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REVOLUTIONIZING FAULT DETECTION IN HIGH-VOLTAGE TRANSMISSION LINES THROUGH ANN MODELS

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Abstract

Transmission lines, critical to ensuring a constant flow of electricity, are susceptible to various problems because they are on the surface. Faults occurring in the system after relays are used to determine the type of the fault and its location. However, failures of the relays occasionally happen, and these failures can significantly impact the operation of the power system, resulting in noticeably delayed fault recovery. Advanced, efficient, and sensitive fault detection systems are necessary to overcome this issue. This study aims to propose an intelligent and automated fault detection method for a 117 km, 500 kV power system. The transmission line is simulated using MATLAB and Simulink to generate an extensive dataset. In this sense, the dataset is used to train, validate, and test an Artificial Neural Network (ANN) designed for fault detection based solely on instantaneous voltage and current measurements, as well as a multilayer ANN trained using a backpropagation algorithm. The Mean Square Error (MSE) and confusion matrix were utilized to evaluate the system's performance, achieving an MSE of 2.2498e-9 and 100% accuracy, thereby showcasing the effectiveness of the proposed NN-based algorithm in a practical application, such as transmission lines.

INTRODUCTION

Electric power transmission is the long-distance transfer of electrical energy from a power plant to a substation via a transmission network. On the other hand, electric power distribution handles the local wiring from high-voltage substations to end-users. Depending on the transmission line length and voltage levels, short lines are usually defined as lines less than 50 km long and voltages below 20 kV; medium lines are represented as lines with a length between 50 and 150 km and voltages [1] between 20 kV and 100 kV, and long lines are payment with a length greater than 150 m and voltages higher than 100 kV [2]. The faults in the power system can occur due to failures in transformers, generators, bus bars, and other components. Genetic problems, such as failures of Insulation material, can cause short circuits in conductors or interruptions in the conductor path. Under regular operation, power systems operate at balanced voltage and current levels; however, faults lead to an imbalance. Symmetrical faults are extreme but rare faults that occur in all three phases, typically caused by three-phase short circuits or ground faults, resulting in uniform fault currents with a phase shift of 120 degrees [3].

A treat line-to-ground fault (LG) is a protected condition where all three conductors fail or hit each other, impacting the phases of the system and ground terminals, with a chance of 2~3%. With uneven faults more common but less powerful, 60% to 75% of failures were single-line ground faults, 5%–15% were line-to-line faults, and 15%–25% were double line-to-ground faults [4]. Fault detection, fault classification, and fault location are all essential aspects of protection systems, which allow for the segregation of faulty lines from the grid. Essentially serving as protection and switching devices, relays respond to fluctuations in voltage and current by breaking or making connections to stop the flow of electricity in the event of a fault. Typically, such relays are characterized by distance, impedance, and mho [5] and are also utilized in power systems, as well as in residential, industrial, and digital applications. Artificial intelligence (AI) opens up new avenues for various fields, including engineering and informatics, based on the human brain's ability to recognize patterns. Artificial neural networks (ANNs), which mimic the brain's complex functions by using a network of interacting nodes, are exceptionally efficient in handling large datasets with incomplete features and solving nonlinear problems. They play essential roles in power system operations, including fault detection and power quality [6-7]. These tools include genetic algorithms, fuzzy and adaptive fuzzy logic, and expert systems. These enable power engineers to improve system reliability and efficiency. They help identify power quality issues, such as disturbance classification using fuzzy logic [8], while expert systems address harmonic distortion and damaged waveform analysis [9-10]. When properly trained, artificial neural networks (ANNs) can be utilized for prediction, estimation, classification, forecasting, and various other applications. Artificial neural networks (ANNs) can be divided into two main types: the simpler single-layer perceptron (SLP) and multilayer perceptrons (MLPs), which are more suitable for solving complex tasks [11-12]. ANN training is conducted iteratively using the backpropagation algorithm, with weights adjusted to minimize errors. Learning may be done in a supervised, unsupervised, or reinforcement manner. Also known as feed-forward networks, they process data in a straight path from input nodes to output nodes. In contrast, backpropagation networks improve weights over time through error backpropagation, with the gradient descent method being a significant aspect in current machine learning methods [13-14].

$$h_n = f(\textstyle\sum_m x_n . w_{nm} \quad (1)$$

$$h_n = f(\textstyle\sum_l h_n . w_{ml} \quad (2)$$

Where h, x, w, and y represent the hidden layer, input node, weight, and output, respectively. Next, obtain the error signal, the difference between the estimated value t and the actual value δ, and the error term for both output and hidden nodes.

$$\delta y_n = y_n(1 - y_n).(t - y_n) \ (3)$$

$$\delta h_n = h_n(1 - h_n)\delta y_n . w_{nl} \ (4)$$

Adjust all the weights in the network, from the output layer to the input layer, to propagate the error of the nodes' information, denoted as δm, back through the network.

$$\Delta w_{ml} = \eta .\ \delta y_n .\ h_n \ 3.5$$

$$\Delta w_{nm} = \eta .\ \delta h_n .\ x_n \ 3.6$$

$$new = \Delta w + w_{old} \ 3.7$$

Where η is the rate of learning $y_n = f \sum h_n$ wml 3.8

hn= f $\sum x_n\, w_4$ 3.9

In supervised learning algorithms, such as backpropagation, the process begins by propagating the inputs through the network to obtain the output. This error is computed to see if there is any difference between the predicted outputs and the desired output. The algorithm then uses this error to update the weights in the network—the parameters that determine the strength of connections between different units in the network. This allows for a reduction in the error of future outputs[15-16]: double backpropagation, with varying functions of error for the output layer and the hidden layer. The process repeats with iterations until the network performs better than a certain threshold (e.g., a low mean squared error or reaching a specified number of iterations). The article highlights that while relays are designed to detect faults in transmission lines and identify their type, they occasionally fail. This failure to detect faults can lead to significant problems across the entire power system, as the fault remains unresolved and cannot be restored or recovered within the necessary timeframe. To address this challenge, a more accurate, efficient, and sensitive system is needed. This research aims to develop an innovative, precise, and automated solution to detect faults and mitigate such issues effectively.

The main focus of the article is to

- The primary objective is to develop a robust and efficient method for identifying high-current faults in power system transmission lines. The approach aims to minimize detection time while maintaining high accuracy and promptly identifying faults to prevent widespread damage. By leveraging advanced algorithms, real-time monitoring, and intelligent systems, the research seeks to enhance the reliability of fault detection, ultimately contributing to stable performance and power grid resilience.
- This objective focuses on minimizing the time required to isolate and apparent faults in the power system. The research aims to significantly reduce system downtime and ensure an uninterrupted power supply by implementing rapid fault detection and clearance mechanisms. Faster fault resolution enhances system reliability, mitigates economic losses, and reduces operational disruptions, ultimately benefiting both utilities and end-users. The goal is to optimize fault management processes for improved grid performance.
- The research aims to enhance the overall efficiency and security of the power system by integrating advanced fault detection and clearance techniques. The approach seeks to minimize energy losses, optimize resource utilization, and prevent cascading failures by enhancing system responsiveness to faults. Additionally, the research emphasizes strengthening the power grid's security against potential threats, ensuring a stable and resilient infrastructure that can meet growing energy demands while safeguarding against vulnerabilities.

1. Literature Review

Fundamentally, the electric power system comprises generation, transmission, and distribution subsystems interconnected through power transmission lines, forming the transmission subsystem. Nevertheless, these lines are susceptible to defects with environmental effects [17-18]. Typically, the power system operates at nominal voltage and current levels. The faults, which are transmission line errors that occur between phases (within the wiring for a single incoming supply) or between the phase and the ground, mostly cause equipment overheating due to an increase in current and a voltage drop at the fault point [19-20]. They can be symmetrical and unsymmetrical [21], symmetrically unaffected and unsymmetrically affected systems such as line-to-line, line-to-ground, and double line-to-ground. Single-phase ground faults are the most common type, accounting for approximately 70% of all faults on transmission lines. 15% and 10% of overall short-circuit incidences are line-to-line and double line-to-ground faults, respectively, & the remaining 5% are three-phase faults. Artificial Neural Networks (ANNs) are utilized due to their generalization capability, noise immunity, robustness, and fault tolerance, which enhance the value of the protection system, thereby preventing a slight change in system properties from severely impacting system performance. With their prominence in all power system applications [22-23], they are primarily known for their high computational speed and ability to manage nonlinear and incomplete data. These networks, known as biological neurons, learn nonlinear input-output mappings and are widely used for classification, recognition, optimization, prediction, and control. All ANN applications effectively perform vector mapping, though they may differ structurally and in training methods [24]. An ANN model consists of interconnected nodes resembling brain neurons, organized into input, hidden, and output layers [25-26]. This sentence describes the process in detail: training begins with an Excel sheet, where inputs are multiplied by weights and biases and then activated in multiple layers, resulting in an output that is compared to the target output. This feedforward process progresses from the input to the output layers. At the same time, backpropagation is used to modify weights in response to errors, utilizing activation functions such as the sigmoid in the hidden and output layers but not in the input layer (Chen et al., 2023). Below is an illustration of how the model works [28].

ANNs can generalize, resist noise, and are robust and fault-tolerant, making them useful for power system applications. This work focuses on developing a SCADA-like system for detecting and localizing AC grid and HVDC faults using artificial neural networks (ANNs) [29-30].

2. Materials and Methods

As discussed in the previous section, the protection of transmission lines has been implemented for the artificial neural network. NN is widely used due to its capability to address desertion for clever attacks and the challenges of the transmission line. In object detection under complex elementary failure conditions, an artificial neural network employs several algorithms. [60] ANN to detect faults during a fault in an overhead transmission line in this desertion. This paper strongly recommends a specific type of neural network-based algorithm for analyzing abnormalities in power transmission lines. A case in point is a 500 kV transmission line between Tarbella and the Sheikh Muhammad Grid Station, spanning 117 km in length. This line was then mirrored in Simulink, where all parameters were set accordingly. Given these faults, numerous graphs were produced to be evaluated against them, such as L-G, L-L, L-L-G, and others. In each fault instance, the GM graph was chosen to match the variation in length. Multiple samples (I, V) were analyzed per fault, including both faulty and non-faulty 3-phase current and voltage measurements. This data was aggregated and compiled into an Excel file to create the dataset for training and testing on a model. This data was then used as input in the Simulink workspace, which provided unique codes (one for each fault type) as output. The final step was to run the ANN tool, which trained the ANN using both faulty and non-faulty data, ultimately determining the defective condition.

2.1. ANN Design for Fault Detection

The ANN classifier applied for fault diagnosis is presented in Figure 1. The network is constructed with six inputs, comprising three-phase currents and voltages. It consists of 700 training samples for both input and output, respectively, which equals 100 samples for each of the nine faults and the fault-free condition. Table I indicates whether 1 represents a fault or 0 represents no fault for the target outputs of the data. Figure 3.1 illustrates that the architecture comprises an input layer with six neurons, a hidden layer with ten neurons, and an output layer with a single neuron. Hidden and output layers use tan-sigmoid and linear transfer functions, respectively. A training algorithm, such as the Levenberg-Marquardt algorithm, successfully diagnosed faults during testing [13].

