neurons for MLP    | PD recognition | 90%      | Power Transformer |
| (Khan et al., 2019)     | 5-layer neurons for CNN    | PD recognition | 97.38%   | HV Cables         |
| (Mas'ud et al., 2014)   | 6-layer neurons for ENN    | PD recognition | 98%      | Power Transformer |
| (Chen, 2013)            | 18-layer neurons for MNN   | PD recognition | 98.6%    | Power Transformer |
| (Florkowski, 2020)      | Multilayer neurons for CNN | PD recognition | 99%      | HV Insulation     |
| (Yeo et al., 2020)      | Multilayer neurons for CNN | PD recognition | 98%      | HV Cables         |
| (Khan et al., 2017)     | 170-layer neurons for MLP  | PD recognition | 90%      | HV Cables         |

Based on the findings in Table 2.4, over the period of 10 years, most of the ANN-based techniques are used for PD recognition. The multilayer neuron techniques for CNN and MLP have exhibited significant accuracy of more than 90%. However, there is no research work that uses single-perceptron for PD signal identification. Therefore, in this research, a single-perceptron is proposed for EM signal identification, aiming for a similar

accuracy performance. In this research, the SPSS antenna model is an amplitude-weighting antenna used as a transceiver. A transceiver is usually a unit that has a small mixer-amplifier unit where a weight factor is introduced as a multiplier to each antenna element. Each antenna array element is assigned a specific weight or amplitude before being combined to form an overall antenna RP. In a Linear Array Antenna, for instance, each antenna element contributes to forming the overall RP, and by adjusting the amplitude (or weight) of the signal from each element, the shape of the RP in a controlled manner. This is called a beamforming process, a method of combining all the antenna arrays to form a single array, transmitting towards any particular direction of interest instead of transmitting in all directions. In this research, the antenna sensor is performed as a transceiver. Therefore, in a transceiver unit, each array element usually has its own small amplifier unit (Jin, 2017; Taravati et al., 2020). The weight factor of the array element is introduced as a multiplier factor that amplifies the RP of the antenna sensor. This is to be verified in the analysis in Chapter 3. The model of the SP-ANN array antenna is modeled by combining the linearly arrayed antenna with the SP-ANN, constructing the SP-ANN algorithm to smartly optimize the weight of each antenna element, hence producing an amplitude-weighting SA. This novel work has developed a cohesive unit that is able to direct the beamform radiation toward the desired ED source and concurrently amplify the signal received by the antenna.

## **2.5 EDs Signal Identification**

Despite detection and localization, ED signal identification is also essential for condition monitoring in a power substation. The effective identification of the ED helps to understand the characteristics of the internal insulation defects accurately and has important engineering significance for mastering the insulation condition of equipment (X. Zhou et al., 2019). Many researchers have successfully developed ED pattern recognition and

classification techniques. The recognition techniques involve many high-performance algorithms such as Fuzzy C-means Clustering (FCM), Convolutional Neural Networks (CNN), and SVMs (Che et al., 2019; Sun et al., 2021; Wei et al., 2018). These algorithms have been remarkably established for their ED pattern recognition and classification efficiency. Other than that, Phase Resolved Partial Discharge (PRPD) is also among the famous techniques used for data cleaning and feature extraction during signal classification. However, the PRPD technique is only suitable for a specific degradation process and when the electrical noise level is low compared to the magnitudes of the ED signals (Ardila-Rey et al., 2018). Most of these techniques comprise the UHF ED signals, analyzed in the frequency domain, requiring a larger data of ED samples for classification. Some may apply an intricate MLP training algorithm, thus giving a higher ANN complexity to ensure a complete monitoring process. Increasing the complexity may increase the training time for signal processing (Karimi et al., 2020; Tang et al., 2020). These techniques are only significant when the EDs have already occurred from the power equipment.

The signals detected and processed were the known sample data. They can only identify the discharge types existing in the known sample library, and when a new type of discharge sample appears, it will result in some errors in recognizing the ED type (Gao et al., 2018). This technique is referred to as automatic recognition (Araújo et al., 2021; Kordi et al., 2018; Mantach et al., 2021; Mor et al., 2020; Yao et al., 2021). However, automatic identification tools are still unrealistic for devising effective maintenance strategies for power transformers (Ganeshan et al., 2017). When the EDs have been generated from a source, the UHF signal is easy to detect regardless of whether the contact or non-contact sensor is used. So far, little effort has been made to detect, localize, and identify the early stage of ED formation, which has become the concern of this research work. Therefore, this

research proposes a new algorithm for UHF signal identification that involves a waveform-based model ED\_EMP signal to represent Corona and Arc discharges. The advantages of the proposed signal identification technique bring the analysis work in the waveform-based. It allows identification to use a single source of ED signal, which diminishes the collection of ED extensive data samples. Most important is that the features of the signal, such as the magnitude and the peak time of occurrence, are relative to the source of the ED (Shafiq et al., 2013) and efficient for analyzing defect types (Janani et al., 2020; Zhang et al., 2014). It also requires no data-cleaning process as this technique does not need signal classification. The detected signal will be processed and analyzed using MATLAB tools.

**Table 2.5:** Comparison of Performance for ED Detection, Localization and Recognition Methods and Techniques

| Authors / Year        | Method/Technique                                    | Signal Measurement Technique                               | Performance / Accuracy | Comment                                                                                            |
|-----------------------|-----------------------------------------------------|------------------------------------------------------------|------------------------|----------------------------------------------------------------------------------------------------|
| (Wan et al., 2018)    | One-Dimension CNN (1-D CNN) Method using UHF sensor | Oscilloscope for images processing                         | 88.9% of recognition   | - Requires 24000 sets of iteration with 1800 pre-defined samples.                                  |
| (Ndifon et al., 2018) | 2x2 phase array Antenna Array                       | Radio Frequency Identification (RFID) system               | 100% of detection      | - A fixed cell with at least 4 units of phase array antenna<br>- 200 iterations simulation process |
| (Chai et al., 2018)   | Microstrip-Fed Planar Elliptical Monopole Antenna   | Voltage Standing Wave Ratio (VSWR)                         | 67% of detection       | - Specific sensor for transformer                                                                  |
| (Wang et al., 2019)   | MobileNets convolutional neural network (MCNN)      | Deep Convolutional Neural Network (DCNN)                   | 96.5% of recognition   | - Specific for Gas-Insulated Switchgear (GIS)<br>- Require 5000 dataset                            |
| (Dhara et al., 2020)  | UHF Sensor                                          | Nearest-Neighbour and Probabilistic Grid-Search algorithms | 97.88% of localization | - Require 4 UHF sensors at a time<br>- 392 test samples                                            |

**Table 2.5** continued

|                      |                                                                                                                        |                                                                                             |                       |                                                                                                                                                                         |
|----------------------|------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|-----------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| (Duan et al., 2019)  | Deep Learning (DL) Method using IEC-60270 sensor                                                                       | Principle Component Analysis (PCA) and t-distributed stochastic neighbour embedding (T-SNE) | 99.7% of recognition  | <ul style="list-style-type: none"> <li>- Specific for Transformer</li> <li>- Require 7268 samples sets</li> </ul>                                                       |
| (Che et al., 2019)   | Fiber-optic distributed acoustic sensing (FDAS) with phase-sensitive optical time-domain reflectometry ( $\phi$ -OTDR) | Mel-frequency Cepstrum Coefficients (MFCC) & CNN Method                                     | 96.3% of recognition  | <ul style="list-style-type: none"> <li>- Specific acoustic sensors</li> <li>- Requires 1280 training samples and 832 test samples for recognition</li> </ul>            |
| (Tang et al., 2021)  | PRPD Spectrum data samples                                                                                             | Random Forest (RF) Algorithm                                                                | 97% of recognition    | <ul style="list-style-type: none"> <li>- Specific for Switchgears</li> </ul>                                                                                            |
| (Jiang et al., 2021) | 4 units of UHF Sensors to detect the PD signal in the 110 kV Brushings                                                 | Signal Vector Machine (SVM) algorithm for signal recognition                                | 96% of recognition    | <ul style="list-style-type: none"> <li>- Specific for Brushings</li> <li>- Use multiple sensors at a time</li> <li>- Requires big data samplings (6400 sets)</li> </ul> |
| (Azam et al., 2022)  | Wideband Antenna UHF Sensor                                                                                            | Voltage Standing Wave Ratio (VSWR)                                                          | 99.5% of detection    | <ul style="list-style-type: none"> <li>- Specific for smart grid system</li> <li>- Requires 2 antennas to perform detection &amp; recognition.</li> </ul>               |
| (Jing et al., 2022)  | UHF sensor                                                                                                             | Auxiliary Classifier Generative Adversarial Network                                         | 95.75% of recognition | <ul style="list-style-type: none"> <li>- Specific for Switchgears (GIS)</li> <li>- Require 300 dataset samples for significant recognition.</li> </ul>                  |

In most cases of signal detection, localization, and recognition, every method and technique have a different requirement for significant performance, as illustrated Table 2.5. To date, ED detection, localization, and recognition are specifically designed for specific equipment. Some of the methods and techniques still require numerous sensor applications for signal detection, intricate algorithms, and extensive dataset samples for significant signal recognition. Thus, it increases the complexity of signal processing and data usage.

## 2.6 Chapter Summary

This chapter is divided into four parts; part one reviews the power substation, relating to the breakdown and monitoring system in general. Here, pre-fault monitoring is discussed, and the existing techniques and methods related to condition monitoring in a substation are reviewed. Pre-fault monitoring is a crucial instrument for contemporary power systems that demand high levels of reliability, and it helps to pre-define any abnormal activities of power apparatus, hence preventing breakdown, improving safety, and minimizing costs before they happen. In this part, one also reviews the fundamentals of Corona or Arcs EDs formation and how it influences the performance of a power substation. Every Corona or Arc event depends on the nature of the generation mechanism and where the severity occurred. In this research, the UHF frequency spectrum between 300 MHz and 3 GHz is taken as the sampling frequency range for the ED\_EMP signal to represent the EDs of the Corona and Arcs.

Part two reviews ED signal detection and the technique used for ED signal detection. The initial stage in ED diagnostics is ED detection to ensure accurate and reliable ED signals are obtained before utilizing any procedures for ED signal localization and ED signal recognition. Common insulation faults are listed in Table 2.1 for various types of power apparatus. ED detection techniques are classified into conventional and unconventional techniques. Conventional techniques are very specific in application as they are subjected to specific environmental conditions and the severity of the faults. In some cases, it can be costly as it utilizes high power consumption and requires an offline setting for installation. Table 2.2 presents a list of ED detection techniques that have emerged in recent years. It highlighted the type of detection measurement techniques where array antennas are mostly applied in the reviewed methods. Here, it also reviews the elementary principles of an array antenna as a sensor. Reviews concluded that the UWB wireless sensor is preferable for

indoor localization as it has wide coverage and the ability to operate reliably in high multipath environments. Reviews have agreed that a small number of linear array elements reduces the costs and the complexity of the system and provides a broader detection range containing more information; thus, higher accuracy of the EDs detection can be achieved. Fundamental elementary principles are reviews, focusing on the parameters and antenna radiation properties to be applied in Chapter 3.

Part three reviews the ED signal localization. The focus of ED diagnosis for power apparatus is on the accuracy and speedy localization method. It is essential to conduct a diagnostic test with accurate ED source localization and to determine the type of ED source to prevent power system breakdown. Effective ED localization will enable the planning of maintenance processes for power apparatus. Several localization techniques were reviewed; the application and implementation depend on the nature of the faults. Different measurement methods have advantages in various applications for power equipment. In this research, the DOA is selected for the localization of ED sources due to low complexity and cost efficiency. In this part two, the smart sensor is also reviewed as it can perform an adaptive beamform to dynamically scan and adjust its RP to optimize some characteristics of the signal received. This sensing technique provides reliable information in the communication system as it can cut off any unwanted signals while maximizing the beamform towards the desired user. AI is adopted in developing methods and techniques for a smart sensor. ANN is widely used in many applications as it has fast convergence characteristics, low memory requirements, and the ability to adapt to complex changes. This part has enclosed the perceptron theory to aid the formation of SPSS in Chapter 3. The SPSS antenna model is an amplitude-weighting antenna used as a transceiver. This is the novel work of this research. The SPSS is modeled by combining the linearly arrayed antenna with

the SP-ANN, constructing a new SP-ANN algorithm to smartly optimize the weight of each antenna element, hence producing an amplitude-weighting SA. This novel work has developed a cohesive unit that is able to direct the beamform radiation toward the desired ED source and concurrently amplify the signal received by the antenna.

The last part of this chapter studies the ED signal recognition. For condition monitoring in a power substation, ED signal identification is just as important as detection and localization. Accurately identifying the ED is crucial for interpreting the characteristics of faults and provides significant practical value when evaluating the fault condition of equipment. Many researchers have successfully developed ED pattern recognition and classification techniques. In this part, the recognition techniques involving many high-performance algorithms are reviewed. The recognition techniques involve many high-performance algorithms adopting ML and DL for smart ED recognition and classification. Most of these techniques comprise the UHF ED signals, analyzed in the frequency domain, requiring a larger dataset of ED samples and data library for classification. Some may apply an intricate MLP training algorithm, thus giving a higher complexity to ensure a complete monitoring process. Therefore, in this research, another novel ED identification technique is developed for the early monitoring of ED signals. This technique requires a waveform-based model ED signal for simpler and direct ED signal feature extraction, allowing identification of a single source of ED signal, hence diminishing the collection of ED big dataset samples. It also requires no data-cleaning process as this technique does not need signal classification. The detected signal will be processed and analyzed using MATLAB tools.

## CHAPTER 3

### METHODOLOGY

#### 3.1 Overview

In this chapter, the correlated analysis works in developing the Single Perceptron Smart Sensor (SPSS), which is elaborated sequentially. It involves a series of empirical simulations and evaluations. Analysis works are divided into THREE (3) parts to accomplish the pre-fault monitoring system. The analysis begins with Part A to investigate the most suitable  $N$ -element array antenna as the SPSS model, which has broad radiation and adapts to the changes in the propagation phase. Part B focuses on developing a novel SPSS, utilizing the Single Perceptron-Artificial Neural Network (SP-ANN) Algorithm for Electric Discharge Electromagnetic Impulse (ED\_EMP) signal detection and localization. Lastly, Part C evaluates the performance of the novel SP-Identifier Technique for ED\_EMP signal identification using waveform-based testing for Corona or Arc Electric Discharges (EDs) samples. All results and observations are discussed in Chapter 4, and the conclusion is made in Chapter 5.

##### 3.1.1 Framework of the Single Perceptron-ANN for Smart Sensor Formation

The framework of the SP-ANN for SPSS for indoor substation pre-fault monitoring is displayed in Figure 3.1. It illustrates the flow of the research work from Part A to Part C. This research aims to achieve an ANN-based smart sensor to detect, localize, and identify the signal within the Ultra-High Frequency (UHF) of specific EDs such as Corona and Arc discharges. Figure 3.2 portrays the overall model of the pre-fault monitoring system in an indoor substation, illustrating the SPSS as the smart sensor. The system specifications are defined based on Figure 3.2 as illustrated in Table 3.1.

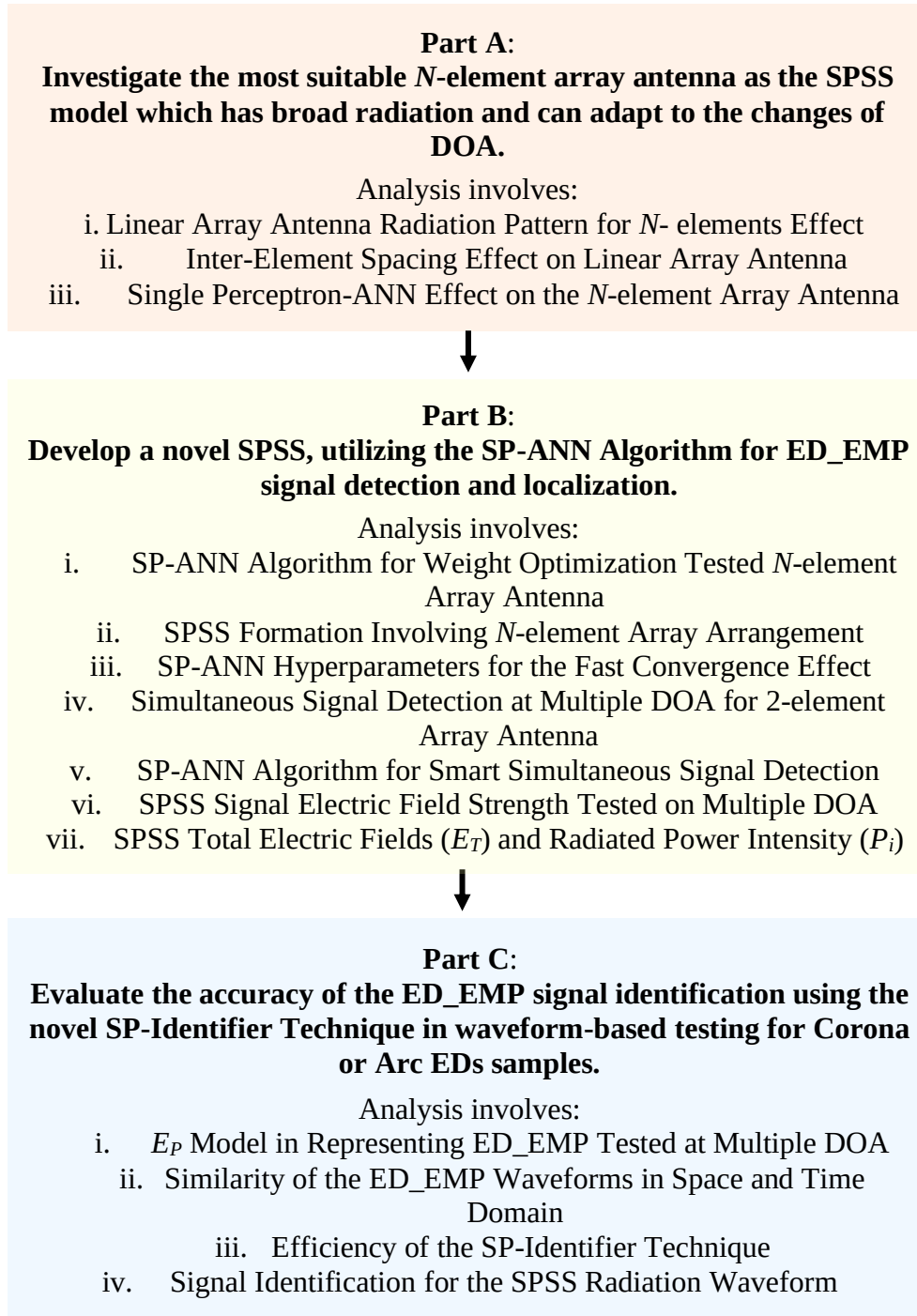


**Figure 3.1:** Framework of Single Perceptron-ANN for Smart Sensor

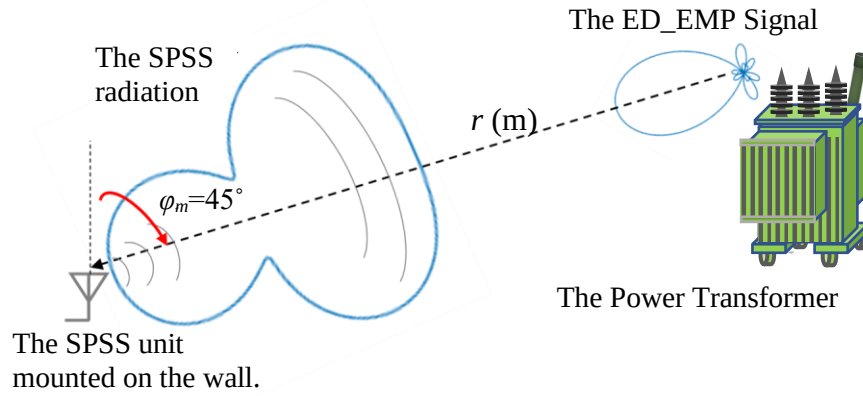


**Figure 3.2:** The overall model of the pre-fault monitoring system in an indoor substation

**Table 3.1:** The Overall system specification

| Parameter                      | Specification    |
|--------------------------------|------------------|
| ED_EMP Frequency Range         | 300 MHz - 3 GHz  |
| SPSS operating frequency range | 40 MHz - 0.4 GHz |
| Sampled ED_EM DOA source       | $45^\circ$       |
| Localization elevation angle   | $<2^\circ$       |
| SPSS receiving distance        | 1.524m (5feet)   |
| Signal Identification accuracy | $>98\%$          |

This research work begins with Part A to investigate the most suitable  $N$ -element array antenna as the SPSS model. The selection of a Linear Array Antenna as a sensor takes the antenna input Radiation Pattern (RP) as the observed parameter. It does not involve any new design of Linear Array Antenna. All the existing properties of Linear Array Antenna are applicable when the selected array antenna is identified. The investigation focused on the RP of the  $N$ -element array antennas, looking for the most suitable array length ( $N$ ) that complies with the required antenna characteristics mentioned in Chapter 2. This selection

includes the effect of the SP-ANN when incorporated with each sampled array length, and the geometry arrangement of each array length is also observed for the RP of each sample.

Next, Part B is the development of a novel SPSS, utilizing the SP-ANN Algorithm for ED\_EMP signal detection and localization. Here, the SP-ANN Algorithm for weight optimization is constructed and tested on an  $N$ -element Linear Array Antenna. The hyperparameters, such as the learning rate and bias of the perceptron, are carefully tuned to obtain the optimal weights for the algorithm to achieve convergence. In Part B, a new signal localization technique is introduced by integrating the selected antenna sensor in Part A with the SP-ANN algorithm to form the SPSS. Here, the capability of SPSS to maximize and null the signals from the desired DOAs is observed for the RP plot in the space domain. The SPSS optimized weights are the observed parameters that define the accuracy of the signal identification in Part C. Since a pre-fault monitoring system is developed, it is important to analyze some parameters from the SPSS Electric Field RP such as signal Total Electric Fields ( $E_T$ ), Radiated Power Intensity ( $P_i$ ). These parameters are useful for antenna placement recommendations in indoor substations relative to the desired DOAs.

Part C is the final stage of the research. It introduces a new signal identification technique called the SP-Identifier Technique. It was developed to reduce the complexity of the existing signal feature extraction techniques. This technique uses the optimized weights of SP-ANN in Part B to identify the SPSS-detected signal waveforms in the time domain and space domain. This technique uses a model-based waveform testing that allows the execution of the EM impulses. Figure 3.3 illustrates the overall research activities of the pre-fault monitoring system in an indoor substation.

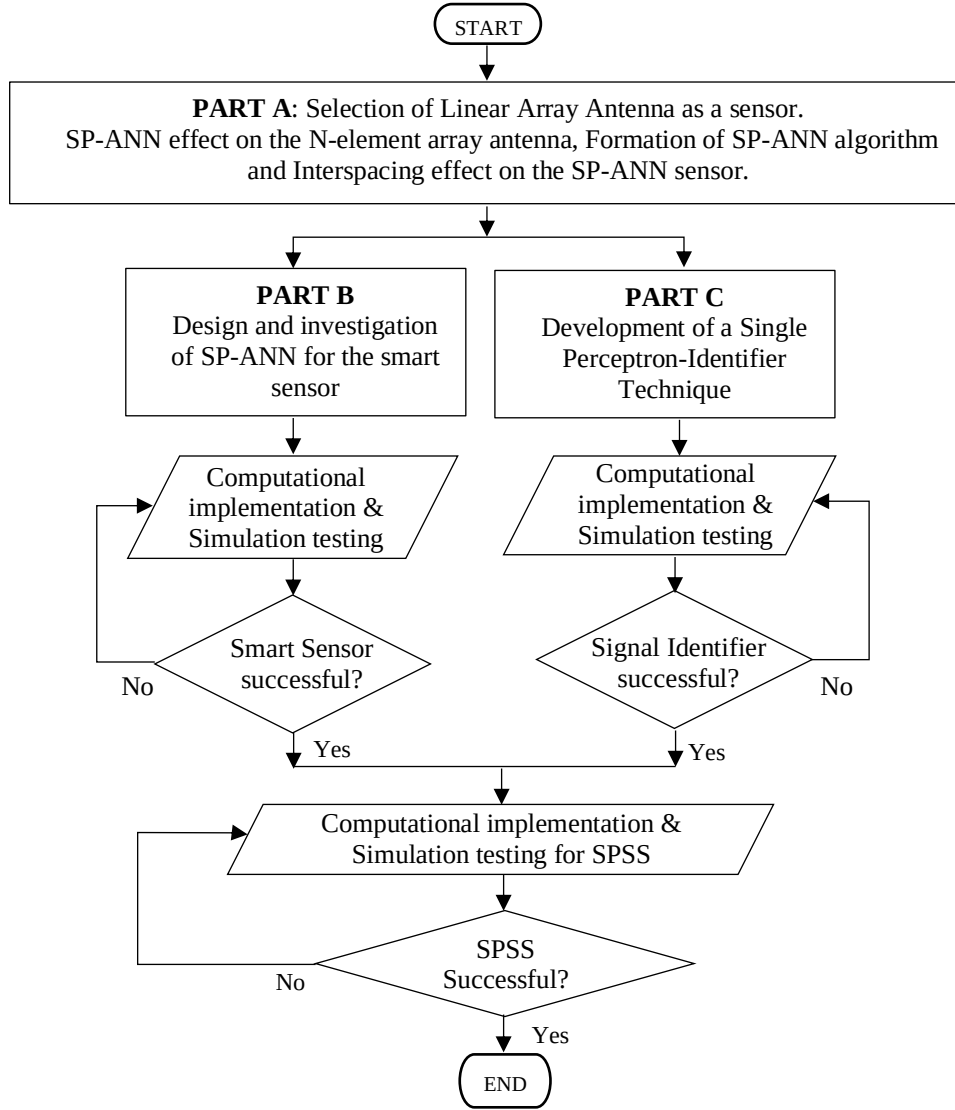


**Figure 3.3:** Overall research activities for the pre-fault monitoring system

### 3.2 **PART A: Investigate the most suitable $N$ -element array antenna as the SPSS model which has broad radiation and can adapt to the changes of DOA**

This part consists of THREE (3) analyses. The first analysis is to analyze the Linear Array Antenna RP for the effect of  $N$ -elements. The second analysis is the inter-element spacing effect on the Linear Array Antenna, and the third analysis is the SP-ANN effect on the  $N$ -element array antenna. At the end of these analyses, the final array length ( $N$ ) of the Linear Array Antenna is identified to meet the characteristics of the SPSS model.

### 3.2.1 Linear Array Antenna Radiation Pattern for $N$ - elements Effect

The SPSS modeling begins with the analysis to evaluate the RP of the sampled Linear Array Antenna. The array antenna is a linearly arrayed isotropic antenna of equal spacing and amplitude. This analysis aims to observe every Array Factor (AF) and antenna input RP, selecting the most acceptable  $N$ -element to fulfill the SPSS characteristics. The  $N$ -element array antenna is linearly arranged and oriented at the  $z$ -axis with element spacing,  $d$ . Assuming the potential Electromagnetic (EM) signal,  $E_p$  as the ED source is generated from a far-field at distances  $r_1, r_2, \dots, r_{(n-1)}$ , as illustrated in Section 2.3.1. Each  $N$ -elements array equation input signal is obtained based on the selection of the geometrical linear array placed on the  $z$ -axis arrangement and the fundamental study of antenna elementary theory; therefore, the input element,  $f(\varphi)$ , is derived as follows (Visser, 2006).

$$f(\varphi) = 1 + e^{j1\varphi} + e^{j2\varphi} + e^{j3\varphi} + \dots + e^{j(N-1)\varphi} \quad \text{Equation 3.1}$$

where  $\varphi = kd \cos \theta$  represents the propagation phase, the difference between radiation from two adjacent elements. A MATLAB program is employed to visualize the AF radiation and the input element  $f(\varphi)$  RP in a polar plot. In this analysis, six array lengths are sampled at  $N = 2, 3, 4, 6, 8$ , and  $10$ , which are executed individually. Assuming the elements are identical, having the same amplitude and each with a propagation phase. From the input element (refer to Equation 3.1), the normalized AF for the  $N$ -element Linear Array Antenna is defined as follows (Visser, 2006).

$$AF_N = \frac{1}{N} \left[ \frac{\sin\left(\frac{N}{2}\varphi\right)}{\sin\left(\frac{1}{2}\varphi\right)} \right] \quad \text{Equation 3.2}$$

where the element spacing,  $d = \lambda/2$ , the wavenumber,  $k = 2\pi/\lambda$ , the progressive phase shift angle,  $\theta$  between  $0^\circ$  to  $360^\circ$ . Further analysis is also held to introduce a delay signal,  $\beta$  so

that  $\varphi = kd \cos \theta + \beta$ . This signal is intentionally introduced to simulate any abnormal electrical activity that may occur in a specific direction from a power apparatus in a substation. Firstly, the evaluation occurs at a fixed  $\beta = 45^\circ$  and is tested on all six sampled array lengths. Next, the observation continues at the varied  $\beta = 15^\circ, 30^\circ, 60^\circ, 90^\circ, 240^\circ$  and  $270^\circ$  and tested on the 2-element array antenna. RPs of the array antenna are plotted in polar form. Some parameters for this work are defined as follows: the wavelength,  $\lambda = c/f$ , where the velocity of light,  $c = 3 \times 10^8$  m/s, and the antenna sampled frequency,  $f = 1$  GHz. The analysis emphasizes the RP of every sampled array length, and the significance of each array element is observed. In addition, this simulation is also performed to evaluate the sensitivity and the ability of the array antenna as a sensor adapted to the changes of propagation phase,  $\beta$  as the induced signal. In the other upcoming analysis, this induced signal is used to represent the DOA of an ED\_EMP source. The MATLAB code for the simulation work is provided in Appendix A.

### 3.2.2 Inter-Element Spacing Effect on Linear Array Antenna

Mutual coupling is the EM interactivity that occurs between the antenna array elements. The mutual coupling can significantly affect the gain, beam width, and RPs, hence degrading the array performance. Succinctly, the mutual coupling is reversely proportional to the element spacing,  $d$ . Therefore, it has a detrimental effect on the RP if invoking inappropriate inter-element spacing. In many studies, the preferable element spacing is usually larger than half a wavelength ( $d > \lambda/2$ ). Thus, deciding the appropriate element spacing for any array antenna design is crucial. Figure 3.4 displays the  $N$ -element array antennas linearly arranged and oriented at the  $z$ -axis with element spacing,  $d$ , considering the Partial Discharge (PD) sources from the far-field zone observed at point  $P$ .

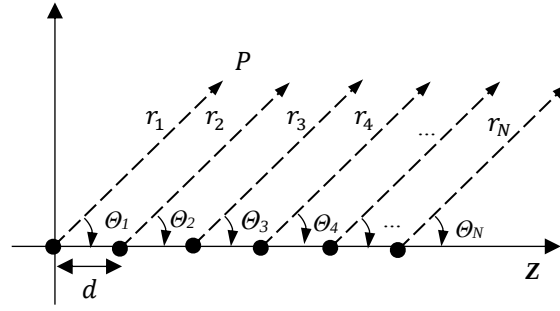


**Figure 3.4:** Linear Array Antenna with  $N$ -elements in the  $z$ -axis (Hoole, 2001)

This analysis aims to obtain a directive and broadside RP observed from the array antenna input element,  $f(\varphi)$  (from Equation 3.1). Based on the result obtained in Section 3.2.1, the analysis executed for the antenna array length of  $N = 2$ , at element spacing,  $d = 0.125\lambda$ ,  $0.25\lambda$ ,  $0.5\lambda$ , and  $1.0\lambda$ . This work is carried out to validate the significant wavelength for the SPSS model. The MATLAB code for the simulation work is attached in Appendix B.

### 3.2.3 Single Perceptron-ANN Effect on the $N$ -element Array Antenna

This analysis illustrates the formation of a smart sensor from the Linear Array Antenna and the SP-ANN. It focuses on the effect of the perceptron complex weights when incorporated with the antenna input element. This scheme aims to improve the quality of the radiation as well as the sensing coverage. Figure 3.5 illustrates the configuration of the 2-element array antenna, illustrating that each element is multiplied with a weight factor of the single perceptron. The array is assumed to be identical, with the same signal magnitude, and the progressive phase shift angle,  $\theta$  between elements, is uniformly spaced. The input signal picked up by the array,  $A_1, A_2, A_3, \dots, A_n$  are defined as  $X_1, X_2, X_3, \dots, X_n$  whereas the perceptron weight factors are defined as  $W_1, W_2, W_3, \dots, W_n$ . In this analysis, the evaluation focuses on the final output signal ( $Y_o$ ) RP.

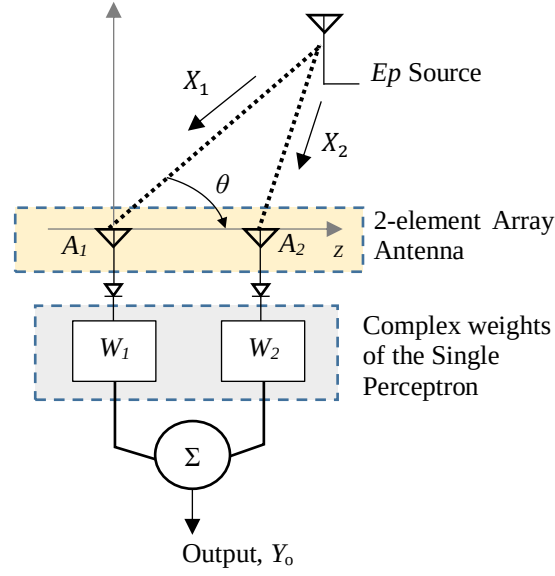


**Figure 3.5:** The Smart sensor model with a 2-element array antenna

Referring to Figure 3.5, each array input element is derived according to the selected geometrical linear array placed on the z-axis arrangement (Equation 3.1). Thus, the 2-element array input equation is defined as:

$$f(\varphi) = 1 + e^{j1\varphi} \quad \text{Equation 3.3}$$

and the output signal,  $Y_o$  equation is defined as:

$$Y_o = W_1 + W_2 e^{j\varphi} \quad \text{Equation 3.4}$$

where  $\varphi = kd \cos \theta$ . For computational settings, the element spacing,  $d = \lambda/2$ , the wavenumber,  $k = 2\pi/\lambda$ , the progressive phase shift angle,  $\theta$  azimuth is set between  $0^\circ$  to  $360^\circ$  and the weights,  $W_1, W_2, \dots, W_n$  are all initialized at complex weight,  $W = 0.1 + j0$ . The first simulation is carried out by considering six cases of array length sampled at  $N = 2, 3, 4, 6, 8$ , and  $10$ . A specific angle,  $\beta$  is induced as a delay to the Propagation Phase,  $\varphi$  to represent

the possible  $E_P$  picked up by the antenna at any identified angle between  $0^\circ$  and  $360^\circ$ . Here, the delay is fixed at  $\beta = 45^\circ$  and therefore,  $\varphi = kd \cos \theta + \beta$ . The observation focuses on the effect of the initial weights. The next simulation is conducted on the same arrays, and the values of the initial complex weight are increased to  $W = 2.0 + j0$ . Again, the same evaluation concentrated on the effect of the increased perceptron weights. Every observed RP is plotted in polar form. The MATLAB code for the simulation work is attached in Appendix C.

### **3.3 PART B: Develop a novel SPSS, utilizing the SP-ANN Algorithm for ED\_EMP signal detection and localization**

This part consists of SEVEN (7) analyses. It begins with the SP-ANN algorithm for weight optimization tested  $N$ -element array antenna. It is followed by the analysis to observe the SPSS formation involving the  $N$ -element array arrangement. Then, the analysis continues with SP-ANN hyperparameters for the fast convergence effect. Next is the simultaneous signal detection at multiple DOA for a 2-element array antenna. The analysis continues with the analysis of the SP-ANN algorithm for simultaneous signal detection. Next is the analysis of the SPSS for signal electric field strength tested on multiple DOA, and lastly is the analysis of the SPSS for the total electric fields ( $E_T$ ) and radiated power intensity ( $P_i$ ) at a fixed DOA with multiple ranges of signal distance,  $r$  (in meter).

#### **3.3.1 SP-ANN Algorithm for Weight Optimization Tested $N$ -element Array Antenna**

The previous analysis emphasizes the conceptual design of a smart sensor utilizing a Single Perceptron (SP). The complex weights of the perceptron have effectively changed the quality of the antenna radiation. Therefore, this analysis focuses on developing the SP Algorithm employing the ANN as the soft-computing technique to train the perceptron. Specifically, this SP-ANN algorithm is constructed to optimize the complex weight, thus allowing the sensor to become cohesively smart.

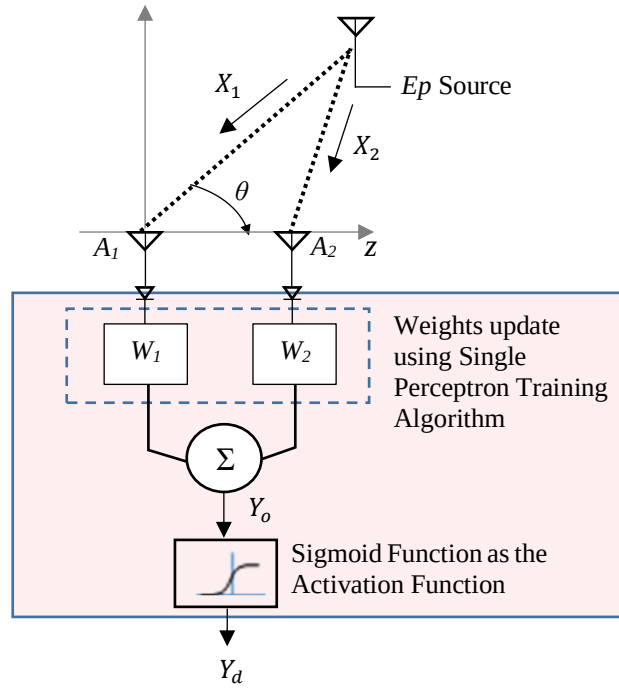


**Figure 3.6:** The SPSS Model with a 2-element array antenna

Figure 3.6 portrays the configuration of the SPSS model, comprising a 2-element Array Antenna and an SP-ANN geometrically arrayed on the  $z$ -axis. As observed, a single perceptron (neuron) combined with a non-linear Sigmoid activation function reduces the complexity and minimizes time delay processing in achieving the desired output. The complex weights are trained or updated using the Sigmoid ( $\sigma$ ) activation function to generate the mean value of the weight training error,  $Err_{(train)}$ . The Sigmoid activation function allows a smoother, continuous output in the range value between 0 and 1. Technically, the SPSS model is divided into three sections; the first section defines the inputs ( $X_1, X_2, \dots, X_n$ ) multiplied individually by the weights ( $W_1, W_2, \dots, W_n$ ). The second section contains the net function that sums up all the weighted inputs with a bias,  $b$  where  $z = b + \sum_{k=1}^n W_k X_k$  (Basheer et al., 2000). The actual output is defined by:

$$Y_o = W_1 + W_2 e^{j(kd \cos \theta)} \quad \text{Equation 3.5}$$

where  $\varphi = kd \cos \theta$ . For the element spacing,  $d \leq \lambda$ , the small-angle approximation employed for the denominator and, therefore, from Equation 3.2:

$$AFN = \text{sinc}(\varphi) \quad \text{Equation 3.6}$$

thus, the desired output of the SP is defined as:

$$Y_d = \text{sinc}[\varphi - \beta] \quad \text{Equation 3.7}$$

where  $\beta$  represents the direction of the angle of the potential  $E_P$  signal picked up by the antenna. The third section includes a non-linear Sigmoid ( $\sigma$ ) activation function (Basheer et al., 2000) is used to find out the desired output:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad \text{Equation 3.8}$$

This net function simplifies the calculation of the complexity and reduces the processing delay time. The weights optimization relies on the deviation of the absolute error,  $\Delta|E|$ :

$$\Delta|E| = |Y_d - Y_o| \quad \text{Equation 3.9}$$

The weights are continuously trained until the mean value of the training error,  $Err_{(train)}$ , reaches below the predefined value,  $Err_{(p)}$ . The training error is derived as follows:

$$Err_{(train)} = \frac{\Delta}{Y_d} \times 100 \quad \text{Equation 3.10}$$

The SP-ANN training algorithm is constructed to train and optimize the weights based on the iteration, and the control structure of the algorithm is illustrated as follows:

**Step 1:** The weights ( $W_k$ ) is initialized with random values, learning rate  $\eta$ , and the vector  $\vec{X}_k$  is taken as input pattern where  $k=1, 2, 3, \dots, n$ .

**Step 2:** The calculation of the parameters involves the actual output,  $Y_o$ , using the Sigmoid activation function for  $Y_o = \sigma(z)$  and the weight updating with a learning rate ( $\eta$ ) for:

$$\Delta w_{k+1} = W_k + \eta(Y_d - Y_o)X_k \quad \text{Equation 3.11}$$

**Step 3:** The for-loop control; *IF*:  $Err_{(train)} < Err_{(p)}$ , convergence achieved, and weights updating is stopped. *ELSE*: the weight updating and iterations continue until convergence is achieved. *IF*: the iteration does not converge. The updating is stopped. Step 2 is repeated until zero error or convergence is achieved.

Figure 3.7 displays the SP-ANN training algorithm flowchart for the weight optimization. In this analysis, the additional Adjustable Scalar Parameters (also known as hyperparameters) of the Perceptron (i.e., the bias,  $b$ , and learning rate,  $\eta$ ) are applied to the algorithms. These parameters are varied to meet the desired behavior as part of the network training process. The flowchart illustrates the flow of the training algorithm based on the settings: The initial weights,  $W_1, W_2, \dots, W_n = 0.1 + j0$ , the initial bias,  $b = 0.001$ , the initial learning rate,  $\eta = 0.5$ , the delay,  $\beta = \pi/4$  radians, the element spacing,  $d = \lambda/2$  and the iteration,  $i < 1000$  Counts,  $C$ . Upon these settings, the algorithm is executed on the 2, 3, 4, 6, 8 and 10 array lengths individually. The antenna performs a cyclical scan at a scanning angle of  $\theta$ , at azimuth between  $0^\circ$  to  $360^\circ$ .

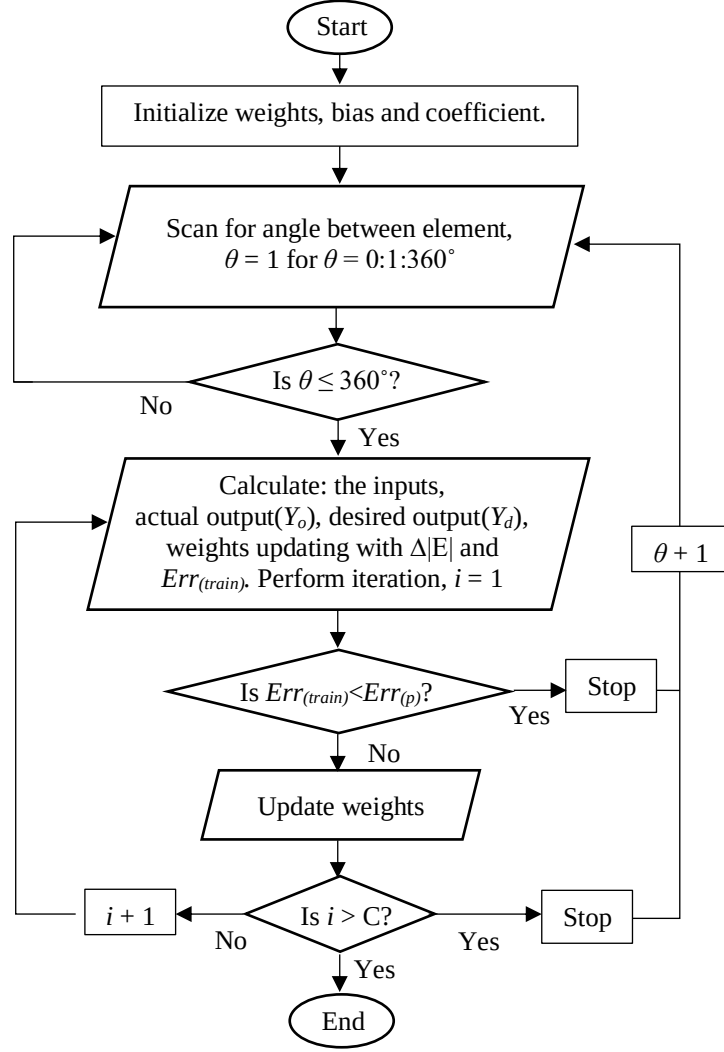


**Figure 3.7:** Flowchart of the SP-ANN Training Algorithm

The Perceptron is trained to steer the array antenna to the desired direction. A phase delay,  $\beta$ , is induced at a specific angle of  $\pi/4$  radians to represent the desired direction as the desired output. Hence, the desired output equation is derived as a trigonometric function (Equation 3.7). Specifically, weight optimization is carried out to achieve the desired output by training the weights based on the deviation of the absolute error  $\Delta|E|$ . The training continues until the mean value of  $Err_{(train)}$  reaches below than the predefined value,  $Err_{(p)}$ ; the  $Err_{(train)} < Err_{(p)}$ . Once this condition occurs, convergence is achieved, and the training

process stops. However, the iteration of the training is limited to the given value of counts,  $C$ . The iteration continues for  $\theta = \theta + 1$  as long as the iteration,  $i < C$ , or when the non-convergence is achieved. The MATLAB code for the simulation work is attached in Appendix D. In the end, the efficacy of the SP-ANN algorithm is evaluated for every input RP plotted in polar form. Next, an analysis is conducted to investigate the effect of the inter-element spacing of the arrays. The inter-element may generate a mutual coupling effect to the elements of an array antenna.

### 3.3.2 SPSS Formation Involving $N$ -element Array Arrangement

The geometrical array arrangement is another factor that needs to be selected properly before finalizing the configuration of the SPSS. The geometrical configuration has many impacts on antenna detection. The accuracy of the DOA estimation with an antenna array depends on the antenna element positions (Qin et al., 2020; Shaalan et al., 2019). Optimum array configurations have derived the quality of the beamforming (Ghosh et al., 2019; Tu et al., 2020) and the mutual coupling suppression between the elements (Zhang et al., 2019). Since the SPSS is modeled using a 2-element Linear Array Antenna, the array arrangement selection is less complicated. However, an analysis is carried out to observe the effect of the geometrical array arrangement on the SPSS input radiation by taking the samples of the array length at  $N = 2, 3, 4, 6$ , and  $8$ . This analysis aims to verify that the array arrangement of  $N = 2$  selected in Part A has a high amplitude with broadside beamform for the SPSS model. In this analysis, the SP-ANN training is applied with the same initial SP Learning rate,  $\eta = 0.5$ , and the bias,  $b = 0.001$ . The setup of the array antennas is applied based on the setup from the previous analysis (in Section 3.3.1) by assuming the uniform spacing between elements and letting the array antennas be isotropic. To study the effect of this array arrangement, the MATLAB program (as indicated in Appendix E) has been

developed by applying Equation 3.1. First, each SPSS input RP corresponding to the sampled array length is plotted in polar form. Then, the  $N$ -elements array equation for each sample is derived, as shown in Appendix E, based on the randomly selected geometrical linear array placed on a  $z$ -axis arrangement (see Figure 3.4). The Propagation Phase difference between radiation from two adjacent elements is given by  $\varphi = kd \cos \theta + \beta$  at the induced delay of DOA,  $\beta = 45^\circ$ . The input radiation,  $f(\varphi)$  pattern of each  $N$ -element, is observed.

### 3.3.3 SP-ANN Hyperparameters for the Fast Convergence Effect

The SP-ANN algorithm (in Section 3.3.1) is a crucial machine-learning model for the SPSS. To adapt this Machine Learning (ML) model to different situations of signal sources, its hyperparameters must be properly tuned as it has a direct impact on the algorithm performance as well as increasing the convergence speed (Khandelwal et al., 2018; Lee et al., 2021; Liu et al., 2021; Xiang et al., 2019; Yoo, 2019). Selecting the best hyperparameters may be a time-consuming process. Nevertheless, it has to be analyzed heuristically to find the optimum range of the hyperparameters for the SPSS to achieve fast convergence. In this analysis, the SP-ANN hyperparameters are identified as the Learning rate  $\eta$  and the Bias,  $b$ . Then, these hyperparameters are analyzed individually for the array length sampled at  $N = 2, 3, 4, 6$ , and  $8$ . Finally, the relative array input equation is derived, as illustrated in Appendix E, based on the performance of the selected geometrical array (in Section 3.3.2) placed on the  $z$ -axis arrangement. The SP-ANN algorithm is executed at the same set-up as in Section 3.3.1, using the desired output in Equation 3.7 as the detected signal where the desired DOA is denoted as the induced delay,  $\theta$ . The multiple DOAs of the source to be emitted by the sensor are tested at different angles at  $\pi/2, \pi/3, \pi/4, 3\pi/2, 2\pi/3$  and  $5\pi/3$  radians (or at  $45^\circ, 60^\circ, 90^\circ, 120^\circ, 270^\circ$  and  $300^\circ$ ). It is important to choose the appropriate range of

these hyperparameters for the SPSS to have the same sensor that will scan optimally for multiple angles simultaneously. Therefore, this analysis is carried out with the  $\eta$  and  $b$ , both varied in the range between 0.001 to 1.000, and the convergence status of the SPSS at the identified DOAs for each sampled  $N$ -element is observed (refer to Appendix F).

### 3.3.4 Simultaneous Signal Detection at Multiple DOA for 2-element Array Antenna

Having the potential element array antenna and its initial parameters ready for the Smart Antenna (SA) as a smart sensor modeling for the SPSS, the next analysis work is conducted to test the application of the SA. The aim is to investigate the ability of a 2-element array antenna to detect and localize the desired signal from a specified DOA. Fundamental works for the smart sensor begins with Figure 3.8, which illustrates the 2-element SA Model.

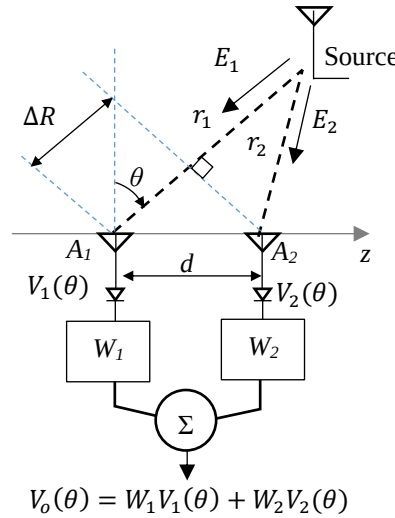


**Figure 3.8:** The 2-element SA Model

The configuration of the antennas is simulated based on the electrical activities that occur in an indoor substation from a DOA at an angle,  $\theta$ . The Electric fields,  $E_1(\theta)$  and  $E_2(\theta)$ , from the source, such as Electric Corona or Arc discharge picked up by the 2-element SA, give

the total electric fields,  $E_T$  (measured in V/m) as defined in Equation 3.12. It is then expressed as a resultant signal of an antenna output voltage given Equation 3.13.

$$E_T = W_1 E_1 + W_2 E_2 \quad \text{Equation 3.12}$$

$$V_o(\theta) = W_1 V_1(\theta) + W_2 V_2(\theta) \quad \text{Equation 3.13}$$

The objective of this analysis is to investigate the ability of the 2-element array antenna to simultaneously nullify the interference signal and maximize the desired signal. These conditions are illustrated in Figure 3.9 and Figure 3.9 displays the SA nullifying the interference signal originating from a source. When  $\theta = \theta_i$ , then the output,  $V_o(\theta) = 0$ .

