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DETERMINING POWER SYSTEM FAULT LOCATION USING NEURAL NETWORK APPROACH

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Edward O. Ojini, Student

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DETERMINING POWER SYSTEM FAULT LOCATION USING NEURAL NETWORK APPROACH

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in the
College of Engineering
at the University of Kentucky

By

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ABSTRACT OF THESIS

DETERMINING POWER SYSTEM FAULT LOCATION USING NEURAL NETWORK APPROACH

Fault location remains an extremely pivotal feature of the electric power grid as it ensures efficient operation of the grid and prevents large downtimes during fault occurrences. This will ultimately enhance and increase the reliability of the system. Since the invention of the electric grid, many approaches to fault location have been studied and documented. These approaches are still effective and are implemented in present times, and as the power grid becomes even more broadened with new forms of energy generation, transmission, and distribution technologies, continued study on these methods is necessary. This thesis will focus on adopting the artificial neural network method for fault location for a high-impedance grounded system, where fault currents are small for single phase to ground faults. This approach will be performed on a single 2-terminal distribution network. This thesis will also give a comprehensive explanation on the process of developing artificial neural networks (ANN) using MATLAB's neural network app designers. The main objective of the experimental approach is to investigate the effects of different variations in ANN structures (such as number of neurons, number of hidden layers, input features, and data preprocessing) on predicting fault locations. Study results from the simulations have been presented to show performance of each ANN structure for fault location on the sample distribution system.

KEYWORDS: Fault Location, Artificial Neural Network, Feed Forward Neural Network, Distribution System, Power Systems, Fault Classification

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DETERMINING POWER SYSTEM FAULT LOCATION USING A NEURAL NETWORK APPROACH

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CHAPTER 1. INTRODUCTION

1.1 Background

The electric power grid consists of three main sections: generation, transmission, and distribution. Power generation is concerned with all the technologies and resources involved in creation of energy e.g., Coal, Natural Gas, Hydro, Solar PV, etc. Power Transmission includes the infrastructure required to transmit the generated electric power from the generation sites to the distribution sites like high voltage lines and high voltage transformers. The distribution end consists of mainly local substations where the high voltage delivered by the transmission lines is stepped down and the further distributed to end users like factories, homes, schools, hospitals, etc. The distribution section of the electric grid is currently expanding as new emerging technologies are being introduced such as renewable energy sources and more complex load requirements. Given this, it is pivotal that accurate fault location systems are in place to ensure efficient and reliable operation of the entire grid.

Fault occurrences on the distribution network can be because of many situations such as a fallen tree short circuiting the system, lightning strikes, or wildlife influence. Nevertheless, adequate detection of the fault type and characteristics, such as location, are needed to ensure seamless recovery of the system with as little casualties to the end users as possible. Fault types include single phase to ground (L-L), two phase to ground (L-L-G), and three phase to ground (L-L-L-G). The most common of these types is L-G and this accounts for 70-80% of all faults [1].

There are multiple methods for detecting fault location including impedance-based method and the traveling wave method and artificial intelligent methods that include fuzzy logic, artificial neural networks, and adaptive network-based fuzzy inference system techniques [2]. This thesis will discuss on a subset of the artificial network approach, specifically the feedforward artificial neural network approach.

1.2 Motivation and Objective

During a single phase to ground fault on a high-impedance grounded distribution system, the fault current is small and thus the current measurements don't vary much in comparison with pre-fault currents. The small fault currents pose challenges to locating faults in such scenarios. One of the most common and difficult problems to solve in industrial power systems is the location and elimination of the ground fault. Ground faults that occur in ungrounded and high-resistance grounded systems do not draw enough current to trigger circuit breaker or fuse operation, which makes them rather difficult to localize [7]. This research focuses on locating single phase to ground faults on a high-impedance grounded distribution system.

The main objective of this paper is to present an artificial neural network (ANN) approach to determining fault location using an in-built neural network creation tool on MATLAB. Multiple ANN structures were developed to identify the fault location that occurred on a single two-terminal distribution network line. These structures varied in number of neurons per layer with a fixed number of layers of three (3) for every ANN structure.

Two (2) 3-Phase VI measurement blocks were setup with one on either side of the simulated fault to capture the power flow measurements from each terminal. The signals that would be fed into the various ANN would be the 3-phase voltage and current data from either measurement block of the distribution network during the fault occurrence. These signals would then be preprocessed using either or both of two main techniques of normalization & standardization. Based on these inputs into the network structure, the fault location is then determined or predicted.

After the fault location is predicted, the post processing stage will involve an overview on the performance of the network in determining the fault location. This overview will include the mean squared error, average, max, and min errors, and a graph to show the accuracy of the prediction in comparison to the actual location of the fault.

This thesis will give the reader an insight on how to develop various ANN structures for locating faults on a distribution line and will help display certain characteristics of these ANN structures to best decide on a good estimate on how to vary the network's structure for the optimum prediction and performance.

1.3 Thesis Organization

Chapter 2 of the thesis is dedicated to explaining the distribution network that was modeled and simulated to generate fault location cases and voltage and current signals to be used by the ANN structures. This chapter will cover as much detail necessary to understand the modeling of the distribution network and the simulation processes.

Chapter 3 will give details on how to design a basic neural network using MATLAB's nnStart tool, which is an in-built tool for developing neural networks. The start tool is included in the Deep Learning Toolbox app which can be downloaded from the MATLAB App Installer. This chapter will give as many details as possible to understand the concept of the operation of a basic feedforward neural network and how to design and train a basic feedforward neural network using the tool.

Chapter 4 will go over the collection of voltage and current data for this study, and how this data is preprocessed before being fed into the ANN for appropriate training and testing of the network.

Chapter 5 will discuss on the various structures of the ANNs built for this study and how this can be achieved using the ANN tool on MATLAB. This section will also go over some basic code that can be used an alternative to the tool. This process will give a bit more flexibility to changing the number of layers of the network structure.

CHAPTER 2. DISTRIBUTION SYSTEM MODEL & SIMULATION

2.1 Power System Model

This study will involve modeling a power system network for a single two-terminal circuit distribution line using the MathWorks MATLAB 2021b and Simulink software to perform all the required simulations. The length of the distribution line is modeled at 1500 feet with bus 1 connected to a generation source and bus 2 connected to a 300-kW load. This source has a grounding resistance of 10k ohms, thus representing a high-impedance grounded system. The SimPowersystem model was provided by Dr. Yuan Liao. A program was developed by Dr. Yuan Liao to automatically pose faults on the system and run the simulation to generate voltage and current waveforms. This program was used in this research.

Instantaneous voltage and current measurements are recorded in per unit at each terminal/bus of the distribution line at a rate of 128 samples per cycle. The per unit values are measured by MATLAB using a power base of 1.5 MVA and a voltage base of 1.2 kV. Instantaneous voltage and current samples instead of fundamental frequency phasors are recorded and utilized for locating the faults.. A visual representation of the modeled power system configuration is shown in figure 1.

2.2 Power System Properties

The distribution line is modeled with two (2) bus system with two (2) measurement blocks on either bus. The first bus is connected to a generation source while the second bus is connected to a 300-kW load block. A sliding fault block is then added between each bus and measurement blocks to simulate the desired fault scenarios. The fault distance parameter of the fault block is varied to sweep from both ends of the bus and the measurements are recorded by the measurement blocks during each simulation. The source impedance has the following properties:

- Positive Sequence R1: 2.3E-2 Ohms
- Positive Sequence L1: 6.0E-4 H
- Zero Sequence R0: 1.5E-2 Ohms
- Zero Sequence L0: 4.0E-4 H

2.3 Power System Model Simulation

The simulation duration was set at 0.1s and the fault inception time was set at 0.05s. A three phase fault block was used to simulate a single line to ground fault (phase A to Ground) with five (5) varied fault resistances. After each fault inception, the system is not cleared, and the fault remains throughout the rest of the simulation. The length of each step size for the fault inception was 10 feet resulting in 151 different fault inception locations. The total number of simulation cases would be 755 fault cases.

ANNs typically require a large number of input data to properly train the network for optimum prediction so the simulation was run 5 times, simulating a new set of 151 fault inception points with 5 various fault resistances. This would eventually sum up the total number of case simulations to be 3775. In addition to each fault inception scenario, a normal state scenario is also simulated. This will provide us a normal operation reference signal which would be used later for data preprocessing prior to being fed into the neural network. The Matlab program developed by Dr. Yuan Liao was used to automatically simulate the system under various fault conditions and generate voltage and current measurements.

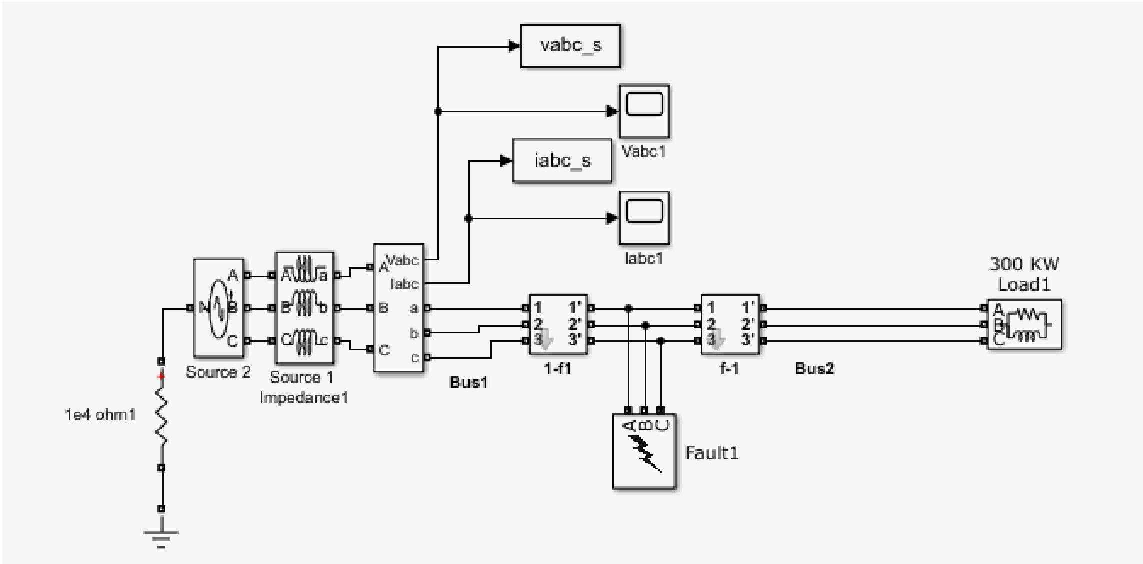

Figure 1: Two-terminal distribution network simulation model

CHAPTER 3. DESIGNING ANN USING MATLAB NNSTART TOOL

3.1 Introduction

This chapter goes over the process of designing a basic feedforward neural network using MATLAB's nnStart tool, which is an add on tool to the Deep Learning Toolbox app that can be installed on to MATLAB. This type of ANN uses a method of training to create a regression line between two elements (input and output) and uses this learned regression to predict the output of a new set of input data fed into the network. To effectively train and test the network, both input and output datasets are provided to the tool, and it uses these datasets to train, validate and test the network [8]. This chapter will go into detail about properly selecting datasets and choosing appropriate network structures to properly design the desired ANN. A flowchart will also be provided at the end of the chapter to give a more concise visual guideline of the process.

3.2 Starting up the nnStart tool on MATLAB

Launch the most recently installed version of MATLAB executable file. The version of the software used in this study is the R2021b release. In the case where an older or newer version of the software is being used, the process will be similar. It is also important that the Deep Learning Toolbox app be installed prior to launching the ANN tool. Once the MATLAB application launches and with the deep learning toolbox installed, type the following into the command window line: "nnstart". This will begin a new instance of the neural network designing tool on MATLAB.

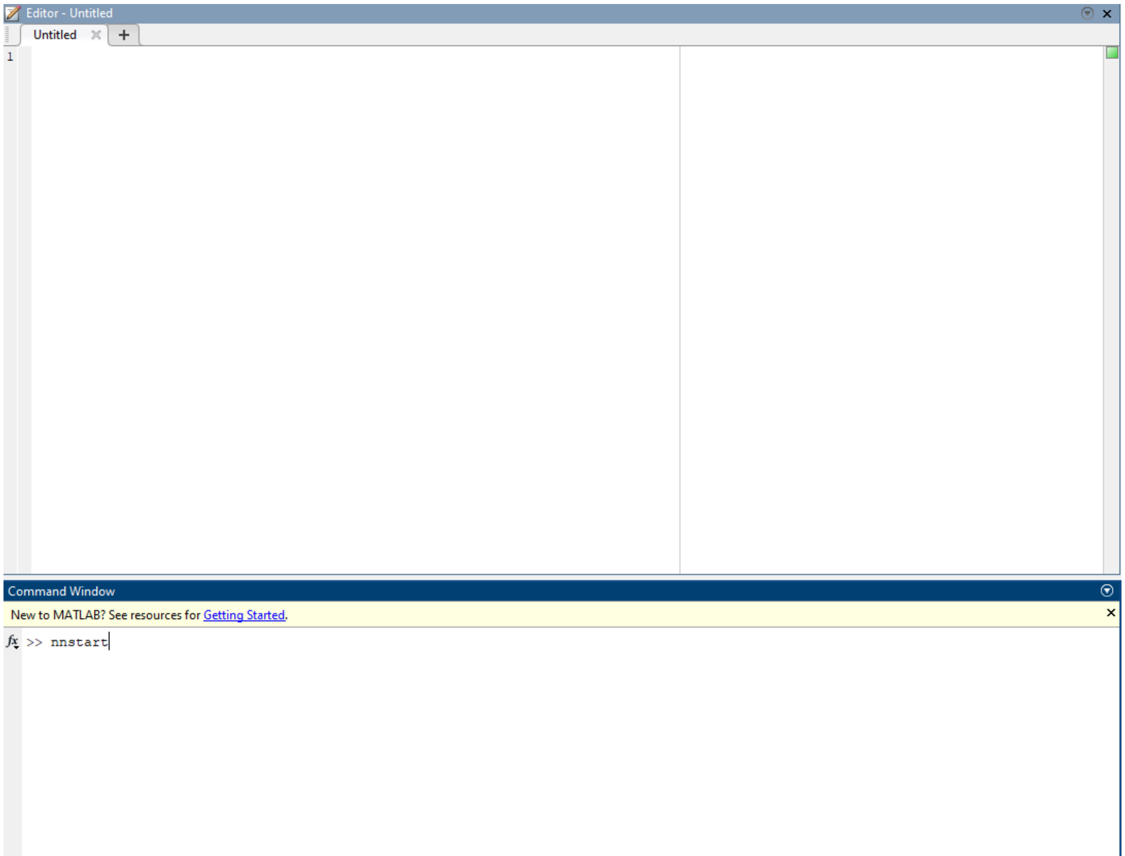

Figure 2: Launching MATLAB nnStart tool from command line

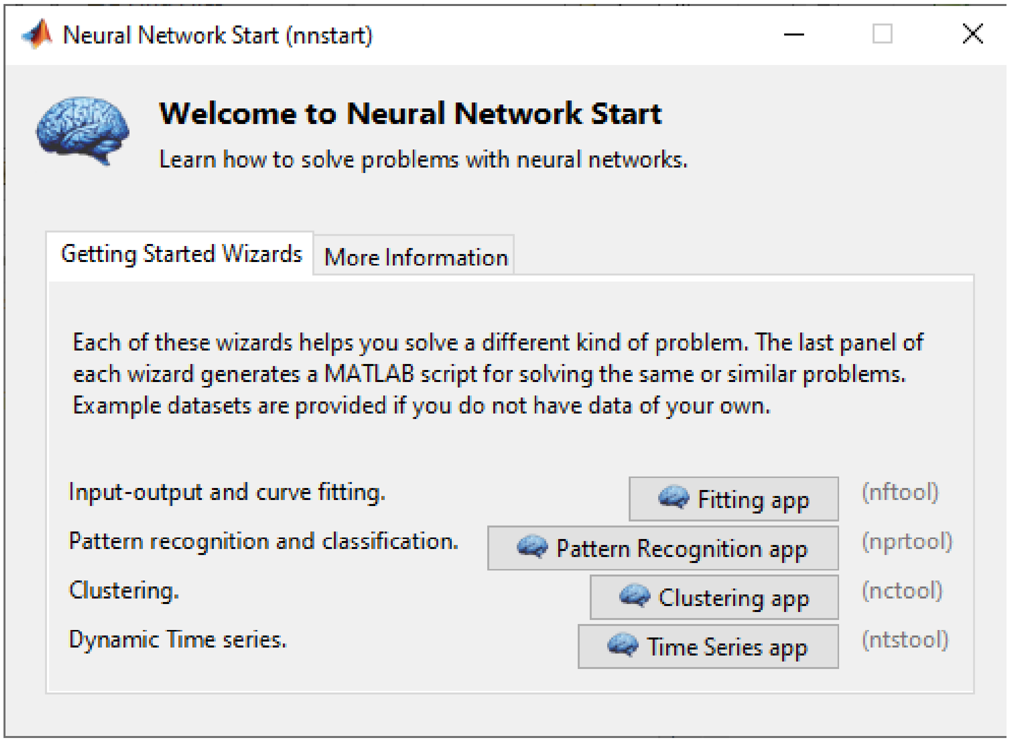

Figure 3: Neural Network Start toolbox

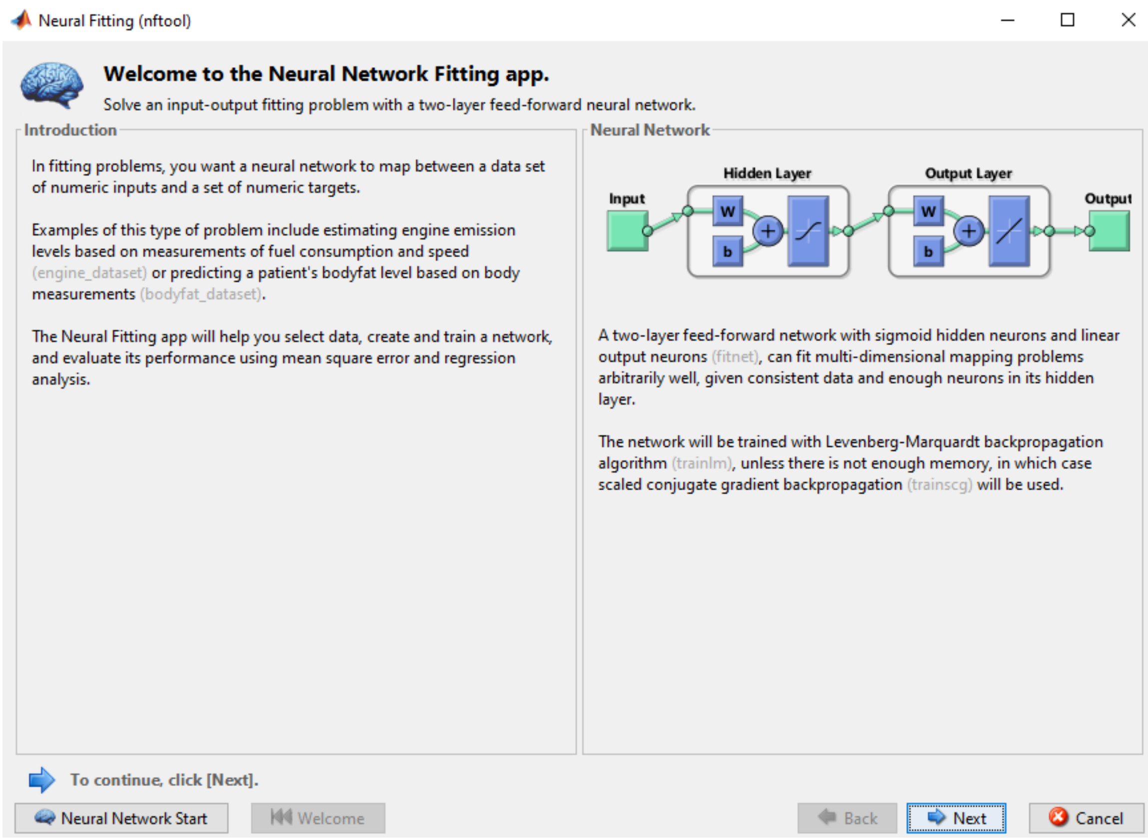

Figure 4: Welcome window for neural network fitting app

3.3 *Determining input and output training & testing data within the tool*

On the welcome pop-up menu, select the Fitting app option. A new pop-up window instance should load, and this is the section where the input and output training data are defined. It is important to feed the input and output training data in the right format. This would involve deciding whether the training data be fed in as a row vector/matrix or a column vector/matrix. Depending on the nature of the training data, an appropriate format of the data would be decided and fed into the ANN for training purposes. For this study, the inputs were fed in as matrix rows where the rows of the data represent the static data, and the columns represent the elements or features of the input/output training data.

