Identification of Line-To-Line-To-Ground Fault Location in Electrical Power Network Using Artificial Neural Network

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ABSTRACT:
The identifying of fault location line-to-line-to-ground (LLG) fault in electrical power network is critical for ensuring the system reliability, safety, and reducing the downtime, and minimizing outage times, and optimizing maintenance to efforts. Various faults that can occur, with line-to-line-to-ground (LLG) faults are complex and less frequent but can cause significant damage if not detected and resolved promptly. The study focuses on identifying the fault location of LLG fault in electrical power network.
The ANN model uses voltage and current readings from both ends of the line to predicting the under LLG of fault location. The ANN model it was trained and tested using simulated fault data generated by a power system under various fault location. The result demonstrated the effectiveness of artificial neural Network in accurately identifying of the fault location with line-to-line-to-ground (LLG) faults in electrical power network.

KEYWORDS: Artificial Neural Network, Overhead Transmission Lines, Fault Detection, Distance Protection, Power System Stability.

1. INTRODUCTION

The electrical power systems are susceptible to various faults, with Line-to-Line-to-Ground (LLG) faults posing a significant threat to equipment and power supply reliability. Prompt and precise of fault localization is essential for minimizing operational disruptions, lowering repair expenses, and maintaining the overall power system efficiency.
The fault location in a power system is crucial for ensuring the system reliability, safety, and efficiency of electrical power network. The detecting faults promptly allows for rapid response and minimize the impact of faults on the power system. The detection of three types of faults-three-phase faults line-to-ground (LG) and line-to-line faults (LL) and line-to-line-to-ground (LLG) faults using Simulink. Simulink is a powerful simulation tool widely used for modeling and simulating dynamic systems, making it suitable for studying power system behavior under the various fault conditions.
Conventional of fault location techniques, like impedance-based on the methods, often struggle with accuracy and reliability, especially in intricate in electrical power networks. Artificial Neural Networks (ANNs) offer a compelling alternative for fault location prediction due to their capacity to discern complex data patterns and correlations.
This project focuses on creating an ANN-driven system for predicting LLG fault locations within power systems, employing the MATLAB Simulink for its implementation. The system will analyze voltage and

current data from the affected transmission line to estimate the fault's position. A comprehensive dataset generated through simulations of diverse fault scenarios will be used to train the ANN.
The anticipated outcome of this system is accurate and dependable of fault location prediction. This capability will empower power system operators to swiftly identifying and address faults, thereby reducing the downtime and enhancing the overall efficiency of the power infrastructure.

2. UNSYMMETRICAL FAULTS IN POWER TRANSMISSION SYSTEM

Fault analysis is a crucial aspect of electrical power network design and operation. It involves identifying and analyzing potential faults or abnormalities in the network to ensure reliable and efficient power delivery and taking corrective actions. Fault analysis has several techniques to braking down the fault into symmetrical components and also involves analyzing the fault in phase coordinates and the fault analysis involves analyzing positive, negative and zero-sequence networks to determine the fault current and voltage. Fault analysis in power system is essential in order to supply enlightenment for the selection of switchgear ,setting of relays and stability of system operation and other protective equipment's in the in the power system. By conducting fault analysis, engineers can ensure that the system can withstand faults, and quickly identify the type of faults and also respond to faults and also set protective relays that can detect and clear faults to minimize downtime and prevent potential damage to equipment.
The different types of faults in electrical power transmission system, such as LLL, LLLG, LG, LL, LLG faults. In electrical power transmission system faults are mainly categorized into two types:
1. Open circuit fault 2.short circuit fault