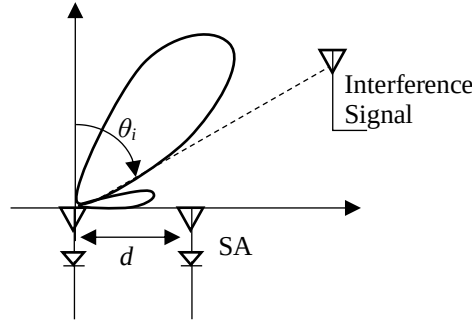


**Figure 3.9:** The SA nullifying the interference signal

Subsequently, the SA is also capable of maximizing the output,  $V_o(\theta) = V_{max}$  when a transmitting signal is picked up from the desired direction at  $\theta = \theta_m$ , as illustrated in Figure 3.10. For these two conditions, the nullifying and the maximizing of the signals are feasible by manually varying the values of weights,  $W_1$  and  $W_2$ , to strongly steer the beamform at the direction,  $\theta$ .

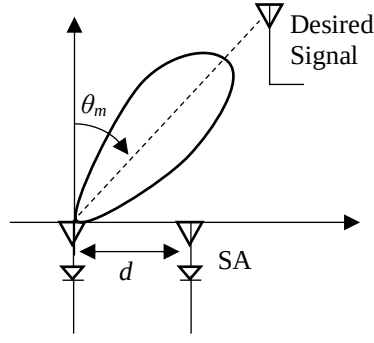


**Figure 3.10:** The SA maximizing the desired signal

Figure 3.11 illustrates the SA when applied in an indoor substation. The beamform is focused at maximum ( $V_o(\theta) = V_{max}$ ) when the SA is directed to the desired point, e.g.,  $\theta = \theta_t$  to scan for the potential Corona or Arc discharge at the transformer and then maximum again when  $\theta = \theta_s$  to examine string insulators.

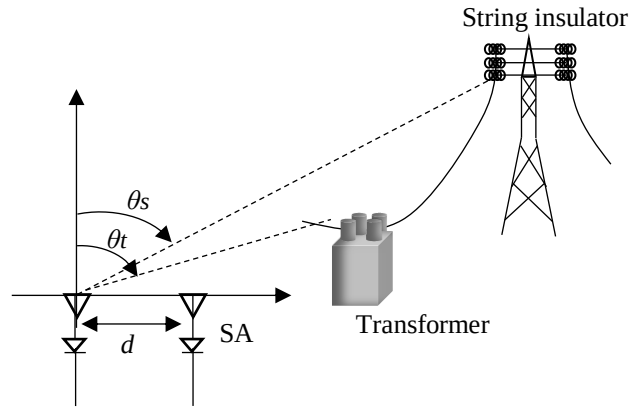


**Figure 3.11:** The SA scanning process at two possible Corona or Arc sources

This scanning process continues from one desired point to other points, such as a circuit breaker and transformers. It switches within the substation to detect and localize the exact source of Corona or Arc discharge being radiated from. To perform the nullifying condition, refer to the configuration in Figure 3.8, where the 2-element SA ( $A_1$  and  $A_2$ ) is

placed with element spacing,  $d = \lambda/2$ . Assuming the source radiating pattern is uniform in all directions, the RP of the SA is observed by its AF. Consider the arriving angle of an interferer signal,  $V_i$  at direction  $\theta = \theta_i$ . The SA shall nullify any signal received from the direction  $\theta_i$  so that the resultant signal,  $V_o(\theta_i) = 0$ . Using the input element  $f(\varphi)$  for  $N = 2$ , the Normalized Array Factor (AFN) of the SA for nullifying and maximizing conditions is fundamentally derived in the following steps. This is the first novelty of the research where the design of the SA for nullifying and maximizing conditions are derived carefully. The detail of the derivation works is attached in Appendix G. Firstly, to nullify the interference signal, the value of the complex weights,  $W_1$  and  $W_2$ , are set to  $W_1 = 1$  and  $W_2 = e^{j\delta}$ , respectively, where  $\delta$  is the unknown source. Let

$$V_1(\theta) = V_i e^{-jkr_1} \quad \text{Equation 3.14}$$

$$V_2(\theta) = V_i e^{-jkr_2} \quad \text{Equation 3.15}$$

where  $r_1$  and  $r_2$  are the distances from the transmitted source to the antenna elements,  $A_1$  and  $A_2$ . These distances are derived by Equation 3.16, and the resultant output is given by Equation 3.17. Therefore, the AF is derived as Equation 3.18.

$$r_2 = r_1 - d \sin \theta \quad \text{Equation 3.16}$$

$$V_o(\theta) = V_i e^{-jkr_1} [1 + e^{j(kd \sin \theta + \delta)}] \quad \text{Equation 3.17}$$

$$\text{AF} = 1 + e^{j(kd \sin \theta + \delta)} \quad \text{Equation 3.18}$$

To nullify the interference signal at  $\theta = \theta_i$  so that  $V_o(\theta_i) = 0$ ; hence, the AF must be set to zero, i.e.,  $\text{AF} = 0$ . To achieve this, let  $kd \sin \theta + \delta = \beta$ . For  $e^{j\beta} = -1$  then  $\beta = \pm\pi$ . Thus,  $kd \sin \theta_i + \delta_i = \pi$ . When the direction is at  $\theta = \theta_i$ , the value of  $\delta = \delta_i$  identified will give  $\text{AF} = 0$  or  $\beta =$

$\pm\pi$ . Therefore, to nullify the interference signal,  $\delta_i = \pi - kd \sin \theta_i$ . Hence, the nullifying condition is represented by Equation 3.19.

$$AFN_1 = \left| \sin \left( \frac{\gamma}{2} \right) \right| \quad \text{Equation 3.19}$$

Next, consider the SA to maximize the arriving signal at direction  $\theta = \theta_m$ , as displayed in Figure 3.11. The SA shall maximize any signal picked up from the desired direction at  $\theta_m$ . Thus, the  $AF = 2$ . To achieve this, let  $kd \sin \theta + \delta = \beta$ . For  $e^{j\beta} = 1$ , we obtain  $\beta = 0$ . Hence,  $kd \sin \theta_m + \delta_m = 0$ . When the direction is at  $\theta_m$ , the value of  $\delta = \delta_m$  needs to be identified to give  $AF = 2$  or  $\beta = 0$ . Therefore, to maximize the signal,  $\delta_m = -kd \sin \theta_m$ . Hence, the maximizing condition is represented by Equation 3.20.

$$AFN_2 = \left| \cos \left( \frac{\gamma}{2} \right) \right| \quad \text{Equation 3.20}$$

To better understand the SA application, Figure 3.12 portrays the 2-element SA mounted vertically to the wall to scan the potential ED from a Distribution Transformer unit in an indoor substation.

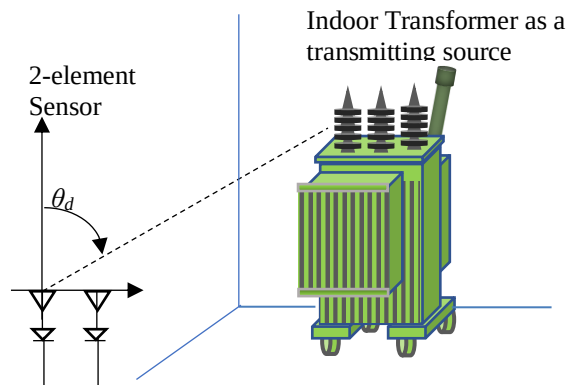


**Figure 3.12:** The wall-mounted SA to detect and localize the ED from a Transformer

This simulation work lets the desired radiation source come from the transformer, where the direction is first identified and denoted in angle  $\theta$ . Then, this desired direction is maximized as the 2-element SA is steered to the desired DOA at  $\theta = \theta_d$ . Practically, this scanning process is conducted cyclically at multiple DOAs from one desired point to other points, such as at the Bushing, transformer tank, relay, circuit breaker, and switches within the substation to detect and localize the ED such as Corona or Arc being radiated from.

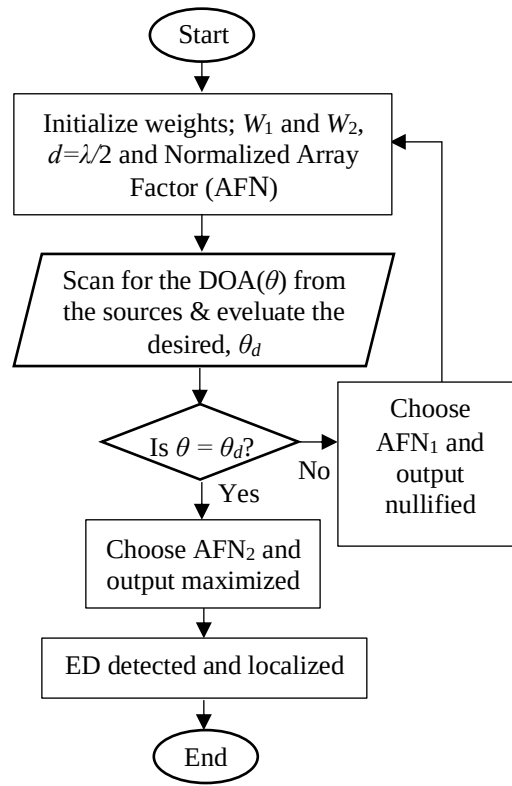


**Figure 3.13:** The flowchart of the SA model for signal nullifying and maximizing

The MATLAB Code (in Appendix G) is programmed based on the flowchart provided in Figure 3.13. The scanning process for both conditions is simulated simultaneously by taking some initial parameter settings. The scanning azimuth is between  $0^\circ$  to  $360^\circ$ . The desired signals are set at DOA,  $\theta_d = 45^\circ, 60^\circ, 165^\circ$  and  $320^\circ$ . Signals received

at DOAs other than  $\theta_d$  are denoted as interference to be nullified. In this simulation, interference signals are set at DOA,  $\theta_i = 50^\circ, 165^\circ, 255^\circ$  and  $320^\circ$ . The initial parameters for the SA are clarified as follows: Array element,  $N = 2$ , Weights,  $W_1 = 0.1, W_2 = 0.1$ , Operating Frequency,  $f = 1$  GHz, Inter-element spacing,  $d = \lambda/2$  and Wavenumber,  $k = 2\pi/\lambda$ . At the end of this analysis, the SA performance is observed. These simulation results allow the SA model to be used in the next analysis, where the SP Algorithm is combined with the SA for the SPSS application.

### 3.3.5 SP-ANN Algorithm for the Smart Simultaneous Signal Detection

From the analysis in Section 3.3.1, the SP-ANN training algorithm is developed to optimize the complex weights ( $W$ ) of a perceptron, and the SA is modeled using a 2-element array antenna. This upcoming analysis aims to observe the performance of the SA model when integrated with the SP Algorithm, forming the SPSS unit. Furthermore, this feasibility study is conducted to verify the training algorithm that has the potential to optimize the  $W$  of the SPSS when both conditions (maximizing and nullifying signal) are tested on it. The simulation work begins by considering the same parameters set as in Sections 3.3.1 and 3.3.4.

The initial values of the SPSS weights are set as  $W_1 = 0.1$  and  $W_2 = 0.1$ . The MATLAB code (in Appendix H) is programmed based on the flowchart displayed in Figure 3.14. Upon the setting of the initial parameter and training algorithm, the SPSS starts to scan cyclically at the scanning azimuth between  $0^\circ$  to  $360^\circ$  with the increment  $\theta+1^\circ$ . Here, the SPSS is set to maximize any signal picked up from the desired location at DOA,  $\theta_d = 65^\circ$ . The training algorithm continues to iterate until convergence is achieved so that the input elements of the SPSS attain the optimum weights for the signal detection process.

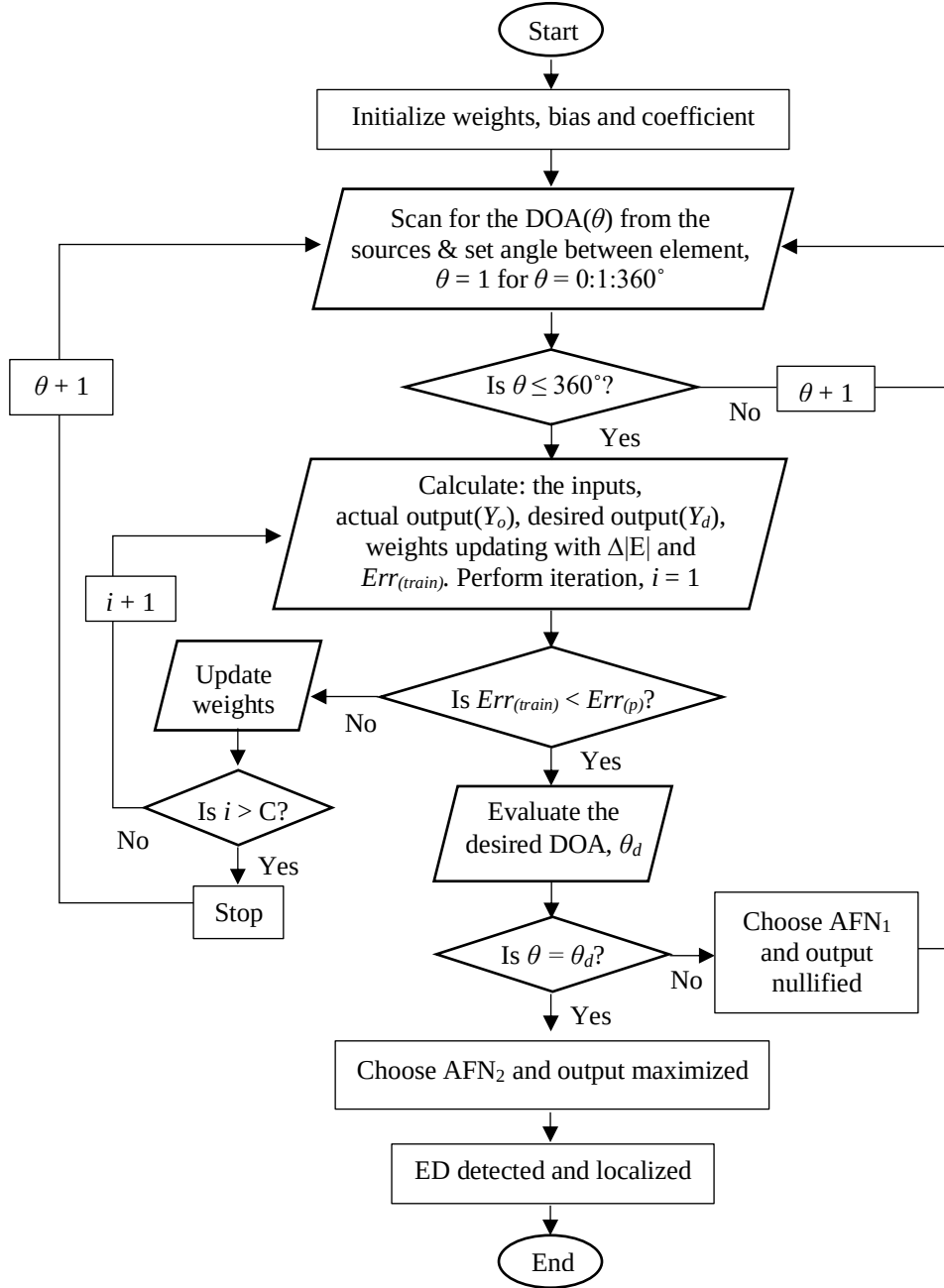


**Figure 3.14:** The flowchart of the SPSS for signal nullifying and maximizing

When the targeted signal,  $\theta_d$ , is detected, the signal maximizing process is executed at AFN<sub>2</sub> (Equation (3.20)), and the training process stops. Any signal that arrives at the SPSS other than  $\theta_d$  is considered an interference and shall be nullified, and the nullifying process

will be executed at  $AFN_1$  (Equation (3.19)). For this analysis, the interference signal is set at  $\theta_i = 100^\circ$ . The scanning process continues as long as there is no arrival of a signal from the desired location detected. For a further step, the observation is also made for the SPSS input RP before and after convergence is achieved. Optimizing the weights on the SPSS input elements shall naturally improve the RP of the SPSS from its initial RP. In the next analysis, the SPSS signal electric field strength is studied.

### **3.3.6 SPSS for Signal Electric Field Strength Tested on Multiple DOA**

Previous analysis has successfully demonstrated the performance of the SPSS in detecting and eliminating the desired and undesired signals from specific DOAs. Any signal randomly generated from an unknown source can also be localized by applying this SPSS, provided that the direction of the power apparatus in the substation is pre-identified. Besides that, the SPSS is proven to significantly improve the antenna input RP when the SP-ANN algorithm is introduced. Furthermore, its fast convergence feature yields the ability of the SPSS to transmit and receive a signal within seconds. Thus, this characteristic and feature transformed the SPSS into a cohesive unit as a transceiver for UHF signals detection and localization technique. However, this technique is still insufficient in providing information about the properties of the detected signal. The properties include the signal frequency (in Hertz), peak-time pulse magnitude measured in a real-time domain (in seconds), and space domain (in radian or degree angle). The SPSS aims to detect and localize signals projected from the desired direction and to identify the signal based on the signal properties. Hence, signal Electric Field Strength becomes an important characteristic that enables the properties of the signal to be analyzed later in PART C. Therefore, a further investigation is carried out to verify the signal Electric Field Strength using the SPSS based on the pre-determined DOAs of the signal source. Each DOA provides vital information about the detected

ED\_EMP, represented as an  $E_P$  signal. In this analysis, the observation focuses on the DOA with the most significant signal Electric Field Strength. The magnitude of the signal is observed. The SPSS initial parameters settings remain the same as in the previous analysis. The objective of this analysis is to identify which DOA may potentially give the antenna input the highest magnitude of the radiation Electric Field Strength. Figure 3.15 illustrates the topology of the SPSS placement for  $E_P$  detection from a power transformer. The positions represent the DOA, the angle-based possible placement of the SPSS towards a power transformer.

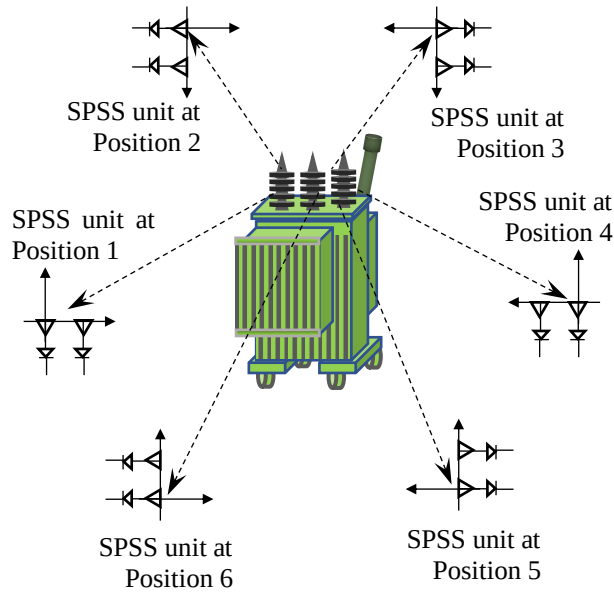


**Figure 3.15:** The topology of the SPSS toward a Power Transformer

In this analysis, the placement of the SPSS is arranged based on the pre-determined DOAs of the desired  $E_P$  signal,  $\theta_d$ , where  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$ . The SPSS input RP corresponding with each DOA is visualized in the polar plot, and the magnitude of the Electric Field Strength is analyzed in the space domain. At the end of the analysis, the signal

Electric Field Strength of different DOAs (refer to Appendix I) provides information for the ideal placement of the SPSS when implemented in an indoor substation.

### 3.3.7 SPSS Total Electric Fields ( $E_T$ ) and Radiated Power Intensity ( $P_i$ )

Previous analysis has efficiently proven the technique of  $E_P$  detection and localization based on the DOA by applying the powerful method of the SP-ANN algorithm. Conceptually, the total electric fields ( $E_T$ ) and the Radiation Power Intensity ( $P_i$ ) also provide another option for signal detection and localization by applying the same method. Therefore, in this analysis, the computation of total electric fields ( $E_T$ ) and its power intensity,  $P_i$ , is carried out based on the multiple ranges of source distance,  $r$ , measured in meters. This analysis aims to determine the relationship between the SPSS receiving distance with the SPSS radiation total electric field strength,  $E_T$ , and its power intensity,  $P_i$ . It is an alternative in providing a better recommendation of the SPSS placement for the efficacy of  $E_P$  localization.

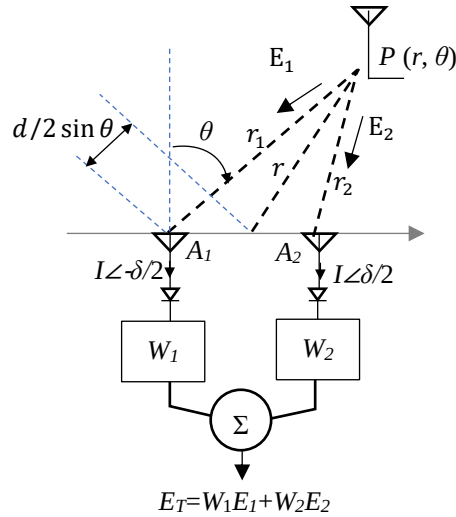


**Figure 3.16:** The SPSS configuration for signal detection

The fundamentals of the 2-element array antenna are elaborated in Chapter 2. Figure 3.16 portrays the SPSS configuration to scan the region around the indoor substation in the plane parallel to the earth's surface. From the configuration, the total Electric fields ( $E_T$ ) from the 2-element array antenna given by  $E_T = W_1E_1 + W_2E_2$  (refer to Equation 3.12) are measured in V/m. Each antenna is assumed to carry a constant current ( $I$ ) along with the detected  $E_P$  signal. In this analysis,  $I = 0.1A$  to simulate the Corona or Arc currents during the formation of Corona discharge (ranging in mA) or Arc discharge (in A). For an  $E_P$  signal occurring at a distance,  $r$  from the apparatus, and at an azimuth angle  $\theta$ , considering the SPSS picks up the  $E_T$  of Equation 3.21 (Hoole, 2001) is given by:

$$E_T = \frac{j\eta kIL}{4\pi} \left[ \frac{e^{-j(kr_1+\delta/2)} \sin \theta_1}{r_1} + \frac{e^{-j(kr_2-\delta/2)} \sin \theta_2}{r_2} \right] \quad \text{Equation 3.21}$$

Here,  $\eta$  denotes the free space intrinsic impedance ( $\eta = 120\pi\Omega$ ),  $L$  is the length of the antenna ( $L = \lambda/2$  and the wavenumber  $k = 2\pi/\lambda$ ),  $r$  is the receiving distance (in meter), and  $I$  (in Ampere) is the current flowing along with the  $E_P$  signal. However, since the  $E_P$  signal is generated at far fields, assuming  $r_1, r_2 \gg d$ ,  $\theta_1 \approx \theta_2 \approx \theta$ , the distances,  $r_1 = r_2 = r$ , therefore, the  $E_T$  at point  $P$  for this analysis is given by Equation 3.22 (Hoole, 2001). This allows the Radiated Power Intensity ( $P_i$ ) measured in  $W/m^2$  to be obtained using Equation 3.23 (Hoole, 2001).

$$E_T = \frac{j\eta kIL e^{-jkr} \sin \theta}{4\pi r} [1 + e^{j(kd \sin \theta + \delta)}] \quad \text{Equation 3.22}$$

$$P_i = \frac{1}{2\eta} |E_T|^2 \quad \text{Equation 3.23}$$

The SP weights,  $W_1$  and  $W_2$ , are determined and trained using the SP-ANN algorithm based on the specific location (DOA) of each apparatus and must be cyclically kept under

observation. The rotating antenna beam captures the maximum  $E_P$  signal in the direction of  $\theta = \theta_d$ , indicating the direction of the  $E_P$ . Finally, a MATLAB program (refer to Appendix I) is executed to visualize the RP of both  $E_T$  and  $P_i$  plotted in the space domain for data collection. The analysis highlights the relationship of the  $E_T$  and  $P_i$  with the Receiving Distance,  $r$ . The results are attached in Appendix I.

### **3.4 Part C: Evaluate the accuracy of the ED\_EMP signal identification using the novel SP-Identifier Technique in waveform-based testing for Corona or Arc EDs samples.**

Part C consists of FOUR (4) analyses to evaluate the performance of the SP-Identifier technique in identifying the ED\_EMP signal detected by the SPSS. The analysis begins with a simulation of an  $E_P$  model representing ED\_EMP tested at multiple DOAs. Next is the analysis to evaluate the similarity of the ED\_EMP waveforms in space and time domains using the DataTip Alignment method. After that, the efficiency of the SP-Identifier technique in identifying the ED\_EMP signal detected by the SPSS is evaluated. Lastly, the performance of signal identification for the SPSS radiation waveform in space and time domains is evaluated.

#### **3.4.1 $E_P$ Model in Representing ED\_EMP Tested at Multiple DOA**

An impulsive noise process commonly occurs in substations due to EDs. The degradation of the electric equipment causes dielectric breakdown and results in the EDs in the form of impulsive noise (Dhara et al., 2020; Hu et al., 2020; Mei et al., 2020; Shan et al., 2011; Tao et al., 2018). The ED usually carries a power frequency sinusoidal current, embedding the ED\_EMP superimposed. This ED\_EMP normally carries the UHF spectrum, including the Corona or Arc discharges. The ED\_EMP is superimposed on the sinusoidal signal at an operating frequency,  $f = 50$  Hz, and the period is taken at  $T = 0.02$ s for the one-

cycle waveform, as displayed in Figure 3.17. The Power frequency sinusoidal signal is defined by Equation 3.24.

$$f(t) = \sin(\omega t) \quad \text{Equation 3.24}$$

In this analysis, the simulation is carried out to conceptualize the ED\_EMP signal generation represented as the  $E_P$  signal model for a frequency of 1 GHz. For this purpose, simulation work uses a Sinc function as the  $E_P$  signal model, and the DOA,  $\theta_d = 45^\circ, 120^\circ, 225^\circ$  and  $300^\circ$  for  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$  are the spatial locations of the  $E_P$  signal occurred. Since the UHF spectrum of the ED\_EMP impulse is the signal captured by the SPSS, the Perceptron is given to process only the UHF impulse in the time domain to detect its presence. The ED\_EMP is represented as an  $E_P$  signal for simulation purposes.

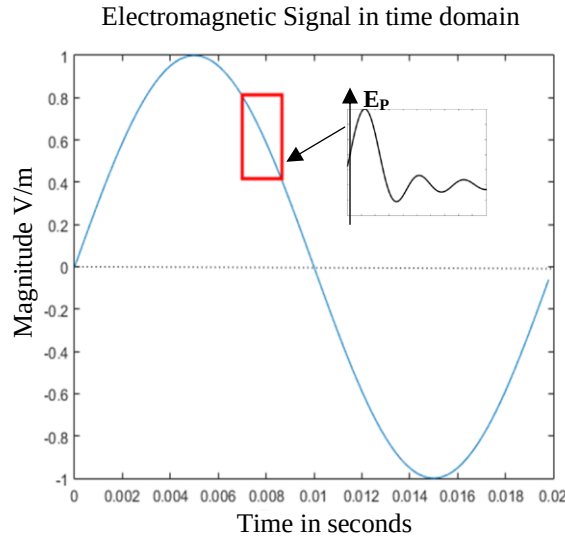


**Figure 3.17:** An ED\_EMP generated in time domain

The SPSS is trained to steer the beamform to scan for the  $E_P$  signal (desired output) from the power apparatus positioned in specific angular positions (DOA) towards which the antenna beam may cyclically rotate to observe ED activities, and this  $E_P$  signal is presented as a Sinc Function in time domain defined by Equation 3.25.

$$E_p(t) = \text{sinc}(\varphi(t) - \varphi_m(t)) \quad \text{Equation 3.25}$$

The SPSS RP of the desired output signal,  $E_p$ , with a series of DOA,  $\varphi_m$  for  $\varphi$ , is between  $0^\circ$  and  $360^\circ$ . In this analysis, the efficiency of the  $E_p$  generation corresponding to the respective DOA is visualized for DOA sampled at  $\varphi_m = 45^\circ, 120^\circ, 270^\circ$  and  $300^\circ$ . Let the ED current radiating  $E_p$  event happens within the boxed region in Figure 3.7, it is a UHF ED phenomenon that lasts over a few nanoseconds. The SPSS is placed respectively to the power transformer at DOA,  $\varphi_m = 45^\circ$ . Hence, the desired output,  $E_p = \text{sinc}(\varphi - \pi/4)$ . This simulation is also carried out for samples frequency 915 MHz and 2.4 GHz, representing the impacts of substation ED impulsive noise on the 915 MHz and 2.4 GHz of ZigBee frequency bands (Jia et al., 2013). The ZigBee model is chosen for this comparison as it utilizes MATLAB DataTip to extract the PD signals and uses a Sinc function to represent the ED signals. The accuracy of signal identification based on the modeled impulsive noise for both SPSS and ZigBee are compared and simulated using MATLAB code (refer to Appendix K), and the results of the generated ED\_EMP RPs are observed and discussed in Chapter 4.

### 3.4.2 Similarity of the ED\_EMP Waveforms in Space and Time Domain

In Section 3.4.1, the information of a signal is retrievable when visualized in the space domain. The analysis seeks the similarity of the  $E_p$  signal observed in the space and time domain. Having the similarity verifies the ability of the received signal to be efficiently analyzed with minimal computational complexity, thus giving another cost-efficient wireless technique for the UHF signal interpretation and identification. Additionally, this analysis implies the DataTip Alignment Method for signal interpretation. Therefore, this analysis

aims to seek the similarity when the ED\_EMP signal is plotted in space-domain and time-domain, yielding insight information for the signal interpretation.

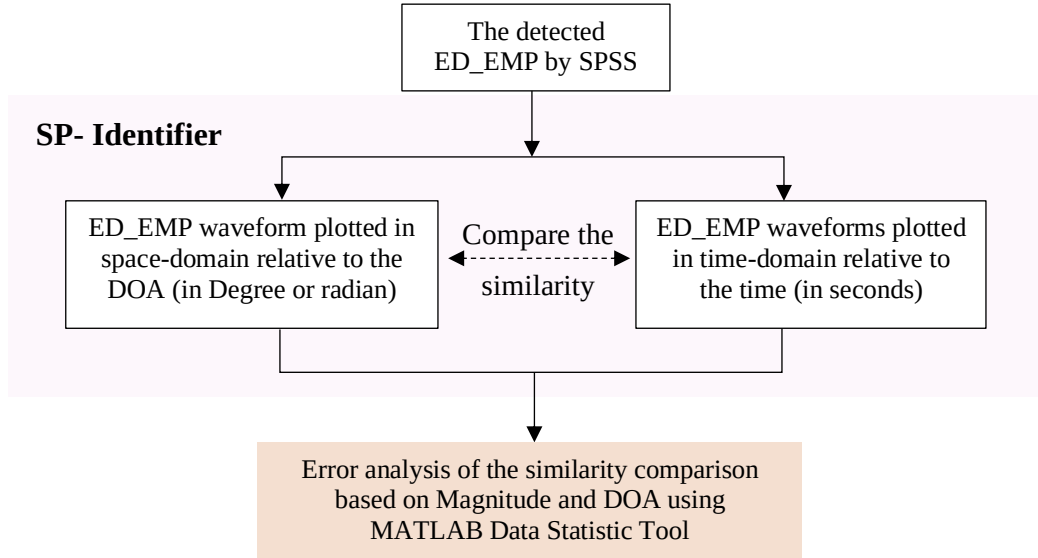


**Figure 3.18:** The framework for the Similarity Comparison for the ED\_EMP

Figure 3.18 displays the framework of the SP-Identifier technique. The simulation begins by adapting the ED\_EMP from Section 3.4.1. Assuming in the event of the ED\_EMP current radiating an  $E_P$ , an impulsive signal occurred at a peak time ( $t_p$ ) of 1 ns, which allows the SPSS to receive a 1 GHz of the  $E_P$  spectrum. A Sinc function representing the ED\_EMP signal is executed for DOAs sampled at  $\theta_d = 45^\circ$  and  $225^\circ$ . In the SP-Identifier technique, the focal point is the magnitude ( $Y$ ) of the waveforms. The  $Y$  value obtained in the space domain becomes the referral point to find the  $Y$  value in the time domain. It defines the similarity of the waveforms in both space and time domains, utilizing the MATLAB Data Statistic Tool to observe the  $Y$  value. The  $Y_S$  represents the magnitude of the waveform observed in the space domain and  $Y_T$  in the time domain. A further case study is the error analysis to verify the significance of the error in this technique at  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$  for a series of

comparisons. This study involves more samples of DOAs,  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$  to obtain the Mean Average Value (MAV) error for overall similarity.

The measurement accuracy comparison is made between  $E_P$  model signals, the Electromyography (EMG) method for musculoskeletal systems (Jali et al., 2015), and the Chemometric toolbox (Erny et al., 2016), all using the MATLAB DataTip Alignment Method for signal feature extraction in the time domain. The advantage of selecting the Sinc function is that the beamform of the Sinc function carries only one maximum peak pointed directly from the desired DOA. Consequently, it simplifies the observation using the MATLAB Data Statistic tool. The difference between the  $Y_S$  and  $Y_T$  defines the absolute error,  $|E|$  of the signal identification. Lastly, the average value of the  $|E|$  is evaluated for the Percentage Error,  $\%E$ , from the series of comparison results. The MATLAB code is attached in Appendix L. The accuracy of the data interpretation between both domains determines the efficiency of this technique. The similarity of the desired output waveforms makes the technique cost-efficient, which demands minimal complexity in the computational works as the spectral line of the ED\_EMP signal can be observed directly from these domains.

### 3.4.3 Efficiency of the SP-Identifier Technique

In the previous analysis, the similarity of the ED\_EMP waveforms obtained in the space and time domains verifies the efficiency for signal identification. Hence, the SP-Identifier Technique is introduced to interpret the SPSS received signal. The framework of the SP-Identifier Technique is displayed in Figure 3.19. This novel technique utilizes the SP-ANN optimized weights and the DOA of the  $E_P$  source, incorporating the DataTip Alignment Method for  $E_P$  signal identification. This analysis aims to evaluate the efficiency

by first investigating the waveforms' similarity and then the error analysis for the significance of the error in signal identification.

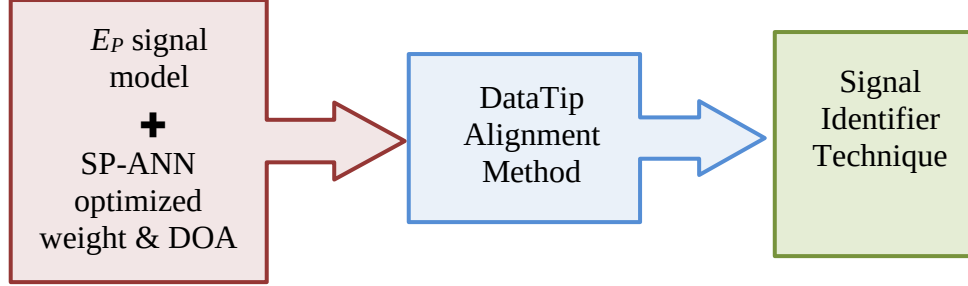


**Figure 3.19:** Framework of SP-Identifier Technique

Adapting the same framework illustrated in Figure 3.19, the block diagram in Figure 3.20 composes the framework of the similarity comparison process for the SPSS radiation waveforms. For the similarity verification process, the same Sinc Function represents the ED\_EMP signal received by the SPSS. The similarity comparison process involves the same desired DOAs of the ED\_EMP signal sampled at  $\theta_d = 45^\circ$  ( $\pi/4$  in radian) and  $225^\circ$  ( $5\pi/4$  in radian). However, the error analysis employs a different method to obtain the value of  $Y_S$  and  $Y_T$ . Previously, the technique utilized the MATLAB Data Statistic Tool to observe the  $|E|$  on the ED\_EMP signal. However, this tool has become inefficient in interpreting the RP of the SPSS. Unlike the ED\_EMP waveform, the SPSS RP displayed a broad beamform. Therefore, the DataTip Alignment Method is applied to obtain the values of  $Y_S$  and  $Y_T$ . First, the  $Y_S$  becomes the referral point. Then, the DataTip is aligned carefully to the nearest Data Vertex of  $Y_S$  to observe for  $Y_T$ .

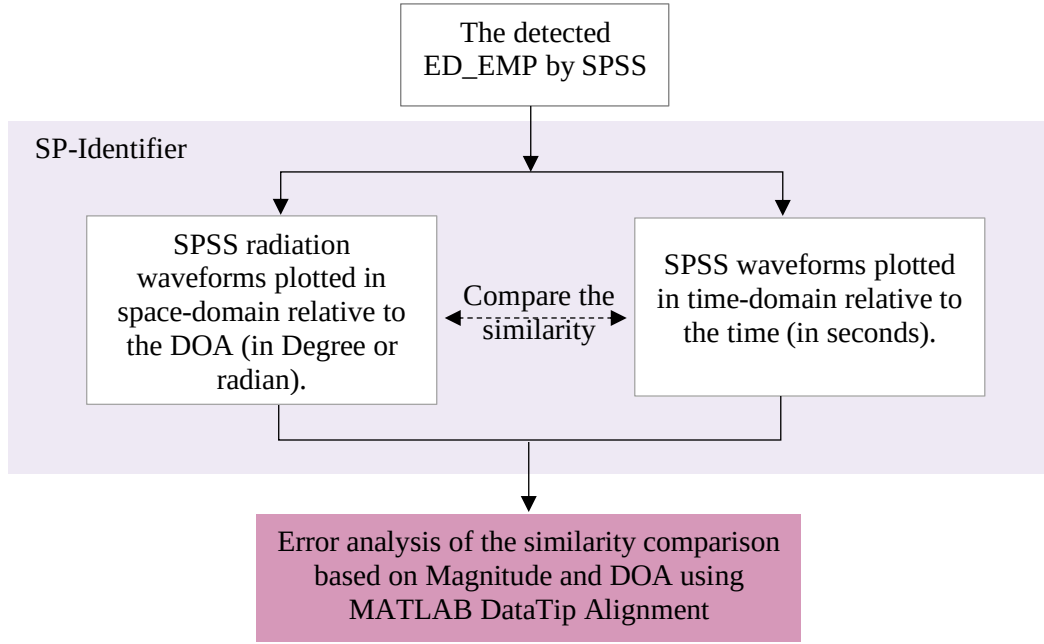


**Figure 3.20:** The framework for the Similarity Comparison for SPSS radiation

Figure 3.21 illustrates the simplified procedure for the SP-Identifier Technique using the DataTip Alignment Method. Lastly, the percentage of error analysis is carried out to determine the efficiency of the SP-Identifier Technique on the SPSS RP by applying the same error analysis in Section 3.4.2. This is to verify the significance of the error in this technique for a series of 20 samples DOA of comparisons at  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$  and localization error is also determined for five computations for each 19 samples at  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$ . The MATLAB code and the results are provided in Appendix M. The SPSS is trained to allow 1 GHz of the ED\_EMP signal from the sampled  $\theta_d$ . The accuracy of the data interpretation between both domains determines the efficiency of this technique, establishing the significance of the SP-Identifier Technique for the SPSS development.

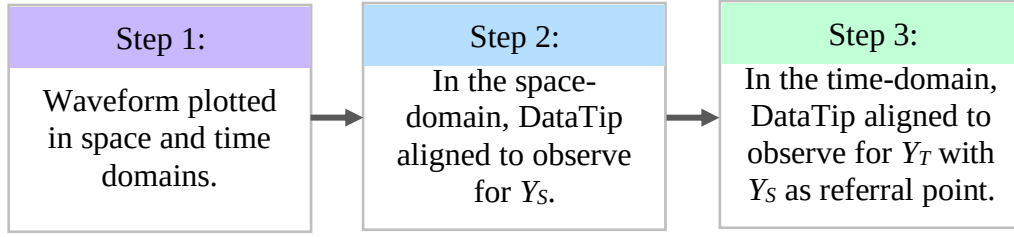


**Figure 3.21:** SP-Identifier Technique using the DataTip Alignment Method

#### 3.4.4 Signal Identification for the SPSS Radiation Waveform

The accuracy in signal identification defines the cohesiveness of the SPSS in the signal monitoring process. This final analysis demonstrates the application of the Signal Identifier Technique to evaluate the overall performance of the SPSS in corresponding to the detected ED\_EMP signal. Rapid degradation in power equipment usually results in an impulsive ED\_EMP occurring within nanoseconds and in the microwave frequency range. The capability of the SPSS to detect up to microwave spectrums depends on the time domain training of the SP-ANN of the SPSS. From reviews, the preferable spectrum range of the ED\_EMP detection lies between 300 MHz to 3 GHz as this range consists of low noise effectual for sensing methods. Figure 3.2 in Section 3.1.1 illustrates the SPSS proportionate to the harmonized ED\_EMP signal from a power transformer at a distance,  $r$  (in meters), in an indoor substation. Assuming the ED\_EMP phenomenon has occurred and generated the  $E_P$  at the period,  $t_{EP}$  lasts in nanoseconds. For this analysis, the  $E_P$  localized source at DOA is fixed at  $\text{DOA} = 45^\circ$  (0.7854 rad), SP-ANN Optimized Weights,  $W_1 = -66.14 + j2.029$  and  $W_2 = 21.31 + j31.21$ . The SPSS Training Frequency,  $F_{SPSS(Train)}$ , is at 2.4 GHz -24 GHz, the  $E_P$  model Frequency  $F_{EP(model)}$  is taken in the range of 300 MHz -3 GHz, and lastly, SPSS Training Frequency  $T_{SPSS(Train)}$  is set at a period of 0.42ns to 0.042ns.

The selection for the  $E_P$  models is in the microwave spectrum. For example, if the  $E_P$  phenomenon happens at  $T_{Ep} = 1$  ns, this allows the SPSS to receive about  $F_{Ep (SPSS)} = 1$  GHz. In this investigation, the significance of the signal identification involves samples of the time domain training period of the SPSS, allowing the sensor to receive sampling frequency,  $E_P$  of 0.5 GHz, 1 GHz, and 2 GHz for the  $E_P$  localized at DOA,  $\varphi_m = 45^\circ$ . These sampling frequencies represent the early formation frequency of Corona or Arcs EDs. An individual simulation is conducted for each sample. Table 3.3 lists the  $E_P$  model,  $E_P$  period,  $T_{Ep}$ , and the SPSS Training Period,  $T_{SPSS}$ .

**Table 3.2:** The  $E_P$  models for the SPSS Detection

| $E_P$ model sampling Signal |               | SPSS Training Period |
|-----------------------------|---------------|----------------------|
| $E_P$ (GHz)                 | $T_{Ep}$ (ns) | $T_{SPSS}$ (ns)      |
| 0.5                         | 2.0           | 16.0                 |
| 1.0                         | 1.0           | 8.0                  |
| 2.0                         | 0.5           | 4.0                  |

Based on Table 3.2, the signal identification involves the feature extraction of the  $E_P$  signal, applying the Signal Identifier to synthesize a single source  $E_P$  model in the waveform-based. The MATLAB coding can be observed in Appendix N. The performance of the SPSS is measured through the accuracy of identification of each  $E_P$  sample. Further investigations are conducted to seek the average accuracy value of localization and identification, which involves 19  $E_P$  samples ranging from 300 MHz to 3 GHz and computed for five readings per sample. All findings are discussed in Chapter 4.

### 3.5 Chapter Summary

This chapter highlights the analysis works in developing the SPSS for the pre-fault monitoring system in an indoor substation. It involves a series of empirical simulations and

evaluations. This chapter begins by elaborating on the framework of the SP-ANN for Smart Sensor formation. The overall framework of methodology consists of THREE (3) main parts: Part A, Part B, and Part C.

Part A represents the first research objective, which is to investigate the most suitable  $N$ -element array antenna as the SPSS model that has a broad radiation beamform and adapts to the changes of the propagation phase. In order to achieve this objective, Part A has included THREE (3) analyses where the results and discussion are elaborated in Chapter 4. In Part A, the first analysis is to analyze Linear Array Antenna RPs for the effect of  $N$ -elements. Here, the array antenna is a linearly arrayed isotropic antenna of equal spacing and amplitude. This analysis aims to observe every AF and antenna input RP, selecting the most acceptable  $N$ -element to fulfill the SPSS characteristics. The analysis emphasizes the RP of every sampled array length at  $N = 2, 3, 4, 6, 8, 10$ , and the significance of each array element is observed. In addition, a simulation is also carried out to evaluate the sensitivity and the ability of the array antenna as a sensor adapted to the changes of the propagation phase,  $\beta$  as the induced signal. The second analysis is a Linear Array Antenna RP for the inter-element spacing effect. This analysis aims to obtain a directive and broadside RP observed from the array antenna input element,  $f(\varphi)$ . The analysis was executed for the antenna array length of  $N = 2$ , at element spacing,  $d=0.125\lambda$ ,  $0.25\lambda$ ,  $0.5\lambda$ , and  $1.0\lambda$ . This work is carried out to validate the significant wavelength for the SPSS model. The third analysis is to analyze the SP-ANN effect on the  $N$ -element array antenna. This analysis illustrates the formation of a Smart Sensor (SS) from the Linear Array Antenna, integrating the SP-ANN. It focuses on the effect of the perceptron complex weights when incorporated with the antenna input element. This scheme aims to improve the quality of the SS radiation as well as the sensing coverage.

Part B reflects the second research objective, which is to develop a novel SPSS utilizing the SP-ANN Algorithm for ED\_EMP signal detection and localization. Part B consists of SEVEN (7) analyses, where the results and discussion are explained in Chapter 4. The first analysis is the development of the SP-ANN algorithm for weight optimization tested  $N$ -element array antenna. This analysis focuses on developing the SP Algorithm employing the ANN as the soft-computing technique to train the perceptron. Specifically, this SP-ANN algorithm is constructed to optimize the complex weight, thus allowing the sensor to become cohesively smart. The second analysis is the SPSS formation involving the  $N$ -element array arrangement. Here, a 2-element array antenna is selected, making the array arrangement selection less complicated. However, the analysis is carried out to observe the effect of the geometrical array arrangement on the SPSS input radiation by taking the samples of the array length at  $N = 2, 3, 4, 6$ , and  $8$ . In the end, the efficacy of the SP-ANN algorithm is evaluated for every sample input RP plotted in polar form. The next analysis is the SP-ANN hyperparameters for the fast convergence effect. In this analysis, the SP-ANN hyperparameters are identified as the Learning rate  $\eta$  and the Bias,  $b$ , both varied in the range between  $0.001$  to  $1.000$  and analyzed individually for the array length sampled at  $N = 2, 3, 4, 6$ , and  $8$ . This analysis seeks the convergence status of the SPSS at the identified DOAs for each sampled  $N$ -element. The fourth analysis is the simultaneous signal detection at multiple DOA for a 2-element Array Antenna. This analysis aims to investigate the ability of a 2-element array antenna to simultaneously nullify the interference signal and maximize the desired signal at the desired DOA. The 2-element array antenna is integrated with SP-ANN to form the SA model. Here, the values of perceptron weights,  $W_1$  and  $W_2$ , are manually varied to observe the ability of the SA model to simultaneously nullify the interference signal and maximize the desired signal at the desired DOA. The fifth analysis is the SP-ANN

algorithm for smart simultaneous signal detection. This is the novel design in this research. The analysis is performed to observe the performance of the SA model when integrated with the SP Algorithm, forming the SPSS unit. Here, the values of perceptron weights,  $W_1$  and  $W_2$ , are automatically and smartly optimized by the SP algorithm, seeking the ability of the SA model to simultaneously nullify the interference signal and maximize the desired signal at the desired DOA. The sixth analysis is SPSS for signal Electric Field Strength tested on multiple DOAs. The objective of this analysis is to identify which DOA may potentially give the antenna input the highest magnitude of the radiation Electric Field Strength. The signal Electric Field Strength of different DOAs provides information for the ideal placement of the SPSS when implemented in an indoor substation. The last analysis of Part B is SPSS Total Electric Fields ( $E_T$ ) and Radiated Power Intensity ( $P_i$ ). The analysis highlights the relationship of the  $E_T$  and  $P_i$  with the Receiving Distance,  $r$ . In this analysis, the computation of total electric fields ( $E_T$ ) and its power intensity,  $P_i$ , is carried out based on the multiple ranges of source distance,  $r$ , measured in meters. This analysis aims to determine the relationship between the SPSS receiving distance with the SPSS radiation total electric field strength,  $E_T$ , and its power intensity,  $P_i$ . It is an alternative in providing a better recommendation of the SPSS placement for the efficacy of  $E_P$  localization. The evaluation is carried out to observe the effect of the  $E_T$  and  $P_i$  when a signal is induced at a fixed DOA,  $\theta_d = 45^\circ$  in different ranges of the  $E_P$  distance,  $r$ .

Part C demonstrates the third research objective, which is to evaluate the accuracy of the ED\_EMP signal identification using the novel SP-Identifier Technique in waveform-based testing for Corona or Arc EDs samples. Part C consists of FOUR (4) analyses, the results and discussion of which are also explained in Chapter 4. The first analysis is the  $E_P$  model representing ED\_EMP tested at multiple DOAs. In this analysis, the simulation is

carried out to conceptualize the ED\_EMP signal generation represented as the  $E_P$  signal model. The aim of this analysis is to enable the retrieval of information from the  $E_P$  model when it is visualized in the space domain. For this purpose, simulation work uses a Sinc function representing the  $E_P$  signal model, and the DOA,  $\theta_d = 45^\circ, 120^\circ, 225^\circ$  and  $300^\circ$  for  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$  are the spatial locations of the  $E_P$  signal occurred. The results of the generated ED\_EMP RPs are observed and plotted in the space domain. The second analysis of Part C is the Similarity of the ED\_EMP waveforms in the space and time domain. This analysis aims to seek the similarity when the ED\_EMP signal is plotted in space-domain and time-domain, yielding insight information for the signal interpretation. In this analysis, the ED\_EMP waveform is firstly plotted in the space domain relative to the DOA (in Degree or radian). Secondly, the waveform is plotted in the time domain relative to the time (in seconds). Then, the similarity comparison error between these two domains is evaluated using MATLAB Data Statistic Tool. The third analysis is the efficiency of the SP-Identifier Technique. Here, the SP-Identifier Technique is introduced to interpret the SPSS received signal. This novel technique utilizes the SP-ANN optimized weights and the DOA of the  $E_P$  source, incorporating the DataTip Alignment Method for  $E_P$  signal identification. This analysis aims to evaluate the efficiency by first investigating the waveform similarity and then the error analysis for the significance of the error in signal identification. The accuracy of the data interpretation between both domains determines the efficiency of this technique, establishing the significance of the SP-Identifier technique for the SPSS development. The last analysis in Part C is Signal identification for the SPSS radiation waveform. This analysis demonstrates the application of the SP-Identifier technique to evaluate the performance of the SPSS corresponding to the detected ED\_EMP signal. The signal identification employs the SP-Identifier technique to perform the single-source ED\_EMP signal feature extraction,

hence identifying the signal for its frequency spectrum. This technique provides less calculation, and data can be directly retrieved from the waveforms illustrated in the space and time domains. This analysis is the final analysis to evaluate the performance of the SPSS in ED\_EMP detection and identification for the pre-monitoring system.

