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(Research Article)

Fault location prediction under line-to-ground fault in transmission line using artificial neural network

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Abstract

The electrical power system occasionally suffers from failures, often caused by the faults occurring within the system. Accurate fault location prediction is important to ensure the reliable operation of the power system and to minimize the downtime during the occurrence of fault conditions. While traditional methods of fault location detection remain effective for specific scenarios, Artificial Neural Network (ANN) provide a more versatile, efficient, and cost-effective approach to fault location detection. This study focuses on predicting fault positions under line-to-ground (L-G) fault using ANN.

Keywords: Power System Analysis; L-G Fault; Artificial Neural Network; Artificial Neural Network

1. Introduction

In a power system, a fault refers to an abnormal condition that disrupts the normal flow of electrical current, often resulting in significant operational disturbances. Fault occur when unintended connections, disconnections, or disruptions happen in the system, leading to abnormal currents voltage imbalances or equipment malfunctions. Which can be the consequences of variety of situations like, environmental conditions, equipment failures or human errors and are a critical concern for the reliability and safety of the power system.

Ensuring the stability and reliability of an Electrical Power system is crucial for uninterrupted power flow. Common disturbances i.e, Line-to-Ground (L-G), Line-to-Line (LL) and Double Line-to-Ground (L-L-G) faults can adversely affect the performance of the power system. Accurate and early detection of faults are essential for maintenance of system stability and to prevent extensive damage. Among them, single line-to-ground faults are particularly prevalent, often leading to system instability and power quality degradation. Compared to traditional methods, Artificial Neural Network provides a more versatile, efficient, cost effective and fast estimation of fault location.

This study focuses on fault detection and fault prediction in Electrical power system using Artificial Neural Network (ANN). ANNs are computational models inspired by structure and function of the human brain. A simple model of the neuron, the fundamental cell of the brain is the building block of any ANN [1]. ANN consists of numerous interconnected layers of neurons that process data through weighted connections. By learning patterns and relationship ANN can effectively perform tasks like fault prediction.

In this paper, the ANN is trained with simulated data generated in MATLAB Simulink enabling it to identify distances at which fault occurred based on the input parameters which is fault currents at three phases of power system.

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2. Fault analysis of electrical power network

Fault analysis in power systems is a critical aspect of ensuring reliable and safe operation of electrical networks. When faults occur in power systems, they can lead to disruptions, equipment damage, and even pose safety hazards. Therefore, it's essential to thoroughly analyze faults to understand their causes, effects, and implications for system stability.

Fault analysis in a power system is needed in order to provide information for the selection of switchgear, setting of relays and stability of system operation, and other protective equipment's in the power system.

Fault analysis in power systems is a critical process for ensuring the reliability and stability of electrical grids. It involves identifying and diagnosing faults or abnormalities in the system, such as short circuits, ground faults, and equipment failures.

By conducting fault analysis, engineers can determine the location, type, and severity of faults, allowing for prompt corrective actions to be taken to minimize downtime and prevent potential damage to equipment. Techniques used in fault analysis include fault simulation, transient stability analysis, and relay coordination studies. The types of faults in electrical power network are:

2.1. Open circuit fault

The open circuit fault mainly occurs because of the failure of one or two conductors. It takes place with the line, and because of this, it is also known as the series fault. It can be classified as: Open conductor fault, two conductor open circuit, three conductor open circuit.

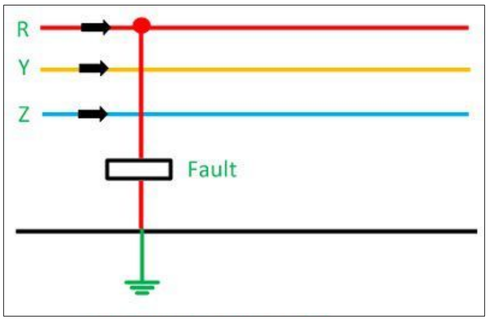
2.2. Short circuit fault

The short circuit fault occurs when conductors of different phases come in contact with a power line, power transformer or any other circuit element due to which the large current flow in one or two phases. The short circuit fault can be further divided into 2 types:

2.2.1. Symmetrical Fault

Symmetrical faults involve all the 3 phases, and so, remain balanced even after the fault. They mainly occur at the terminal of generators. Symmetrical faults can be sub-categorized into: Line-Line-Line (L-L-L) Fault, Line-Line-Line-Ground (L-L-L-G) Fault.