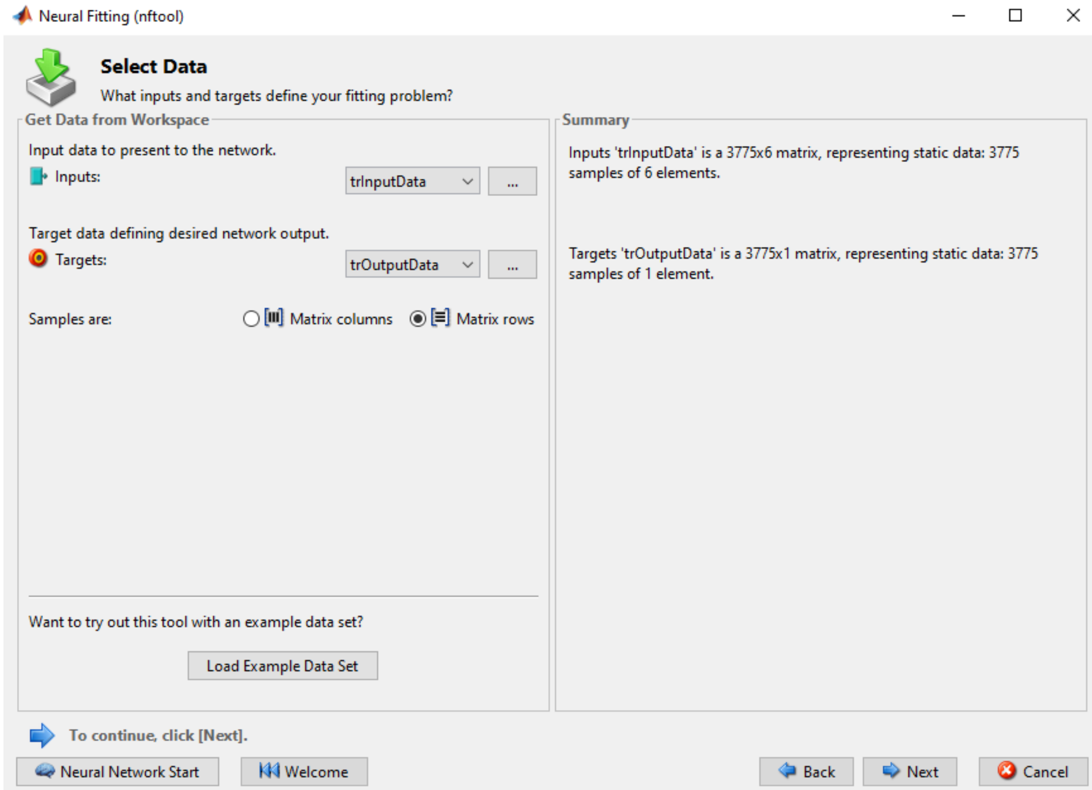

Figure 5: Determining the input and output training data for ANN

3.4 Partitioning training dataset

The next step of the process is to assign the proportion of the dataset to be used for training, validation, and testing. The ANN tool requires that some portion of the training input and output dataset is set aside for testing and validation. The default partitioning on the tool is 70 15 15 splits where 70% is used for training the ANN, while the 2 sets of 15% would be used for validation and testing. It is important to note that this testing data partition is only for self-evaluation process of the ANN. New sets of test inputs can be fed into the network after it has been created to get an output dataset prediction using the regression line established.

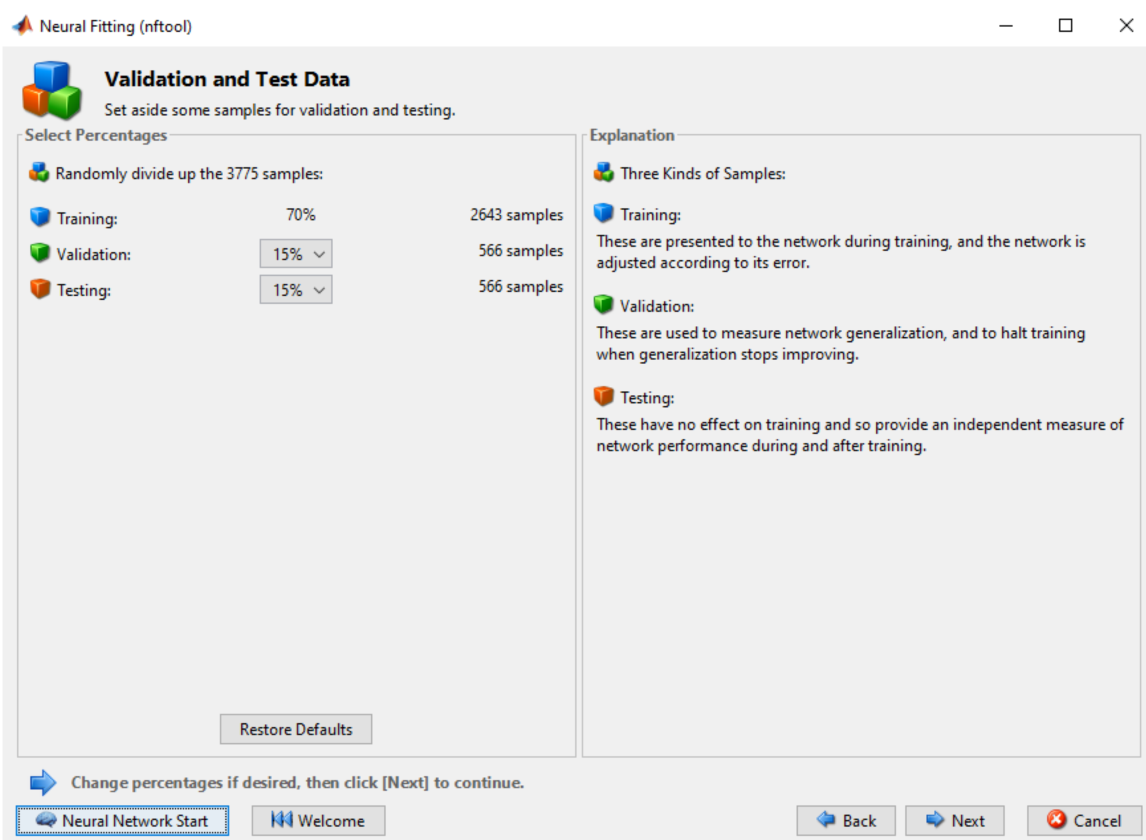

Figure 6: Partitioning the training input & output dataset for training ANN

3.5 *Selecting/Changing ANN structure & computational architecture*

The next section of the tool provides the option to select the number of neurons per layer which would be used to train the network. The tool however does not give the option to change the number of layers with the default number being one (1) layer. The number of layers can be manually changed only after the initial one-layer network, with the desired number of neurons per that layer, has been created. This will be discussed further in the chapter.

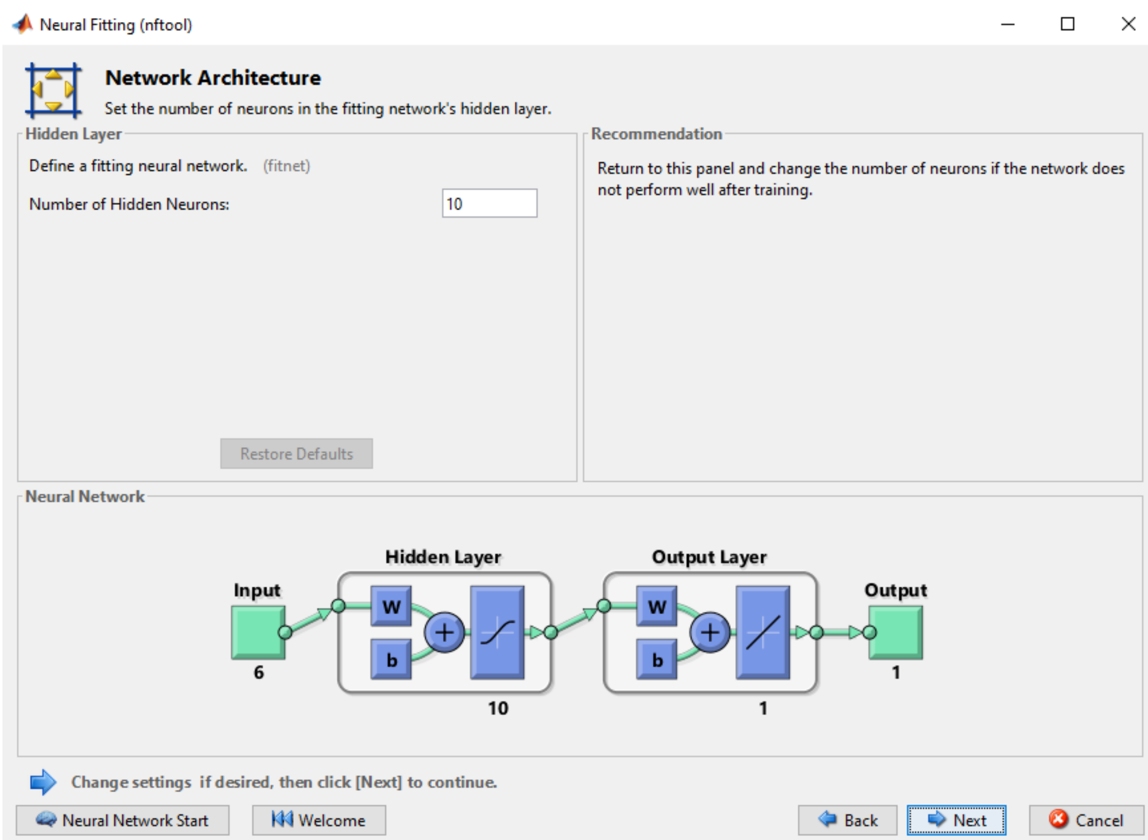

Figure 7: Changing/Selecting the number of neurons per layer for ANN training

3.6 Training the ANN

Once the dataset is partitioned into the desired percentage ratio, the tool is then ready to create and train the feedforward network. In this section, the tool gives the option to select and change what training algorithm would be used to train the network. In this study, the Levenberg-Marquardt algorithm is implemented solely, and no other algorithms were used. This part of the tool provides some more details on the previous steps like displaying the data partition ratio.

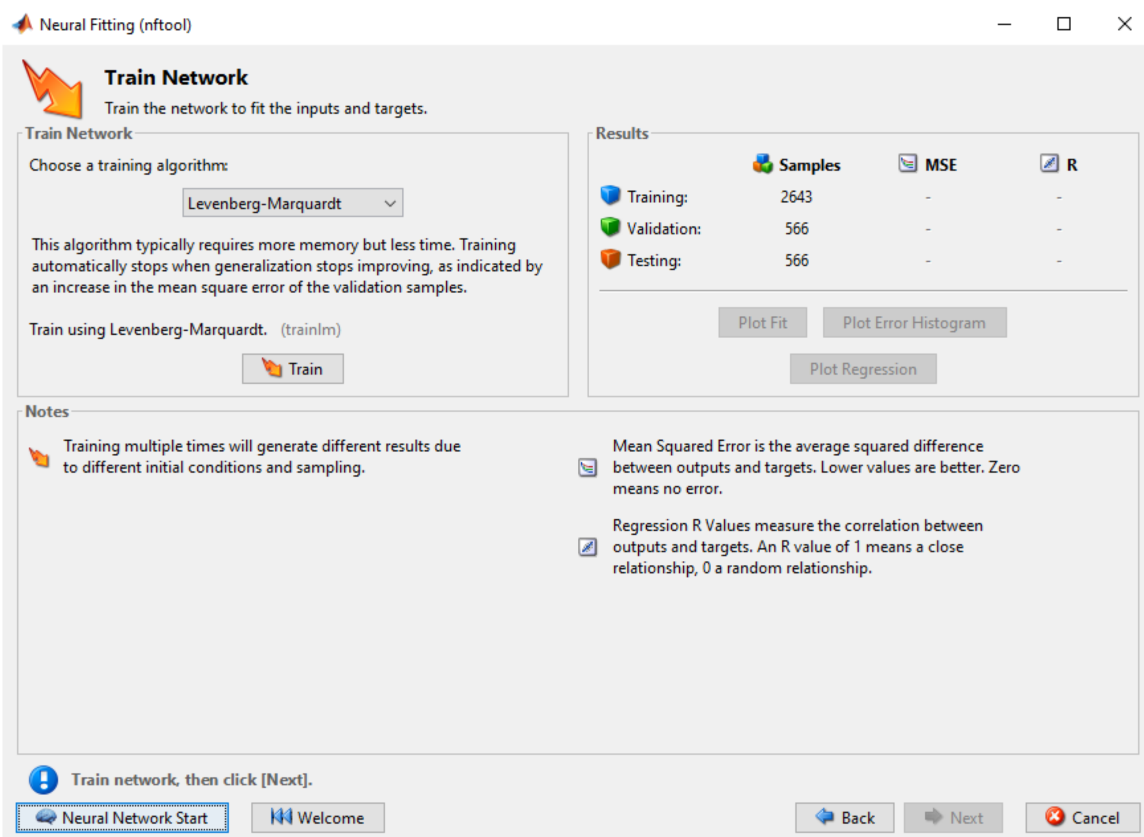

Figure 8: Training the ANN

3.7 *Evaluation of trained ANN & performance*

Once the training has been completed, the toolbox opens a new pop-up window signifying the conclusion of the process. This window will provide a visual representation of the network's architecture, the selected training algorithm, and a brief detail of the performance of the network. Various plots such as the performance plot, regression line, and other plots are also provided at this stage of the process. Using the performance details provided, the network can be trained further to better for better performance. However, for this study the process of training was done once across all the testing cases. This was to avoid any oversaturation of the network as retraining would involve passing the same dataset which could lead to some redundancy in prediction.

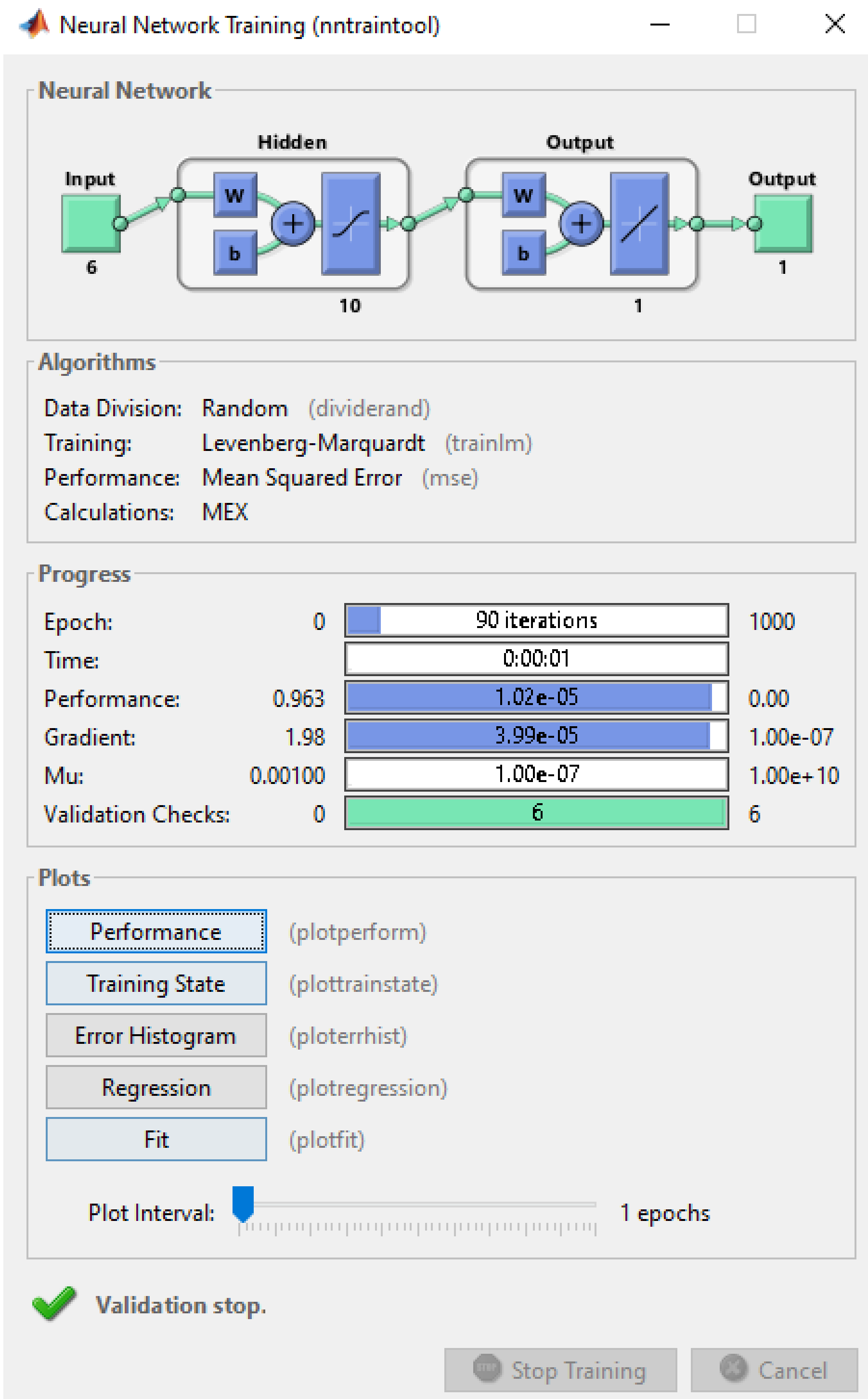

Figure 9: ANN post-training performance evaluation

3.8 Exporting trained network to MATLAB workspace & generating ANN script

The tool provides the option, once training is completed, to export the completed trained network to the workspace for further use. Once the network and its properties have been exported to the workspace, the network can then be used to test new input datasets and give a prediction based on the regression results from the trained ANN. At this point of the process, there is also an option to generate either a simple or advanced MATLAB script of the network that was just trained. This option allows for changes to be made to the number of layers of the ANN structure as the variable which determines this number is included in the script and can be manually edited before running the script.

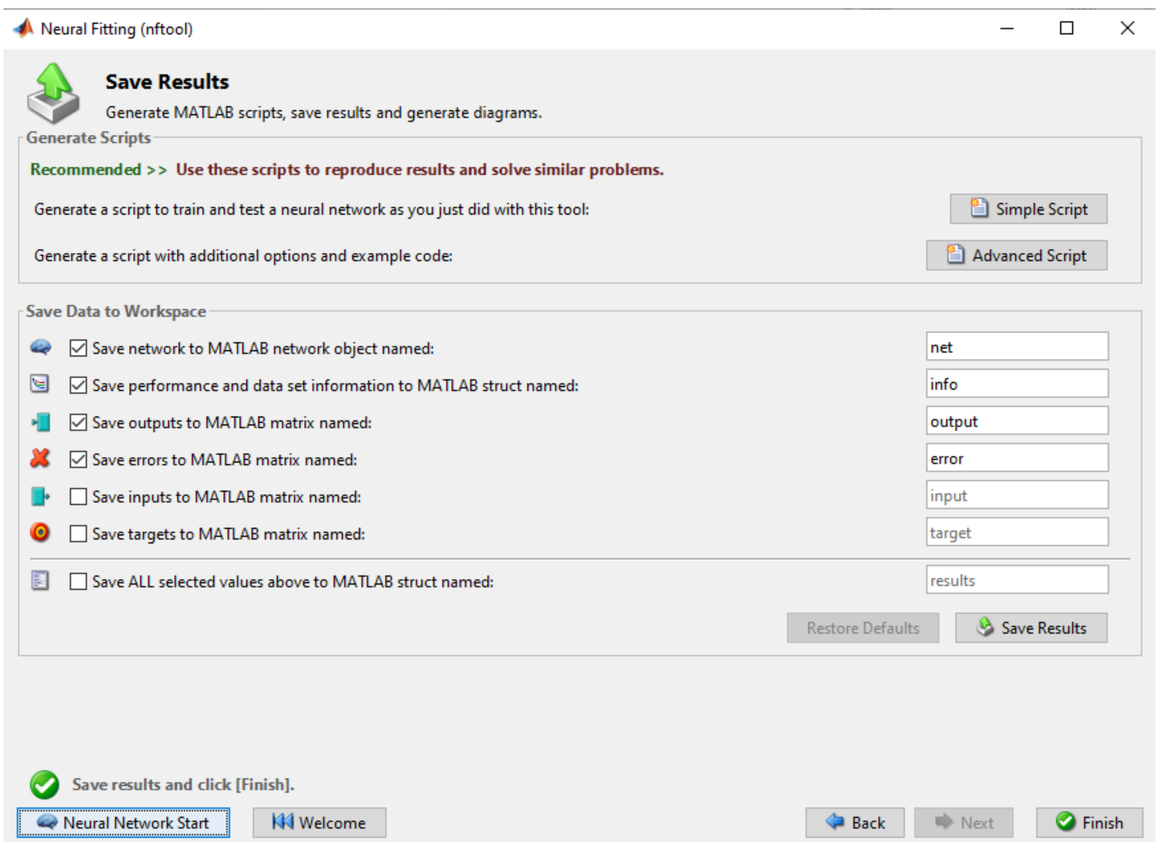

Figure 10: Saving and exporting trained ANN to MATLAB workspace

3.9 Flowchart

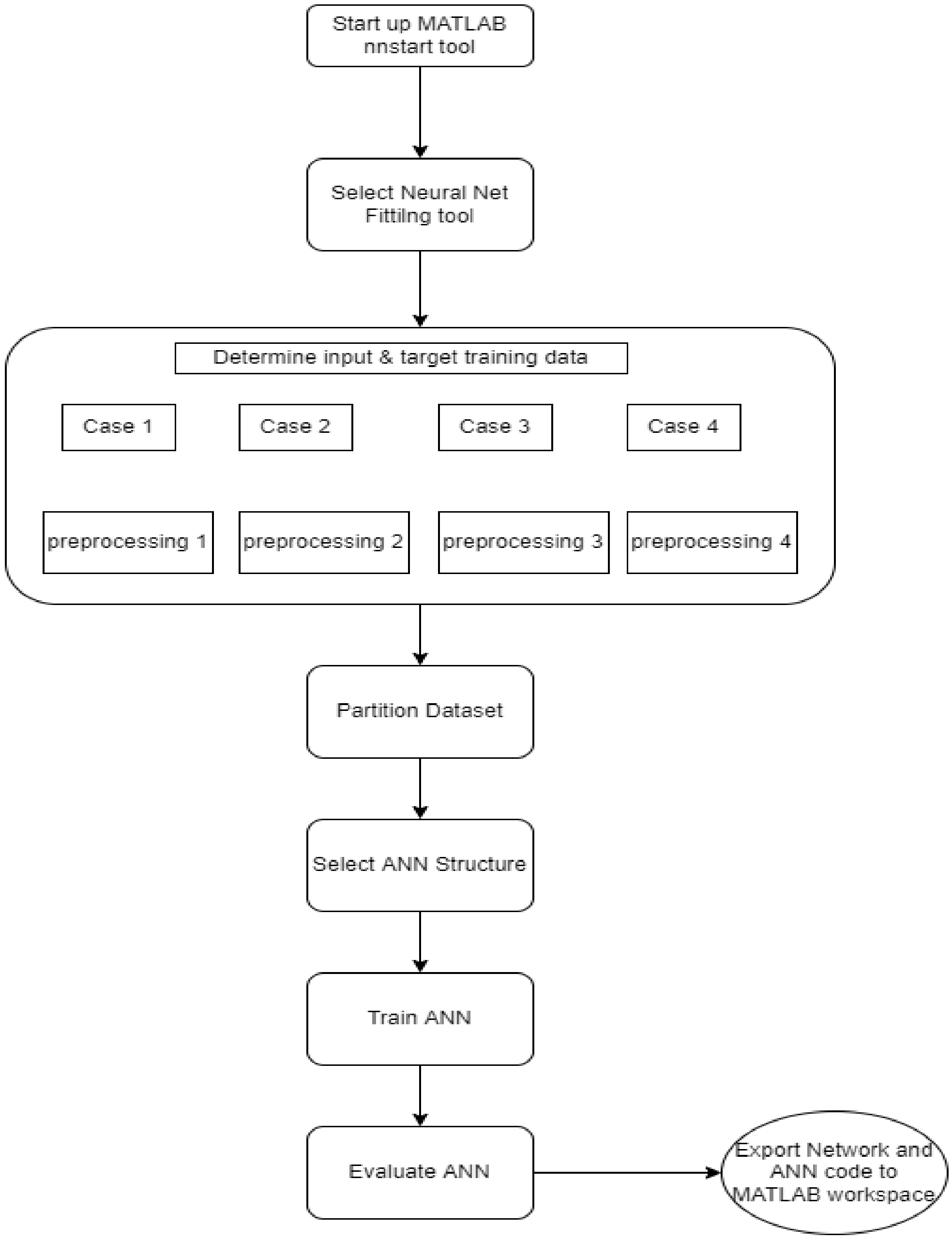

Figure 11: Building a simple feedforward ANN

CHAPTER 4. COLLECTING & PREPOCESSING TRAINING AND TESTING DATASET

4.1 *Overview*

As mentioned in the previous chapter, the feedforward ANN adopts a method of training where both the input dataset and the output/target are fed into the network to create a regression line. The training input dataset is introduced to the network in a similar dimension and format (i.e., matrix columns or matrix rows) as the output dataset and the network uses both sets of data to create a mapping function and adjust weights of bias of the neurons to establish the regression line to relate the input to the output. This chapter will give details on how the training dataset was collected from the simulation model. The sets of values that will be derived from the simulation to use as input and target data would be the voltage and current phasors from the two measurement blocks on either bus 1 and bus 2 to be used as input dataset, and the location of the sliding fault during simulation as the target/output dataset.

