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Fault Classification and Location in Microgrid Using Artificial Neural Networks

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***Abstract*—A microgrid is a compact, localized power system that independently generates, distributes, and regulates electricity, either standalone or in sync with the main grid. These microgrids are designed to ensure a dependable power supply to specific areas. Intelligent microgrids have been made possible through the use of advanced sensors and the most recent grid communication standards. Nonetheless, when utilized in microgrids, conventional protection methods do not yield dependable results. This article presents a technique that employs measurements of three-phase voltage, current, and angle during a fault as input data for a module that classifies and locates faults. This module, constructed using an artificial neural network (ANN) technique, is part of the central protection system. The effectiveness of the suggested approach is evaluated by taking into account actual grid situations with different fault locations and types. A 7-bus meshed AC Microgrid Test System, which includes two Distributed Generators (DGs) and two grid sources, is simulated in the Simulink platform. MATLAB-2021b's data analytic capabilities have been utilized for the development of ANN-based fault classification and location modules for microgrids.**

***Index Terms*—Distributed Generator, Fault Location, Microgrid, Artificial Neural Network.**

I. Introduction

The idea of microgrids (MGs) has brought about a significant change in the current power system, propelled by the swift increase in energy consumption. This idea is put into practice to encourage the widespread use of distributed energy resources (DERs) sourced from renewables, with the goal of alleviating the pressure on the power grid that depends on fossil fuels. The primary difficulties linked with the protection of microgrids (MGs) are as follows:

- The occurrence of bidirectional power flow.
- There is a notable variation in the short circuit level when operating in grid-connected and islanded modes.
- The output of renewable energy resources is characterized by inconsistency.
- The constraint of inverter-based distributed generators (DGs) in delivering fault current is acknowledged [1].

Hence, developing a unified protection scheme to address these challenges remains a key research focus. The availability of Intelligent Electronic Devices (IEDs), digital relays, Phasor Measurement Units (PMUs), and high-speed communication lines with the IEC61850-enabled protocol has enhanced the functionality of microgrids, making them smarter. As a result, numerous electrical parameters are measured and stored simultaneously for future valuable analysis [1].

In the past few years, the complexity of electrical power systems, encompassing distributed generation installations, has seen a rise. This has rendered the incorporation of conventional fault location methods, such as travelling wave and impedance-based strategies, into intricate power systems more difficult. However, alternative, cost-effective, and simpler methods for fault location have been proposed, including knowledge-based approaches like Artificial Neural Networks (ANN), fuzzy logic, support vector machines, and deep learning. These methods have proven to be highly accurate compared to conventional approaches [2].

ANN have been extensively studied for their use in classifying and locating faults in power systems. This literature review will highlight a number of research works that utilize ANN for the purpose of fault classification and localization, particularly in the context of transmission and distribution networks. The methodology for using ANN in fault localization and classification in power systems will be discussed. The findings indicate that ANN are fast and flexible, able to operate in real-time situations and react promptly to alterations [3]- [4].

This paper is organized as follows: Section II details a seven-bus AC microgrid in Simulink and discusses ANN modeling, including feature selection and training. Section III describes the result and discussion on hidden layers. Ultimately, Section IV brings this paper to a close.

II. Intelligent Protection System Design for Microgrids

Consider a seven-bus meshed AC microgrid test system, simulated in Simulink, that incorporates two distributed generators (DGs) and two sources from the grid. The AC microgrid shown in Fig. 1 is a meshed network that includes four energy sources operating at 50 Hz. The two primary grid supplies are Grid1 (G_1) and Grid2 (G_2), along with two synchronously based distributed generators, DG_1 and DG_2. The MG is segmented into eight line segments, each measuring 10 km. The parameters used in the design of the test system are detailed in Table I, Table II, and Table III. The linked system of 7 buses, which operates at a medium voltage of

33 kV, is modeled using the SIMULINK platform (MATLAB R2021b). Fig. 2 depicts the simulation setup, which is aimed at generating a dataset for training an ANN model [3].