2.2.2. Unsymmetrical Fault



Source: https://circuitglobe.com/wp-content/uploads/2017/03/single-line-to-ground-fault.jpg

Figure 1 Line-to-ground fault

The unsymmetrical fault gives rise to unsymmetrical current, i.e. current differing in magnitude and phases of the power system. The unsymmetrical fault makes the system unbalanced. It is the most common type of fault that occurs in the power system. The unsymmetrical fault and its types are as follows:

Single Line-to-Ground Fault: It occurs when one conductor falls to the ground or contact the neutral conductor. The single line to ground fault constitutes 70-80% of the fault in power system.

Single Line-to-Line Fault: It occurs when two conductors are short-circuited. The Major cause of this type of fault is heavy wind. The percentage of such type of faults is nearly 5-10%.

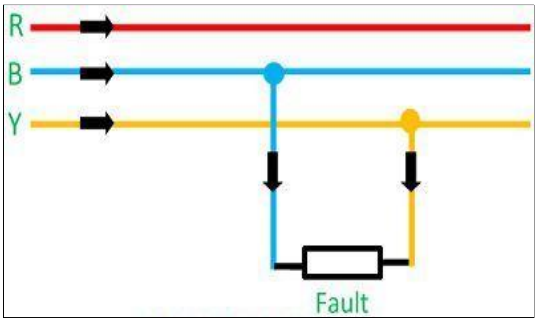


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Figure 2 Line-to-line fault

Double Line-to- Line Ground Fault: A double line-to-ground fault refers to a fault where two lines come in contact with each other along with the ground. The probability of such types of faults is nearly 15-20%. This fault is the most severe among all others mentioned above.

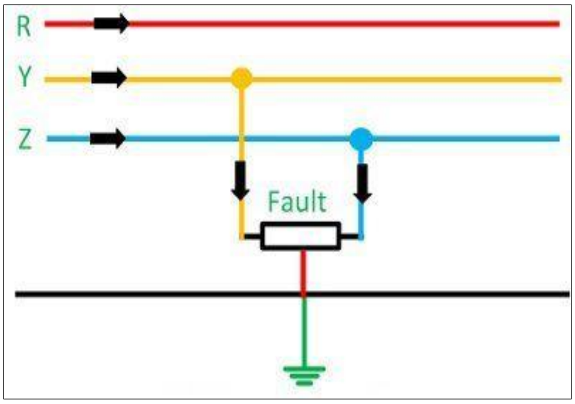

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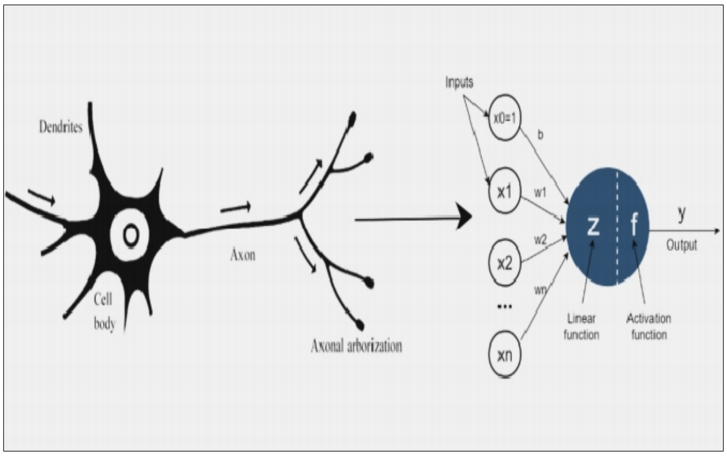
Figure 3 Double line-to-ground fault