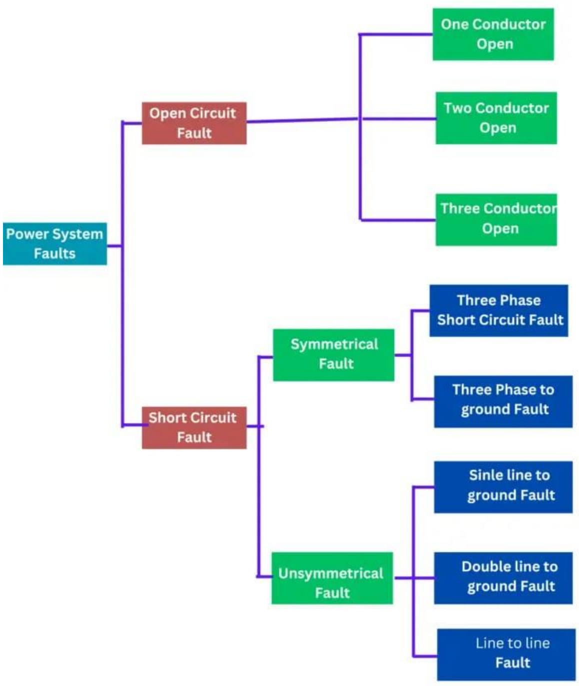

Fig 1: Types of faults

Open circuit Fault: An open circuit fault is a type of electrical fault that occurs when there is a break or interruption in the circuit, resulting in a loss of continuity and preventing the flow of electric current. The open circuit fault is categorized as follows: one conductor fault, two conductor fault, three conductor fault.

Short circuit Fault: A short circuit fault is a type of electrical fault that occurs when there is an unintended path of electricity with little to no resistance, causing excessive current to flow. Short circuit fault can be categorized as: symmetrical fault and unsymmetrical fault.

Symmetrical Fault: Symmetrical faults involve in all three phases, and so, remain balanced even after the fault. They mainly occur at the terminal of generators. Sy6mmetrical faults can be sub-categorized into: Line-Line-Line (L-L-L) fault, Line-Line-Line-Ground (L-L-L-G) fault.

Unsymmetrical Fault: An unsymmetrical fault is a type of electrical fault that occurs when there is an imbalance in the Three-phase system, resulting in unequal fault currents in the three phases. There are three types of unsymmetrical faults: L-G fault, L-L fault, L-L-G fault.

Single Line-to-Ground fault: A single line-to-ground fault is a type of electrical fault that occurs when one phase of a three-phase system is short circuited to ground. This fault comprises 70-80% of all power system faults.

Single Line-to-Line Fault: A line-to-line fault is a type of electrical fault that occurs when two phases of a three-phase system are short circuited. The percentage of this kind of fault is roughly around 15-20%

Double Line-to-Line Ground Fault: A double line-to-ground fault is a type of electrical fault that occurs when two phases of a three-phase system are short circuited to ground. The probability of this type of fault occurring approximately 10%.

3. ARTIFICIAL NEURON NETWORK

An artificial neural network is a computational model is inspired by the structure and function of the human brain. In electrical network system artificial neural network used according to the level of complexity of fault issues and is widely used in machine learning to solve different difficult problems like pattern recognition, classification, regression and decision making.

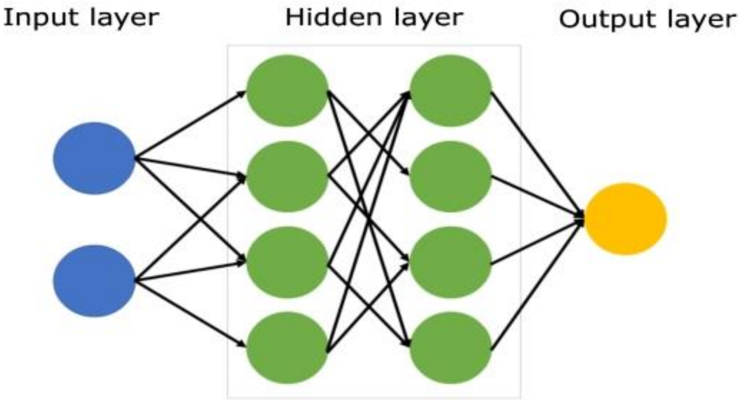

Fig 2: Simple architecture diagram of ANN

The artificial neural network is trained on a dataset, where it learns to recognize patterns and relationships. The input data flows through the network and the output is calculated. Using backward propagation the error between the predicted output and the actual output is calculated, and the network is adjusted to minimize the error.