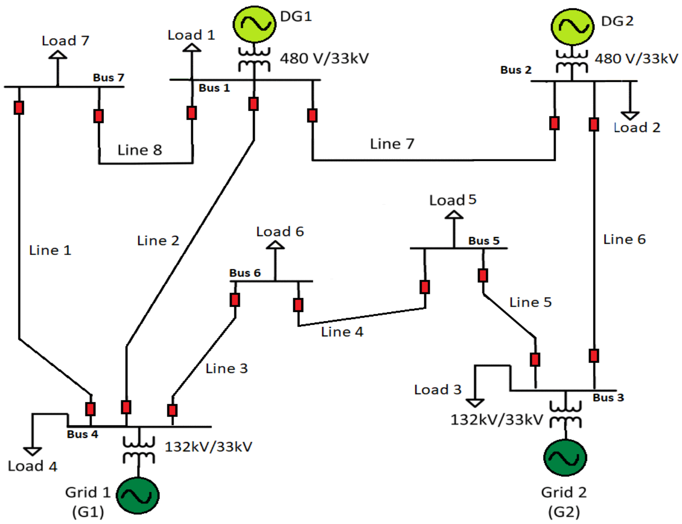

Fig. 1. Structure of the Meshed AC Microgrid [5].

TABLE I
LINE PARAMETERS OF THE MICROGRID TEST SYSTEM

Transmission Line	Resistance (Ω/km)		Inductance (H/km)	
	R_1	R_0	L_1	L_0
1	2.1416	6.4248	0.0142	0.0426
2	1.1526	3.4578	0.0073	0.0217
3	1.6549	4.9647	0.0110	0.0331
4	1.4297	4.2889	0.0107	0.0321
5	0.5543	1.6629	0.0141	0.0423
6	2.2148	6.6444	0.0149	0.0447
7	2.9782	8.9346	0.0193	0.0579
8	3.8494	11.5482	0.0110	0.0330

- Line: Capacitance of Positive Sequence $= 12.74nF/km$, R_1 = Resistance of Positive Sequence, R_0 = Resistance of Zero Sequence, L_1 = Inductance of Positive Sequence, L_0 = Inductance of Zero Sequence.

TABLE II
GENERATOR AND TRANSFORMER PARAMETERS OF THE MICROGRID

Component	Parameter
Grid Sources (G_1, G_2)	Line Voltage $=$ $132kV$ Internal resistance $=$ 0.8929Ω, Internal inductance $= 16.58mH$
DG Sources (DG_1, DG_2)	Line Voltage $=$ $480V$ Internal resistance$=$ 0.8929Ω, Internal inductance $= 16.58mH$
Transformer (T_1, T_2, T_3, T_4)	T_1 and T_2 $480V/33kV$, $R_{pu} = 0.002$, $X_{pu} = 0.008$, T_3 and T_4 $132kV/33kV$, $R_{pu} = 0.002$, $X_{pu} = 0.008$

TABLE III
LOAD PARAMETERS OF THE MICROGRID

Load	Voltage (kV)	Real Power (MW)	Reactive Power (MVAR)
1	33	13.5	5.8
2	33	14.9	5.0
3	33	29.5	16.6
4	33	11.2	7.5
5	33	9	5.8
6	33	3.5	1.8
7	33	6.1	1.6
		$P_{total} = 87.7MW$	$Q_{total} = 44.1MVAR$

A. Collecting Data and Choosing Features

The highest value of the current after a fault, in addition to voltage and angle readings taken at four buses, are collected as input attributes for model training. For the construction of a durable and resilient model, it's essential to educate it with data encompassing all possible operational scenarios of the microgrid.

TABLE IV
FAULT CASES CONSIDERED FOR DATA COLLECTION

Cases	Location steps and fault type	No. of cases
Fault Location	Every 0.5 km in each line	19×8
Fault Types	AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABC	10

The measurement of three-phase voltages, currents, and their respective angles from four buses results in 48 input features (4 buses with 12 measurements) [4].

Therefore, based on Table IV, the total number of data collected for the mentioned cases can be calculated as 48 (input features) multiplied by 19 (locations) multiplied by 8 (lines) multiplied by 10 (types of faults), resulting in 72,960 data points. The input matrix for the ANN consists of 1520 rows (data points) and 48 columns (features) derived from the collected data (72,960). Each row represents a specific data point, and each column represents a feature such as voltage, current and angle measured at the four-generation buses. The distance measurement of the fault location is taken from the lower bus number to the higher bus number. Once all data were collected, In this study the ANN tool is utilized for identifying and categorizing faults. In the ANN tool, I utilized 48 input values representing voltages, currents, and their corresponding angles at four generation buses. The ANN model was trained using a dataset consisting of 1520 rows and 48 columns for the input set, and the output set comprised three components i.e. The count of lines, the nature of the fault, and and the fault location. The conditioned model is examined with a novel input dataset to evaluate its efficiency and trustworthiness. The following section thoroughly discusses the machine learning technique of ANN.