3. Artificial neural network



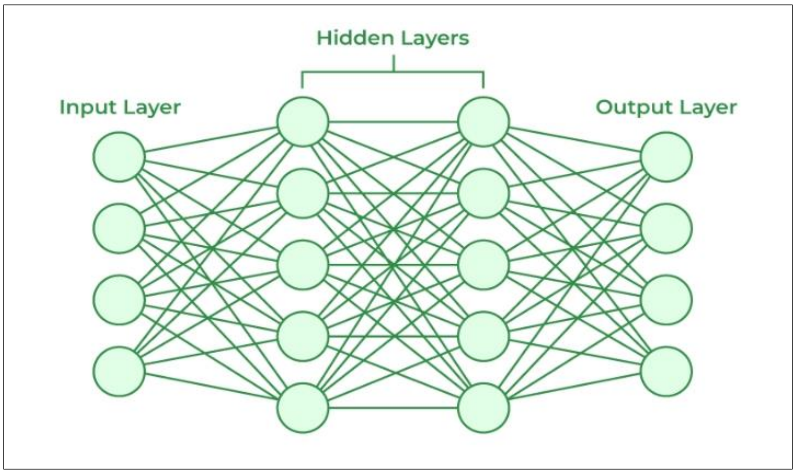
Source: www.irjet.net (Mayuri Thorat, Shraddha V. pandit, Supriya Balote, 2023)

Figure 4 Comparison between a simple neuron and ANN

The Artificial Neural Network is a sophisticated intelligent system that adapts itself according to the level of complexity of fault issues and is widely used in machine learning to solve complex problems involving pattern recognition, classification, regression and decision making. Artificial Neural Network (ANNs) are computational models that are inspired by the biological functioning of human brain as shown in Figure 4 [2].

They consist of interconnected layers of nodes (neurons) that process information in a way similar to how neurons communicate in the brain [3]. Similar to the functioning of a neuron, ANN also receives input, process it using an activation function, and transmits the output to the next layer.

The architecture of this advanced computational system typically includes an input layer, one or more hidden layers, and output layer as shown in Figure 5. The input layer of neurons receives the raw data from input files or directly from electronic sensors in real-time applications, whereas the output layer delivers information to the external world, a secondary computer process. In between these two layers there can be numerous hidden layers which transforms the raw data in input layer through weighted connections [4]. The weights determine the influence of one neuron on another, and during training, these weights are adjusted to minimize errors in prediction using algorithms like backpropagation.



Source: https://media.geeksforgeeks.org/wp-content/cdn-uploads/20230602113310/Neural-Networks-Architecture.png

Figure 5 Simple Architecture Diagram of ANN

ANNs can be widely categorized into various types based on their architecture, such as the feed forward neural networks, where information flows in one direction, and recurrent neural networks, which allow feedback loops for processing sequential data.

4. Result and simulation

4.1. Determination of fault current under lg fault

A 300 KM long transmission line has been modelled in MATLAB Simulink, as shown in Figure 6, to measure the fault current at the three phases.