4.2 *Input Training Data*

To obtain the input training data, the simulation model was run with a sliding fault of 10 feet incremental steps from 0 – 1500 feet. The fault is instanced at each of these step increments. This would lead to a 151 simulation fault cases. In addition, for each of the fault step instances, the fault resistance is randomly varied five (5) times. This is to ensure as many multiple fault resistance cases are considered as this is a property that cannot be varied in real world applications. In total, for each fault location traversal down the line with the five (5) varied resistances per each fault instance, the number of fault cases would be 755 cases. For the ANN to perform better with training and predicting, more cases and datapoints are needed so the simulation was repeated five (5) times, i.e., a complete traversal and simulation of fault cases was run and then repeated five more times. This would ultimately bring the total number of cases used for this study to 3775 cases. For each of the cases, the input values that were collected were the instantaneous voltage and current signals from bus 1 and bus 2 during each fault simulation run. These instantaneous signals are then passed through a Fourier transform and as such the phasor content of the signals are obtained and stored as variable in the workspace. The signals were collected from the entire duration of the simulation. Later, prior to preprocessing, a sample cycle of the signals is obtained to be used as the input dataset. In addition, a no fault case scenario was simulated and will be used later for preprocessing the dataset.

4.3 Target Output Training Data

For the target dataset, it was very much a straightforward process as for each fault simulation run using the sliding fault block, the location of the block is recorded into a separate vector matrix. This matrix is stored in the workspace and will be fed alongside the input dataset for ANN training. As stated prior, the dimension of the input and target datasets are kept the same to ensure proper learning from the ANN. In this study, the dimension of the training input dataset was 3775 x n and the training output was 3775 x 1 (where n is the number of input variables being considered). The value n changes as this study also considered the effect of varying the number of features (voltage and current from the two measurement blocks) from the simulation that are used as input training data for the ANN. For the study, there were 4 cases of the features used as training input:

- Case 1: Using the 3-phase voltage from bus 1

- Case 2: Using the 3-phase voltage and current from bus 2
- Case 3: Using the 3-phase voltage from bus 1 and bus 2 and the current from bus 1
- Case 4: Using the 3-phase voltage from bus 1 and bus 2 and the current from bus 1 and bus 2

4.4 Preprocessing methods

Prior to feeding the input and target training datasets collected from the simulation model to be trained by the ANN, it is important to preprocess the training dataset. Preprocessing is recommended because it is a way to bring the dataset into a form that would be easily understood by the ANN during training and testing. MATLAB also recommends the preprocessing stage. The common preprocessing method is to normalize the dataset between -1 to 1 or 0 to 1. This would involve obtaining the max and min values from the input and target datasets and using these values to normalize the dataset. Another processing is to use superimposed signal obtained by subtracting prefault signal from during fault signal. For convenience of presentation, this process is named standardization of signal, i.e., standardize the data by offsetting each fault case dataset from the normal no fault condition dataset. For this study, the training input data was passed through 4 preprocessing methods and each of this preprocessed training sets are then studied. These preprocessing methods are:

- Preprocessing 1: The input dataset is first standardized and normalized (-1 to 1). The superimposed signal is obtained as the during fault signal minus prefault signal. The absolute value of the superimposed signal is then summed over a selected cycle and over each phase, which is then normalized to (-1 to 1).

- Preprocessing 2: The input dataset is only normalized (0 to 1) with no standardization. Compared to preprocessing 1, in this method, the input signal instead of the superimposed signal is used. Its absolute value is summed over a selected cycle and over each phase, which is then normalized to (0, 1).
- Preprocessing 3: The input dataset is standardized and normalized (-1 to 1). This is the same as Preprocessing 1, except that the signal of each phase is summed over a cycle. The phase values are not summed together and are instead left as 3-phase (i.e., 3 column vectors for each input variable considered)
- Preprocessing 4: This is the same as Preprocessing 2, except that the signal of each phase is summed over a cycle. The phase values are not summed together and are instead left as 3-phase (i.e., 3 column vectors for each input variable considered)

In addition, the output/target training data was normalized between 0 – 15 feet, where every actual 10 steps the sliding fault makes during each simulation corresponds to a 0.1 step size when normalized.

4.5 Flowchart

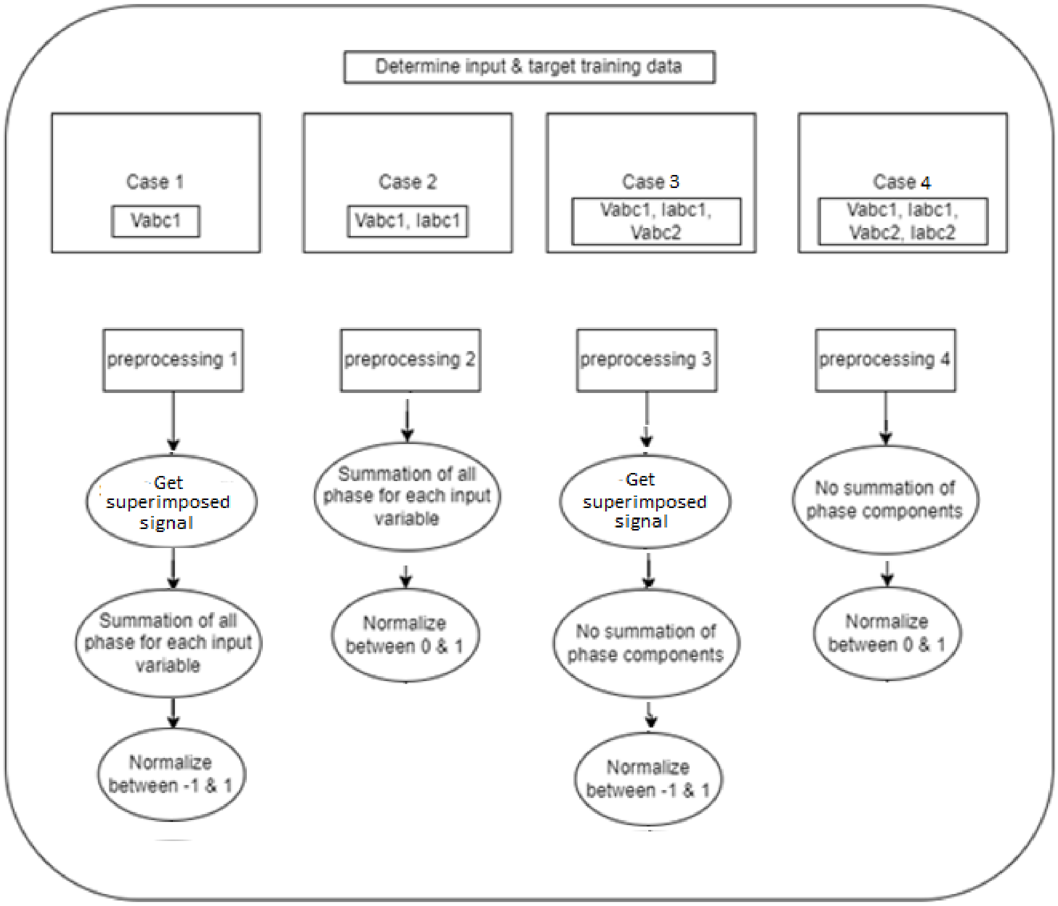

Figure 12: Collecting and preprocessing training input dataset

CHAPTER 5. FEEDFORWARD ANN ARCHITECTURE

Determining the structure of the feedforward ANN is the next step of the training process. It is necessary to determine which architecture will yield the best predictions for the fault location. For this study, the technique used was varying the number of neurons per layer of the ANN starting from 1 up to either 50 or 25 neurons depending on the number of training input variables. The number of layers used for the ANN structures was kept constant at three (3) layers, and the number of neurons per each layer was varied. For cases 1 and 2 where the voltage and current signals from only one bus are used, the maximum number of input data columns would be 1 to 6 given the preprocessing stages. So, for these cases, the maximum number of neurons was varied from 1 to 50. Cases 3 and 4 which involve input data columns between 3 to 12, the number of neurons per layer was varied between 1 and 25 neurons given the preprocessing stages. (For example, Case 1 with preprocessing method 1 will give a one column training input dataset which is the normalization and standardization of the voltage abc from bus 1 and summation of each phase values together. While Case 1 with preprocessing method 4 will yield 3 columns for the input training dataset which represents the normalization of each phase column of voltage abc from bus 1). Table 1 below shows the range of number of neurons per layer that was adopted for this study for each case being considered.

Table 1: Range of neurons per layer for each study case

Case	Input Dataset Variable (s)	Preprocess	No. of columns	No. of layers	No. of neurons
1	Vabc1	1	1	3	1 to 50
		2	1	3	1 to 50
		3	3	3	1 to 50
		4	3	3	1 to 50
2	Vabc1, Iabc1	1	2	3	1 to 50
		2	2	3	1 to 50
		3	6	3	1 to 50
		4	6	3	1 to 50
3	Vabc1, Iabc1, Vabc2	1	3	3	1 to 25
		2	3	3	1 to 25
		3	9	3	1 to 25
		4	9	3	1 to 25
4	Vabc1, Iabc1, Vabc2, Iabc2	1	4	3	1 to 25
		2	4	3	1 to 25
		3	12	3	1 to 25
		4	12	3	1 to 25

5.1 Design of ANN Structures

The ANN structures studied and implemented in this study had a constant number of layers of three (3) and the number of neurons per each layer was varied. The main goal of the study was focused on analyzing the effects of varying the number of neurons per layer, the number of training input dataset variables, and the preprocessing stages on the prediction accuracy of feedforward ANN fault location. To summarize, multiple ANNs were trained while varying the number of the neurons per layer depending on the criteria explained using Table 1. The number of columns of the training input data was dependent on the case and preprocess method used to obtain the dataset. To keep the structures as consistent as possible across all cases a set combination of neurons per layer were developed. The only structures that differed between cases were the last test combinations of 25-25-25 (25 neurons per layer) and 50-50-50 (50 neurons per layer). This was done as the ANN tool became relatively slower in training a larger number of input variables with a large number of neurons per layer as 50-50-50. So, for Cases 1& 2, the max number of neuron combination was 50-50-50 and for Cases 3 & 4 with more input variables and number of columns, a combination of 25-25-25 was used. For the rest of the paper, the format used for describing the ANN structure will be in the form "(no. of input layer)-(no. of neurons 1st hidden layer)-(no. of neurons 2nd hidden layer)-(no. neurons 3rd hidden layer)-(no. of output layers)". So as an example, 1-3-6-9-1 would correspond to 1 input layer, 3 neurons per 1st hidden layer, 6 neurons per 2nd hidden layer, 9 neurons per 3rd hidden layer, and 1 output layer. The number of input and output layer was kept at 1 throughout the experiment.

Table 2: Max number of neurons per layer

Case	Input Variable	Preprocess	No. of columns	Max. no of Neurons per Layer
1	Vabc1	1	1	50
		2	1	50
		3	3	50
		4	3	50
2	Vabc1, Iabc1	1	2	50
		2	2	50
		3	6	50
		4	6	50
3	Vabc1, Iabc1, Vabc2	1	3	25
		2	3	25
		3	9	25
		4	9	25
4	Vabc1, Iabc1, Vabc2, Iabc2	1	4	25
		2	4	25
		3	12	25
		4	12	25

5.2 Testing ANN prediction

To test the ANN structures that were built and trained, a new set of input dataset (fault location scenarios) was introduced to the ANN to predict the location of the fault. After testing this new dataset and getting the predicted output from the ANN, the results were compared with the actual fault locations to observe any errors in prediction and ultimately evaluate the performance of the ANN.

5.3 Post-processing ANN predicted outputs

The target dataset, used for training, and the predicted output of the ANN, after testing, were normalized between 0 and 15 where every sliding fault inception of 10 feet corresponds to 0.1 step size when normalized. It was necessary to revert the normalization so the outputs would correspond to a reasonable length of the distribution line. This would allow the fault location data to be compared with the actual fault location data to determine the amount of error produced by the ANN prediction.

Another post processing step was sorting the dataset into a more understandable format. Since the generation of fault cases for one full traversal of the sliding fault only resulted in 755 cases, the process was repeated five (5) times to generate a larger sample case size of 3775 cases. This resulted in an unsorted arrangement of the total dataset. So, to transform it to a more comprehensive and sequential format, the entire input and target datasets were put through a sorting function in MATLAB.

CHAPTER 6. TEST RESULTS

As stated in the previous chapter, after the various ANN structures have been developed and trained, each of the ANN was then tested with a new set of test data different from the original training data. This test data was obtained by simulating the same simulation model of the two terminal distribution line. As fault resistances cannot be kept the exact same as fault resistances vary and said resistance can occur at any point of the distribution line, a randomized fault resistance was used for each new test fault case scenario.

The 1500 feet distribution was divided up into 10 equidistant sections where each section of 10 feet was instanced with a fault scenario. This results in 151 fault case instances along the line. For each of these cases, 5 different fault resistances were implemented. This results in 755 cases in total for one complete traversal of the sliding fault down the line. This complete traversal was repeated four more times with a total of 5 times altogether. This would ultimately result into 3775 cases in total.

A larger test dataset was simulated and collated to further test the ANN structures and the effects of the varying factors on the fault location predictions. The new size of the test dataset was 10,571 cases. This is about three times the size of the first test dataset. This larger dataset is necessary to check for congruencies when repeating the experiment with a different size. It is important to note that to increase the size of the dataset, the ANN structures would have to be retrained. This means that the ANNs used for the larger dataset were not the exact networks adopted for the smaller dataset. However, all the structural and computational properties of the ANN were implemented.

The tables 3 – 18 show the results of testing the ANN structures developed. The tables provide the specific case that was simulated, alongside the preprocessing stage and what ANN structure was used for training and testing. The maximum, minimum, average errors for the fault location predictions have also been provided. The mean square error (MSE) and the root mean square error (RMSE) are also included in the tables.

The tables are ordered in a manner where all the cases for each preprocess method as these cases will have the same number of input variables and the same type of ANN structure. This will highlight the effect of changing the number of input variables on the accuracy in prediction of the specific ANN structure and preprocess method.

6.1 Results of ANN prediction case 1-4 using preprocess 1

Table 3: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1: - Vabc (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
1 – 1 – 1 – 1 – 1	2.55E-04	0.015953	1.3744E-02	0.0453037	1.22E-05
1 – 3 – 3 – 3 – 1	2.52E-04	0.015889	1.3623E-02	0.0450803	8.45E-06
1 – 6 – 6 – 6 – 1	2.52E-04	0.015863	1.3598E-02	0.0431138	4.77E-06
1 – 9 – 9 – 9 – 1	2.57E-04	0.016045	1.3672E-02	0.0430499	6.66E-06
1 – 3 – 6 – 9 – 1	2.52E-04	0.015883	1.3613E-02	0.0441666	1.49E-06
1 – 6 – 9 – 12 – 1	2.51E-04	0.015854	1.3581E-02	0.0449121	6.96E-06
1 – 12 – 18 – 24 – 1	2.55E-04	0.015972	1.3676E-02	0.0457062	6.21E-06
1 – 50 – 50 - 50 – 1	2.61E-04	0.01615	1.3769E-02	0.0475768	1.44E-05

Table 4: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2: - Vabc, Iabc (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
2 – 1 – 1 – 1 – 1	2.55E-04	0.015967088	1.3396E-02	0.073107487	2.66E-06
2 – 3 – 3 – 3 – 1	1.20E-03	0.0347071	2.4930E-02	0.134882527	1.81E-05
2 – 6 – 6 – 6 – 1	1.34E-03	0.036589953	2.5194E-02	0.124012464	9.33E-07
2 – 9 – 9 – 9 – 1	7.81E-04	0.027952244	2.1114E-02	0.086425164	3.59E-06
2 – 3 – 6 – 9 – 1	5.55E-04	0.023560138	1.9429E-02	0.065580128	2.56E-05
2 – 6 – 9 – 12 – 1	3.80E-03	0.06163118	3.8204E-02	0.224060498	5.68E-06
2 – 12 – 18 – 24 – 1	2.19E-03	0.046754848	2.7899E-02	0.169484683	7.37E-06
2 – 50 – 50 - 50 – 1	3.15E-03	0.056165747	3.2931E-02	0.481191817	3.22E-05

Table 5: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3: - Vabc1, Iabc1, Vabc2 (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 – 1 – 1 – 1 – 1	2.52E-04	0.01587872	1.3384E-02	0.06879188	3.11E-06
3 – 3 – 3 – 3 – 1	7.35E-04	0.02710396	2.1051E-02	0.08295551	8.10E-06
3 – 6 – 6 – 6 – 1	2.90E-03	0.05387917	3.0399E-02	0.23286188	1.17E-08
3 – 9 – 9 – 9 – 1	3.16E-03	0.05625456	3.1705E-02	0.30130653	2.19E-06
3 – 3 – 6 – 9 – 1	7.03E-04	0.02652178	1.9962E-02	0.11565034	6.38E-06
3 – 6 – 9 – 12 – 1	6.17E-04	0.02484265	1.9396E-02	0.07572847	2.87E-06
3 – 12 – 18 – 24 – 1	1.46E-03	0.03824941	2.7620E-02	0.09773225	1.15E-05
3 – 25 – 25 - 25 – 1	1.96E-03	0.0442905	2.7839E-02	0.22308025	3.70E-06

Table 6: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4: - Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
4 – 1 – 1 – 1 – 1	1.98E-04	0.0140583	1.1049E-02	0.05005158	6.02E-07
4 – 3 – 3 – 3 – 1	2.16E-04	0.0146812	1.1965E-02	0.06972235	6.40E-06
4 – 6 – 6 – 6 – 1	1.42E-03	0.0376514	2.7995E-02	0.09586981	7.07E-08
4 – 9 – 9 – 9 – 1	1.73E-03	0.041646	2.9779E-02	0.10081013	1.17E-06
4 – 3 – 6 – 9 – 1	1.48E-03	0.0384447	2.8623E-02	0.1150746	6.21E-06
4 – 6 – 9 – 12 – 1	1.58E-03	0.0397371	2.6024E-02	0.12009869	1.04E-06
4 – 12 – 18 – 24 – 1	1.83E-03	0.0427456	2.8005E-02	0.14419092	8.22E-06
4 – 25 – 25 - 25 – 1	2.15E-03	0.0464118	3.2434E-02	0.1255646	9.39E-06

6.2 Results of ANN prediction case 1-4 using preprocess 2

Table 7: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1: - Vabc (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
1 – 1 – 1 – 1 – 1	4.21E-04	0.020529	1.61E-02	0.1070952	6.18E-06
1 – 3 – 3 – 3 – 1	4.17E-04	0.020422	1.60E-02	0.1052904	5.69E-06
1 – 6 – 6 – 6 – 1	4.17E-04	0.020423	1.60E-02	0.1072505	3.35E-06
1 – 9 – 9 – 9 – 1	4.20E-04	0.020495	1.61E-02	0.1050418	3.50E-06
1 – 3 – 6 – 9 – 1	4.19E-04	0.020463	1.61E-02	0.1038296	1.12E-06
1 – 6 – 9 – 12 – 1	4.14E-04	0.020346	1.60E-02	0.1071647	2.12E-06
1 – 12 – 18 – 24 – 1	4.30E-04	0.020741	1.63E-02	0.1064744	9.76E-07
1 – 50 – 50 - 50 – 1	4.41E-04	0.020994	1.66E-02	0.1083105	1.21E-05

Table 8: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2: - Vabc, Iabc (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
2 – 1 – 1 – 1 – 1	4.56E-04	0.021344218	1.70E-02	0.082770076	1.51E-06
2 – 3 – 3 – 3 – 1	5.46E-04	0.02336491	1.88E-02	0.095359059	1.20E-05
2 – 6 – 6 – 6 – 1	6.05E-04	0.024605429	1.98E-02	0.143976683	2.24E-06
2 – 9 – 9 – 9 – 1	5.24E-04	0.02288137	1.86E-02	0.06421686	9.96E-06
2 – 3 – 6 – 9 – 1	6.83E-04	0.026127268	2.00E-02	0.581444088	2.24E-07
2 – 6 – 9 – 12 – 1	6.60E-04	0.025684788	1.91E-02	5.67E-06	6.60E-04
2 – 12 – 18 – 24 – 1	7.79E-04	0.027915947	2.28E-02	0.171909948	1.31E-05
2 – 50 – 50 - 50 – 1	7.07E-04	0.026590965	2.09E-02	0.111734783	1.82E-06

