Application of Artificial Intelligence in Detecting & Locating Different Faults in Grid-Integrated Microgrid

Smrutimayee Nanda[1], Dr. Subrat Kumar Barik[2], Dr. Rudranarayan Senapati[3], Bikash Pattanayak[4]

1. Research Scholar, School of Electrical Engineering, KIIT Bhubaneswar, Odisha, India
2. Associate Professor, School of Electrical Engineering, KIIT Bhubaneswar, Odisha, India
3. Asst. Professor, School of Electrical Engineering, KIIT Bhubaneswar, Odisha, India
4. Research Scholar, Department of Electrical Engineering, NIT Jamshedpur, Jharkhand, India

Abstract

In recent years, the integration of artificial intelligence (AI) techniques in power systems has gained significant traction, particularly for enhancing the reliability and efficiency of fault management processes. This paper introduces an advanced method using Artificial Neural Networks (ANNs) for fault detection and location on the AC side of microgrids. Microgrids, integrating distributed energy resources and operating in grid-connected or islanded mode, face various fault challenges. Timely and accurate fault detection is essential for stability and reliability. The proposed approach utilizes ANNs' pattern recognition capabilities to identify and locate faults accurately. Training on a comprehensive dataset covering diverse fault scenarios enables the ANN model to achieve high accuracy in detecting single-line-to-ground, line-to-line, double-line-to-ground, and three-phase faults. Simulation results demonstrate minimal error in fault localization, indicating the ANN's potential for real-time integration into microgrid management systems. This study underscores the ANN's efficacy, offering a robust solution to enhance microgrid fault resilience and operational efficiency.

Keywords: ***Fault Detection, Fault Location, Artificial Neural Network (ANN), Microgrid, Intelligent Grid Operations***.

1. Introduction

Microgrids, integrating various distributed energy resources (DERs) such as solar panels, wind turbines, fuel cell, and batteries, offer a flexible and resilient alternative to traditional centralized power systems. Their capability to operate in both grid-connected and islanded modes enhances reliability, especially during grid disturbances. However, this complexity and dynamic operation introduce significant challenges in fault management, particularly on the AC side. Effective fault detection and location are crucial to prevent power outages, equipment damage, and safety hazards. Traditional fault detection methods, such as impedance-based and traveling wave techniques, often fall short in microgrids due to their variable operating conditions and the presence of multiple DERs. These methods may not provide the necessary speed and accuracy, posing a risk to the microgrid's stability and reliability. To address these limitations, this paper explores the use of Artificial Neural Networks (ANNs) for fault detection and location in the AC side of microgrids. ANNs excel in complex pattern recognition tasks, learning from historical data and adapting to new patterns. This makes them well-suited for the dynamic and diverse fault scenarios present in microgrids. The proposed approach involves training an ANN with a comprehensive dataset that encompasses various fault conditions. Extensive simulations demonstrate the ANN's high accuracy in detecting and locating faults, outperforming traditional methods.

.

2. Literature review

A coordination control system for hybrid AC/DC smart microgrid using artificial neural networks (ANNs) for fault localization, diagnosis, and online detection has been developed by *Jasim. et. all* [1]. The study showed effective fault handling but limited its applicability to specific microgrid types and fault scenarios.[2] proposed an ANN architecture based on wavelet-multi resolution analysis for DC microgrid fault localization and detection, demonstrating precise fault identification. Scalability to larger or more complex systems was not explored.[3] introduced an ANN-based method for fault localization and detection in DC microgrids, enhancing fault management precision. The study did not address the training requirements and computational costs for real-time applications.[4] investigated the use of ANNs for locating, classifying, and detecting transmission line faults, proving their effectiveness in transmission systems. However, the emphasis on transmission lines might not be applicable to microgrids, which have different operating features and fault scenarios.[5] presented an ANN-based method for power system fault localization, categorization, and detection, showing improvements in fault management. The study lacked discussion on the challenges and limitations of integrating ANN-based fault detection in real-world power systems with diverse failure situations and operating characteristics.[6] demonstrated effective use of ANNs for power system defect detection but noted the absence of real-time execution, limiting practical usefulness.[7] employed wavelets and ANNs for defect detection and classification in medium voltage DC shipboard power systems, proving effective identification but highlighting the challenge of real-time implementation due to high processing power requirements.[8] suggested using Taguchi-based ANN and wavelet transform for fault detection, classification, and placement in microgrids, achieving accurate results but requiring significant parameter adjustment and optimization.[9] introduced a fault classification and detection technique in compensating networks combining relay and ANN, showing efficient fault identification but dependent on specific relay and ANN architecture, reducing flexibility.[10] created an ANN-based photovoltaic defect detection method, effectively identifying solar system faults but limited by the range of input parameters examined, potentially impacting comprehensive fault detection.[11] proposed an ANN solution for defect detection and classification of power system busbars, demonstrating accuracy but lacking detailed discussion on ANN drawbacks for this specific application.[12] described using neural networks and the S-transform for fault identification, categorization, and location estimation on overhead transmission lines, demonstrating efficacy but not addressing ANN drawbacks in this context.