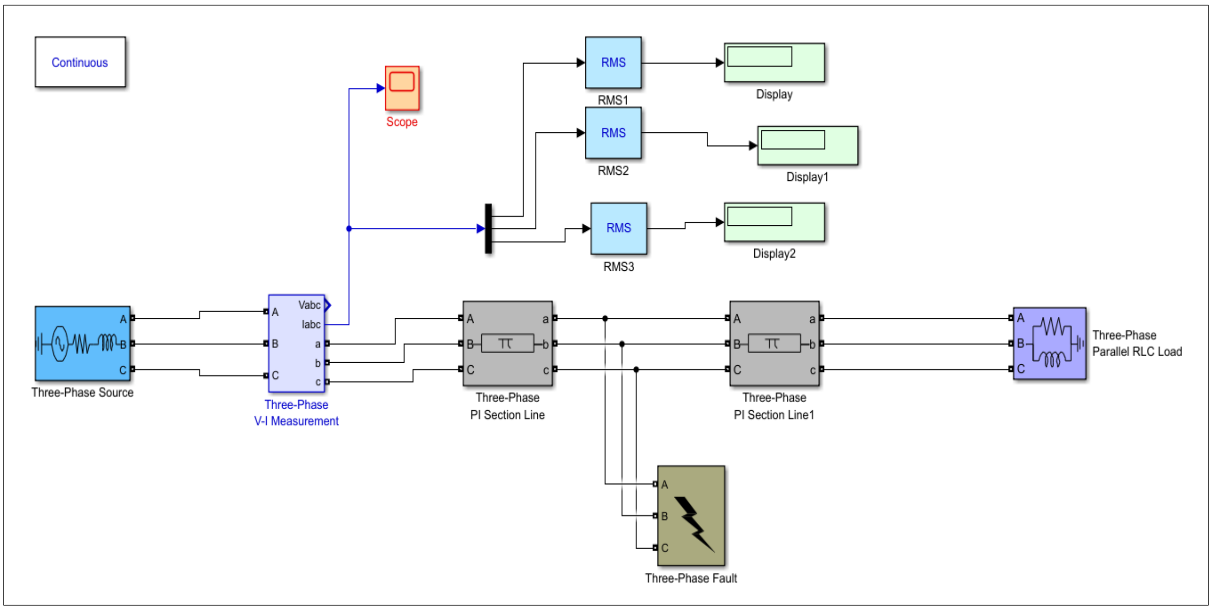


Figure 6 300km long Transmission line model

At first, an L-G fault is created in phase A at different line lengths for example, fault is created near the source end of the transmission line i.e, 0 km distance and after running the model it is observed that fault current at phase A (IA=2327 Amp) much higher than that of the other two phases (IB=88.78 and IC=94.54) of the system. Similarly fault currents at different fault positions are acquired by changing the fault locations or line lengths. Some of them are listed in the Table 1.

Table 1 Fault current at different fault locations under L-G fault at phase A

Sl. No.	Line Length (KM)	Fault Current (Amp)		
		Phase A	Phase B	Phase C
1	5	1546	89.13	100.2
2	20	790.8	90.88	106.4
3	35	544.1	91.44	108.7
4	55	393.4	91.72	110.1
5	75	314.2	91.53	111.3
6	90	275.6	91.37	111.9
7	110	239.4	90.95	112.8
8	125	219.8	90.59	113.5
9	145	198.9	90.03	114.3
10	180	173.7	88.88	116.1
11	215	157.1	87.6	118.4
12	255	145	86.36	121.7
13	300	137.4	86.41	126.2

In the similar manner L-G fault is created at phase B and C and sets of fault currents at numerous fault positions are acquired. Some of them are listed in Table 2.

Table 2 Fault current at different fault locations under L-G fault

Sl. No.	Line Length (KM)	Phase at which fault is created	Fault Current (Amp)		
			Phase A	Phase B	Phase C
1	0	B	95.13	2516	88.28
2	15	B	105.4	990.7	90.32
3	55	B	110.6	410.6	91.59
4	85	B	112.1	298.7	91.37
5	105	B	113	256.9	91.03
6	135	B	114.3	216.1	90.32
7	160	B	115.4	193.4	89.59
8	190	B	117.1	174	88.61
9	215	B	118.7	162.3	87.71
10	245	B	121.1	152	86.8
11	285	B	124.9	143.4	86.36
12	5	C	88.86	100.4	1564
13	45	C	91.29	109.8	460.6
14	70	C	91.25	111.4	334.7
15	105	C	90.68	112.9	251
16	135	C	80.96	114.2	211
17	180	C	88.54	116.5	177.1
18	215	C	87.31	118.8	160.6
19	265	C	85.93	123.1	146.3
20	300	C	86.22	126.7	141.2

From Table 1 and Table 2 it can be observed that as the fault is moving away from the generator the severity of the fault keeps decreasing. Thus, it has been analyzed that fault current at the phase at which fault occurred is higher than that of other two phases. And the fault current at the faulted phase decreases as the line length increases.

4.2. Application of neural network for the estimation of fault location

ANNs are computational models inspired by structure and function of the human brain. ANN consists of numerous interconnected layers of neurons that process data through weighted connections. By learning patterns and relationship ANN can effectively perform tasks like fault prediction.

While Artificial Neural Networks (ANNs) as a data-driven approach for fault distance prediction have shown exceptional performance in pattern recognition and regression tasks making it well-suited for performing tasks like locating fault distance.

Here, the ANN is trained with simulated data generated in MATLAB Simulink enabling it to identify distances at which fault occurred based on the input parameters which is fault currents at three phases of power system.

4.2.1. Data preparation

The data preparation is a crucial step to ensure the accuracy and reliability of the ANN in predicting fault locations in three-phase power system. Employing the same methodology which has been described earlier during the determination of fault current in LG condition, a vast range of data has been generated from the MATLAB Simulink model to train an ANN model with precision.

To enhance the performance and accuracy of the ANN, the data underwent several processing steps like normalization where input data i.e fault current is normalized so all features are on a consistent scale, noise filtering where any noise or irrelevant fluctuations are removed and training and testing split where the dataset was divided into three subsets: training (70%), validation (10%) and testing (20%). The training set was utilized to optimize the ANN weights, the validation set was employed for hyperparameter tuning and the testing set was reserved for evaluating the model's performance on unseen data.