B. Artificial Neural Network

The idea of ANN draws its inspiration from the biological neurons present in animal brains. This biological influence is Table V, as outlined in [6], highlighting the many similarities in both structure and function between ANN and biological neural networks.

TABLE V
BIOLOGICAL ARTIFICIAL NEURONS

Biological Neurons	Artificial Neurons
Dendrite	Inputs
Cell nucleus or Soma	Nodes
Synapses	Weights
Axon	Output

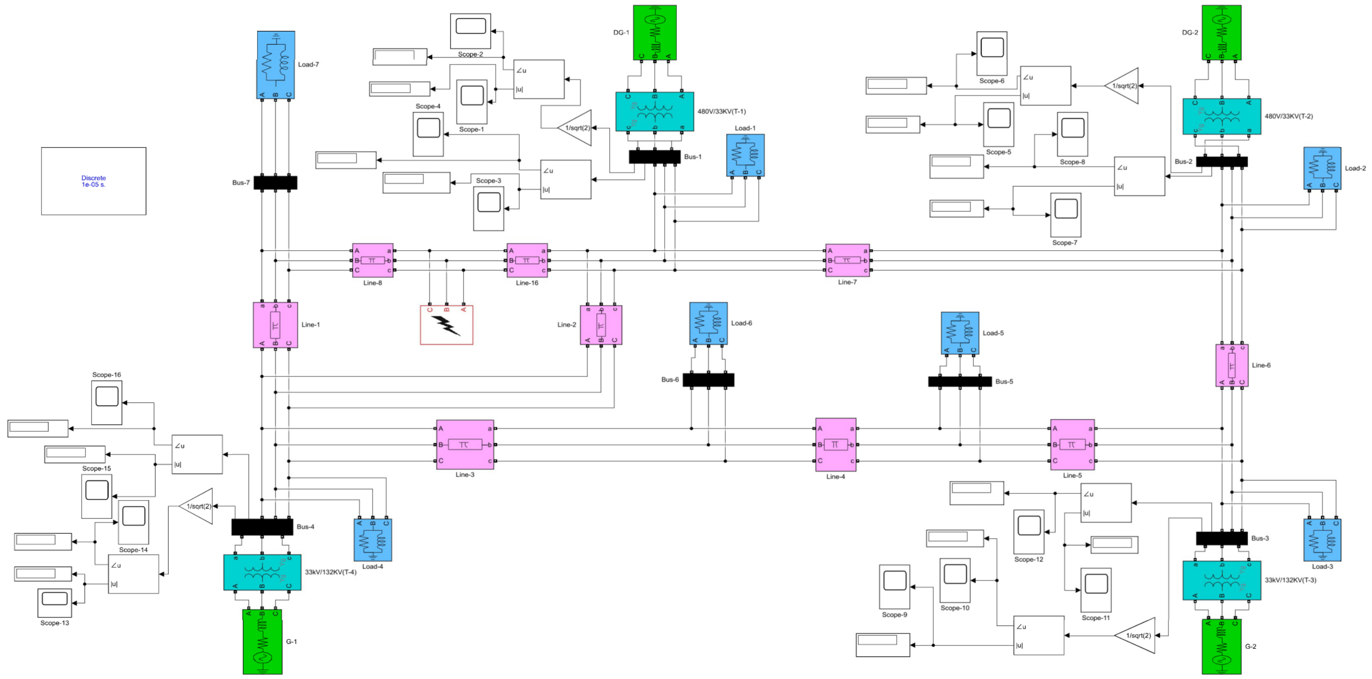

Fig. 2. Simulink model for fault detection and locations.

*1) **Structure**:* A biological neuron consists of a cell body, or soma, that processes impulses, dendrites that accept these impulses, and an axon that conveys them to other neurons. Similarly, in ANNs, the input nodes receive input signals, the nodes in the hidden layer process these signals, and the nodes in the output layer determine the final output by processing the results from the hidden layers using activation functions.