This paper proposes a novel approach utilizing ANNs for fault detection and location on the AC side of microgrids. The methodology involves training the ANN with a comprehensive dataset that includes various fault scenarios and operating conditions. The trained ANN is then tested through extensive simulations to evaluate its performance in accurately detecting and locating different types of faults. The results demonstrate the effectiveness of the ANN-based approach, highlighting its potential for enhancing the resilience and reliability of microgrids.

3. AC/DC Microgrid

The schematic presentation of the AC/DC Microgrid has been illustrated in “Figure 1”. The designed Microgrid has different power sources like AC main grid with 415volt as distribution voltage, PV based solar power plant, Wind turbine-based power plant, Fuel Stack based Power plant, ESS for emergency load, AC and DC loads. A bidirectional regulator manages power flow between the wind turbine, PV module, Fuel stack, and ESS, regulating the DC bus voltage. The ESS stores spare energy and provides backup power when renewable sources are insufficient. The solar PV array contributes DC electricity, and an inverter connects the DC bus to the grid, allowing for energy export/import.

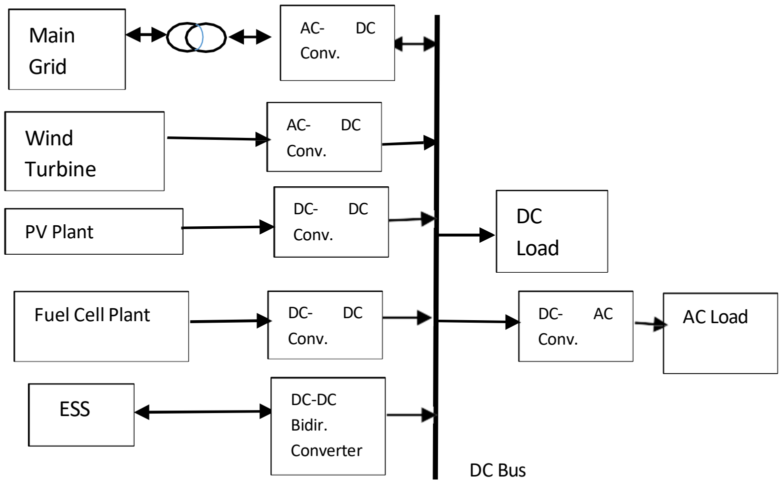


Figure 1. Basic block diagram of the proposed Microgrid

A. Components of the Microgrid:

The components of the designed Microgrid consists of Main Grid with distribution voltage of 415Volt(L-L), 50KWp PV based solar power plant, 11KW wind-based power plant, Fuel cell stack-based power plant and ESS.

B. PV based power plant:

The specifications of the designed PV power plant are mentioned in Table I, below.

Table I. PV Module Parameters

Sl. No	Parameter	Value
1	Max. Power per module in watt	89.7
2	Cells per module	60
3	No. of parallel string	47
4	No. of series string	12
5	Open ckt. voltage in volt	37.1
6	Short circuit current in amp	3.5
7	Voltage at Max. power in volt	29.9
8	Current at Max. power in amp	3
9	Max. Power Output from Plant (W)	50590

C. PV Characteristics:

"Figure 2" represents the PV module Voltage, Current, and Power characteristics at maximum power point against different irradiance. It can be observed that maximum power output from the plant is 50590.8 at 1KW/m^2 irradiance.