Diagnosed the faults during testing [13].

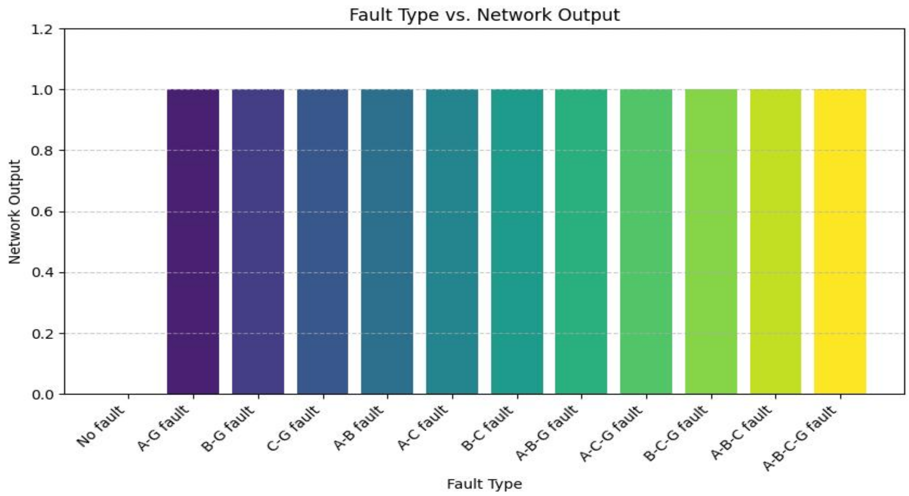
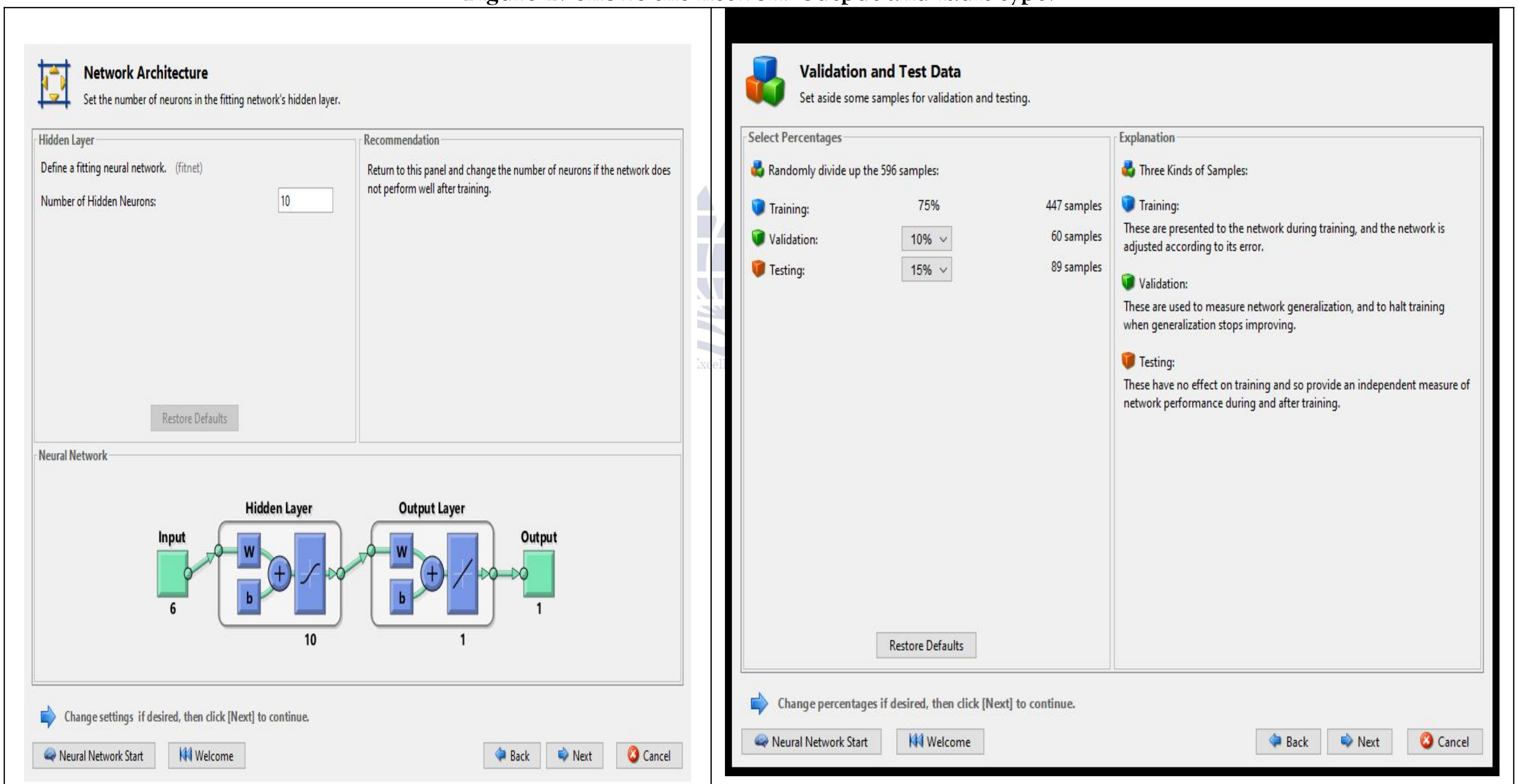


Figure 1. Shows the network output and fault type.



(a) (b)

Figure 2. Shows the network architecture and data set training, test, and validation

2.2. Data generation

The data used in this study include input and target values arranged in an Excel sheet to train an artificial neural network (ANN). Such training helps the NN recognize the intricate relationship between input and target data. The input data must be appropriately formatted for the training to be practical, so the answer is yes. This dataset was created using a simulated modeling approach in MATLAB, which allowed for the controlled synthesis of environmental data. Such a methodology helps establish the correctness of the data and the proper functioning of the neural network predicting patterns.

2.3. Simulation model

The system implemented here uses a 500 kV transmission line to improve the systematic application of ANNs. The simulations and modeling were performed using SunPower Systems in MATLAB/Simulink 2017a. The model is created based on the system's architecture to depict and examine it accurately. Below is a screenshot of the model running. Additionally, Figure 3.3 provides a comprehensive breakdown of the complete dataset used for the ANN training, validation, and testing phases.

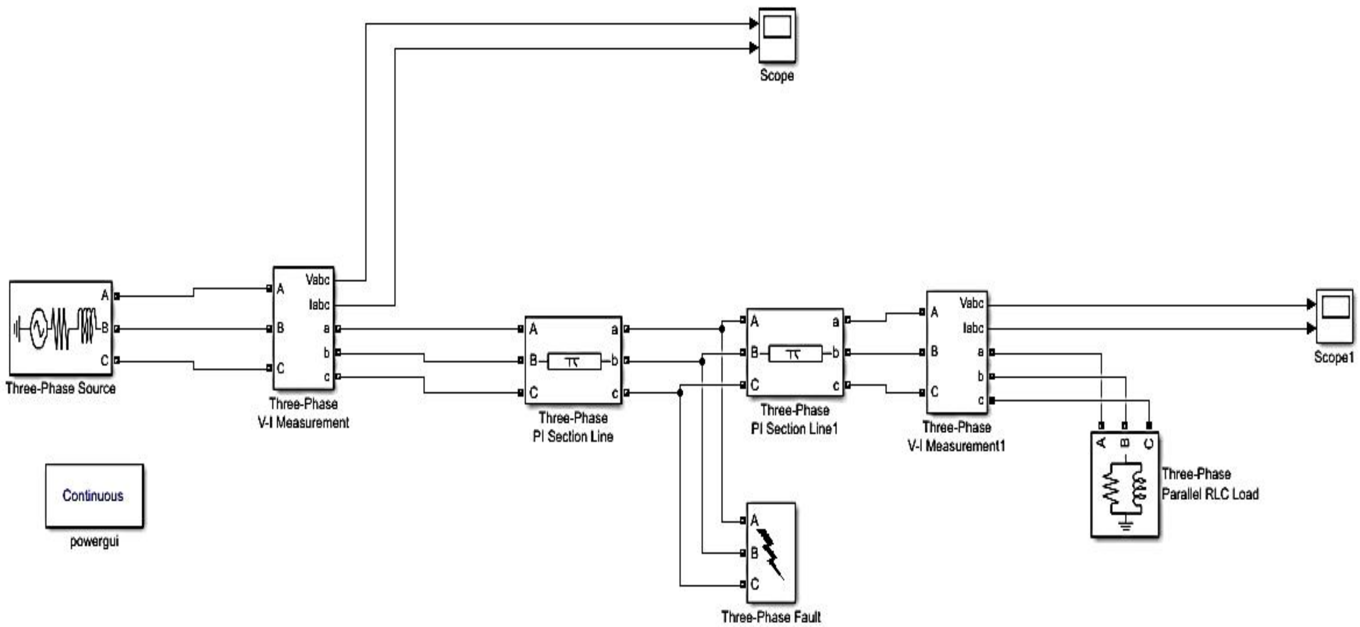


Figure. 3. The Simulink model for the simulation

The methodology begins by designing the power transmission system, where relevant physical and operational features are defined. This covers the types of conductors, towers, insulation, and routing of transmission lines. These design parameters are important because they must conform to the standard of capacity and reliability to build a stable and efficient power distribution. Let's define the system: After the initial design, important power system parameters, including voltage and current, are accurately controlled according to different load requirements and operation modes. The protocols allow for necessary adjustments based on the diverse electrical demands of the system, which are essential for optimizing performance under different circumstances. A comprehensive dataset is generated, containing tightly recorded voltage and current measurements across various scenarios, utilizing well-optimized parameters. These scenarios encompass normal operations and simulate peak and low-demand conditions, providing a comprehensive view of system behavior across various operational conditions.

Then, the data captured is categorized according to different line conditions, i.e., Line to Ground, Line to Line, and double Line to Ground faults. These conditions are divided into symmetrical and asymmetrical when the system parameters are balanced. This classification is an intermediate step necessary for the next part of the methodology, where ANN models will be utilized. All classified data sets were formatted properly as ANN input, including standard and faulty operational data. This helps train and test the neural network, enabling it to learn effectively to distinguish between different operational states and fault conditions.