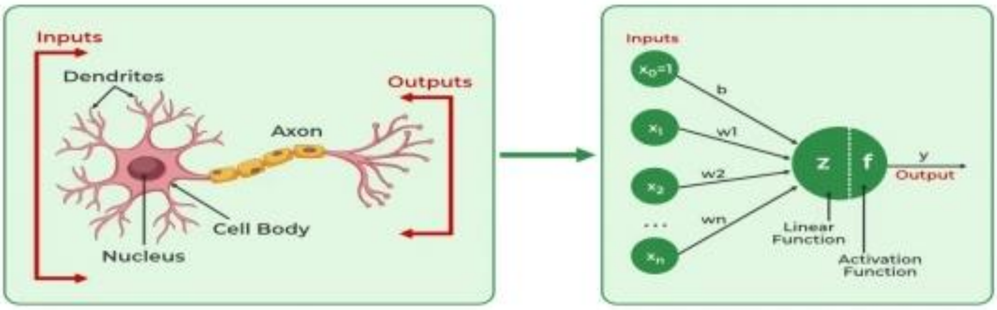

Fig 3: Comparison between a simple neuron and ANN

The architecture of this advanced computational system includes neurons, connections, input layer, hidden layer, output layer. The neurons of an ANN, which receive and process the inputs. Connections links between neurons which allow them to exchange information. The input layer receives raw data, which is then transformed by the hidden layers through weighted connections and during the training the weights are adjusted to minimize errors in prediction using algorithms like back propagation.

4. RESULT AND SIMULATION

4.1 ANALYSIS OF FAULT CURRENT UNDER LLG FAULT.

A 300 km-long overhead transmission line model designed in MATLAB Simulink to analyze fault current variations in phases A, B, and C under different fault conditions, including Line-to-Ground (L-G), Line-to-Line (L-L), and Line-to-Line-to-Ground (L-L-G). The model consists of several key components, including a 25 kV three-phase AC voltage source, a distributed transmission line with specified electrical parameters (R=0.21673 Ω/km, L=0.9337e-3 H/km, C=12.74e-9 F/km), and a load of 100 kW active power and 100 kVAR reactive power. The simulation setup incorporates various Simulink blocks such as V-I measurement, RMS calculation, scope, display, parallel RLC load, and a three-phase fault block to facilitate the analysis. By simulating fault scenarios at different positions along the transmission line, the study aims to evaluate system behavior, fault current characteristics, and potential protection strategies.

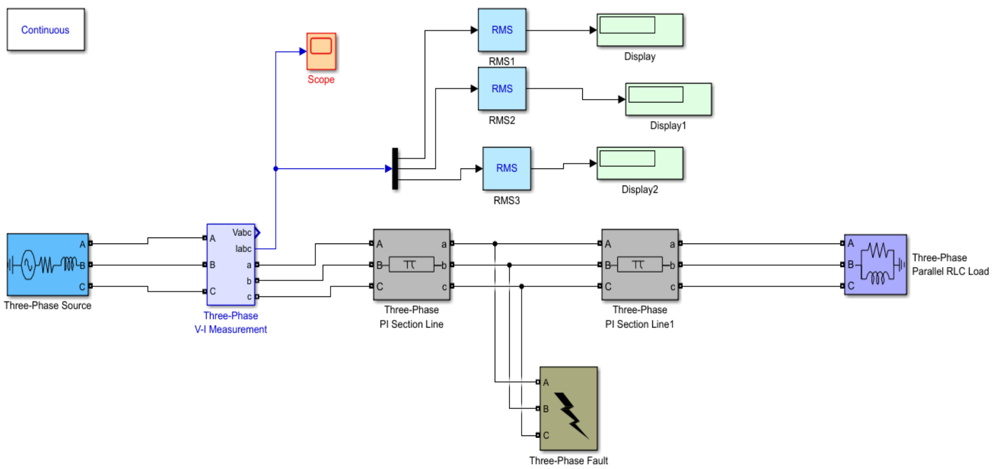

Figure 4: Transmission line model of line length 300km

To evaluate the behavior of fault currents under double line-to-ground (LLG) fault conditions, simulations are performed by initiating an LLG fault between two phases and ground at various points along the transmission line. Initially, the LLG fault is introduced between phases A and B with respect to ground, close to the sending end of the line (i.e., at 0 km distance from the source). Upon running the model, it is observed that the fault current in phase A (IA = 2333 A) and phase B (IA =2515) which is significantly higher compared to the fault currents in phases C, indicating the asymmetrical nature of the fault and the impact of proximity to the source.

Following this, similar LLG fault scenarios are created between different combinations of phases—namely A-B, B-C, and A-C.

A comprehensive set of fault current values is collected at multiple fault locations, and the results for selected cases are summarized in **Table 1**.