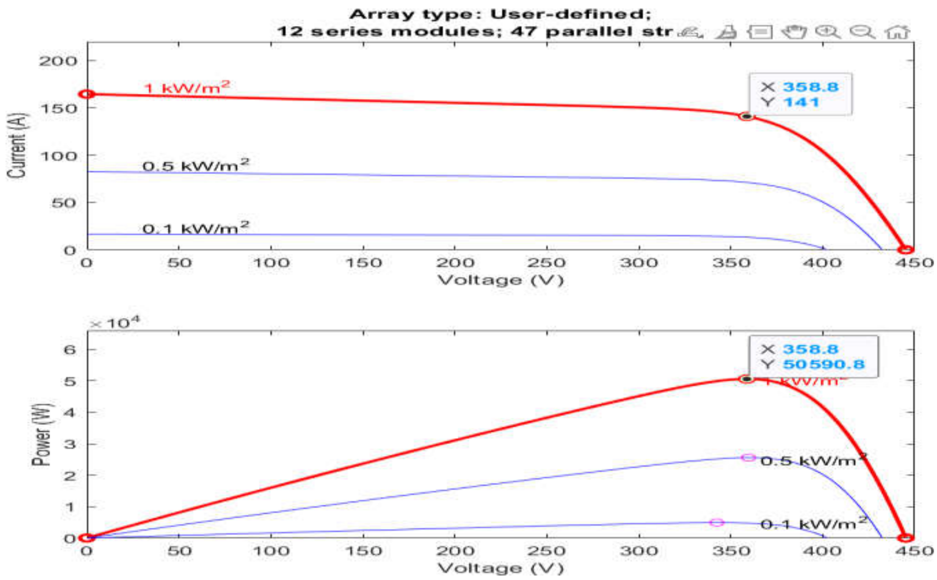


Figure 2. PV characteristics

D. Maximum Power Point Tracking:

The PV output depends on irradiance, temperature and direction if sun etc. The maximum power point of the PV array shifts under varying situations. Therefore, MPPT technology needs to extract maximum power from the array. Here, the selected MPPT algorithm is Perturb and Observer (P & O). The controller will move the photoelectric array operating point in the desired direction if the output voltage of the array changes in accordance with the operating voltage change.

E. Wind Turbine Source:

The specifications of the designed wind power plant are presented in Table II .

Table II. Wind Turbine Parameter

Sl. No	Parameter	Value
1	Nominal mechanical power output (w)	11000
2	Base power of generator(W)	12222.22
3	Base wind speed (m/s)	12
4	Max. power at base wind speed (In pu of mech. Power o/p)	1.2
5	Base pu rotational speed	1

F. Fuel Cell Source:

The specifications of the designed fuel cell stack-based power plant are presented in Table III.

Table II. Wind Turbine Parameter

Sl.No	Parameter	Value
1	No. of cells	65
2	Stack efficiency (%)	5500%
3	Operating temp. in degree	65
4	Nominal air flow (Ipm)	300
5	Nominal supply pressure	1.5bar-Fuel, 1 bar-Air
6	Voltage at 0A & 1Amp	65 & 63
7	Nominal operating point	133.3 amp & 45v
8	Nominal stack power (w)	5998.5
9	Max. stack power(w)	8325

4. Artificial neural Networks

Artificial Neural Networks (ANNs) have seen significant growth due to their ability to uncover complex patterns in data that linear methods struggle with. ANNs learn from input-output mappings through iterative training, enabling them to recognize patterns and generalize models. They consist of neurons organized into layers: input, hidden, and output. In this study, we propose models based on multi-layer Feedforward Neural Networks (FFNN) with exponential activation functions for fault detection and fault Location (FL) identification. The input layer receives features, the hidden layers process them, and the output layer computes final outcomes. Each neuron performs computations detailed by equation (1), facilitating effective pattern recognition and model creation in ANNs.