The ANN is then trained in three independent steps: Training, Testing, and Validation. Training step:

The network is trained on the data, allowing the model to learn by updating its weights and biases to minimize the error between actual and predicted output values. During the testing stage, a different data subset is used to evaluate the network's predictive accuracy. Finally, the validation process evaluates how well the ANN can generalize to novel or unseen situations and how well it will perform across a range of operational conditions. The Results and Discussion section presents the results of using the ANN in our power system model. The results show the ability of ANN to identify complex types of faults and abnormalities in operation. The proposed approach offers significant improvements in both response times and diagnostic accuracy compared to traditional diagnostic techniques, further demonstrating the potential of utilizing machine learning technologies to manage power systems. The study concludes by stating that the combined use of ANNs in designing and operating power system transmission lines represents a new frontier in electrical engineering. This approach enhances fault identification and system visibility while also playing a crucial role in the reliability and efficiency of power distribution networks, which are essential for the sustainable and secure operation of electrical power systems.

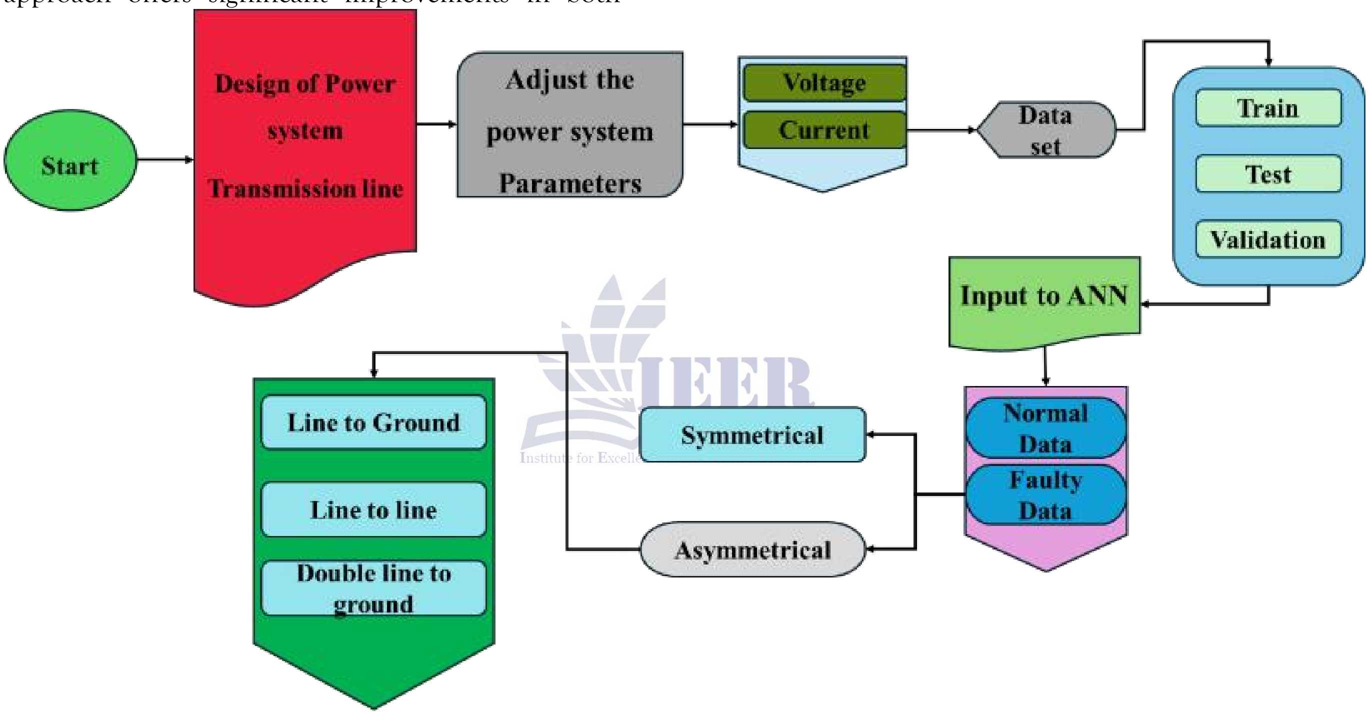


Figure 4. Proposed methodology for the research

3. SIMULATION RESULTS

3.1. Fault Simulation:

The results obtained from fault simulation are shown in Figure 4 for the single-line-to-ground fault, as listed in Table 1. There are successive changes in V(voltage) and I(current) values shown in Figure 1, where a-v fault for phase A of equivalents to work has been short-circuited to earth, shown in F waveforms. This arrangement holds for both line-to-line and multiple faults across phases in the simulation. Note: All types of charts and their respective values are stored in the Value section of Excel. 4.2 V and I Signals Without a Fault and With a Fault —The impact of a fault in the transmission line on the quality of the current and voltage signals has been noted in the previous section. The voltage drops, and the current surges to levels that can harm power system equipment and devices during a fault. From Fig: 4.1 to 4.6, table 4.1 to 4.6, detailed data on all types of faults and their waveforms are given.

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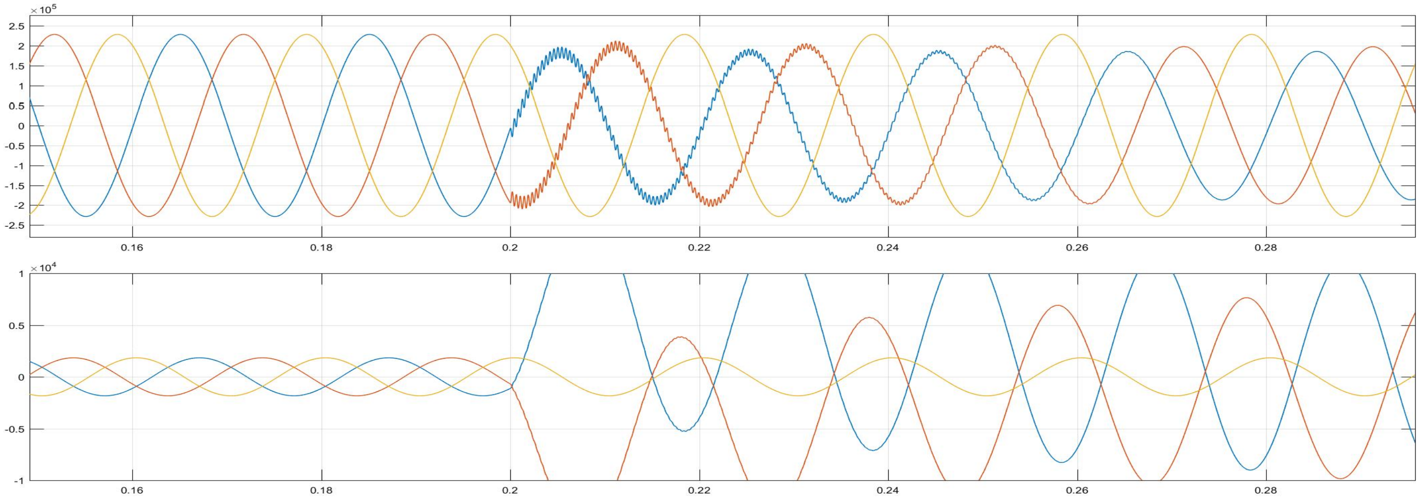

Figure .5. Current and voltage waveform with A to B

Table 1: Data for AB Short Circuit Fault about Distance Variation.

S#	D#	V_y	V_b	V_r	I_y	I_b	I_r
1	30	228600	228600	228600	24570	13090	1917
2	30.5	228600	228600	228600	24340	12940	1915
3	31	228600	228600	228600	24120	12790	1913
4	31.5	228600	228600	228600	23880	12640	1912
5	32	228600	228600	228600	23660	12500	1910
6	32.5	228600	228600	228600	23450	12360	1908
7	33	228600	228600	228600	23241	12220	1907
8	33.5	228600	228600	228600	23020	12090	1905
9	34	228600	228600	228600	22820	11960	1903
10	34.5	228600	228600	228600	22620	11820	1902
11	35	228600	228600	228600	22420	11700	1900
12	35.5	228600	228600	228600	22220	11570	1899
13	36	228600	228600	228600	22020	11450	1897
14	36.5	228600	228600	228600	21840	11330	1895
15	37	228600	228600	228600	21660	11210	1894
16	37.5	228600	228600	228600	21480	11100	1892
17	38	228600	228600	228600	21290	10990	1890
18	38.5	228600	228600	228600	21110	10880	1889
19	39	228600	228600	228600	20950	10770	1887
20	39.5	228600	228600	228600	20780	10660	1885
21	40	228600	228600	228600	20610	10560	1884
22	40.5	228600	228600	228600	20440	10450	1882
23	41	228600	228600	228600	20270	10350	1880
24	41.5	228600	228600	228600	20120	10250	1879
25	42	228600	228600	228600	19970	10150	1877
26	42.5	228600	228600	228600	19810	10060	1876
27	43	228600	228600	228600	19660	9963	1874
28	43.5	228600	228600	228600	19500	9870	1872

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29	44	228600	228600	228600	19350	9779	1871
30	44.5	228600	228600	228600	19210	9689	1869
31	45	228600	228600	228600	19070	9600	1867
32	45.5	228600	228600	228600	18930	9514	1866
33	46	228600	228600	228600	18790	9428	1864
34	46.5	228600	228600	228600	18650	9344	1863
35	47	228600	228600	228600	18510	9261	1861
36	47.5	228600	228600	228600	18370	9180	1859
37	48	228600	228600	228600	18250	9100	1858
38	48.5	228600	228600	228600	18120	9021	1856
39	49	228600	228600	228600	18000	8943	1854
40	49.5	228600	228600	228600	17870	8867	1853
41	50	228600	228600	228600	17750	8791	1851
42	50.5	228600	228600	228600	17620	8717	1850
43	51	228600	228600	228700	17490	8644	1848
44	51.5	228600	228600	228700	17370	8573	1846
45	52	228600	228600	228700	17260	8502	1845
46	52.5	228600	228600	228700	17150	8433	1843
47	53	228600	228600	228700	17040	8364	1842
48	53.5	228600	228600	228700	16930	8297	1840
49	54	228600	228600	228700	16820	8230	1838

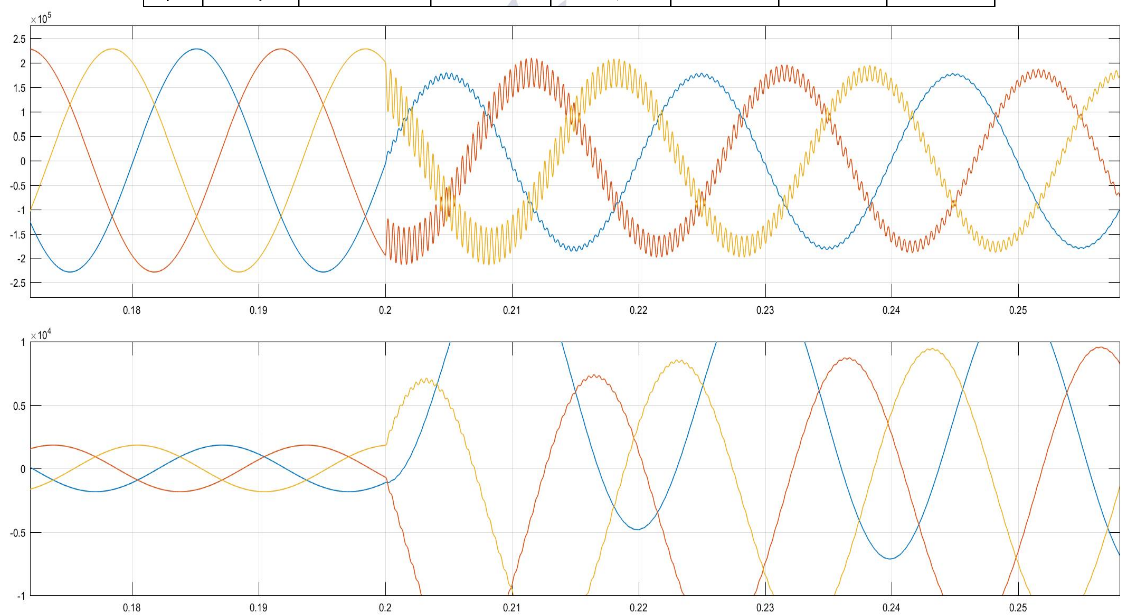


Figure 6: Current and voltage waveform with A-B-C

Table 2: Data for ABC Short Circuit Fault about Distance Variation.