*2) **Synapses**:* In biological neurons, the synapses form connections that allow impulses to move from dendrites to the cell body. In artificial neurons, these synapses are symbolized by weights that link nodes from one layer to the nodes of the next layer. The value of these weights signifies the intensity of these connections.

*3) **Learning**:* In biological neurons, the learning process takes place in the soma, or the cell body nucleus, which contains a nucleus that aids in processing impulses. If the impulses are strong enough to exceed the threshold, an action potential is created and travels along the axons. This is facilitated by synaptic plasticity—the capacity of synapses to change their strength over time in response to variations in their activity. In ANN, backpropagation is a learning technique that modifies node weights based on differences or errors between expected and actual results.

*4) **Activation**:* Biological neurons activate when impulses surpass thresholds, similarly, in ANN, activation functions determine neuron outputs based on inputs, introducing non-linearity for pattern interpretation. Applied to weighted inputs and biases, activation functions like Sigmoid, ReLU, Tanh, and Softmax enable complex data pattern interpretation and learning across network layers.

*5) **Feedforward Backpropagation Neural Network**:* I have utilized a feed-forward backpropagation neural network, as depicted in Fig. 3.

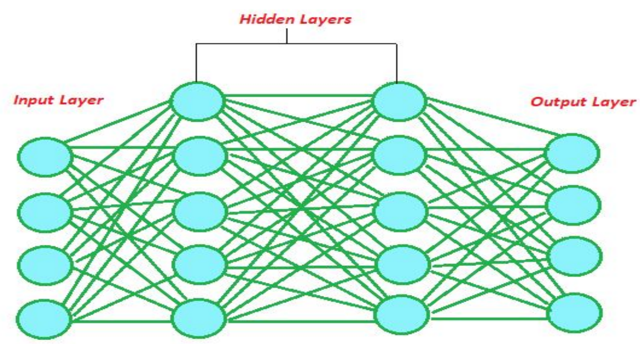

Fig. 3. Neural-Networks-Architecture.

A feed-forward backpropagation neural network is a type of ANN where data moves in a single direction—from input to output. Neurons in each layer apply an activation function to their inputs and forward the outcome to the subsequent layer. Backpropagation, the main learning algorithm, iteratively modifies network parameters (weights and biases) to reduce the discrepancy between expected and actual outputs. This procedure, encompassing both forward and backward passes, allows the network to learn from training data and make predictions. Owing to their efficiency, feed-forward backpropagation neural networks are commonly employed for supervised learning tasks such as classification and regression [7].

Table VI serves as a reference for the input and output parameters chosen for ANN Model. It specifies the inputs as voltage magnitudes (Va, Vb, Vc), voltage phase angles (θ_{Va}, θ_{Vb}, θ_{Vc}), current magnitudes (Ia, Ib, Ic), and current phase angles (θ_{Ia}, θ_{Ib}, θ_{Ic}). The outputs are defined as the number of lines, type of fault, and location of the fault in km along the line. These parameters will be utilized for training and testing your ANN model to predict fault-related information based on the input data [8].

TABLE VI
INPUT–OUTPUT PARAMETERS CONSIDERED

Features (Input)	Targets (Output)
V_a, V_b, V_c, θ_{Va}, θ_{Vb}, θ_{Vc} I_a, I_b, I_c, θ_{Ia}, θ_{Ib}, θ_{Ic}	Line number, Fault type, Fault location in km

III. RESULT AND DISCUSSION

The initial setup for the feedforward backpropagation neural networks involved 1520 samples, each with 48 input features. The outputs included fault type, line number, and fault location. The training used 10 neurons and 1-4 hidden layers. After training, the ANN model was tested with new data points for voltage, current, and angles, generated at different locations and not part of the training data. This fresh data was utilized to assess the effectiveness of the conditioned ANN model. Unfortunately, the testing phase did not yield satisfactory results.