$$f_i = \sum_{j=1}^{n} w_{ij} x_{ij} + b_i \qquad (1)$$

If w_{ij} is the weight related with neuron i and input j, x_{ij} is the input value traveling from j to i, and b_i is the bias related to unit i. The computation result is subsequently sent via an AF that generates the neuron's output, as indicated below:

$$y_i = \varphi(f_i) \tag{2}$$

where φ is the AF and fi is the neuron's final output. Each neuron within the network performs a calculation. It first takes in values from other neurons as inputs, sums up all of the weighted inputs, and then uses the AF to compute the output. Given a collection of N input–output pairings (s={(x1,y1)…..(xN,yN)}), the proposed method's learning process entails iteratively changing the weights of the network and preferences in order to reduce an error function, such as the MSE. It is crucial to remember that the neural network's weights and biases must all be randomly initialized before the training process can begin. The output values in forward propagation may be computed as O={(o1) …..(oN)} since the input values or features s={(x1)…..(xN)} are transmitted to the network that has already been initialized. This forward propagation approach aims to offer projections that may be linked to the true quantities of the sample provided by Y={(y1) …..(yN)} using a specified error function. The error function compares the projected outcome values of the network with the actual values that are obtained from it. The MSE is used to estimate the error E(X) among the real (y) and projected values (o).

$$E(X) = \frac{1}{2N}\sum_{i=1}^{N}(o_i - y_i)^2 \tag{3}$$

The last phase in this procedure is to use gradient descent to backpropagate the computed error through the network and modify the neural network's parameters (w_{ij}^k, b_i^k) in accordance with

$$\Delta w_{ij}^k = -\alpha \frac{\partial E(X)}{\partial w_{ij}^k} \tag{4}$$

$$\Delta b_i^k = -\alpha \frac{\partial E(X)}{\partial b_i^k} \tag{5}$$

where α is the neural network's learning rate, for a certain number of periods, till the error is as little as feasible, this training process is repeated.

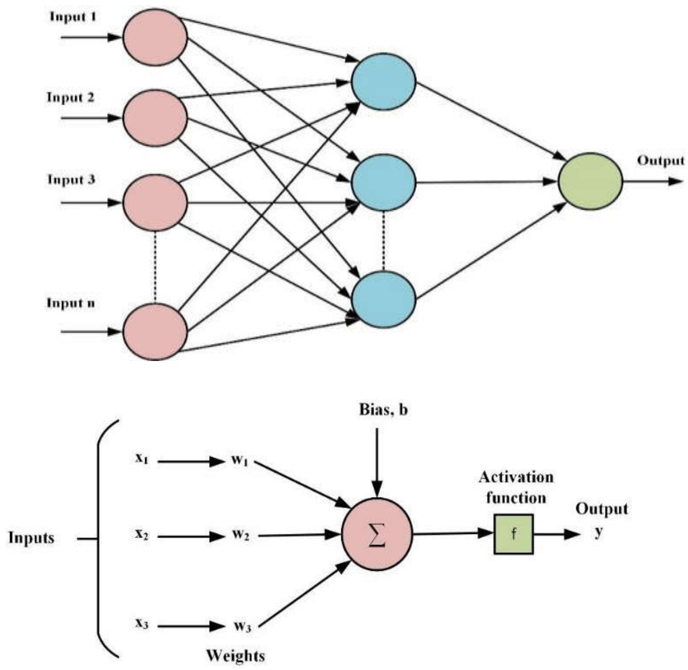


Figure3. General structure of ANN

4.1 Fault Detection in AC Side Using ANN

Fault detection is the initial and crucial step in managing power system anomalies, ensuring that any irregularities are identified swiftly to mitigate potential damage. In the AC side of power systems, fault detection using Artificial Neural Networks (ANN) leverages the ability of ANNs to recognize patterns and learn from data. The ANN is trained with a comprehensive dataset that includes various normal and fault conditions, enabling it to differentiate between regular operating states and faults such as short circuits, open circuits, and ground faults. Once trained, the ANN can continuously monitor the system, providing real-time detection of faults with high accuracy and speed, thereby enhancing the overall reliability and stability of the power grid.

4.2 Fault Location in AC Side Using ANN

After detecting a fault, pinpointing its exact location is essential for quick and effective remediation. Traditional methods often involve manual inspection and interpretation of electrical measurements, which can be time-consuming and prone to errors. In contrast, using ANN for fault location involves feeding the network with data such as voltage and current waveforms from different parts of the power system. The ANN processes this data to identify the specific segment or component where the fault has occurred. This automated process significantly reduces the time required to locate faults, minimizes downtime, and allows for targeted maintenance, ultimately improving the efficiency of fault management operations.