## CHAPTER 4

### RESULTS AND DISCUSSION

#### 4.1 Overview

This chapter consecutively discloses the findings of all the investigations and analyses elaborated in Chapter 3. The results and discussion are divided into THREE (3) parts to accomplish the pre-fault monitoring system. The discussion begins with part A, which investigates the most suitable  $N$ -element array antenna, the Single Perceptron Smart Sensor (SPSS) model, which has broad radiation and adapts to the changes in the propagation phase. The discussion goes on to part B, which focuses on developing a novel SPSS utilizing the Single Perceptron-Artificial Neural Network (SP-ANN) Algorithm for Electric Discharge Electromagnetic Impulse (ED\_EMP) signal detection and localization. Lastly, in part C, the discussion focuses on the performance of the novel SP-Identifier technique for ED\_EMP signal identification using waveform-based testing for Corona or Arc Electric Discharges (EDs) samples. All results and observations are discussed in Chapter 4, and the conclusion is made in Chapter 5. Every part is then summarized at the end of the chapter, and some findings are attached in the appendices.

#### 4.2 **Part A: Investigate the most suitable $N$ -element array antenna as the SPSS model which has broad radiation and can adapt to the changes of $\beta$ .**

Part A consists of THREE (3) analyses. The first one is the analysis of the Linear Array Antenna radiation pattern (RP) for the  $N$ -elements effect. The aim is to observe the RP of every array length, select the most acceptable array length to fulfill the characteristics required for the SPSS model and observe the sensitivity of the beamform when a delay signal  $\beta$  induced to the propagation phase. The second part is the analysis of the inter-element

spacing effect on the Linear Array Antenna. The aim is to verify the effect of various element spacing for the SPSS model. The third one is the analysis of the SP-ANN effect on the  $N$ -element array antenna. This analysis aims to observe the effect of SP-ANN on the  $N$ -element array when a property of the perceptron, a complex weight ( $W$ ), is introduced to an input element,  $f(\varphi)$ . The outcome of every analysis is discussed subsequently.

#### 4.2.1 Analysis of Linear Array Antenna for $N$ - elements Effect

Having a Linear Array Antenna selected as an Ultra-High Frequency (UHF) sensor to form the SPSS model, it is crucial to verify its properties, particularly the RP. The analysis begins by varying the array length of the antenna to evaluate the RP. Here, the number of an array element ( $N$ ) denotes the array length. This analysis aims to observe the RP of every array length, select the most acceptable array length to obtain a strong beamwidth and observe the RP from the Array Factor (AF) and the antenna input element,  $f(\varphi)$ . In addition, this analysis is also carried out to observe the sensitivity of the beamform when a delay signal  $\beta$  induced to the propagation phase,  $\varphi$ , so that  $\varphi = kd \cos \theta + \beta$ . This signal represents a specific direction of the Electromagnetic (EM) radiation from a power apparatus in an indoor substation. A MATLAB program is employed to visualize the RP of AF and the input element,  $f(\varphi)$ , in a polar plot. In this analysis, six array lengths sampled at  $N = 2, 3, 4, 6, 8$ , and 10 are executed individually. Figure 4.1 depicts the RPs of the samples executed for the AF. As observed, at  $N = 2$ , the array RP displayed a strong directive broadside beamform at an amplitude of 1.0. At  $N = 3$ , the sidelobe starts to develop despite the strong directive beamform shown.

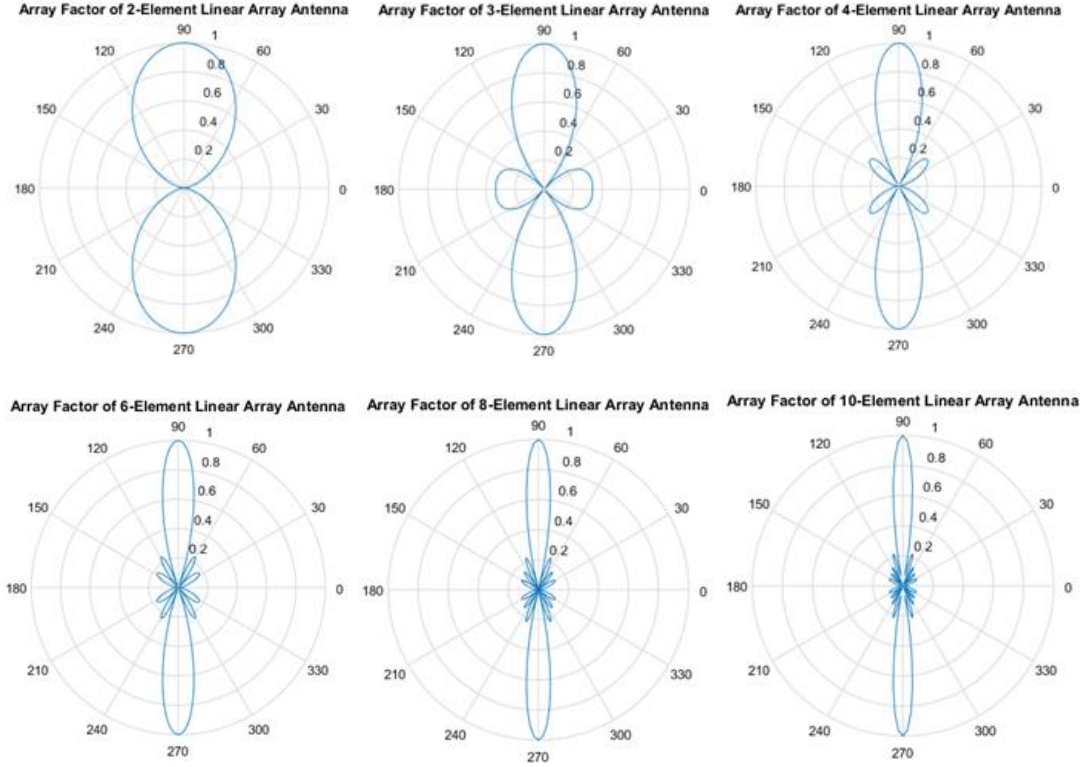


**Figure 4.1:** The AF radiation patterns with the varying array lengths

A further investigation is carried out to evaluate the outputs of more  $N$ , wherefore the  $N$ -element is repetitively increased following the samples for  $N = 4, 6, 8$ , and  $10$ . In all cases, the RPs display the beamform at the same magnitude of  $1.0$ . As the  $N$  increases, the main lobes begin to narrow down and become more directive, and more side lobes are developed. Figure 4.2 displays the RPs of the input element,  $f(\varphi)$ . It can be observed that both the AF and the  $f(\varphi)$  execution have displayed a similar RP for each sample. However, as observed in

Figure 4.2, at  $N = 2$ , the magnitude increases to  $2$ , followed by  $N = 3$ . The increment of the  $N$  has proportionally increased the magnitude of the radiation. Since PD emits radiation over a wide range of frequencies, it is necessary to use antennas with bandwidths

wide enough to optimize the measurement (Robles et al., 2016). Therefore, the 2-element Linear Array Antenna is most suitable for the SPSS model. High directivity and relatively wide beamform are desirable for long-distance or far-field detection (Abimbola et al., 2016). Furthermore, it must be able to detect a UHF spectrum and adapt to any induced signal during cyclical scanning. In practice, any abnormal electrical activity may occur in a specific direction from a power apparatus. Thus, this direction is represented by the induced signal,  $\beta$ . The following simulation is carried out to evaluate the sensitivity and the ability of the sensor to adapt to the changes in  $\beta$ . Since the AF and  $f(\varphi)$  execution have displayed a similar RP, both equations can be used to simulate the effect of the induced  $\beta$ .

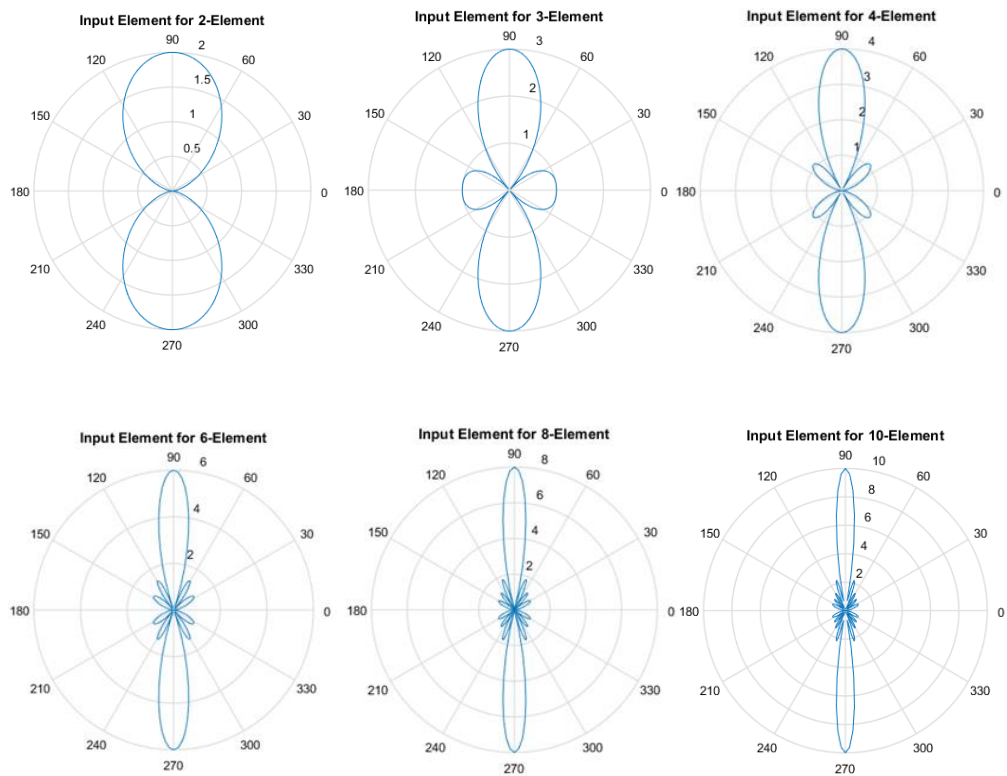


**Figure 4.2:** The  $f(\varphi)$  radiation patterns of the 2, 3, 4, 6, 8 and 10-element

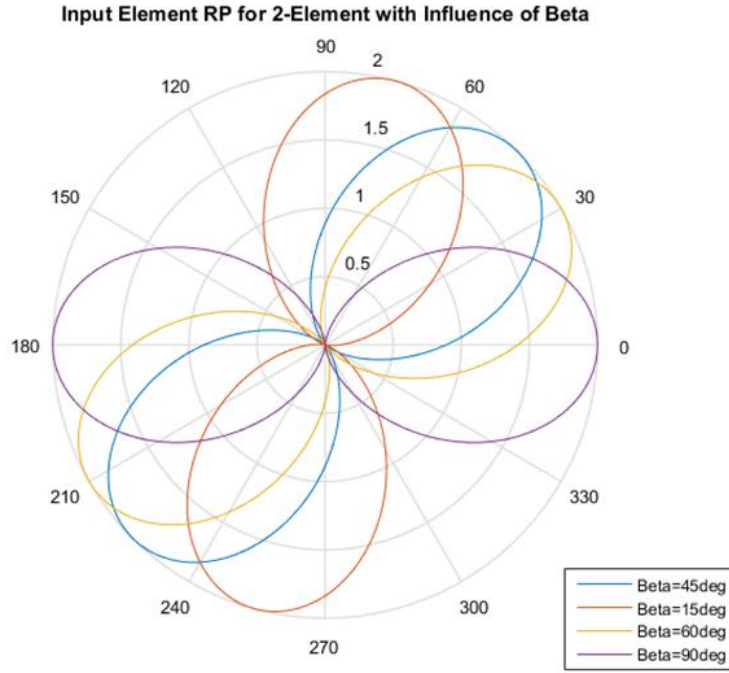


**Figure 4.3:** The  $f(\varphi)$  radiation patterns at  $\beta=15^\circ$ ,  $45^\circ$ ,  $65^\circ$  and  $90^\circ$

Figure 4.3 depicts the RPs of the  $f(\varphi)$  for  $N = 2$  tested at  $\beta = 15^\circ$ ,  $45^\circ$ ,  $65^\circ$  and  $90^\circ$ . As observed, the RP has adapted and is sensitive to the changes in  $\beta$ . By tuning the propagation phase,  $\varphi$ , it has been verified that the Linear Array Antenna can adapt to the changes of  $\beta$ .

#### 4.2.2 Analysis of Inter-Element Spacing Effect on Linear Array Antenna

In an array antenna, despite the array length, the array configuration of  $f(\varphi)$  can directly influence the radiation quality, especially the inter-element spacing,  $d$ . In some cases, inter-element spacing is kept to half a wavelength to the grating lobes effect (Mandal et al., 2010, 2015; Sallam et al., 2020), and the spacing between elements directly affects the beamwidth, the number of side lobes and fewer side lobes resulting to less interference (Slimani et al., 2017). Therefore, next is an investigation to verify the effect of various element spacing  $d = 0.125\lambda$ ,  $0.25\lambda$ ,  $0.5\lambda$ , and  $1.0\lambda$  on the array length of  $N = 2$ .

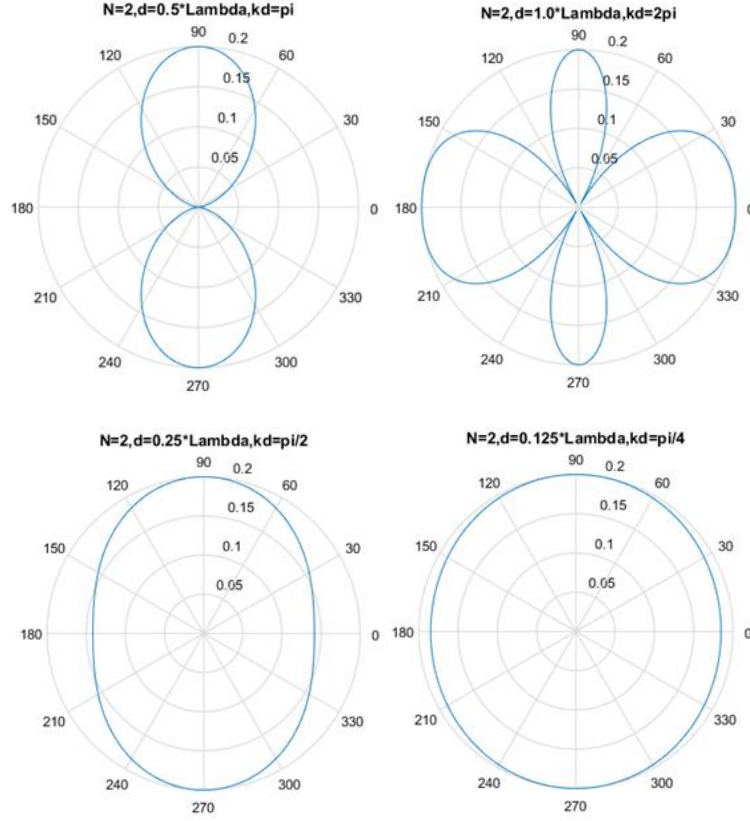


**Figure 4.4:** The radiation patterns at samples of  $d$  for the  $N=2$

Figure 4.4 depicts the RPs of the  $N = 2$  at the sampled  $d$ . As observed, the  $d = 0.5\lambda$  produces a strong broadside RP compared to other  $d$  samples. At  $d = 1.0\lambda$ , the high level of side lobes takes over the main lobe, thus causing the grating lobes effect to the radiation. Meanwhile, when the setting of  $d$  at  $d = 0.125\lambda$  and  $d = 0.25\lambda$ , the mutual coupling becomes significant, resulting in radiation almost equally radiating in all directions, thus lowering the directivity. Therefore, the element spacing  $d = 0.5\lambda$  is the most significant for the SPSS model as it gives a strong beamwidth with no side lobes to interfere the signal received.

#### 4.2.3 Analysis of the SP-ANN Effect on the $N$ -element Array Antenna

The next analysis is carried out for the  $N$ -element array antenna integrated with an SP-ANN. Figure 3.8 in Section 3.3.4 is referred to, and the total electric field,  $E_T$  measured

in V/m, is considered, representing the unnormalized RP for each  $N$ -element sampled in this analysis. This analysis reveals the effect of SP-ANN on the  $N$ -element array when a property of the perceptron, a complex weight ( $W$ ), is introduced to an input element,  $f(\varphi)$ . The weights are varied manually to the  $f(\varphi)$  equation. The radiation of each  $N$ -element array length is presented in unnormalized polar plots to observe the effect of the perceptron weights on the array antenna RP.

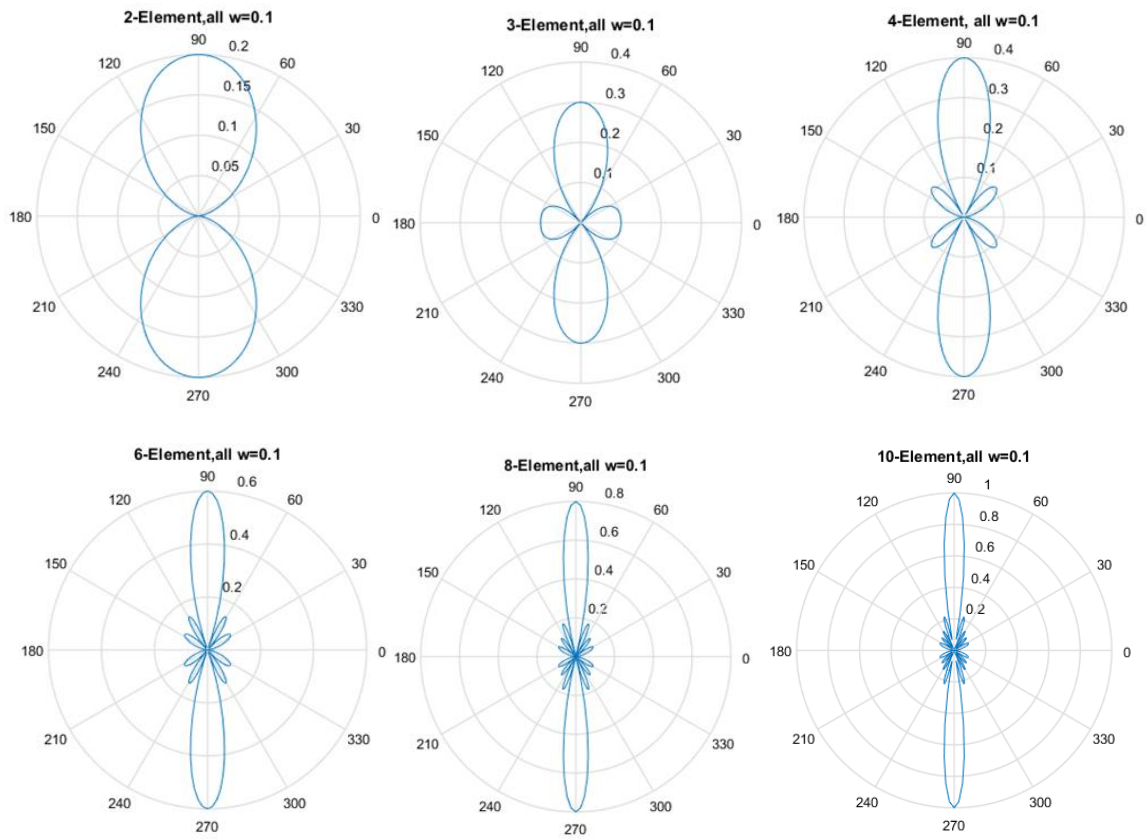


**Figure 4.5:** The  $f(\varphi)$  patterns of  $N$ -element at all initial  $W=0.1+j0$

Figure 4.5 illustrates the unnormalized input element,  $f(\varphi)$  RPs of the  $N$ -element array antenna at the complex initial weights,  $W = 0.1+j0$ . As observed, the RPs are similar to those in Figure 4.2 (in Section 4.2.1).

However, the maximum amplitude is decreased to a magnitude of 0.2 V/m for  $N = 2$  if compared to the same array length obtained, which is 2.0 V/m in Figure 4.2. This is due to the weights being multiplied by the input element equation (refer to Equation (3.4)), making the total input element an amplitude-weighting radiation pattern. For  $N = 3$ , the amplitude is at 0.3, and for  $N = 4, 6, 8$ , and 10, the amplitudes (in V/m) are at 0.4, 0.6, 0.8, and 1.0, respectively. When the  $N$  increases, the main lobe becomes narrower with more sidelobes developed, and the amplitude also varies proportionally to the increment of each  $N$ . This is due to the changes in the weights multiplied by the input element properties as derived in Equation (3.4) (in Section 3.2.3). Further investigation is conducted for new weights set to  $W = 2.0+j0$ .

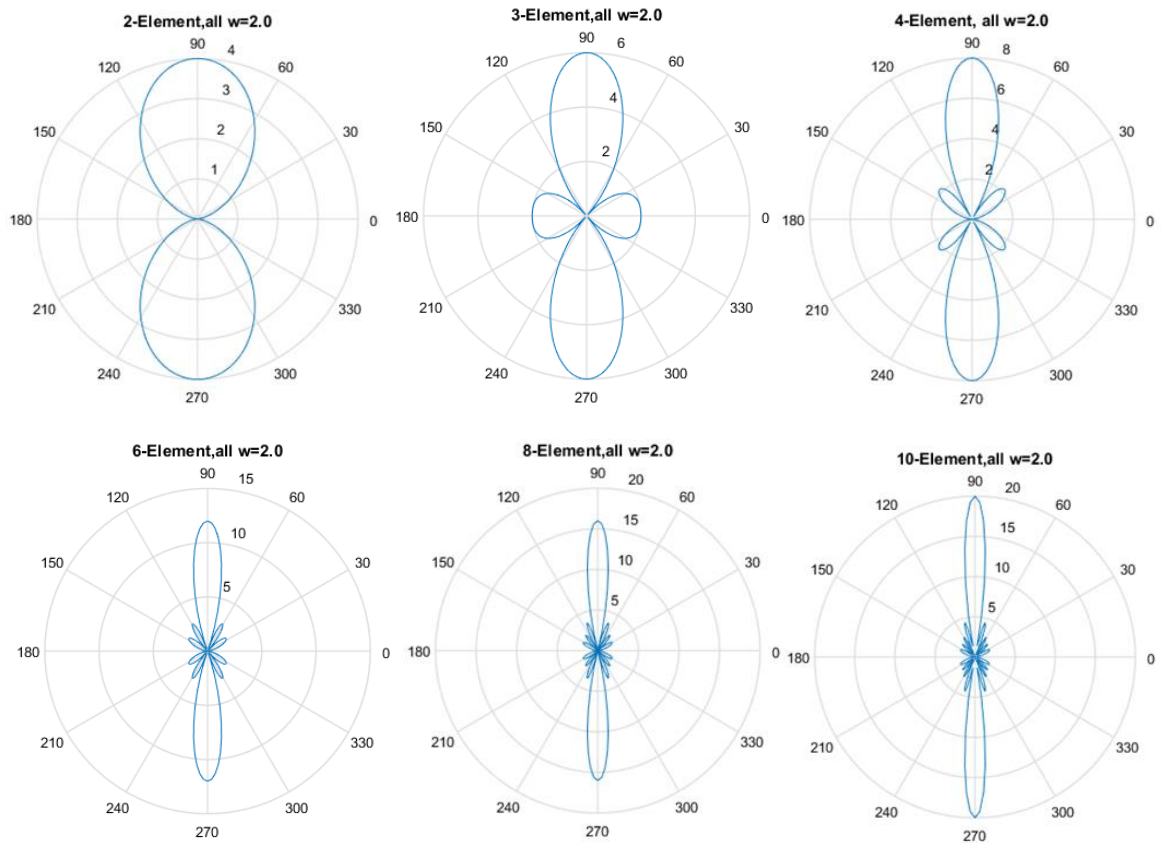


**Figure 4.6:** The  $f(\varphi)$  radiation patterns of  $N$ -element at all initial  $W=2.0+j0$

Figure 4.6 illustrates the  $f(\varphi)$  RPs corresponding to the new weights. As observed, for  $N = 2$ , the RP is unchanged, but the amplitude has increased to maximum magnitude = 4. For  $N = 3$ , the magnitude of the amplitude = 6, and for  $N = 4, 6, 8$ , and  $10$ , the magnitudes of the amplitudes are 8, 12, 16, and 20, respectively. From these findings, the weights of a perceptron have significantly affected the RPs of the  $N$ -element arrays. In conclusion, when the SP-ANN is integrated with a Linear Array Antenna, it changes the radiation quality of the input element,  $f(\varphi)$ . The amplitude of the  $f(\varphi)$  has significantly increased following the increment of the perceptron weights. When the weights of the perceptron increase, the vector length of the amplitude and phase excitation of all antenna elements also increase (Zhang et al., 2022). This finding has opened another opportunity to improve the sensing coverage by auto-varying the perceptron weights. In the upcoming analysis, an Artificial Neural Network (ANN)-based weight optimization training algorithm is developed to train the perceptron weight automatically and smartly. From the three analyses, it can be concluded that this investigation has successfully exhibited the most suitable  $N = 2$  array antenna as the SPSS model, which has broad radiation and can adapt to the changes of  $\beta$  when induced to the propagation phase.

#### **4.3 Part B: Develop a novel SPSS, utilizing the SP-ANN Algorithm for ED\_EMP signal detection and localization.**

Part B consists of SEVEN (7) analysis. The outcomes of every analysis are discussed by section accordingly. It begins with (i) The analysis of the SP-ANN algorithm for weight optimization. Next is (ii) The analysis to observe the SPSS formation involves an  $N$ -element array arrangement. Then, (iii) The analysis of SP-ANN hyperparameters for the fast convergence effect. Next is (iv) The analysis involving the simultaneous signal detection at multiple DOA for a 2-element array antenna. The analysis continues to (v) The analysis of

the SP-ANN algorithm for simultaneous signal detection, (vi) The analysis of the SPSS for signal electric field strength was tested on multiple DOAs, and lastly, (vii) The analysis of the SPSS for the total electric fields ( $E_T$ ) and radiated power intensity ( $P_i$ ) at a fixed DOA with multiple ranges of signal distance,  $r$  (in meter). Some of the results are attached in the appendix section.

#### 4.3.1 Analysis of the SP-ANN Algorithm for Weight Optimization

Machine learning (ML) techniques have been extensively explored and utilized in antenna optimization over the past years. Through training, ML may learn new abilities using simulated antenna data and subsequently speed up the entire antenna optimization (Wu et al., 2020). ANN became available to the Electromagnetic (EM) sector as one of the most popular ML techniques (El Misilmani et al., 2020). This analysis focuses on developing an ANN-based weight optimization algorithm called the SP-ANN algorithm. Integrating this algorithm with a Linear Array Antenna allows the antenna to become cohesively smart, providing a new smart method for signal detection and localization. Considering the 2-element design in Figure 3.8 (in section 3.3.4) for the Total Electric Field,  $E_T$  representing the final input,  $f(\varphi)$ , the computational work is carried out to evaluate algorithm performance, using the same samples of  $N$ -element at  $N = 2, 3, 4, 6, 8$  and  $10$  and induced delay angle,  $\beta = 45^\circ$ . Figure 4.7 depicts the unnormalized  $E_T, f(\varphi)$  RPs of the samples  $N=2, 3, 4, 6$ , and  $10$  at optimum weights. The SP-ANN algorithm has optimized the complex weight within seconds of the training until the process converges. As observed, the  $f(\varphi)$  RPs plotted differed from the outcomes of the same samples obtained in Section 4.2.3. This is due to the delay angle,  $\beta$ , induced by the propagation phase,  $\varphi$ . Recalling  $\beta$  is the specific desired direction to represent the real  $E_P$  picked up by the antenna.

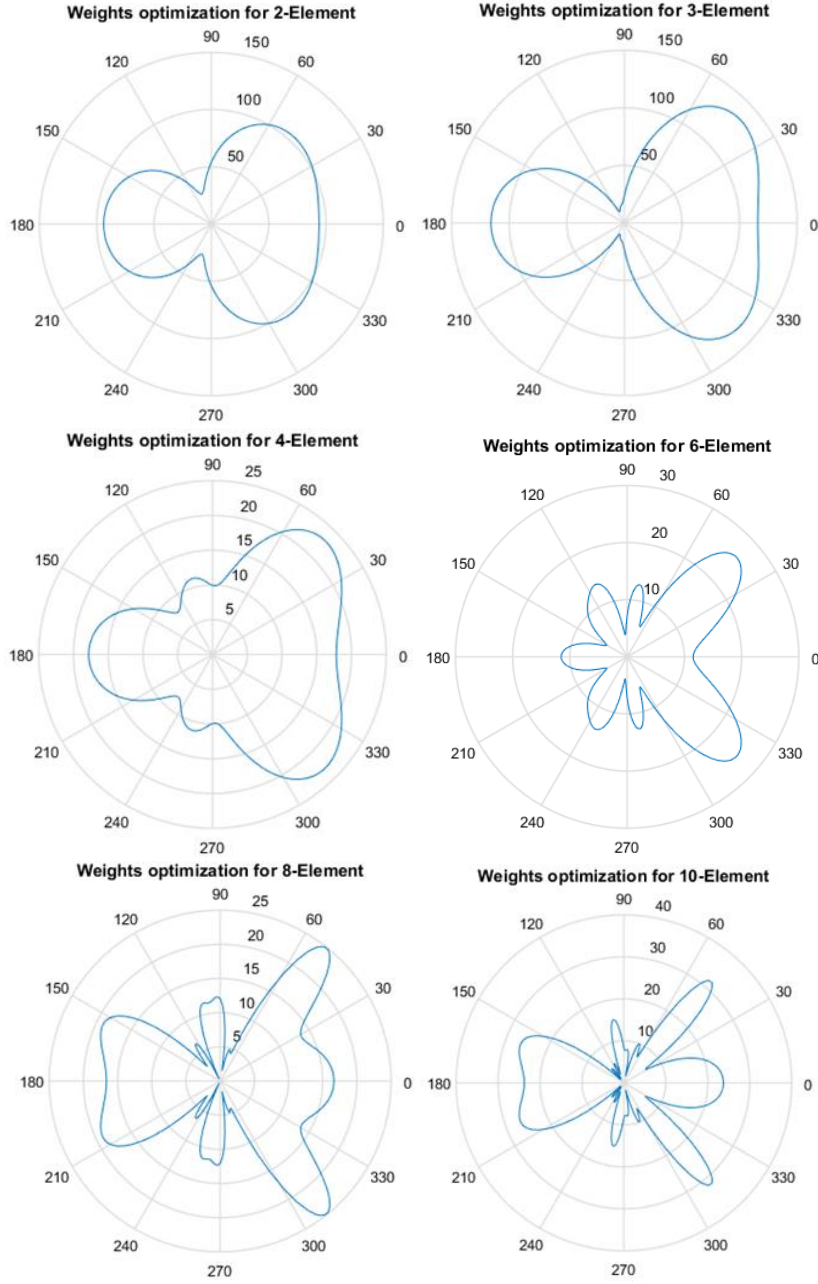


**Figure 4.7:** The  $f(\varphi)$  radiation patterns of  $N$ -element at the optimized weight

The SP-ANN Algorithm generates a final value to equalize the desired output. When the absolute error ( $\Delta$ ) deviation occurs, the algorithm updates the weights based on the  $\Delta$ . It aligns the input ( $E_1$  and  $E_2$ ) of each array antenna to match the desired output of the

perceptron. After convergence, the radiation is maximized towards the desired direction,  $\beta = 45^\circ$ . The coverage of the radiation has responded to the induced  $\beta = 45^\circ$ . As observed, this algorithm responded sufficiently at lower array lengths such as  $N = 2, 3$ , and 4-element. As the  $N$ -element increased, more sidelobes developed, as indicated in the  $N = 6, 8$ , and 10. From the initial weights,  $W = 0.1+j0$  (in Figure 4.5 for  $N=2$ ), the final magnitude of  $E_T = 0.089$  V/m is observed at  $\beta = 45^\circ$ . After optimization, the new weights become  $W_1 = -66.11+j2.029$  and  $W_2 = 21.31-j32.21$  (in Figure 4.7 for  $N=2$ ), the magnitude of  $f(\varphi) = 104.7$  V/m at  $\beta = 45^\circ$ . As the SP-ANN algorithm converged, the radiation amplitude naturally amplified with a wide broadside band due to the multiplication of the  $W$  to the input element of  $f(\varphi)$ . The RPs for  $N = 2$  and  $N = 3$  displayed the highest amplitude. However, the amplitudes are lower at higher array lengths of  $N = 4, 6, 8$ , and 10. As observed, the SP-ANN algorithm is most suitable for lower array lengths. All the initial weight settings for the algorithm are at  $W = 0.1+ j0.1$  and applied to all array length samples, and the difference between initial weights and the optimized weights are shown in Appendix D. In conclusion, the SP-ANN algorithm has optimized the perceptron complex weights in a short training period of seconds to achieve early stopping convergence. This early stopping reduces the complexity of the computational method, thus reducing the use of memory (Hamdi et al., 2016a). From the finding, the algorithm works significantly with a lower array length at optimum perceptron weights, while a higher array length needs a Multilayer Perceptron (MLP) scheme. The final finding for  $N = 2$  is that the optimum perceptron weights are  $W_1 = -66.11+j2.029$  and  $W_2 = 21.31- j32.21$ . These weights became the fixed parameters in this research and were applied to other related analyses for SPSS modeling.

### 4.3.2 Analysis of the SPSS Formation Involving $N$ -element Array Arrangement

The geometrical arrangement of a Linear Array Antenna has to be properly selected, as this arrangement affects the antenna characteristics (Reddy et al., 2013). The geometrical arrangement is also related to the configuration of an antenna (Liu et al., 2017). Arranging the array in the right dimensional structure of arrays can reduce the side lobes and produce good radiation characteristics (Lakshmi et al., 2015; Shaikh et al., 2019). To justify this issue, an analysis is conducted to verify the effect of the geometrical arrangement of the  $N$ -elements array antenna. The aim of this analysis is to verify that the array arrangement of  $N = 2$  selected in part A has a high amplitude with broadside beamform for the SPSS model.

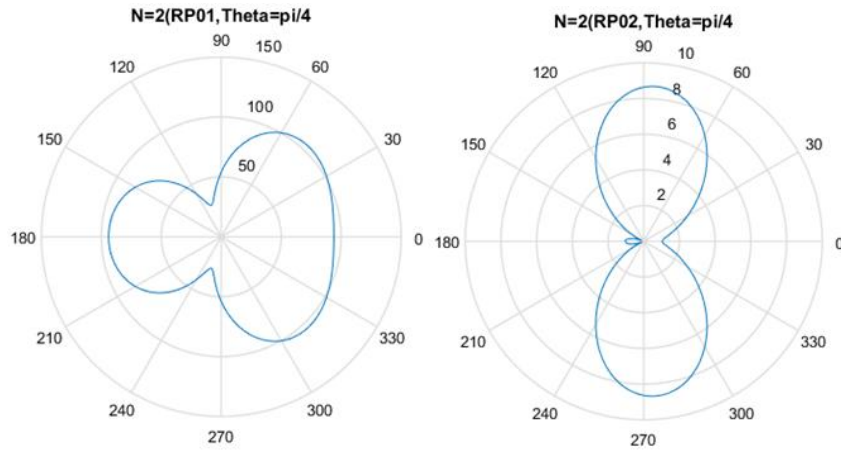


**Figure 4.8:** The  $N=2$  for RP01 and RP02 at  $\theta_d = 45^\circ$

The results are illustrated in Figure 4.8 through Figure 4.12. The  $f(\varphi)$  RP is plotted in polar form for every sampled array length at  $N = 2, 3, 4, 6$ , and  $8$ . The array arrangement is randomly selected, referring to the array length. Generally, the array geometrical arrangement takes place in the preference coordinate hyperplanes. In this analysis, the geometrical arrangement takes place at the  $z$ -axis to ensure the placement of the SPSS is

parallel to the ground when mounted on the wall. A delay signal at DOA,  $\theta_d = 45^\circ$ , is induced to the SPSS so that the RP of  $f(\varphi)$  focuses on the  $\theta_d$ . Figure 4.8 represents the RP of  $f(\varphi)$  of two possible arrangements for  $N = 2$ . The  $N = 2RP01$  is the RP of  $f(\varphi)$  for the first array arrangement, and the  $N = 2RP02$  denotes the second array arrangement. As observed, in the first pattern,  $N = 2RP01$  covers the  $\theta_d$  significantly with a higher amplitude with a broadside beamform, while  $N = 2RP02$  suggests a lower amplitude with a directive beamform. However, the increment of the element offers more possibilities for arrangement. Figure 4.9 represents the RP of  $f(\varphi)$  of three possible arrangements for  $N = 3$  projected to the  $\theta_d$ .  $N = 3RP01$ ,  $N = 3RP02$  and  $N = 3RP03$ .

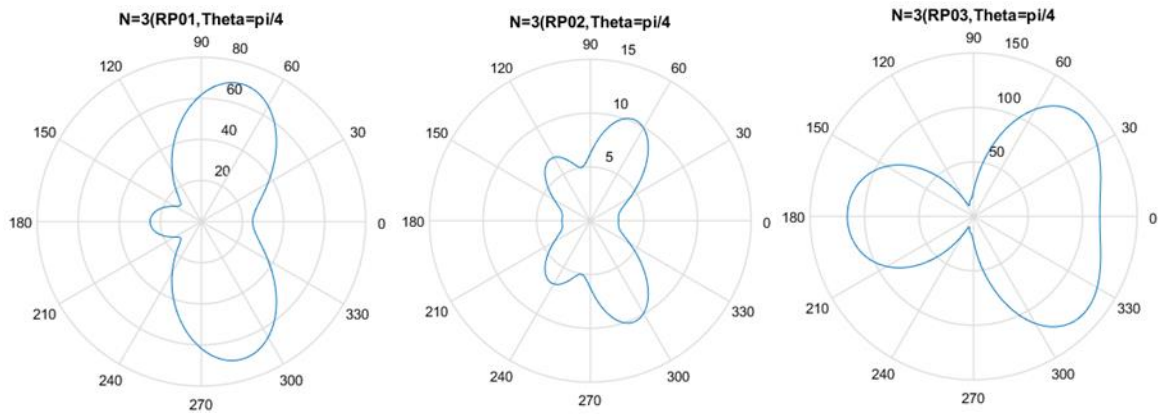


**Figure 4.9:** The  $N=3$  for RP01, RP02 and RP03 at  $\theta_d = 45^\circ$

As observed,  $N = 3RP03$  exhibits the most desirable RP with the highest amplitude compared to  $N = 3RP01$  and  $N = 3RP02$ . The pattern of  $N = 3RP03$  is comparably similar to  $N = 2RP01$  in Figure 4.8 as it covers the  $\theta_d$  significantly.

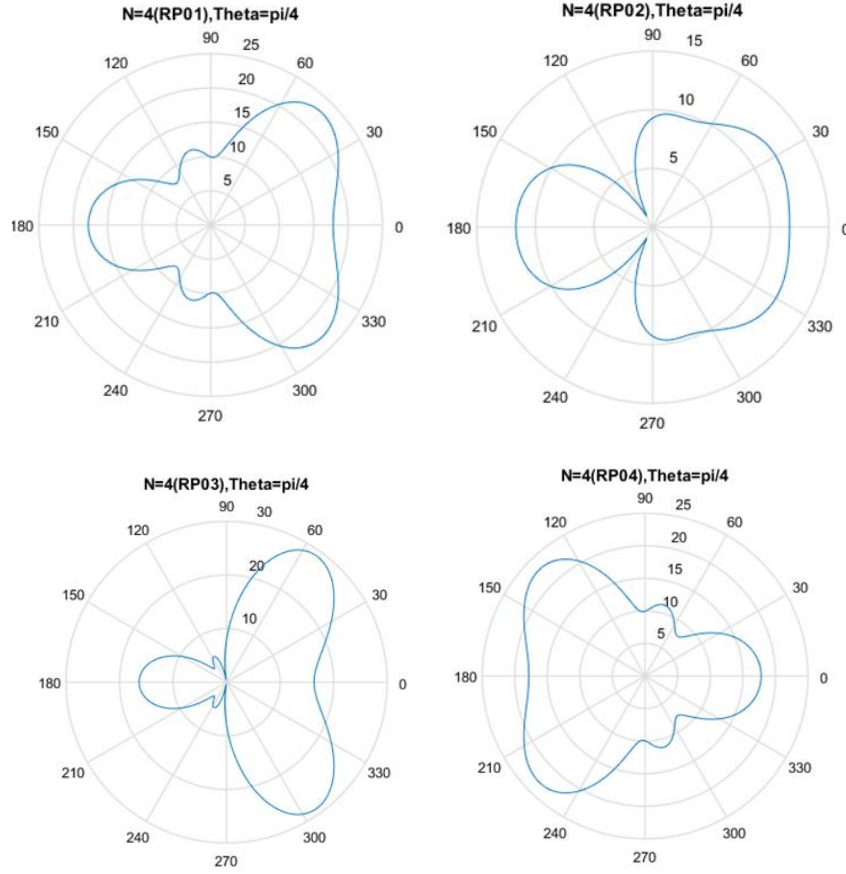


**Figure 4.10:** The  $N=4$  for RP01, RP02, RP03 and RP04 at  $\theta_d = 45^\circ$

Another observation from this analysis is that the improper selection of the array arrangement may cause a flip to the radiation, as displayed in Figure 4.10 for  $N = 4\text{RP01}$  and  $N = 4\text{RP04}$ . As the array length increased to  $N = 6$  and  $N = 8$ , a more directive radiation beamform was generated, as illustrated in Figure 4.11 and Figure 4.12, with more side lobes developed. Figure 4.11 portrays the significant array arrangement by the RP of  $f(\varphi)$  at  $N = 6\text{RP01}$ . Meanwhile,  $N = 6\text{RP02}$  suggests the flipped radiation of  $N = 6\text{RP01}$ . The third array arrangement resulting in  $N = 6\text{RP03}$  is insignificant for the SPSS, while  $N = 6\text{RP04}$  reveals that the side lobe overtook the main lobe.

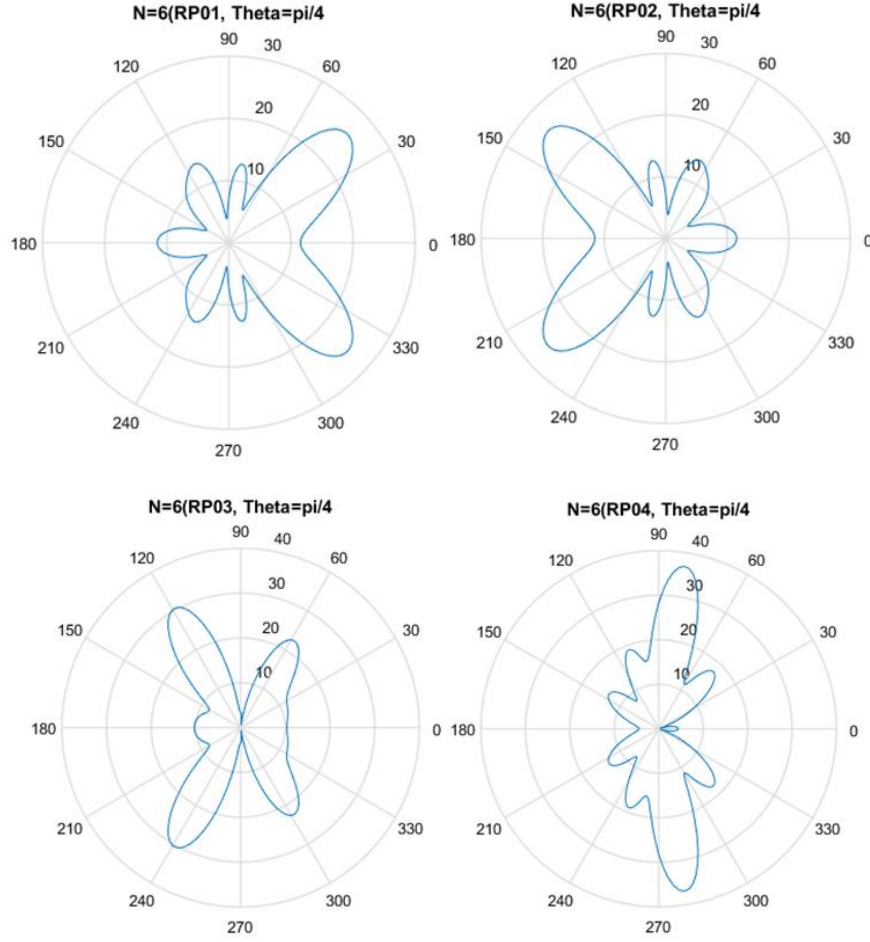


**Figure 4.11:** The  $N=6$  for RP01, RP02, RP03 and RP04 at  $\theta_d = 45^\circ$

In Figure 4.12, the first array arrangement for  $N = 8$ RP01 and the third array arrangement for  $N = 8$ RP04 are significant for the SPSS as the RPs focus on the  $\theta_d$ . The RP,  $N = 8$ RP02, is the flip of the  $N = 8$ RP01. For the RP,  $N = 8$ RP04, the radiation did not cover the  $\theta_d$ , and the sidelobes took over the main lobe. From this analysis, it can be concluded that not every possible array geometrical arrangement is significant for the SPSS model, and not all array lengths are suitable for the SP-ANN algorithm. In this analysis,  $N = 3$  has the potential to be selected as the SPSS model. However, in terms of significant amplitude,  $N = 2$  suggests the highest amplitude compared to  $N = 3$ .

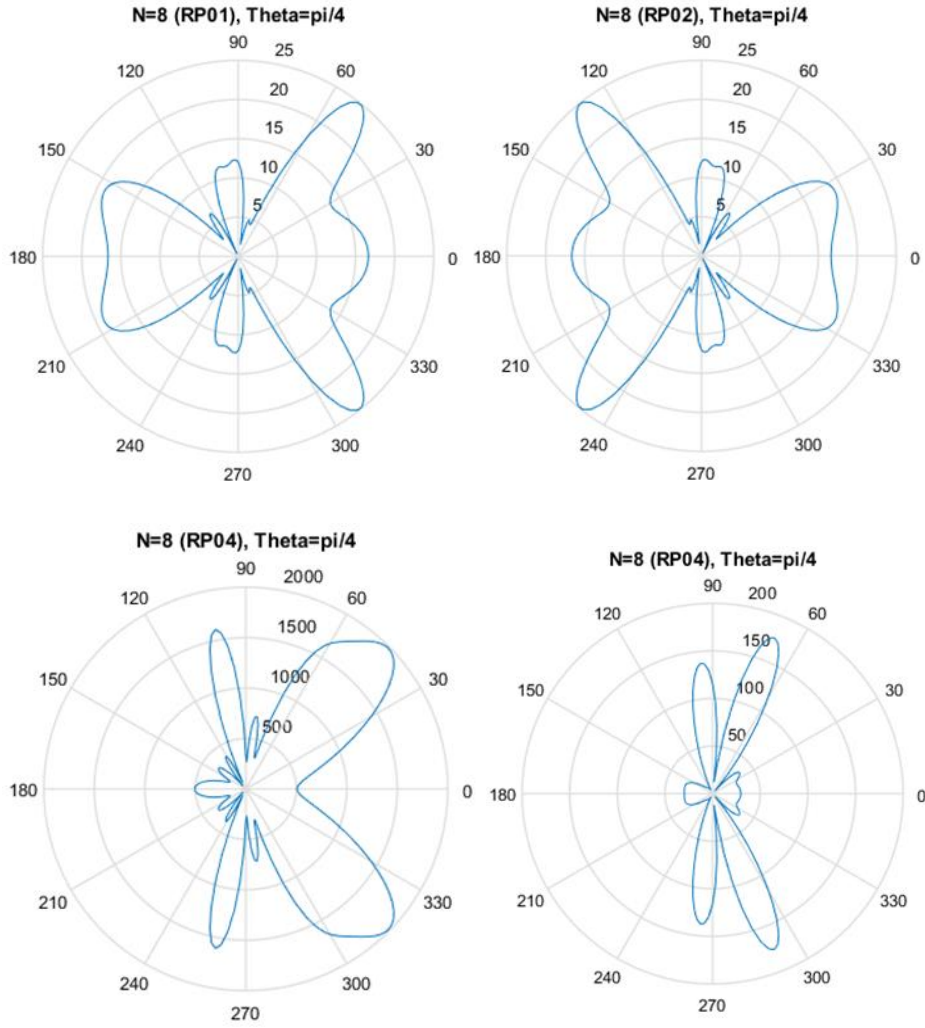


**Figure 4.12:** The  $N=8$  for RP01, RP02, RP03 and RP04 at  $\theta_d = 45^\circ$

For higher array lengths, MLP, Convolution Neural Network (CNN), and Particle Swarm Optimization (PSO) models are frequently used in solving the significance of side lobes issues (Elies et al., 2016; Hamdi et al., 2016; Iorkyase et al., 2018; Merad et al., 2007; Rawat et al., 2012). Therefore, the selection must be made carefully to achieve the best antenna RP. However, since the SPSS model is developed using  $N = 2$ , it is proven that there is no difficulty in deciding the geometrical arrangement as it only involves two elements of array length. From the analysis, it can be observed that the performance of each array length

also varies relative to the changes in DOA. According to (Liu et al., 2017), it is due to the time delay of the EM signal, which is also influenced by the array geometry.

#### **4.3.3 Analysis of the SP-ANN Hyperparameters for the Fast Convergence Effect**

(Yang et al., 2020) mentioned that every ML system has two parameters in ML for its algorithm model: one is called the model parameter that can be initialized and updated during the training, such as the weights of a perceptron. The other one is called hyperparameters, such as learning rate and threshold, which must be set before the data learning process as they define the construction of the model. Selecting the hyperparameter values is crucial in indicating the performance of a model, and generally, the selection process involves heuristics rules, followed by a manual fine-tuning process (Diaz et al., 2017). Hyperparameters need to be identified before the training process begins, as they can greatly impact the performance of the training. However, choosing appropriate values can be challenging. Best practice still relies on manually fine-tuning based on multiple training trials (Safarik, 2018), and it needs to be tuned to fit a specific dataset (Yang et al., 2020). Apart from manual tuning techniques, automatic tuning techniques have been increasingly popular recently (Snoek, 2012). Bayesian Optimization is used widely in automated hyperparameter tuning approaches for optimum performance in the least number of steps (Zhang et al., 2019). However, it is significant for large datasets and may require a longer training process time (Klein et al., 2017). In this analysis, the SP-ANN hyperparameters tuning is manually tuned for the fast convergence of the SP-ANN, hence optimizing the weights of the perceptron. There is no clear guideline about learning rate value; however, the smaller the value of the learning rate, the smoother the trajectory in the weight domain (Nagori, 2016). Therefore, in this analysis, the hyperparameters, the Learning rate,  $\eta$  is set between  $0.001 \leq \eta \leq 0.01$  and  $0.001 \leq \eta \leq 1.000$  for bias,  $b$ . Here, the weights optimization

involves antenna array length sampled at  $N = 2, 3, 4, 6$ , and  $8$  at the multiple DOAs,  $\theta_d = 45^\circ, 60^\circ, 90^\circ, 120^\circ, 270^\circ$  and  $300^\circ$ . The reason for choosing multiple samples is to verify that every tuning process results in a different pattern of convergence. From the analysis, it can be observed that the SP-ANN algorithm has responded to the learning rate and bias. The data for the manual tuning activities of the with respect to  $\eta$  and  $b$  is shown in Appendix F. The SP-ANN algorithm has responded significantly throughout the tuning process. This analysis aims to seek the most optimal hyperparameter setting of the SP-ANN algorithm at array length  $N = 2$  at single source DOA =  $45^\circ$ . However, the computational work is also held to evaluate the significance of the same hyperparameters on other array lengths. For the array length  $N = 2$ , when the  $\eta = 0.001$  and the  $b$  is varied between  $0.001 \leq \eta \leq 1.000$ , the convergence is zero (Convergence loop = 0). It indicates that the weights have been unsuccessfully trained and optimized. Figure 4.13 illustrates the graph of the SP-ANN convergence status versus  $b$  sampled at DOA =  $45^\circ$  with a fixed  $\eta = 0.001$ . As observed, the response of the SP-ANN corresponding with array length,  $N = 2, 3, 4$ , and  $6$ , suggests zero convergence, while it converged at the convergence loops = 2 for  $N = 8$ .