In the fault location detection, data processing is a crucial step [5]. Once the preprocessing of the data is done, the generated data is imported into MATLAB's Neural Network Toolbox (nntool). The nntool interface provides a user-friendly graphical environment to work with Neural Networks, enabling seamless integration of datasets and configuration of network parameters using 'nntool'. The datasets have been verified with the help of visual examination of data scaling. The abnormalities and defect were identified and eradicated to achieve linearity.

4.2.2. Determination of fault location using ANN

A feed-forward backpropagation network is configured in MATLAB for fault location detection. To train the ANN, about 161 sets of input data (magnitudes of fault current at three phases of transmission line under L-G fault) and 161 number of target (distances at which the fault has occurred) values are prepared and about 18 sets of sample values are selected to test the performance of ANN. Through simulation, the validation of the trained ANN is assessed, where the accuracy of the results and its performance is thoroughly examined [6].

The network properties of ANN are shown in Figure 7. It is vital to choose an appropriate network size, to reduce training and to improve the neural network's ability to effectively address the given problem. Unfortunately, no universal principle exists to specify the perfect number of hidden layers and hidden-layer neurons for this purpose [7].

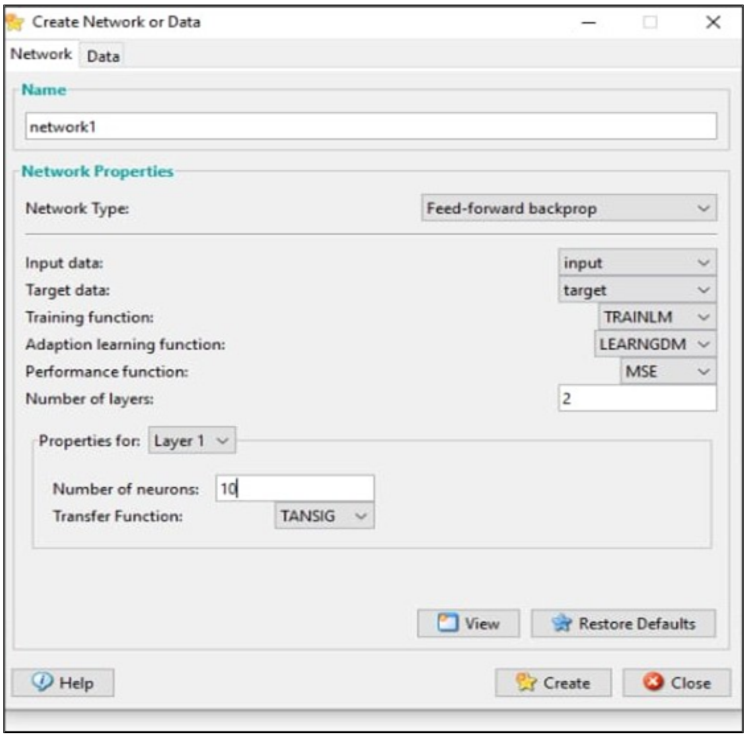


Figure 7 Network properties of Artificial Neural Network

The network utilized the TRAINLM as training function which is efficient in updating weight and bias values according to Levenberg–Marquardt optimization and widely used for small and medium-sized networks due to its fast convergence properties. LEARNGDM adaptation learning function is employed and Mean Squared Error is selected as performance function to minimize the error between predicted value and actual fault location. The network consisted of two layers: a hidden layer of 10 neurons (for this study), and an output layer.