5. Simulation results & Discussions

The simulation of the system was carried out in MATLAB/SIMULINK, incorporating a comprehensive setup that includes PV panels, a battery unit, a wind turbine, and a fuel cell, all interconnected and linked to the grid through a common bus for integrated energy management. In the fault-free scenario, the PV panels operated at full irradiance of 1KW/m², generating approximately 42 kW of power, while the wind turbine maintained a constant wind velocity of 12 m/s, ensuring a stable energy supply. The fuel cell provided an additional 6950 W of power, further enhancing the system's energy output. The DC load parameters were kept constant at around 4.9 kW, ensuring a steady supply of energy to DC loads.

Case-1 Results without fault condition

The PV Voltage, Current & Power are represented in Figure 4. As the PV is operated at constant irradiance, the PV power obtained is around 42 KW.

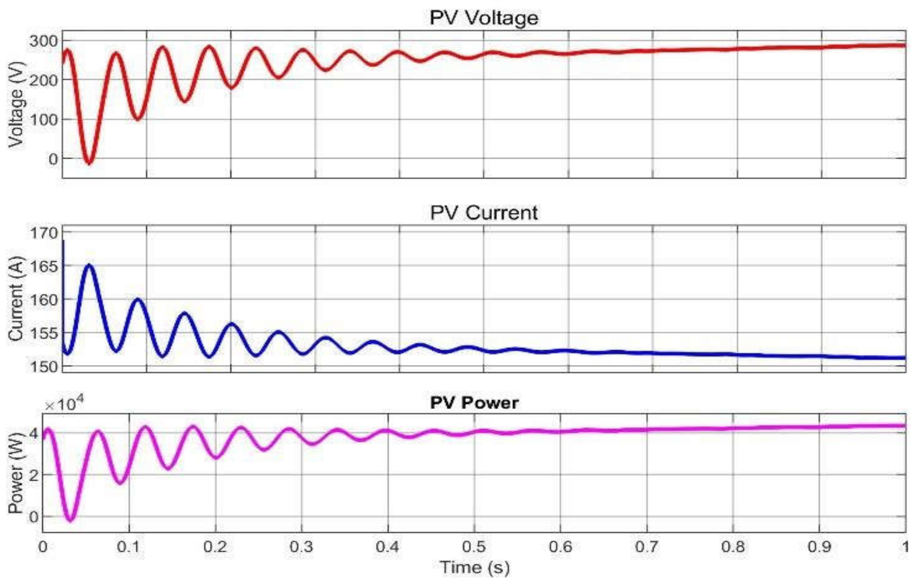


Figure 4. PV Voltage, Current & power without Fault

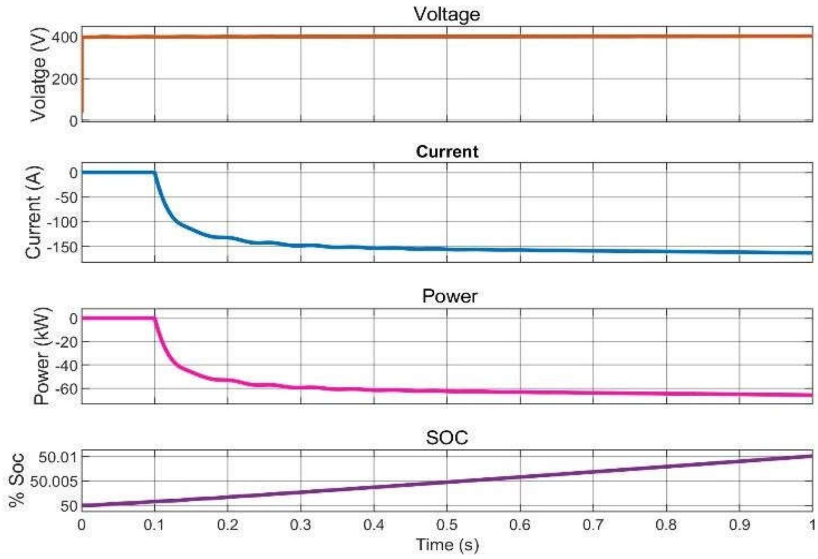


Fig.5 Battery Voltage, Current, Power & SOC

The Battery Voltage, Current, Power & SOC are depicted in Fig.5. The wind rectifier voltage, current & power was represented in Fig.6. The Fuel cell specification is represented in Fig. 7. The power obtained from the fuel cell is around 6950 W.