Table 9: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3: - Vabc1, Iabc1, Vabc2 (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 – 1 – 1 – 1 – 1	8.30E-04	0.02881125	2.54E-02	0.1213744	3.49E-05
3 – 3 – 3 – 3 – 1	9.71E-04	0.0311553	2.73E-02	0.1034523	1.72E-05
3 – 6 – 6 – 6 – 1	1.98E-03	0.04446153	3.83E-02	0.37002531	5.64E-06
3 – 9 – 9 – 9 – 1	3.68E-03	0.06062432	5.22E-02	0.41033934	7.41E-05
3 – 3 – 6 – 9 – 1	1.12E-03	0.03353953	3.04E-02	0.11145392	7.29E-06
3 – 6 – 9 – 12 – 1	2.14E-03	0.04623535	4.02E-02	1.57E-01	2.79E-05
3 – 12 – 18 – 24 – 1	2.65E-03	0.05143201	4.25E-02	0.2104702	3.34E-05
3 – 25 – 25 - 25 – 1	2.08E-03	0.04556193	3.75E-02	0.36242981	6.63E-06

Table 10: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4: - Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
4 – 1 – 1 – 1 – 1	7.09E-04	0.0266275	2.33E-02	0.135799	1.09E-05
4 – 3 – 3 – 3 – 1	7.48E-04	0.0273478	2.42E-02	0.07416541	1.49E-05
4 – 6 – 6 – 6 – 1	1.00E-03	0.0316165	2.76E-02	0.07544415	2.53E-05
4 – 9 – 9 – 9 – 1	2.34E-03	0.0483514	3.98E-02	0.18482633	9.13E-06
4 – 3 – 6 – 9 – 1	9.76E-04	0.0312419	2.57E-02	0.1260978	1.53E-05
4 – 6 – 9 – 12 – 1	9.52E-04	0.0308508	2.43E-02	1.47E-01	8.51E-06
4 – 12 – 18 – 24 – 1	2.92E-03	0.0540177	3.88E-02	0.2181342	5.75E-06
4 – 25 – 25 - 25 – 1	1.98E-03	0.0445332	3.70E-02	0.43885012	1.74E-05

6.3 Results of ANN prediction case 1-4 using preprocess 3

Table 11: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 – 1 – 1 – 1 – 1	2.57E-04	0.016032	1.38E-02	0.0445604	9.01E-06
3 – 3 – 3 – 3 – 1	2.26E-04	0.015038	1.28E-02	0.0711746	1.61E-06
3 – 6 – 6 – 6 – 1	2.48E-04	0.015748	1.28E-02	0.0508916	3.76E-06
3 – 9 – 9 – 9 – 1	2.55E-04	0.015981	1.37E-02	0.0441153	1.56E-05
3 – 3 – 6 – 9 – 1	2.55E-04	0.015971	1.37E-02	0.0453451	9.98E-07
3 – 6 – 9 – 12 – 1	2.52E-04	0.015874	1.36E-02	0.0497407	9.85E-07
3 – 12 – 18 – 24 – 1	2.10E-04	0.014491	1.19E-02	0.0744766	2.32E-06
3 – 50 – 50 - 50 – 1	1.69E-04	0.013005	1.04E-02	0.0831344	3.34E-06

Table 12: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
6 – 1 – 1 – 1 – 1	2.76E-04	0.016617272	1.38E-02	0.086269979	2.63E-06
6 – 3 – 3 – 3 – 1	4.78E-04	0.021869805	1.60E-02	0.079154181	1.90E-06
6 – 6 – 6 – 6 – 1	2.45E-03	0.049484974	3.73E-02	0.147645323	6.87E-06
6 – 9 – 9 – 9 – 1	1.03E-03	0.032095986	2.65E-02	0.080977624	3.04E-06
6 – 3 – 6 – 9 – 1	6.08E-04	0.024661852	2.00E-02	0.074352391	1.87E-05
6 – 6 – 9 – 12 – 1	8.08E-04	0.028428255	2.30E-02	0.101288353	2.52E-05
6 – 12 – 18 – 24 – 1	2.72E-03	0.052159953	3.63E-02	0.208895434	1.16E-05
6 – 50 – 50 - 50 – 1	4.28E-03	0.065453412	4.84E-02	0.424409494	8.11E-06

Table 13: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3 :- Vabc1, Iabc1, Vabc2 (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
9 – 1 – 1 – 1 – 1	3.00E-04	0.01732762	1.44E-02	0.08581811	6.44E-06
9 – 3 – 3 – 3 – 1	2.43E-03	0.04930015	4.48E-02	0.14060917	3.78E-05
9 – 6 – 6 – 6 – 1	5.64E-04	0.0237444	1.86E-02	0.0717089	9.95E-06
9 – 9 – 9 – 9 – 1	5.64E-04	0.02374222	1.95E-02	0.07194873	1.35E-05
9 – 3 – 6 – 9 – 1	4.51E-04	0.02123314	1.78E-02	0.07865023	3.22E-06
9 – 6 – 9 – 12 – 1	8.50E-04	0.02915598	2.23E-02	0.10581068	1.27E-06
9 – 12 – 18 – 24 – 1	1.37E-03	0.03702102	2.47E-02	0.18543699	2.82E-05
9 – 25 – 25 - 25 – 1	4.73E-03	0.06880128	4.49E-02	0.38479853	4.37E-05

Table 14: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
12 – 1 – 1 – 1 – 1	7.05E-04	0.0265575	2.44E-02	0.06310881	1.97E-04
12 – 3 – 3 – 3 – 1	2.99E-04	0.0172929	1.40E-02	0.05449248	8.50E-06
12 – 6 – 6 – 6 – 1	5.60E-03	0.0748291	5.93E-02	0.37036115	6.38E-07
12 – 9 – 9 – 9 – 1	6.04E-03	0.0777025	6.41E-02	0.18693461	2.93E-05
12 – 3 – 6 – 9 – 1	4.10E-04	0.0202602	1.60E-02	0.06091254	1.45E-06
12 – 6 – 9 – 12 – 1	6.36E-03	0.0797579	6.21E-02	0.28482265	1.59E-05
12 – 12 – 18 – 24 – 1	1.22E-02	0.1103445	8.30E-02	0.23772882	2.68E-05
12 – 25 – 25 - 25 – 1	4.96E-03	0.0704271	5.51E-02	0.20292939	2.25E-05

6.4 Results of ANN prediction case 1-4 using preprocess 4

Table 15: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1: - Vabc (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 – 1 – 1 – 1 – 1	4.23E-05	0.006503	4.03E-03	0.0770144	7.54E-07
3 – 3 – 3 – 3 – 1	4.00E-05	0.006325	3.89E-03	0.0696028	2.56E-07
3 – 6 – 6 – 6 – 1	3.88E-05	0.006227	3.87E-03	0.0634037	1.80E-06
3 – 9 – 9 – 9 – 1	4.15E-05	0.006438	4.85E-03	0.1047851	3.23E-06
3 – 3 – 6 – 9 – 1	3.98E-05	0.006308	3.84E-03	0.0696687	1.55E-07
3 – 6 – 9 – 12 – 1	7.32E-05	0.008558	5.83E-03	0.1070722	8.87E-07
3 – 12 – 18 – 24 – 1	5.41E-05	0.007354	5.68E-03	0.0756968	1.33E-07
3 – 50 – 50 - 50 – 1	4.04E-05	0.006357	4.90E-03	0.0750011	2.52E-06

Table 16: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2: - Vabc, Iabc (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
6 – 1 – 1 – 1 – 1	4.54E-03	0.067382751	6.71E-02	0.105687896	5.02E-03
6 – 3 – 3 – 3 – 1	5.85E-03	0.076507229	7.60E-02	0.120048067	2.69E-02
6 – 6 – 6 – 6 – 1	1.78E-03	0.042214564	3.80E-02	0.184127585	1.65E-06
6 – 9 – 9 – 9 – 1	3.01E-03	0.054822487	4.46E-02	0.262095515	3.75E-07
6 – 3 – 6 – 9 – 1	1.29E-02	0.113399494	1.13E-01	0.160344966	4.16E-02
6 – 6 – 9 – 12 – 1	1.07E-02	0.103575423	9.43E-02	0.838608015	2.17E-04
6 – 12 – 18 – 24 – 1	1.19E-02	0.10911716	9.25E-02	0.273443422	1.31E-04
6 – 50 – 50 - 50 – 1	5.86E-02	0.24198638	2.04E-01	0.727261181	5.31E-05

Table 17: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3: - Vabc1, Iabc1, Vabc2 (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
9 – 1 – 1 – 1 – 1	1.10E-03	0.03314811	3.30E-02	0.05316781	7.16E-03
9 – 3 – 3 – 3 – 1	1.72E-04	0.01312706	1.26E-02	0.0306495	2.59E-04
9 – 6 – 6 – 6 – 1	8.64E-03	0.09293514	8.85E-02	0.19448039	7.84E-04
9 – 9 – 9 – 9 – 1	1.89E-03	0.04341736	3.77E-02	0.10773964	1.29E-04
9 – 3 – 6 – 9 – 1	1.85E-04	0.01361483	1.07E-02	0.10940773	1.36E-06
9 – 6 – 9 – 12 – 1	2.43E-02	0.15589523	1.24E-01	0.35849755	3.76E-05
9 – 12 – 18 – 24 – 1	7.34E-04	0.02709293	2.35E-02	0.06993544	9.86E-06
9 – 25 – 25 - 25 – 1	6.80E-03	0.08247744	6.24E-02	0.71884183	9.81E-05

Table 18: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4: - Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
12 – 1 – 1 – 1 – 1	5.49E-01	0.7412454	7.41E-01	1.38708809	7.17E-01
12 – 3 – 3 – 3 – 1	3.81E-01	0.6174585	6.16E-01	1.0453067	5.34E-01
12 – 6 – 6 – 6 – 1	1.09E-01	0.3297853	3.25E-01	0.47287141	1.40E-02
12 – 9 – 9 – 9 – 1	5.53E-04	0.023522	1.99E-02	0.04937716	5.01E-04
12 – 3 – 6 – 9 – 1	2.22E-01	0.4715955	4.71E-01	0.89143822	4.35E-01
12 – 6 – 9 – 12 – 1	8.22E-03	0.0906846	8.05E-02	0.18384895	2.34E-04
12 – 12 – 18 – 24 – 1	1.20E-01	0.3470583	3.05E-01	0.62474913	2.88E-02
12 – 25 – 25 - 25 – 1	2.70E-02	0.1642715	1.43E-01	0.36217845	8.27E-05

6.5 Additional Test Results

A larger training and testing dataset of sample size of 10,571 fault cases were simulated and fed through the same ANN structures from the initial dataset of 3775 cases. The number of cases was increased to study if the results from the previous sample were congruent with the new sample dataset. The addition of cases meant that the network had more sample data points to use for training. This led to a higher resolution regression line with less error between actual and predicted fault locations.

Table 19: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
1 – 1 – 1 – 1 – 1	2.59E-04	0.016109	1.3852E-02	0.0450969	2.63E-07
1 – 3 – 3 – 3 – 1	2.57E-04	0.016031	1.3750E-02	0.0443204	1.31E-06
1 – 6 – 6 – 6 – 1	2.57E-04	0.016041	1.3748E-02	0.04536	5.53E-06
1 – 9 – 9 – 9 – 1	2.56E-04	0.016004	1.3722E-02	0.0448517	9.60E-06
1 – 3 – 6 – 9 – 1	2.56E-04	0.015988	1.3720E-02	0.043037	1.62E-07
1 – 6 – 9 – 12 – 1	2.56E-04	0.015985	1.3713E-02	0.0437964	5.87E-07
1 – 12 – 18 – 24 – 1	2.57E-04	0.016038	1.3746E-02	0.0467359	5.55E-06
1 – 50 – 50 - 50 – 1	2.59E-04	0.016104	1.3774E-02	0.0456486	7.15E-07

Table 20: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
2 – 1 – 1 – 1 – 1	3.98E-04	0.019947702	1.62E-02	0.077719242	3.59E-06
2 – 3 – 3 – 3 – 1	2.13E-03	0.046190942	3.3120E-02	0.146985737	1.66E-06
2 – 6 – 6 – 6 – 1	4.12E-03	0.064213496	4.7957E-02	0.16055135	1.06E-05
2 – 9 – 9 – 9 – 1	1.74E-03	0.041667815	3.2979E-02	0.163995995	1.08E-06
2 – 3 – 6 – 9 – 1	1.74E-03	0.041667815	3.2979E-02	0.163995995	1.08E-06
2 – 6 – 9 – 12 – 1	3.19E-03	0.056510999	4.5050E-02	0.16129638	2.70E-06
2 – 12 – 18 – 24 – 1	1.11E-02	0.105530706	6.9699E-02	0.465897302	8.22E-06
2 – 50 – 50 - 50 – 1	6.22E-02	0.24934851	1.4985E-01	0.988904434	9.31E+03

Table 21: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3 :- Vabc1, Iabc1, Vabc2 (process 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1 - 1	4.22E-04	0.02053717	1.6603E-02	0.08035663	4.98E-07
3 - 3 - 3 - 3 - 1	6.77E-03	0.08226609	4.9946E-02	0.31097541	1.55E-06
3 - 6 - 6 - 6 - 1	2.49E-02	0.15770619	9.0310E-02	0.7223372	2.12E-05
3 - 9 - 9 - 9 - 1	3.79E-02	0.19470418	1.0234E-01	0.92145691	7.45E-06
3 - 3 - 6 - 9 - 1	3.91E-03	0.06256022	4.2558E-02	0.19821992	2.71E-06
3 - 6 - 9 - 12 - 1	1.70E-01	0.41276992	2.3154E-01	1.57136526	3.28E-07
3 - 12 - 18 - 24 - 1	2.87E-02	0.16928143	9.2843E-02	0.55834758	8.11E-06
3 - 25 - 25 - 25 - 1	2.72E-03	0.05213641	3.8792E-02	0.26640455	1.55E-06

Table 22: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preoprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
4 – 1 – 1 – 1 – 1	3.22E-04	0.01795796	1.4463E-02	0.05860384	8.64E-08
4 – 3 – 3 – 3 – 1	1.84E-03	0.04291078	2.8469E-02	0.14956626	6.22E-09
4 – 6 – 6 – 6 – 1	9.11E-03	0.09544558	5.9160E-02	0.39651099	8.22E-07
4 – 9 – 9 – 9 – 1	1.43E-02	0.1196722	7.4689E-02	0.62318173	7.43E-07
4 – 3 – 6 – 9 – 1	2.23E-02	0.14929501	7.8196E-02	0.44721237	1.10E-07
4 – 6 – 9 – 12 – 1	2.52E-03	0.05018743	3.6209E-02	0.50982355	3.52E-08
4 – 12 – 18 – 24 – 1	4.00E-01	0.63244655	3.3311E-01	1.89937365	1.73E-06
4 – 25 – 25 - 25 – 1	2.41E-01	0.4909194	2.7096E-01	1.53392771	4.72E-05

Table 23: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
1 - 1 - 1 - 1 - 1	2.98E-04	0.017272	1.36E-02	0.1013336	8.07E-07
1 - 3 - 3 - 3 - 1	2.88E-04	0.01697	1.3353E-02	0.0998136	5.01E-07
1 - 6 - 6 - 6 - 1	2.88E-04	0.016958	1.3332E-02	0.0999204	1.80E-06
1 - 9 - 9 - 9 - 1	2.89E-04	0.016998	1.3366E-02	0.1005238	2.17E-06
1 - 3 - 6 - 9 - 1	2.88E-04	0.016958	1.3334E-02	0.0996402	1.96E-06
1 - 6 - 9 - 12 - 1	2.90E-04	0.017037	1.3379E-02	0.1005737	1.23E-06
1 - 12 - 18 - 24 - 1	2.89E-04	0.017008	1.3380E-02	0.1014529	2.71E-07
1 - 50 - 50 - 50 - 1	2.92E-04	0.017093	1.3415E-02	0.1025369	7.00E-07

Table 24: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
2 - 1 - 1 - 1 - 1	3.21E-04	0.017923478	1.40E-02	0.081891023	4.76E-07
2 - 3 - 3 - 3 - 1	5.84E-04	0.024166619	1.84E-02	0.102533616	1.97E-07
2 - 6 - 6 - 6 - 1	3.97E-04	0.019932763	1.58E-02	0.180512058	1.38E-06
2 - 9 - 9 - 9 - 1	7.17E-04	0.026774539	2.10E-02	0.124758252	5.57E-06
2 - 3 - 6 - 9 - 1	5.43E-04	0.023309278	1.83E-02	0.319885456	8.98E-06
2 - 6 - 9 - 12 - 1	5.24E-04	0.022882113	1.82E-02	1.63E-01	8.30E-07
2 - 12 - 18 - 24 - 1	1.33E-03	0.036518348	2.47E-02	0.551399903	2.78E-06
2 - 50 - 50 - 50 - 1	8.25E-04	0.028723173	2.10E-02	0.579099115	2.80E-07

Table 25: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3:- Vabc1, Iabc1, Vabc2 (process 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1 - 1	4.50E-04	0.0212031	1.69E-02	0.11472719	1.19E-07
3 - 3 - 3 - 3 - 1	4.96E-04	0.02227301	1.86E-02	0.06701352	4.43E-07
3 - 6 - 6 - 6 - 1	3.10E-03	0.05567863	3.77E-02	0.97405799	1.05E-05
3 - 9 - 9 - 9 - 1	1.72E-03	0.04149446	3.08E-02	0.24979463	1.85E-08
3 - 3 - 6 - 9 - 1	4.56E-04	0.02134295	1.80E-02	0.20541561	7.49E-07
3 - 6 - 9 - 12 - 1	2.44E-03	0.04940647	3.34E-02	4.55E-01	4.35E-07
3 - 12 - 18 - 24 - 1	3.84E-03	0.06195988	4.11E-02	0.40617979	2.89E-06
3 - 25 - 25 - 25 - 1	8.81E-04	0.02968336	2.39E-02	0.24889587	9.98E-08

Table 26: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
4 - 1 - 1 - 1 - 1	4.05E-04	0.02013062	1.62E-02	0.11401112	1.04E-07
4 - 3 - 3 - 3 - 1	5.99E-04	0.02448281	1.94E-02	0.09395375	1.28E-06
4 - 6 - 6 - 6 - 1	8.55E-04	0.02923815	2.42E-02	0.27999094	1.71E-06
4 - 9 - 9 - 9 - 1	8.24E-04	0.02870324	2.26E-02	0.64691857	8.01E-06
4 - 3 - 6 - 9 - 1	5.38E-04	0.02319878	1.91E-02	0.08512082	6.16E-06
4 - 6 - 9 - 12 - 1	8.69E-04	0.02948076	2.18E-02	1.70E-01	6.75E-07
4 - 12 - 18 - 24 - 1	1.29E-03	0.00129334	2.75E-02	0.24358581	3.39E-07
4 - 25 - 25 - 25 - 1	6.88E-04	0.02623684	2.02E-02	0.13205723	3.78E-07

Table 27: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1 - 1	2.72E-04	0.016506	1.38E-02	0.2244794	1.92E-06
3 - 3 - 3 - 3 - 1	2.61E-04	0.016157	1.38E-02	0.047695	7.71E-07
3 - 6 - 6 - 6 - 1	2.57E-04	0.016025	1.37E-02	0.0545101	2.47E-06
3 - 9 - 9 - 9 - 1	3.85E-04	0.019632	1.56E-02	0.0743771	1.05E-06
3 - 3 - 6 - 9 - 1	2.56E-04	0.016014	1.37E-02	0.0518926	1.91E-07
3 - 6 - 9 - 12 - 1	2.56E-04	0.016014	1.37E-02	0.0518926	1.91E-07
3 - 12 - 18 - 24 - 1	5.20E-04	0.022793	1.78E-02	0.1592159	2.24E-06
3 - 25 - 25 - 25 - 1	4.52E-04	0.02127	1.69E-02	0.1572754	9.42E-06

Table 28: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
6 - 1 - 1 - 1 - 1	2.45E-04	0.015667134	1.25E-02	0.066134673	2.84E-07
6 - 3 - 3 - 3 - 1	7.56E-04	0.027487744	1.93E-02	0.109497163	3.93E-07
6 - 6 - 6 - 6 - 1	1.46E-03	0.038183007	3.15E-02	0.112914646	4.02E-06
6 - 9 - 9 - 9 - 1	3.67E-02	0.191671545	8.82E-02	0.866572274	1.58E-05
6 - 3 - 6 - 9 - 1	5.45E-04	0.02333801	1.82E-02	0.069192238	6.43E-06
6 - 6 - 9 - 12 - 1	1.44E-03	0.037913919	2.89E-02	0.147984071	7.09E-07
6 - 12 - 18 - 24 - 1	6.57E-03	0.081043716	5.34E-02	0.284250844	1.04E-05
6 - 25 - 25 - 25 - 1	2.69E-02	0.163926677	1.11E-01	0.430237158	1.98E-07

Table 29: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3 :- Vabc1, Iabc1, Vabc2 (process 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
9 – 1 – 1 – 1 – 1	2.28E-04	0.01509262	1.21E-02	0.05903725	5.48E-07
9 – 3 – 3 – 3 – 1	1.28E-03	0.03583574	2.38E-02	0.13452191	2.10E-06
9 – 6 – 6 – 6 – 1	1.86E-02	0.13645518	6.72E-02	0.68841773	9.13E-06
9 – 9 – 9 – 9 – 1	2.76E-02	0.16611271	7.18E-02	0.88579728	2.60E-05
9 – 3 – 6 – 9 – 1	1.13E-02	0.10624918	5.99E-02	0.48219782	4.72E-07
9 – 6 – 9 – 12 – 1	1.22E-03	0.03491317	2.76E-02	0.23511944	8.90E-06
9 – 12 – 18 – 24 – 1	1.16E-01	0.34052055	1.31E-01	1.36138083	3.76E-06
9 – 25 – 25 - 25 – 1	8.66E-04	0.02942699	2.28E-02	0.15576125	4.58E-06