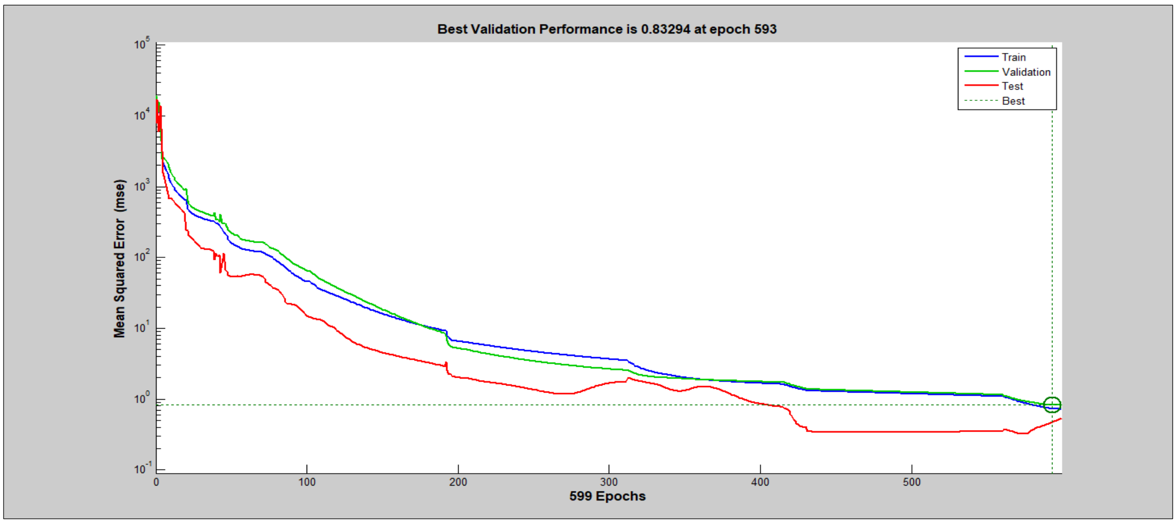


Figure 8 Performance plot using ANN in MATLAB

The acquired performance plot is shown in Figure 8, where initially the training (blue line), validation (green line) and testing (red line) of ANN had high Mean Squared error (mse) however with increasing number of iterations the errors reduced coinciding with the dotted line i.e, the best performance margin. The regression plot of the network is shown in Figure 9.

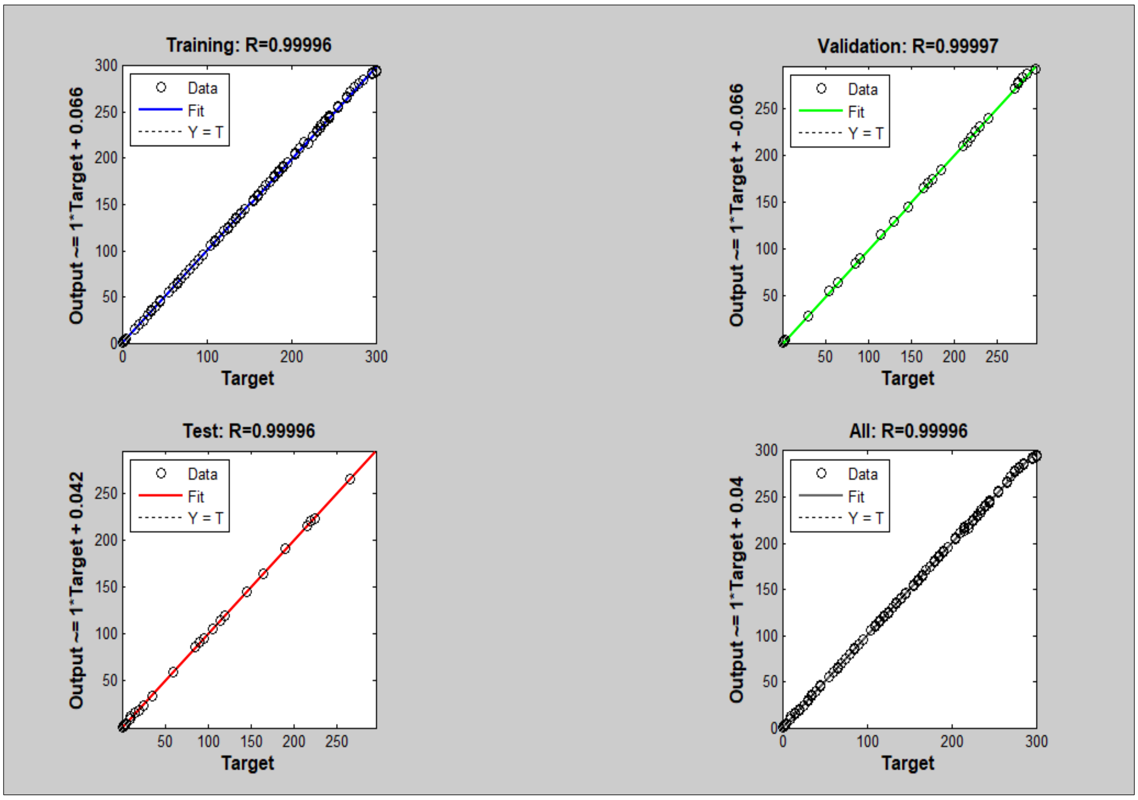


Figure 9 Regression plot using ANN in MATLAB

It can be observed from the regression plot that the training, validation and test curve are all linear in nature which is ideal and indicates that the ANN is performing efficiently.

