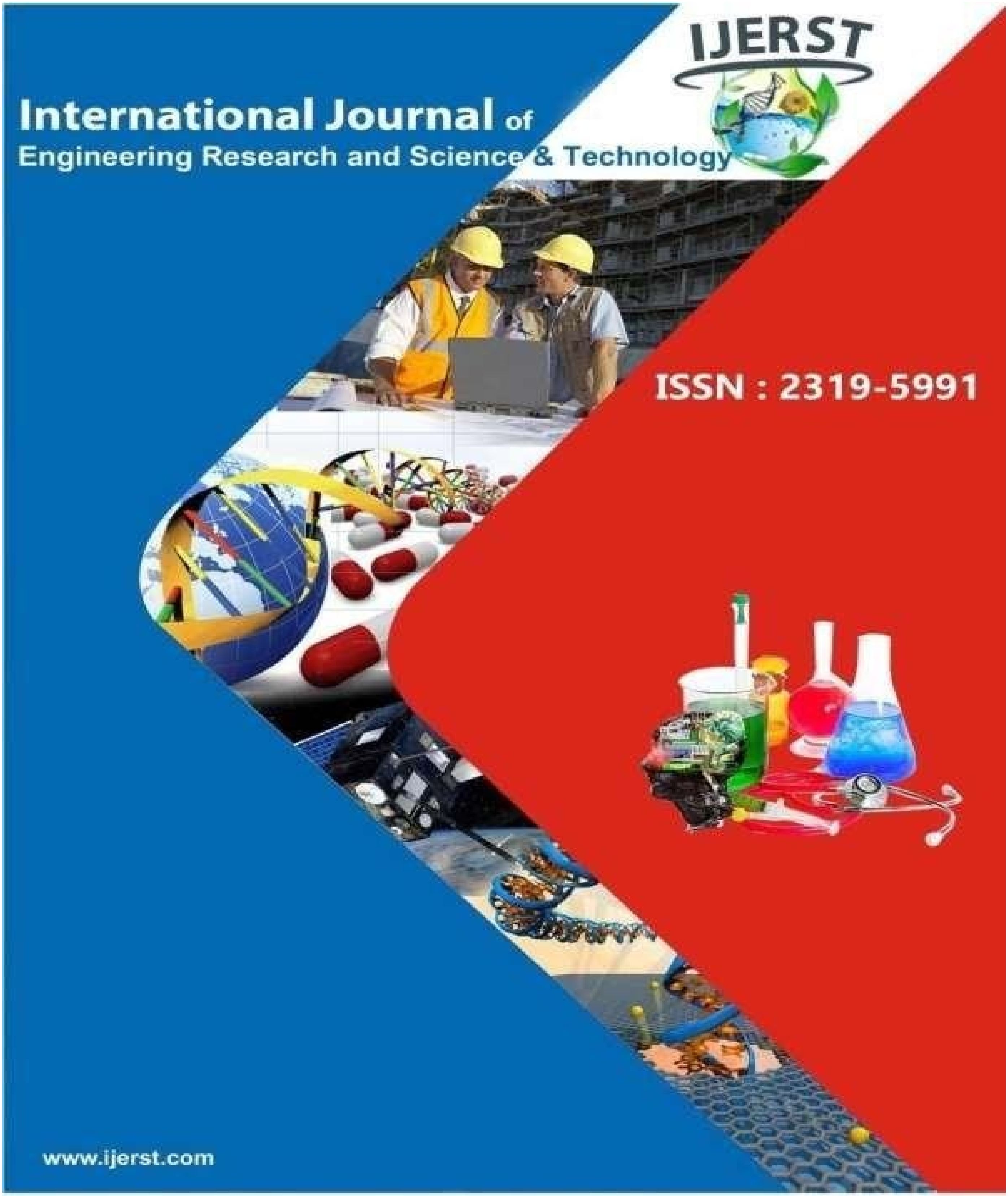

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Identification Of Faults In Microgrid using Artificial Neural Networks

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ABSTRACT:

This research offers a method to identify microgrid defects using Artificial Neural Networks (ANN). A diesel generator, a solar photovoltaic system, and a wind generator are all included in the microgrid model under consideration. Simulink is used to model both normal operation and fault scenarios for the microgrid. The faults encountered by a distribution line are represented by the simulated fault conditions. The ANN is trained using the fault voltages and currents. Using the Levenberg-Marquardt approach, the feedforward neural network in MATLAB trained effectively. Next, simulated data is used to assess the trained ANN's ability to identify different errors. Using both trained and untrained data, the ANN successfully detects defects in the microgrid.

1. INTRODUCTION:

The already burdened traditional electric power grid is facing additional challenges due to high infrastructure and development expenses, including low energy transmission efficiency, environmental deterioration, system failures, and operating limitations. Researchers are now required to look at alternate methods of supplying the rising demand for electricity in order to lessen the strain on the traditional grid. This is due to changes in electric utility functions and more regulation. By building microgrids, one method of reducing the load is to integrate it with newly developed distributed resource technologies made of renewable energy sources as wind and solar photovoltaic (PV) [1]. Through the use of power electronics, control, and protection devices, microgrids make this integration possible. Creating a dependable protection system is one of the issues with microgrid deployment. Due to low fault currents, recent research has shown that typical protection strategies may not be effective for microgrids, especially in islanded mode [2, 3]. Because the microgrid may operate in both islanded and grid-connected modes, protection techniques must work in both scenarios. A number of research have suggested several ways to preserve the microgrid [4]. Using overcurrent differential protection for every Distributed Generation (DG) source is one strategy [5]. This technique has only been tested on systems with a small number of buses and expensive communication equipment. Other protection strategies that have recently been suggested for the microgrid include differential, adaptive, and other approaches [6–9]. Fuzzy logic and artificial neural networks are two AI approaches that some academics have been using to secure microgrids [10–14].