Table 30: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
12 – 1 – 1 – 1 – 1	4.53E-04	0.02127467	1.88E-02	0.06913275	7.33E-08
12 – 3 – 3 – 3 – 1	4.60E-03	0.06780866	6.06E-02	0.22091995	2.96E-05
12 – 6 – 6 – 6 – 1	1.67E-02	0.12905628	9.44E-02	0.42476653	3.95E-06
12 – 9 – 9 – 9 – 1	6.41E-03	0.08004877	5.04E-02	0.23195543	2.75E-06
12 – 3 – 6 – 9 – 1	8.15E-03	0.09026048	6.92E-02	0.32830958	2.96E-06
12 – 6 – 9 – 12 – 1	3.18E-02	0.17837406	9.50E-02	0.59239847	2.37E-06
12 – 12 – 18 – 24 – 1	1.49E-01	0.38646089	1.87E-01	1.35436035	2.43E-06
12 – 25 – 25 - 25 – 1	2.68E-01	0.51759706	2.99E-01	1.60674874	1.15E-06

Table 31: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 – 1 – 1 – 1 – 1	4.78E-05	0.006913	4.86E-03	0.0959263	1.61E-06
3 – 3 – 3 – 3 – 1	4.70E-05	0.006854	4.92E-03	0.0932198	2.01E-07
3 – 6 – 6 – 6 – 1	4.55E-05	0.006746	5.04E-03	0.0927752	1.94E-07
3 – 9 – 9 – 9 – 1	1.05E-04	0.010243	7.17E-03	0.0685537	9.95E-07
3 – 3 – 6 – 9 – 1	5.16E-05	0.007187	0.00401111	3.96E-01	8.58E-07
3 – 6 – 9 – 12 – 1	8.09E-05	0.008996	6.72E-03	0.072921	7.33E-06
3 – 12 – 18 – 24 – 1	8.65E-05	0.0093	7.21E-03	0.2466106	2.13E-07
3 – 25 – 25 - 25 – 1	7.35E-05	0.008576	6.26E-03	0.0900196	7.70E-07

Table 32: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
6 – 1 – 1 – 1 – 1	1.75E-03	0.041841018	4.15E-02	0.083597061	1.18E-03
6 – 3 – 3 – 3 – 1	1.01E-03	0.031764352	2.71E-02	0.137402925	1.64E-06
6 – 6 – 6 – 6 – 1	2.43E-03	0.049261045	4.39E-02	0.139830313	1.75E-05
6 – 9 – 9 – 9 – 1	7.80E-03	0.088304606	6.51E-02	0.422328137	1.42E-05
6 – 3 – 6 – 9 – 1	1.85E-03	0.043036926	3.76E-02	0.1946387	3.39E-06
6 – 6 – 9 – 12 – 1	7.11E-04	0.026663682	2.32E-02	0.089389023	4.52E-06
6 – 12 – 18 – 24 – 1	1.30E-02	0.114077589	9.49E-02	0.898158607	2.70E-05
6 – 25 – 25 - 25 – 1	2.97E-03	0.054485889	4.05E-02	0.354859993	4.65E-06

Table 33: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3:- Vabc1, Iabc1, Vabc2 (process 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
9 - 1 - 1 - 1 - 1	3.63E-04	0.01904287	1.87E-02	0.03907207	5.30E-04
9 - 3 - 3 - 3 - 1	7.52E-05	0.00867198	7.37E-03	0.01623953	4.90E-08
9 - 6 - 6 - 6 - 1	1.70E-03	0.04120123	2.32E-02	0.19246517	1.11E-06
9 - 9 - 9 - 9 - 1	3.49E-04	0.0186835	1.59E-02	0.4266026	1.05E-05
9 - 3 - 6 - 9 - 1	1.20E-04	0.01095722	9.30E-03	0.03489704	5.19E-07
9 - 6 - 9 - 12 - 1	9.38E-04	0.03062382	2.12E-02	0.09977291	7.56E-08
9 - 12 - 18 - 24 - 1	8.39E-05	0.00915939	5.56E-03	0.19422553	4.13E-08
9 - 25 - 25 - 25 - 1	2.41E-03	0.04914009	3.72E-02	0.20605801	1.16E-06

Table 34: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
12 - 1 - 1 - 1 - 1	1.70E-01	0.4122278	4.12E-01	0.89431895	3.57E-01
12 - 3 - 3 - 3 - 1	1.70E-01	0.4122278	4.12E-01	0.89431895	3.57E-01
12 - 6 - 6 - 6 - 1	3.99E-01	0.63128074	6.29E-01	0.7641362	1.37E-01
12 - 9 - 9 - 9 - 1	1.58E-01	0.39715979	3.47E-01	0.7331747	7.41E-05
12 - 3 - 6 - 9 - 1	1.45E+00	1.2021664	1.20E+00	1.43804677	7.44E-03
12 - 6 - 9 - 12 - 1	7.12E-02	0.26690491	2.58E-01	0.43097516	7.63E-03
12 - 12 - 18 - 24 - 1	7.63E-03	0.49685719	3.99E-01	0.92640317	1.15E-04
12 - 25 - 25 - 25 - 1	1.19E-01	0.34497782	3.27E-01	0.64382089	9.52E-03

CHAPTER 7. FURTHER EXPERIMENTATION ON REDUCING FFNET TO 2-LAYER ANN STRUCTURE

To further expand the experiment and better understand how the structure of the FFNet ANN affects the prediction accuracy, the number of hidden layers for each FFNet ANN used for testing the various cases and preprocessing combinations was reduced to 2. The range of the new structures still ranged between 1 and 50 but now with different subsections. This will be shown in the tables included in the paper. The same processes of determining the case, preprocessing method and using the nnStart tool to design the ANNs were repeated for this experiment.

7.1 Results of ANN prediction case 1-4 using preprocess 1

Table 35: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
1 - 1 - 1 - 1	2.55E-04	1.60E-02	1.37E-02	4.55E-02	1.15E-08
1 - 3 - 3 - 1	2.51E-04	1.58E-02	1.36E-02	4.35E-02	3.44E-06
1 - 6 - 6 - 1	2.52E-04	1.59E-02	1.36E-02	4.36E-02	1.35E-06
1 - 9 - 9 - 1	2.53E-04	1.59E-02	1.36E-02	4.44E-02	4.16E-07
1 - 3 - 6 - 1	2.52E-04	1.59E-02	1.36E-02	4.36E-02	1.89E-05
1 - 6 - 9 - 1	2.53E-04	1.59E-02	1.36E-02	4.41E-02	2.07E-06
1 - 12 - 18 - 1	2.54E-04	1.59E-02	1.36E-02	4.59E-02	1.07E-06
1 - 25 -25 - 1	2.59E-04	1.61E-02	1.37E-02	4.62E-02	1.13E-06

Table 36: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
2 - 1 - 1 - 1	2.54E-04	1.59E-02	1.34E-02	7.16E-02	4.42E-06
2 - 3 - 3 - 1	6.67E-04	2.58E-02	1.99E-02	8.09E-02	1.97E-06
2 - 6 - 6 - 1	1.60E-03	4.00E-02	2.63E-02	3.27E-01	9.41E-06
2 - 9 - 9 - 1	2.86E-03	5.35E-02	3.49E-02	1.56E-01	6.59E-06
2 - 3 - 6 - 1	9.97E-04	3.16E-02	2.25E-02	1.01E-01	1.86E-06
2 - 6 - 9 - 1	1.83E-03	4.28E-02	2.70E-02	1.81E-01	2.33E-05
2 - 12 - 18 - 1	2.27E-03	4.77E-02	2.92E-02	1.68E-01	1.90E-07
2 - 25 -25 - 1	3.55E-03	5.96E-02	3.24E-02	2.41E-01	3.59E-06

Table 37: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3 :- Vabc1, Iabc1, Vabc2 (process 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1	2.52E-04	1.59E-02	1.34E-02	6.95E-02	2.12E-06
3 - 3 - 3 - 1	4.82E-04	2.20E-02	1.80E-02	9.56E-02	3.14E-06
3- 6 - 6 - 1	3.05E-03	5.52E-02	3.33E-02	2.96E-01	5.38E-07
3 - 9 - 9 - 1	1.19E-03	3.45E-02	2.43E-02	1.14E-01	5.50E-06
3 - 3 - 6 - 1	1.00E-03	3.16E-02	2.44E-02	9.26E-02	1.94E-05
3 - 6 - 9 - 1	2.98E-03	5.46E-02	3.24E-02	2.12E-01	8.26E-07
3- 12 - 18 - 1	9.89E-04	3.15E-02	2.26E-02	3.17E-01	4.88E-06
3- 25 -25 - 1	1.76E-02	1.33E-01	5.98E-02	6.35E-01	3.17E-06

Table 38: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preoprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
4 - 1 - 1 - 1	2.02E-04	1.42E-02	1.12E-02	5.09E-02	2.54E-06
4 - 3 - 3 - 1	7.91E-04	2.81E-02	2.11E-02	7.55E-02	7.86E-07
4 - 6 - 6 - 1	2.18E-03	4.67E-02	3.28E-02	1.27E-01	2.08E-06
4 - 9 - 9 - 1	2.41E-03	4.91E-02	3.30E-02	1.74E-01	2.40E-06
4 - 3 - 6 - 1	7.08E-04	2.66E-02	1.94E-02	8.69E-02	1.01E-05
4 - 6 - 9 - 1	1.37E-03	3.70E-02	2.57E-02	1.12E-01	1.37E-05
4 - 12 - 18 - 1	2.99E-03	5.47E-02	3.49E-02	2.20E-01	2.11E-06
4 - 25 - 25 - 1	2.68E-03	5.18E-02	3.34E-02	5.14E-01	1.05E-05

7.2 Results of ANN prediction case 1-4 using preprocess 2

Table 39: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
1 - 1 - 1 - 1	4.27E-04	2.07E-02	1.62E-02	1.07E-01	1.48E-06
1 - 3 - 3 - 1	4.14E-04	2.03E-02	1.60E-02	1.05E-01	1.79E-05
1 - 6 - 6 - 1	4.16E-04	2.04E-02	1.60E-02	1.07E-01	7.72E-06
1 - 9 - 9 - 1	4.22E-04	2.06E-02	1.61E-02	1.04E-01	3.96E-06
1 - 3 - 6 - 1	4.17E-04	2.04E-02	1.60E-02	1.05E-01	2.05E-05
1 - 6 - 9 - 1	4.26E-04	2.07E-02	1.62E-02	1.07E-01	7.24E-07
1 - 12 - 18 - 1	4.38E-04	2.09E-02	1.65E-02	1.08E-01	5.50E-06
1 - 25 -25 - 1	4.20E-04	2.05E-02	1.61E-02	1.05E-01	1.07E-05

Table 40: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
2 - 1 - 1 - 1	4.64E-04	2.15E-02	1.72E-02	8.51E-02	3.92E-06
2 - 3 - 3 - 1	5.61E-04	2.37E-02	1.93E-02	6.65E-02	2.44E-06
2 - 6 - 6 - 1	5.80E-04	2.41E-02	1.91E-02	3.21E-01	5.66E-06
2 - 9 - 9 - 1	5.71E-04	2.39E-02	1.92E-02	6.62E-02	1.40E-05
2 - 3 - 6 - 1	4.33E-04	2.08E-02	1.66E-02	6.31E-02	1.00E-06
2 - 6 - 9 - 1	5.69E-04	2.39E-02	1.89E-02	2.54E-01	1.42E-05
2 - 12 - 18 - 1	9.22E-04	3.04E-02	2.27E-02	4.50E-01	1.65E-08
2 - 25 -25 - 1	7.56E-04	2.75E-02	2.16E-02	2.99E-01	2.37E-06

Table 41: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3:- Vabc1, Iabc1, Vabc2 (process 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1	7.96E-04	2.82E-02	2.47E-02	1.29E-01	3.15E-05
3 - 3 - 3 - 1	8.90E-04	2.98E-02	2.67E-02	1.90E-01	1.17E-04
3- 6 - 6 - 1	2.40E-03	4.90E-02	4.17E-02	1.71E-01	4.98E-06
3 - 9 - 9 - 1	1.49E-03	3.86E-02	3.39E-02	1.16E-01	3.98E-05
3 - 3 - 6 - 1	9.47E-04	3.08E-02	2.72E-02	1.23E-01	2.16E-05
3 - 6 - 9 - 1	5.21E-04	2.28E-02	1.87E-02	9.78E-02	5.67E-06
3- 12 - 18 - 1	2.06E-03	4.53E-02	3.67E-02	1.56E-01	5.67E-07
3- 25 -25 - 1	1.45E-03	3.81E-02	3.24E-02	3.56E-01	4.91E-06

Table 42: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
4 - 1 - 1 - 1	7.36E-04	2.71E-02	2.39E-02	1.36E-01	1.89E-05
4 - 3 - 3 - 1	1.29E-03	3.59E-02	3.08E-02	1.07E-01	5.21E-05
4 - 6 - 6 - 1	9.82E-04	3.13E-02	2.29E-02	8.09E-01	3.42E-06
4 - 9 - 9 - 1	1.35E-03	3.67E-02	3.05E-02	1.17E-01	3.54E-06
4 - 3 - 6 - 1	7.95E-04	2.82E-02	2.50E-02	7.57E-02	1.59E-04
4 - 6 - 9 - 1	1.19E-03	3.45E-02	2.83E-02	1.08E-01	2.70E-05
4 - 12 - 18 - 1	1.81E-03	4.25E-02	3.68E-02	6.02E-01	1.64E-06
4 - 25 - 25 - 1	1.55E-03	3.93E-02	3.19E-02	3.52E-01	1.08E-07

7.3 Results of ANN prediction case 1-4 using preprocess 3

Table 43: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1	2.35E-04	1.53E-02	1.30E-02	1.13E-01	4.48E-06
3 - 3 - 3 - 1	2.55E-04	1.60E-02	1.36E-02	4.82E-02	3.49E-06
3- 6 - 6 - 1	2.53E-04	1.59E-02	1.36E-02	5.01E-02	1.13E-05
3 - 9 - 9 - 1	2.04E-04	1.43E-02	1.17E-02	6.68E-02	1.96E-06
3 - 3 - 6 - 1	2.54E-04	1.60E-02	1.36E-02	4.84E-02	5.22E-06
3 - 6 - 9 - 1	2.55E-04	1.60E-02	1.37E-02	4.57E-02	2.69E-06
3- 12 - 18 - 1	2.51E-04	1.59E-02	1.35E-02	5.20E-02	3.47E-05
3- 25 -25 - 1	1.98E-04	1.41E-02	1.15E-02	4.74E-02	3.18E-07

Table 44: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
6- 1 - 1 - 1	1.70E-04	1.30E-02	1.09E-02	6.72E-02	5.11E-06
6 - 3 - 3 - 1	1.66E-03	4.07E-02	2.84E-02	6.31E-01	1.48E-06
6 - 6 - 6 - 1	1.20E-03	3.46E-02	2.69E-02	1.33E-01	1.56E-05
6 - 9 - 9 - 1	1.11E-03	3.33E-02	2.82E-02	1.65E-01	1.99E-05
6 - 3 - 6 - 1	2.29E-03	4.78E-02	4.40E-02	1.20E-01	5.33E-05
6 - 6 - 9 - 1	2.71E-03	5.21E-02	3.77E-02	2.83E-01	7.72E-06
6 - 12 - 18 - 1	1.14E-03	3.38E-02	2.82E-02	1.82E-01	1.71E-06
6 - 25 -25 - 1	3.44E-03	5.87E-02	4.97E-02	1.71E-01	1.85E-05

Table 45: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3 :- Vabc1, Iabc1, Vabc2 (process 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
9- 1 - 1 - 1	2.29E-04	1.51E-02	1.19E-02	6.33E-02	1.60E-06
9 - 3 - 3 - 1	2.78E-03	5.28E-02	4.37E-02	1.44E-01	2.23E-05
9 - 6 - 6 - 1	8.27E-04	2.87E-02	2.00E-02	1.37E-01	1.95E-06
9 - 9 - 9 - 1	9.04E-04	3.01E-02	2.48E-02	2.99E-01	8.65E-07
9 - 3 - 6 - 1	2.24E-03	4.73E-02	4.22E-02	1.55E-01	6.92E-06
9 - 6 - 9 - 1	1.07E-03	3.28E-02	2.52E-02	1.15E-01	3.12E-06
9 - 12 - 18 - 1	7.93E-04	2.82E-02	2.26E-02	9.98E-02	5.53E-06
9 - 25 -25 - 1	5.52E-03	7.43E-02	5.60E-02	7.88E-01	2.48E-05

Table 46: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
12 - 1 - 1 - 1	6.82E-04	2.61E-02	2.35E-02	6.69E-02	6.07E-05
12 - 3 - 3 - 1	8.75E-04	2.96E-02	2.42E-02	8.89E-02	2.52E-06
12 - 6 - 6 - 1	3.52E-03	5.93E-02	4.39E-02	2.63E-01	1.01E-05
12- 9 - 9 - 1	1.13E-02	1.06E-01	8.30E-02	3.04E-01	8.28E-05
12 - 3 - 6 - 1	1.52E-03	3.90E-02	2.83E-02	3.00E-01	1.47E-05
12 - 6 - 9 - 1	1.01E-02	1.00E-01	8.33E-02	2.16E-01	2.40E-05
12 - 12 - 18 - 1	1.28E-02	1.13E-01	9.00E-02	3.14E-01	5.96E-05
12 - 25 - 25 - 1	8.22E-03	9.06E-02	7.72E-02	2.05E-01	8.29E-05

7.4 Results of ANN prediction case 1-4 using preprocess 4

Table 47: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1	4.30E-05	6.56E-03	4.04E-03	7.81E-02	1.86E-07
3 - 3 - 3 - 1	4.21E-05	6.49E-03	3.96E-03	7.19E-02	8.12E-08
3- 6 - 6 - 1	3.55E-05	5.95E-03	3.76E-03	6.43E-02	1.38E-06
3 - 9 - 9 - 1	4.25E-05	6.52E-03	4.83E-03	7.93E-02	9.72E-07
3 - 3 - 6 - 1	3.76E-05	6.13E-03	3.95E-03	1.03E-01	2.64E-06
3 - 6 - 9 - 1	4.17E-05	6.46E-03	4.26E-03	6.64E-02	9.60E-07
3- 12 - 18 - 1	3.48E-05	5.90E-03	4.12E-03	7.35E-02	1.30E-06
3- 25 -25 - 1	4.26E-05	6.53E-03	4.80E-03	7.30E-02	1.27E-06

Table 48: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
6- 1 - 1 - 1	4.50E-03	6.71E-02	6.68E-02	1.05E-01	1.55E-03
6 - 3 - 3 - 1	2.09E-03	4.58E-02	3.86E-02	2.90E-01	1.19E-05
6 - 6 - 6 - 1	4.06E-02	2.01E-01	1.61E-01	4.14E-01	1.04E-05
6 - 9 - 9 - 1	2.01E-02	1.42E-01	1.20E-01	2.78E-01	8.63E-03
6 - 3 - 6 - 1	5.44E-03	7.38E-02	7.34E-02	1.25E-01	1.44E-03
6 - 6 - 9 - 1	4.68E-03	6.84E-02	5.15E-02	1.60E-01	1.25E-05
6 - 12 - 18 - 1	5.72E-03	7.56E-02	7.24E-02	1.90E-01	1.24E-03
6 - 25 -25 - 1	2.96E-03	5.44E-02	4.83E-02	2.00E-01	4.78E-05

Table 49: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3:- Vabc1, Iabc1, Vabc2 (process 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
9- 1 - 1 - 1	7.90E-04	2.81E-02	2.79E-02	5.63E-02	5.86E-03
9 - 3 - 3 - 1	1.86E-04	1.36E-02	1.18E-02	9.06E-02	4.28E-05
9 - 6 - 6 - 1	1.80E-03	4.24E-02	3.98E-02	1.10E-01	3.17E-05
9 - 9 - 9 - 1	5.12E-04	2.26E-02	1.62E-02	1.16E-01	1.29E-05
9 - 3 - 6 - 1	2.93E-04	1.71E-02	1.58E-02	6.29E-02	3.98E-06
9 - 6 - 9 - 1	5.43E-04	2.33E-02	2.28E-02	9.01E-02	3.41E-04
9 - 12 - 18 - 1	1.11E-03	3.33E-02	2.69E-02	2.16E-01	2.94E-05
9 - 25 -25 - 1	1.24E-03	3.52E-02	3.01E-02	1.52E-01	2.58E-05

Table 50: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
12 - 1 - 1 - 1	4.32E-01	6.57E-01	6.57E-01	1.22E+00	6.34E-01
12 - 3 - 3 - 1	2.78E-01	5.27E-01	5.26E-01	8.73E-01	4.35E-01
12 - 6 - 6 - 1	1.93E-01	4.39E-01	4.38E-01	6.76E-01	3.52E-01
12- 9 - 9 - 1	6.62E-02	2.57E-01	2.50E-01	3.55E-01	1.46E-01
12 - 3 - 6 - 1	1.46E-01	0.38245828	3.69E-01	5.92E-01	6.47E-02
12 - 6 - 9 - 1	2.07E-02	1.44E-01	1.41E-01	2.29E-01	2.64E-03
12 - 12 - 18 - 1	4.12E-01	6.41E-01	6.37E-01	8.21E-01	1.96E-01
12 - 25 - 25 - 1	1.96E-02	1.40E-01	1.29E-01	2.56E-01	2.36E-03

7.5 Additional Test Results

The tables below show the results of the ANN predictions using the larger dataset. Similar processes to the smaller dataset were conducted for the larger dataset.