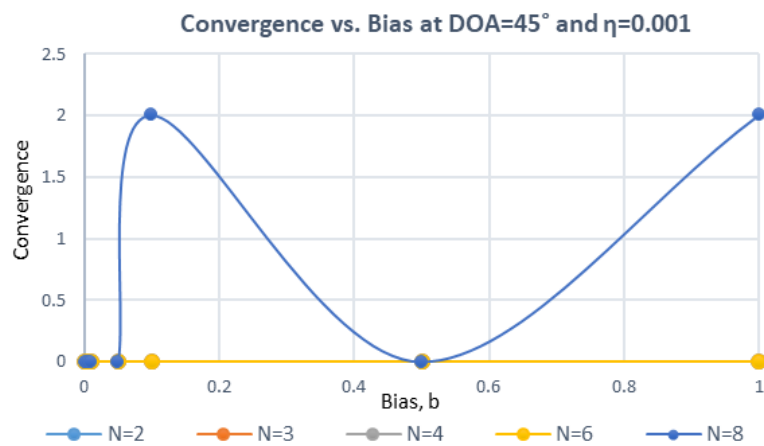


**Figure 4.13:** Graph of the SP-ANN response at DOA= $45^\circ$  and  $\eta=0.001$

For this case, only  $N = 8$  has responded to  $\eta = 0.001$  while the  $b$  varied from  $b = 0.001$  to  $b = 1.000$ . This indicates that only SPSS designed with an 8-element array will work at an initial learning rate of  $\eta = 0.001$  for a range of bias  $b = 0.001$  to  $b = 1.000$ . As the  $\eta$  increases to  $\eta = 0.005$  and  $\eta = 0.01$ , the convergence of the  $N = 2$  is still zero, while for other array lengths, the convergence loops are inconsistently achieved between loop 2 to loop 10 (for  $\eta = 0.005$ ) and between loop 3 to loop 30 (for  $\eta = 0.01$ ), as displayed in Figure 4.14.

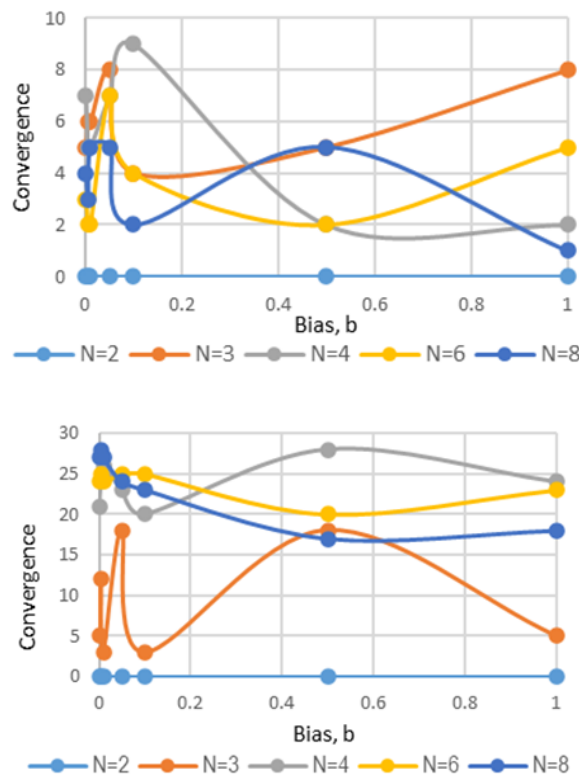


**Figure 4.14:** Graphs of the SP-ANN corresponded to  $\eta=0.005$  and  $\eta=0.01$

This indicates that if the SPSS is designed using an array element between 3 and 8, the initial setting for the hyperparameters should be at these values. However, the convergence loop for each training is a priority. The higher convergence loop indicates the longer time consumed for the optimization process.

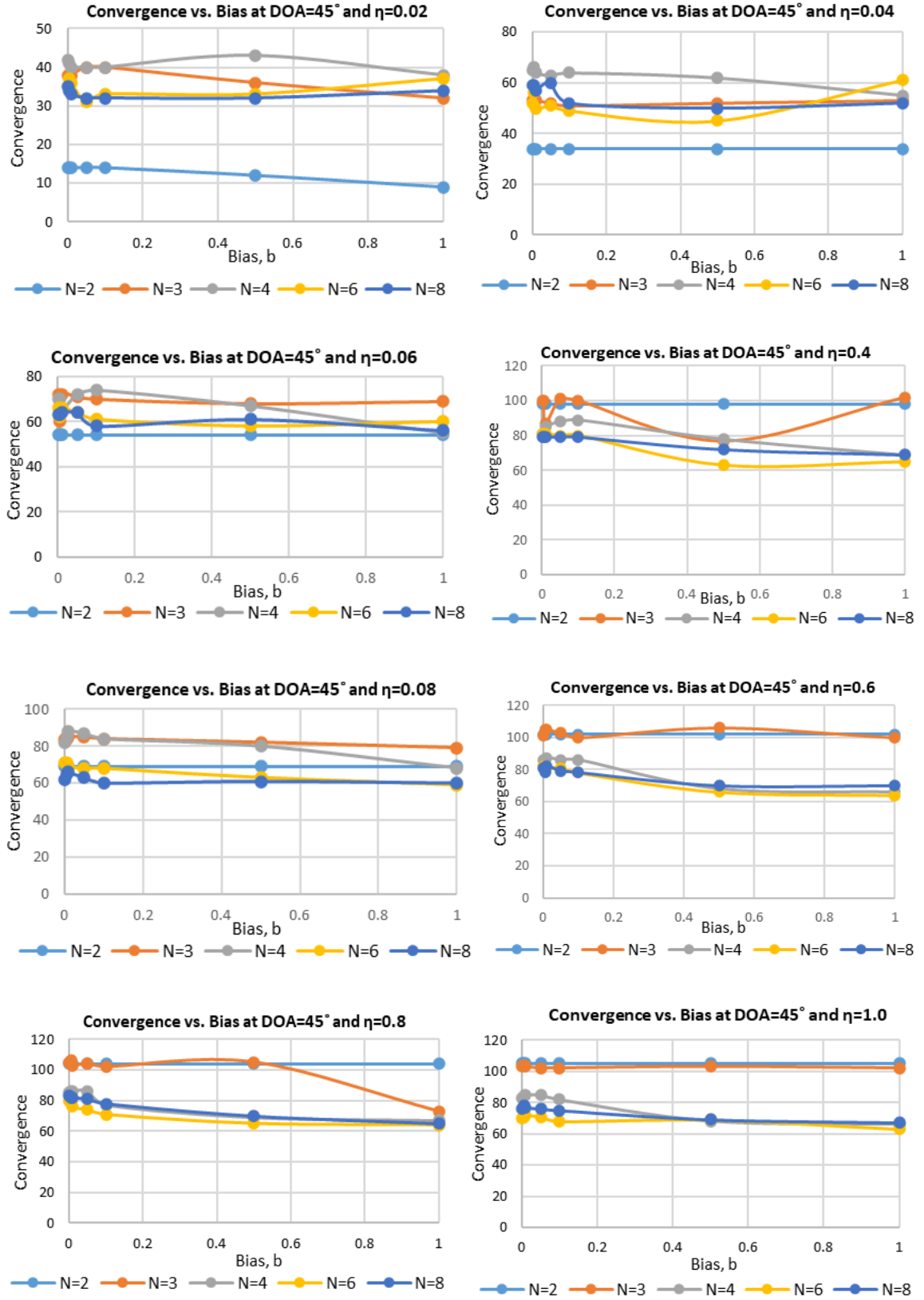


**Figure 4.15:** Graphs of the SP-ANN responses at  $\text{DOA}=45^\circ$  and  $0.02 \leq \eta \leq 1.0$

Figure 4.15 illustrates the overall tuning activities at the DOA = 45° for  $\eta = 0.02$  until  $\eta = 1.000$ . The SPSS converged consistently at  $N = 2$ , while the others suggest that convergence was achieved steadily. Besides different array lengths, the analysis is also performed on multiple DOAs, and the results are attached in Appendix K. The result reveals that the tuning is also influenced by different factors, and therefore, every hyperparameter must be tuned to fit a specific dataset (Van Rijn et al., 2018). From this analysis, the main focus is to determine the best setting value of learning rate and bias for the SP-ANN algorithm. In this case,  $N = 2$  suggests the most consistency in the weight optimization compared to other array elements. For  $N = 2$ , the SP-ANN hyperparameter settings are  $0.02 \leq \eta \leq 1.0$  for the  $\eta$  and  $0.001 \leq b \leq 1.0$  for the  $b$ . The same hyperparameters have significantly affected the convergence status of other array lengths. It is important to tune these hyperparameters before applying a Neural Network (NN) algorithm, as choosing the wrong value may affect the convergence process during the perceptron training.

#### **4.3.4 Analysis of Simultaneous Signal Detection and localization at Multiple DOA for 2-element Array Antenna**

ED detection and localization methods are based on the measurement and analysis of the ED pulses. Signal detection and localization of EM signals can benefit significantly from the DOA. DOA monitoring has been effective in identifying the ED source (Ishimaru et al., 2014; Polak et al., 2014). This measurement technique uses directional antenna arrays to calculate the DOA of the EM waves that propagated from the ED source. The experimental results suggested that the DOA of the ED source is usually determined with high accuracy if compared with the Time Difference of Arrival (TDOA) (Dong et al., 2016; Han et al., 2020; Qiang et al., 2018; Saravanakumar et al., 2018; Wang, et al., 2017). Therefore, this analysis aims to develop signal detection and localization techniques relative

to the DOA. According to the previous evaluation, the 2-element array antenna has proven its performance. Hence, these techniques utilized the 2-element array antenna for the Smart Antenna (SA) modeling. The computational work takes place to form a SA to detect and localize a signal simultaneously from a specified direction. To simulate the maximizing condition, first, every desired DOA is sampled at  $\theta_d = 45^\circ, 60^\circ, 165^\circ$  and  $320^\circ$ . The  $\theta_d$  represents the spatial locations of the EDs from an identified power apparatus. Then, the SA is computed manually by stages relative to each sampled DOA, taking the scanning azimuth,  $\theta$  between  $0^\circ$  to  $360^\circ$ .

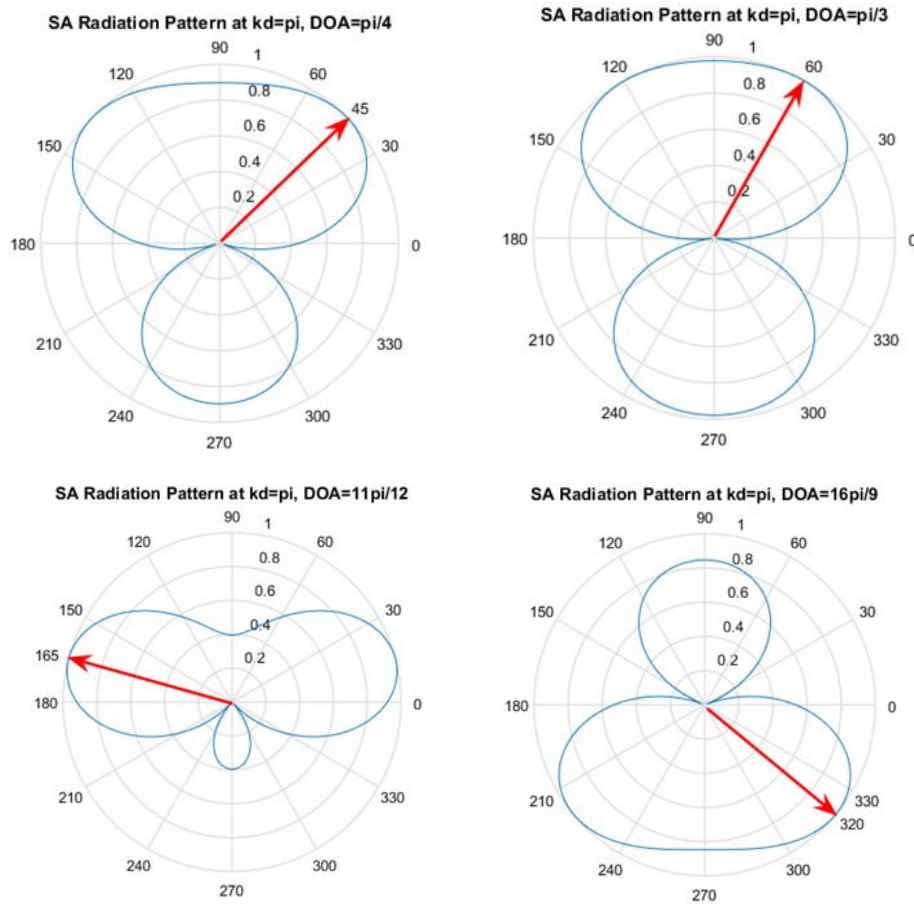


**Figure 4.16:** The radiation patterns of maximized  $\theta_d$

After the detection of the desired DOA takes place, the output of the SA is maximized at  $AFN_2 = |\cos(\gamma/2)|$  (refer to Equation 3.20) where  $\gamma = kd(\sin\theta - \sin\theta_d)$  for the RP. As observed in Figure 4.16, the SA has responded to each DOA by maximizing the beamform in phase with the  $\theta_d$ . To simulate the nulling condition, the DOAs of the interference signals are identified as  $\theta_i = 50^\circ, 165^\circ, 255^\circ$  and  $320^\circ$ . The  $\theta_i$  represents the location at which the undesired signal might occur. Again, the SA is computed manually by stages relative to each  $\theta_i$ . Once the  $\theta_i$  is detected, the output of the SA nulled at  $AFN_1 = |\sin(\gamma/2)|$  (refer to Equation 3.19), where  $\gamma = kd(\sin\theta - \sin\theta_i)$  for the RP. As observed in Figure 4.17, the SA has responded to each DOA by nulling the beamform relative to the  $\theta_i$ .

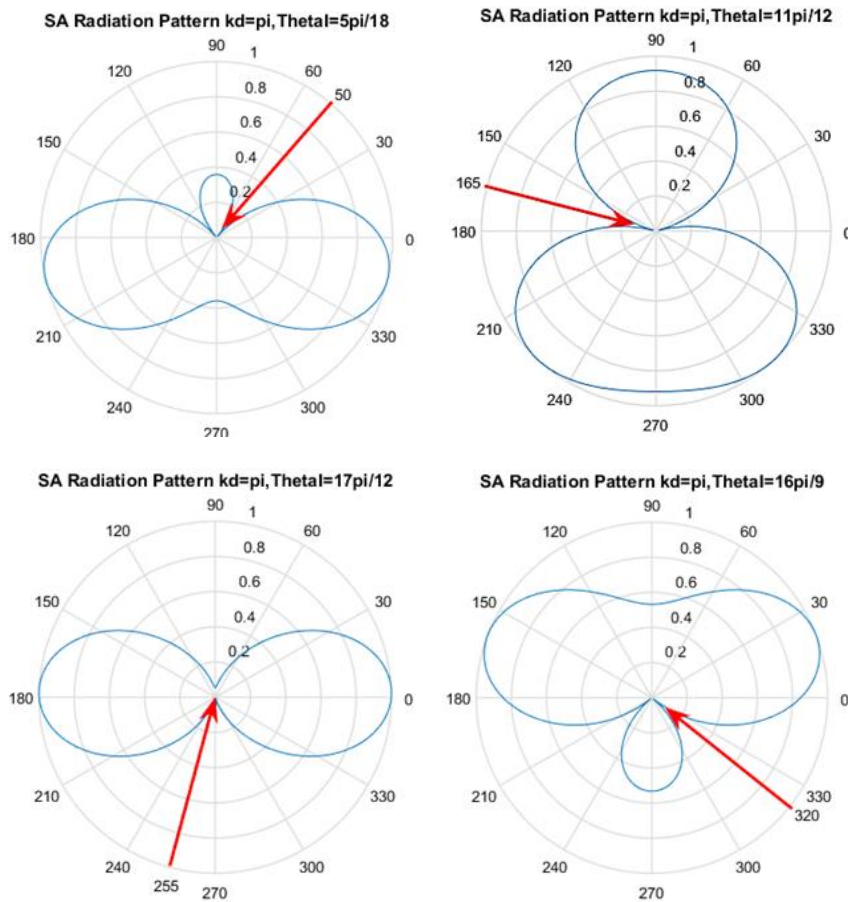


**Figure 4.17:** The radiation patterns of nullified  $\theta_i$

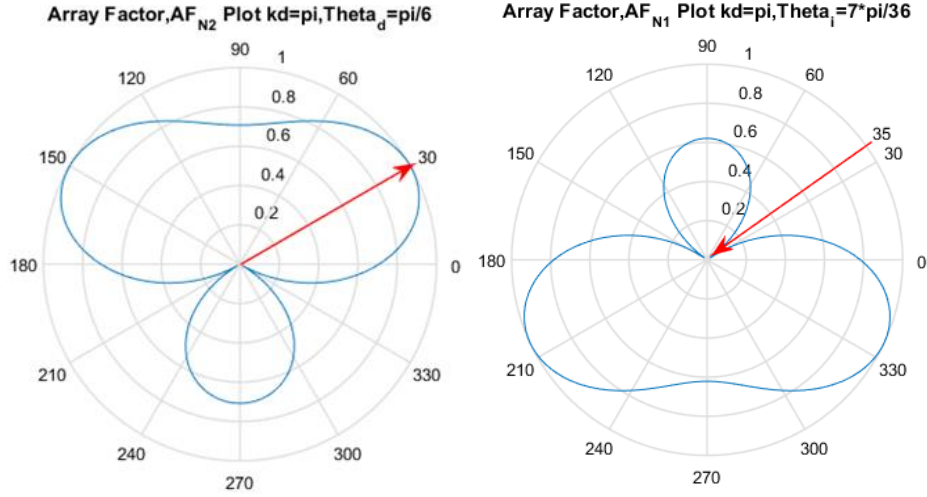


**Figure 4.18:** The SA responded to a small gap of  $5^\circ$

Changes take place by setting a small gap at  $5^\circ$  between  $\theta_d$  and  $\theta_i$  so that  $\theta_d = 30^\circ$  and  $\theta_i = 35^\circ$ . Figure 4.18 verifies that the SA has efficiently responded to the changes. In this work, the 2-element SA has efficiently maximized and eliminated signal correlative to the DOA. Thus, this SA model has the potential to act as a cohesive unit to monitor the abnormal electrical activities in the indoor substation by cyclically scanning each apparatus. In this simultaneous scheme, the signal received by the SA is either in phase or out of phase. When the received signal is in phase, the signal is added to the propagation phase of SA, resulting in an additive amplitude. When the received signal is out of phase, the signal is observed to cancel out each other. Therefore, any indoor substation can employ this SA for fault monitoring as a preventative approach for substation breakdown and to improve the efficiency of the fault monitoring technique.

#### 4.3.5 Analysis of SP-ANN Algorithm for the Smart Simultaneous Signal Detection and Localization

The previous analysis (Section 4.3.4) illustrates that the array antenna is modeled and programmed without the ANN integration to maximize and nullify the signal. In this analysis, the novel SPSS is developed by employing the same SA model being integrated with the SP-ANN Algorithm to perform the same simultaneous scanning. The SA Normalized Array Factor (AFN) verifies the nulling and maximizing conditions for the detected signals. The observation focuses on the changes in the SA RP,  $f(\varphi)$ , before and after signal detection. Upon the detection, the algorithm updates and optimizes the weights  $W$  of the perceptron, and the training continues until the perceptron converges. Figure 4.19 depicts the SA RP,  $f(\varphi)$ , in the initial condition with the  $W$  setting at  $W_1 = 0.1 + j0$  and  $W_2 = 0.1 + j0$  without any induced angle (zero detection). The magnitude is 0.2. Upon detection at an induced angle, DOA of  $45^\circ$ , the perceptron converged at the new  $W$  of  $W_1 = -66.11 + 2.029j$ ,  $W_2 = 21.31 - 32.21j$ , and the new SA RP,  $f(\varphi)$  is illustrated in Figure 4.20.

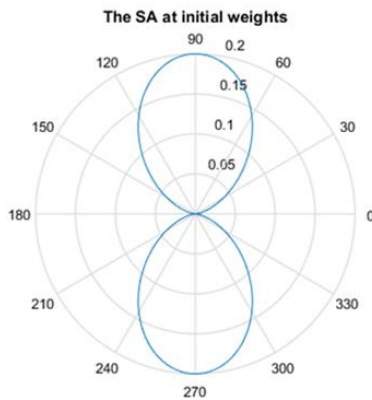


**Figure 4.19:** The RP with initial weights

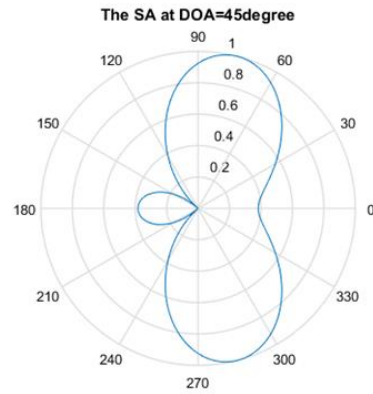


**Figure 4.20:** The RP with updated weights

In Figure 4.20, after being induced with a DOA and the convergence achieved, the RP has responded to the DOA, and the maximum amplitude is 1.0. The polar plots in Figure

4.21 and Figure 4.22 verify that the algorithm has influenced the magnitude and pattern of the radiation. Note that the  $f(\varphi)$  patterns varied significantly after the weight optimization process. The amplitude at DOA =  $65^\circ$  and DOA =  $100^\circ$  are now amplified to 500 V/m and 150 V/m, respectively.

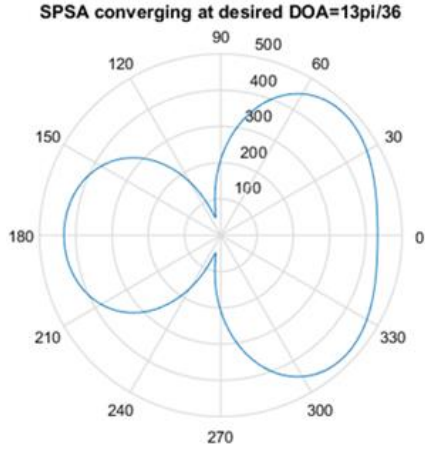


**Figure 4.21:** The  $f(\varphi)$  at  $\theta_d = 65^\circ$

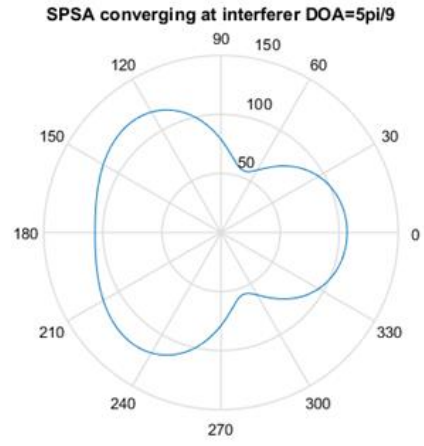


**Figure 4.22:** The  $f(\varphi)$  at  $\theta_i = 100^\circ$

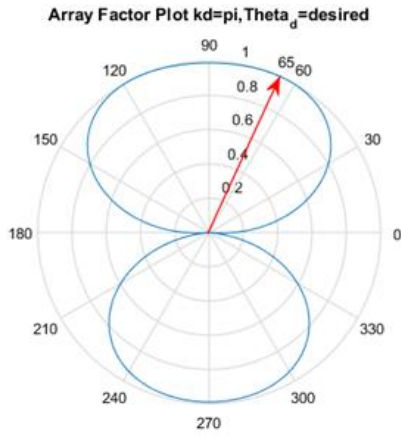


**Figure 4.23:** AF plotted at  $\theta_d = 65^\circ$

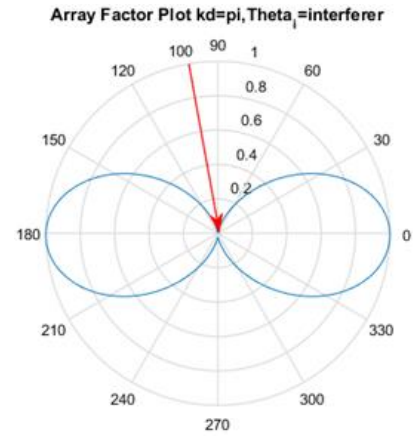


**Figure 4.24:** AF plotted at  $\theta_i = 100^\circ$

When the SA responds to the maximizing and the nullifying process, the AFN RP can also be observed. Figure 4.23 portrays that the AFN<sub>2</sub> of the SA is maximized at the desired angle,  $\theta_d = 65^\circ$ . The AFN<sub>1</sub> of the SA in Figure 4.24 is nullified at the interference

angle,  $\theta_i = 100^\circ$ . From this analysis, the SA has responded efficiently by integrating the SP-ANN Algorithm. This fast convergence (within seconds) algorithm allows the SA to have a distinctively high amplitude to amplify any signal picked up from the far field, thus improving the signal detection range. This analysis has provided a better way of electronically steering beamforming techniques responding to the RP. Frequency scanning is possible for the SPSS, which definitely does not require any phase-shifter unit, but the transmitted frequency from a desired DOA can be used for the beam steering. Thus, in terms of hardware complexity, SPSS is less cost and less complex as it replaces phase shifters with a single NN element. At the same time, phased-shifter electronic steering has higher complexity and cost as it requires phase shifters for each antenna element (Nikfalazar et al., 2017). For SPSS, the complexity lies in the NN and training process, while for phase shifters, the complexity lies in the design, calibration, and integration of phase shifters (Kalyoncu et al., 2019). In terms of cost, SPSS is potentially cost-effective and energy-efficient due to reduced hardware, while phase-shifter shifters are costlier and consume more power depending on the active device (Trinh et al., 2019). Other than that, in terms of adaptability, SPSS has a high degree of adaptability to shifting conditions due to immediate phase adjustments, while phased shifters need manual settings or require extra components for adaptive control (Rajruangrabin et al., 2019). The novelty of this research work is that the SP-ANN algorithm has replaced the use of a phase shifter to shift the array antenna electronically. Thus, it has successfully suppressed the cost and complexity of the detection and localization system.

#### **4.3.6 Analysis of the SPSS for Signal Electric Field Strength Tested on Multiple DOA**

NNs are beneficial for numerous study areas, including the optimization of array antennas (Hamdi et al., 2016). It has good learning ability and can be trained at any number

of array antenna elements, spacing, and excitation (Ghayoula et al., 2016). It is commonly known that choosing the best position or best excitation coefficient for array elements can improve the beamwidth and sidelobe levels of an array antenna (Merad et al., 2007b). Therefore, this analysis visualizes the SPSS placement topology at the multiple spatial locations (the DOAs) anchored by a power apparatus such as a Power Transformer. The observation focused on the signal electric field strength magnitude responded to the DOAs sampled at  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$ . This analysis aims to evaluate the placement of the SPSS for the efficacy of signal detection measured based on signal electric field strength. Figure 4.25 and Figure 4.26 depict the RPs of the antenna radiation,  $f(\varphi)$  of each  $\theta_d$ . Figure 4.25 illustrates the initial RP,  $f(\varphi)$ , of a 2-element array antenna plotted in the polar and space domain, generated without the SP-ANN. The Y-axis represented the magnitude of the  $f(\varphi)$ , and the X-axis represented the desired angle,  $\theta_d$  in radians. The values of X and Y are obtained via MATLAB Tools. As observed, at DOA =  $45^\circ$  for  $X = 0.7854$  rad, the magnitude of  $Y = -1.231$  dB. However, after the 2-element array antenna is integrated with the SP-ANN algorithm, the value of Y in Figure 4.26 increased from -1.231 dB to 20.2 dB.

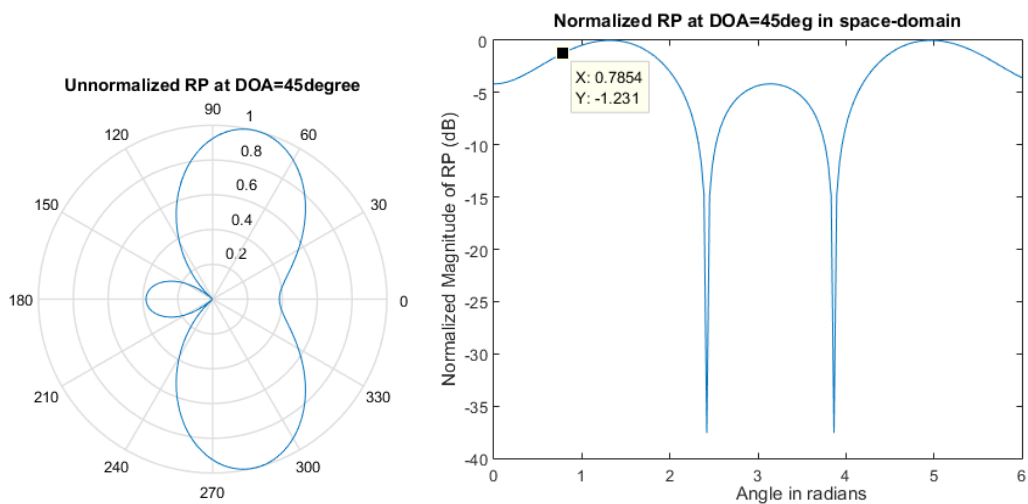


**Figure 4.25:** The DOA= $45^\circ$  and the  $Y=-1.231$  dB without SP-ANN

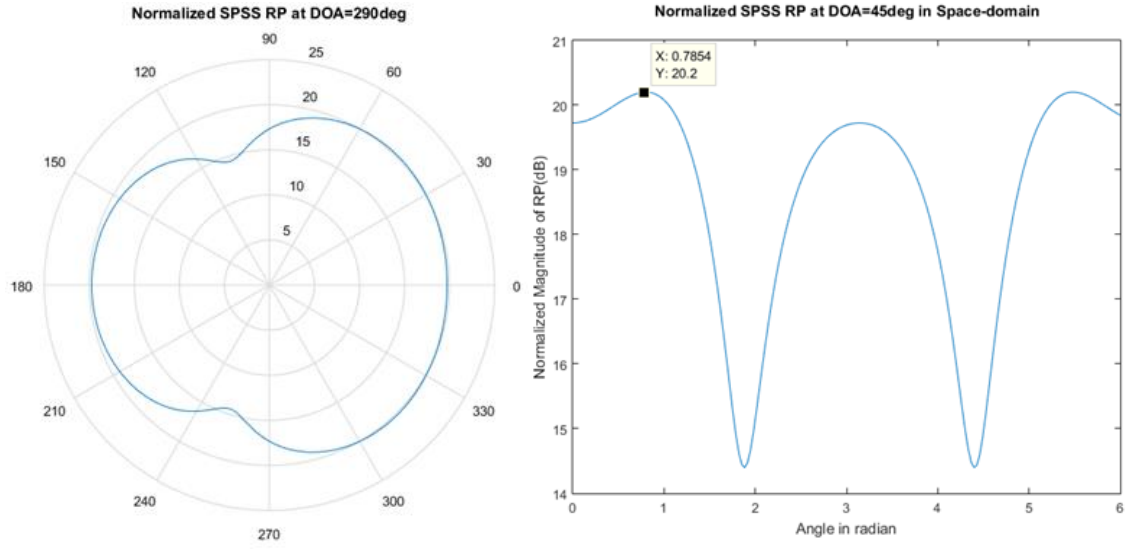


**Figure 4.26:** The DOA=45° and the Y=20.2 dB with SP-ANN

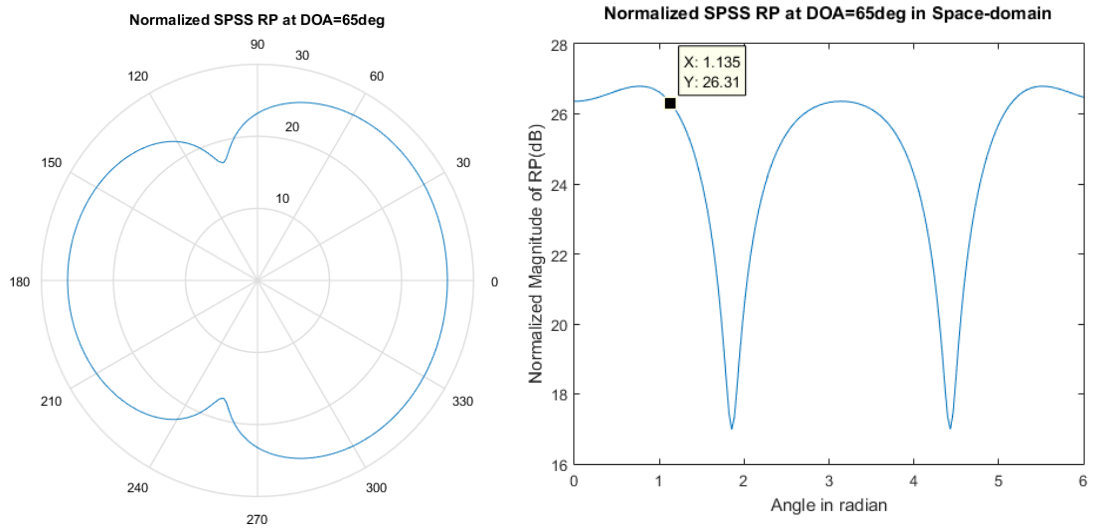


**Figure 4.27:** The DOA=65° and the Y= 26.31 dB with SP-ANN

When the desired angle,  $\theta_d$ , is at DOA = 65°, the value is  $X = 1.345$ , and the magnitude of  $Y = 26.31$  dB, as displayed in Figure 4.27. Meanwhile in Figure 4.28, when the DOA = 290° at  $X = 5.062$ , the magnitude of  $Y = 25.02$  dB. From the observation, the SP-ANN has improved the RP that occurred at every tested DOA.

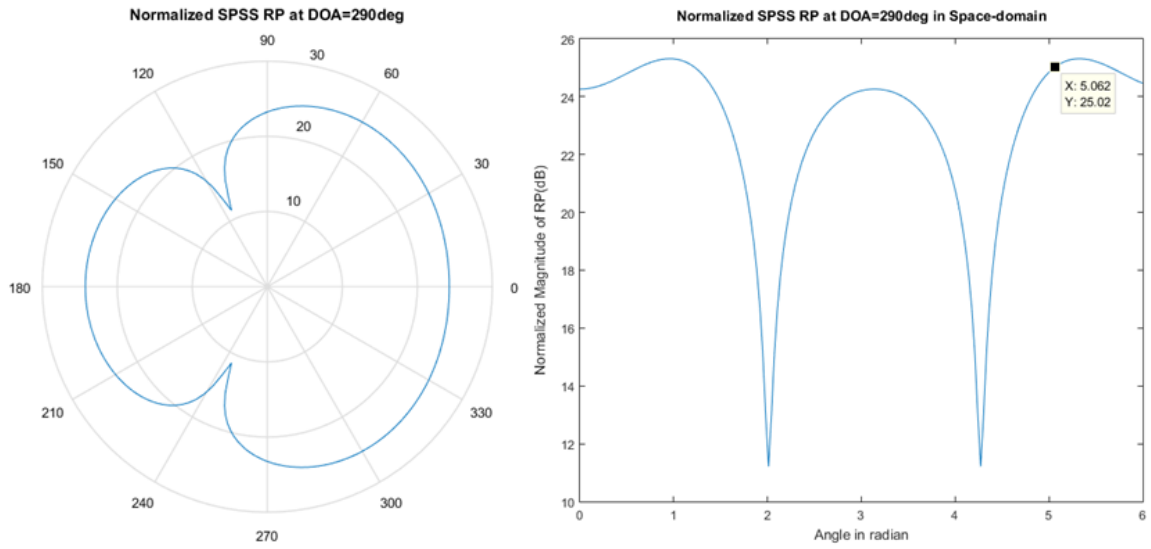


**Figure 4.28:** The DOA=290° and the Y= 25.02 dB with SP-ANN

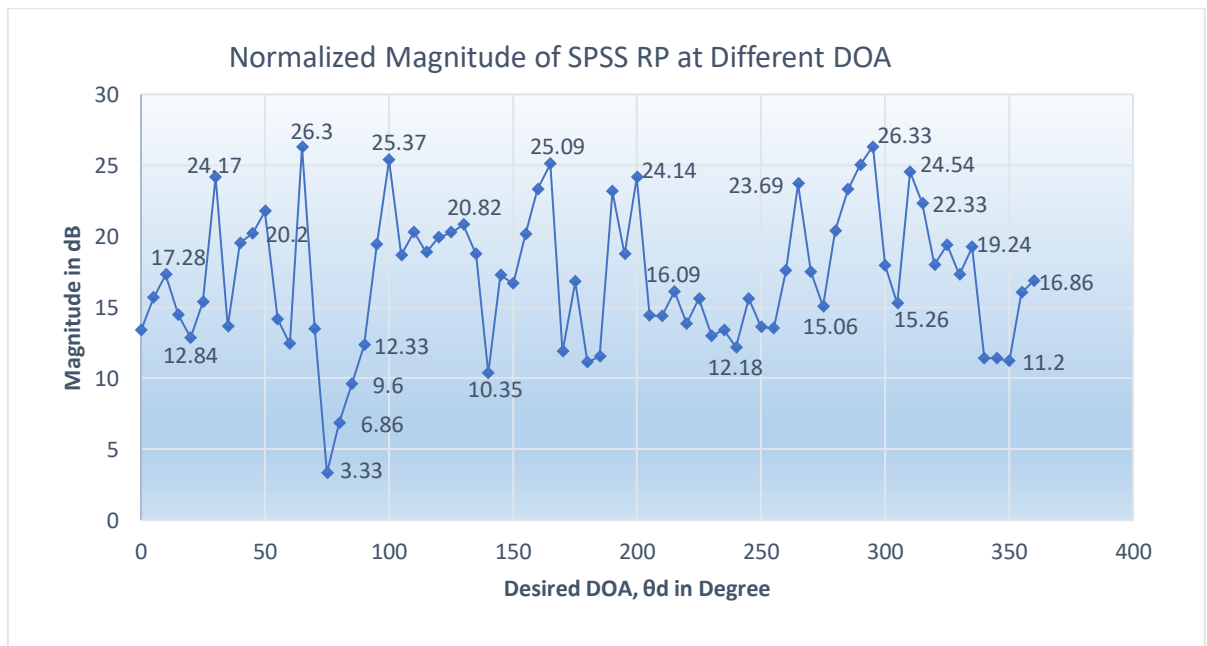


**Figure 4.29:** The overall Y observed at the DOAs of  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$

Figure 4.29 highlights the statistical dataset in Appendix I of the Y readings for the SPSS radiations relative to the DOAs. The data is sufficient to substantiate the electric field strength of signals at every different DOA. This is the effect of SP-ANN-optimized weights

at different DOAs. As can be observed, the SPSS radiates the highest magnitude of 26.33 dB at  $\text{DOA} = 295^\circ$  and 26.31 dB at  $\text{DOA} = 65^\circ$ . These findings yield a better recommendation of the SPSS placement wherein the desired location is in the indoor substation. The placement of an antenna at the position of a strong electric field will appreciably affect its intensity (Fakhte et al., 2015).

#### **4.3.7 Analysis of the SPSS for the Total Electric Fields ( $E_T$ ) and Radiated Power Intensity ( $P_i$ ) at A Fixed DOA and Multiple Ranges of Signal Distance, $r$**

Electric fields can be identified by several parameters, such as electric charge, electric charge intensity, and electric field strength, amongst others. However, the electric field strength is the factor that provides the most useful information (Kuchanskyy et al., 2020). In wireless networks, it is essential to understand the electric field strength for optimal antenna placement (Beura et al., 2019). By measuring the electric field strength at different locations, areas with attenuation of signal coverage can be identified; hence, antenna placement and orientation can be recommended to improve network performance. In this analysis, the computation of total electric fields ( $E_T$ ) is carried out based on the multiple ranges of source distance,  $r$ , measured in meters. This analysis aims to determine the relationship between the SPSS receiving distance with the SPSS radiation total electric field strength,  $E_T$ , and its power intensity,  $P_i$ . It is an alternative method of providing a better recommendation of the SPSS placement for the efficacy of  $E_P$  localization (Robles et al., 2016). Here, the detected electric field is assumed to carry the current,  $I = 100\text{mA}$ , to simulate the ED currents during the formation of Corona or Arc discharge, ranging in milliamperes (mA) to Amperes (A) (Götz et al., 2020; Grosu et al., 2015; Ren et al., 2016). Figure 4.30 depicts the space domain plots of the  $E_T$  at  $\theta_d = \pi/4$  rad (0.7854 rad) and  $r = 1.524\text{m}$ . The space domain provides an uncomplicated way and a piece of reliable

information about the RP. From the waveform,  $E_T$ , at  $X = 0.7854$  (DOA=  $45^\circ$ ), yields the magnitude of the  $E_T$  at  $Y = 458$  V/m and normalized at  $Y = 26.61$  dB.

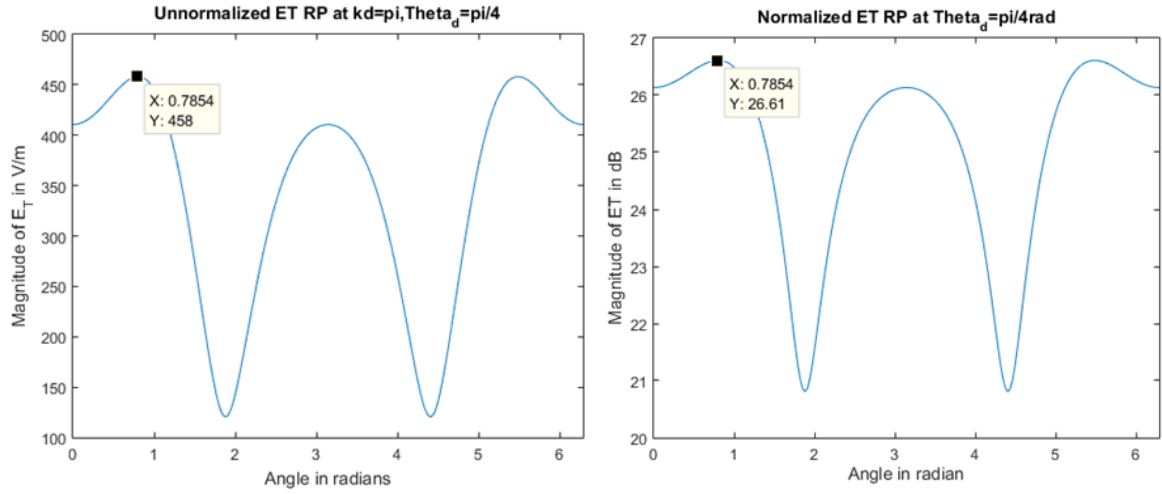


**Figure 4.30:** The  $E_T = 458$  V/m normalized at 26.61 dB

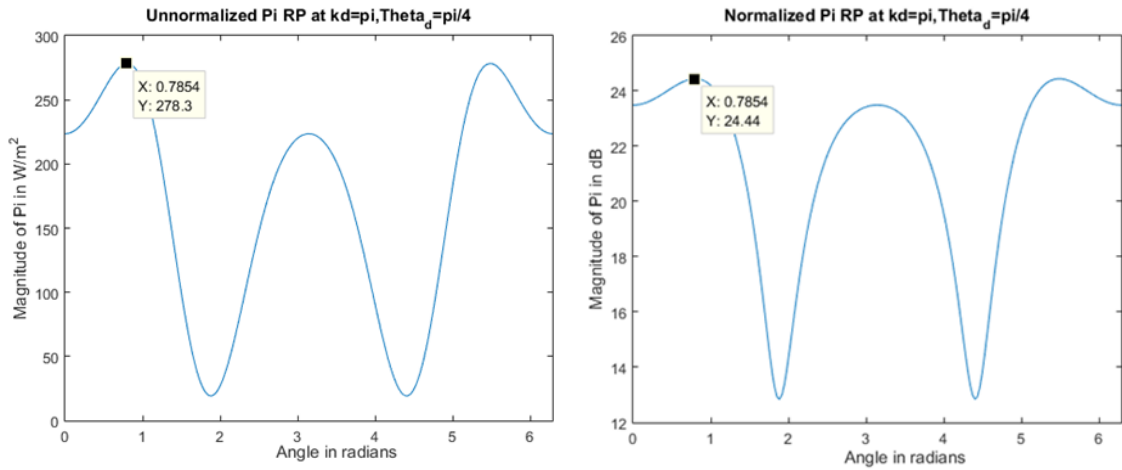


**Figure 4.31:** The  $P_i = 278.3$  W/m<sup>2</sup> normalized at 24.44 dB

Meanwhile, Figure 4.31 illustrates the space domain plots of radiated power intensity,  $P_i$ , at the same reference angle of  $X = 0.7854$ . It can be observed that the magnitude of  $P_i$  is given at  $Y = 278.3$  W/m<sup>2</sup> or normalized at  $Y = 24.44$  dB. The electric field strength

is an essential parameter in ED measurement as it reflects the stress on the insulation material. When it exceeds a certain threshold, Corona or Arc discharge can occur. Besides electric field strength, power intensity, which is essentially the energy released during an ED event, is another useful parameter for ED measurement. It provides information about the severity of the discharge. The power intensity measurement usually indicates that ED is harmless at low-energy discharges and more critical at high-energy discharges. Different severity may produce different magnitudes of ED discharges (Zhang et al., 2016). Table 4.1 indicates the various magnitudes of electric field strength measurements for ED activities observed. Therefore, a specific range of electric field strength and power intensity Corona or Arc discharge is undecidable. However, these parameters are efficient in pinpointing the location and magnitude of ED activity, thus making it valuable for condition monitoring and maintenance.

**Table 4.1:** Magnitude of electric field strength measurement for ED activities

| Author/Year            | E-field Magnitude (dB) | E-field frequency (GHz) | Partial Discharge       | Measurement device                                          |
|------------------------|------------------------|-------------------------|-------------------------|-------------------------------------------------------------|
| (Mohamed et al., 2016) | 23.00                  | 0.05-0.8                | Corona discharge        | Universal Software Radio Peripheral N200 transceiver        |
| (Zhang et al., 2014)   | 20.00                  | 0.12-0.8                | Corona discharge        | coplanar waveguide CPW-fed UWB antenna                      |
| (Zhang et al., 2016)   | 40.00                  | 0.8-1.0                 | Corona discharge        | Time-delay of Arrival (TDOA) of RF antenna array            |
| (Cheng et al., 2021)   | 40.00                  | 0.2-0.8                 | Corona discharge        | High Frequency Current Transformers (HFCT) method           |
| (Feng et al., 2016)    | 60.00                  | 0.02-0.2                | E-field transient pulse | Anti-jamming electrical fast transient/burst (EFT/B) method |
| Research work          | 26.61                  | 1.0                     | Corona / arc discharge  | Single Perceptron Smart Sensor (SPSS)                       |

A further investigation is conducted for a sample of the antenna receiving distance,  $r$ . A set of data is collected as attached in Appendix J, and Figure 4.32 displays the graph

of  $E_T$  and  $P_i$  corresponding to  $r$ . As the receiving distance increased, the value of  $E_T$  and  $P_i$  decreased. Referring to Equation 3.22 (in Section 3.3.7), the electric field strength is inverse of receiving distance,  $r$ , which means that the strength of the electric field decreases with the distance from the ED source. As the antenna varies farther away from the ED source, the electric field strength diminishes rapidly. This is due to the electric field spreading out in a spherical manner and polarized waves around the source (Stutzman et al., 2012). Consequently, increasing the receiving distance from the source will decrease the measured electric field strength.

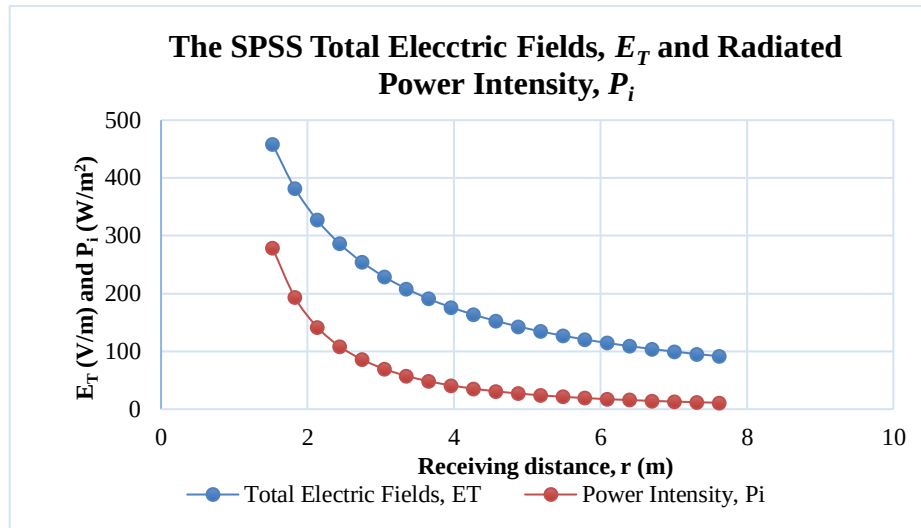


**Figure 4.32:** The graph of  $E_T$  and  $P_i$  versus Receiving Distance,  $r$

Referring to Equation 3.23 (in Section 3.3.7), the power intensity of the electric field is directly related to the square of the electric field strength ( $P \propto E^2$ ). Therefore, if the receiving distance is increased and the electric field strength decreases, the power intensity of the received signal will decrease even more significantly. Weaker signals may result in lower measured power intensity, and the increase in the distance of receiving may decrease the amplitude of the EM signal (Zhou et al., 2018). From Figure 4.32, SPSS best placement

recommendation is between 1.524m to 7.62m (5ft to 25ft) for optimal receiving distance, giving the range of electric field strength at magnitude of 26.61 dB to 19.62 dB. In conclusion, the value of  $E_T$  and  $P_i$  decreased proportionally to the increment of the receiving distance,  $r$  (Beura et al., 2019).