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

Sl. No.	Fault at a Distance (km)	Phase at which fault is created	Fault Current (Amp)		
			Phase A	Phase B	Phase C
1.	0	A-B	2333	2515	77.05
2.	50	A-B	729.5	671.5	100.8
3.	100	A-B	435.6	383.5	102.1
4.	150	A-B	309.3	206.1	102.9
5.	200	A-B	239.4	192.1	104.1
6.	250	A-B	195.7	149.8	107
7.	300	A-B	167.4	120.7	114.4
8.	0	B-C	77.1	2521	2353
9.	50	B-C	100.9	765.6	678.7
10.	100	B-C	102.2	467.4	402.5
11.	150	B-C	103	338.8	283.4
12.	200	B-C	104.1	266.6	217
13.	250	B-C	106.9	220.4	174.9
14.	300	B-C	114	189	144.8
15.	0	A-C	2322	76.76	2356
16.	50	A-C	571.5	100.9	662.1
17.	100	A-C	327.5	102.1	395.3
18.	150	A-C	230.7	103.1	295.3
19.	200	A-C	178.4	104.2	237.1
20.	250	A-C	147	107.1	201
21.	300	A-C	125.1	114.2	177.1

From the observations in Table 1, it is evident that as the fault location moves progressively farther from the generator along the transmission line, the severity of the LLG fault gradually decreases. This trend is reflected in the diminishing magnitudes of the fault currents with increasing distance from the source.

In the case of LLG faults, the fault current is notably higher in the two faulted phases compared to the healthy (un faulted) phase. Among the two faulted phases, the phase closer to the point of initiation may experience a slightly higher fault current depending on system impedance and fault resistance. The simulation results clearly demonstrate that the fault current in the faulted phase decreases as the fault point is shifted away from the source end of the transmission line.

4.2 FAULT LOCATION IDENTIFICATION IN POWER SYSTEMS USING NEURAL NETWORKS

Artificial Neural Networks (ANNs) are brain-inspired models capable of learning complex patterns through interconnected layers of neurons. In power systems, ANNs have proven highly effective for tasks like fault distance estimation due to their strong pattern recognition and regression capabilities.
In this work, an ANN is trained using simulated data from MATLAB Simulink, where fault currents from all three phases serve as inputs. The model learns to predict the fault location based on these inputs, offering a fast and reliable method for identifying fault distances along the transmission line.

4.2.1 TRAINING DATA PREPARATION FOR NEURAL NETWORK

Preparing the data is one of the most important steps to make sure the Artificial Neural Network (ANN) can correctly predict where a fault has occurred during a double line-to-ground (LLG) fault in a three-phase power system. For this purpose, a large amount of data was generated using MATLAB Simulink. In the simulations, LLG faults were created between different pairs of phases—such as A-B, B-C, and A-C—along various points on the transmission line. These faults were introduced at different distances from the source to provide a wide and diverse dataset.
Once the fault current values were collected from all three phases, the data was processed before training the ANN. First, normalization was done to bring all the input values to a common scale, which helps the network learn more efficiently and avoids bias due to large differences in values. Next, noise or unnecessary fluctuations in the data were removed to ensure the input data was clean and meaningful. After cleaning, the dataset was divided into three parts: 70% was used to train the network, 10% was used for validation (to help adjust network settings during training), and 20% was used to test how well the trained model can predict new, unseen data.
After preprocessing, the final dataset was loaded into MATLAB’s Neural Network Toolbox (nntool). This toolbox provides a simple and user-friendly interface for designing and training neural networks. Inside the toolbox, the structure of the network was set up, the data was linked, and training was carried out. To ensure the data was ready for learning, visual checks were done to confirm that the values were properly scaled and that there were no unusual spikes or errors. Any inconsistencies were corrected to keep the data accurate and reliable.
Thanks to this careful preparation, the ANN was able to learn the relationship between the fault currents and the actual location of the LLG faults. As a result, the model can now predict where a fault has occurred along the line with good accuracy.

4.2.2 TRAINING AND TESTING OF ARTIFICIAL NEURAL NETWORKS (ANN)

To train the ANN, about 181 sets of input data(magnitudes of fault current at three phases of transmission line under L-L-G fault) and 181 number of target(distances at which the fault has occurred) values are prepared and about 11 sets of sample values are prepared to test the performance of ANN.
A feed-forward backpropagation network is configured in MATHLAB for fault location detection. The network properties of ANN is shown in Figure 1.