S#	D#	V_y	V_b	V_r	I_y	I_b	I_r
1	30	228600	228600	228600	28580	16260	16050
2	30.5	228600	228600	228600	82300	16080	15870
3	31	228600	228600	228600	28020	14890	15180
4	31.5	228600	228600	228600	27740	15740	15530
5	32	228600	228600	228600	27480	15580	15370
6	32.5	228600	228600	228600	27210	15420	15210
7	33	228600	228600	228600	26940	15250	15050
8	33.5	228600	228600	228600	26690	15110	14910
9	34	228600	228600	228600	26440	14940	14760
10	34.5	228600	228600	228600	26180	14800	14610
11	35	228600	228600	228600	25950	14660	14470
12	35.5	228600	228600	228600	25720	14500	14330
13	36	228600	228600	228600	25480	14000	13720
14	36.5	228600	228600	228600	25240	14220	14050
15	37	228600	228600	228600	25020	14080	13920
16	37.5	228600	228600	228600	24800	13950	13790
17	38	228600	228600	228600	24580	13820	13650
18	38.5	228600	228600	228600	24360	13710	13550
19	39	228600	228600	228600	24160	13570	13410
20	39.5	228600	228600	228600	23950	13090	12840
21	40	228600	228600	228600	23750	13320	13160
22	40.5	228600	228600	228600	23530	13200	13050
23	41	228600	228600	228600	23350	13080	12940
24	41.5	228600	228600	228600	23160	12160	12820
25	42	228600	228600	228600	22960	12490	12720
26	42.5	228600	228600	228600	22770	12740	12600
27	43	228600	228600	228600	22580	12630	12520
28	43.5	228600	228600	228600	22410	12160	11970
29	44	228600	228600	228600	22230	12420	12300
30	44.5	228600	228600	228600	22050	11960	12200
31	45	228600	228600	228600	21870	11840	12090
32	45.5	228600	228600	228600	21590	11750	12000
33	46	228600	228600	228600	21530	12000	11900
34	46.5	228600	228600	228600	21370	11910	11790
35	47	228600	228600	228600	21210	11460	11720
36	47.5	228600	228600	228600	21040	11370	11620
37	48	228600	228600	228600	20880	11610	11520
38	48.5	228600	228600	228600	20710	11530	11440
39	49	228600	228600	228600	20560	11090	11360
40	49.5	228600	228600	228600	20420	11000	11260
41	50	228600	228600	228600	20270	11250	11170
42	50.5	228600	228600	228600	20120	10280	10720
43	51	228600	228600	228600	19970	11080	11000
44	51.5	228600	228600	228600	19820	11000	10920

45	52	228600	228600	228600	19670	10570	10850
46	52.5	228600	228600	228600	19540	10490	10760
47	53	228600	228600	228600	19410	10420	10700
48	53.5	228600	228600	228600	19270	10680	10620
49	54	228600	228600	228600	19140	10250	10170
50	54.5	228600	228600	228600	19000	10510	10470
51	55	228600	228600	228600	18860	10430	10380

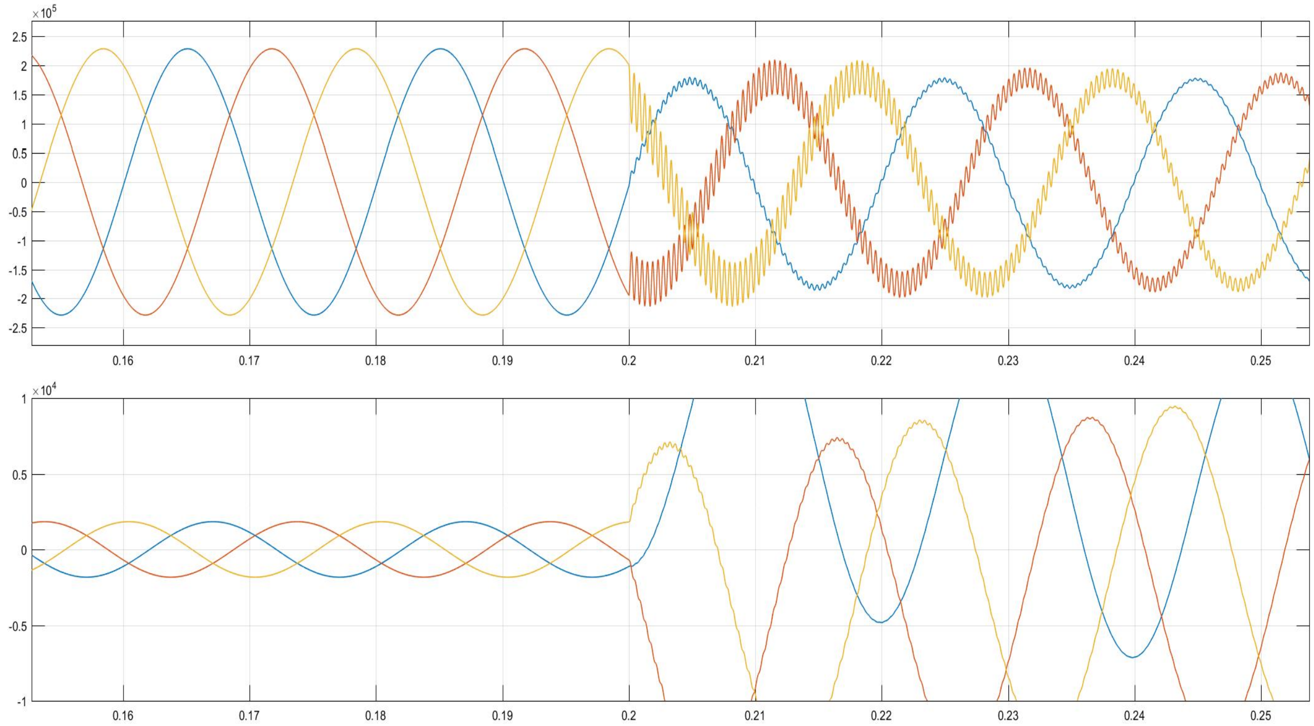


Figure 7: Current and voltage waveform with A-B-C-G

Table 3: Data for ABC Phase-to-Ground Fault about Distance Variation

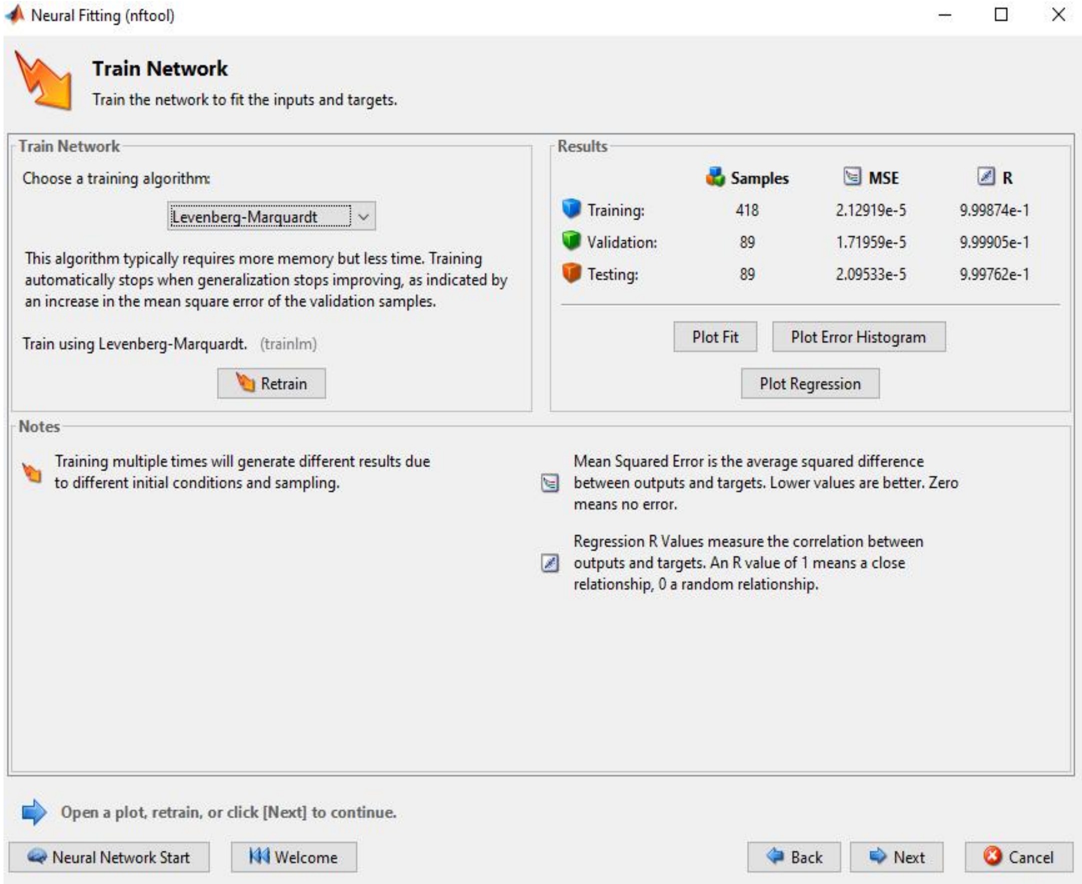
S#	D#	V_y	V_b	V_r	I_y	I_b	I_r
1	30	228600	228600	228600	28580	15900	15510
2	30.5	228600	228600	228600	28300	15710	15870
3	31	228600	228600	228600	28010	15540	15590
4	31.5	228600	228600	228600	27740	15360	15530
5	32	228600	228600	228600	27470	15210	14840
6	32.5	228600	228600	228600	27210	15050	15220
7	33	228600	228600	228600	26940	15250	15050
8	33.5	228600	228600	228600	26690	15100	14900
9	34	228600	228600	228600	26440	14470	14250
10	34.5	228600	228600	228600	26180	14430	14610
11	35	228600	228600	228600	25950	14280	14460
12	35.5	228600	228600	228600	25720	14510	14330
13	36	228600	228600	228600	25470	14000	13700
14	36.5	228600	228600	228600	25240	13850	14050