#### **4.4 Part C: Evaluate the accuracy of the ED\_EMP signal identification using the novel SP-Identifier Technique in waveform-based testing for Corona or Arc EDs samples.**

Part C consists of FOUR (4) final analyses to evaluate the performance of the SP-Identifier technique in identifying the ED\_EMP signal detected by the SPSS. The analysis begins with (i) Analysis of the  $E_P$  model representing ED\_EMP tested at multiple DOAs. Next is (ii) Analysis to evaluate the similarity of the ED\_EMP waveforms in space and time domain using the DataTip Alignment method. After that, (iii) Analysis of the evaluation of the efficiency of the SP-Identifier technique in identifying the ED\_EMP signal detected by the SPSS. Lastly, (iv) Analysis will be used to evaluate the performance of signal identification for the SPSS radiation waveform.

##### **4.4.1 Analysis of the $E_P$ Model in Representing ED\_EMP Tested at Multiple DOA**

HV equipment has the ability to produce impulsive EM (EMP) signals with high levels of energy and significant Radio Frequency (RF) components (Xiao et al., 2007). Any ED detected from a power apparatus usually carries a power frequency sinusoidal current (Jia et al., 2013), embedding the ED\_EMP superimposed on it (Au et al., 2013). In this analysis, the simulation is carried out to conceptualize the ED\_EMP signal generation represented as the  $E_P$  signal model. For this purpose, simulation work uses a Sinc function as the  $E_P$  signal model with frequency sampled at 1 GHz for DOA,  $\theta_d = 45^\circ, 120^\circ, 225^\circ$  and  $300^\circ$  for  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$  are the spatial locations of the  $E_P$  signal occurred. Figure 4.33

depicts the results of the  $E_P$  model beamforming. As observed, each beamform responded to the subjected DOA,  $\theta_d$ . Next, the  $E_P$  model is plotted in the space domain for  $\theta_d = 45^\circ$ ,  $120^\circ$ ,  $225^\circ$  and  $300^\circ$ , as illustrated in Figure 4.34. The information for the signal is retrievable when visualized in the space domain, and the maximum peak rests at  $Y = 1$ .

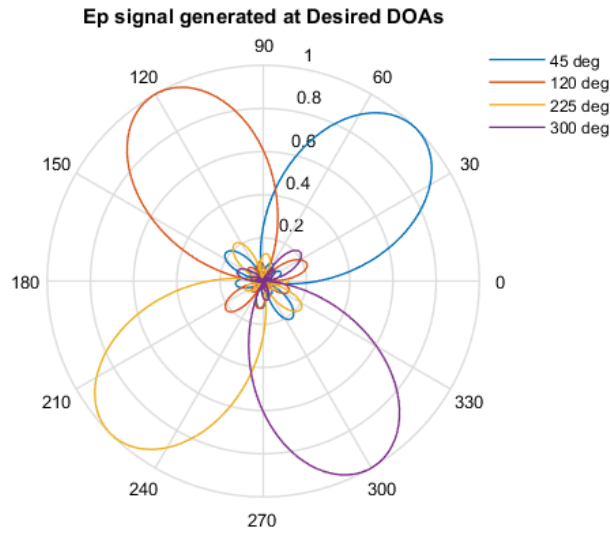


**Figure 4.33:** The  $E_P$  models at subjected DOA= $45^\circ$ ,  $120^\circ$ ,  $225^\circ$  and  $300^\circ$

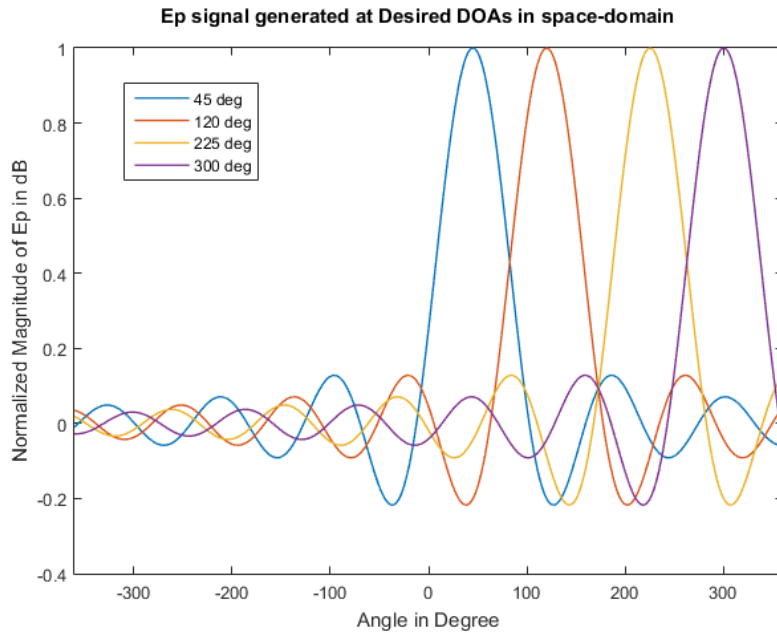


**Figure 4.34:** The  $E_P$  models in the space domain for DOA=  $45^\circ$ ,  $120^\circ$ ,  $225^\circ$  and  $300^\circ$

This analysis has successfully visualized the RPs of the simulated ED\_EMP signal in the space domain. Any frequency sample can be analyzed, and the accuracy of the  $E_P$  model measured and analyzed in the Sinc function is compared with the work (Jia et al., 2013) displayed in Figure 4.35.

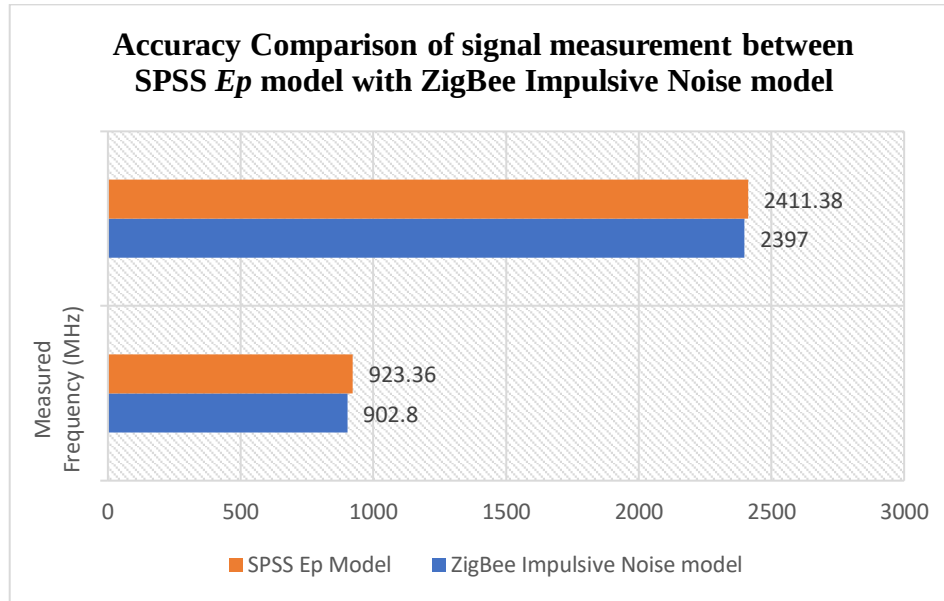


**Figure 4.35:** The accuracy comparison chart of the SPSS  $E_P$  model and ZigBee Impulsive Noise model measurement

The impacts of substation PD impulsive noise on the 915 MHz and 2.4 GHz ZigBee frequency bands are evaluated using a novel statistical model (Jia et al, 2013) and the SPSS  $E_P$  model. ZigBee model is chosen for this comparison as it utilizes the same MATLAB DataTip to extract the PD signals. Similarly, it uses a Sinc function to represent the PD signals. The accuracy of signal identification based on the modeled impulsive noise for both SPSS and ZigBee are illustrated in Figure 4.35. From the comparison, the ZigBee method yields a measured value of 902.8 MHz for the frequency sampled at 915 MHz and 2397 MHz for the frequency sampled at 2.4 GHz. Meanwhile, the SPSS method yields 923.36 MHz for the frequency sampled at 915 MHz and 2411.38 MHz for the frequency sampled

at 2.4 GHz. From both methods, the ZigBee method yields 1.33% for the frequency sampled at 915 MHz and 0.125% for the frequency sampled at 2.4 GHz. Meanwhile, the SPSS method yields 0.914% for the frequency sampled at 915 MHz and 0.474% for the frequency sampled at 2.4 GHz. The differences in accuracy measurement for both methods are 0.416% and 0.349% for impulsive noise of the 915 MHz and 2.4 GHz. The findings in this analysis yield an opportunity to understand the frequency content of an ED signal, visualized in the Sinc function. It makes signal detection and identification more significant and reliable. Furthermore, the Sinc function is very useful for modeling the real signal of  $E_P$  in the analysis for signal identification.

#### **4.4.2 Analysis of Similarity of the ED\_EMP Waveforms in Space and Time Domain**

In Section 4.2.1, the information of a signal is retrievable when visualized in the space domain. The analysis seeks the similarity of the  $E_P$  signal observed in the space and time domain. Since  $E_P$  signal is a transient response with high broadband, space and time domain computational EM method is selected (Sankaran, 2019). Having the similarity verifies the ability of the received signal to be efficiently analyzed with minimal computational complexity, thus giving another cost-efficient wireless technique for the UHF signal interpretation and identification. Additionally, this analysis implies the DataTip Alignment Method for signal interpretation. MATLAB Data Tip toolbar has been used in many applications such as frequency analysis (Capra, 2019), post-processing datasets for chemometric toolbox (Erny et al., 2016), Electromyography (EMG) technique for musculoskeletal systems (Jali et al., 2015), visual representation of signal extraction by Short-Time Fourier Transform (STFT) (Zhivomirov, 2018) and many more. The Data Tip toolbar allows the data cursor to display data directly from the graph, making it easy to retrieve the signal content from a single signal source.

In this analysis, assuming an event of ED\_EMP current to radiate an impulsive  $E_P$  signal that occurred at a peak time,  $t_p = 1$  ns, yielding the frequency of about 1 GHz received by the SPSS. Figure 4.36 depicts the generation of the  $E_P$  models that originated from the  $\text{DOA} = 45^\circ$  and  $\text{DOA} = 225^\circ$ . As observed, both waveforms are similar in the space domain and time domain.

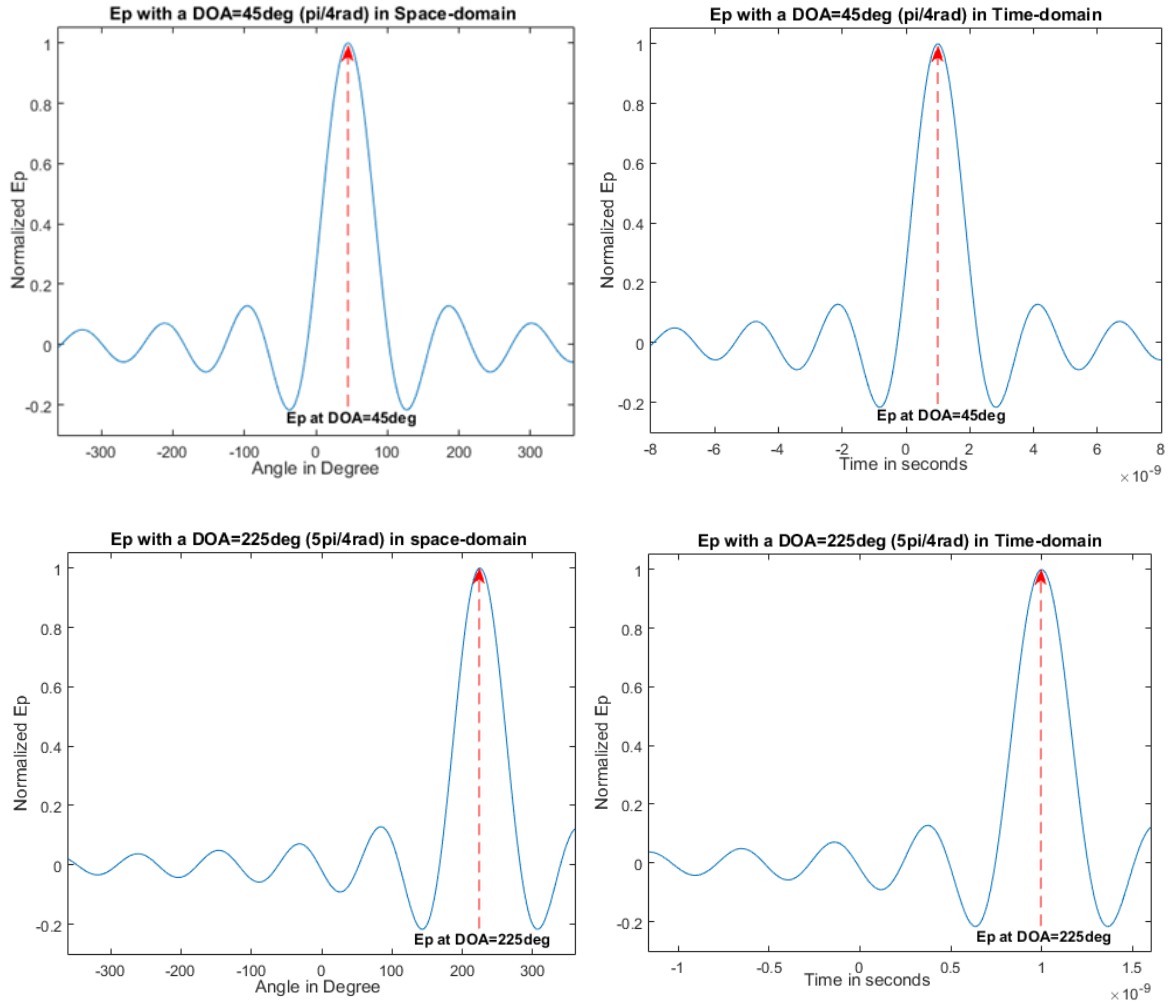


**Figure 4.36:** The  $E_P$  plotted in the space and time-domain for  $\text{DOA} = 45^\circ$  and  $225^\circ$

Meanwhile, Figure 4.37 illustrates that when the  $\text{DOA} = 45^\circ$ , the magnitude of  $Y_S = 1$  and  $Y_T = 0.9984$ . Using the DataTip Alignment Method, the  $Y_S$  represented the magnitude of  $Y$  in the space domain, and the  $Y_T$  represented the magnitude of  $Y$  in the time domain. In

the signal interpretation, the  $Y_S$  obtained in the space domain becomes the referral point to find the  $Y_T$  in the time domain. The absolute error,  $|E|$  between both magnitudes is  $|E| = 0.0016$ . This verifies that the similarity of signal interpretation is 99.84%.

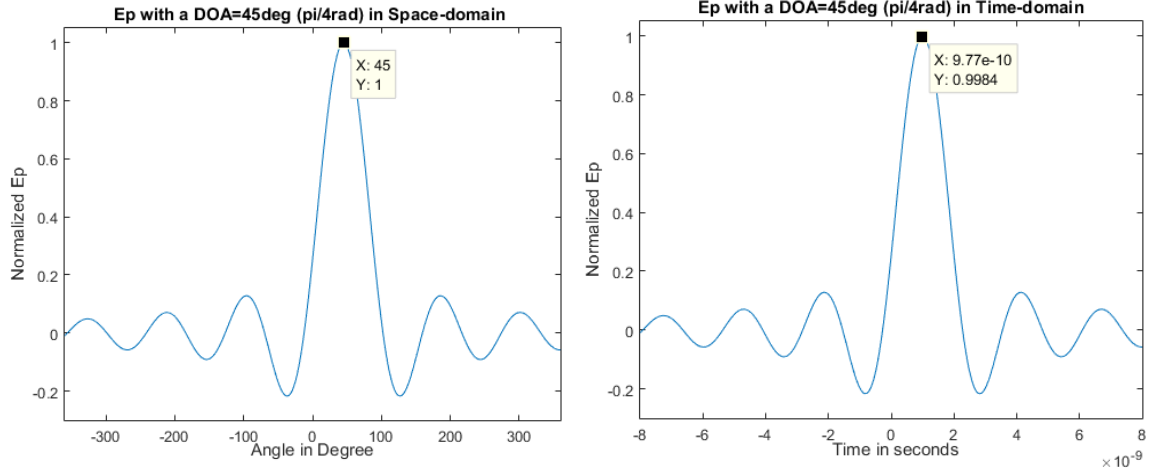


**Figure 4.37:** The Magnitudes  $Y_S$  and  $Y_T$  at DOA= 45°

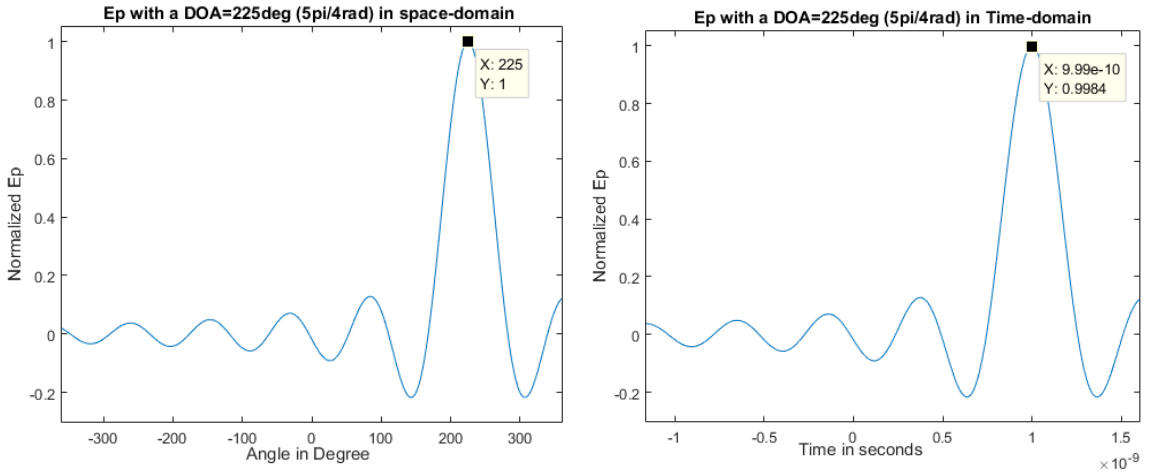


**Figure 4.38:** The Magnitudes  $Y_S$  and  $Y_T$  at DOA= 225°

From Figure 4.38, when the DOA = 225°,  $Y_S = 1$  and  $Y_T = 0.9984$ , the absolute error between both magnitudes is also given as  $|E| = 0.0016$ ; therefore, the similarity of signals in each domain is also 99.84%. A further case study involves more samples of DOAs,  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$ , to obtain the Mean Average Value (MAV) error for overall similarity. Figure

4.39 displays the average values of  $Y_S$  and  $Y_T$  observed at different DOAs. Inconsistency occurred for both  $Y_S$  and  $Y_T$ . However, the average value of the  $Y_S$  is 0.9999, and for  $Y_T$ , it is 0.9996. Thus, by calculation, the inconsistency of the average absolute error between  $Y_S$  and  $Y_T$  sampled at DOAs of  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$  is  $\%|E| = 0.03\%$  of error in the similarity. The average similarity percentage for the  $E_P$  signal models observed in both domains is 99.97%. This indirectly gives measurement accuracy for both domains at 0.03% when the DataTip Alignment method is applied.

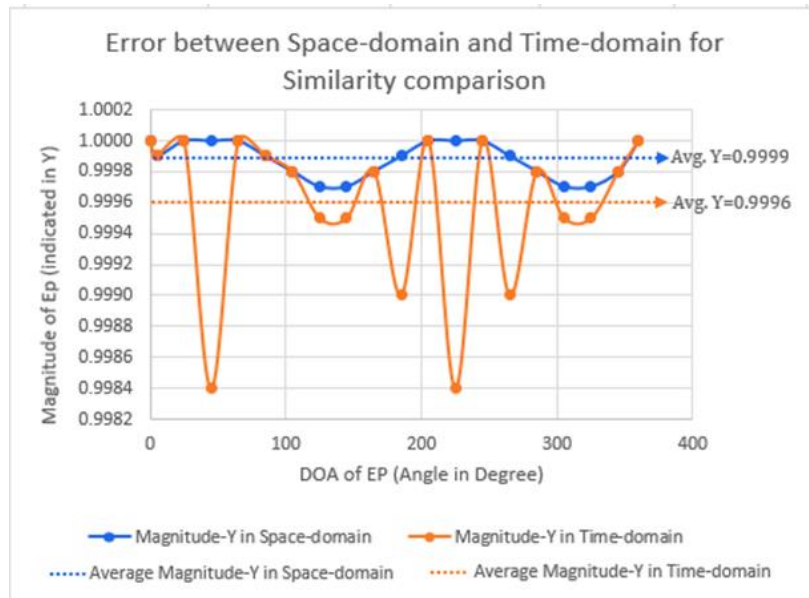


**Figure 4.39:** The error analysis for similarity comparison

Next, the measurement accuracy comparison is made between  $E_P$  model signals, the EMG method for musculoskeletal systems (Jali et al., 2015), and the Chemometric toolbox (Erny et al., 2016), all using the MATLAB DataTip Alignment Method for signal feature extraction in the time domain. Figure 4.40 illustrates that the DataTip applied to the  $E_P$  signal models has the highest accuracy with a MAV error percentage of 0.03% if compared to others. The EMG signal measurement accuracy is read as 98.53%. In comparison, the Finnee Signal Chemometric toolbox has revealed an accuracy of 99.76% when all of the extraction

has successfully utilized the DataTip alignment method for the signal feature extraction. The similarity of the waveforms displayed in both space and time domains enables a waveform-based analysis with respect to time, implying the DataTip Alignment Method has efficiently simplified the computational complexity in the feature extraction of a signal. It also provides less calculation and simpler judgments.

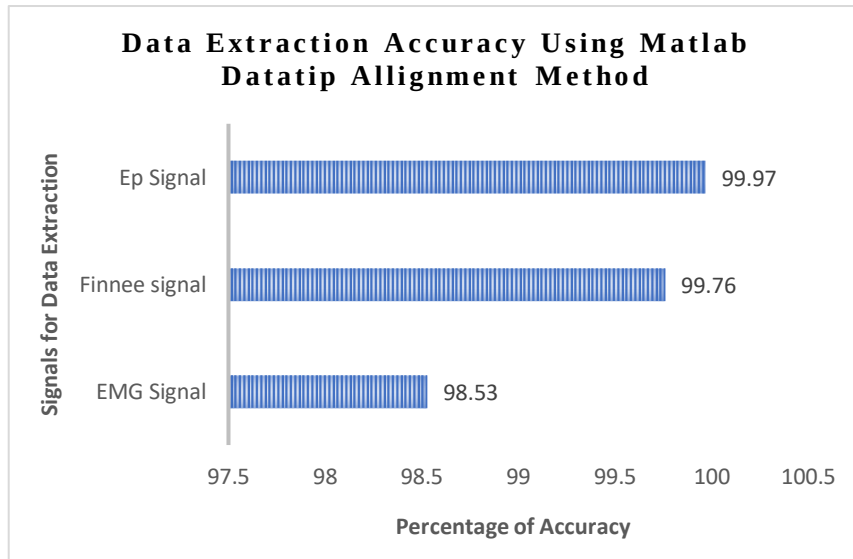


**Figure 4.40:** Data Extraction Accuracy using MATLAB DataTip Alignment Method

#### 4.4.3 Analysis of the Efficiency of the SP-Identifier Technique

Previously, the similarity of the  $E_P$  waveforms visualized in both space and time domains has provided a simpler technique for signal feature extraction. The outcome conclusively gives another room to evaluate the RP of the SPSS upon detection of the ED\_EMP signal from the desired DOA. This section introduces the SP-Identifier technique as a novel technique for signal identification. It utilizes the SP-ANN optimized weights of  $W_1 = -66.11 + j2.029$ ,  $W_2 = 21.31 - j32.21$ , and the DOA of the  $E_P$  source, incorporating the DataTip Alignment Method for  $E_P$  signal feature extraction. Unlike many researches works

that utilized ANN for signal recognition and classification due to multiple sources of ED (Florkowski, 2020; Yeo et al., 2020), the SP-Identifier technique can perform signal feature extraction based on a single source from a specific DOA. Therefore, this analysis aims to evaluate the accuracy of the SP-Identifier technique by first performing the similarity-comparing test for the SPSS radiation waveform corresponding to the  $E_P$  model. Then, an error test is conducted to verify the accuracy of the signal identification. Both tests utilize the DataTip Alignment Method as applied in Section 4.4.2. For the similarity-comparing test, the SPSS is set to detect a 1 GHz of the  $E_P$  signal, modeled at  $\theta_d = 45^\circ$  and  $\theta_d = 225^\circ$ . Figure 4.41 and Figure 4.42 are the SPSS RPs responding to the  $E_P$  model from the respective DOAs illustrated in space and time domains. The DataTip Alignment Method is applied to obtain the value of  $X$  and  $Y$  in both domains. In the space domain plot,  $X$  represents the  $\theta_d$ , and  $Y$  represents the magnitude of the  $E_P$  signal. Meanwhile, in the time domain plot, the value of  $Y$  from the space domain becomes the referral point to seek the value of  $Y$  in the time domain, hence yielding the value of  $X$ . Here, the value of  $X$  represents the period of the  $E_P$  model, received at 1 ns (or 1 GHz).

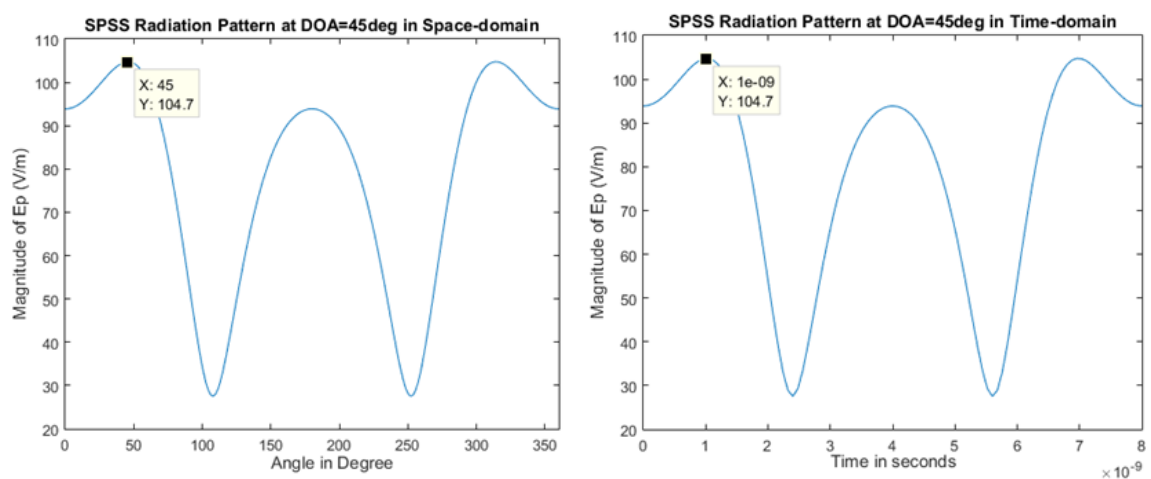


**Figure 4.41:** SPSS Radiation Patterns in Space and Time domain at DOA=45°

Through observation, the RP plotted in the space domain is similar to the RP in the time domain. Referring to Figure 4.41, the DataTip in the space domain plot is aligned to seek the value of  $X = 45$  (representing  $\theta_d = 45^\circ$ ), yielding the magnitude of  $E_P$  at  $Y = 104.7$  V/m. Then, the DataTip at the time domain plot is aligned to seek the  $Y = 104.7$  V/m, and the value of  $X$  is obtained. Figure 4.41 and Figure 4.42 indicated that both samples significantly suggest that the SPSS received the targeted  $E_P$  signal at  $X = 1.0\text{e-}09\text{s}$  (or 1 GHz).

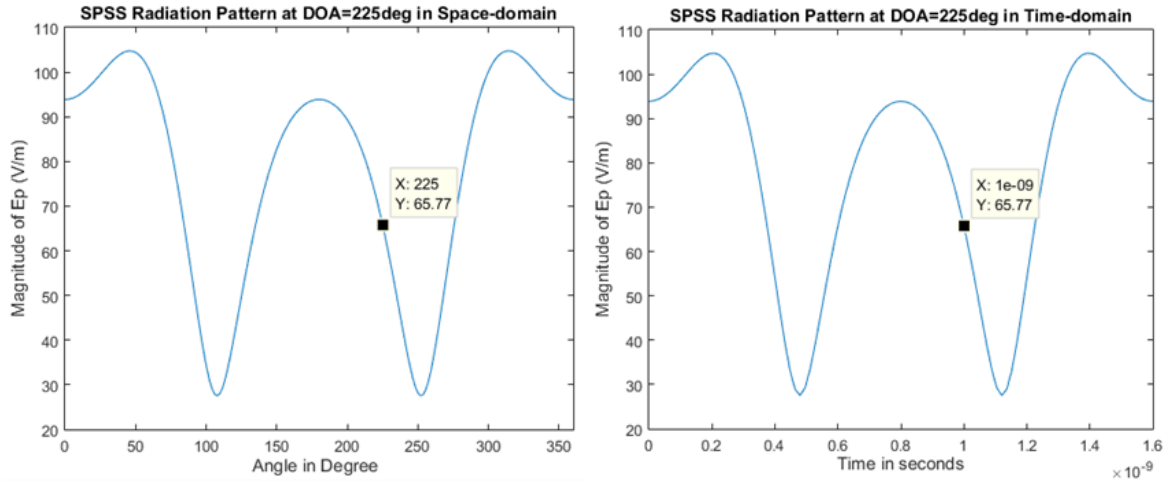


**Figure 4.42:** SPSS Radiation Patterns in Space and Time domain at DOA=225°

A further case study is the error test analysis. The percentage of error emphasizes the accuracy of the SP-Identifier technique when integrating the SPSS. Utilizing about 20 samples of DOA at  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$ , the values of  $Y$  are indicated in Appendix M. The absolute error,  $|E|$ , and the percentage of error,  $\%|E|$ , are obtained via a comparison between the  $Y_S$  and  $Y_T$ . From the result, the average absolute error,  $\%|E| = 0.03\%$ , yields a similarity of 99.97%. From the findings, it can be concluded that the Signal Identifier Technique has significantly demonstrated the similarity of SPSS RP waveforms in both space and time

domains. This is supported by the accuracy of 99.97% of the signal identification. In Section 4.4.2, the similarity comparison is performed for  $E_P$  waveforms as generated ED source. Meanwhile, in this analysis, the similarity comparison is performed for SPSS RP waveforms, representing the SPSS received signal. Both similarity-comparing works have successfully utilized the DataTip Alignment method for the signal feature extraction, yielding an MAV error percentage of 0.03%.

#### **4.4.4 Analysis of the Signal Identification for the SPSS Radiation Waveform**

The choice of signal identification technique often depends on the nature of the ED signals (Luo et al., 2017), the specific equipment being monitored (Álvarez et al., 2015), and the available data (Contin et al., 2009). In practice, a combination of these techniques, such as ML models incorporating time-frequency analysis (Li et al., 2016) and statistical features (Lu et al., 2020), is frequently used to enhance the accuracy and reliability of ED signal preprocessing stages for feature extraction. Different types of PD identification techniques have been applied to detect and recognize different types of PD patterns. Among them are Back-Propagation Neural Network (BPNN), Support Vector Machine (SVM), Ensemble Neural Network (ENN), Probabilistic Neural Network (PNN), MLP, Multilayer Neural Network (MNN), Back Propagation-Particle Swarm Optimization (BP-PSO), Sparse Representation Classifier (SRC), CNN and many more. All these methods work significantly with the extensive PD datasets from multi-source PDs (Mantach et al., 2021; Song et al., 2018).

In this research work, the signal identification employs the SP-Identifier Technique to perform the single-source ED\_EMP signal feature extraction, hence identifying the signal for its frequency spectrum. This technique provides less calculation, and data can be directly

retrieved from the waveforms illustrated in the space and time domains. This analysis is the final analysis to evaluate the performance of the SPSS in ED\_EMP detection and identification. Here, the signal identification involves the feature extraction of the ED\_EMP represented as  $E_P$  signal, applying the SP-Identifier technique to synthesize a single source  $E_P$  signal model in the waveform-based. The SPSS is to receive the  $E_P$  signal, modeled in the frequency of 0.5 GHz, 1 GHz, and 2 GHz for the  $E_P$  localized at DOA,  $\theta_d = 45^\circ$ . The capability of an antenna to admit the detection of EM signals up to microwave spectrums depends on the time domain training the algorithm (Youssef et al., 2018). Therefore, the SPSS receiving capability also depends on the training time  $T_{SPSS (train)}$  of the SP-ANN algorithm. Table 4.7 provides the specification table of the SP-Identifier Technique, summarizing  $E_P$  signal, modeled in the frequency of 0.5 GHz, 1 GHz, and 2 GHz localized at DOA,  $\theta_d = 45^\circ$  for SP-ANN optimized weights,  $W_1 = -66.11+j2.029$  and  $W_2 = 21.31-j32.21$ .

**Table 4.2:** Specification Table of SP-Identifier Technique

| Parameters                                 | Value                         |
|--------------------------------------------|-------------------------------|
| $E_P$ localized source at DOA              | $45^\circ$ (0.7854 rad)       |
| SP-ANN Optimized Weights, $W_1, W_2$       | $-66.14+j2.029, 21.31+j31.21$ |
| SPSS Training Frequency, $F_{SPSS(Train)}$ | 2.4 GHz -24 GHz               |
| $E_P$ model Frequency, $F_{E_P(model)}$    | 300 MHz -3 GHz                |
| SPSS Training Time, $T_{SPSS(Train)}$      | 0.42 ns - 0.042 ns            |

Figure 4.43 to Figure 4.44 display the waveform-based analysis performed for the sampling frequency,  $E_P$ . Figure 4.43 illustrates the SPSS RPs for  $E_P = 1$  GHz generated at  $t_{E_P} = 1$  ns. For the feature extraction in the space domain, at  $X = 0.7854$ , the value of  $Y = 104.7$ . Meanwhile, in the time domain, at  $Y = 104.7$ , the value of  $X = 9.966e^{-10}$  s. From the

result, the received frequency of the SPSS,  $F_{Ep}(\text{SPSS}) = 1.0003 \text{ GHz}$  at  $t_{Ep}(\text{SPSS}) = 0.9966 \text{ ns}$ . Hence, in comparison to the  $E_P$  model, the  $\%|E|$  between the  $E_P$  model ( $F_{Ep}(\text{model})$ ) and the received by SPSS ( $F_{Ep}(\text{SPSS})$ ) is  $\%|E| = 0.03\%$ . The accuracy of the identification is 99.97%.

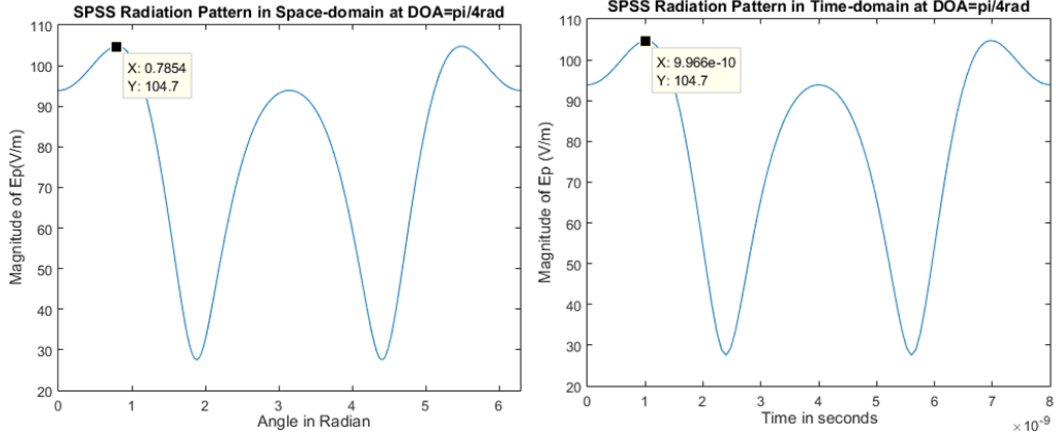


**Figure 4.43:** The SPSS radiation patterns for  $E_P = 1 \text{ GHz}$

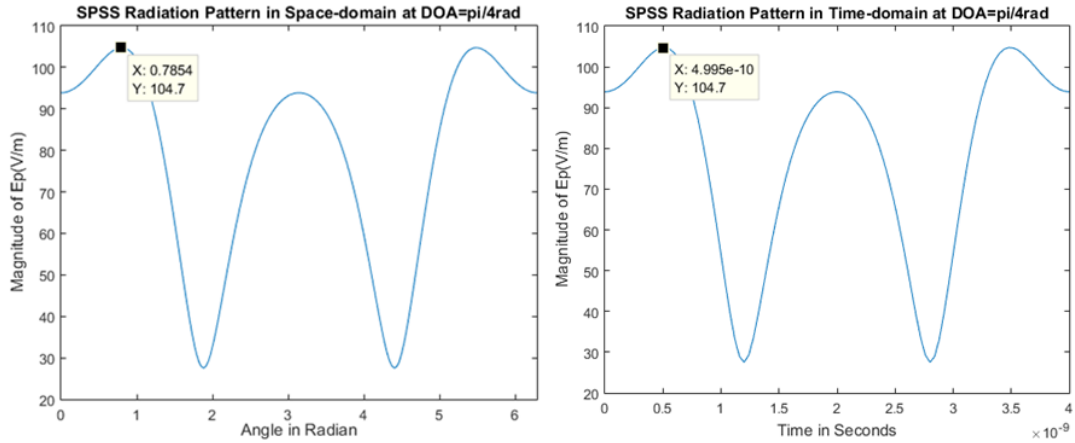


**Figure 4.44:** The SPSS radiation patterns for  $E_P = 2 \text{ GHz}$

Figure 4.44 displays the SPSS RPs for  $E_P = 2 \text{ GHz}$  generated at  $t_{Ep} = 0.5 \text{ ns}$ . For the feature extraction in the space domain at  $X = 0.7854$ , the magnitude of  $Y = 104.7$ . Meanwhile, in the time domain at  $Y = 104.7$ , the value of  $X = 4.995e^{-10} \text{ s}$ . From the result, the received

frequency of the SPSS,  $F_{Ep} \text{ (SPSS)} = 2.002 \text{ GHz}$  at  $t_{Ep} \text{ (SPSS)} = 0.4995 \text{ ns}$ . Hence, in comparison to the  $E_P$  model, the  $\%|E|$  between the  $E_P$  model ( $F_{Ep} \text{ (model)}$ ) and the received by SPSS ( $F_{Ep} \text{ (SPSS)}$ ) is  $\%|E| = 0.1\%$ . The accuracy of the identification is 99.90%.

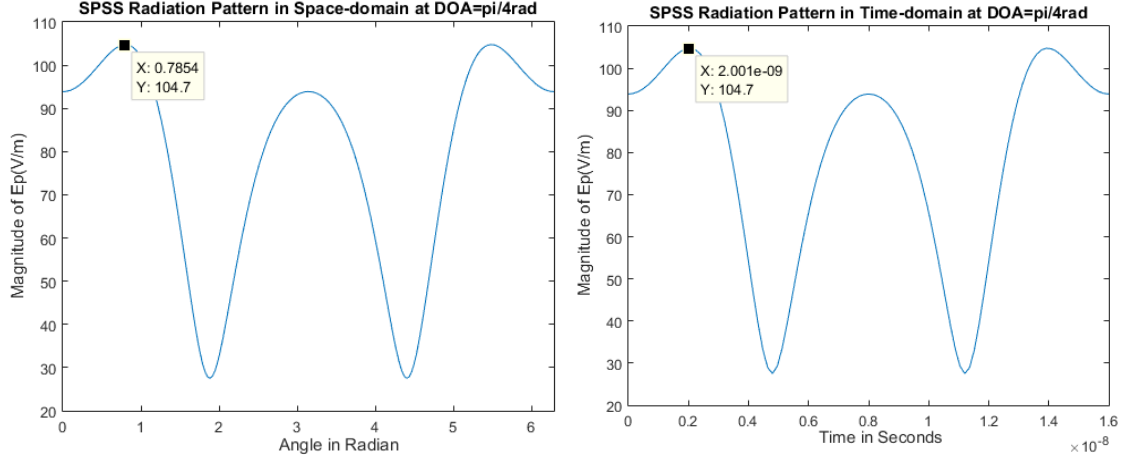


**Figure 4.45:** The SPSS radiation patterns for  $E_P = 0.5 \text{ GHz}$

Figure 4.45 illustrates the SPSS RPs for  $E_P = 0.5 \text{ GHz}$  generated at  $t_{Ep} = 2 \text{ ns}$ . For the feature extraction in the space domain at  $X = 0.7854$ , the value of  $Y = 104.7$ . Meanwhile, in the time domain at  $Y = 104.7$ , the value of  $X = 2.001\text{e-}9 \text{ s}$ . From the result, the received frequency of the SPSS,  $F_{Ep} \text{ (SPSS)} = 0.4998 \text{ GHz}$  at  $T_{Ep} \text{ (SPSS)} = 2.001 \text{ ns}$ . Hence, the  $\%|E|$  between the  $E_P$  model ( $F_{Ep} \text{ (model)}$ ) and the received by SPSS ( $F_{Ep} \text{ (SPSS)}$ ) is  $\%|E| = 0.04\%$ , yielding an accuracy of 99.96%. Based on the findings, the average accuracy of the identification for these  $E_P$  samples is 99.94%. Table 4.3 summarizes the accuracy rate (%) of the SP-Identifier technique, extracting  $E_P$  signal, modeled in the frequency of 0.5 GHz, 1 GHz, and 2 GHz localized at DOA,  $\theta_d = 45^\circ$ .

**Table 4.3:** Summary of the accuracy rate (%) of SP-Identifier Technique

| $F_{EP} (model)$<br>(GHz) | $T_{EP} (model)$<br>(ns) | $F_{EP} (SPSS)$<br>(GHz) | $T_{EP}(SPSS)$<br>(ns) | $E_P$ Error<br>(%) | Accuracy<br>(%) |
|---------------------------|--------------------------|--------------------------|------------------------|--------------------|-----------------|
| 0.5                       | 2.0                      | 0.4998                   | 2.001                  | 0.04               | 99.96           |
| 1.0                       | 1.0                      | 1.0003                   | 0.9966                 | 0.03               | 99.97           |
| 2.0                       | 0.5                      | 2.002                    | 0.4995                 | 0.1                | 99.90           |

An investigation is to seek the average accuracy value of the signal identification, which involves 19  $E_P$  samples ranging from 300 MHz to 3 GHz at a fixed DOA,  $\theta_d = 45^\circ$  for SP-ANN optimized weights,  $W_1 = -66.11 + j2.029$  and  $W_2 = 21.31 - j32.21$ . The result reveals that the SPSS responded distinctively to different DOAs at a multi-range of the frequency spectrum. The average signal identification is 99.86% when five readings per sample are computed for each sample, as indicated in Appendix N. This research compares several types of NN-based signal identification techniques. The comparison is made based on the same sample of Corona or Arc discharges at frequencies ranging from 300 MHz – 3 GHz. Table 4.4 compares the ED signal identification accuracy rate (%) of different analysis methods.

**Table 4.4:** Comparison of SP-Identifier accuracy rate (%) of different analysis methods

| Author/Year             | Method  | Accuracy Rate (%) | Discharge Types      |
|-------------------------|---------|-------------------|----------------------|
| (Chen, 2013)            | MNN     | 98.60             | Artificial HV corona |
| (Majidi et al., 2015)   | SCR     | 97.97             | Power Transformer    |
| (Florkowski, 2020)      | CNN     | 93.09             | HV Insulation        |
| (Khan et al., 2017)     | MLP     | 97.38             | HV cable             |
| (Candela et al., 2000)  | BP-NN   | 98.00             | HV bushings          |
| (Kuo, 2010)             | BP- PSO | 94.00             | HV Insulation        |
| (Mas'ud et al., 2014)   | ENN     | 98.00             | Optical Receiver     |
| (Evagorou et al., 2010) | PNN     | 97.49             | HV Insulation        |
| <b>SP-Identifier</b>    |         | 99.86             | HV Insulation        |

Based on the findings Table 4.4, over the period of 20 years, most of the ANN-based techniques are used for ED recognition. The multilayer neuron techniques have exhibited a significant accuracy rate of more than 90% in multi-source ED signal identification. So far, research works employing single perceptron for ED signal identification techniques are yet to be discovered. Therefore, this research is a novel signal identification technique that has significantly achieved an accuracy rate of 99.86%, which is numerically comparable to other research works. Nevertheless, another comparison is made to verify that the SP-Identifier is significant for ED identification by comparing the identification accuracy rate (%) of CNN while using a single-source ED sample, as indicated in Table 4.5. Therefore, in this research, a single-perceptron is proposed for EM signal identification, aiming for a similar accuracy performance.

**Table 4.5:** The comparison of ED identification accuracy rate(%) for Single-source ED

| Author/Year            | Technique | Accuracy rate (%) | Discharge |
|------------------------|-----------|-------------------|-----------|
| (Mantach et al., 2021) | CNN       | 99.6              | Corona    |
| (Song et al., 2018)    | CNN       | 98.5              | Corona    |
| SP-Identifier          |           | 99.86             | Corona    |

A further investigation continued with the evaluation of the SPSS for signal localization, implementing the SP-Identifier technique. The average error of signal localization is conducted, which involves 19  $E_p$  samples ranging from 300 MHz to 3 GHz at a fixed DOA,  $\theta_d = 45^\circ$  for five computations of each sample. From the investigation, the average error of the signal localization is  $2^\circ$  as provided in Appendix N. Table 4.6 indicates that SPSS localization is compared to other methods while employing the same localization DOA method. It can be observed that despite having different sensors for detection, the

localization error exhibits a comparative performance among them. From the findings, it can be concluded that if the monitoring at DOA = 45° is targeting the early formation of Corona discharge frequency at 1 GHz, the SPSS will be set according to the frequency of 1 GHz, and the signal identification will be monitored at that particular desired DOA as the focal point.

**Table 4.6:** Based-Method Comparison for ED localization

| Author/Year            | Methods of Localization | Sensor type                           | Error of localization | PD Source          |
|------------------------|-------------------------|---------------------------------------|-----------------------|--------------------|
| (Wu et al., 2020)      | DOA method              | Monopole array sensor                 | 3.5°                  | 1100MHz            |
| (Zhou et al., 2018)    | DOA Method              | 4 x 4 UHF array sensor                | 4°                    | 300M-1.5GHz        |
| (Yongfen et al., 2015) | DOA Method              | 16 x16 UHF array sensor               | 2°                    | 150 kHz and 50 kHz |
| (Han et al., 2020)     | DOA Method              | UHF array sensor                      | <6°                   | 300 MHz-1500 MHz   |
| (Xu et al., 2022)      | DOA Method              | Spiral antenna circular array         | 3.39°                 | 1.5 GHz and 2 GHz  |
| (Liu et al., 2017)     | DOA Method              | 4-elements uniform circular array     | <5°                   | 300 MHz - 1.5GHz   |
| Research work          | DOA Method              | Single Perceptron Smart Sensor (SPSS) | 2°                    | 300MHz – 3GHz      |

#### 4.5 Chapter Summary

This chapter discloses all of the results and discussion related to the analysis held in Chapter 3. The results and discussion are divided into THREE (3) parts to accomplish the SPSS for pre-fault monitoring system. Part A demonstrates the first objective of this research, which is to investigate the most suitable *N*-element array antenna as the SPSS model, which has broad radiation and adapts to changes in the propagation phase. The result suggests a remarkable performance demonstrated by the 2-element array antenna. It fulfills the desired characteristics of the SPSS model in terms of the broad beamwidth RP, and it

has significantly adapted to the changes in the propagation phase by inducing a delay signal,  $\beta$ , keeping the inter-element spacing at  $d = 0.5\lambda$ . When the SP-ANN is integrated with a Linear Array Antenna, it changes the radiation quality of the array input element,  $f(\varphi)$ . The amplitude of the  $f(\varphi)$  has significantly increased following the increment of the perceptron weights. This finding has opened another opportunity to improve the sensing coverage by auto-varying the perceptron weights.

Part B demonstrates the second objective of the research, which is to develop a novel SPSS utilizing the SP-ANN Algorithm for ED\_EMP signal detection and localization. To achieve this, SEVEN (7) analyses are conducted in part B. It begins with the first analysis of the SP-ANN algorithm for weight optimization. This analysis focuses on developing an ANN-based weight optimization algorithm called the SP-ANN algorithm. Integrating this algorithm with a Linear Array Antenna allows the perceptron to optimize its weights smartly, producing a novel SPSS to detect and localize the ED signal smartly. The computational work is carried out to evaluate the performance of the algorithm on an  $N$ -element array antenna at  $N = 2, 3, 4, 6, 8$ , and  $10$  for a fixed induced delay angle,  $\beta = 45^\circ$ . As observed, the SP-ANN algorithm is most suitable for lower array lengths and not suitable for  $N = 4, 6, 8$ , and  $10$ . The SP-ANN algorithm has optimized its complex weights in seconds to achieve convergence. For  $N = 2$ , the optimum perceptron weights are  $W_1 = -66.11 + j2.029$  and  $W_2 = 21.31 - j32.21$  at the SP-ANN hyperparameter settings between  $0.02 \leq \eta \leq 1.0$  for the  $\eta$  and  $0.001 \leq b \leq 1.0$  for the  $b$ . The SPSS is capable of maximizing the desired DOA,  $\theta_d$ , and nulling the interference signal for undesired DOA,  $\theta_i$ . This fast convergence (within seconds) algorithm allows the SA to have a distinctively high amplitude to amplify any signal picked up from the far field, thus improving the signal detection range. This analysis has provided a better way of using beamforming techniques to respond to the RP. Frequency scanning is

possible for the SPSS, which definitely does not require any phase shifter unit, but the transmitted frequency from a desired DOA can be used for the beam steering. This is the novelty of this research work, where the simplest SP-ANN algorithm has replaced the use of a phase shifter to shift the array antenna electronically. Thus, it has successfully suppressed the cost and complexity of the detection and localization system, which again has overcome the gap of this research. Besides that, signal electric field strength for multiple DOAs has visualized the SPSS placement topology at the multiple spatial locations (the DOAs) efficacy of signal detection measured based on signal electric field strength. The electric field strength of signals is different at every different DOA due to the effect of SP-ANN optimized weights at different DOAs. These findings yield a better recommendation of the SPSS placement wherein the desired location is in the indoor substation. Other than that, the total electric fields ( $E_T$ ) and radiated power intensity ( $P_i$ ) at a fixed DOA with multiple ranges of signal distance,  $r$  (in meter). In this analysis, the computation of total electric fields ( $E_T$ ) is carried out based on the multiple ranges of source distance,  $r$ , measured in meters. This analysis aims to determine the relationship between the SPSS receiving distance with the SPSS radiation total electric field strength,  $E_T$ , and its power intensity,  $P_i$ . It is an alternative in providing a better recommendation of the SPSS placement for the efficacy of  $E_P$  localization. The finding of this work is compared to various methods of electric field strength measurement, demonstrating that a specific range of electric field strength and power intensity Corona or Arc discharge is undecidable. However, these parameters are efficient in pinpointing the location and magnitude of ED activity, thus making it valuable for condition monitoring and maintenance.