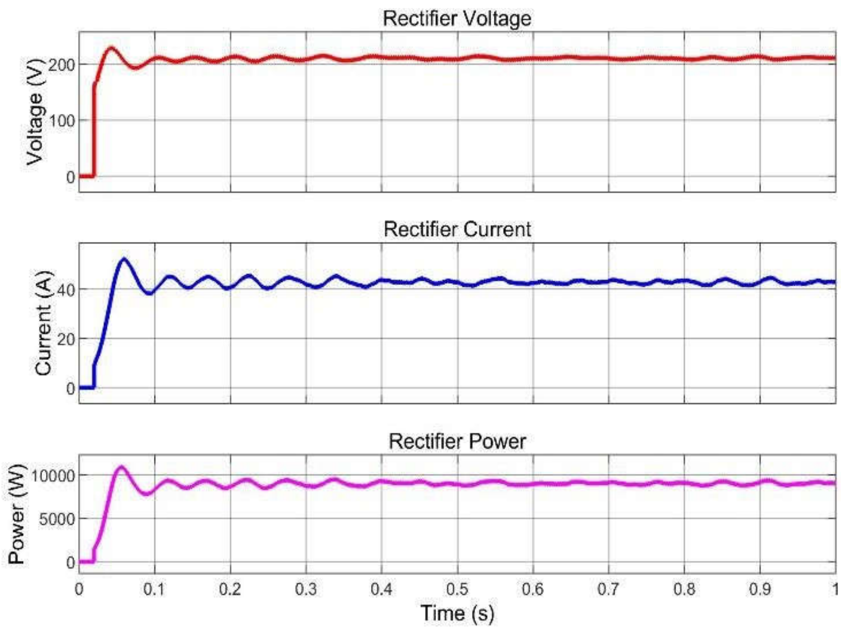


Figure 6. Wind Rectifier Voltage, Current & Power

Case 2 Results during fault condition

The Fault is created at 0.1 s. The following analysis shows the Fault detection,& location using ANN. The power response of source shown in "Figure 8".