TABLE VII
PERFORMANCE OF ANN WITH 10 NEURONS IN EACH HIDDEN LAYER

Hidden layers	Faulty Line		Fault Type		Fault Location		Error (%)
	Actual	Predcited	Actual	Predcited	Actual	Predicted	
1	3	2	ABG	CA	6	5.7719	3.95
2	3	3	ABG	CA	6	5.829	2.93
3	3	3	ABG	ABG	6	6.3206	5.07
4	3	3	ABG	ABG	6	6.1667	2.7

TABLE VIII
PERFORMANCE OF ANN WITH 20 NEURONS IN EACH HIDDEN LAYER

Hidden layers	Faulty Line		Fault Type		Fault Location		Error (%)
	Actual	Predcited	Actual	Predcited	Actual	Predicted	
1	2	2	AB	AB	5.123	4.7206	7.85
2	2	2	AB	AB	5.123	5.3002	3.45
3	2	2	AB	AB	5.123	4.8602	5.407
4	2	2	AB	AB	5.123	5.049	1.4656

TABLE IX
PERFORMANCE OF ANN WITH 30 NEURONS IN EACH HIDDEN LAYER

Hidden layers	Faulty Line		Fault Type		Fault Location		Error (%)
	Actual	Predcited	Actual	Predcited	Actual	Predicted	
1	2	2	AB	AB	5.123	4.7999	6.73
2	2	2	AB	AB	5.123	5.2253	1.95
3	2	2	AB	AB	5.123	5.2267	1.98
4	2	2	AB	AB	5.123	5.0632	1.18

These outcomes are observable in Table VII, Table VIII, Table IX, Table X, and Table XI. At first, the results were not up to the mark, prompting modifications in the count of neurons and hidden layers in the neural network. It was then

TABLE X
PERFORMANCE OF ANN WITH 48 NEURONS IN EACH HIDDEN LAYER

Hidden layers	Faulty Line		Fault Type		Fault Location		Error (%)
	Actual	Predcited	Actual	Predcited	Actual	Predicted	
1	2	3	AB	AB	5.123	4.8966	4.62
2	2	2	AB	AB	5.123	5.4054	5.224
3	2	2	AB	AB	5.123	5.004	2.45
4	2	2	AB	AB	5.123	5.1739	1.09

TABLE XI
PERFORMANCE OF ANN WITH 55 NEURONS IN EACH HIDDEN LAYER

Hidden layers	Faulty Line		Fault Type		Fault Location		Error (%)
	Actual	Predcited	Actual	Predcited	Actual	Predicted	
1	2	3	AB	AB	5.123	5.1913	1.33
2	2	2	AB	AB	5.123	4.8664	5.272
3	2	2	AB	AB	5.123	5.2262	2.0144
4	2	2	AB	AB	5.123	5.7911	11.53

tested for various configurations, ranging from 10 to 100 neurons and 1 to 4 hidden layers. After thorough experimentation, it was determined that the optimal configuration consisted of 80 neurons and 3 hidden layers.

Hence, I have opted for a configuration of 3 hidden layers, with each layer consisting of 80 neurons, as this network structure delivers the most effective results. The ANN classifier for fault detection and location, depicted in Figure 4, consists of 1 input layer with 48 neurons, 3 hidden layers with 80 neurons each, and 1 output layer with 3 neurons. The transfer function employed at the hidden layers is tan-sigmoid, whereas a linear transfer function is utilized at the output layer. The training algorithm employed was the Levenberg-Marquardt algorithm (trainlm), which efficiently identifies and locates faults.

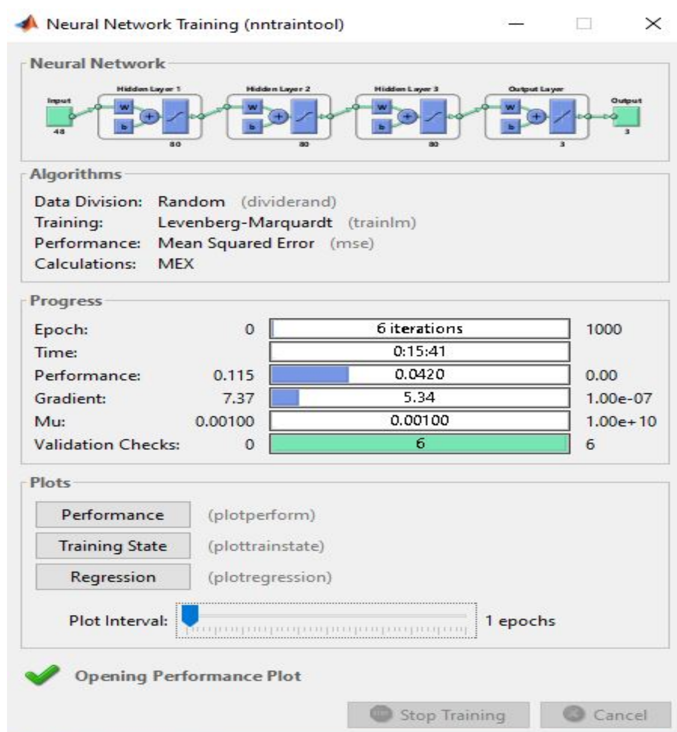

Fig. 4. Neural network training status.