Table 51: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
1 - 1 - 1 - 1	2.60E-04	1.61E-02	1.39E-02	4.53E-02	6.20E-06
1 - 3 - 3 - 1	2.56E-04	1.60E-02	1.37E-02	4.36E-02	2.94E-06
1 - 6 - 6 - 1	2.57E-04	1.60E-02	1.37E-02	4.49E-02	2.42E-07
1 - 9 - 9 - 1	2.57E-04	1.60E-02	1.37E-02	4.52E-02	1.51E-06
1 - 3 - 6 - 1	2.59E-04	1.61E-02	1.38E-02	4.43E-02	1.07E-06
1 - 6 - 9 - 1	2.56E-04	1.60E-02	1.37E-02	4.48E-02	1.97E-06
1 - 12 - 18 - 1	2.57E-04	1.60E-02	1.37E-02	4.45E-02	1.15E-05
1 - 25 -25 - 1	2.57E-04	1.60E-02	1.37E-02	4.37E-02	7.05E-07

Table 52: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
2 - 1 - 1 - 1	4.18E-04	2.04E-02	1.65E-02	8.10E-02	2.48E-06
2 - 3 - 3 - 1	8.10E-04	2.85E-02	2.32E-02	8.81E-02	6.34E-06
2 - 6 - 6 - 1	2.83E-02	1.68E-01	9.57E-02	5.76E-01	8.76E-06
2 - 9 - 9 - 1	8.00E-03	8.95E-02	5.50E-02	3.38E-01	3.09E-07
2 - 3 - 6 - 1	3.08E-04	1.75E-02	1.46E-02	9.44E-02	1.46E-06
2 - 6 - 9 - 1	9.03E-03	9.50E-02	6.95E-02	2.17E-01	2.77E-07
2 - 12 - 18 - 1	2.65E-02	1.63E-01	8.60E-02	5.95E-01	5.29E-06
2 - 25 -25 - 1	3.34E-02	1.83E-01	1.08E-01	5.23E-01	6.35E-06

Table 53: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3 :- Vabc1, Iabc1, Vabc2 (process 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1	4.28E-04	2.07E-02	1.67E-02	8.21E-02	1.68E-06
3 - 3 - 3 - 1	3.60E-03	6.00E-02	3.94E-02	1.93E-01	1.38E-06
3- 6 - 6 - 1	1.69E-03	4.12E-02	3.04E-02	1.41E-01	4.65E-06
3 - 9 - 9 - 1	1.56E-03	3.95E-02	3.07E-02	1.38E-01	5.67E-06
3 - 3 - 6 - 1	5.47E-04	2.34E-02	1.98E-02	5.51E-02	1.05E-06
3 - 6 - 9 - 1	4.03E-03	6.35E-02	4.17E-02	1.97E-01	1.50E-06
3- 12 - 18 - 1	1.43E-02	1.20E-01	7.16E-02	4.01E-01	1.39E-05
3- 25 -25 - 1	7.60E-03	8.72E-02	5.26E-02	4.66E-01	1.22E-05

Table 54: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preoprocess 1)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
4 - 1 - 1 - 1	3.34E-04	1.83E-02	1.47E-02	5.95E-02	6.29E-07
4 - 3 - 3 - 1	4.19E-04	2.05E-02	1.67E-02	6.45E-02	2.50E-06
4 - 6 - 6 - 1	6.14E-03	7.84E-02	4.60E-02	2.86E-01	3.39E-06
4 - 9 - 9 - 1	3.42E-03	5.85E-02	3.55E-02	2.22E-01	9.65E-06
4 - 3 - 6 - 1	1.78E-03	4.22E-02	2.69E-02	1.51E-01	1.74E-06
4 - 6 - 9 - 1	5.64E-03	7.51E-02	4.07E-02	6.51E-01	5.21E-06
4 - 12 - 18 - 1	8.16E-03	9.03E-02	5.30E-02	3.15E-01	5.63E-06
4 - 25 - 25 - 1	1.47E-02	1.21E-01	7.47E-02	4.52E-01	5.01E-06

Table 55: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
1 - 1 - 1 - 1	2.92E-04	1.71E-02	1.35E-02	1.01E-01	2.71E-07
1 - 3 - 3 - 1	2.91E-04	1.70E-02	1.34E-02	1.00E-01	2.35E-06
1 - 6 - 6 - 1	2.87E-04	1.69E-02	1.33E-02	1.00E-01	3.22E-06
1 - 9 - 9 - 1	2.88E-04	1.70E-02	1.34E-02	9.81E-02	1.51E-06
1 - 3 - 6 - 1	2.87E-04	1.69E-02	1.33E-02	9.97E-02	5.26E-06
1 - 6 - 9 - 1	2.86E-04	1.69E-02	1.33E-02	1.00E-01	2.55E-06
1 - 12 - 18 - 1	2.89E-04	1.70E-02	1.34E-02	1.01E-01	4.02E-07
1 - 25 -25 - 1	2.93E-04	1.71E-02	1.34E-02	1.05E-01	2.81E-06

Table 56: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
2 - 1 - 1 - 1	3.22E-04	1.79E-02	1.40E-02	8.33E-02	2.85E-06
2 - 3 - 3 - 1	3.43E-04	1.85E-02	1.46E-02	7.83E-02	4.79E-07
2 - 6 - 6 - 1	5.23E-04	2.29E-02	1.77E-02	1.14E-01	3.66E-06
2 - 9 - 9 - 1	4.81E-04	2.19E-02	1.70E-02	8.72E-02	8.49E-07
2 - 3 - 6 - 1	5.49E-04	2.34E-02	1.80E-02	4.07E-01	2.42E-06
2 - 6 - 9 - 1	4.24E-04	2.06E-02	1.64E-02	6.88E-02	1.02E-06
2 - 12 - 18 - 1	6.44E-04	2.54E-02	1.94E-02	4.34E-01	9.05E-08
2 - 25 -25 - 1	1.59E-03	3.04E-03	2.85E-02	8.61E-01	1.73E-06

Table 57: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3:- Vabc1, Iabc1, Vabc2 (process 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1	4.50E-04	2.12E-02	1.69E-02	1.10E-01	2.85E-07
3 - 3 - 3 - 1	6.61E-04	2.57E-02	2.22E-02	1.04E-01	1.57E-06
3- 6 - 6 - 1	7.56E-04	2.75E-02	2.16E-02	1.06E-01	3.55E-06
3 - 9 - 9 - 1	9.69E-04	3.11E-02	2.51E-02	1.48E-01	1.66E-06
3 - 3 - 6 - 1	4.75E-04	2.18E-02	1.85E-02	8.41E-02	1.11E-06
3 - 6 - 9 - 1	5.25E-04	2.29E-02	1.94E-02	1.09E-01	3.07E-06
3- 12 - 18 - 1	7.57E-04	2.75E-02	2.28E-02	5.86E-01	2.65E-07
3- 25 -25 - 1	2.26E-03	4.75E-02	3.59E-02	9.66E-01	1.96E-06

Table 58: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 2)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
4 - 1 - 1 - 1	3.86E-04	1.97E-02	1.57E-02	1.09E-01	3.47E-06
4 - 3 - 3 - 1	3.77E-04	1.94E-02	1.58E-02	1.07E-01	3.71E-07
4 - 6 - 6 - 1	1.07E-03	3.27E-02	2.66E-02	1.89E-01	9.75E-06
4 - 9 - 9 - 1	1.01E-03	3.17E-02	2.56E-02	1.36E-01	1.03E-05
4 - 3 - 6 - 1	8.45E-04	2.91E-02	2.14E-02	1.61E-01	2.17E-06
4 - 6 - 9 - 1	7.34E-04	2.71E-02	2.19E-02	1.39E-01	1.85E-06
4 - 12 - 18 - 1	1.45E-03	3.81E-02	2.95E-02	1.70E-01	3.92E-06
4 - 25 - 25 - 1	1.09E-03	3.29E-02	2.48E-02	4.54E-01	5.22E-07

Table 59: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1	2.63E-04	1.62E-02	1.39E-02	4.72E-02	5.20E-06
3 - 3 - 3 - 1	2.58E-04	1.60E-02	1.37E-02	4.96E-02	1.91E-06
3- 6 - 6 - 1	2.53E-04	1.59E-02	1.36E-02	5.13E-02	6.92E-07
3 - 9 - 9 - 1	2.55E-04	1.60E-02	1.37E-02	4.99E-02	1.12E-06
3 - 3 - 6 - 1	2.59E-04	1.61E-02	1.38E-02	4.90E-02	4.43E-06
3 - 6 - 9 - 1	2.59E-04	1.61E-02	1.38E-02	4.81E-02	1.41E-07
3- 12 - 18 - 1	2.74E-04	1.65E-02	1.39E-02	4.56E-02	1.76E-06
3- 25 -25 - 1	2.76E-04	1.66E-02	1.37E-02	1.38E-01	3.22E-06

Table 60: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
6- 1 - 1 - 1	3.18E-04	1.78E-02	1.40E-02	8.21E-02	7.07E-07
6 - 3 - 3 - 1	3.61E-04	1.90E-02	1.50E-02	2.80E-01	5.87E-07
6 - 6 - 6 - 1	7.29E-04	2.70E-02	2.03E-02	1.11E-01	2.16E-06
6 - 9 - 9 - 1	6.26E-04	2.50E-02	1.88E-02	6.15E-01	6.78E-06
6 - 3 - 6 - 1	1.04E-03	3.22E-02	2.16E-02	2.50E-01	1.05E-07
6 - 6 - 9 - 1	5.04E-04	2.25E-02	1.76E-02	2.79E-01	3.74E-06
6 - 12 - 18 - 1	7.36E-04	2.71E-02	2.14E-02	2.57E-01	3.99E-06
6 - 25 -25 - 1	6.61E-04	2.57E-02	2.01E-02	4.41E-01	5.52E-06

Table 61: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3 :- Vabc1, Iabc1, Vabc2 (process 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
9- 1 - 1 - 1	2.49E-04	1.58E-02	1.25E-02	6.22E-02	1.63E-06
9 - 3 - 3 - 1	5.07E-04	2.25E-02	1.73E-02	1.38E-01	2.79E-06
9 - 6 - 6 - 1	5.16E-04	2.27E-02	1.71E-02	1.53E-01	1.12E-06
9 - 9 - 9 - 1	1.95E-02	1.40E-01	8.98E-02	3.39E-01	1.24E-06
9 - 3 - 6 - 1	1.22E-03	3.49E-02	2.39E-02	1.17E-01	5.93E-06
9 - 6 - 9 - 1	3.67E-02	1.92E-01	1.10E-01	6.20E-01	1.69E-07
9 - 12 - 18 - 1	4.58E-02	2.14E-01	1.11E-01	9.09E-01	1.55E-06
9 - 25 -25 - 1	7.32E-03	8.56E-02	5.60E-02	3.46E-01	2.03E-08

Table 62: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 3)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
12 - 1 - 1 - 1	5.24E-04	2.29E-02	2.05E-02	6.95E-02	1.09E-05
12 - 3 - 3 - 1	4.53E-03	6.73E-02	3.98E-02	2.10E-01	1.44E-06
12 - 6 - 6 - 1	2.00E-02	1.41E-01	6.71E-02	5.60E-01	2.90E-07
12- 9 - 9 - 1	2.31E-02	1.52E-01	8.92E-02	6.83E-01	8.39E-07
12 - 3 - 6 - 1	9.30E-02	3.05E-01	2.45E-01	5.72E-01	1.12E-05
12 - 6 - 9 - 1	6.56E-02	2.56E-01	1.53E-01	1.04E+00	1.85E-06
12 - 12 - 18 - 1	2.50E-02	1.58E-01	8.07E-02	1.08E+00	4.23E-06
12 - 25 - 25 - 1	5.57E-02	2.36E-01	1.44E-01	8.96E-01	1.10E-05

Table 63: Fault location prediction using 3-Phase Voltage from Bus 1

Case 1 :- Vabc (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
3 - 1 - 1 - 1	4.73E-05	6.87E-03	4.78E-03	9.67E-02	6.80E-07
3 - 3 - 3 - 1	5.53E-05	7.44E-03	5.33E-03	2.04E-01	1.30E-06
3- 6 - 6 - 1	4.34E-05	6.59E-03	4.96E-03	8.75E-02	2.23E-06
3 - 9 - 9 - 1	5.71E-05	7.56E-03	5.94E-03	1.15E-01	1.65E-06
3 - 3 - 6 - 1	5.44E-05	7.37E-03	5.94E-03	1.06E-01	1.22E-06
3 - 6 - 9 - 1	4.89E-05	6.99E-03	5.67E-03	1.04E-01	4.66E-06
3- 12 - 18 - 1	6.37E-05	7.98E-03	5.81E-03	9.76E-02	5.84E-08
3- 25 -25 - 1	6.47E-05	8.05E-03	5.72E-03	9.69E-02	2.24E-06

Table 64: Fault location prediction using 3-Phase Voltage & Current from Bus 1

Case 2 :- Vabc, Iabc (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
6- 1 - 1 - 1	1.86E-03	4.32E-02	4.28E-02	8.50E-02	1.71E-03
6 - 3 - 3 - 1	9.76E-04	3.12E-02	3.09E-02	9.75E-02	3.18E-03
6 - 6 - 6 - 1	2.77E-03	5.27E-02	4.42E-02	1.83E-01	4.64E-07
6 - 9 - 9 - 1	2.22E-03	4.71E-02	3.66E-02	1.45E-01	3.23E-06
6 - 3 - 6 - 1	3.58E-03	5.99E-02	5.81E-02	1.90E-01	9.80E-04
6 - 6 - 9 - 1	1.65E-03	4.07E-02	3.36E-02	5.93E-01	5.72E-06
6 - 12 - 18 - 1	2.27E-02	1.51E-01	1.14E-01	6.75E-01	7.95E-07
6 - 25 -25 - 1	6.10E-03	7.81E-02	5.86E-02	9.70E-01	1.66E-05

Table 65: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1

Case 3:- Vabc1, Iabc1, Vabc2 (process 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
9- 1 - 1 - 1	3.62E-04	1.90E-02	1.87E-02	3.86E-02	2.59E-04
9 - 3 - 3 - 1	1.70E-04	1.31E-02	1.15E-02	5.63E-02	2.07E-07
9 - 6 - 6 - 1	1.62E-04	1.27E-02	9.02E-03	2.37E-01	2.68E-06
9 - 9 - 9 - 1	1.28E-04	1.13E-02	9.15E-03	5.33E-02	2.42E-06
9 - 3 - 6 - 1	2.06E-04	1.44E-02	1.26E-02	8.37E-02	8.73E-07
9 - 6 - 9 - 1	1.84E-03	4.29E-02	3.01E-02	1.34E-01	2.86E-07
9 - 12 - 18 - 1	4.61E-04	2.15E-02	1.46E-02	1.18E-01	6.52E-07
9 - 25 -25 - 1	4.16E-04	2.04E-02	1.40E-02	4.82E-01	3.07E-06

Table 66: Fault location prediction using 3-Phase Voltage from Bus 1&2 and 3-Phase Current from Bus 1&2

Case 4 :- Vabc1, Iabc1, Vabc2, Iabc2 (preprocess 4)					
Structure	MSE	RMSE	Avg. Error	Max Error	Min Error
12 - 1 - 1 - 1	4.15E-04	2.04E-02	2.01E-02	4.01E-02	1.09E-04
12 - 3 - 3 - 1	1.54E-04	1.24E-02	1.13E-02	2.84E-02	1.26E-05
12 - 6 - 6 - 1	4.99E-03	7.06E-02	5.85E-02	2.44E-01	8.38E-06
12- 9 - 9 - 1	6.32E-04	2.51E-02	1.96E-02	9.37E-02	3.22E-06
12 - 3 - 6 - 1	2.81E-04	1.68E-02	1.49E-02	7.07E-02	2.50E-07
12 - 6 - 9 - 1	1.77E-03	4.21E-02	3.65E-02	1.02E-01	3.66E-06
12 - 12 - 18 - 1	3.86E-04	1.96E-02	1.55E-02	6.42E-02	2.98E-06
12 - 25 - 25 - 1	1.28E-03	3.58E-02	2.79E-02	3.49E-01	3.75E-06

CHAPTER 8. RESULT ANALYSIS

8.1 Analysis

The results shown in the tables from the previous chapters present the necessary data to evaluate the performance and accuracy of the ANN structure developed for each case and preprocessing. For every new fault simulation presented to the ANN, after initial training and self-testing, the predicted fault location was recorded and compared to the actual fault location for the test cases. Using this comparison, an error vector was created by taking the difference in predicted and actual fault location. This error vector was then analyzed to obtain the maximum and average errors between the outputs. The main criteria used to measure the accuracy of the ANN prediction was the average error from all the predictions for a given case, preprocessing method, and ANN architecture. The results from both the smaller and the larger sample dataset show congruency in the ANN structures prediction and performance.

8.1.1 *Results from Chapter 6 using 3- hidden layer ANN*

From the results, it was observed that the predictions from the ANN structures with only one input variable data (Case 1) yielded the least average error per preprocessing method all round in comparison. For both the larger and smaller testing dataset, about 3 out of every 4 of the preprocessing method predicted the least average error using Case 1. The ANN structures with all four (4) input variable data yielded the largest average errors in fault location prediction.

The preprocessing method 4, which involves the standardization & normalization of each of the phase columns of the input variables with no column addition, predicted the fault locations with the least average error compared to other methods. When compared to the other methods from each case, 3 out of 4 of the cases with the least error per process were predicted from an ANN structure tested with preprocessing method 4.

To corroborate the prior observations, for each of the test datasets, the ANN structure with the least average error out of all the structures, cases, and preprocessing methods was determined. The result from both the larger and smaller dataset highlighted that the structure containing 3-6-9 neuron to hidden layer ratio yielded the least average error out of every case simulated and observed. This exact structure with the least average errors was built and tested using the test dataset which contained only one input variable (Case 1) and implemented the preprocessing method 4. The least average error from the 3775 cases was 3.8364E-03 (3.83E-02 feet) while the least average error from the 10,571 cases was 4.01E-03 (4.01E-02 feet).

Given the observations from this study, it could be inferred that implementing Case 1 and Preprocessing method 4 would yield the best results for detecting fault location on a distribution line. It can also be determined that the ANN structure of 3-6-9 hidden layers would be the most ideal structure of the feedforward ANN to build for the most accurate results. Both the least average prediction errors for the 3,755 case and the 10,571 case simulations occurred using

Ultimately the largest error across all cases and preprocessing methods was about 1.38 (13.8 feet) for the 3775 case dataset and this occurred when adopting case 4 for collating the input dataset. The largest error for the 10,571 case dataset was 1.90 (19 feet) and this occurred also when adopting case 4 for data collation. This would be congruent with the largest error comparison conclusion made about Case 4 yielding larger errors when compared to other preprocessing methods.

8.1.2 *Results from Chapter 7 using 2- hidden layer ANN*

From the observations from the experiments carried out, the 2- hidden layer ANN seemed to show some correlation in results as the 3- hidden layer ANN experiments. Both the larger and smaller datasets showed the absolute least error of prediction occurred using Case 1 and preprocessing method 4 to train and test the ANN structures for prediction.

From this new experiment setup, it could be observed that the change in hidden layer number from 3 to 2 had little effect on the result. This can be seen as the least average errors for each testing case and preprocessing method for the 2- hidden layer ANNs were similar in degree of magnitude to the results obtained from the 3-hidden layer ANNs. This can be seen in the tables below.

Table 67: Least Average Error Comparison between 2 and 3 Layer ANNs

	All Preprocess. Methods	2-layer ANN	3-layer ANN
		Least Average Error	Least Average Error
3775 datasets	Case 1	3.84E-03	3.76E-03
	Case 2	1.34E-02	1.09E-02
	Case 3	1.07E-02	1.18E-02
	Case 4	1.10E-02	1.12E-02
10571 datasets	Case 1	4.01E-03	4.78E-03
	Case2	1.25E-02	1.40E-02
	Case 3	5.56E-03	9.02E-03
	Case 4	1.45E-02	1.13E-02

Table 68: Least Average Error Comparison between 2 and 3 Layer ANNs

		2-layer ANN	3-layer ANN
	All Cases	Least Average Error	Least Average Error
3775 datasets	Preprocess 1	1.10E-02	1.12E-02
	Preprocess 2	1.60E-02	1.60E-02
	Preprocess 3	1.04E-02	1.09E-02
	Preprocess 4	3.84E-03	3.76E-03
10571 datasets	Preprocess 1	1.37E-02	1.37E-02
	Preprocess 2	1.33E-02	1.33E-02
	Preprocess 3	1.21E-02	1.25E-02
	Preprocess 4	4.01E-03	4.78E-03

8.2 Graph of Error between Predicted & Actual Target Fault Location

Figures 13 to 28 show the relationship between the actual fault location and the predicted fault location using the ANN. As the correlation between the two quantities increases, the graph would show less fluctuations (oscillations). This can be noticed from the graphs below. Figure 16 shows the graph of the actual vs predicted fault locations for case 1 and preprocessing method 4 which we observed to give the least average error between the quantities. The graph has a smoother trend (less oscillations) in comparison to the other graphs. This also corresponds with our observations.