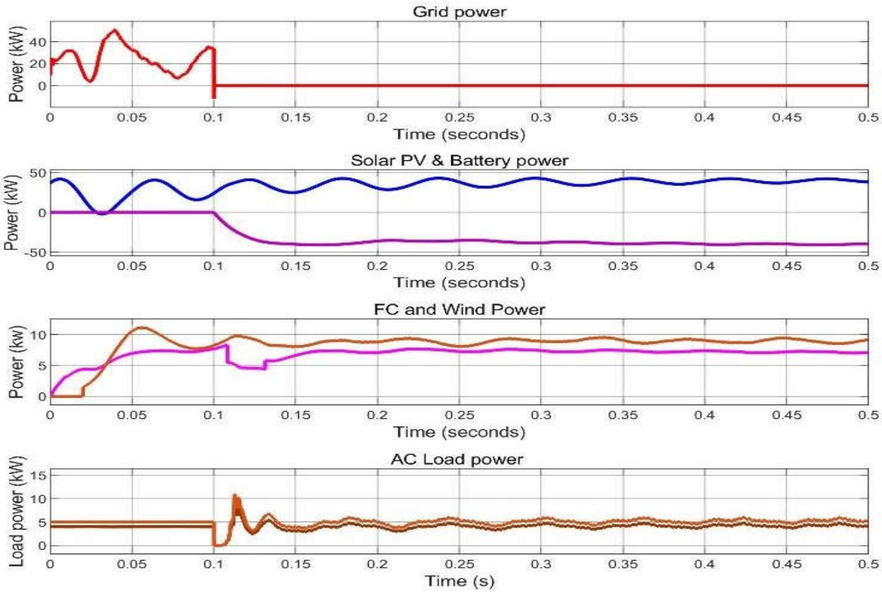
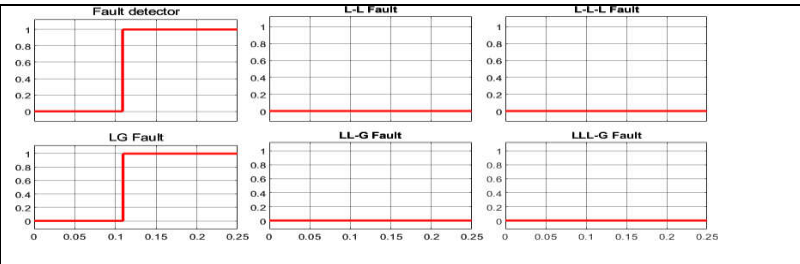
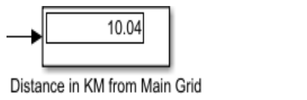
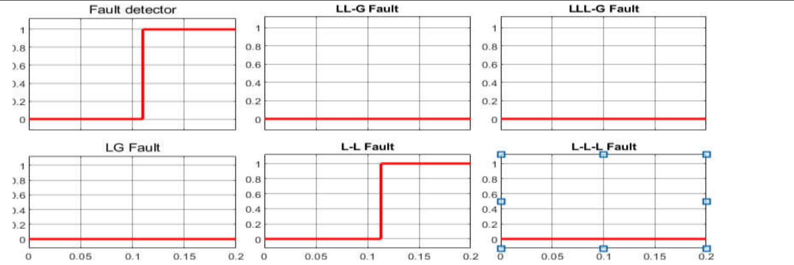
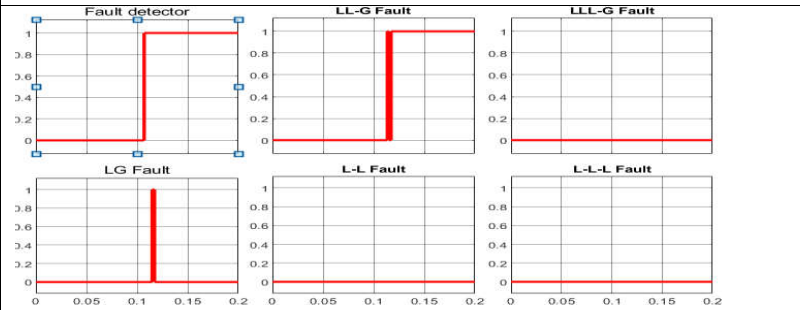
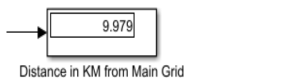
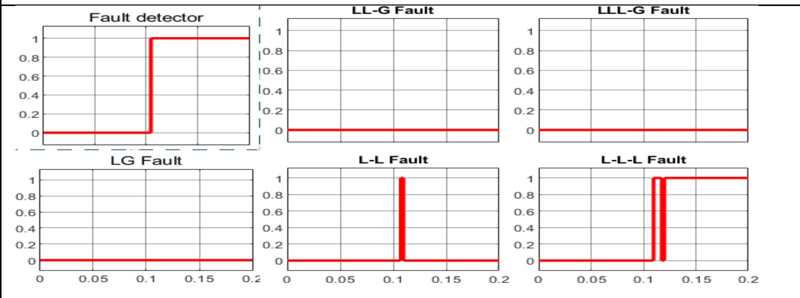
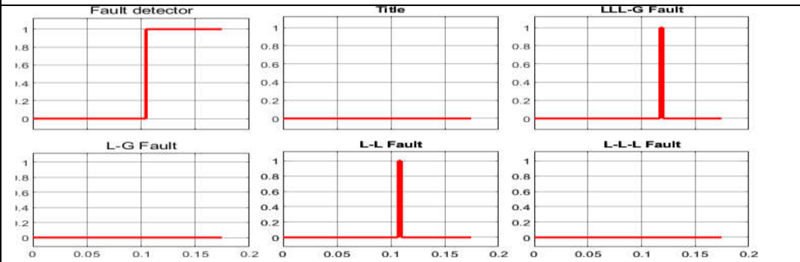
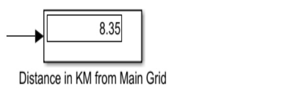


Figure 8. Power of all Sources & loads connected to the system

After 0.1s the Grid power becomes zero. The battery power is zero up to 0.1s, After 0.1s the battery charges & SOC of the battery increases.

Table IV, presents a simulated results of different type of faults, their detection and location. Here, "Fault detector," indicates the overall detection of a fault, with the signal rising from 0 to 1 around 0.1 seconds, signaling a fault's presence. The other graphs illustrate specific fault types: Single line to ground, double line, double line to ground, three phase and three phase to ground Faults and their respective location. The entire length of the line considered is 11 KM (10 KM from main Grid and 1 KM from PCC).