Part C demonstrates the second objective of the research, which is to evaluate the accuracy of the ED\_EMP signal identification using the novel SP-Identifier Technique in

waveform-based testing for Corona or Arc Eds samples. In this part C, FOUR (4) analyses have been conducted to achieve this objective. The first analysis is the analysis of the  $E_P$  model representing ED\_EMP tested at multiple DOAs. HV equipment has the ability to produce impulsive EM signals with high levels of energy and significant RF components. Any ED detected from a power apparatus usually carries a power frequency sinusoidal current, embedding the ED\_EMP superimposed on it. In this analysis, the simulation is carried out to conceptualize the ED\_EMP signal generation represented as the  $E_P$  signal model. For this purpose, simulation work uses a Sinc function as the  $E_P$  signal model with frequency sampled at 1 GHz, DOA,  $\theta_d = 45^\circ, 120^\circ, 225^\circ$  and  $300^\circ$  for  $\theta_d \in \{0^\circ \leq \theta_d \leq 360^\circ\}$  is the Spatial locations of the  $E_P$  signal occurred. ZigBee model is chosen for this comparison as it utilizes the same MATLAB DataTip to extract the PD signals. Similarly, it uses a Sinc function to represent the PD signals. The accuracy of signal identification based on the modelled impulsive noise for both SPSS and ZigBee are compared. This analysis has successfully visualized the RPs of the simulated ED\_EMP signal in the space domain. The differences in accuracy measurement for both methods are 0.416% and 0.349% for impulsive noise of the 915 MHz and 2.4 GHz. The findings in this analysis yield an opportunity to understand the frequency content of an ED signal when visualized in the Sinc function. It makes signal detection and identification more significant and reliable. Furthermore, the Sinc function is very useful for modelling the real signal of  $E_P$  in the analysis for signal identification. The second analysis is to evaluate the similarity of the ED\_EMP waveforms in space and time domain using the DataTip Alignment method. The analysis seeks the similarity of the  $E_P$  signal observed in the space and time domain. Having the similarity verifies the ability of the received signal to be efficiently analysed with minimal computational complexity, thus giving another cost-efficient wireless technique for

the UHF signal interpretation and identification. Additionally, this analysis implies the DataTip Alignment Method for signal interpretation. In this analysis, assuming an event of ED\_EMP current to radiate an impulsive  $E_P$  signal that occurred at a peak time,  $t_p = 1$  ns, yielding the frequency of about 1 GHz received by the SPSS. The average percentage of similarity for the  $E_P$  signal models observed in both domains is 99.97%. Hence, it gives the accuracy of measurement for both domains at 0.03% when the DataTip Alignment method is applied. The similarity of the waveforms displayed in both space and time domains enables a waveform-based analysis with respect to time, implying the DataTip Alignment Method has efficiently simplified the computational complexity in the feature extraction of a signal. It also provides less calculation and simpler judgments. The third analysis is to evaluate the efficiency of the SP-Identifier technique in identifying the ED\_EMP signal detected by the SPSS. This section introduces the Signal Identifier as a novel technique for signal identification. It utilizes the SP-ANN optimized weights and the DOA of the  $E_P$  source, incorporating the DataTip Alignment Method for  $E_P$  signal feature extraction. The SP-Identifier technique can perform signal feature extraction based on a single source from a specific DOA. This analysis aims to evaluate the accuracy of the SP-Identifier Technique by first performing the similarity-comparing test for the SPSS radiation waveform corresponding to the  $E_P$  model. Then, an error test is conducted to verify the accuracy of the signal identification. From the findings, it can be concluded that the SP-Identifier technique has significantly exhibited the similarity of SPSS RP waveforms in both space and time domains. This is supported by the accuracy of 99.97% of the signal identification. A similarity comparison is performed for SPSS RP waveforms, representing the SPSS received signal. Both similarity-comparing works have successfully utilized the DataTip Alignment method for the signal feature extraction, yielding an MAV error percentage of 0.03%. Lastly,

the fourth analysis evaluates the performance of signal identification for the SPSS radiation waveform. In this research, the signal identification employs the SP-Identifier Technique to perform the single-source ED\_EMP signal feature extraction, hence identifying the signal for its frequency spectrum. This technique provides less calculation, and data can be directly retrieved from the waveforms illustrated in the space and time domains. This analysis is the final analysis to evaluate the performance of the SPSS in ED\_EMP detection and identification. Here, the signal identification involves the feature extraction of the ED\_EMP represented as  $E_P$  signal, applying the SP-Identifier technique to synthesize a single source  $E_P$  signal model in the waveform-based. The SPSS is to receive the  $E_P$  signal, modelled in the frequency of 0.5 GHz, 1 GHz, and 2 GHz for the  $E_P$  localized at DOA,  $\theta_d = 45^\circ$ . So far, research works employing single perceptron for ED signal identification techniques are yet to be discovered. Therefore, this research is a novel signal identification technique that has significantly achieved an accuracy rate of 99.86%, which is numerically comparable to other research works. A further investigation continued with the evaluation of the SPSS for signal localization, implementing the SP-Identifier technique. The average error of signal localization is conducted, which involves 19  $E_P$  samples ranging from 300 MHz to 3 GHz at a fixed DOA,  $\theta_d = 45^\circ$  for five computations of each sample. From the investigation, the average error of the signal localization is  $2^\circ$  thus, the localization error exhibits a comparative performance among other localization methods. From the findings, it can be concluded that if the monitoring at DOA =  $45^\circ$  is targeting the early formation of Corona discharge frequency at 1 GHz, the SPSS will be set according to the frequency of 1 GHz, and the signal identification will be monitored at that particular desired DOA as the focal point.

## CHAPTER 5

### CONCLUSION AND RECOMMENDATIONS

#### 5.1 Conclusion

This research study has successfully developed a Single Perceptron Smart Sensor (SPSS) Technique for Pre-fault Monitoring in an Indoor Substation. It involves a series of empirical simulations and evaluations to accomplish the study. Part A represents the first research objective, which is to investigate the most suitable  $N$ -element array antenna as the SPSS model that has a broad radiation beamform and adapts to the changes of the propagation phase. The 2-element array antenna performed exceptionally well, meeting the requirements of the SPSS model in terms of a broad beamwidth Radiation Pattern (RP) and demonstrating a significant ability to adapt to changes in the propagation phase by inducing a delay signal ( $\beta$ ) and maintaining the inter-element spacing at  $d = 0.5\lambda$ . The quality of the array input element,  $f(\varphi)$ , varies when the Single Perceptron-Artificial Neural Network (SP-ANN) integrates with the 2-element array antenna. As the perceptron weights increased, the amplitude of the RP also increased significantly. The significant findings indicated that the magnitude (in V/m) had increased from the initial magnitude of 0.7531 V/m (or -1.231dB) to the magnitude of 104.7 V/m (or 20.2 dB) after weight optimization. This finding provides another opportunity to improve the sensing coverage by auto-varying the perceptron weights.

Part B represents the second objective of the research, which is to develop a novel SPSS utilizing the SP-ANN Algorithm for Electric Discharge Electromagnetic Impulse (ED\_EMP) signal detection and localization. In this part, an Artificial Neural Network (ANN)-based weight optimization algorithm called SP-ANN algorithm has been

successfully developed. The SP-ANN algorithm has optimized the perceptron complex weights in a short training period to achieve early stopping convergence. This early stopping reduces the complexity of the computational method, thus reducing the use of memory, which is the gap in this research. The algorithm works significantly with a 2-element array antenna,  $N = 2$ , for the optimum perceptron weights are  $W_1 = -66.11 + j2.029$  and  $W_2 = 21.31 - j32.21$ . These weights became the fixed parameters in this research and were applied to other related analyses for SPSS modeling. Other than that, it is essential to tune the hyperparameters of the perceptron before applying a Neural Network (NN) algorithm, as choosing the wrong value may affect the convergence process during the perceptron training. For  $N = 2$ , the SP-ANN hyperparameter settings are  $0.02 \leq \eta \leq 1.0$  for the learning rate,  $\eta$  and  $0.001 \leq b \leq 1.0$  for the bias,  $b$ . The SPSS is capable of maximizing the desired DOA,  $\theta_d$ , and nulling the interference signal for undesired DOA,  $\theta_i$ . This fast convergence algorithm allows the SA to have a distinctively high amplitude to amplify any signal picked up from the far field, thus improving the signal detection range. SPSS has provided a better beamforming technique to respond to the RP. Frequency scanning is possible for the SPSS, which definitely does not require any phase shifter unit, but the transmitted frequency from a desired DOA can be used for the beam steering. This is the novelty of this research work, where the simplest SP-ANN algorithm has replaced the use of a phase shifter to shift the array antenna electronically. Thus, it has successfully suppressed the cost and complexity of the detection and localization system, which again has overcome the gap of this research. Besides that, signal electric field strength for multiple DOA has visualized the SPSS placement topology at the multiple spatial locations, providing the efficacy of signal detection measured based on signal electric field strength. The electric field strength of signals is different at every different DOA due to the effect of SP-ANN optimized weights

at different DOAs. This finding yields a better recommendation of the SPSS placement wherein the desired location is in the indoor substation. Other than that, for the total electric fields ( $E_T$ ) and radiated power intensity ( $P_i$ ) at a fixed DOA with multiple ranges of signal distance,  $r$  (in meter), a comparable outcome reveals that a specific range of electric field strength and power intensity Corona or Arc discharge is undecidable. However, these parameters efficiently pinpoint the location and magnitude of Electric Discharge (ED) activity, thus making it valuable for condition monitoring and maintenance. SPSS's best placement recommendation is between 1.524m to 7.62m (5ft to 25ft) for optimal receiving distance, giving the range of electric field strength at a magnitude of 26.61 dB to 19.62 dB.

Lastly, Part C evaluates the performance of the novel SP-Identifier Technique for ED\_EMP signal identification using waveform-based testing for Corona or Arc ED samples. It has successfully developed to reduce the complexity of the existing signal feature extraction techniques. SP-Identifier Technique uses the optimized weights of SP-ANN in Part B to identify the SPSS-detected signal waveforms in the time domain and space domain. The signal identification involves the feature extraction of the ED\_EMP represented as  $E_P$  signal, applying the SP-Identifier technique to synthesize a single source  $E_P$  signal model in the waveform-based. The SPSS is to receive the  $E_P$  signal, modeled in the frequency of 0.5 GHz, 1 GHz, and 2 GHz for the  $E_P$  localized at DOA,  $\theta_d = 45^\circ$ . So far, research works employing single perceptron for ED signal identification techniques are yet to be discovered. Therefore, this research is a novel signal identification technique that has significantly achieved an accuracy rate of 99.86%, which is numerically comparable to other research works. The average error of signal localization is conducted, which involves 19  $E_P$  samples ranging from 300 MHz to 3 GHz at a fixed DOA,  $\theta_d = 45^\circ$  for five computations of each sample. The finding suggests that the average error of the signal localization is  $2^\circ$  thus, the

localization error exhibits a comparative performance among other localization methods. In conclusion, if the monitoring at DOA =  $45^\circ$  targeting the early formation of Corona discharge frequency at 1 GHz, the SPSS will be set according to the frequency of 1 GHz, and the signal identification will be monitored at that particular desired DOA as the focal point.

## **5.2 Contribution of Study**

This research has successfully developed a novel smart wireless SPSS for ED signal detection and localization, utilizing a novel SP-ANN algorithm to electronically scan the indoor environment of a substation, hence, improves pre-fault monitoring for rapid detection and localization of the UHF Electromagnetic (EM) Signal, mainly the Corona and Arc EDs. It gives room of improvement for the online pre-fault monitoring system in the rural area substation, which is a time-consuming action for maintenance. A novel Signal Identifier Technique has been successfully developed to identify the early formation of the Corona or Arcs EDs significantly for speedy signal processing with less computational complexity and sufficiently small data usage and memory which has solved the problems mentioned in the problem statement.

## **5.3 Future Recommendations**

For future recommendations, the SPSS can be adopted as a wireless communication sensor to improve online monitoring and control systems since this sensor works efficiently at a wide range of frequency spectrums. The research can be enhanced by designing an online control unit with a data logger system for online monitoring. The wireless SPSS can provide significant data for the early warning system for the rural area substation through online monitoring.

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## APPENDIX A

```
%% Plotting the N-element with AF
n=<Insert value of N>
f=1e9; c=3e8;
lambda=c/f; kd=pi;
phi=0:pi/100:2*pi;
psi=(pi*cos(phi));
Y=(1/n)*(sin((n*psi)/2)/sin(psi/2));
Yd=abs(Y);
polar(phi,Yd)
title('Array Factor of N-Element Linear Array Antenna');
%% plotting the N-element with input radiation
fi=0:pi/100:2*pi;
z=exp(1i*(kd)*cos(fi))+1;
polar(fi,abs(z))
hold on;
title ('Input Element for N-Element');
%%Program N-elements induced signal Effect
delta=pi/4;
psi=(pi*cos(phi)-delta);
Y=(1/n)*(sin((n*psi)/2)/sin(psi/2));
Yd=abs(Y);
polar(phi,Yd)
title('N-Element Linear Array Antenna');
```

## APPENDIX B

```
%% The N-elements intergrated with SP-ANN for Inter-spacing Effect
n=<insert N>
f=1e9; c=3e8 lambda=c/f;
kd=<Insert value of kd>
phi=0:pi/100:2*pi;
delta=<insert induced signal>
psi=(pi*cos(phi));
z=(1/n)*(sin((n*psi)/2)/sin(psi/2));
Z=abs(z);
polar(phi,Z)
title('N,kd=pi');
```

## APPENDIX C

```
%%Analysis of the N-element integrated with the SP-ANN
Nx = <Insert N>
kd=pi;
w1=0.1+j0;
w2=0.1+j0;
fi=0:pi/100:2*pi;
z=w1+w2*exp(-1i*kd*cos(fi));
polar(fi,abs(z))
hold on
title ('N-Element,all w=0.1');
%%Analysis of the N-element integrated with the SP-ANN
Nx = <Insert N>
w1=2.0+j0;
w2=2.0+j0;
w3=2.0+j0;
kd=pi;
fi=0:pi/100:2*pi;%Progressive angle between the elements
z=exp(1i*kd*cos(fi))+1+exp(-1i*kd*cos(fi));
polar(fi,abs(z))
hold on
title ('N-Element,all w=2');
```

## APPENDIX D

```

%% SP-ANN coding for N-element
numIn = <Insert N>;
bias = <Insert b>;
coeff = <Insert Neta>;
theta= <Induced signal>;
weights = [0.1  0.1  0.1];
weightsup =[0.1  0.1  0.1];
count = 0; t=0;
for fi=0:2:360
    inputs = [exp(1j*pi*cos(fi*pi/180));1 ;exp(-1j*pi*cos(fi*pi/180))];
    desired_out = sinc(fi*pi/180-theta);
    learn=0; c=1;
    while (learn==0)
        b = bias;
        for k = 1:numIn
            y = b + (inputs(k)*weights(k));
        end
        outcome=1/(1+exp(-y));
        delta = desired_out-outcome;
        error=real(delta/desired_out)*100;
        if (abs(error)<0.1)
            weightsup(1) = weights(1);
            weightsup(2) = weights(2);
            weightsup(3) = weights(3);
            count=count+1; t(count)=fi;
            learn=1;
        else
            weights(1) = weights(1)+(coeff*inputs(1)*delta);
            weights(2) = weights(2)+(coeff*inputs(2)*delta);
            weights(3) = weights(3)+(coeff*inputs(3)*delta);
            c=c+1;
        end
        if (c >1000)
            learn=1;
            weights(1) = weightsup(1);
            weights(2) = weightsup(2);
            weights(3) = weightsup(3);
        end
        end
        fprintf('.');
    end
    fprintf('fi %d\n',t);
    fprintf('\nconverge %d\n',count);
    fprintf('  W1      W2      W3      \n');
    for a=1:numIn
        fprintf('%8.4g+%8.4gj  ',[real(weights(a)) imag(weights(a))]);
    end
    fprintf('\n');

```

### The Difference of Optimized Weights of $N$ -element

| Array Length | Initial Weights                                                                                                                                                                                         | Optimized Weights                                                                                                                                                                                                                               |
|--------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| $N=2$        | $W_1 = 0.1+j0.1$<br>$W_2 = 0.1+j0.1$                                                                                                                                                                    | $W_1 = -66.11+j2.029$<br>$W_2 = 21.31-j32.21$                                                                                                                                                                                                   |
| $N=3$        | $W_1 = 0.1+j0.1$<br>$W_2 = 0.1+j0.1$<br>$W_3 = 0.1+j0.1$                                                                                                                                                | $W_1 = 26.78-j15.09$<br>$W_2 = -66.11-j2.029$<br>$W_3 = 21.31+j32.21$                                                                                                                                                                           |
| $N=4$        | $W_1 = 0.1+j0.1$<br>$W_2 = 0.1+j0.1$<br>$W_3 = 0.1+j0.1$<br>$W_4 = 0.1+j0.1$                                                                                                                            | $W_1 = 2.964+j5.648$<br>$W_2 = -5.41-j10.03$<br>$W_3 = -7.33+j2.114$<br>$W_4 = 0.1+j0$                                                                                                                                                          |
| $N=6$        | $W_1 = 0.1+j0.1$<br>$W_2 = 0.1+j0.1$<br>$W_3 = 0.1+j0.1$<br>$W_4 = 0.1+j0.1$<br>$W_5 = 0.1+j0.1$<br>$W_6 = 0.1+j0.1$                                                                                    | $W_1 = 3.064-j2.918$<br>$W_2 = -6.025-j5.764$<br>$W_3 = 2.964+j5.648$<br>$W_4 = 0.1+j0$<br>$W_5 = -7.33+j2.114$<br>$W_6 = 0.1+j0$                                                                                                               |
| $N=8$        | $W_1 = 0.1+j0.1$<br>$W_2 = 0.1+j0.1$<br>$W_3 = 0.1+j0.1$<br>$W_4 = 0.1+j0.1$<br>$W_5 = 0.1+j0.1$<br>$W_6 = 0.1+j0.1$<br>$W_7 = 0.1+j0.1$<br>$W_8 = 0.1+j0.1$                                            | $W_1 = -3.052-j1.114$<br>$W_2 = 2.06+j0.6218$<br>$W_3 = 0.7141+j2.736$<br>$W_4 = -1.435-j4.139$<br>$W_5 = -7.33+j2.114$<br>$W_6 = 2.82-1.406$<br>$W_7 = -4.18-j1.016$<br>$W_8 = -4.393+j0$                                                      |
| $N=10$       | $W_1 = 0.1+j0.1$<br>$W_2 = 0.1+j0.1$<br>$W_3 = 0.1+j0.1$<br>$W_4 = 0.1+j0.1$<br>$W_5 = 0.1+j0.1$<br>$W_6 = 0.1+j0.1$<br>$W_7 = 0.1+j0.1$<br>$W_8 = 0.1+j0.1$<br>$W_9 = 0.1+j0.1$<br>$W_{10} = 0.1+j0.1$ | $W_1 = -1.881+j1.163$<br>$W_2 = 5.569-j1.792$<br>$W_3 = -3.052-j1.114$<br>$W_4 = 2.06+j0.6218$<br>$W_5 = 0.7141+j2.736$<br>$W_6 = -1.435-j4.139$<br>$W_7 = -3.965+j8.107$<br>$W_8 = 2.82-1.406$<br>$W_9 = -4.18-j1.016$<br>$W_{10} = -4.393+j0$ |

## APPENDIX E

### %N-element geometrical arrangement

```
N=4;
coeff =<insert value>
b=<insert value>;
theta==<insert value>;
weights = [0.1    0.1    0.1    0.1];
weightsup =[0.1    0.1    0.1    0.1];
loop = 0; c=0;
for fi=0:2:360

inputs=[exp(-3j*(pi)*cos(fi*pi/180));exp(-2j*(pi)*cos(fi*pi/180));exp(-
1j*(pi)*cos(fi*pi/180));1];
    Yd = sinc(fi*pi/180-theta);
    train=0; c=1;
    while (train==0)
        for k = 1:N
            y = b + (inputs(k)*weights(k));
        end
        Yo=1/(1+exp(-y));
        delta = Yd-Yo;
        error=real(delta/Yd)*100;
        if (abs(error)<0.1)
            weightsup(1) = weights(1);
            weightsup(2) = weights(2);
            weightsup(3) = weights(3);
            Weightsup(4) = weights(4);
            loop=loop+1;
            train=1;
        else
            weights(1) = weights(1)+(coeff*inputs(1)*delta);
            weights(2) = weights(2)+(coeff*inputs(2)*delta);
            weights(3) = weights(3)+(coeff*inputs(3)*delta);
            weights(4) = weights(4)+(coeff*inputs(4)*delta);
            c=c+1;
        end
        if (c >1000)
            train=1;
            weights(1) = weightsup(1);
            weights(2) = weightsup(2);
            weights(3) = weightsup(3);
            weights(4) = weightsup(4);
        fprintf(' ');
    end
    fprintf('fi %d\n',t);
    fprintf('\nconverge %d\n',loop);
    fprintf('      W1          W2          W3          W4 \n');
    for a=1:N
        fprintf('%5.4g+%5.4gj      ', [real(weights(a)) imag(weights(a))]);
    end
    fprintf('\n');
```

**The Array Geometrical Arrangement of  $N$ -element.**

| <b>N</b> | <b>Geometrical arrangement</b>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              |
|----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| $N=2$    | $f(\varphi) = 1 + e^{j1\varphi}$<br>$f(\varphi) = e^{-j1\varphi} + 1$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
| $N=3$    | $f(\varphi) = 1 + e^{j1\varphi} + e^{2j\varphi}$<br>$f(\varphi) = e^{j1\varphi} + 1 + e^{-j1\varphi}$<br>$f(\varphi) = e^{-2j\varphi} + e^{-1j\varphi} + 1$                                                                                                                                                                                                                                                                                                                                                                                                 |
| $N=4$    | $f(\varphi) = 1 + e^{j1\varphi} + e^{2j\varphi} + e^{3j\varphi}$<br>$f(\varphi) = e^{-1j\varphi} + 1 + e^{1j\varphi} + e^{2j\varphi}$<br>$f(\varphi) = e^{-2j\varphi} + e^{-1j\varphi} + 1 + e^{1j\varphi}$<br>$f(\varphi) = e^{-3j\varphi} + e^{-2j\varphi} + e^{-1j\varphi} + 1$                                                                                                                                                                                                                                                                          |
| $N=6$    | $f(\varphi) = 1 + e^{j1\varphi} + e^{2j\varphi} + e^{3j\varphi} + e^{4j\varphi} + e^{5j\varphi}$<br>$f(\varphi) = e^{-5j\varphi} + e^{-4j\varphi} + e^{-3j\varphi} + e^{-2j\varphi} + e^{-1j\varphi} + 1$<br>$f(\varphi) = e^{-2j\varphi} + e^{-1j\varphi} + 1 + e^{1j\varphi} + e^{2j\varphi} + e^{3j\varphi}$<br>$f(\varphi) = e^{-3j\varphi} + e^{-2j\varphi} + e^{-1j\varphi} + 1 + e^{1j\varphi} + e^{2j\varphi}$                                                                                                                                      |
| $N=8$    | $f(\varphi) = 1 + e^{j1\varphi} + e^{2j\varphi} + e^{3j\varphi} + e^{4j\varphi} + e^{5j\varphi} + e^{6j\varphi} + e^{7j\varphi}$<br>$f(\varphi) = e^{-7j\varphi} + e^{-6j\varphi} + e^{-5j\varphi} + e^{-4j\varphi} + e^{-3j\varphi} + e^{-2j\varphi} + e^{-1j\varphi} + 1$<br>$f(\varphi) = e^{-3j\varphi} + e^{-2j\varphi} + e^{-1j\varphi} + 1 + e^{1j\varphi} + e^{2j\varphi} + e^{3j\varphi} + e^{4j\varphi}$<br>$f(\varphi) = e^{-5j\varphi} + e^{-4j\varphi} + e^{-3j\varphi} + e^{-2j\varphi} + e^{-1j\varphi} + 1 + e^{1j\varphi} + e^{2j\varphi}$ |

**The Array Geometrical Arrangement of  $N$ -element for Hyperparameters.**

| <b>N</b> | <b>Geometrical arrangement</b>                                                                                                   |
|----------|----------------------------------------------------------------------------------------------------------------------------------|
| $N=2$    | $f(\varphi) = 1 + e^{j1\varphi}$                                                                                                 |
| $N=3$    | $f(\varphi) = e^{j1\varphi} + 1 + e^{-j1\varphi}$                                                                                |
| $N=4$    | $f(\varphi) = 1 + e^{j1\varphi} + e^{2j\varphi} + e^{3j\varphi}$                                                                 |
| $N=6$    | $f(\varphi) = 1 + e^{j1\varphi} + e^{2j\varphi} + e^{3j\varphi} + e^{4j\varphi} + e^{5j\varphi}$                                 |
| $N=8$    | $f(\varphi) = 1 + e^{j1\varphi} + e^{2j\varphi} + e^{3j\varphi} + e^{4j\varphi} + e^{5j\varphi} + e^{6j\varphi} + e^{7j\varphi}$ |

## APPENDIX F

### The convergence analysis for a 2-element array antenna

| Learning rate, $\eta$ | Bias, $b$ | Convergence at DOA |         |         |          |          |          |
|-----------------------|-----------|--------------------|---------|---------|----------|----------|----------|
|                       |           | $\pi/2$            | $\pi/3$ | $\pi/4$ | $3\pi/2$ | $2\pi/3$ | $5\pi/3$ |
| 0.001                 | 0.001     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.005     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.010     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.050     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.100     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.500     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 1.000     | 0                  | 0       | 0       | 0        | 0        | 0        |
| 0.005                 | 0.001     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.005     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.010     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.050     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.100     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.500     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 1.000     | 0                  | 0       | 0       | 0        | 0        | 0        |
| 0.01                  | 0.001     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.005     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.010     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.050     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.100     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.500     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 1.000     | 0                  | 0       | 0       | 0        | 0        | 0        |
| 0.02                  | 0.001     | 13                 | 13      | 14      | 13       | 13       | 13       |
|                       | 0.005     | 13                 | 13      | 14      | 13       | 13       | 13       |
|                       | 0.010     | 13                 | 13      | 14      | 13       | 13       | 13       |
|                       | 0.050     | 12                 | 12      | 14      | 13       | 12       | 12       |
|                       | 0.100     | 12                 | 12      | 14      | 12       | 12       | 12       |
|                       | 0.500     | 10                 | 10      | 12      | 10       | 10       | 10       |
|                       | 1.000     | 9                  | 9       | 9       | 9        | 9        | 9        |
| 0.03                  | 0.001     | 28                 | 28      | 28      | 28       | 28       | 28       |
|                       | 0.005     | 28                 | 28      | 28      | 28       | 28       | 28       |
|                       | 0.010     | 28                 | 28      | 28      | 28       | 28       | 28       |
|                       | 0.050     | 28                 | 28      | 28      | 28       | 28       | 28       |
|                       | 0.100     | 28                 | 28      | 28      | 28       | 28       | 28       |
|                       | 0.500     | 27                 | 27      | 28      | 28       | 27       | 27       |
|                       | 1.000     | 27                 | 27      | 27      | 27       | 27       | 27       |
| 0.04                  | 0.001     | 35                 | 35      | 34      | 35       | 35       | 35       |
|                       | 0.005     | 35                 | 35      | 34      | 35       | 35       | 35       |

|      |       |    |    |    |    |    |    |
|------|-------|----|----|----|----|----|----|
|      | 0.010 | 35 | 35 | 34 | 35 | 35 | 35 |
|      | 0.050 | 35 | 35 | 34 | 35 | 35 | 35 |
|      | 0.100 | 35 | 35 | 34 | 35 | 35 | 35 |
|      | 0.500 | 35 | 35 | 34 | 35 | 35 | 35 |
|      | 1.000 | 35 | 35 | 34 | 35 | 35 | 35 |
| 0.05 | 0.001 | 50 | 50 | 44 | 39 | 50 | 39 |
|      | 0.005 | 50 | 50 | 44 | 39 | 50 | 39 |
|      | 0.010 | 50 | 50 | 44 | 39 | 50 | 39 |
|      | 0.050 | 50 | 50 | 44 | 39 | 50 | 39 |
|      | 0.100 | 50 | 50 | 44 | 39 | 50 | 39 |
|      | 0.500 | 50 | 50 | 44 | 39 | 50 | 39 |
|      | 1.000 | 50 | 50 | 44 | 39 | 50 | 39 |
| 0.06 | 0.001 | 56 | 56 | 54 | 42 | 56 | 42 |
|      | 0.005 | 56 | 56 | 54 | 42 | 56 | 42 |
|      | 0.010 | 56 | 56 | 54 | 42 | 56 | 42 |
|      | 0.050 | 56 | 56 | 54 | 42 | 56 | 42 |
|      | 0.100 | 56 | 56 | 54 | 42 | 56 | 42 |
|      | 0.500 | 56 | 56 | 54 | 42 | 56 | 42 |
|      | 1.000 | 56 | 56 | 54 | 42 | 56 | 42 |
| 0.07 | 0.001 | 60 | 60 | 65 | 57 | 60 | 57 |
|      | 0.005 | 60 | 60 | 65 | 57 | 60 | 57 |
|      | 0.010 | 60 | 60 | 65 | 57 | 60 | 57 |
|      | 0.050 | 60 | 60 | 65 | 57 | 60 | 57 |
|      | 0.100 | 60 | 60 | 65 | 57 | 60 | 57 |
|      | 0.500 | 60 | 60 | 65 | 57 | 60 | 57 |
|      | 1.000 | 60 | 60 | 65 | 57 | 60 | 57 |
| 0.08 | 0.001 | 73 | 73 | 69 | 60 | 62 | 60 |
|      | 0.005 | 73 | 73 | 69 | 60 | 62 | 60 |
|      | 0.010 | 73 | 73 | 69 | 60 | 62 | 60 |
|      | 0.050 | 73 | 73 | 69 | 60 | 62 | 60 |
|      | 0.100 | 73 | 73 | 69 | 60 | 62 | 60 |
|      | 0.500 | 73 | 73 | 69 | 60 | 62 | 60 |
|      | 1.000 | 73 | 73 | 69 | 60 | 62 | 60 |
| 0.09 | 0.001 | 78 | 78 | 75 | 64 | 65 | 64 |
|      | 0.005 | 78 | 78 | 75 | 64 | 65 | 64 |
|      | 0.010 | 78 | 78 | 75 | 64 | 65 | 64 |
|      | 0.050 | 78 | 78 | 75 | 64 | 65 | 64 |
|      | 0.100 | 78 | 78 | 75 | 64 | 65 | 64 |
|      | 0.500 | 78 | 78 | 75 | 64 | 65 | 64 |
|      | 1.000 | 78 | 78 | 75 | 64 | 65 | 64 |
| 0.1  | 0.001 | 80 | 80 | 78 | 66 | 66 | 66 |
|      | 0.005 | 80 | 80 | 78 | 66 | 66 | 66 |
|      | 0.010 | 80 | 80 | 78 | 66 | 66 | 66 |
|      | 0.050 | 80 | 80 | 78 | 66 | 66 | 66 |
|      | 0.100 | 80 | 80 | 78 | 66 | 66 | 66 |
|      | 0.500 | 80 | 80 | 78 | 66 | 66 | 66 |

|     |       |     |     |     |     |    |     |
|-----|-------|-----|-----|-----|-----|----|-----|
|     | 1.000 | 80  | 80  | 78  | 66  | 66 | 66  |
| 0.2 | 0.001 | 92  | 96  | 92  | 92  | 78 | 94  |
|     | 0.005 | 92  | 96  | 92  | 92  | 78 | 94  |
|     | 0.010 | 92  | 96  | 92  | 92  | 78 | 94  |
|     | 0.050 | 92  | 96  | 92  | 92  | 78 | 94  |
|     | 0.100 | 92  | 96  | 92  | 92  | 78 | 94  |
|     | 0.500 | 92  | 96  | 92  | 92  | 78 | 94  |
|     | 1.000 | 92  | 96  | 92  | 92  | 78 | 94  |
| 0.3 | 0.001 | 98  | 103 | 98  | 99  | 86 | 103 |
|     | 0.005 | 98  | 103 | 98  | 99  | 86 | 103 |
|     | 0.010 | 98  | 103 | 98  | 99  | 86 | 103 |
|     | 0.050 | 98  | 103 | 98  | 99  | 86 | 103 |
|     | 0.100 | 98  | 103 | 98  | 99  | 86 | 103 |
|     | 0.500 | 98  | 103 | 98  | 99  | 86 | 103 |
|     | 1.000 | 98  | 103 | 98  | 99  | 86 | 103 |
| 0.4 | 0.001 | 99  | 103 | 98  | 99  | 86 | 104 |
|     | 0.005 | 99  | 103 | 98  | 99  | 86 | 104 |
|     | 0.010 | 99  | 103 | 98  | 99  | 86 | 104 |
|     | 0.050 | 99  | 103 | 98  | 99  | 86 | 104 |
|     | 0.100 | 99  | 103 | 98  | 99  | 86 | 104 |
|     | 0.500 | 99  | 103 | 98  | 99  | 86 | 104 |
|     | 1.000 | 99  | 103 | 98  | 99  | 86 | 104 |
| 0.5 | 0.001 | 101 | 107 | 102 | 101 | 88 | 107 |
|     | 0.005 | 101 | 107 | 102 | 101 | 88 | 107 |
|     | 0.010 | 101 | 107 | 102 | 101 | 88 | 107 |
|     | 0.050 | 101 | 107 | 102 | 101 | 88 | 107 |
|     | 0.100 | 101 | 107 | 102 | 101 | 88 | 107 |
|     | 0.500 | 101 | 107 | 102 | 101 | 88 | 107 |
|     | 1.000 | 101 | 107 | 102 | 101 | 88 | 107 |
| 0.6 | 0.001 | 104 | 110 | 102 | 104 | 92 | 110 |
|     | 0.005 | 104 | 110 | 102 | 104 | 92 | 110 |
|     | 0.010 | 104 | 110 | 102 | 104 | 92 | 110 |
|     | 0.050 | 104 | 110 | 102 | 104 | 92 | 110 |
|     | 0.100 | 104 | 110 | 102 | 104 | 92 | 110 |
|     | 0.500 | 104 | 110 | 102 | 104 | 92 | 110 |
|     | 1.000 | 104 | 110 | 102 | 104 | 92 | 110 |
| 0.7 | 0.001 | 105 | 111 | 104 | 105 | 93 | 111 |
|     | 0.005 | 105 | 111 | 104 | 105 | 93 | 111 |
|     | 0.010 | 105 | 111 | 104 | 105 | 93 | 111 |
|     | 0.050 | 105 | 111 | 104 | 105 | 93 | 111 |
|     | 0.100 | 105 | 111 | 104 | 105 | 93 | 111 |
|     | 0.500 | 105 | 111 | 104 | 105 | 93 | 111 |
|     | 1.000 | 105 | 111 | 104 | 105 | 93 | 111 |
| 0.8 | 0.001 | 105 | 112 | 104 | 105 | 93 | 111 |
|     | 0.005 | 105 | 112 | 104 | 105 | 93 | 111 |
|     | 0.010 | 105 | 112 | 104 | 105 | 93 | 111 |

|     |       |     |     |     |     |    |     |
|-----|-------|-----|-----|-----|-----|----|-----|
|     | 0.050 | 105 | 112 | 104 | 105 | 93 | 111 |
|     | 0.100 | 105 | 112 | 104 | 105 | 93 | 111 |
|     | 0.500 | 105 | 112 | 104 | 105 | 93 | 111 |
|     | 1.000 | 105 | 112 | 104 | 105 | 93 | 111 |
| 0.9 | 0.001 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.005 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.010 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.050 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.100 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.500 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 1.000 | 105 | 112 | 105 | 105 | 93 | 112 |
| 1.0 | 0.001 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.005 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.010 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.050 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.100 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 0.500 | 105 | 112 | 105 | 105 | 93 | 112 |
|     | 1.000 | 105 | 112 | 105 | 105 | 93 | 112 |

**The convergence analysis for a 3-element array antenna**

| Learning rate, $\eta$ | Bias, $b$ | Convergence at DOA |         |         |          |          |          |
|-----------------------|-----------|--------------------|---------|---------|----------|----------|----------|
|                       |           | $\pi/2$            | $\pi/3$ | $\pi/4$ | $3\pi/2$ | $2\pi/3$ | $5\pi/3$ |
| 0.001                 | 0.001     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.005     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.010     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.050     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.100     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.500     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 1.000     | 0                  | 0       | 0       | 0        | 0        | 0        |
| 0.005                 | 0.001     | 6                  | 4       | 5       | 2        | 4        | 4        |
|                       | 0.005     | 8                  | 5       | 6       | 2        | 3        | 5        |
|                       | 0.010     | 7                  | 2       | 6       | 1        | 5        | 5        |
|                       | 0.050     | 9                  | 3       | 8       | 2        | 5        | 3        |
|                       | 0.100     | 7                  | 4       | 4       | 4        | 8        | 5        |
|                       | 0.500     | 4                  | 2       | 5       | 5        | 5        | 6        |
|                       | 1.000     | 6                  | 1       | 8       | 3        | 8        | 12       |
| 0.01                  | 0.001     | 8                  | 23      | 5       | 1        | 14       | 12       |
|                       | 0.005     | 4                  | 25      | 12      | 6        | 14       | 14       |
|                       | 0.010     | 4                  | 28      | 3       | 1        | 14       | 12       |
|                       | 0.050     | 4                  | 25      | 18      | 1        | 14       | 14       |
|                       | 0.100     | 4                  | 24      | 3       | 1        | 15       | 7        |

|      |       |    |    |    |    |    |    |
|------|-------|----|----|----|----|----|----|
|      | 0.500 | 5  | 26 | 18 | 2  | 14 | 11 |
|      | 1.000 | 5  | 26 | 5  | 10 | 13 | 7  |
| 0.02 | 0.001 | 6  | 30 | 38 | 9  | 43 | 33 |
|      | 0.005 | 5  | 36 | 38 | 3  | 43 | 33 |
|      | 0.010 | 4  | 34 | 38 | 5  | 43 | 34 |
|      | 0.050 | 5  | 39 | 40 | 9  | 44 | 33 |
|      | 0.100 | 4  | 36 | 40 | 5  | 43 | 24 |
|      | 0.500 | 4  | 33 | 36 | 4  | 39 | 19 |
|      | 1.000 | 5  | 35 | 32 | 4  | 39 | 37 |
|      |       |    |    |    |    |    |    |
| 0.03 | 0.001 | 6  | 43 | 50 | 9  | 32 | 38 |
|      | 0.005 | 5  | 38 | 50 | 9  | 32 | 42 |
|      | 0.010 | 4  | 50 | 49 | 9  | 51 | 42 |
|      | 0.050 | 9  | 53 | 50 | 7  | 49 | 33 |
|      | 0.100 | 5  | 38 | 50 | 7  | 48 | 39 |
|      | 0.500 | 5  | 48 | 51 | 8  | 50 | 40 |
|      | 1.000 | 5  | 47 | 50 | 8  | 38 | 43 |
|      |       |    |    |    |    |    |    |
| 0.04 | 0.001 | 9  | 49 | 53 | 16 | 39 | 41 |
|      | 0.005 | 15 | 52 | 52 | 16 | 53 | 37 |
|      | 0.010 | 8  | 46 | 53 | 15 | 53 | 41 |
|      | 0.050 | 4  | 55 | 52 | 19 | 52 | 31 |
|      | 0.100 | 6  | 50 | 51 | 16 | 51 | 36 |
|      | 0.500 | 6  | 52 | 52 | 20 | 53 | 35 |
|      | 1.000 | 9  | 51 | 53 | 15 | 46 | 43 |
|      |       |    |    |    |    |    |    |
| 0.05 | 0.001 | 40 | 58 | 55 | 25 | 58 | 43 |
|      | 0.005 | 15 | 60 | 63 | 25 | 41 | 43 |
|      | 0.010 | 5  | 55 | 62 | 26 | 54 | 43 |
|      | 0.050 | 15 | 55 | 61 | 23 | 57 | 43 |
|      | 0.100 | 10 | 52 | 63 | 27 | 56 | 43 |
|      | 0.500 | 34 | 55 | 61 | 24 | 47 | 45 |
|      | 1.000 | 27 | 50 | 55 | 23 | 48 | 46 |
|      |       |    |    |    |    |    |    |
| 0.06 | 0.001 | 44 | 65 | 72 | 27 | 35 | 53 |
|      | 0.005 | 34 | 61 | 60 | 28 | 43 | 57 |
|      | 0.010 | 42 | 52 | 72 | 27 | 44 | 53 |
|      | 0.050 | 44 | 61 | 71 | 28 | 56 | 57 |
|      | 0.100 | 31 | 60 | 70 | 26 | 58 | 49 |
|      | 0.500 | 40 | 59 | 68 | 27 | 59 | 36 |
|      | 1.000 | 30 | 54 | 69 | 29 | 50 | 58 |
|      |       |    |    |    |    |    |    |
| 0.07 | 0.001 | 52 | 65 | 79 | 26 | 34 | 68 |
|      | 0.005 | 54 | 60 | 79 | 26 | 45 | 68 |
|      | 0.010 | 56 | 66 | 80 | 28 | 45 | 68 |
|      | 0.050 | 52 | 62 | 82 | 34 | 69 | 68 |
|      | 0.100 | 54 | 67 | 71 | 34 | 51 | 68 |
|      | 0.500 | 51 | 68 | 78 | 33 | 57 | 67 |
|      | 1.000 | 32 | 73 | 75 | 29 | 70 | 51 |
|      |       |    |    |    |    |    |    |
| 0.08 | 0.001 | 37 | 80 | 84 | 35 | 73 | 79 |
|      | 0.005 | 41 | 75 | 84 | 41 | 39 | 80 |

|      |       |    |     |     |    |    |    |
|------|-------|----|-----|-----|----|----|----|
|      | 0.010 | 39 | 67  | 85  | 42 | 69 | 80 |
|      | 0.050 | 55 | 69  | 85  | 38 | 69 | 63 |
|      | 0.100 | 51 | 74  | 84  | 41 | 38 | 81 |
|      | 0.500 | 36 | 63  | 82  | 39 | 72 | 51 |
|      | 1.000 | 28 | 71  | 79  | 32 | 72 | 79 |
| 0.09 | 0.001 | 43 | 73  | 84  | 42 | 47 | 40 |
|      | 0.005 | 72 | 68  | 85  | 41 | 73 | 69 |
|      | 0.010 | 46 | 77  | 84  | 40 | 39 | 74 |
|      | 0.050 | 31 | 68  | 84  | 41 | 71 | 67 |
|      | 0.100 | 49 | 79  | 85  | 41 | 39 | 71 |
|      | 0.500 | 69 | 73  | 83  | 41 | 59 | 56 |
|      | 1.000 | 70 | 74  | 83  | 39 | 66 | 61 |
| 0.1  | 0.001 | 54 | 67  | 88  | 39 | 71 | 69 |
|      | 0.005 | 49 | 77  | 90  | 39 | 71 | 81 |
|      | 0.010 | 36 | 79  | 89  | 41 | 68 | 80 |
|      | 0.050 | 53 | 74  | 91  | 38 | 72 | 59 |
|      | 0.100 | 31 | 80  | 89  | 41 | 40 | 73 |
|      | 0.500 | 27 | 78  | 88  | 42 | 71 | 56 |
|      | 1.000 | 50 | 59  | 81  | 42 | 74 | 57 |
| 0.2  | 0.001 | 54 | 80  | 99  | 54 | 61 | 65 |
|      | 0.005 | 57 | 84  | 97  | 56 | 61 | 61 |
|      | 0.010 | 60 | 86  | 98  | 56 | 61 | 61 |
|      | 0.050 | 59 | 76  | 97  | 54 | 53 | 49 |
|      | 0.100 | 59 | 85  | 99  | 54 | 52 | 65 |
|      | 0.500 | 69 | 90  | 100 | 52 | 46 | 61 |
|      | 1.000 | 49 | 86  | 100 | 50 | 46 | 46 |
| 0.3  | 0.001 | 54 | 81  | 100 | 52 | 65 | 85 |
|      | 0.005 | 56 | 80  | 100 | 55 | 65 | 85 |
|      | 0.010 | 56 | 83  | 102 | 56 | 65 | 64 |
|      | 0.050 | 71 | 81  | 101 | 54 | 33 | 51 |
|      | 0.100 | 54 | 86  | 101 | 55 | 64 | 66 |
|      | 0.500 | 71 | 84  | 106 | 55 | 60 | 50 |
|      | 1.000 | 62 | 84  | 107 | 40 | 49 | 66 |
| 0.4  | 0.001 | 59 | 81  | 100 | 55 | 64 | 65 |
|      | 0.005 | 53 | 82  | 100 | 55 | 32 | 70 |
|      | 0.010 | 53 | 83  | 87  | 56 | 65 | 86 |
|      | 0.050 | 52 | 85  | 101 | 57 | 64 | 50 |
|      | 0.100 | 52 | 88  | 100 | 54 | 59 | 80 |
|      | 0.500 | 67 | 83  | 77  | 55 | 56 | 51 |
|      | 1.000 | 46 | 100 | 102 | 55 | 56 | 67 |
| 0.5  | 0.001 | 56 | 83  | 103 | 56 | 65 | 85 |
|      | 0.005 | 56 | 84  | 102 | 56 | 66 | 86 |
|      | 0.010 | 55 | 72  | 102 | 56 | 66 | 86 |
|      | 0.050 | 56 | 82  | 102 | 56 | 58 | 78 |
|      | 0.100 | 54 | 83  | 107 | 56 | 57 | 66 |
|      | 0.500 | 74 | 81  | 104 | 59 | 58 | 67 |

|     |       |    |    |     |    |    |    |
|-----|-------|----|----|-----|----|----|----|
|     | 1.000 | 51 | 81 | 89  | 63 | 58 | 35 |
| 0.6 | 0.001 | 56 | 84 | 101 | 56 | 73 | 80 |
|     | 0.005 | 57 | 83 | 105 | 56 | 73 | 80 |
|     | 0.010 | 60 | 82 | 105 | 56 | 73 | 79 |
|     | 0.050 | 56 | 85 | 103 | 56 | 75 | 69 |
|     | 0.100 | 58 | 80 | 100 | 56 | 76 | 70 |
|     | 0.500 | 70 | 84 | 106 | 61 | 75 | 68 |
|     | 1.000 | 52 | 86 | 100 | 55 | 75 | 68 |
| 0.7 | 0.001 | 57 | 72 | 102 | 57 | 74 | 72 |
|     | 0.005 | 54 | 68 | 106 | 57 | 73 | 71 |
|     | 0.010 | 54 | 58 | 102 | 58 | 63 | 83 |
|     | 0.050 | 55 | 83 | 103 | 57 | 74 | 72 |
|     | 0.100 | 56 | 84 | 102 | 56 | 75 | 26 |
|     | 0.500 | 74 | 89 | 103 | 57 | 75 | 70 |
|     | 1.000 | 34 | 81 | 102 | 55 | 73 | 69 |
| 0.8 | 0.001 | 57 | 71 | 105 | 54 | 72 | 81 |
|     | 0.005 | 58 | 94 | 106 | 54 | 72 | 72 |
|     | 0.010 | 57 | 82 | 103 | 58 | 72 | 79 |
|     | 0.050 | 55 | 58 | 104 | 54 | 74 | 81 |
|     | 0.100 | 39 | 72 | 102 | 58 | 74 | 82 |
|     | 0.500 | 36 | 82 | 105 | 56 | 72 | 68 |
|     | 1.000 | 70 | 84 | 73  | 43 | 73 | 67 |
| 0.9 | 0.001 | 38 | 71 | 102 | 57 | 72 | 81 |
|     | 0.005 | 38 | 58 | 105 | 56 | 72 | 73 |
|     | 0.010 | 58 | 72 | 105 | 59 | 71 | 74 |
|     | 0.050 | 54 | 79 | 103 | 54 | 72 | 79 |
|     | 0.100 | 54 | 83 | 105 | 56 | 74 | 82 |
|     | 0.500 | 55 | 83 | 103 | 56 | 73 | 66 |
|     | 1.000 | 71 | 82 | 106 | 55 | 72 | 69 |
| 1.0 | 0.001 | 54 | 93 | 103 | 58 | 66 | 81 |
|     | 0.005 | 37 | 93 | 104 | 55 | 67 | 72 |
|     | 0.010 | 54 | 93 | 103 | 55 | 61 | 71 |
|     | 0.050 | 55 | 92 | 102 | 56 | 77 | 80 |
|     | 0.100 | 55 | 94 | 102 | 55 | 78 | 70 |
|     | 0.500 | 53 | 94 | 103 | 57 | 77 | 69 |
|     | 1.000 | 71 | 81 | 102 | 68 | 81 | 69 |