15	37	228600	228600	228600	25020	13730	13930
16	37.5	228600	228600	228600	24800	13580	13790
17	38	228600	228600	228600	24580	13450	13660
18	38.5	228600	228600	228600	24360	13340	13070
19	39	228600	228600	228600	24160	13560	13410
20	39.5	228600	228600	228600	23250	13070	13290
21	40	228600	228600	228600	23740	12960	13170
22	40.5	228600	228600	228600	23530	12830	12600
23	41	228600	228600	228600	23350	12720	12500
24	41.5	228600	228600	228600	23160	12610	12380
25	42	228600	228600	228600	22960	12490	12710
26	42.5	228600	228600	228600	22770	12380	12610
27	43	228600	228600	228600	22580	12280	12060
28	43.5	228600	228600	228600	22410	12160	11970
29	44	228600	228600	228600	22230	12070	11870
30	44.5	228600	228600	228600	22050	11950	12190
31	45	228600	228600	228600	21870	11850	11090
32	45.5	228600	228600	228600	21690	11750	11990
33	46	228600	228600	228600	21530	11640	11900
34	46.5	228600	228600	228600	21370	10980	11390
35	47	228600	228600	228600	21200	11460	11290

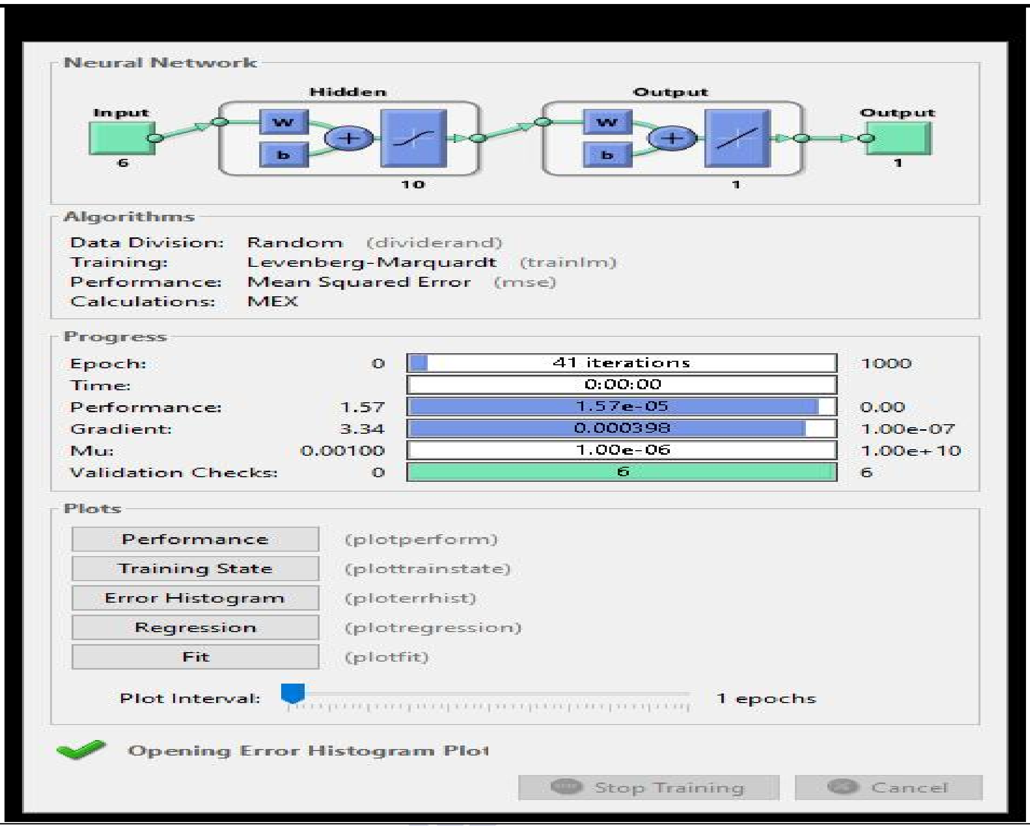
The multi-layer Feedforward Artificial Neural Network (ANN) is an extensively used model for classifying faults. Selecting the best-performing network architecture is a complex process that involves several key factors. These include the number of units in the network, the size of the training dataset, and the type of learning strategy used. The back-propagation algorithm is known to have an optimal topology, a determination resulting from significant trial and error. This paradigm, the slowest learning model among its contemporaries, is distinguished by its ability to optimize and improve. A critical approach to enhancing performance is the implementation of the Levenberg-Marquardt optimization technique. Additionally, it is crucial to select the exemplary architecture and determine the appropriate network sizing. This action significantly accelerates the training phase and enhances the computational power of neural networks, thereby enabling them to solve complex problems. In the study "Fault Detection Using ANN," the initial stage involves identifying faults by simultaneously inputting six variables into the network. These inputs comprise currents and voltages from three phases. We examined symmetric and asymmetric instances of abnormal conditions alongside a case without faults, resulting in 55 data samples per scenario. Ultimately, 700 samples were collected across all scenarios, forming a dataset used to train the neural network (NN). This dataset encompasses approximately 700 sets of inputs and outputs, where each pair consists of six inputs and a single output. The output indicates the presence of a fault, denoted by 1, or its absence, denoted by 0. Initially, the ANN was trained using a 6-10-1 configuration, and the results, including performance and correlation metrics, were detailed in Figures 8 to 11. Subsequently, the network was trained using a 6-12-1 configuration to improve performance and correlations.

After several training sessions, the 6-8-1 ANN configuration emerged as the most effective for fault detection, achieving a Mean Squared Error (MSE) of 2.2498 × 10^ (-9), which is significantly below the preset threshold of 0.0001, as illustrated in Fig. 4.3(c). This indicates that the training, testing, and validation phases were aligned, and learning was effective due to their shared characteristics and a commitment to learning across all stages. The correlation measurements revealed an ideal relationship between the outputs and targets (R = 1), as depicted in Fig. 4 .3 (d). The ANN's fault detection precision reached 100%, verified by a confusion matrix that showed no misclassifications in its red section, underscoring the model's accuracy in fault detection.

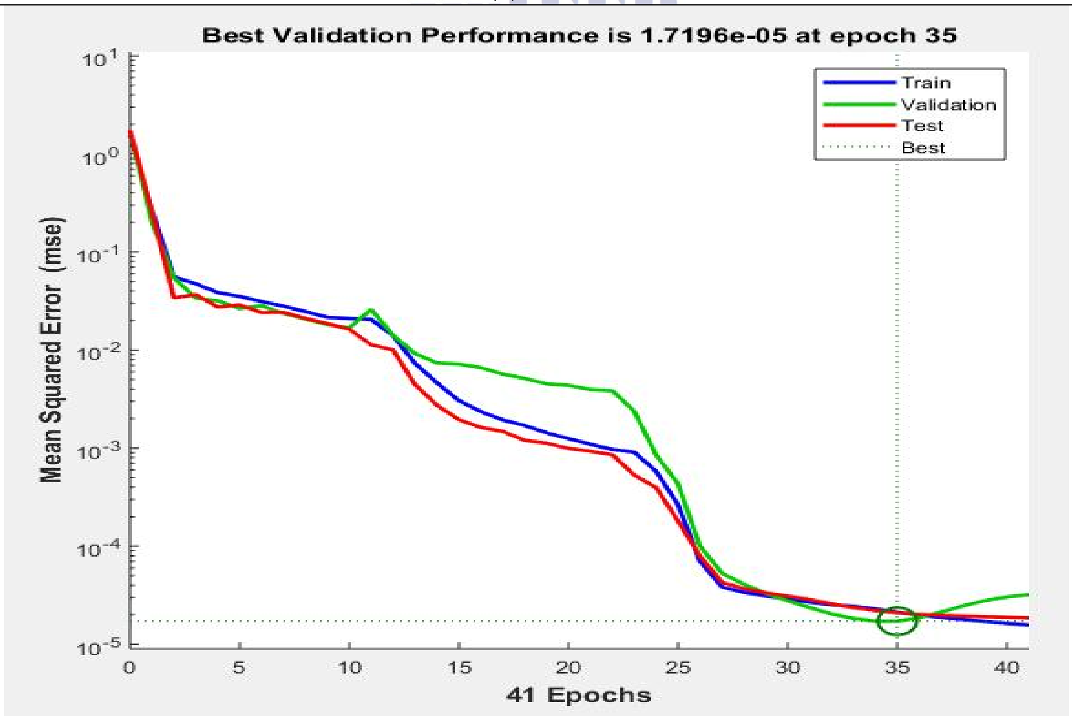
1st attempt



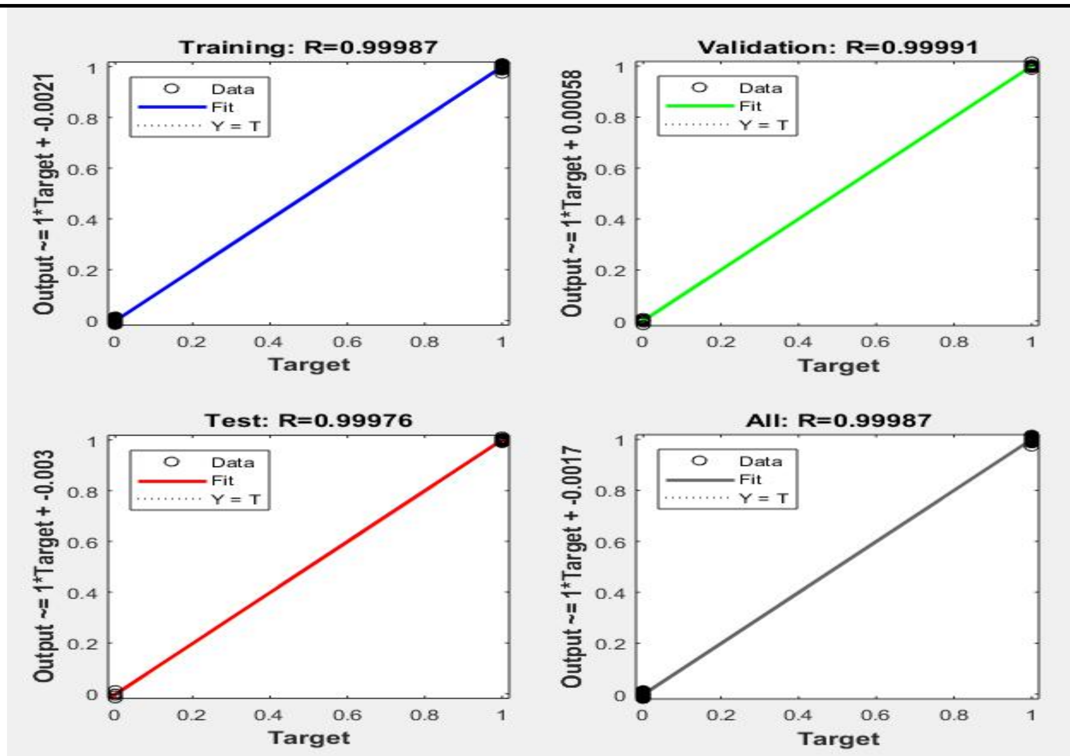
(a)