The error percentage between the actual distance of fault generated by the MATLAB Simulink model and the distance of fault predicted by Artificial Neural Network is listed in Table 3

Table 3 Percentage Error Table of L-G fault

Si no.	Fault current for lg fault			Actual distance of fault (km)	Distance of fault predicted by ANN (km)	Percentage error (%)
	PHASE A	PHASE B	PHASE C			
1	255.9	91.17	112.4	100	100.199	+0.199
2	194.6	89.87	114.6	150	150.4509	+0.3006
3	163.4	88.15	117.4	200	202.1908	+1.0954
4	146.2	86.48	121.2	250	249.9397	-0.0241
5	143.8	86.26	122.1	260	259.8219	-0.0684
6	138.6	86.17	125.1	290	289.1595	-0.2898
7	112.8	265.9	91.13	100	100.42	+0.42
8	115	201.6	89.89	150	150.0281	+0.0187
9	117.7	168.9	88.24	200	200.2066	+0.1033
10	121.5	150.7	86.65	250	249.8814	-0.0474
11	122.5	148.2	86.46	260	262.5736	+0.9898
12	125.4	142.6	86.43	290	288.4027	-0.5507
13	90.78	112.7	259.7	100	100.6781	+0.6781
14	89.53	114.9	198	150	149.1238	-0.5841
15	87.85	117.7	166.9	200	200.8781	+0.4390
16	86.23	121.6	149.7	250	249.2587	-0.2965
17	86.01	122.6	147.4	260	260.8987	+0.3456
18	85.97	125.6	142.3	290	290.3492	+0.1204

From the table 3, it is evident that the gap between the observed and actual values is almost imperceptible. This subtle difference highlights the impressive accuracy of the ANN, showcasing its capability to precisely measure the distance values.

5. Conclusion

This study demonstrates the application of Artificial Neural Network (ANN) for fault distance prediction in a three-phase power system. The ANN is trained to predict the fault positions based on the magnitudes of fault currents at three phases utilizing simulated data generated by a MATLAB Simulink model. It is observed that the percentage error in the predicted fault position, as determined by ANN, with respect to the actual fault position is minimal, which indicates that the ANN is performing efficiently. Integration of this model in smart grid scenario will enhance the system operation and control and will help the human operator in the control centre for taking prompt action.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Jenifer Johnson, Anamika Yadav, "Fault location estimation in HVDC in transmission line using ANN," in International Conference on ICT for Intelligent systems (ICTIS 2015), Ahmedabad, India, 2015.

[2] Mayuri Thorat, Shraddha V. pandit, Supriya Balote, "Artificial Neural Nrtwork: A brief study," International Research Journal of Engineering and Technology, vol. 10, no. 02, pp. 771-776, 2023.

[3] Ahmed Elnozahy, Khairy Sayed, Mohamed Bahyeldin, "Artificial Neural Network based fault classification and location for transmission lines," in 2019 IEE Conference on Power Electronics and Renewable Energy , Aswan, Egypt, 2019.

[4] Yogendra Pratap Pundir, Sudhir Jugran, Arvind Singh Rawat, Arti Rana , "Descriptive analysis of Artificial Neural Network," International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering , vol. 6, no. 7, pp. 5427-5431, 2017.

[5] Prajakta Vikas Dhole, Sahebrao Narsingrao Patil, Aboo Bakar Khan, "Data processing techniques for the ANN based fault location in transmission line," in AIP Conference Proceedings, 2024.

[6] Hammed Waheed Olalekan, Onyegbadue Ikenna Augustine, Guiawa Mathurine, "Artificial Neural Network-Based Fault Detection on Nigerian 330kv Power Transmission Line," International Journal of Research and Review, vol. 11, no. 10, pp. 518-535, 2024.

[7] Saurabh S. Shingare, Brajesh Mohan Gupta, Prabodh Khampariya, Shashikant M. Bakre, "Revolutionizing Fault Detection: A Neural Network Approach for Transmission Line," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 2, pp. 779-786, 2024.