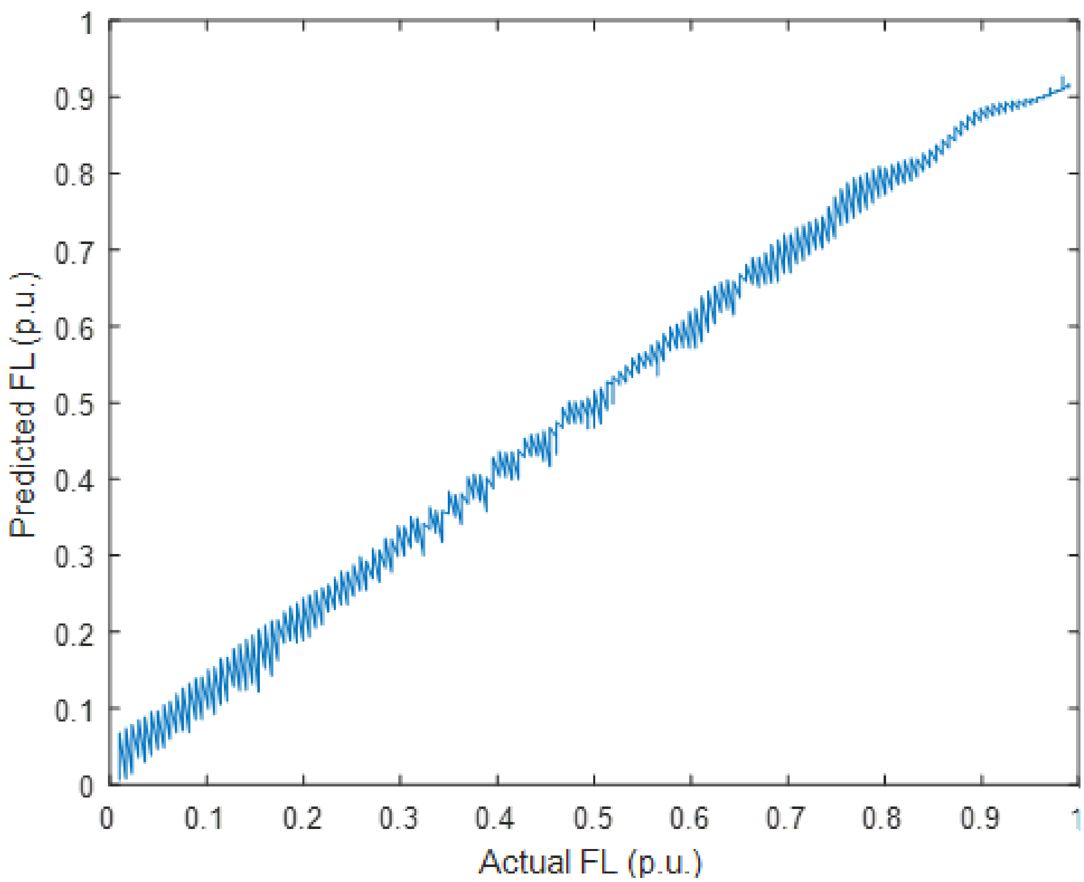

Figure 13: Fault Location error for Case 1 Preprocessing 1 (ANN 1-3-6-9-1)

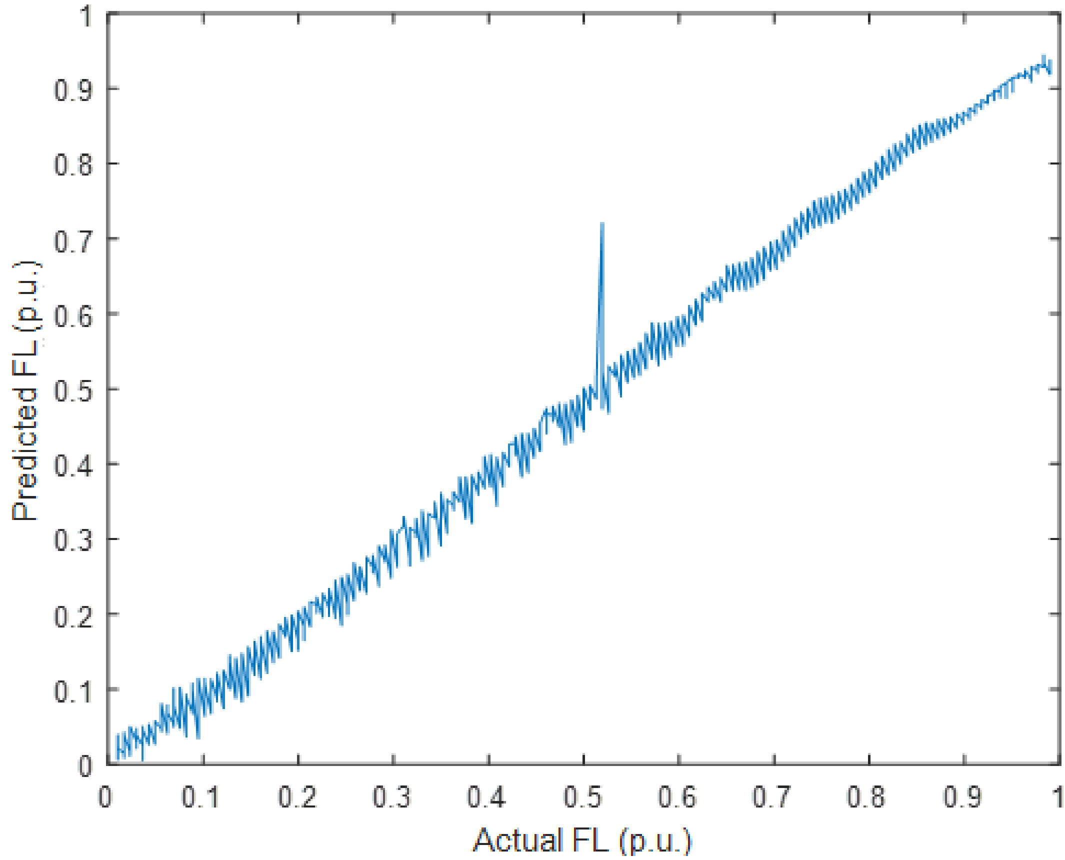

Figure 14: Fault Location error for Case 1 Preprocessing 2 (ANN 1-3-6-9-1)

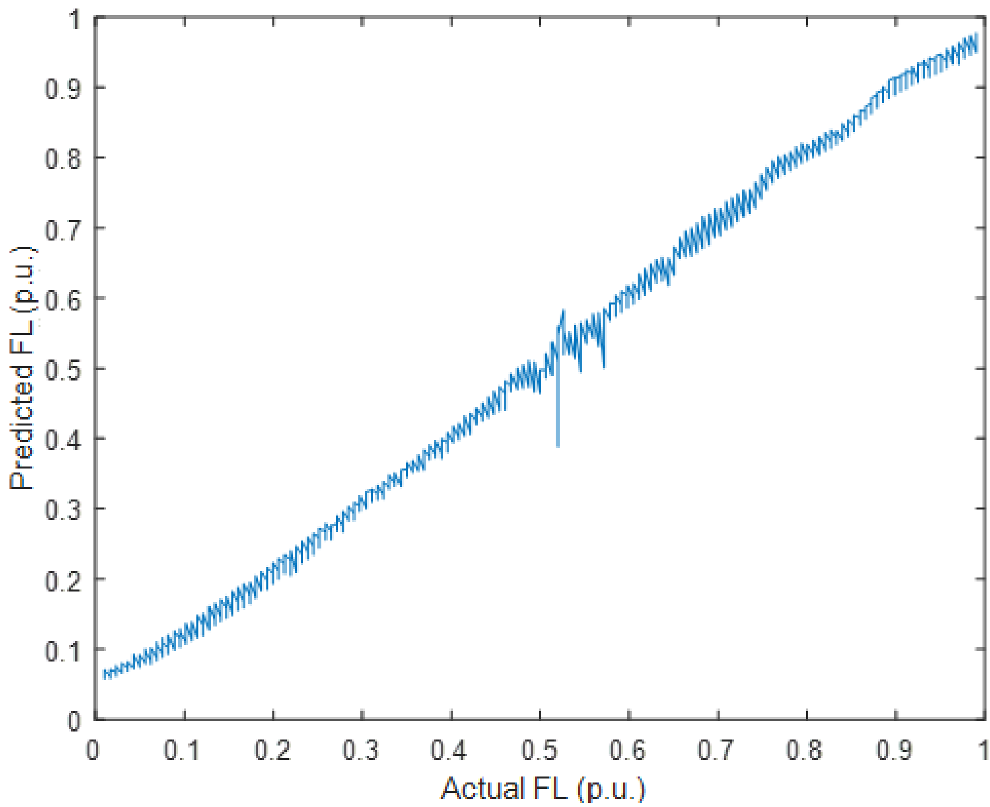

Figure 15: Fault Location error for Case 1 Preprocessing 3 (ANN 1-3-6-9-1)

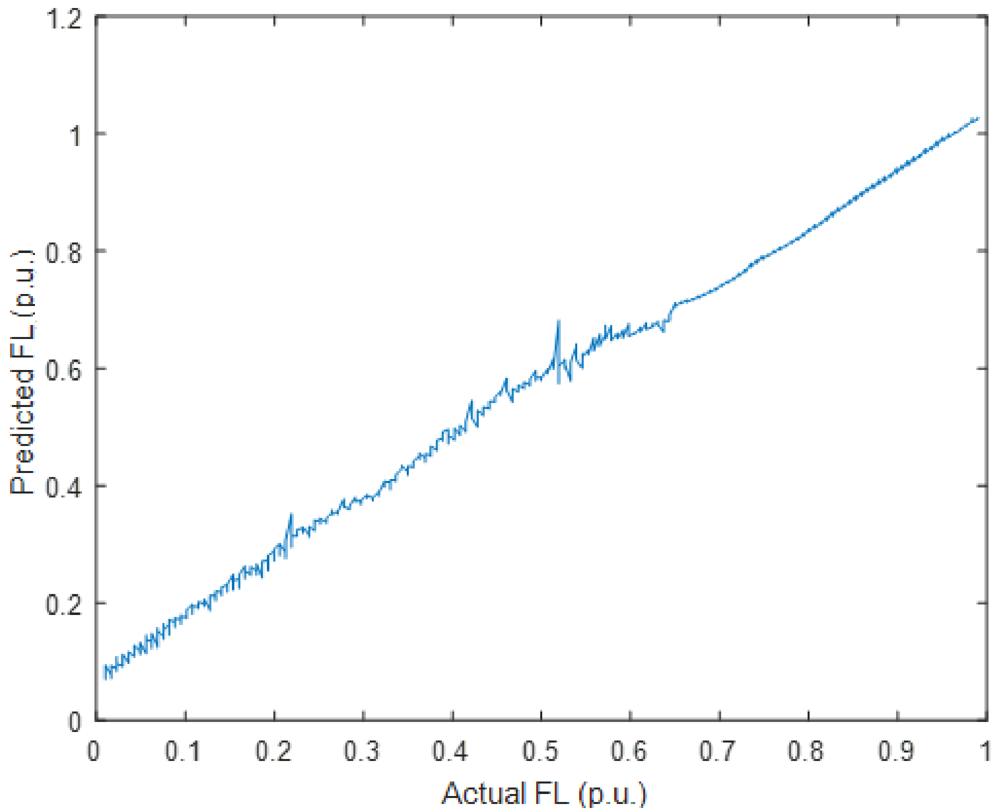

Figure 16: Fault Location error for Case 1 Preprocessing 4 (ANN 1-3-6-9-1)

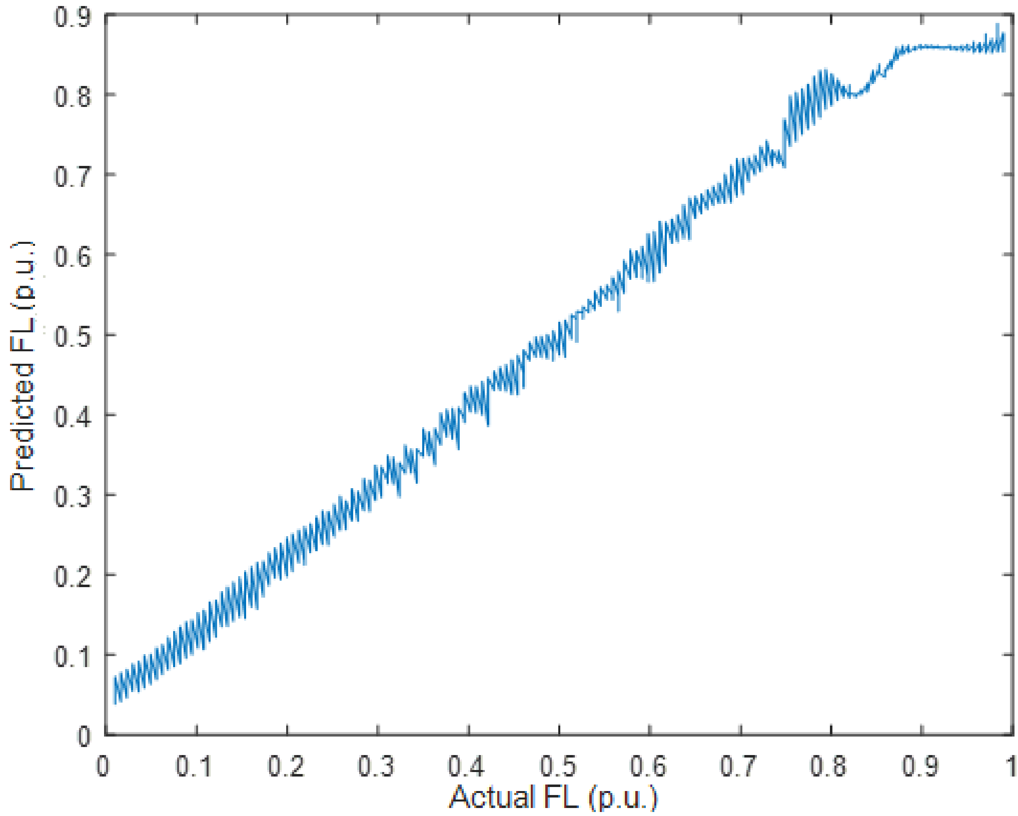

Figure 17: Fault Location error for Case 2 Preprocessing 1 (ANN 1-3-6-9-1)

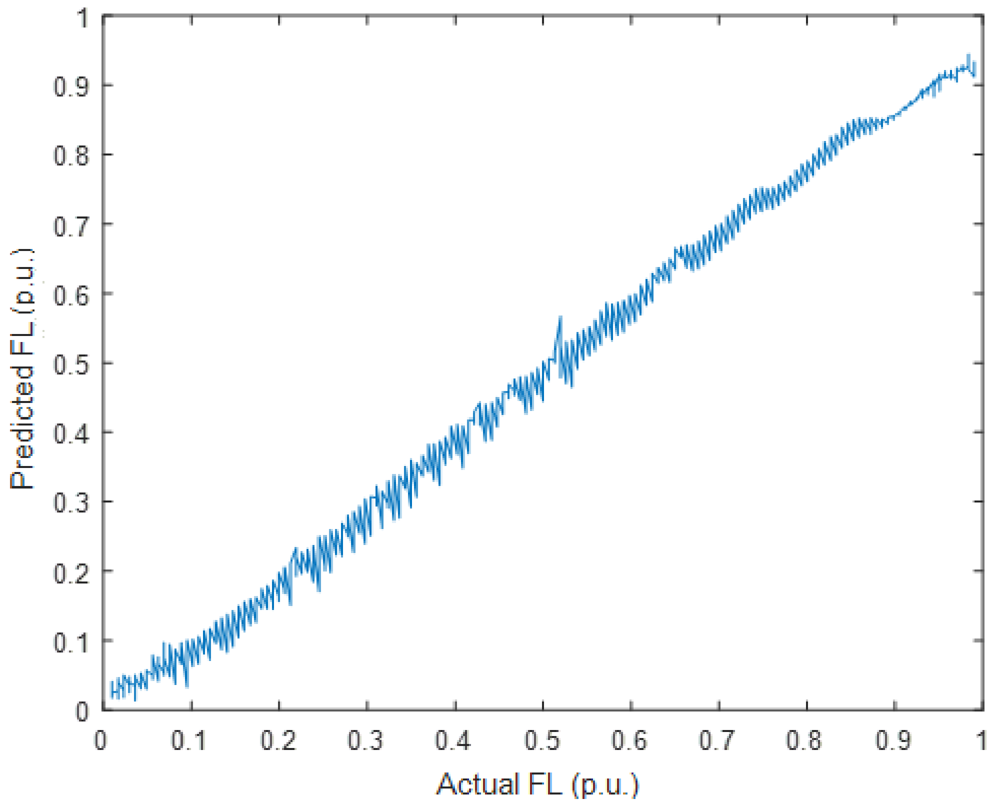

Figure 18: Fault Location error for Case 2 Preprocessing 2 (ANN 1-3-6-9-1)

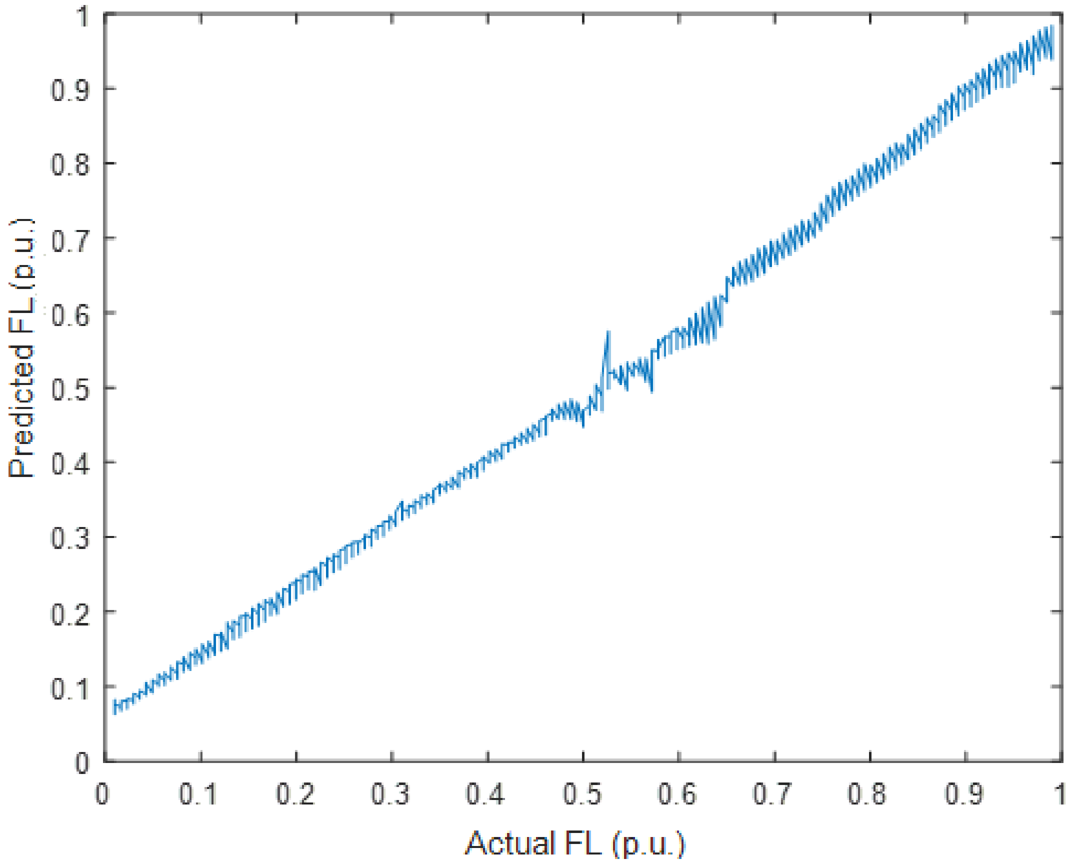

Figure 19: Fault Location error for Case 2 Preprocessing 3 (ANN 1-3-6-9-1)

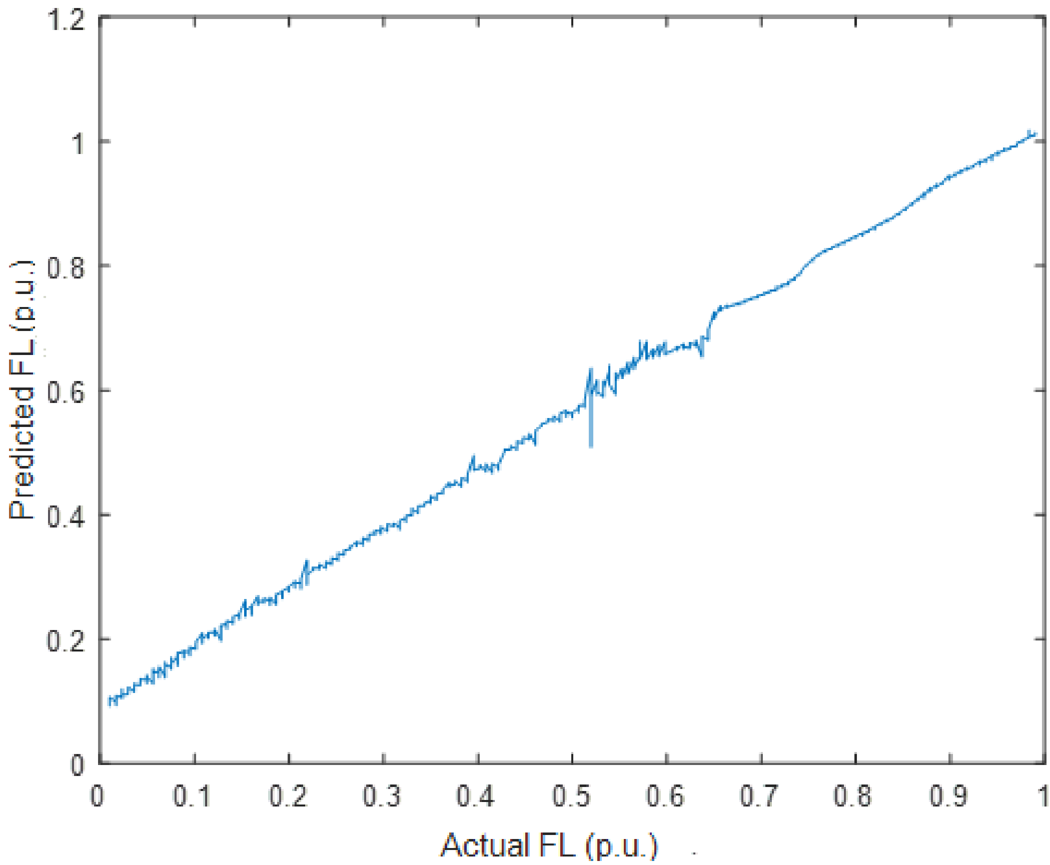

Figure 20: Fault Location error for Case 2 Preprocessing 4 (ANN 1-3-6-9-1)