**The convergence analysis for a 4-element array antenna**

| Learning rate, $\eta$ | Bias, $b$ | Convergence at DOA |         |         |          |          |          |
|-----------------------|-----------|--------------------|---------|---------|----------|----------|----------|
|                       |           | $\pi/2$            | $\pi/3$ | $\pi/4$ | $3\pi/2$ | $2\pi/3$ | $5\pi/3$ |
| 0.001                 | 0.001     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.005     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.010     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.050     | 0                  | 0       | 0       | 0        | 0        | 0        |

|       |       |    |    |    |    |    |    |
|-------|-------|----|----|----|----|----|----|
|       | 0.100 | 0  | 0  | 0  | 0  | 0  | 0  |
|       | 0.500 | 0  | 0  | 0  | 0  | 0  | 0  |
|       | 1.000 | 0  | 0  | 0  | 0  | 0  | 0  |
| 0.005 | 0.001 | 8  | 15 | 7  | 8  | 8  | 7  |
|       | 0.005 | 9  | 14 | 5  | 9  | 8  | 9  |
|       | 0.010 | 7  | 10 | 5  | 7  | 6  | 4  |
|       | 0.050 | 9  | 13 | 7  | 9  | 7  | 8  |
|       | 0.100 | 3  | 12 | 9  | 4  | 7  | 6  |
|       | 0.500 | 3  | 8  | 2  | 4  | 8  | 5  |
|       | 1.000 | 0  | 1  | 2  | 0  | 0  | 1  |
| 0.01  | 0.001 | 26 | 26 | 21 | 26 | 24 | 22 |
|       | 0.005 | 31 | 29 | 24 | 27 | 23 | 22 |
|       | 0.010 | 30 | 32 | 26 | 24 | 25 | 30 |
|       | 0.050 | 25 | 28 | 23 | 19 | 26 | 30 |
|       | 0.100 | 27 | 29 | 20 | 21 | 29 | 29 |
|       | 0.500 | 26 | 26 | 28 | 20 | 33 | 35 |
|       | 1.000 | 31 | 21 | 24 | 31 | 22 | 25 |
| 0.02  | 0.001 | 42 | 41 | 42 | 38 | 40 | 43 |
|       | 0.005 | 44 | 42 | 41 | 41 | 39 | 42 |
|       | 0.010 | 40 | 42 | 40 | 39 | 40 | 43 |
|       | 0.050 | 42 | 39 | 40 | 40 | 39 | 39 |
|       | 0.100 | 39 | 45 | 40 | 35 | 42 | 42 |
|       | 0.500 | 39 | 38 | 43 | 37 | 42 | 43 |
|       | 1.000 | 38 | 33 | 38 | 38 | 31 | 36 |
| 0.03  | 0.001 | 42 | 51 | 60 | 37 | 50 | 50 |
|       | 0.005 | 38 | 51 | 62 | 35 | 50 | 49 |
|       | 0.010 | 45 | 51 | 62 | 41 | 48 | 47 |
|       | 0.050 | 39 | 46 | 51 | 38 | 47 | 46 |
|       | 0.100 | 41 | 54 | 59 | 38 | 49 | 49 |
|       | 0.500 | 42 | 48 | 58 | 40 | 37 | 39 |
|       | 1.000 | 40 | 37 | 46 | 35 | 41 | 45 |
| 0.04  | 0.001 | 51 | 51 | 65 | 45 | 55 | 51 |
|       | 0.005 | 42 | 57 | 66 | 40 | 53 | 49 |
|       | 0.010 | 40 | 45 | 64 | 41 | 50 | 49 |
|       | 0.050 | 38 | 56 | 63 | 41 | 51 | 50 |
|       | 0.100 | 39 | 54 | 64 | 42 | 53 | 53 |
|       | 0.500 | 38 | 56 | 62 | 39 | 54 | 52 |
|       | 1.000 | 44 | 47 | 55 | 47 | 44 | 48 |
| 0.05  | 0.001 | 47 | 56 | 69 | 43 | 59 | 49 |
|       | 0.005 | 43 | 56 | 67 | 42 | 58 | 53 |
|       | 0.010 | 47 | 54 | 68 | 44 | 63 | 52 |
|       | 0.050 | 45 | 57 | 70 | 4  | 59 | 51 |
|       | 0.100 | 46 | 63 | 70 | 44 | 56 | 54 |
|       | 0.500 | 44 | 58 | 63 | 40 | 60 | 55 |
|       | 1.000 | 50 | 47 | 54 | 46 | 34 | 40 |
| 0.06  | 0.001 | 45 | 57 | 70 | 43 | 71 | 56 |

|      |       |    |    |    |    |    |    |
|------|-------|----|----|----|----|----|----|
|      | 0.005 | 51 | 55 | 70 | 46 | 69 | 55 |
|      | 0.010 | 43 | 58 | 65 | 42 | 73 | 56 |
|      | 0.050 | 49 | 58 | 72 | 43 | 73 | 57 |
|      | 0.100 | 47 | 58 | 74 | 46 | 61 | 54 |
|      | 0.500 | 44 | 56 | 67 | 38 | 41 | 45 |
|      | 1.000 | 42 | 50 | 55 | 36 | 38 | 42 |
| 0.07 | 0.001 | 54 | 55 | 78 | 49 | 73 | 60 |
|      | 0.005 | 51 | 59 | 79 | 49 | 70 | 60 |
|      | 0.010 | 53 | 60 | 78 | 52 | 69 | 61 |
|      | 0.050 | 51 | 59 | 81 | 47 | 72 | 59 |
|      | 0.100 | 52 | 59 | 77 | 49 | 69 | 60 |
|      | 0.500 | 48 | 60 | 74 | 41 | 70 | 63 |
|      | 1.000 | 47 | 48 | 64 | 49 | 41 | 45 |
| 0.08 | 0.001 | 53 | 64 | 82 | 52 | 73 | 60 |
|      | 0.005 | 53 | 68 | 85 | 51 | 72 | 62 |
|      | 0.010 | 47 | 66 | 88 | 52 | 70 | 60 |
|      | 0.050 | 55 | 67 | 87 | 53 | 70 | 57 |
|      | 0.100 | 52 | 64 | 84 | 49 | 71 | 63 |
|      | 0.500 | 49 | 65 | 80 | 49 | 74 | 67 |
|      | 1.000 | 49 | 48 | 68 | 45 | 38 | 43 |
| 0.09 | 0.001 | 53 | 70 | 90 | 52 | 70 | 64 |
|      | 0.005 | 51 | 65 | 89 | 52 | 69 | 61 |
|      | 0.010 | 52 | 65 | 91 | 50 | 73 | 64 |
|      | 0.050 | 45 | 65 | 87 | 49 | 72 | 63 |
|      | 0.100 | 51 | 65 | 89 | 49 | 71 | 65 |
|      | 0.500 | 52 | 66 | 90 | 54 | 75 | 68 |
|      | 1.000 | 43 | 49 | 72 | 47 | 42 | 45 |
| 0.1  | 0.001 | 52 | 66 | 94 | 54 | 73 | 64 |
|      | 0.005 | 54 | 70 | 90 | 51 | 77 | 66 |
|      | 0.010 | 59 | 69 | 91 | 52 | 74 | 64 |
|      | 0.050 | 49 | 67 | 92 | 54 | 73 | 64 |
|      | 0.100 | 55 | 67 | 92 | 54 | 65 | 62 |
|      | 0.500 | 50 | 65 | 85 | 45 | 72 | 66 |
|      | 1.000 | 40 | 51 | 75 | 44 | 40 | 48 |
| 0.2  | 0.001 | 62 | 75 | 89 | 63 | 78 | 78 |
|      | 0.005 | 61 | 75 | 87 | 62 | 80 | 78 |
|      | 0.010 | 59 | 75 | 89 | 60 | 79 | 75 |
|      | 0.050 | 57 | 79 | 88 | 58 | 78 | 76 |
|      | 0.100 | 61 | 76 | 91 | 58 | 83 | 81 |
|      | 0.500 | 59 | 70 | 81 | 51 | 79 | 77 |
|      | 1.000 | 52 | 57 | 71 | 51 | 45 | 55 |
| 0.3  | 0.001 | 61 | 81 | 86 | 60 | 85 | 81 |
|      | 0.005 | 61 | 76 | 89 | 59 | 83 | 79 |
|      | 0.010 | 60 | 82 | 87 | 55 | 82 | 78 |
|      | 0.050 | 58 | 84 | 86 | 57 | 84 | 79 |
|      | 0.100 | 59 | 82 | 88 | 57 | 82 | 82 |

|     |       |    |    |    |    |    |    |
|-----|-------|----|----|----|----|----|----|
|     | 0.500 | 61 | 78 | 79 | 52 | 86 | 83 |
|     | 1.000 | 48 | 62 | 79 | 47 | 49 | 60 |
| 0.4 | 0.001 | 62 | 84 | 81 | 50 | 84 | 81 |
|     | 0.005 | 63 | 82 | 80 | 58 | 83 | 81 |
|     | 0.010 | 60 | 82 | 85 | 57 | 82 | 80 |
|     | 0.050 | 66 | 86 | 88 | 62 | 83 | 81 |
|     | 0.100 | 59 | 86 | 89 | 55 | 82 | 81 |
|     | 0.500 | 60 | 80 | 78 | 51 | 85 | 82 |
|     | 1.000 | 50 | 60 | 69 | 49 | 51 | 61 |
| 0.5 | 0.001 | 63 | 85 | 84 | 61 | 83 | 82 |
|     | 0.005 | 65 | 85 | 84 | 62 | 84 | 82 |
|     | 0.010 | 64 | 84 | 86 | 61 | 82 | 80 |
|     | 0.050 | 65 | 84 | 86 | 61 | 83 | 81 |
|     | 0.100 | 63 | 85 | 85 | 61 | 83 | 81 |
|     | 0.500 | 62 | 82 | 82 | 55 | 86 | 82 |
|     | 1.000 | 49 | 62 | 69 | 50 | 63 | 76 |
| 0.6 | 0.001 | 66 | 88 | 86 | 62 | 85 | 82 |
|     | 0.005 | 66 | 88 | 80 | 63 | 86 | 83 |
|     | 0.010 | 65 | 89 | 87 | 57 | 87 | 84 |
|     | 0.050 | 66 | 87 | 86 | 61 | 85 | 84 |
|     | 0.100 | 62 | 88 | 86 | 63 | 88 | 86 |
|     | 0.500 | 64 | 72 | 68 | 54 | 88 | 86 |
|     | 1.000 | 51 | 63 | 66 | 52 | 53 | 65 |
| 0.7 | 0.001 | 65 | 88 | 87 | 64 | 85 | 82 |
|     | 0.005 | 64 | 82 | 86 | 63 | 86 | 82 |
|     | 0.010 | 64 | 82 | 85 | 63 | 85 | 81 |
|     | 0.050 | 65 | 87 | 84 | 62 | 85 | 83 |
|     | 0.100 | 66 | 88 | 88 | 57 | 88 | 82 |
|     | 0.500 | 64 | 72 | 69 | 54 | 63 | 63 |
|     | 1.000 | 50 | 64 | 77 | 49 | 53 | 64 |
| 0.8 | 0.001 | 66 | 90 | 85 | 62 | 89 | 84 |
|     | 0.005 | 66 | 88 | 86 | 63 | 88 | 82 |
|     | 0.010 | 65 | 88 | 86 | 62 | 87 | 83 |
|     | 0.050 | 65 | 89 | 86 | 62 | 86 | 82 |
|     | 0.100 | 65 | 83 | 77 | 57 | 85 | 83 |
|     | 0.500 | 59 | 66 | 69 | 53 | 67 | 66 |
|     | 1.000 | 52 | 65 | 67 | 52 | 55 | 66 |
| 0.9 | 0.001 | 65 | 89 | 85 | 63 | 65 | 72 |
|     | 0.005 | 64 | 89 | 84 | 62 | 74 | 72 |
|     | 0.010 | 65 | 88 | 84 | 63 | 75 | 71 |
|     | 0.050 | 67 | 88 | 78 | 58 | 86 | 83 |
|     | 0.100 | 65 | 82 | 80 | 56 | 86 | 83 |
|     | 0.500 | 64 | 70 | 67 | 56 | 66 | 72 |
|     | 1.000 | 50 | 65 | 65 | 50 | 54 | 64 |
| 1.0 | 0.001 | 64 | 88 | 83 | 62 | 86 | 83 |
|     | 0.005 | 64 | 87 | 84 | 62 | 86 | 82 |

|  |       |    |    |    |    |    |    |
|--|-------|----|----|----|----|----|----|
|  | 0.010 | 65 | 82 | 85 | 62 | 67 | 72 |
|  | 0.050 | 66 | 89 | 85 | 57 | 88 | 86 |
|  | 0.100 | 65 | 82 | 82 | 56 | 65 | 74 |
|  | 0.500 | 54 | 65 | 68 | 61 | 74 | 73 |
|  | 1.000 | 50 | 65 | 66 | 52 | 51 | 63 |

**The convergence analysis for a 6-element array antenna**

| Learning rate, $\eta$ | Bias, $b$ | Convergence at DOA |         |         |          |          |          |
|-----------------------|-----------|--------------------|---------|---------|----------|----------|----------|
|                       |           | $\pi/2$            | $\pi/3$ | $\pi/4$ | $3\pi/2$ | $2\pi/3$ | $5\pi/3$ |
| 0.001                 | 0.001     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.005     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.010     | 0                  | 1       | 0       | 0        | 1        | 1        |
|                       | 0.050     | 0                  | 0       | 1       | 0        | 0        | 0        |
|                       | 0.100     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.500     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 1.000     | 0                  | 0       | 0       | 0        | 0        | 0        |
| 0.005                 | 0.001     | 7                  | 4       | 3       | 7        | 3        | 4        |
|                       | 0.005     | 3                  | 2       | 2       | 3        | 4        | 2        |
|                       | 0.010     | 4                  | 4       | 2       | 4        | 2        | 4        |
|                       | 0.050     | 3                  | 2       | 7       | 3        | 1        | 2        |
|                       | 0.100     | 4                  | 3       | 4       | 4        | 4        | 3        |
|                       | 0.500     | 2                  | 4       | 2       | 2        | 3        | 4        |
|                       | 1.000     | 7                  | 2       | 5       | 5        | 3        | 2        |
| 0.01                  | 0.001     | 34                 | 31      | 24      | 20       | 29       | 36       |
|                       | 0.005     | 34                 | 30      | 25      | 31       | 31       | 37       |
|                       | 0.010     | 35                 | 31      | 24      | 31       | 30       | 36       |
|                       | 0.050     | 29                 | 32      | 25      | 30       | 30       | 36       |
|                       | 0.100     | 35                 | 31      | 25      | 30       | 31       | 34       |
|                       | 0.500     | 28                 | 22      | 20      | 29       | 21       | 25       |
|                       | 1.000     | 28                 | 21      | 23      | 27       | 26       | 25       |
| 0.02                  | 0.001     | 46                 | 46      | 35      | 45       | 41       | 46       |
|                       | 0.005     | 44                 | 44      | 37      | 41       | 42       | 44       |
|                       | 0.010     | 44                 | 44      | 36      | 40       | 39       | 43       |
|                       | 0.050     | 46                 | 45      | 31      | 45       | 38       | 43       |
|                       | 0.100     | 50                 | 44      | 33      | 47       | 40       | 38       |
|                       | 0.500     | 41                 | 33      | 33      | 35       | 29       | 33       |
|                       | 1.000     | 42                 | 36      | 37      | 38       | 39       | 36       |
| 0.03                  | 0.001     | 49                 | 49      | 41      | 46       | 54       | 49       |
|                       | 0.005     | 40                 | 61      | 41      | 38       | 53       | 50       |
|                       | 0.010     | 48                 | 47      | 44      | 46       | 55       | 50       |
|                       | 0.050     | 39                 | 50      | 42      | 37       | 53       | 49       |
|                       | 0.100     | 46                 | 50      | 41      | 45       | 52       | 47       |
|                       | 0.500     | 41                 | 41      | 38      | 39       | 32       | 37       |

|      |       |    |    |    |    |    |    |
|------|-------|----|----|----|----|----|----|
|      | 1.000 | 41 | 39 | 37 | 39 | 38 | 35 |
| 0.04 | 0.001 | 52 | 54 | 52 | 48 | 57 | 54 |
|      | 0.005 | 55 | 58 | 56 | 50 | 57 | 53 |
|      | 0.010 | 52 | 56 | 50 | 49 | 59 | 57 |
|      | 0.050 | 52 | 56 | 51 | 49 | 56 | 52 |
|      | 0.100 | 53 | 50 | 49 | 48 | 57 | 50 |
|      | 0.500 | 41 | 47 | 45 | 39 | 36 | 42 |
|      | 1.000 | 41 | 46 | 61 | 39 | 48 | 49 |
| 0.05 | 0.001 | 52 | 59 | 64 | 51 | 59 | 59 |
|      | 0.005 | 57 | 62 | 63 | 54 | 62 | 60 |
|      | 0.010 | 52 | 57 | 62 | 52 | 62 | 61 |
|      | 0.050 | 55 | 59 | 62 | 55 | 63 | 60 |
|      | 0.100 | 54 | 57 | 60 | 54 | 62 | 59 |
|      | 0.500 | 48 | 47 | 59 | 44 | 38 | 48 |
|      | 1.000 | 48 | 49 | 62 | 47 | 35 | 44 |
| 0.06 | 0.001 | 59 | 60 | 66 | 57 | 64 | 64 |
|      | 0.005 | 58 | 58 | 62 | 58 | 63 | 64 |
|      | 0.010 | 50 | 60 | 66 | 49 | 64 | 67 |
|      | 0.050 | 55 | 56 | 64 | 52 | 62 | 60 |
|      | 0.100 | 57 | 60 | 61 | 58 | 59 | 59 |
|      | 0.500 | 45 | 50 | 58 | 48 | 38 | 44 |
|      | 1.000 | 49 | 49 | 60 | 49 | 38 | 45 |
| 0.07 | 0.001 | 55 | 58 | 67 | 61 | 61 | 61 |
|      | 0.005 | 54 | 66 | 69 | 58 | 63 | 62 |
|      | 0.010 | 55 | 61 | 62 | 58 | 63 | 66 |
|      | 0.050 | 58 | 61 | 64 | 63 | 64 | 67 |
|      | 0.100 | 56 | 62 | 65 | 61 | 65 | 67 |
|      | 0.500 | 54 | 48 | 59 | 51 | 30 | 48 |
|      | 1.000 | 46 | 51 | 62 | 52 | 38 | 50 |
| 0.08 | 0.001 | 55 | 64 | 71 | 59 | 72 | 70 |
|      | 0.005 | 54 | 61 | 71 | 59 | 71 | 69 |
|      | 0.010 | 57 | 64 | 69 | 63 | 72 | 70 |
|      | 0.050 | 54 | 66 | 68 | 58 | 65 | 64 |
|      | 0.100 | 58 | 67 | 68 | 62 | 66 | 64 |
|      | 0.500 | 51 | 51 | 63 | 53 | 41 | 50 |
|      | 1.000 | 51 | 48 | 59 | 56 | 41 | 47 |
| 0.09 | 0.001 | 62 | 64 | 75 | 62 | 69 | 71 |
|      | 0.005 | 66 | 61 | 73 | 63 | 70 | 73 |
|      | 0.010 | 59 | 69 | 70 | 61 | 68 | 70 |
|      | 0.050 | 65 | 67 | 69 | 65 | 65 | 66 |
|      | 0.100 | 59 | 68 | 69 | 63 | 69 | 68 |
|      | 0.500 | 55 | 57 | 58 | 55 | 40 | 51 |
|      | 1.000 | 54 | 56 | 55 | 54 | 41 | 53 |
| 0.1  | 0.001 | 64 | 67 | 71 | 65 | 72 | 70 |
|      | 0.005 | 60 | 68 | 75 | 62 | 73 | 75 |
|      | 0.010 | 63 | 68 | 74 | 67 | 75 | 76 |

|     |       |    |    |    |    |    |    |
|-----|-------|----|----|----|----|----|----|
|     | 0.050 | 62 | 70 | 73 | 66 | 69 | 67 |
|     | 0.100 | 56 | 64 | 75 | 65 | 70 | 69 |
|     | 0.500 | 55 | 58 | 64 | 53 | 38 | 54 |
|     | 1.000 | 52 | 55 | 63 | 56 | 48 | 52 |
| 0.2 | 0.001 | 67 | 74 | 79 | 71 | 74 | 78 |
|     | 0.005 | 68 | 74 | 77 | 73 | 74 | 79 |
|     | 0.010 | 76 | 73 | 79 | 81 | 75 | 75 |
|     | 0.050 | 68 | 78 | 75 | 72 | 76 | 76 |
|     | 0.100 | 66 | 70 | 77 | 73 | 67 | 71 |
|     | 0.500 | 60 | 67 | 63 | 58 | 43 | 60 |
|     | 1.000 | 55 | 63 | 62 | 57 | 43 | 57 |
| 0.3 | 0.001 | 73 | 77 | 80 | 77 | 80 | 80 |
|     | 0.005 | 71 | 77 | 79 | 76 | 81 | 81 |
|     | 0.010 | 78 | 76 | 79 | 81 | 83 | 81 |
|     | 0.050 | 68 | 73 | 80 | 72 | 80 | 83 |
|     | 0.100 | 67 | 73 | 77 | 72 | 76 | 75 |
|     | 0.500 | 70 | 65 | 62 | 65 | 47 | 63 |
|     | 1.000 | 58 | 59 | 64 | 59 | 48 | 60 |
| 0.4 | 0.001 | 72 | 77 | 81 | 76 | 81 | 81 |
|     | 0.005 | 73 | 79 | 81 | 78 | 84 | 83 |
|     | 0.010 | 73 | 79 | 81 | 78 | 86 | 84 |
|     | 0.050 | 74 | 77 | 80 | 77 | 78 | 76 |
|     | 0.100 | 73 | 78 | 80 | 76 | 79 | 79 |
|     | 0.500 | 65 | 68 | 63 | 63 | 51 | 68 |
|     | 1.000 | 61 | 61 | 65 | 62 | 50 | 61 |
| 0.5 | 0.001 | 72 | 78 | 80 | 77 | 77 | 76 |
|     | 0.005 | 74 | 78 | 81 | 78 | 80 | 78 |
|     | 0.010 | 73 | 77 | 82 | 75 | 80 | 77 |
|     | 0.050 | 75 | 77 | 83 | 79 | 76 | 75 |
|     | 0.100 | 72 | 72 | 81 | 76 | 77 | 76 |
|     | 0.500 | 64 | 68 | 67 | 62 | 53 | 68 |
|     | 1.000 | 61 | 60 | 65 | 63 | 51 | 58 |
| 0.6 | 0.001 | 72 | 79 | 82 | 76 | 82 | 79 |
|     | 0.005 | 78 | 80 | 81 | 82 | 79 | 76 |
|     | 0.010 | 73 | 82 | 81 | 77 | 80 | 79 |
|     | 0.050 | 73 | 73 | 81 | 77 | 77 | 76 |
|     | 0.100 | 71 | 74 | 78 | 75 | 77 | 80 |
|     | 0.500 | 63 | 63 | 66 | 61 | 53 | 64 |
|     | 1.000 | 59 | 64 | 64 | 59 | 51 | 60 |
| 0.7 | 0.001 | 72 | 76 | 82 | 76 | 80 | 79 |
|     | 0.005 | 72 | 76 | 82 | 76 | 78 | 77 |
|     | 0.010 | 74 | 72 | 81 | 78 | 78 | 77 |
|     | 0.050 | 72 | 72 | 77 | 76 | 76 | 79 |
|     | 0.100 | 72 | 71 | 72 | 70 | 74 | 77 |
|     | 0.500 | 60 | 68 | 67 | 62 | 59 | 65 |
|     | 1.000 | 61 | 62 | 64 | 62 | 52 | 60 |

|     |       |    |    |    |    |    |    |
|-----|-------|----|----|----|----|----|----|
| 0.8 | 0.001 | 72 | 72 | 80 | 77 | 77 | 79 |
|     | 0.005 | 72 | 74 | 80 | 77 | 79 | 77 |
|     | 0.010 | 72 | 73 | 76 | 78 | 76 | 76 |
|     | 0.050 | 74 | 70 | 74 | 74 | 72 | 76 |
|     | 0.100 | 72 | 71 | 71 | 73 | 60 | 76 |
|     | 0.500 | 59 | 63 | 65 | 59 | 52 | 61 |
|     | 1.000 | 59 | 59 | 64 | 59 | 52 | 59 |
| 0.9 | 0.001 | 71 | 72 | 70 | 74 | 72 | 78 |
|     | 0.005 | 71 | 74 | 71 | 74 | 75 | 78 |
|     | 0.010 | 73 | 72 | 71 | 75 | 73 | 75 |
|     | 0.050 | 70 | 72 | 70 | 72 | 65 | 75 |
|     | 0.100 | 64 | 70 | 71 | 65 | 52 | 69 |
|     | 0.500 | 57 | 64 | 64 | 57 | 54 | 66 |
|     | 1.000 | 59 | 62 | 69 | 64 | 54 | 63 |
| 1.0 | 0.001 | 69 | 73 | 70 | 70 | 76 | 76 |
|     | 0.005 | 69 | 71 | 71 | 70 | 75 | 75 |
|     | 0.010 | 70 | 71 | 72 | 71 | 74 | 73 |
|     | 0.050 | 73 | 71 | 71 | 74 | 70 | 80 |
|     | 0.100 | 72 | 72 | 68 | 71 | 60 | 75 |
|     | 0.500 | 58 | 60 | 69 | 57 | 52 | 62 |
|     | 1.000 | 57 | 59 | 63 | 59 | 53 | 61 |

**The convergence analysis for an 8-element array antenna**

| Learning rate, $\eta$ | Bias, $b$ | Convergence at DOA |         |         |          |          |          |
|-----------------------|-----------|--------------------|---------|---------|----------|----------|----------|
|                       |           | $\pi/2$            | $\pi/3$ | $\pi/4$ | $3\pi/2$ | $2\pi/3$ | $5\pi/3$ |
| 0.001                 | 0.001     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.005     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.010     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 0.050     | 0                  | 0       | 1       | 0        | 0        | 0        |
|                       | 0.100     | 2                  | 1       | 0       | 2        | 1        | 1        |
|                       | 0.500     | 0                  | 0       | 0       | 0        | 0        | 0        |
|                       | 1.000     | 2                  | 0       | 0       | 2        | 0        | 0        |
| 0.005                 | 0.001     | 2                  | 9       | 4       | 2        | 5        | 8        |
|                       | 0.005     | 2                  | 8       | 3       | 2        | 8        | 7        |
|                       | 0.010     | 4                  | 7       | 5       | 5        | 5        | 7        |
|                       | 0.050     | 0                  | 4       | 5       | 5        | 3        | 4        |
|                       | 0.100     | 3                  | 8       | 2       | 3        | 6        | 6        |
|                       | 0.500     | 3                  | 2       | 5       | 3        | 4        | 2        |
|                       | 1.000     | 4                  | 3       | 1       | 3        | 1        | 4        |
| 0.01                  | 0.001     | 25                 | 26      | 27      | 24       | 28       | 27       |
|                       | 0.005     | 24                 | 26      | 28      | 25       | 28       | 28       |
|                       | 0.010     | 28                 | 26      | 27      | 26       | 30       | 28       |
|                       | 0.050     | 28                 | 25      | 24      | 25       | 29       | 28       |

|      |       |    |    |    |    |    |    |
|------|-------|----|----|----|----|----|----|
|      | 0.100 | 31 | 28 | 23 | 29 | 28 | 27 |
|      | 0.500 | 22 | 24 | 17 | 20 | 25 | 24 |
|      | 1.000 | 23 | 22 | 18 | 23 | 23 | 28 |
| 0.02 | 0.001 | 39 | 41 | 35 | 37 | 40 | 35 |
|      | 0.005 | 39 | 42 | 34 | 36 | 44 | 39 |
|      | 0.010 | 41 | 40 | 33 | 39 | 39 | 38 |
|      | 0.050 | 40 | 40 | 32 | 36 | 37 | 32 |
|      | 0.100 | 40 | 40 | 32 | 38 | 39 | 38 |
|      | 0.500 | 38 | 36 | 32 | 35 | 37 | 36 |
|      | 1.000 | 35 | 37 | 34 | 32 | 33 | 38 |
| 0.03 | 0.001 | 48 | 48 | 46 | 46 | 49 | 45 |
|      | 0.005 | 46 | 47 | 47 | 43 | 52 | 46 |
|      | 0.010 | 51 | 45 | 46 | 48 | 49 | 45 |
|      | 0.050 | 45 | 49 | 47 | 43 | 50 | 46 |
|      | 0.100 | 46 | 44 | 45 | 44 | 48 | 44 |
|      | 0.500 | 40 | 44 | 40 | 40 | 40 | 41 |
|      | 1.000 | 38 | 42 | 41 | 38 | 34 | 41 |
| 0.04 | 0.001 | 49 | 55 | 59 | 45 | 56 | 51 |
|      | 0.005 | 51 | 54 | 59 | 47 | 55 | 50 |
|      | 0.010 | 49 | 52 | 57 | 45 | 54 | 49 |
|      | 0.050 | 50 | 50 | 60 | 46 | 56 | 50 |
|      | 0.100 | 50 | 50 | 52 | 46 | 58 | 53 |
|      | 0.500 | 43 | 45 | 50 | 41 | 40 | 41 |
|      | 1.000 | 38 | 46 | 52 | 38 | 44 | 50 |
| 0.05 | 0.001 | 57 | 53 | 62 | 55 | 64 | 56 |
|      | 0.005 | 55 | 55 | 59 | 53 | 61 | 51 |
|      | 0.010 | 56 | 56 | 59 | 53 | 63 | 54 |
|      | 0.050 | 54 | 57 | 59 | 52 | 59 | 52 |
|      | 0.100 | 54 | 54 | 57 | 52 | 63 | 55 |
|      | 0.500 | 46 | 53 | 56 | 47 | 45 | 45 |
|      | 1.000 | 44 | 45 | 54 | 43 | 35 | 43 |
| 0.06 | 0.001 | 55 | 53 | 63 | 52 | 62 | 51 |
|      | 0.005 | 49 | 55 | 63 | 47 | 63 | 52 |
|      | 0.010 | 53 | 57 | 64 | 51 | 62 | 52 |
|      | 0.050 | 55 | 57 | 64 | 52 | 70 | 56 |
|      | 0.100 | 53 | 52 | 58 | 51 | 64 | 51 |
|      | 0.500 | 40 | 54 | 61 | 39 | 49 | 43 |
|      | 1.000 | 40 | 49 | 56 | 41 | 45 | 53 |
| 0.07 | 0.001 | 58 | 59 | 63 | 58 | 68 | 54 |
|      | 0.005 | 55 | 64 | 65 | 55 | 71 | 57 |
|      | 0.010 | 54 | 56 | 62 | 56 | 71 | 59 |
|      | 0.050 | 53 | 55 | 63 | 54 | 65 | 53 |
|      | 0.100 | 54 | 55 | 59 | 56 | 71 | 58 |
|      | 0.500 | 49 | 51 | 60 | 51 | 50 | 48 |
|      | 1.000 | 49 | 48 | 60 | 46 | 40 | 44 |
| 0.08 | 0.001 | 55 | 57 | 62 | 55 | 70 | 57 |

|      |       |    |    |    |    |    |    |
|------|-------|----|----|----|----|----|----|
|      | 0.005 | 56 | 58 | 65 | 56 | 69 | 56 |
|      | 0.010 | 59 | 59 | 66 | 59 | 67 | 55 |
|      | 0.050 | 53 | 54 | 63 | 53 | 68 | 56 |
|      | 0.100 | 56 | 55 | 60 | 58 | 66 | 55 |
|      | 0.500 | 48 | 59 | 61 | 49 | 50 | 49 |
|      | 1.000 | 47 | 46 | 60 | 47 | 39 | 45 |
| 0.09 | 0.001 | 60 | 60 | 67 | 59 | 70 | 56 |
|      | 0.005 | 61 | 62 | 70 | 60 | 69 | 56 |
|      | 0.010 | 65 | 59 | 66 | 60 | 72 | 60 |
|      | 0.050 | 61 | 54 | 67 | 57 | 70 | 57 |
|      | 0.100 | 63 | 58 | 62 | 59 | 75 | 59 |
|      | 0.500 | 52 | 56 | 58 | 54 | 49 | 48 |
|      | 1.000 | 57 | 51 | 59 | 57 | 41 | 52 |
| 0.1  | 0.001 | 64 | 59 | 70 | 60 | 72 | 61 |
|      | 0.005 | 63 | 59 | 72 | 59 | 72 | 62 |
|      | 0.010 | 63 | 59 | 68 | 60 | 71 | 61 |
|      | 0.050 | 65 | 54 | 71 | 60 | 69 | 57 |
|      | 0.100 | 59 | 54 | 67 | 60 | 73 | 61 |
|      | 0.500 | 53 | 55 | 62 | 53 | 51 | 53 |
|      | 1.000 | 49 | 47 | 61 | 49 | 43 | 53 |
| 0.2  | 0.001 | 69 | 64 | 74 | 70 | 76 | 64 |
|      | 0.005 | 70 | 63 | 75 | 72 | 76 | 64 |
|      | 0.010 | 69 | 63 | 73 | 71 | 73 | 62 |
|      | 0.050 | 69 | 60 | 73 | 69 | 76 | 62 |
|      | 0.100 | 72 | 63 | 71 | 72 | 66 | 62 |
|      | 0.500 | 59 | 55 | 69 | 60 | 57 | 54 |
|      | 1.000 | 53 | 57 | 63 | 54 | 47 | 59 |
| 0.3  | 0.001 | 72 | 66 | 74 | 73 | 85 | 69 |
|      | 0.005 | 73 | 65 | 73 | 73 | 84 | 70 |
|      | 0.010 | 71 | 66 | 73 | 71 | 82 | 68 |
|      | 0.050 | 72 | 65 | 75 | 72 | 81 | 67 |
|      | 0.100 | 74 | 66 | 72 | 74 | 82 | 69 |
|      | 0.500 | 63 | 60 | 71 | 63 | 63 | 59 |
|      | 1.000 | 58 | 55 | 64 | 58 | 52 | 69 |
| 0.4  | 0.001 | 72 | 65 | 79 | 73 | 89 | 71 |
|      | 0.005 | 70 | 64 | 79 | 71 | 88 | 71 |
|      | 0.010 | 71 | 65 | 79 | 71 | 85 | 68 |
|      | 0.050 | 71 | 64 | 79 | 70 | 85 | 71 |
|      | 0.100 | 70 | 64 | 79 | 70 | 84 | 69 |
|      | 0.500 | 56 | 59 | 72 | 57 | 58 | 58 |
|      | 1.000 | 58 | 56 | 69 | 58 | 54 | 57 |
| 0.5  | 0.001 | 71 | 65 | 84 | 71 | 85 | 69 |
|      | 0.005 | 72 | 67 | 84 | 72 | 84 | 68 |
|      | 0.010 | 74 | 65 | 82 | 74 | 86 | 70 |
|      | 0.050 | 73 | 66 | 82 | 73 | 85 | 67 |
|      | 0.100 | 72 | 66 | 80 | 72 | 84 | 59 |

|     |       |    |    |    |    |    |    |
|-----|-------|----|----|----|----|----|----|
|     | 0.500 | 56 | 63 | 75 | 56 | 60 | 59 |
|     | 1.000 | 57 | 61 | 64 | 57 | 55 | 67 |
| 0.6 | 0.001 | 71 | 66 | 81 | 71 | 78 | 66 |
|     | 0.005 | 70 | 66 | 78 | 70 | 81 | 66 |
|     | 0.010 | 70 | 67 | 82 | 70 | 82 | 67 |
|     | 0.050 | 70 | 67 | 79 | 70 | 83 | 67 |
|     | 0.100 | 69 | 66 | 78 | 70 | 81 | 65 |
|     | 0.500 | 55 | 60 | 70 | 55 | 61 | 60 |
|     | 1.000 | 61 | 60 | 70 | 60 | 55 | 59 |
|     |       |    |    |    |    |    |    |
| 0.7 | 0.001 | 71 | 66 | 82 | 73 | 80 | 65 |
|     | 0.005 | 74 | 67 | 81 | 75 | 78 | 65 |
|     | 0.010 | 72 | 66 | 81 | 73 | 84 | 70 |
|     | 0.050 | 72 | 66 | 82 | 72 | 84 | 68 |
|     | 0.100 | 72 | 67 | 78 | 71 | 79 | 69 |
|     | 0.500 | 55 | 64 | 69 | 55 | 59 | 61 |
|     | 1.000 | 58 | 62 | 70 | 58 | 55 | 59 |
|     |       |    |    |    |    |    |    |
| 0.8 | 0.001 | 69 | 68 | 83 | 69 | 85 | 69 |
|     | 0.005 | 71 | 68 | 82 | 70 | 85 | 69 |
|     | 0.010 | 70 | 66 | 82 | 71 | 81 | 65 |
|     | 0.050 | 70 | 66 | 81 | 70 | 80 | 67 |
|     | 0.100 | 65 | 66 | 78 | 63 | 74 | 65 |
|     | 0.500 | 55 | 62 | 70 | 55 | 56 | 61 |
|     | 1.000 | 55 | 58 | 65 | 55 | 56 | 59 |
|     |       |    |    |    |    |    |    |
| 0.9 | 0.001 | 65 | 67 | 78 | 65 | 80 | 68 |
|     | 0.005 | 66 | 68 | 80 | 65 | 81 | 65 |
|     | 0.010 | 65 | 69 | 79 | 64 | 83 | 67 |
|     | 0.050 | 64 | 68 | 78 | 62 | 82 | 67 |
|     | 0.100 | 64 | 68 | 78 | 62 | 73 | 65 |
|     | 0.500 | 55 | 62 | 69 | 54 | 62 | 63 |
|     | 1.000 | 57 | 58 | 70 | 58 | 53 | 59 |
|     |       |    |    |    |    |    |    |
| 1.0 | 0.001 | 69 | 67 | 76 | 67 | 76 | 64 |
|     | 0.005 | 69 | 66 | 78 | 67 | 76 | 67 |
|     | 0.010 | 71 | 68 | 77 | 68 | 77 | 70 |
|     | 0.050 | 64 | 69 | 76 | 62 | 74 | 65 |
|     | 0.100 | 64 | 67 | 75 | 62 | 76 | 69 |
|     | 0.500 | 55 | 60 | 69 | 55 | 57 | 59 |
|     | 1.000 | 57 | 59 | 67 | 57 | 58 | 61 |
|     |       |    |    |    |    |    |    |

## APPENDIX G

### Fundamental derivation works for simultaneous detection and localization

$$\begin{aligned}
 V_0(\theta) &= W_1 V_1(\theta) + W_2 V_2(\theta) \\
 &= (1)V_i e^{-jkr_1} + (e^{j\delta}) V_i e^{-jkr_2} \\
 &= V_i e^{-jkr_1} + (e^{j\delta}) V_i e^{-jk(r_1 - d \sin \theta)} \\
 &= V_i e^{-jkr_1} + V_i e^{-jkr_1} \cdot e^{jk d \sin \theta} \cdot e^{j\delta} \\
 &= V_i e^{-jkr_1} [1 + e^{jk d \sin \theta} \cdot e^{j\delta}] \\
 \therefore V_0(\theta) &= V_i e^{-jkr_1} [1 + e^{j(k d \sin \theta + \delta)}] \rightarrow (\text{Equation 3.17})
 \end{aligned}$$

To cancel the interferer signal at  $\theta = \theta_i$  so that  $V_0(\theta_i) = 0$  hence, the AF must be set to zero i.e.,  $AF = 0$ . To get this, the value of the complex element,  $e^{j(k d \sin \theta + \delta)} = -1$  so that,

$$\begin{aligned}
 AF &= |1 + e^{j(k d \sin \theta + \delta)}| \\
 AF &= |1 + (-1)| \\
 AF &= 0
 \end{aligned}$$

To cancel or null the interferer,  $\delta_i = \pi - k d \sin \theta_i$ . From Equation 3.18,

$$\begin{aligned}
 AF &= |1 + e^{j(k d \sin \theta + \delta_i)}| \\
 AF &= |1 + e^{j(k d \sin \theta + \pi - k d \sin \theta_i)}| \\
 AF &= |1 + e^{jk d \sin \theta} \cdot e^{j\pi} \cdot e^{-jk d \sin \theta_i}| \\
 AF &= |1 + e^{jk d \sin \theta} \cdot (-1) \cdot e^{-jk d \sin \theta_i}| \text{ as } e^{j\pi} = \cos(\pi) + j \sin(\pi) = -1 \\
 AF &= |1 - e^{jk d \sin \theta} \cdot e^{-jk d \sin \theta_i}| \\
 AF &= |1 - e^{j k d (\sin \theta - \sin \theta_i)}| \\
 AF &= |1 - e^{j\gamma}| \text{ where } \gamma = k d (\sin \theta - \sin \theta_i), \\
 AF &= |e^{j\frac{\gamma}{2}} \cdot e^{-j\frac{\gamma}{2}} - e^{j\frac{\gamma}{2}} \cdot e^{j\frac{\gamma}{2}}| \\
 AF &= |e^{j\frac{\gamma}{2}} [e^{-j\frac{\gamma}{2}} - e^{j\frac{\gamma}{2}}]| \text{ from Euler's rule; } \sin \theta = \frac{e^{-j\theta} - e^{j\theta}}{-2j} \\
 AF &= |e^{j\frac{\gamma}{2}} [-2j \sin(\frac{\gamma}{2})]| \text{ as } e^{-j\frac{\pi}{2}} = \cos(\frac{\pi}{2}) - j \sin(\frac{\pi}{2}) = -j
 \end{aligned}$$

$$\begin{aligned}
AF &= \left| e^{j\frac{\gamma}{2}}(2) \left( e^{-j\frac{\pi}{2}} \right) \sin\left(\frac{\gamma}{2}\right) \right| \\
AF &= \left| 2e^{j(\frac{\gamma}{2}-\frac{\pi}{2})} \sin\left(\frac{\gamma}{2}\right) \right| \text{ since } e^{j\frac{\gamma}{2}} \text{ effects the phase not the magnitude, therefore,} \\
AF &= \left| 2\sin\left(\frac{\gamma}{2}\right) \right| \text{ and taking AF normalized, } AF_N \text{ hence,} \\
AF_N &= \frac{1}{2}AF = \left| \sin\left(\frac{\gamma}{2}\right) \right| \\
AF_{N1} &= \left| \sin\left(\frac{\gamma}{2}\right) \right| \rightarrow (\text{Equation 3.19})
\end{aligned}$$

To maximize the arriving signal at direction  $\theta = \theta_m$ , and the SA shall maximize any signal picked up from the desired direction at  $\theta_m$  thus, the  $AF = 1 + 1 = 2$ . In order to get this, the value of the complex element,  $e^{j(kd\sin\theta+\delta)} = 1$  so that,

$$\begin{aligned}
AF &= \left| 1 + e^{j(kd\sin\theta+\delta)} \right| \\
AF &= |1 + 1| \\
AF &= |2|
\end{aligned}$$

To maximize the signal,  $\delta_m = -kd \sin\theta_m$ . From Equation (3.18),

$$\begin{aligned}
AF &= \left| 1 + e^{j(kd\sin\theta+\delta_m)} \right| \\
AF &= \left| 1 + e^{j(kd\sin\theta-kd\sin\theta_m)} \right| \\
AF &= \left| 1 + e^{jkdsin\theta} \cdot e^{-jkdsin\theta_m} \right| \\
AF &= \left| 1 + e^{jkd(\sin\theta-\sin\theta_m)} \right| \\
AF &= \left| 1 + e^{j\gamma} \right| \text{ where } \gamma = kd(\sin\theta - \sin\theta_m) \\
AF &= \left| e^{j\frac{\gamma}{2}} \cdot e^{-j\frac{\gamma}{2}} + e^{j\frac{\gamma}{2}} \cdot e^{j\frac{\gamma}{2}} \right| \\
AF &= \left| e^{j\frac{\gamma}{2}} \left[ e^{-j\frac{\gamma}{2}} + e^{j\frac{\gamma}{2}} \right] \right| \text{ from Euler's rule; } \cos\theta = \frac{e^{j\theta} + e^{-j\theta}}{2} \\
AF &= \left| e^{j\frac{\gamma}{2}} \left[ 2\cos\left(\frac{\gamma}{2}\right) \right] \right| \text{ since } e^{j\frac{\gamma}{2}} \text{ effects the phase not the magnitude,} \\
\text{therefore, } AF &= \left| 2\cos\left(\frac{\gamma}{2}\right) \right| \text{ and taking AF normalized, } AF_N \text{ thus,} \\
AF_N &= \frac{1}{2}AF = \left| \cos\left(\frac{\gamma}{2}\right) \right| \\
AF_{N2} &= \left| \cos\left(\frac{\gamma}{2}\right) \right| \rightarrow (\text{Equation 3.20})
\end{aligned}$$

%The maximizing and nulling

```
freq=1e9; c=3e8; lambda=c/freq;
n=2; p=1/n; kd=pi;
Theta=0:pi/100:2*pi;
ThetaM=<insert ThetaM>
ThetaI=<insert ThetaI>
Gamma=kd*(sin(Theta)-sin(ThetaM));
%Gamma=kd*(sin(Theta)-sin(ThetaI));
AFN=cos(Gamma/2);
%AFN=sin(Gamma/2);
AF=abs(AFN);
polar(Theta,AF);
title("SA Radiation Pattern kd=pi,ThetaI=17pi/12');
```

%The 2-element Array Antenna for Simultaneous Signal detection at Multiple DOA

```
freq=1e9; c=3e8; lambda=c/freq;
n=2;
p=1/n;
kd=pi;
Theta=0:pi/100:2*pi;
Yd=7*pi/36;
Gamma=kd*(sin(Theta)-sin(Yd));
AFN1=sin(Gamma/2);
AF1=abs(AFN1);
AFN2=cos(Gamma/2);
AF2=abs(AFN2);
if ThetaI==pi/6
    polar(Theta,AF2);
    title('insert title');
elseif ThetaI~=pi/6
    polar(Theta,AF1);
    title('insert title ');
end
```

## APPENDIX H

### %% Analysis of the Single Perceptron ANN Training Algorithm for Weight Optimization Tested 2-element Linear Array Antenna

```

Theta=0:pi/100:2*pi; Theta_d=pi/4; N = 2; kd=pi; coeff =0.5; b =0.001;
weights = [0.1  0.1]; weightsup =[0.1  0.1];
loop = 0; c=0;
for fi=0:2:360
    inputs =[1;exp(1j*(kd)*cos(fi*kd/180))];
    Yd = sinc(fi*pi/180-Theta_d);
    train=0; c=1;
    while (train=0)
        for k = 1:N
            y = b + (inputs(k)*weights(k));
        end
        Yo=1/(1+exp(-y));
        delta = Yd-Yo;
        error=real(delta/Yd)*100;
        if (abs(error)<0.1)
            weightsup(1) = weights(1);
            weightsup(2) = weights(2);
            loop=loop+1;
            train=1;
        else
            weights(1) = weights(1)+(coeff*inputs(1)*delta);
            weights(2) = weights(2)+(coeff*inputs(2)*delta);
            c=c+1;
        end
        if (c >1000)
            train=1;
            weights(1) = weightsup(1);
            weights(2) = weightsup(2);
            fprintf(' ');
        end
        fprintf('fi %d\n',t);
        fprintf('\nconverge %d\n',loop);
        fprintf('  W1      W2      \n');
        for a=1:N
            fprintf('%5.4g+%5.4gj  ',[real(weights(a)) imag(weights(a))]);
        end
        Gamma=kd*(sin(Theta)-sin(Theta_d));
        AFN1=sin(Gamma/2); AF1=abs(AFN1);
        AFN2=cos(Gamma/2); AF2=abs(AFN2);
        if Theta_d==pi/4 %If ThetaI is the desired signal/direction
            polar(Theta,AF2);
            title('Array Factor Plot kd=pi,Theta_d=desired');
        elseif Theta_d~=pi/4
            polar(Theta,AF1);%If ThetaI is not the desired signal/direction
            title('Array Factor Plot kd=pi,Theta_i=interferer');
        end
    end

```

## APPENDIX I

### *Analysis of the Signal Electric Field Strength Tested on Multiple DOA*

| No. of Samples | Desired Angle, $\theta_d$ |              | SPSS Optimized Weights          | Normalized Magnitude of RP (in dB) |
|----------------|---------------------------|--------------|---------------------------------|------------------------------------|
|                | $\theta^\circ$            | $\theta$ rad | W1 & W2                         |                                    |
| 1              | 0                         | 0.0000       | -17.77+0.8085j 3.197+6.283j     | 13.36                              |
| 2              | 5                         | 0.0873       | -32.66+6.918j 3.49+4.508e-05j   | 15.66                              |
| 3              | 10                        | 0.1745       | 3.298+-5.095j 28.29+41.87j      | 17.28                              |
| 4              | 15                        | 0.2618       | -22.38+6.162j 5.34+11.83j       | 14.44                              |
| 5              | 20                        | 0.3491       | -20.19+4.571j -0.07517+4.699j   | 12.84                              |
| 6              | 25                        | 0.4363       | -29.15+8.238j -19.53+-17.55j    | 15.35                              |
| 7              | 30                        | 0.5236       | -408.3+-2.451j -112.5+175.1j    | 24.17                              |
| 8              | 35                        | 0.6109       | -10.96+10.89j -10.24+-7.014j    | 13.64                              |
| 9              | 40                        | 0.6981       | -56.66+4.986j 21.74+-24.36j     | 19.52                              |
| 10             | 45                        | 0.7854       | -66.11+2.029j 21.31+-32.21j     | 20.2                               |
| 11             | 50                        | 0.8727       | -82.69+3.601j 48.61+-49.5j      | 21.75                              |
| 12             | 55                        | 0.9599       | -25.81+0.9023j 4.281+0.9845j    | 14.16                              |
| 13             | 60                        | 1.0472       | -5.776+4.919j 5.993+-11.68j     | 12.43                              |
| 14             | 65                        | 1.1345       | -263.8+2.769j 134.1+-166.6j     | 26.31                              |
| 15             | 70                        | 1.2217       | -7.484+8.728j 4.711+-18.71j     | 13.45                              |
| 16             | 75                        | 1.3090       | -3.433+1.076j 4.392+0.008422j   | 3.33                               |
| 17             | 80                        | 1.3963       | -4.214+-2.796j 3.764+2.231e-05j | 6.86                               |
| 18             | 85                        | 1.4835       | 4.337+-5.678j 3.203+6.283j      | 9.6                                |
| 19             | 90                        | 1.5708       | -13.14+-7.392j 2.882+-6.283j    | 12.33                              |
| 20             | 95                        | 1.6581       | -142+-23.02j 2.69+43.98j        | 19.43                              |
| 21             | 100                       | 1.7453       | 28.4+15.55j 2.594+-87.96j       | 25.37                              |
| 22             | 105                       | 1.8326       | -286.3+-12.44j 2.577+100.5j     | 18.67                              |
| 23             | 110                       | 1.9199       | -3.31+-16.47j 2.644+81.68j      | 20.28                              |
| 24             | 115                       | 2.0071       | -3.154+-11.25j 45.35+103.8j     | 18.87                              |
| 25             | 120                       | 2.0944       | 6.683+-18.93j 46.73+ 82j        | 19.91                              |
| 26             | 125                       | 2.1817       | -177.1+17.77j 3.691+-81.68j     | 20.27                              |
| 27             | 130                       | 2.2689       | -7.803+-1.391j 56.88+97.66j     | 20.82                              |
| 28             | 135                       | 2.3562       | 25.64+-2.865j 59.42+80.89j      | 18.74                              |
| 29             | 140                       | 2.4435       | -21.78+4.082j -9.792+-7.56j     | 10.35                              |
| 30             | 145                       | 2.5307       | -26.58+-9.95j 13.54+20.81j      | 17.26                              |

| No. of Samples | Desired Angle, $\theta_d$ |              | SPSS Optimized Weights |                   | Normalized Magnitude of RP (in dB) |
|----------------|---------------------------|--------------|------------------------|-------------------|------------------------------------|
|                | $\theta^\circ$            | $\theta$ rad | W1 & W2                |                   |                                    |
| 31             | 150                       | 2.6180       | -18.1+-12.87j          | 15.5+18.87j       | 16.67                              |
| 32             | 155                       | 2.7053       | -34.11+-8.98j          | 40.69+56.69j      | 20.14                              |
| 33             | 160                       | 2.7925       | -129.8+1.829j          | 77.65+-82.04j     | 23.31                              |
| 34             | 165                       | 2.8798       | -190.7+3.201j          | 115.2+-124.1j     | 25.09                              |
| 35             | 170                       | 2.9671       | 3.365+-2.328j          | 2.047+13.17j      | 11.87                              |
| 36             | 175                       | 3.0543       | 7.966+-9.149j          | -0.5496+37.91j    | 16.79                              |
| 37             | 180                       | 3.1416       | -8.321+-4.321j         | 3.742+0.2565j     | 11.11                              |
| 38             | 185                       | 3.2289       | -2.892+-6.134j         | 3.948+6.352j      | 11.53                              |
| 39             | 190                       | 3.3161       | -166.1+10.73j          | 3.957+-106.8j     | 23.15                              |
| 40             | 195                       | 3.4034       | -31.03+6.604j          | 3.158+-62.83j     | 18.73                              |
| 41             | 200                       | 3.4907       | -255.4+-3.561j         | 2.6+6.283j        | 24.14                              |
| 42             | 205                       | 3.5779       | 8.015+-0.2724j         | 2.265+-25.13j     | 14.43                              |
| 43             | 210                       | 3.6652       | 1.272+1.777j           | 2.057+-25.13j     | 14.36                              |
| 44             | 215                       | 3.7525       | 11.93+-15.8j           | 1.946+-43.98j     | 16.09                              |
| 45             | 220                       | 3.8397       | -16.74+-5.823j         | 1.918+6.288j      | 13.84                              |
| 46             | 225                       | 3.9270       | -34.94+-6.044j         | 1.98+8.7e-05j     | 15.61                              |
| 47             | 230                       | 4.0143       | -24.52+-5.976j         | 2.146+-6.283j     | 12.98                              |
| 48             | 235                       | 4.1015       | -25.96+4.102j          | 2.461+-6.283j     | 13.4                               |
| 49             | 240                       | 4.1888       | -16.23+-0.1002j        | 3.071+-8.401e-04j | 12.18                              |
| 50             | 245                       | 4.2761       | -55.42+-0.5055j        | 27.92+-20.53j     | 15.6                               |
| 51             | 250                       | 4.3633       | -55.68+-3.348j         | 32.83+-24.22j     | 13.62                              |
| 52             | 255                       | 4.4506       | -74.61+-3.833j         | 39.18+ -35j       | 13.51                              |
| 53             | 260                       | 4.5379       | -58.89+-3.962j         | 18.77+ 19j        | 17.56                              |
| 54             | 265                       | 4.6251       | -34.87+2.353j          | 170.4+177.6j      | 23.69                              |
| 55             | 270                       | 4.7124       | -13.38+3.473j          | 43.91+43.57j      | 17.49                              |
| 56             | 275                       | 4.7997       | -63.55+-1.76j          | 50.2+49.13j       | 15.06                              |
| 57             | 280                       | 4.8869       | 65.7+-26.24j           | -19.97+85.65j     | 20.39                              |
| 58             | 285                       | 4.9742       | 132.1+-32.29j          | -19.4+117.8j      | 23.3                               |
| 59             | 290                       | 5.0615       | 174.3+-28.56j          | -11.5+ 163j       | 25.03                              |
| 60             | 295                       | 5.1487       | 258.9+-14.6j           | -5.261+175.9j     | 26.33                              |
| 61             | 300                       | 5.2360       | -24.1+12.23j           | 4.032+-37.67j     | 17.95                              |
| 62             | 305                       | 5.3233       | -0.5025+-6.111j        | 3.136+31.42j      | 15.26                              |
| 63             | 310                       | 5.4105       | 94.44+-7.466j          | 1.798+194.8j      | 24.54                              |
| 64             | 315                       | 5.4978       | 39.58+0.1182j          | 1.082+138.2j      | 22.33                              |
| 65             | 320                       | 5.5851       | 8.147+8.917j           | 0.5299+62.83j     | 17.98                              |
| 66             | 325                       | 5.6723       | -11.08+10.03j          | 0.04006+69.12j    | 19.39                              |

| No. of Samples | Desired Angle, $\theta_d$ |              | SPSS Optimized Weights             | Normalized Magnitude of RP (in dB) |
|----------------|---------------------------|--------------|------------------------------------|------------------------------------|
|                | $\theta^\circ$            | $\theta$ rad | W1 & W2                            |                                    |
| 67             | 330                       | 5.7596       | -43.9+11.01j   -0.4329+-12.57j     | 17.3                               |
| 68             | 335                       | 5.8469       | -44.43+19.86j   -0.9218+-43.98j    | 19.24                              |
| 69             | 340                       | 5.9341       | -12.68+-8.31j   -1.462+-8.115e-05j | 11.4                               |
| 70             | 345                       | 6.0214       | -12.23+2.145j   -2.109+-6.283j     | 11.4                               |
| 71             | 350                       | 6.1087       | -8.584+5.368j   -2.977+-6.284j     | 11.2                               |
| 72             | 355                       | 6.1959       | 4.51+-7.623j   -4.453+31.41j       | 16.03                              |
| 73             | 360                       | 6.2832       | -34.69+4.877j   -5.889+43.96j      | 16.86                              |