Neural Network
Hidden
Output
Input
Output
6
10
1
1
Algorithms
Data Division: Random (dividerand)
Training: Levenberg-Marquardt (trainlm)
Performance: Mean Squared Error (mse)
Calculations: MEX
Progress
Epoch: 0 41 iterations 1000
Time: 0:00:00
Performance: 1.57 1.57e-05 0.00
Gradient: 3.34 0.000398 1.00e-07
Mu: 0.00100 1.00e-06 1.00e+10
Validation Checks: 0 6 6
Plots
Performance (plotperform)
Training State (plottrainstate)
Error Histogram (ploterrhist)
Regression (plotregression)
Fit (plotfit)
Plot Interval: 1 epochs
Opening Error Histogram Plot
Stop Training
Cancel

(b)


Best Validation Performance is 1.7196e-05 at epoch 35
Train
Validation
Test
Best
Mean Squared Error (mse)
41 Epochs

(c)



(d)

Figure 8: (a) ANN Training Architecture, (b) Trained ANN Model, (c) ANN Performance Evaluation, (d) Correlation Graphs.

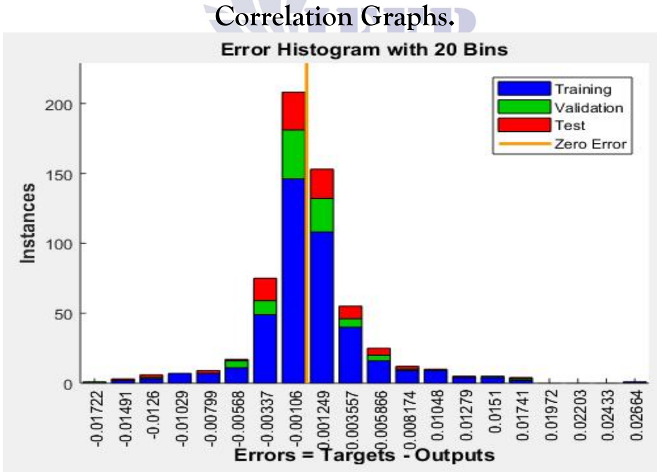


Figure 9 displays a histogram of errors.

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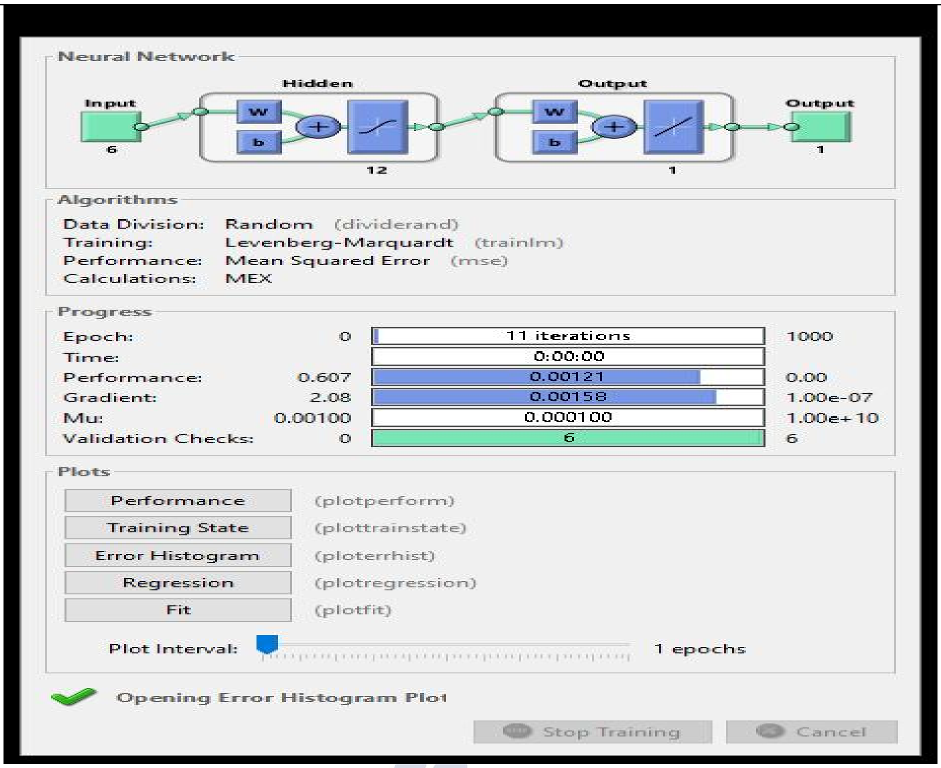
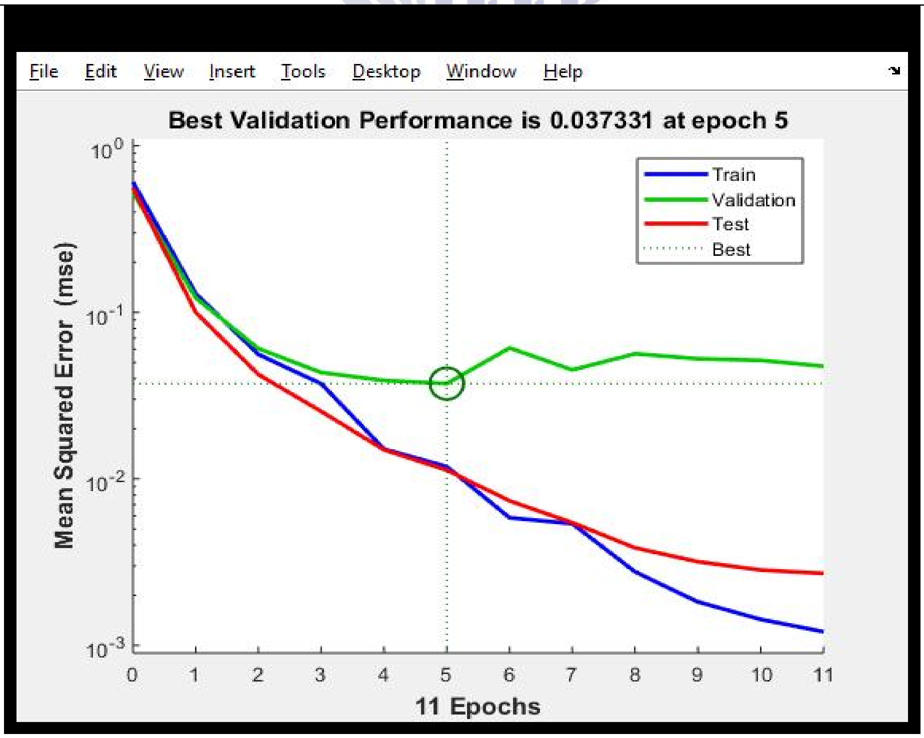
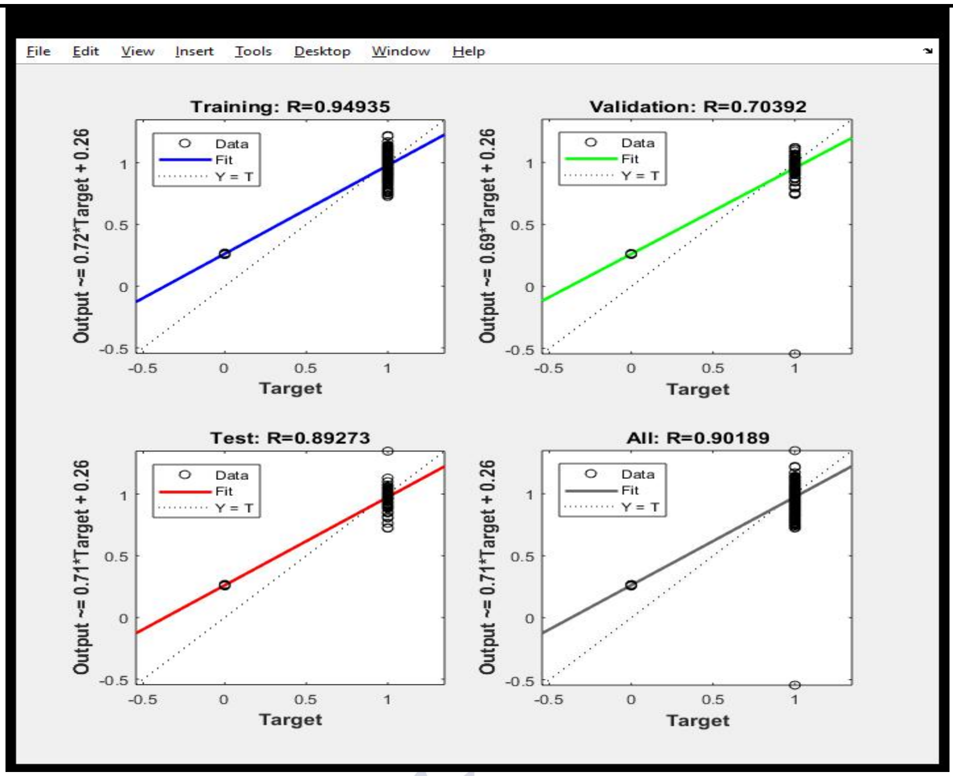
2nd Condition



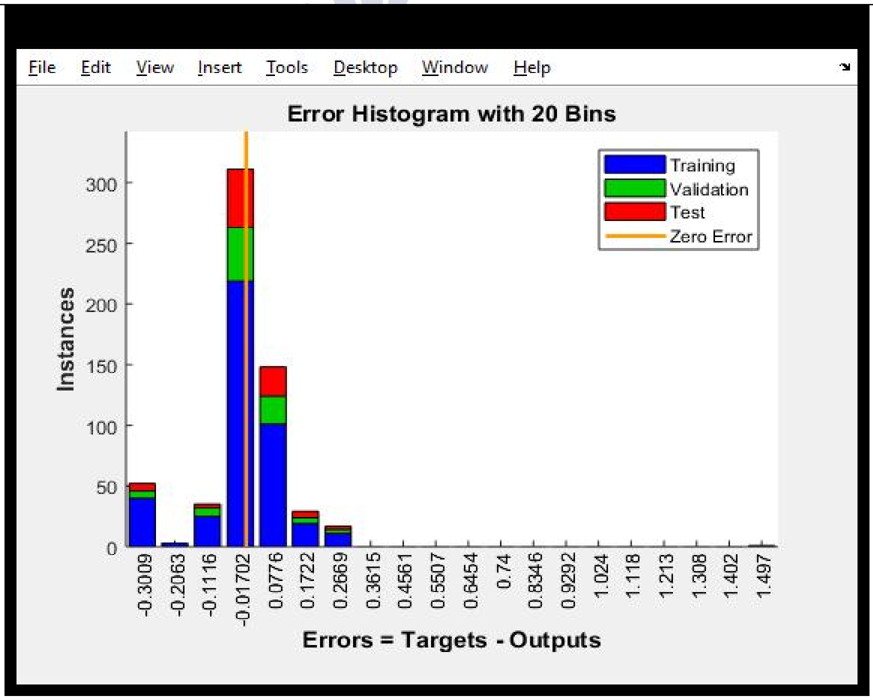
(a)