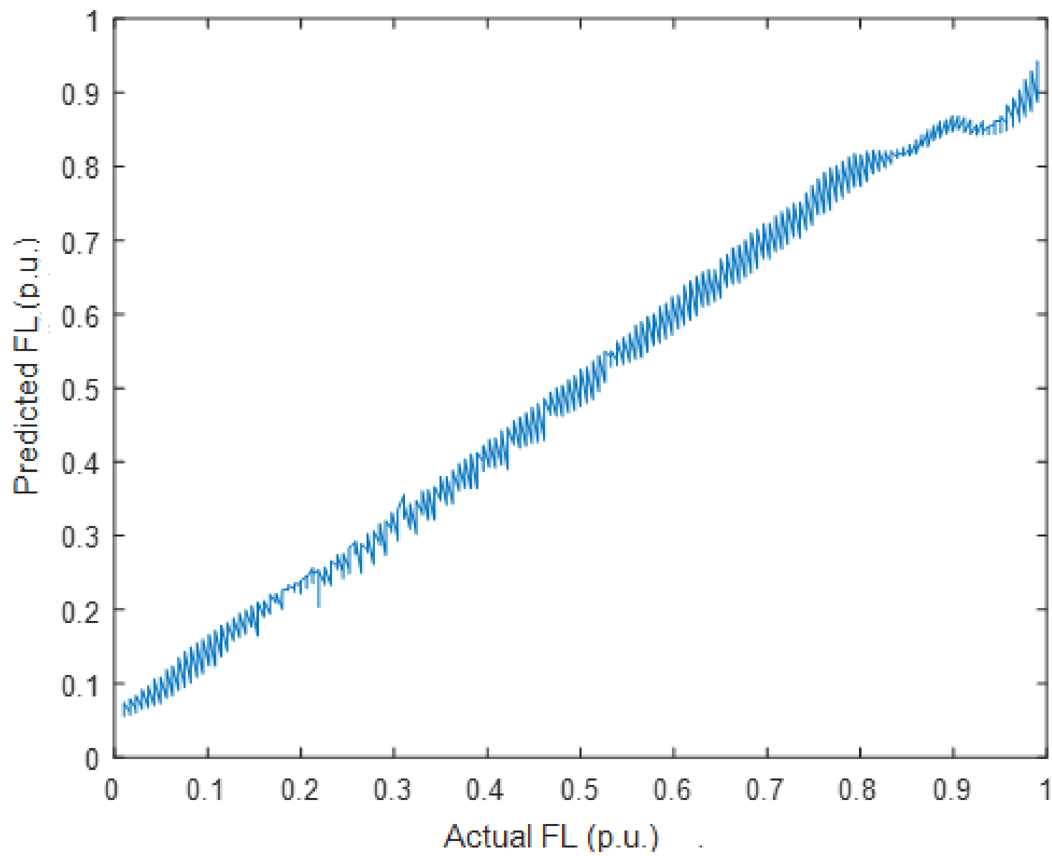

Figure 21: Fault Location error for Case 3 Preprocessing 1 (ANN 1-3-6-9-1)

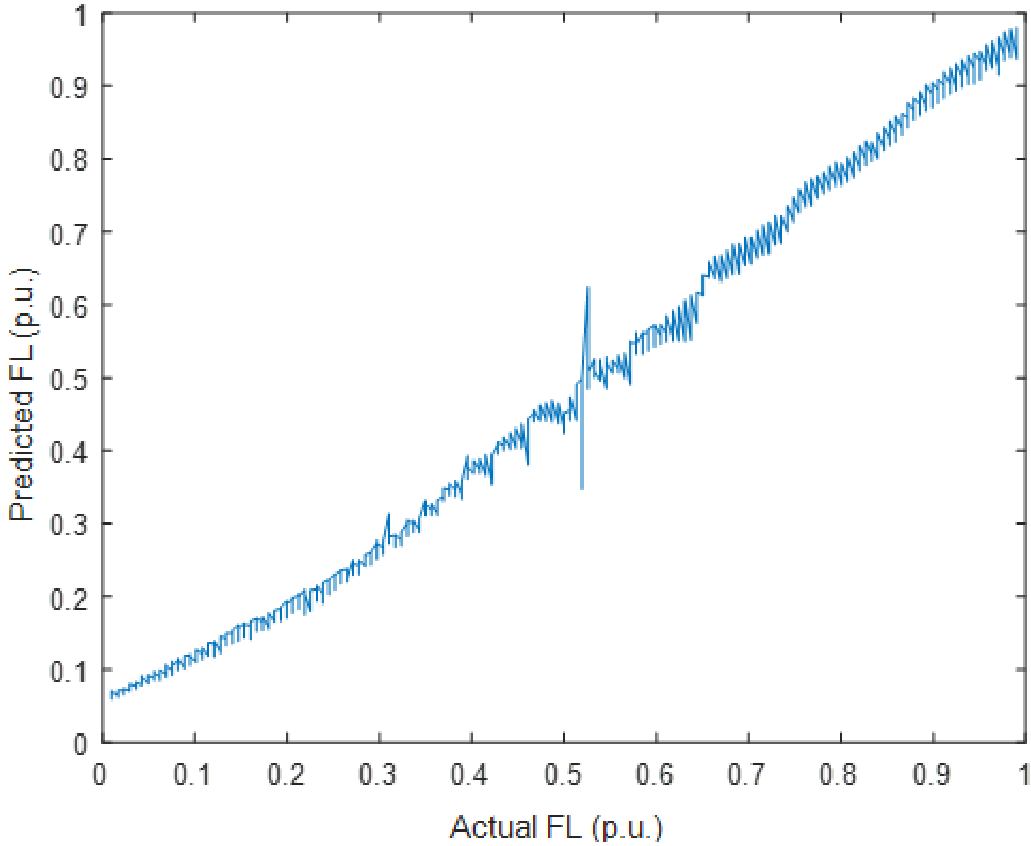

Figure 22: Fault Location error for Case 3 Preprocessing 2 (ANN 1-3-6-9-1)

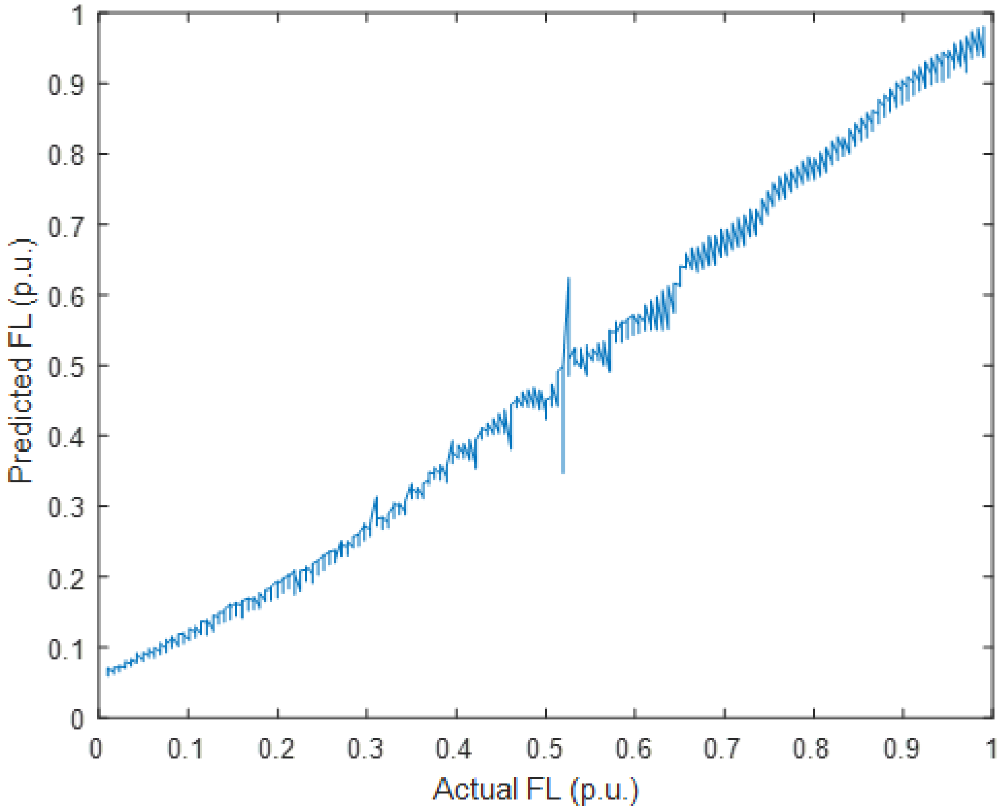

Figure 23: Fault Location error for Case 3 Preprocessing 3 (ANN 1-3-6-9-1)

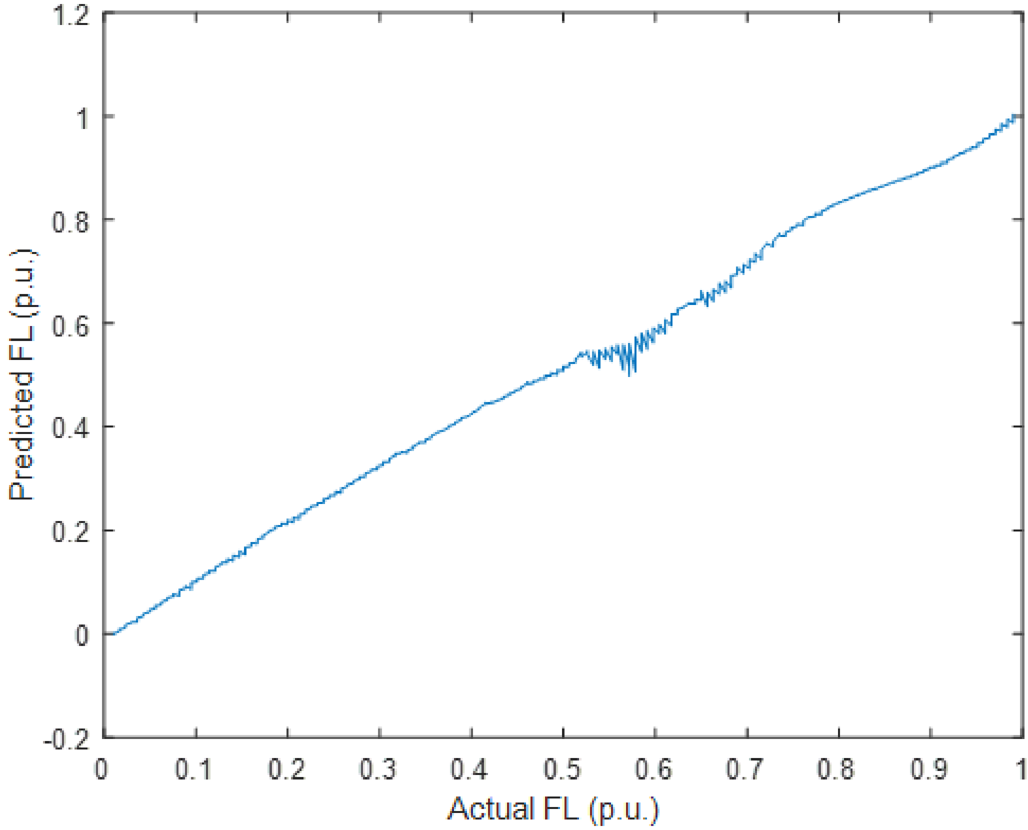

Figure 24: Fault Location error for Case 3 Preprocessing 4 (ANN 1-3-6-9-1)

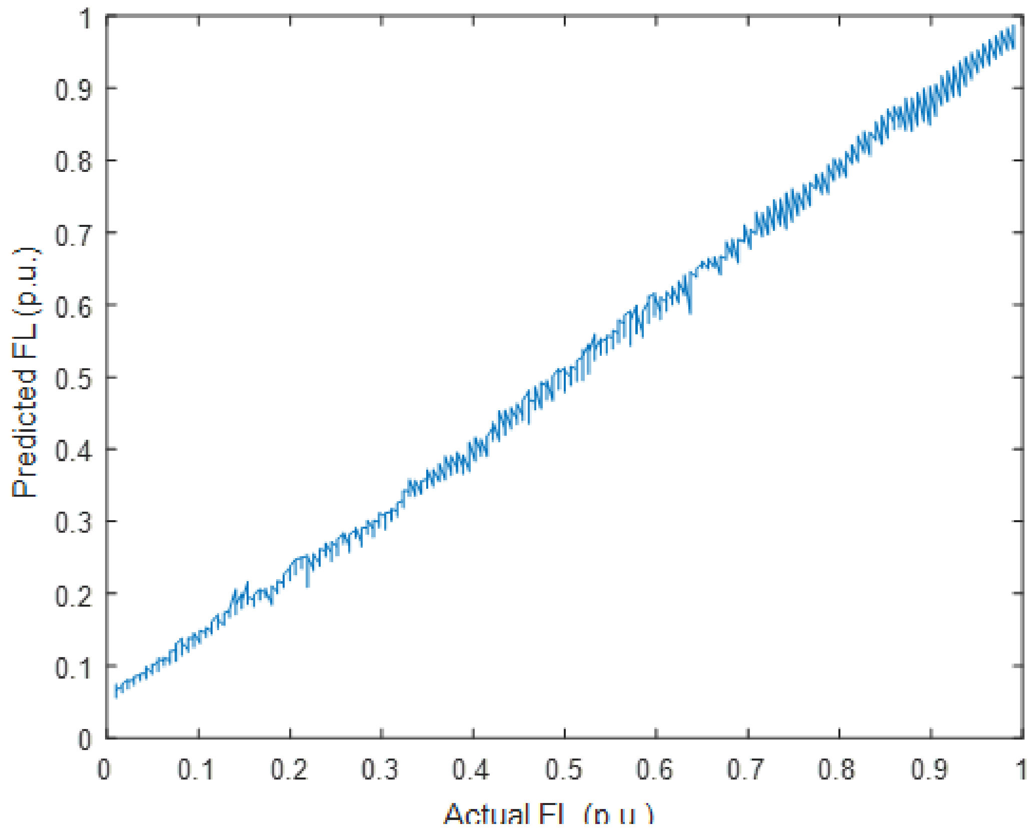

Figure 25: Fault Location error for Case 4 Preprocessing 1 (ANN 1-3-6-9-1)

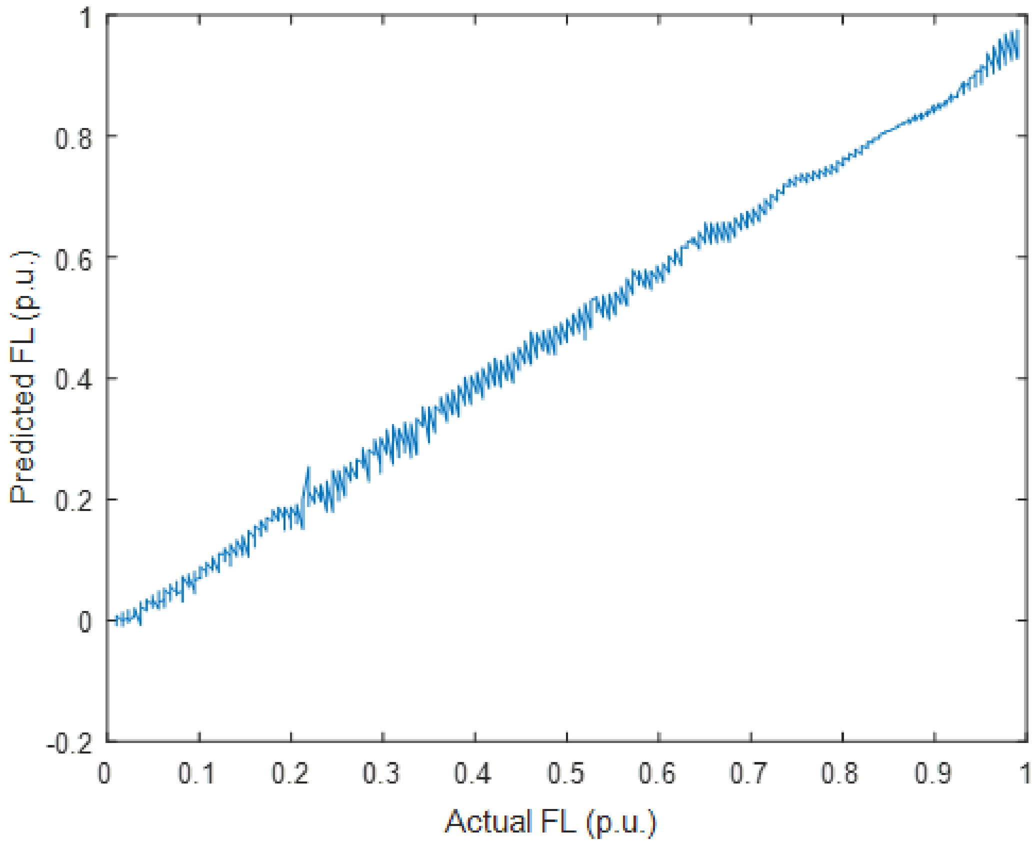

Figure 26: Fault Location error for Case 4 Preprocessing 2 (ANN 1-3-6-9-1)

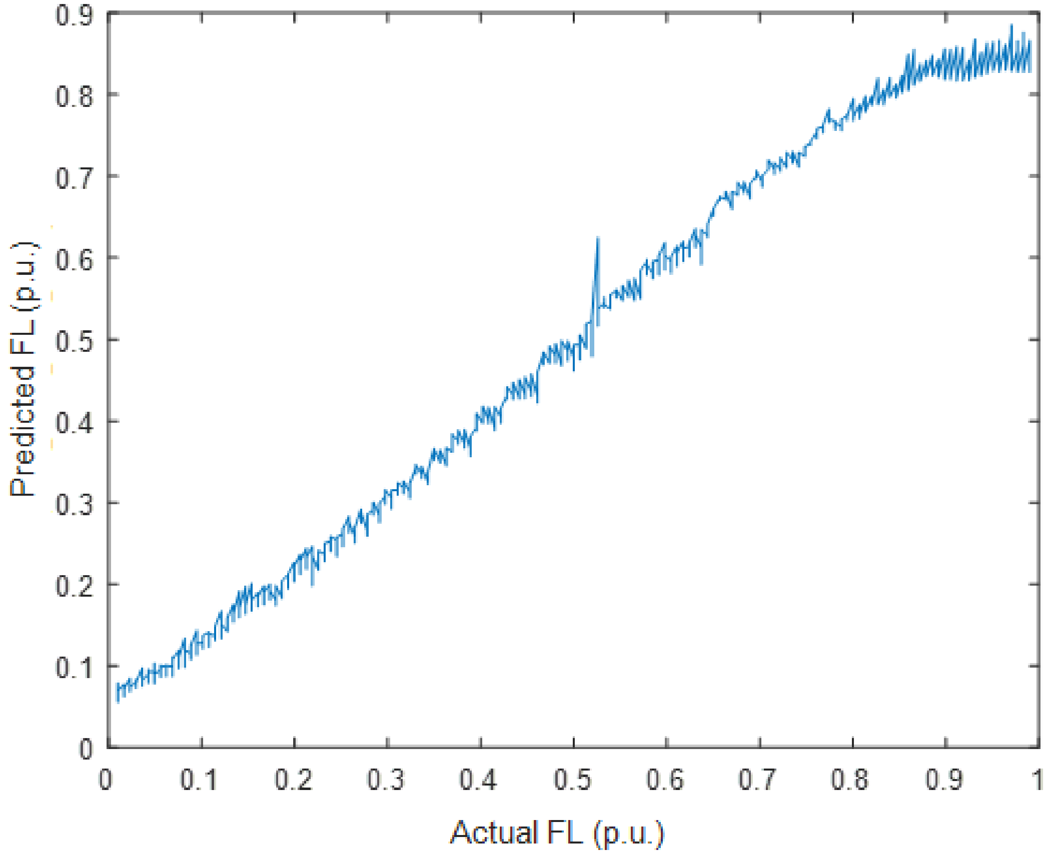

Figure 27: Fault Location error for Case 4 Preprocessing 3 (ANN 1-3-6-9-1)

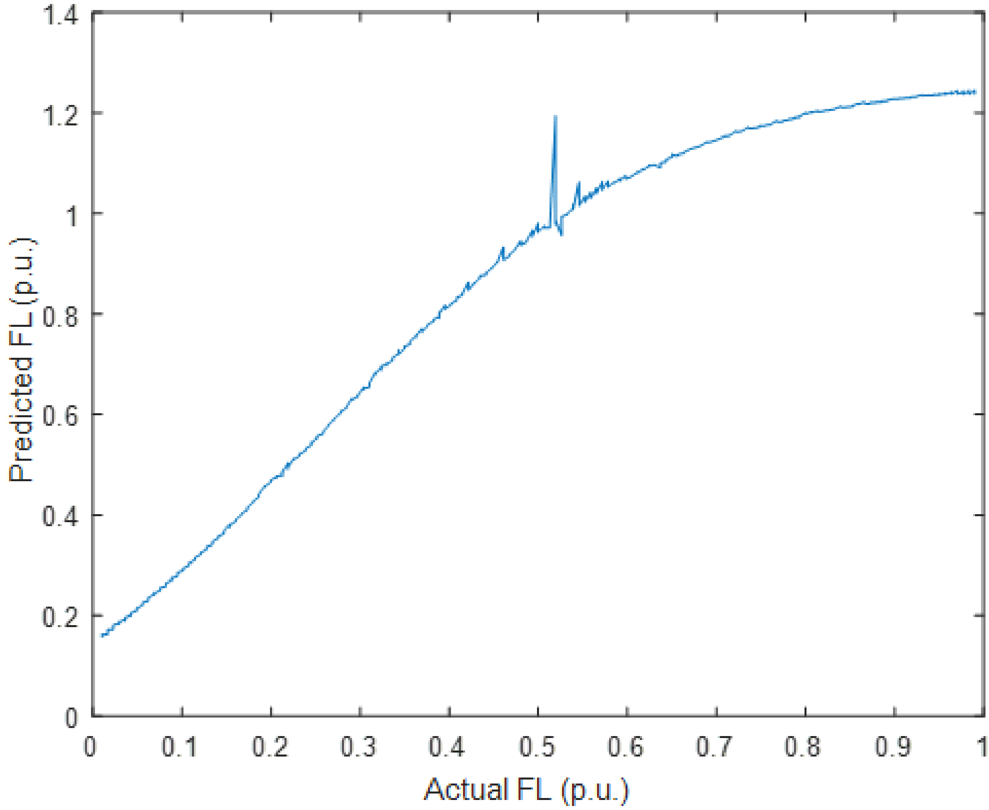

Figure 28: Fault Location error for Case 4 Preprocessing 4 (ANN 1-3-6-9-1)

CHAPTER 9. CONCLUSION

This study presents an approach to determine single phase faults on high-impedance grounded electric distribution network by implementing a feedforward neural network which is provided with training cases of an input and output dataset. Using these datasets, the network uses a combination of algorithms and training functions to develop a regression line that maps the input dataset to the output dataset. Once the training is concluded, the network is provided a new input dataset and will utilize the developed regression line from the training dataset to predict the test case output dataset. For this study, the training inputs were voltage and current signals from either terminal of the distribution line and the output dataset is the fault location on the line.

This thesis presents the effects of varying the number of input variables, the number of neurons per layer, the number of hidden layers, and the method of preprocessing the dataset prior to training and testing. It was discovered that implementing a singular training input variable and using the preprocessing method 4 (normalization + standardization + summation) presents the most accurate predictions for fault location on the distribution line.

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