Table IV. Fault Detection & Location

<table>
<tr><td>L-G Fault</td><td>
</td><td>
</td></tr>
<tr><td>L-L Fault</td><td>
</td><td>
</td></tr>
<tr><td>LL-G Fault</td><td>
</td><td>
</td></tr>
<tr><td>L-L-L Fault</td><td>
</td><td>
</td></tr>
<tr><td>LLL-G Fault</td><td>
</td><td>
</td></tr>
</table>

6. Conclusion

In conclusion, the application of ANN for fault detection, location, on the AC side of power systems signifies a considerable evolution in fault management technology. The ANN-based approach demonstrates superior performance over traditional methods by offering faster detection, higher accuracy, and enhanced adaptability to various fault scenarios and system conditions. Through extensive simulations, the ANN model has proven its effectiveness in minimizing downtime and reducing operational risks, thereby improving the reliability and resilience of power systems. This research highlights the transformative ability of AI-driven solutions in enhancing the efficiency of power grid operations, suggesting that the integration of ANNs can lead to more intelligent, automated, and robust fault management practices. The flexibility of the proposed method also ensures that it can be seamlessly incorporated into existing power system infrastructures, paving the way for future advancements in smart grid technologies.

The future work includes isolation of faulty section by fast responsive breakers and extending

Reference

[1] Jasim, A. M., Jasim, B. H., Neagu, B. C., & Alhasnawi, B. N. (2022). Coordination control of a hybrid AC/DC smart microgrid with online fault detection, diagnostics, and localization using artificial neural networks. *Electronics*, *12*(1), 187.

[2] Jayamaha, D. K. J. S., Lidula, N. W. A., & Rajapakse, A. D. (2019). Wavelet-multi resolution analysis based ANN architecture for fault detection and localization in DC microgrids. *IEEE Access*, *7*, 145371-145384.

[3] Yang, Q., Li, J., Le Blond, S., & Wang, C. (2016). Artificial neural network based fault detection and fault location in the DC microgrid. *Energy Procedia*, *103*, 129-134.

[4] Tayeb, E. B. M., & Rhim, O. A. A. A. (2011, September). Transmission line faults detection, classification and location using artificial neural network. In *2011 International Conference & Utility Exhibition on Power and Energy Systems: Issues and Prospects for Asia (ICUE)* (pp. 1-5). IEEE.

[5] Karić, A., Konjić, T., & Jahić, A. (2018). Power system fault detection, classification and location using artificial neural networks. In *Advanced Technologies, Systems, and Applications*

II: Proceedings of the International Symposium on Innovative and Interdisciplinary Applications of Advanced Technologies (IAT) (pp. 89-101). Springer International Publishing.

[6] Tayeb, E. B. M. (2013). Faults detection in power systems using artificial neural network. *American Journal of Engineering Research*, *2*(6), 69-75.

[7] Li, W., Monti, A., & Ponci, F. (2014). Fault detection and classification in medium voltage DC shipboard power systems with wavelets and artificial neural networks. *IEEE Transactions on Instrumentation and Measurement*, *63*(11), 2651-2665.

[8] Hong, Y. Y., & Cabatac, M. T. A. M. (2019). Fault detection, classification, and location by static switch in microgrids using wavelet transform and taguchi-based artificial neural network. *IEEE systems journal*, *14*(2), 2725-2735.

[9] Altaie, A. S. S., & Asumadu, J. (2015, May). Fault detection and classification for compensating network using combination relay and ANN. In *2015 IEEE International Conference on Electro/Information Technology (EIT)* (pp. 351-356). IEEE.

[10] Hussain, M., Dhimish, M., Titarenko, S., & Mather, P. (2020). Artificial neural network based photovoltaic fault detection algorithm integrating two bi-directional input parameters. *Renewable Energy*, *155*, 1272-1292.

[11] Anika, A., Junaed-Al-Hossain, M., & Alam, S. H. (2019, November). Fault detection and classification of power system busbar using artificial neural network. In 2019 IEEE International Conference on Power, Electrical, and Electronics and Industrial Applications (PEEIACON) (pp. 31-34). IEEE.

[12] Roy, N., & Bhattacharya, K. (2015). Detection, classification, and estimation of fault location on an overhead transmission line using S-transform and neural network. Electric Power Components and Systems, 43(4), 461-472.