(b)



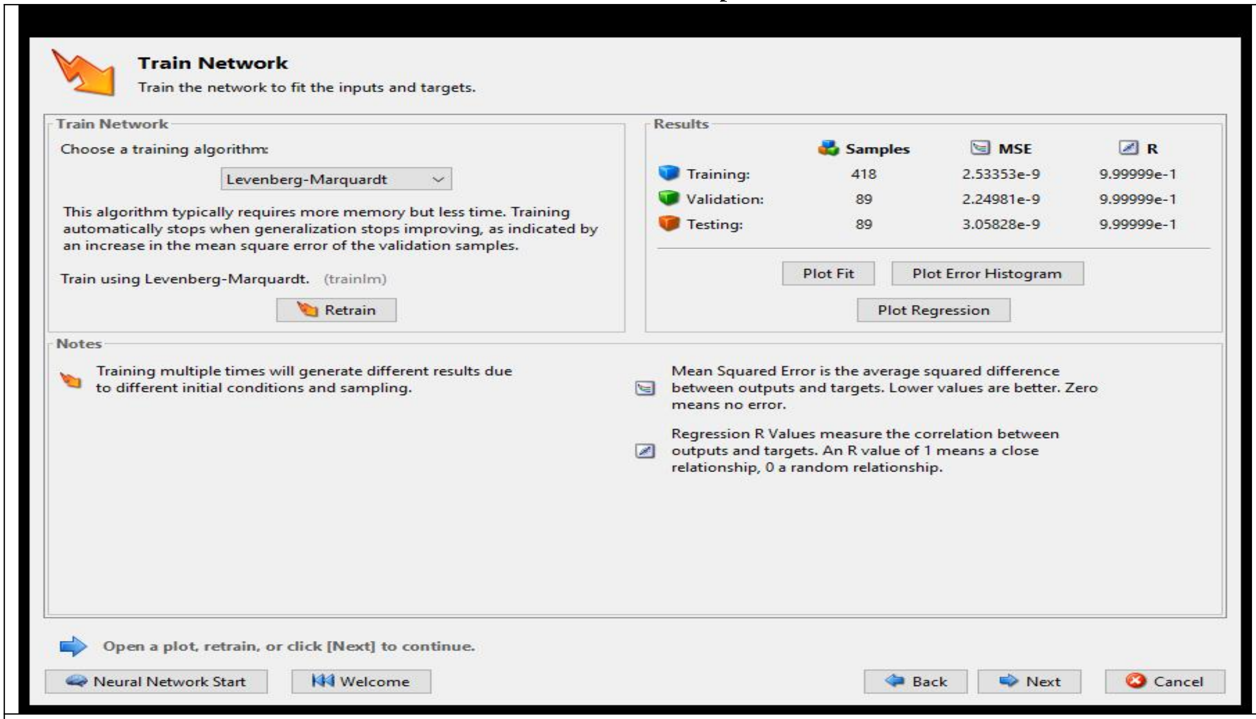
(c)



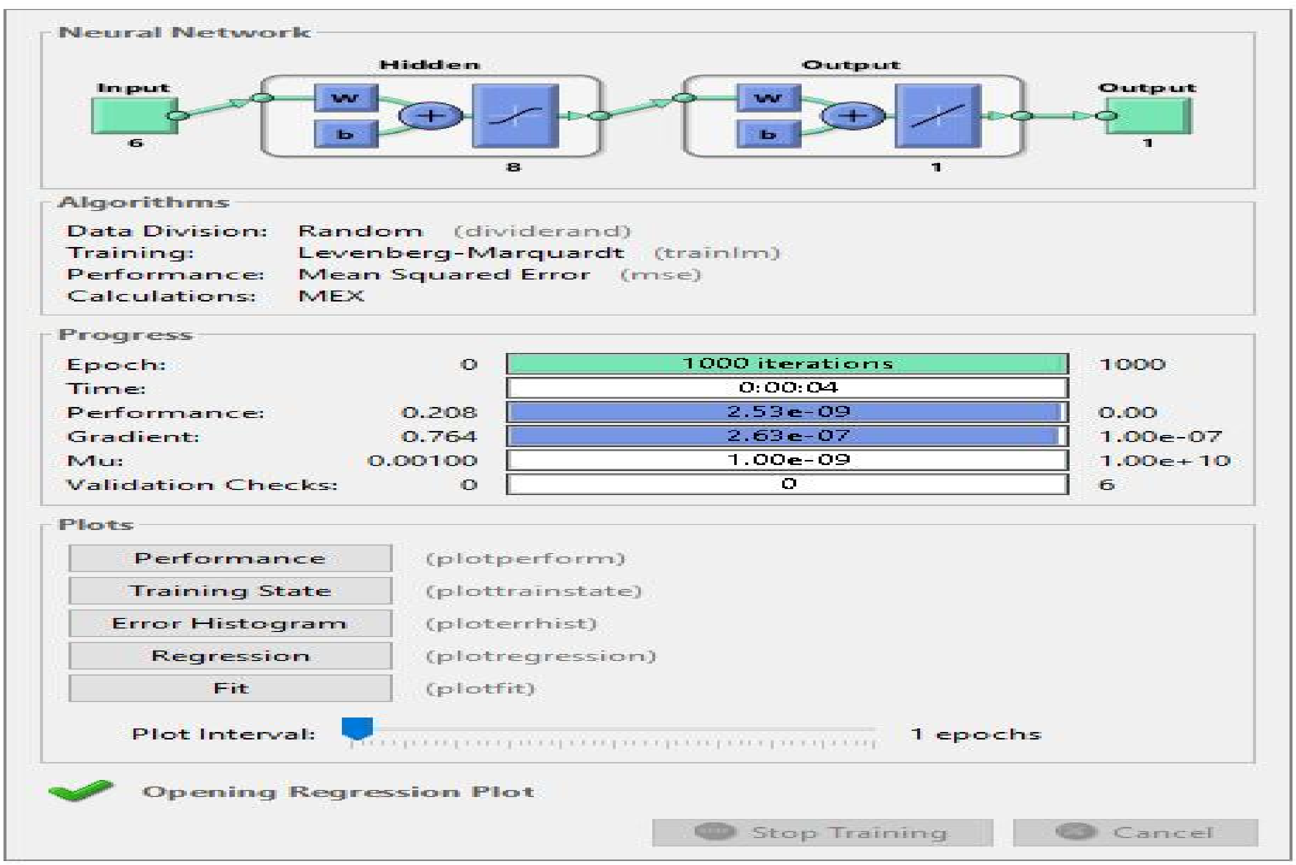
(d)

Figure 10 includes (a) the architecture of the trained artificial neural network (ANN), (b) the performance of the ANN, (c) graphs showing correlations, and (d) a histogram of errors.