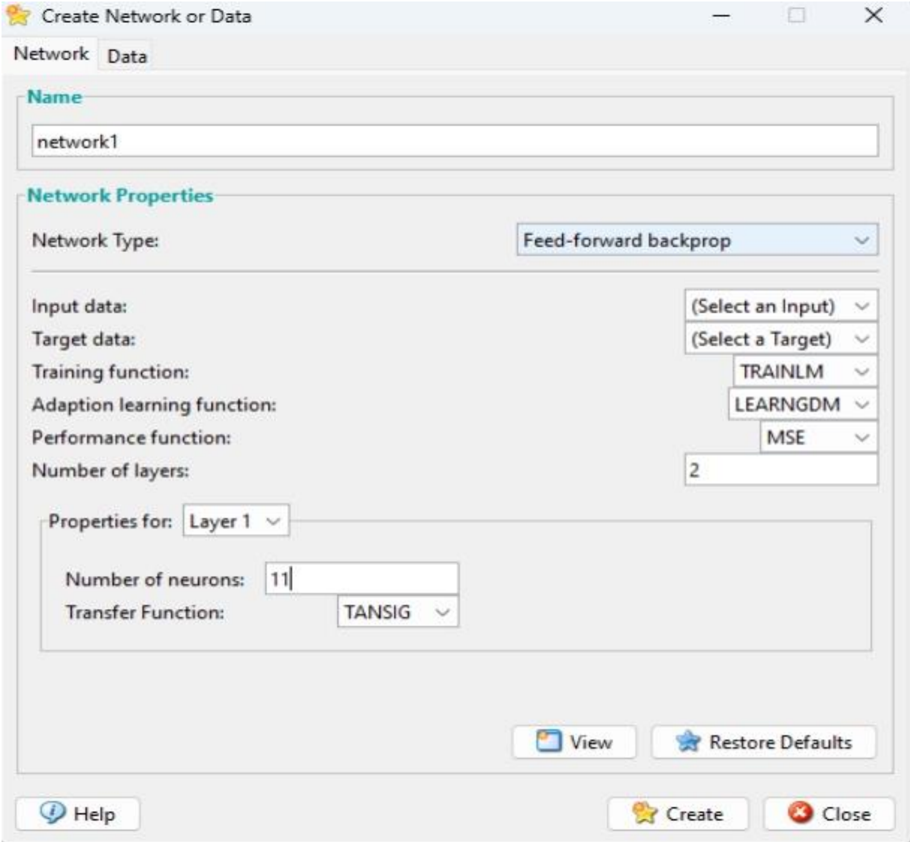

Figure 5- Network properties of Artificial Neural Network

The network functionalized 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 11 neurons (for this study), and an output layer.

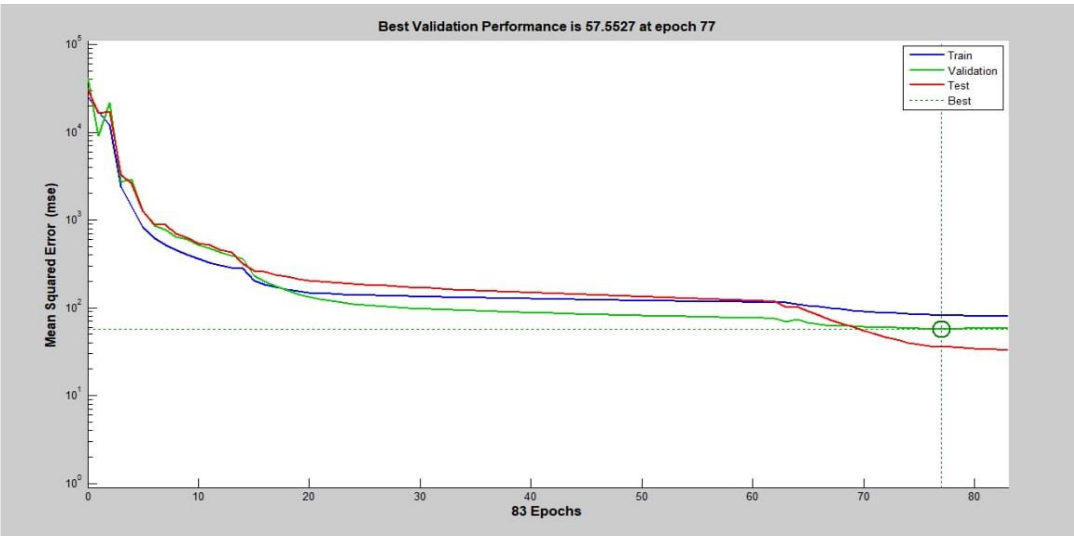

Figure 6- Performance plot using ANN in MATHLAB

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The acquired performance plot is shown in Figure 2,where initially the training (blue line),validation (green line), and testing (red line) of ANN had high mean squared error however with increasing number of iterations the errors reduced coinciding with dotted line i.e., the best margin. The regression plot of the network is shown in Figure 3.