The training outcome is deemed satisfactory as the re-

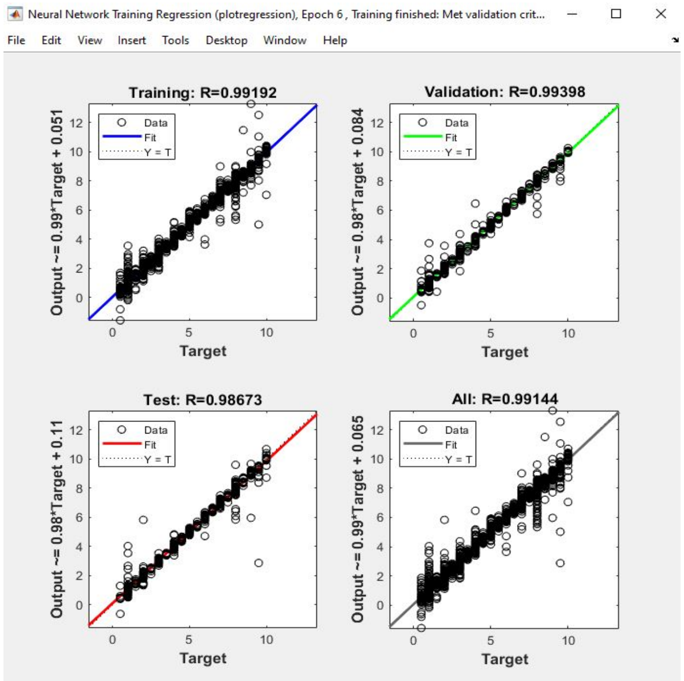

Fig. 5. Regression performance.

gression line aligns closely with the actual values, deviating minimally, as depicted in Figure 5. This indicates that the ANN has understood the intrinsic correlation between the target and output variables, allowing it to generate accurate forecasts.

Table XII, Table XIII, and Table XIV display the research findings concerning the Number of Lines, Types of Faults, and Fault Locations in the Microgrid. Each line was 10 kilometers long, and there were a total of eight lines. Consequently, five arbitrary points were selected on distinct lines to assess the effectiveness of the work across diverse kinds of faults. The research findings are viewed as positive, as the tables show that the computed fault locations align closely with the actual fault locations, and the predicted number of lines and types of faults are accurate.

TABLE XII
PREDICTED LINE NUMBER DURING TESTING

Actual line No.	Predicted Line No.	Remark
2	2	Correctly Identified
3	3	Correctly Identified
6	6	Correctly Identified
7	7	Correctly Identified
8	8	Correctly Identified

TABLE XIII
PREDICTED FAULT TYPE DURING TESTING

Actual Fault Type	Predicted Fault Type	Remark
AB	AB	Correctly Identified
ABC	ABC	Correctly Identified
ABG	ABG	Correctly Identified
BG	BG	Correctly Identified
CAG	CAG	Correctly Identified

TABLE XIV
PREDICTED FAULT LOCATION DURING TESTING

Actual Fault Location (km)	Predicted Fault Location (km)	Error (%)
5.123	5.176	1.023
7.525	7.5905	0.862
4.25	4.1907	1.395
2.9	2.8729	0.934
8.215	8.2719	0.687

IV. CONCLUSION

The optimization of neural networks, particularly by adjusting the number of neurons and hidden layers, frequently leads to improved performance as it allows them to capture complex data patterns and relationships effectively. Employing 80 neurons and 3 hidden layers in my neural network resulted in superior outcomes, demonstrating the significance of architectural decisions in network design. This configuration yielded promising results, with a minimum error of 0.687 % and a maximum error of 1.395 % for fault location prediction, showcasing the network's ability to accurately identify fault locations. These findings underscore the effectiveness of ANN in fault classification and localization tasks. ANNs offer high accuracy and robustness in identifying and pinpointing faults, making them valuable tools in various applications, including power systems and fault diagnosis.

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