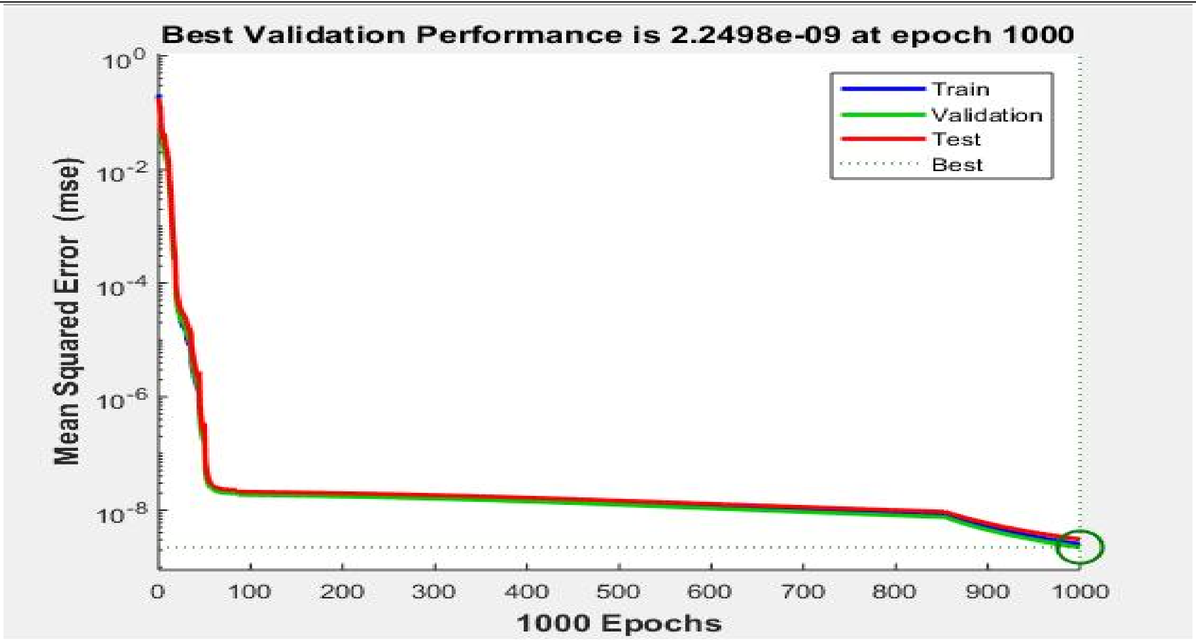
3rd attempts



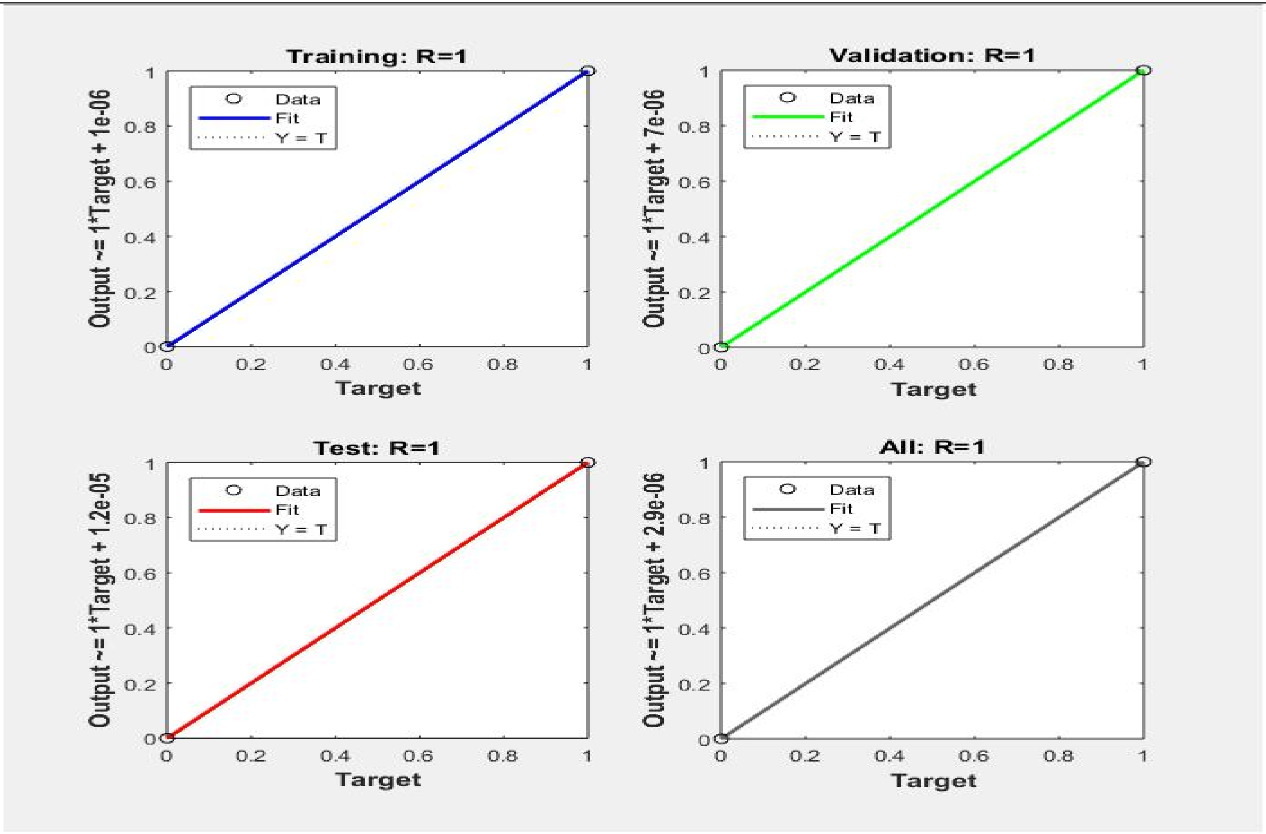
(a)



(b)


Best Validation Performance is 2.2498e-09 at epoch 1000
Mean Squared Error (mse)
Train
Validation
Test
Best
1000 Epochs

(c)


Training: R=1
Validation: R=1
Test: R=1
All: R=1
Output ~= 1*Target + 1e-06
Output ~= 1*Target + 7e-06
Output ~= 1*Target + 1.2e-05
Output ~= 1*Target + 2.9e-06
Data
Fit
Y = T
Target

(d)

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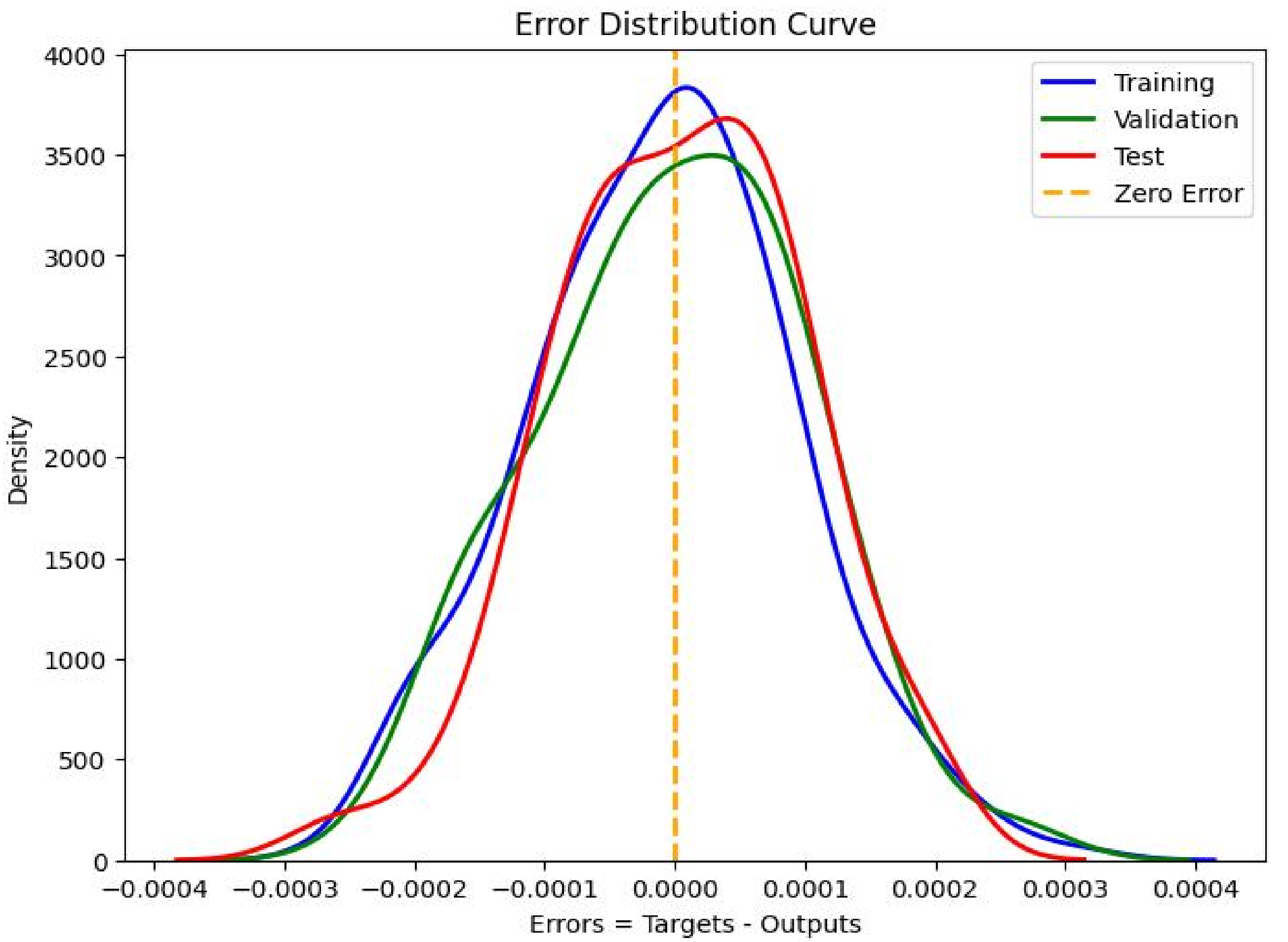

(e)

(f)

Figure 11. (a) ANN Training Architecture (b) Trained ANN Model (c) ANN Performance Evaluation (d) Correlation Plots (e) Error Distribution Histogram (f) Confusion Matrix

4. Discussion

This study has demonstrated the feasibility of Artificial Neural Networks (ANNs) in the effective detection of faults in high-voltage transmission lines. The ANN model used in this research was thoroughly validated using a MATLAB and Simulink simulations dataset, representing different fault conditions in a 500 kV power system of 117 km length. The outcome highlights the high robustness and accuracy of the ANN, achieving a remarkable 100% detection of faults, as reflected in the confusion matrix, and an incredibly low Mean Square Error (MSE) of 2.2498e-9. The success of the ANN model lies in its capacity to emulate the sophisticated decision-making process of the human brain. This enables it to identify minute patterns and inconsistencies in voltage and current readings that can signify faults. Such a capability is imperative in high-voltage transmission lines, where early fault detection is vital to avoid prolonged outages and severe damage to the power grid infrastructure. Our methodology differs from others in that it keeps the detection time as short as possible, thereby enabling faster isolation and correction of faults. Applying a multilayer perceptron (MLP) with backpropagation training further refines the model's learning from the training set, which encompasses a diverse range of fault types and scenarios. Such variability in training enables the ANN to learn not just from theoretical case studies. Still, it is also suitably prepared for realistic, real-case usage where patterns of faults could differ significantly.

Compared to conventional fault detection systems, reliance is more intense on relay-type mechanisms that cannot always trigger or pinpoint the precise characteristics of the fault. Traditional systems are both slower and less reliable due to the occurrence of faults whose characteristics are contingent upon a range of external causes, such as environmental conditions, mechanical damage to units, or process errors. The capacity of the ANN to keep learning and to modify its response based on received data offers a significant enhancement of these traditional techniques. In addition, incorporating artificial neural networks (ANNs) in fault detection systems aligns with the continuous evolution of innovative grid technologies, where automation and real-time data analysis play a central role. The scalability of ANNs enables their application to various grid segments, ranging from local distribution networks to extensive transmission networks, providing a unified solution for fault management. This research also points towards future improvements in fault detection methods. Investigating deeper and more intricate network structures, perhaps incorporating newer types of artificial intelligence, such as deep learning and reinforcement learning, could further enhance the precision and efficiency of fault detection systems. Implementing these systems in a real-world setting would also provide valuable insights into their operational efficiency and areas for improvement. In summary, the ANN-based fault detection model developed in this research represents a significant technological advancement in the maintenance and operation of power transmission systems. It not only facilitates the timely identification and rectification of faults but also helps enhance the stability and efficiency of the electrical power distribution network. Further research and development are recommended to fully leverage the potential of ANNs in this area, potentially revolutionizing the monitoring and maintenance of power systems.

5. Conclusion

This research presents a comprehensive investigation into the use of Artificial Neural Networks (ANNs) for fault detection on power transmission lines. Through a thorough exploration of various data models and iterative design efforts, an artificial neural network (ANN) was determined to be the most effective technical solution for identifying faults in transmission systems [15]. The ANN design process required multiple iterations to refine the model and ensure optimal performance. The neural network was trained and developed through MATLAB software and the ANN toolbox.

The results showed that ANN is an excellent fault detector when trained with reliable and validated datasets. The model successfully classified voltage (V) and current (I) readings collected from each phase, which aided in fault detection. This is particularly important in the modern world, making this type crucial for power transmission systems. It helps detect and correct faults early, ultimately reducing the downtime and damages caused.

Everything starts with prefacing that the ANN was the most successful algorithm in this study, which can lead to further improvements in fault detection. Additional research can be performed to optimize network architectures, including real-time data processing and deploying ANN-based fault detection techniques within innovative grid environments. Using AI-based methods, power transmission systems can enhance their reliability, efficiency, fault detection, and diagnosis without human intervention.

In conclusion, this study highlights the potential of ANN for fault detection and sets the stage for future advancements in power system monitoring and maintenance.

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