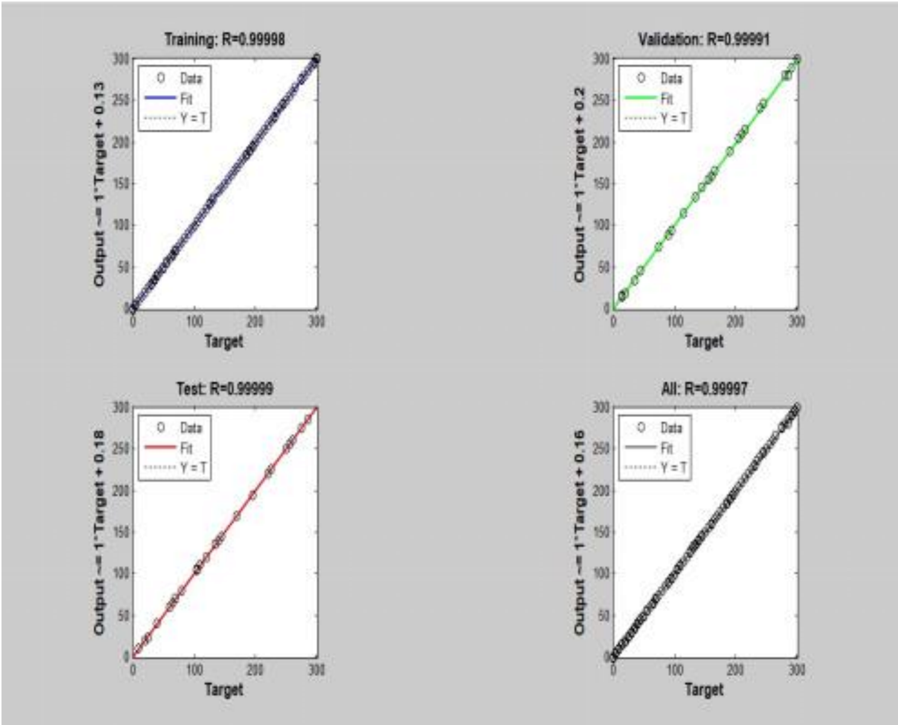

Figure 7- Regression plot using ANN in MATHLAB

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.

Table2: Fault current at different length

SI NO.	FAULT CURRENT FOR LLG FAULT			ACTUAL DISTANCE OF FAULT	DISTANCE OF FAULT PREDICTED BY ANN	PERCENTAGE ERROR (%)
	A	B	C			
1	655.8	572.5	100.6	50	50.2327	+0.46
2	395.5	327.6	102.1	100	100.0792	+0.07
3	287	226.6	102.8	150	150.1624	+0.108
4	227.2	172	103.9	200	199.3059	-0.34
5	189.6	138	106.8	250	251.0689	+0.4274
6	178.4	127.8	109	270	270.76	+0.28
7	102.1	395.4	327.4	100	99.85	-0.15
8	104	227.3	171.8	200	199.727	-0.1365
9	109.1	178.3	127.7	270	270.07	+0.025

10	226.5	102.8	286.7	150	150.10	+0.066
11	127.7	109	178.2	270	270.48	+0.177

The table no 2 provides a detailed overview of the three-phase currents during an L-L-G fault, including the actual fault location, the fault distance estimated by the ANN, and the associated percentage error. These insights collectively illustrate the ANN's effectiveness in fault detection and distance estimation.

CONCLUSION

In this research, we successfully developed and implemented an Artificial Neural Network (ANN) model to accurately detect fault locations in a power system using three-phase fault currents (A, B, and C) as input parameters. The ANN was trained on a diverse dataset to ensure robust performance under various fault conditions and locations. The results demonstrate the effectiveness of the ANN in identifying fault locations with high accuracy and minimal error, showcasing its potential as a reliable tool for fault detection and localization. The proposed method offers significant advantages, including fast computation, adaptability to complex fault scenarios, and the ability to handle non-linear relationships inherent in power system faults. This study underscores the feasibility of integrating ANN-based systems into modern power system protection schemes, paving the way for more intelligent and efficient fault management strategies.

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