## APPENDIX J

### %Power Intensity and Total Electric Fields

```
freq=1.0e9;
c=3e8;
lambda=c/freq;kd=pi;
fi=0:pi/100:2*pi;
ThetaI=pi/4;
w1=-66.11+2.029j;
w2=21.31+-32.21j;
AF=w1*exp(1j*(pi)*cos(fi))+w2;
AFN=abs(AF);
figure,polar(fi,abs(AF));
title('Radiation Pattern at DOA=45degree in polar');
hold on;
I= <insert I>;
r=<insert r>;
L=lambda/2;
et=120*pi;
k=2*pi*freq/c;
q=(et*I*k*L/(4*pi*r))*(sin(ThetaI));
E=q*(AFN);
E2=abs(E);
polar(fi,E2);
title('E_T in Polar Plot at kd=pi,Theta_d=pi/4');
P=((0.5)/et)*(E2).^2;
figure,plot(fi,P);
title('P_i in Space-domain Plot at kd=pi,Theta_d=pi/4');
xlabel('Angle in radians');
ylabel('Magnitude of P_i in W/m^2');
figure,plot(fi,E2);
title('E_T in Space-domain Plot at kd=pi,Theta_d=pi/4');
xlabel('Angle in radians');
ylabel('Magnitude of E_T in V/m');
```

**The SPSS  $E_T$  and  $P_i$  Versus Receiving Distance**

| No. | Receiving distance, r |           | Total Electric Fields, $E_T$ | Power Intensity, $P_i$ |
|-----|-----------------------|-----------|------------------------------|------------------------|
|     | in Feet               | in Meters |                              |                        |
| 1   | 5                     | 1.524     | 458                          | 278.3                  |
| 2   | 6                     | 1.829     | 381.7                        | 193.2                  |
| 3   | 7                     | 2.134     | 327.1                        | 141.9                  |
| 4   | 8                     | 2.438     | 286.3                        | 108.7                  |
| 5   | 9                     | 2.743     | 254.5                        | 85.9                   |
| 6   | 10                    | 3.048     | 229                          | 69.57                  |
| 7   | 11                    | 3.353     | 208.2                        | 57.49                  |
| 8   | 12                    | 3.658     | 190.8                        | 48.3                   |
| 9   | 13                    | 3.962     | 176.2                        | 41.17                  |
| 10  | 14                    | 4.267     | 163.6                        | 35.5                   |
| 11  | 15                    | 4.572     | 152.7                        | 30.92                  |
| 12  | 16                    | 4.877     | 143.1                        | 27.17                  |
| 13  | 17                    | 5.182     | 134.7                        | 24.07                  |
| 14  | 18                    | 5.486     | 127.2                        | 21.47                  |
| 15  | 19                    | 5.791     | 120.5                        | 19.27                  |
| 16  | 20                    | 6.096     | 114.5                        | 17.39                  |
| 17  | 21                    | 6.401     | 109.1                        | 15.77                  |
| 18  | 22                    | 6.706     | 104.1                        | 14.37                  |
| 19  | 23                    | 7.010     | 99.58                        | 13.15                  |
| 20  | 24                    | 7.315     | 95.43                        | 12.08                  |
| 21  | 25                    | 7.620     | 91.61                        | 11.13                  |

## APPENDIX K

### %The EMP Signal Generation

```
f=1.0e9;
c=3e8;lambda=c/f;kd=pi;
fi=-2*pi:0.01*pi:2*pi;
Theta=<insert value>;

x=sinc(fi-Theta);
polar(fi,x);
title('Ep with a DOA=pi/4');

fs=f*100;
dt=1/fs;
n=1;
t=0:dt:n/f;
X=sinc(2*pi*f*t-Theta);

figure,plot(fi*180/pi,x);
title('Ep with a DOA=pi/4 in space-domain ');
xlabel('Angle in Degree');
ylabel('Magnitude of Ep');

figure,plot(t,X);
xlabel('Time in seconds');
ylabel('Magnitude of Ep');
title('Ep with a DOA=pi/4 in Time-domain')
```

## APPENDIX L

### %The EMP Signal Generation for Similarity Error

```
f=0.1250e9;
%f=0.625e9;%for 5pi/4
c=3e8;lambda=c/f;kd=pi;
fi=-2*pi:0.01*pi:2*pi;
Theta=<insert value>;
%Theta=<insert value>;
x=sinc(fi-Theta);
polar(fi,x);
title(<insert title >);
%title(<insert title>;);
```

```
fs=f*100;
dt=1/fs;
n=1;
t=-n/f:dt:n/f;
X=sinc(2*pi*f*t-Theta);
```

```
figure,plot(fi*180/pi,x);
title(=<insert title>;);
%title(=<insert title >');
xlabel(<insert title >);
ylabel(<insert title >);
```

```
figure,plot(t,X);
xlabel(<insert title >);
ylabel(<insert title >);
title(<insert title >);
%title(<insert title >);
```

## APPENDIX M

### %%Efficiency of the Signal Identifier

```
T=<insert Freq_SPSS>;  
f=1/T;  
c=3e8;lambda=c/f;kd=pi;  
fi=0:0.01*pi:2*pi;  
Theta=<insert value>;
```

### %Plotting SPSS Radiation in polar after convergence

```
w1=-66.11+2.029j;  
w2=21.31+-32.21j;  
Ep=w1*exp(1j*(pi)*cos(fi))+w2;  
figure,polar(fi,abs(Ep));  
title('SPSS Radiation Pattern');  
hold on;
```

### %Plotting E-pulse in Space-domain

```
figure,plot(fi*180/pi,abs(Ep));  
title('SPSS Radiation Pattern in Space-domain at DOA=5pi/4rad');  
xlabel('Angle in Degree');  
ylabel('Magnitude of Ep');
```

### %Plotting E-pulse in Time-domain

```
fs=f*100;  
dt=1/fs;  
n=1;  
t=-n/f:dt:n/f;  
Ep=w1*exp(1j*(pi)*cos(2*pi*f*t))+w2;  
figure,plot(t,abs(Ep));  
xlabel('Time in seconds');  
ylabel('Magnitude of Ep');  
title('SPSS Radiation Pattern in Time-domain at DOA=5pi/4rad');
```

**Average error of the Signal Identifier Technique for 20 samples of DOA**

| No.           | Angle in degree | Magnitude-Y in Space-domain | Magnitude-Y in Time-domain | Error         | %Error      | %Accuracy    |
|---------------|-----------------|-----------------------------|----------------------------|---------------|-------------|--------------|
| 1             | 0               | 1.0000                      | 1.0000                     | 0.0000        | 0.00        | 100.00       |
| 2             | 5               | 0.9999                      | 0.9999                     | 0.0000        | 0.00        | 100.00       |
| 3             | 25              | 1.0000                      | 1.0000                     | 0.0000        | 0.00        | 100.00       |
| 4             | 45              | 1.0000                      | 0.9984                     | 0.0016        | 0.16        | 99.84        |
| 5             | 65              | 1.0000                      | 1.0000                     | 0.0000        | 0.00        | 100.00       |
| 6             | 85              | 0.9999                      | 0.9999                     | 0.0000        | 0.00        | 100.00       |
| 7             | 105             | 0.9998                      | 0.9998                     | 0.0000        | 0.00        | 100.00       |
| 8             | 125             | 0.9997                      | 0.9995                     | 0.0002        | 0.02        | 99.98        |
| 9             | 145             | 0.9997                      | 0.9995                     | 0.0002        | 0.02        | 99.98        |
| 10            | 165             | 0.9998                      | 0.9998                     | 0.0000        | 0.00        | 100.00       |
| 11            | 185             | 0.9999                      | 0.9990                     | 0.0009        | 0.09        | 99.91        |
| 12            | 205             | 1.0000                      | 1.0000                     | 0.0000        | 0.00        | 100.00       |
| 13            | 225             | 1.0000                      | 0.9984                     | 0.0016        | 0.16        | 99.84        |
| 14            | 245             | 1.0000                      | 1.0000                     | 0.0000        | 0.00        | 100.00       |
| 15            | 265             | 0.9999                      | 0.9990                     | 0.0009        | 0.09        | 99.91        |
| 16            | 285             | 0.9998                      | 0.9998                     | 0.0000        | 0.00        | 100.00       |
| 17            | 305             | 0.9997                      | 0.9995                     | 0.0002        | 0.02        | 99.98        |
| 18            | 325             | 0.9997                      | 0.9995                     | 0.0002        | 0.02        | 99.98        |
| 19            | 345             | 0.9998                      | 0.9998                     | 0.0000        | 0.00        | 100.00       |
| 20            | 360             | 1.0000                      | 1.0000                     | 0.0000        | 0.00        | 100.00       |
| Average Error |                 |                             |                            | <b>0.0003</b> | <b>0.03</b> | <b>99.97</b> |

## APPENDIX N

```
%%Signal Identification for the SPSS Radiation Waveform in Space & Time domains
```

```
T=< Freq_Train>;  
f=1/T;  
c=3e8;lambda=c/f;kd=pi;  
fi=-2*pi:0.01*pi:2*pi;  
Theta=<DOA>;
```

```
%Plotting SPSS Radiation in polar after convergence
```

```
w1=-66.11+2.029j;  
w2=21.31+-32.21j;  
Ep=w1*exp(1j*(pi)*cos(fi))+w2;  
figure,polar(fi,abs(Ep));  
title('SPSS Radiation Pattern');  
hold on;
```

```
%Plotting E-pulse in Space-domain
```

```
figure,plot(fi*180/pi,abs(Ep));  
title('SPSS Radiation Pattern in Space-domain at DOA');  
xlabel('Angle in Degree');  
ylabel('Magnitude of Ep');
```

```
%Plotting E-pulse in Time-domain
```

```
fs=f*100;  
dt=1/fs;  
n=1;  
t=-n/f:dt:n/f;  
Ep=w1*exp(1j*(pi)*cos(2*pi*f*t))+w2;  
figure,plot(t,abs(Ep));  
xlabel('Time in seconds');  
ylabel('Magnitude of Ep');  
title('SPSS Radiation Pattern in Time-domain at DOA');
```

## The $E_P$ Signal Identification

| $T_{EP(Train)}$ | $F_{SPSS(Train)}$<br>(GHz) | $F_{EP(Generated)}$<br>(Hz) From RP | $T_{EP}$ From RP | $T_{SPSS(Train)}$ (ns) | $T_{EP}$ (ns) From RP | $T_{EP Error}$ | $T_{EP \%Error}$ | Accuracy (%) | Average (%) |
|-----------------|----------------------------|-------------------------------------|------------------|------------------------|-----------------------|----------------|------------------|--------------|-------------|
| 2.67E-08        | 0.30                       | 2.9985E+08                          | 3.3350E-09       | 3.3333                 | 3.3350                | 0.0017         | 0.05100          | 99.95        | 99.91       |
| 2.67E-08        | 0.30                       | 2.9922E+08                          | 3.3420E-09       | 3.3333                 | 3.3420                | 0.0087         | 0.26100          | 99.74        |             |
| 2.67E-08        | 0.30                       | 2.9985E+08                          | 3.3350E-09       | 3.3333                 | 3.3350                | 0.0017         | 0.05100          | 99.95        |             |
| 2.67E-08        | 0.30                       | 2.9985E+08                          | 3.3350E-09       | 3.3333                 | 3.3350                | 0.0017         | 0.05100          | 99.95        |             |
| 2.67E-08        | 0.30                       | 2.9985E+08                          | 3.3350E-09       | 3.3333                 | 3.3350                | 0.0017         | 0.05100          | 99.95        |             |
| 2.29E-08        | 0.35                       | 3.5014E+08                          | 2.8560E-09       | 2.8571                 | 2.8560                | 0.0011         | 0.03850          | 99.96        | 99.98       |
| 2.29E-08        | 0.35                       | 3.5002E+08                          | 2.8570E-09       | 2.8571                 | 2.8570                | 0.0001         | 0.00350          | 100.00       |             |
| 2.29E-08        | 0.35                       | 3.5014E+08                          | 2.8560E-09       | 2.8571                 | 2.8560                | 0.0011         | 0.03850          | 99.96        |             |
| 2.29E-08        | 0.35                       | 3.5002E+08                          | 2.8570E-09       | 2.8571                 | 2.8570                | 0.0001         | 0.00350          | 100.00       |             |
| 2.29E-08        | 0.35                       | 3.5014E-01                          | 2.8560E+00       | 2.8571                 | 2.8560                | 0.0011         | 0.03850          | 99.96        |             |
| 2.00E-08        | 0.40                       | 3.9904E+08                          | 2.5060E-09       | 2.5000                 | 2.5060                | 0.0060         | 0.24000          | 99.76        | 99.88       |
| 2.00E-08        | 0.40                       | 4.0064E+08                          | 2.4960E-09       | 2.5000                 | 2.4960                | 0.0040         | 0.16000          | 99.84        |             |
| 2.00E-08        | 0.40                       | 4.0048E+08                          | 2.4970E-09       | 2.5000                 | 2.4970                | 0.0030         | 0.12000          | 99.88        |             |
| 2.00E-08        | 0.40                       | 3.9984E+08                          | 2.5010E-09       | 2.5000                 | 2.5010                | 0.0010         | 0.04000          | 99.96        |             |
| 2.00E-08        | 0.40                       | 3.9984E+08                          | 2.5010E-09       | 2.5000                 | 2.5010                | 0.0010         | 0.04000          | 99.96        |             |
| 1.78E-08        | 0.45                       | 4.5167E+08                          | 2.2140E-09       | 2.2200                 | 2.2140                | 0.0060         | 0.27027          | 99.73        | 99.84       |
| 1.78E-08        | 0.45                       | 4.5005E+08                          | 2.2220E-09       | 2.2200                 | 2.2220                | 0.0020         | 0.09009          | 99.91        |             |
| 1.78E-08        | 0.45                       | 4.5086E+08                          | 2.2180E-09       | 2.2200                 | 2.2180                | 0.0020         | 0.09009          | 99.91        |             |
| 1.78E-08        | 0.45                       | 4.5005E+08                          | 2.2220E-09       | 2.2200                 | 2.2220                | 0.0020         | 0.09009          | 99.91        |             |
| 1.78E-08        | 0.45                       | 4.5167E+08                          | 2.2140E-09       | 2.2200                 | 2.2140                | 0.0060         | 0.27027          | 99.73        |             |
| 1.60E-08        | 0.50                       | 4.9900E+08                          | 2.0040E-09       | 2.0000                 | 2.0040                | 0.0040         | 0.20000          | 99.80        | 99.79       |
| 1.60E-08        | 0.50                       | 4.9801E+08                          | 2.0080E-09       | 2.0000                 | 2.0080                | 0.0080         | 0.40000          | 99.60        |             |
| 1.60E-08        | 0.50                       | 5.0075E+08                          | 1.9970E-09       | 2.0000                 | 1.9970                | 0.0030         | 0.15000          | 99.85        |             |
| 1.60E-08        | 0.50                       | 5.0075E+08                          | 1.9970E-09       | 2.0000                 | 1.9970                | 0.0030         | 0.15000          | 99.85        |             |
| 1.60E-08        | 0.50                       | 5.0075E+08                          | 1.9970E-09       | 2.0000                 | 1.9970                | 0.0030         | 0.15000          | 99.85        |             |
| 1.45E-08        | 0.55                       | 5.5036E+08                          | 1.8170E-09       | 1.8182                 | 1.8170                | 0.0012         | 0.06600          | 99.93        | 99.79       |
| 1.45E-08        | 0.55                       | 5.5249E+08                          | 1.8100E-09       | 1.8182                 | 1.8100                | 0.0082         | 0.45100          | 99.55        |             |
| 1.45E-08        | 0.55                       | 5.5036E+08                          | 1.8170E-09       | 1.8182                 | 1.8170                | 0.0012         | 0.06600          | 99.93        |             |
| 1.45E-08        | 0.55                       | 5.5127E+08                          | 1.8140E-09       | 1.8182                 | 1.8140                | 0.0042         | 0.23100          | 99.77        |             |
| 1.45E-08        | 0.55                       | 5.5127E+08                          | 1.8140E-09       | 1.8182                 | 1.8140                | 0.0042         | 0.23100          | 99.77        |             |
| 1.33E-08        | 0.60                       | 6.0241E+08                          | 1.6600E-09       | 1.6667                 | 1.6600                | 0.0067         | 0.40199          | 99.60        | 99.88       |
| 1.33E-08        | 0.60                       | 5.9988E+08                          | 1.6670E-09       | 1.6667                 | 1.6670                | 0.0003         | 0.01800          | 99.98        |             |
| 1.33E-08        | 0.60                       | 6.0096E+08                          | 1.6640E-09       | 1.6667                 | 1.6640                | 0.0027         | 0.16200          | 99.84        |             |
| 1.33E-08        | 0.60                       | 5.9988E+08                          | 1.6670E-09       | 1.6667                 | 1.6670                | 0.0003         | 0.01800          | 99.98        |             |
| 1.33E-08        | 0.60                       | 5.9988E+08                          | 1.6670E-09       | 1.6667                 | 1.6670                | 0.0003         | 0.01800          | 99.98        |             |
| 1.23E-08        | 0.65                       | 6.5274E+08                          | 1.5320E-09       | 1.5385                 | 1.5310                | 0.0075         | 0.48749          | 99.513       | 99.75       |
| 1.23E-08        | 0.65                       | 6.5147E+08                          | 1.5350E-09       | 1.5385                 | 1.5350                | 0.0035         | 0.22749          | 99.773       |             |
| 1.23E-08        | 0.65                       | 6.5147E+08                          | 1.5350E-09       | 1.5385                 | 1.5310                | 0.0075         | 0.48749          | 99.513       |             |
| 1.23E-08        | 0.65                       | 6.4977E+08                          | 1.5390E-09       | 1.5385                 | 1.5390                | 0.0005         | 0.03250          | 99.968       |             |
| 1.23E-08        | 0.65                       | 6.4977E+08                          | 1.5390E-09       | 1.5385                 | 1.5390                | 0.0005         | 0.03250          | 99.968       |             |
| 1.14E-08        | 0.70                       | 6.9979E+08                          | 1.4290E-09       | 1.4286                 | 1.4290                | 0.0004         | 0.02800          | 99.972       | 99.97       |
| 1.14E-08        | 0.70                       | 6.9979E+08                          | 1.4290E-09       | 1.4286                 | 1.4290                | 0.0004         | 0.02800          | 99.972       |             |
| 1.14E-08        | 0.70                       | 7.0028E+08                          | 1.4280E-09       | 1.4286                 | 1.4280                | 0.0006         | 0.04200          | 99.958       |             |
| 1.14E-08        | 0.70                       | 6.9979E+08                          | 1.4290E-09       | 1.4286                 | 1.4290                | 0.0004         | 0.02800          | 99.972       |             |
| 1.14E-08        | 0.70                       | 7.0028E+08                          | 1.4280E-09       | 1.4286                 | 1.4280                | 0.0006         | 0.04200          | 99.958       |             |

|          |      |            |            |        |        |        |         |                |              |
|----------|------|------------|------------|--------|--------|--------|---------|----------------|--------------|
| 1.07E-08 | 0.75 | 7.4627E+08 | 1.3400E-09 | 1.3333 | 1.3400 | 0.0067 | 0.50251 | 99.497         | 99.86        |
| 1.07E-08 | 0.75 | 7.4963E+08 | 1.3340E-09 | 1.3333 | 1.3340 | 0.0007 | 0.05250 | 99.947         |              |
| 1.07E-08 | 0.75 | 7.4963E+08 | 1.3340E-09 | 1.3333 | 1.3340 | 0.0007 | 0.05250 | 99.947         |              |
| 1.07E-08 | 0.75 | 7.4963E+08 | 1.3340E-09 | 1.3333 | 1.3340 | 0.0007 | 0.05250 | 99.947         |              |
| 1.07E-08 | 0.75 | 7.4963E+08 | 1.3340E-09 | 1.3333 | 1.3340 | 0.0007 | 0.05250 | 99.947         |              |
| 1.00E-08 | 0.80 | 8.0000E+08 | 1.2500E-09 | 1.2500 | 1.2500 | 0.0000 | 0.00000 | 100.00         | 99.94        |
| 1.00E-08 | 0.80 | 8.0000E+08 | 1.2500E-09 | 1.2500 | 1.2500 | 0.0000 | 0.00000 | 100.00         |              |
| 1.00E-08 | 0.80 | 8.0000E+08 | 1.2500E-09 | 1.2500 | 1.2500 | 0.0000 | 0.00000 | 100.00         |              |
| 1.00E-08 | 0.80 | 8.0000E+08 | 1.2500E-09 | 1.2500 | 1.2500 | 0.0000 | 0.00000 | 100.00         |              |
| 1.00E-08 | 0.80 | 8.0257E+08 | 1.2460E-09 | 1.2500 | 1.2460 | 0.0040 | 0.32000 | 99.68          |              |
| 9.41E-09 | 0.85 | 8.4890E+08 | 1.1780E-09 | 1.1765 | 1.1780 | 0.0015 | 0.12750 | 99.87          | 99.86        |
| 9.41E-09 | 0.85 | 8.5034E+08 | 1.1760E-09 | 1.1765 | 1.1760 | 0.0005 | 0.04250 | 99.96          |              |
| 9.41E-09 | 0.85 | 8.4890E+08 | 1.1780E-09 | 1.1765 | 1.1780 | 0.0015 | 0.12750 | 99.87          |              |
| 9.41E-09 | 0.85 | 8.4890E+08 | 1.1780E-09 | 1.1765 | 1.1780 | 0.0015 | 0.12750 | 99.87          |              |
| 9.41E-09 | 0.85 | 8.5251E+08 | 1.1730E-09 | 1.1765 | 1.1730 | 0.0035 | 0.29749 | 99.70          |              |
| 8.89E-09 | 0.90 | 9.0009E+08 | 1.1110E-09 | 1.1111 | 1.1110 | 0.0001 | 0.00900 | 99.99          | 99.92        |
| 8.89E-09 | 0.90 | 8.9847E+08 | 1.1130E-09 | 1.1111 | 1.1130 | 0.0019 | 0.17100 | 99.83          |              |
| 8.89E-09 | 0.90 | 9.0171E+08 | 1.1090E-09 | 1.1111 | 1.1090 | 0.0021 | 0.18900 | 99.81          |              |
| 8.89E-09 | 0.90 | 9.0009E+08 | 1.1110E-09 | 1.1111 | 1.1110 | 0.0001 | 0.00900 | 99.99          |              |
| 8.89E-09 | 0.90 | 9.0009E+08 | 1.1110E-09 | 1.1111 | 1.1110 | 0.0001 | 0.00900 | 99.99          |              |
| 8.42E-09 | 0.95 | 9.4967E+08 | 1.0530E-09 | 1.0526 | 1.0530 | 0.0004 | 0.03800 | 99.96          | 99.91        |
| 8.42E-09 | 0.95 | 9.4967E+08 | 1.0530E-09 | 1.0526 | 1.0530 | 0.0004 | 0.03800 | 99.96          |              |
| 8.42E-09 | 0.95 | 9.5147E+08 | 1.0510E-09 | 1.0526 | 1.0510 | 0.0016 | 0.15200 | 99.85          |              |
| 8.42E-09 | 0.95 | 9.5147E+08 | 1.0510E-09 | 1.0526 | 1.0510 | 0.0016 | 0.15200 | 99.85          |              |
| 8.42E-09 | 0.95 | 9.5057E+08 | 1.0520E-09 | 1.0526 | 1.0520 | 0.0006 | 0.05700 | 99.94          |              |
| 8.00E-09 | 1.00 | 1.0020E+09 | 9.9800E-10 | 1.0000 | 0.9980 | 0.0020 | 0.20000 | 99.80          | 99.65        |
| 8.00E-09 | 1.00 | 1.0010E+09 | 9.9900E-10 | 1.0000 | 0.9990 | 0.0010 | 0.10000 | 99.90          |              |
| 8.00E-09 | 1.00 | 1.0010E+09 | 9.9900E-10 | 1.0000 | 0.9990 | 0.0010 | 0.10000 | 99.90          |              |
| 8.00E-09 | 1.00 | 1.0067E+09 | 9.9330E-10 | 1.0000 | 0.9933 | 0.0067 | 0.67000 | 99.33          |              |
| 8.00E-09 | 1.00 | 1.0067E+09 | 9.9330E-10 | 1.0000 | 0.9933 | 0.0067 | 0.67000 | 99.33          |              |
| 5.33E-09 | 1.50 | 1.4995E+09 | 6.6690E-10 | 0.6667 | 0.6669 | 0.0002 | 0.03000 | 99.97          | 99.89        |
| 5.33E-09 | 1.50 | 1.4995E+09 | 6.6690E-10 | 0.6667 | 0.6669 | 0.0002 | 0.03000 | 99.97          |              |
| 5.33E-09 | 1.50 | 1.4984E+09 | 6.6740E-10 | 0.6667 | 0.6674 | 0.0007 | 0.10499 | 99.90          |              |
| 5.33E-09 | 1.50 | 1.4959E+09 | 6.6850E-10 | 0.6667 | 0.6685 | 0.0018 | 0.26999 | 99.73          |              |
| 5.33E-09 | 1.50 | 1.4984E+09 | 6.6740E-10 | 0.6667 | 0.6674 | 0.0007 | 0.10499 | 99.90          |              |
| 4.00E-09 | 2.00 | 1.9984E+09 | 5.0040E-10 | 0.5000 | 0.5004 | 0.0004 | 0.08000 | 99.92          | 99.72        |
| 4.00E-09 | 2.00 | 2.0032E+09 | 4.9920E-10 | 0.5000 | 0.4992 | 0.0008 | 0.16000 | 99.84          |              |
| 4.00E-09 | 2.00 | 2.0096E+09 | 4.9760E-10 | 0.5000 | 0.4976 | 0.0024 | 0.48000 | 99.52          |              |
| 4.00E-09 | 2.00 | 2.0133E+09 | 4.9670E-10 | 0.5000 | 0.4967 | 0.0033 | 0.66000 | 99.34          |              |
| 4.00E-09 | 2.00 | 1.9992E+09 | 5.0020E-10 | 0.5000 | 0.5002 | 0.0002 | 0.04000 | 99.96          |              |
| 3.20E-09 | 2.50 | 2.5063E+09 | 3.9900E-10 | 0.4000 | 0.3990 | 0.0010 | 0.25000 | 99.75          | 99.90        |
| 3.20E-09 | 2.50 | 2.5006E+09 | 3.9990E-10 | 0.4000 | 0.3999 | 0.0001 | 0.02500 | 99.98          |              |
| 3.20E-09 | 2.50 | 2.4950E+09 | 4.0080E-10 | 0.4000 | 0.4008 | 0.0008 | 0.20000 | 99.80          |              |
| 3.20E-09 | 2.50 | 2.5006E+09 | 3.9990E-10 | 0.4000 | 0.3999 | 0.0001 | 0.02500 | 99.98          |              |
| 3.20E-09 | 2.50 | 2.5006E+09 | 3.9990E-10 | 0.4000 | 0.3999 | 0.0001 | 0.02500 | 99.98          |              |
| 2.67E-09 | 3.00 | 2.9985E+09 | 3.3350E-10 | 0.3333 | 0.3335 | 0.0002 | 0.06001 | 99.94          | 99.90        |
| 2.67E-09 | 3.00 | 2.9967E+09 | 3.3370E-10 | 0.3333 | 0.3337 | 0.0004 | 0.12001 | 99.88          |              |
| 2.67E-09 | 3.00 | 2.9967E+09 | 3.3370E-10 | 0.3333 | 0.3337 | 0.0004 | 0.12001 | 99.88          |              |
| 2.67E-09 | 3.00 | 2.9985E+09 | 3.3350E-10 | 0.3333 | 0.3335 | 0.0002 | 0.06001 | 99.94          |              |
| 2.67E-09 | 3.00 | 2.9967E+09 | 3.3370E-10 | 0.3333 | 0.3337 | 0.0004 | 0.12001 | 99.88          |              |
|          |      |            |            |        |        |        |         | <b>Average</b> | <b>99.86</b> |

### The $E_P$ Signal Localization at a fixed DOA = $45^\circ$

| $F_{SPSS} \text{ (Train)}$<br>(Hz) | $F_{EP}$<br>(Sample)<br>(GHz) | $F_{EP}$<br>(Measured)<br>(Hz) | $T_{EP} \text{ (Sample)}$<br>(ns) | $T_{EP} \text{ (Measured)}$<br>(s) | $T_{EP}$<br>(Measured)<br>(ns) | $T_{EP}$<br>Error | % $T_{EP}$<br>Error | DOA<br>(Target)<br>(Degree) | DOA<br>(Measured)<br>(Degree) | DOA <sub>(Error)</sub><br>(Degree) |
|------------------------------------|-------------------------------|--------------------------------|-----------------------------------|------------------------------------|--------------------------------|-------------------|---------------------|-----------------------------|-------------------------------|------------------------------------|
| 3.75E+07                           | 0.30                          | 2.88E+08                       | 3.330                             | 3.467E-09                          | 3.467                          | 0.137             | 4.114               | 45                          | 46.85                         | 1.9                                |
| 3.75E+07                           | 0.30                          | 2.88E+08                       | 3.330                             | 3.467E-09                          | 3.467                          | 0.137             | 4.114               | 45                          | 46.85                         | 1.9                                |
| 3.75E+07                           | 0.30                          | 2.89E+08                       | 3.330                             | 3.460E-09                          | 3.460                          | 0.130             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 3.75E+07                           | 0.30                          | 2.89E+08                       | 3.330                             | 3.460E-09                          | 3.460                          | 0.130             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 3.75E+07                           | 0.30                          | 2.89E+08                       | 3.330                             | 3.460E-09                          | 3.460                          | 0.130             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 4.38E+07                           | 0.35                          | 3.37E+08                       | 2.860                             | 2.971E-09                          | 2.971                          | 0.111             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 4.38E+07                           | 0.35                          | 3.38E+08                       | 2.860                             | 2.959E-09                          | 2.959                          | 0.099             | 3.444               | 45                          | 46.55                         | 1.6                                |
| 4.38E+07                           | 0.35                          | 3.37E+08                       | 2.860                             | 2.971E-09                          | 2.971                          | 0.111             | 3.881               | 45                          | 46.75                         | 1.8                                |
| 4.38E+07                           | 0.35                          | 3.37E+08                       | 2.860                             | 2.971E-09                          | 2.971                          | 0.111             | 3.881               | 45                          | 46.75                         | 1.8                                |
| 4.38E+07                           | 0.35                          | 3.38E+08                       | 2.860                             | 2.959E-09                          | 2.959                          | 0.099             | 3.444               | 45                          | 46.55                         | 1.6                                |
| 5.00E+07                           | 0.40                          | 3.85E+08                       | 2.500                             | 2.600E-09                          | 2.600                          | 0.100             | 4.000               | 45                          | 46.80                         | 1.8                                |
| 5.00E+07                           | 0.40                          | 3.85E+08                       | 2.500                             | 2.597E-09                          | 2.597                          | 0.097             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 5.00E+07                           | 0.40                          | 3.85E+08                       | 2.500                             | 2.597E-09                          | 2.597                          | 0.097             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 5.00E+07                           | 0.40                          | 3.85E+08                       | 2.500                             | 2.597E-09                          | 2.597                          | 0.097             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 5.00E+07                           | 0.40                          | 3.85E+08                       | 2.500                             | 2.600E-09                          | 2.600                          | 0.100             | 4.000               | 45                          | 46.80                         | 1.8                                |
| 5.63E+07                           | 0.45                          | 4.33E+08                       | 2.220                             | 2.311E-09                          | 2.311                          | 0.091             | 4.099               | 45                          | 46.84                         | 1.8                                |
| 5.63E+07                           | 0.45                          | 4.33E+08                       | 2.220                             | 2.309E-09                          | 2.309                          | 0.089             | 4.000               | 45                          | 46.80                         | 1.8                                |
| 5.63E+07                           | 0.45                          | 4.33E+08                       | 2.220                             | 2.309E-09                          | 2.309                          | 0.089             | 4.000               | 45                          | 46.80                         | 1.8                                |
| 5.63E+07                           | 0.45                          | 4.34E+08                       | 2.220                             | 2.306E-09                          | 2.306                          | 0.086             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 5.63E+07                           | 0.45                          | 4.34E+08                       | 2.220                             | 2.306E-09                          | 2.306                          | 0.086             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 6.25E+07                           | 0.50                          | 4.81E+08                       | 2.000                             | 2.080E-09                          | 2.080                          | 0.080             | 4.000               | 45                          | 46.80                         | 1.8                                |
| 6.25E+07                           | 0.50                          | 4.81E+08                       | 2.000                             | 2.080E-09                          | 2.080                          | 0.080             | 4.000               | 45                          | 46.80                         | 1.8                                |
| 6.25E+07                           | 0.50                          | 4.81E+08                       | 2.000                             | 2.080E-09                          | 2.080                          | 0.080             | 4.000               | 45                          | 46.80                         | 1.8                                |
| 6.25E+07                           | 0.50                          | 4.81E+08                       | 2.000                             | 2.080E-09                          | 2.080                          | 0.080             | 4.000               | 45                          | 46.80                         | 1.8                                |
| 6.25E+07                           | 0.50                          | 4.81E+08                       | 2.000                             | 2.080E-09                          | 2.080                          | 0.080             | 4.000               | 45                          | 46.80                         | 1.8                                |
| 6.88E+07                           | 0.55                          | 5.29E+08                       | 1.818                             | 1.891E-09                          | 1.891                          | 0.073             | 4.015               | 45                          | 46.81                         | 1.8                                |
| 6.88E+07                           | 0.55                          | 5.29E+08                       | 1.818                             | 1.889E-09                          | 1.889                          | 0.071             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 6.88E+07                           | 0.55                          | 5.29E+08                       | 1.818                             | 1.889E-09                          | 1.889                          | 0.071             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 6.88E+07                           | 0.55                          | 5.29E+08                       | 1.818                             | 1.889E-09                          | 1.889                          | 0.071             | 3.889               | 45                          | 46.75                         | 1.8                                |
| 6.88E+07                           | 0.55                          | 5.29E+08                       | 1.818                             | 1.891E-09                          | 1.891                          | 0.073             | 4.015               | 45                          | 46.81                         | 1.8                                |
| 7.50E+07                           | 0.60                          | 5.77E+08                       | 1.667                             | 1.733E-09                          | 1.733                          | 0.066             | 3.959               | 45                          | 46.78                         | 1.8                                |
| 7.50E+07                           | 0.60                          | 5.77E+08                       | 1.667                             | 1.733E-09                          | 1.733                          | 0.066             | 3.959               | 45                          | 46.78                         | 1.8                                |
| 7.50E+07                           | 0.60                          | 5.77E+08                       | 1.667                             | 1.733E-09                          | 1.733                          | 0.066             | 3.959               | 45                          | 46.78                         | 1.8                                |
| 7.50E+07                           | 0.60                          | 5.77E+08                       | 1.667                             | 1.733E-09                          | 1.733                          | 0.066             | 3.959               | 45                          | 46.78                         | 1.8                                |

|          |      |          |       |           |       |       |       |    |       |     |
|----------|------|----------|-------|-----------|-------|-------|-------|----|-------|-----|
| 7.50E+07 | 0.60 | 5.77E+08 | 1.667 | 1.733E-09 | 1.733 | 0.066 | 3.959 | 45 | 46.78 | 1.8 |
| 8.13E+07 | 0.65 | 6.25E+08 | 1.538 | 1.600E-09 | 1.600 | 0.062 | 4.031 | 45 | 46.81 | 1.8 |
| 8.13E+07 | 0.65 | 6.25E+08 | 1.538 | 1.600E-09 | 1.600 | 0.062 | 4.000 | 45 | 46.80 | 1.8 |
| 8.13E+07 | 0.65 | 6.25E+08 | 1.538 | 1.600E-09 | 1.600 | 0.062 | 4.000 | 45 | 46.80 | 1.8 |
| 8.13E+07 | 0.65 | 6.25E+08 | 1.538 | 1.600E-09 | 1.600 | 0.062 | 4.000 | 45 | 46.80 | 1.8 |
| 8.13E+07 | 0.65 | 6.25E+08 | 1.538 | 1.600E-09 | 1.600 | 0.062 | 4.000 | 45 | 46.80 | 1.8 |
| 8.75E+07 | 0.70 | 6.73E+08 | 1.429 | 1.486E-09 | 1.486 | 0.057 | 3.989 | 45 | 46.79 | 1.8 |
| 8.75E+07 | 0.70 | 6.74E+08 | 1.429 | 1.485E-09 | 1.485 | 0.056 | 3.889 | 45 | 46.75 | 1.8 |
| 8.75E+07 | 0.70 | 6.74E+08 | 1.429 | 1.485E-09 | 1.485 | 0.056 | 3.889 | 45 | 46.75 | 1.8 |
| 8.75E+07 | 0.70 | 6.73E+08 | 1.429 | 1.486E-09 | 1.486 | 0.057 | 3.978 | 45 | 46.79 | 1.8 |
| 8.75E+07 | 0.70 | 6.73E+08 | 1.429 | 1.486E-09 | 1.486 | 0.057 | 3.978 | 45 | 46.79 | 1.8 |
| 9.38E+07 | 0.75 | 7.21E+08 | 1.333 | 1.387E-09 | 1.387 | 0.054 | 4.051 | 45 | 46.82 | 1.8 |
| 9.38E+07 | 0.75 | 7.21E+08 | 1.333 | 1.386E-09 | 1.386 | 0.053 | 4.000 | 45 | 46.80 | 1.8 |
| 9.38E+07 | 0.75 | 7.21E+08 | 1.333 | 1.386E-09 | 1.386 | 0.053 | 4.000 | 45 | 46.80 | 1.8 |
| 9.38E+07 | 0.75 | 7.21E+08 | 1.333 | 1.387E-09 | 1.387 | 0.054 | 4.051 | 45 | 46.82 | 1.8 |
| 9.38E+07 | 0.75 | 7.21E+08 | 1.333 | 1.387E-09 | 1.387 | 0.054 | 4.051 | 45 | 46.82 | 1.8 |
| 1.00E+08 | 0.80 | 7.69E+08 | 1.250 | 1.300E-09 | 1.300 | 0.050 | 4.000 | 45 | 46.80 | 1.8 |
| 1.00E+08 | 0.80 | 7.69E+08 | 1.250 | 1.300E-09 | 1.300 | 0.050 | 4.000 | 45 | 46.80 | 1.8 |
| 1.00E+08 | 0.80 | 7.69E+08 | 1.250 | 1.300E-09 | 1.300 | 0.050 | 4.000 | 45 | 46.80 | 1.8 |
| 1.00E+08 | 0.80 | 7.69E+08 | 1.250 | 1.300E-09 | 1.300 | 0.050 | 4.000 | 45 | 46.80 | 1.8 |
| 1.00E+08 | 0.80 | 7.69E+08 | 1.250 | 1.300E-09 | 1.300 | 0.050 | 4.000 | 45 | 46.80 | 1.8 |
| 1.06E+08 | 0.85 | 8.18E+08 | 1.176 | 1.223E-09 | 1.223 | 0.047 | 3.997 | 45 | 46.80 | 1.8 |
| 1.06E+08 | 0.85 | 8.18E+08 | 1.176 | 1.223E-09 | 1.223 | 0.047 | 3.997 | 45 | 46.80 | 1.8 |
| 1.06E+08 | 0.85 | 8.18E+08 | 1.176 | 1.223E-09 | 1.223 | 0.047 | 3.997 | 45 | 46.80 | 1.8 |
| 1.06E+08 | 0.85 | 8.18E+08 | 1.176 | 1.223E-09 | 1.223 | 0.047 | 3.997 | 45 | 46.80 | 1.8 |
| 1.06E+08 | 0.85 | 8.18E+08 | 1.176 | 1.223E-09 | 1.223 | 0.047 | 3.997 | 45 | 46.80 | 1.8 |
| 1.13E+08 | 0.90 | 8.65E+08 | 1.111 | 1.156E-09 | 1.156 | 0.045 | 4.050 | 45 | 46.82 | 1.8 |
| 1.13E+08 | 0.90 | 8.65E+08 | 1.111 | 1.156E-09 | 1.156 | 0.045 | 4.051 | 45 | 46.82 | 1.8 |
| 1.13E+08 | 0.90 | 8.65E+08 | 1.111 | 1.156E-09 | 1.156 | 0.045 | 4.051 | 45 | 46.82 | 1.8 |
| 1.13E+08 | 0.90 | 8.65E+08 | 1.111 | 1.156E-09 | 1.156 | 0.045 | 4.051 | 45 | 46.82 | 1.8 |
| 1.13E+08 | 0.90 | 8.65E+08 | 1.111 | 1.156E-09 | 1.156 | 0.045 | 4.051 | 45 | 46.82 | 1.8 |
| 1.19E+08 | 0.95 | 9.14E+08 | 1.053 | 1.094E-09 | 1.094 | 0.041 | 3.894 | 45 | 46.75 | 1.8 |
| 1.19E+08 | 0.95 | 9.14E+08 | 1.053 | 1.094E-09 | 1.094 | 0.041 | 3.894 | 45 | 46.75 | 1.8 |
| 1.19E+08 | 0.95 | 9.14E+08 | 1.053 | 1.094E-09 | 1.094 | 0.041 | 3.894 | 45 | 46.75 | 1.8 |
| 1.19E+08 | 0.95 | 9.14E+08 | 1.053 | 1.094E-09 | 1.094 | 0.041 | 3.894 | 45 | 46.75 | 1.8 |
| 1.19E+08 | 0.95 | 9.14E+08 | 1.053 | 1.094E-09 | 1.094 | 0.041 | 3.894 | 45 | 46.75 | 1.8 |
| 1.25E+08 | 1.00 | 9.62E+08 | 1.000 | 1.040E-09 | 1.040 | 0.040 | 4.000 | 45 | 46.80 | 1.8 |
| 1.25E+08 | 1.00 | 9.61E+08 | 1.000 | 1.040E-09 | 1.040 | 0.040 | 4.031 | 45 | 46.81 | 1.8 |

|          |      |          |       |           |       |       |       |    |       |     |
|----------|------|----------|-------|-----------|-------|-------|-------|----|-------|-----|
| 1.25E+08 | 1.00 | 9.61E+08 | 1.000 | 1.040E-09 | 1.040 | 0.040 | 4.031 | 45 | 46.81 | 1.8 |
| 1.25E+08 | 1.00 | 9.61E+08 | 1.000 | 1.041E-09 | 1.041 | 0.041 | 4.051 | 45 | 46.82 | 1.8 |
| 1.25E+08 | 1.00 | 9.61E+08 | 1.000 | 1.041E-09 | 1.041 | 0.041 | 4.051 | 45 | 46.82 | 1.8 |
| 1.88E+08 | 1.50 | 1.44E+09 | 0.667 | 6.933E-10 | 0.693 | 0.027 | 3.990 | 45 | 46.80 | 1.8 |
| 1.88E+08 | 1.50 | 1.44E+09 | 0.667 | 6.927E-10 | 0.693 | 0.026 | 3.894 | 45 | 46.75 | 1.8 |
| 1.88E+08 | 1.50 | 1.44E+09 | 0.667 | 6.927E-10 | 0.693 | 0.026 | 3.894 | 45 | 46.75 | 1.8 |
| 1.88E+08 | 1.50 | 1.44E+09 | 0.667 | 6.927E-10 | 0.693 | 0.026 | 3.894 | 45 | 46.75 | 1.8 |
| 1.88E+08 | 1.50 | 1.44E+09 | 0.667 | 6.933E-10 | 0.693 | 0.027 | 3.990 | 45 | 46.80 | 1.8 |
| 2.50E+08 | 2.00 | 1.92E+09 | 0.500 | 5.200E-10 | 0.520 | 0.020 | 4.000 | 45 | 46.80 | 1.8 |
| 2.50E+08 | 2.00 | 1.92E+09 | 0.500 | 5.200E-10 | 0.520 | 0.020 | 4.000 | 45 | 46.80 | 1.8 |
| 2.50E+08 | 2.00 | 1.92E+09 | 0.500 | 5.200E-10 | 0.520 | 0.020 | 4.000 | 45 | 46.80 | 1.8 |
| 2.50E+08 | 2.00 | 1.92E+09 | 0.500 | 5.200E-10 | 0.520 | 0.020 | 4.000 | 45 | 46.80 | 1.8 |
| 2.50E+08 | 2.00 | 1.92E+09 | 0.500 | 5.200E-10 | 0.520 | 0.020 | 4.000 | 45 | 46.80 | 1.8 |
| 3.13E+08 | 2.50 | 2.40E+09 | 0.400 | 4.160E-10 | 0.416 | 0.016 | 4.000 | 45 | 46.80 | 1.8 |
| 3.13E+08 | 2.50 | 2.40E+09 | 0.400 | 4.160E-10 | 0.416 | 0.016 | 4.000 | 45 | 46.80 | 1.8 |
| 3.13E+08 | 2.50 | 2.40E+09 | 0.400 | 4.160E-10 | 0.416 | 0.016 | 4.000 | 45 | 46.80 | 1.8 |
| 3.13E+08 | 2.50 | 2.40E+09 | 0.400 | 4.160E-10 | 0.416 | 0.016 | 4.000 | 45 | 46.80 | 1.8 |
| 3.13E+08 | 2.50 | 2.40E+09 | 0.400 | 4.160E-10 | 0.416 | 0.016 | 4.000 | 45 | 46.80 | 1.8 |
| 3.75E+08 | 3.00 | 2.88E+09 | 0.333 | 3.467E-10 | 0.347 | 0.013 | 4.020 | 45 | 46.81 | 1.8 |
| 3.75E+08 | 3.00 | 2.88E+09 | 0.333 | 3.466E-10 | 0.347 | 0.013 | 4.000 | 45 | 46.80 | 1.8 |
| 3.75E+08 | 3.00 | 2.88E+09 | 0.333 | 3.466E-10 | 0.347 | 0.013 | 4.000 | 45 | 46.80 | 1.8 |
| 3.75E+08 | 3.00 | 2.88E+09 | 0.333 | 3.467E-10 | 0.347 | 0.013 | 4.020 | 45 | 46.81 | 1.8 |
| 3.75E+08 | 3.00 | 2.88E+09 | 0.333 | 3.467E-10 | 0.347 | 0.013 | 4.020 | 45 | 46.81 | 1.8 |
| Average: |      |          |       |           |       |       |       |    |       | 2   |

## APPENDIX R

### Journal Publications

1. Senthilkumar, K. S., Singkang, L., Hoole, P. R. P., Julai, N., Ang, S., Sahrani, S., ... & Hoole, S. R. H. (2017). A review of a single neuron weight optimization model for adaptive beam forming. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, 9(3-10), 35-40.
2. Singkang, L. (2019). Detection and localization of electric discharges in indoor substation for fault monitoring. *Science Proceedings Series*, 1(2), 94-96.
3. Singkang, L. M. B., Ping, K. A. H., & Hoole, P. R. P. (2020). Electric discharges localization for substation fault monitoring using two elements sensor. *Journal of Computational and Theoretical Nanoscience*, 17(2-3), 1009-1013.
4. Singkang, L. M., Ping, K. A. H., Kunsei, H., Senthilkumar, K., Pirapaharan, K., Haidar, A. M., & Hoole, P. R. (2021). Model based-testing of spatial and time domain artificial intelligence smart antenna for ultra-high frequency electric discharge detection in digital power substations. *Progress In Electromagnetics Research M*, 99, 91-101.