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Wavelets and ANN were utilised by Karmacharya and Gokaraju [10] to locate faults in PV systems. Wavelet neural networks were proposed by Panigrahi et al. [11] as a fault-detection and classification system for microgrids. Microgrid protection was implemented using the Type-2 fuzzy logic approach in [12]. Additionally, data mining methods were used in [13,14] to safeguard microgrids. Further research employing AI approaches is necessary since microgrid protection is complicated. This research provides an ANN-based approach for microgrid fault identification. Section II provides an explanation of the many modes of microgrid operation as well as the numerous kinds of failures that can occur. Simulink is used to mimic both the microgrid's regular functioning and errors in a test system. In Section III, an overview of ANN is then provided. The neural network is trained and tested using MATLAB. Section IV describes the use of ANN to microgrid protection. Using both trained and untrained data for the islanded mode, the trained ANN successfully detects problems. In that part, there is also a discussion of these test results. There are closing thoughts in Section V.

2.MICROGRID, FAULTS AND PROTECTION:

A microgrid is a linked Distributed Energy Resource (DER) that is seen by the main grid as a single controlled power source, according to the US Department of Energy. It may remain operational whether it is connected to or disconnected from the main grid. The microgrid runs in islanded mode when it is cut off from the main grid [1]. The microgrid needs enough distributed generating or storage units to meet the load in order to function in both modes. Because incorporating DG encourages the use of renewable energy resources, they aid in the reduction of carbon emissions. A microgrid configuration that is examined in this work, featuring solar photovoltaic, wind, and diesel power, is depicted in Fig. 1. These Fig. 1 microgrid components are integrated using a modified IEEE 13 node test feeder. The feeder has a 4.16 kV operating voltage, and some of its features are listed in [15]. The system's actual and reactive power loads add up to around 3 MVA. The following describes the properties of the energy sources that are utilised in MATLAB/Simulink [16] simulations that are linked to this feeder.

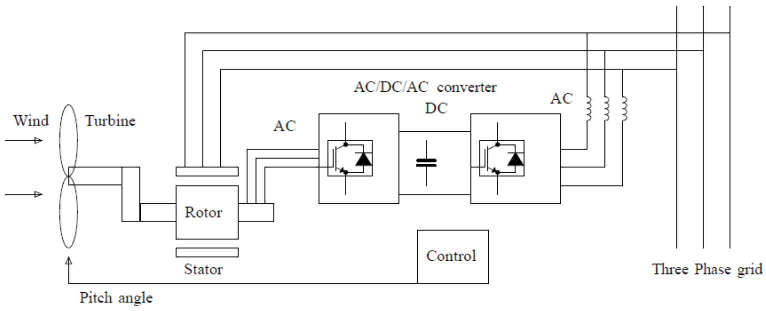

Fig. 2. DFIG wind generator schematic diagram.

The 250 KW, 250 V MATLAB/Simulink solar PV system model is displayed in Fig. 3. A circuit for a three-phase inverter converts DC to AC. A 4.16 kV step is applied to this voltage. After that, it is connected to the test feeder by a 4.16 kV, 0.15 kilometre cable.

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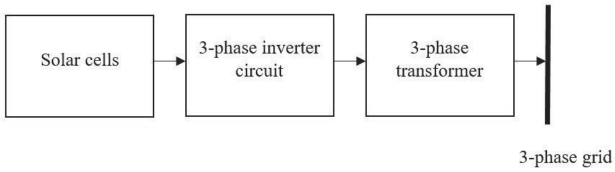

Fig. 3. Schematic diagram of solar PV system.

Diesel generator performance is investigated using MATLAB/Simulink's synchronous generator model. A transfer function is used to represent the diesel engine. The system with ratings of 3.125 MVA and 2.4 kV is depicted in Fig. 4. A transformer is used to increase this produced voltage to 4.16 kV. It is then linked by a 0.2km 4.16 kV cable to the test feeder.

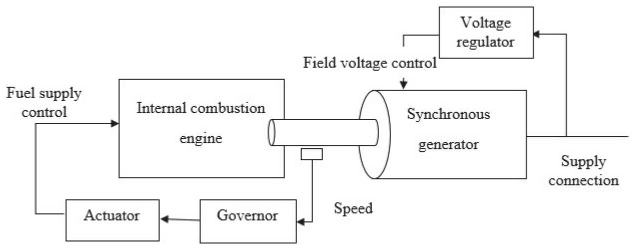

Fig. 4. Schematic diagram of a diesel generator.

The solar PV system and wind generator operate simultaneously in both the grid-connected and islanded mode modes of the microgrid, providing electricity up to their installed capacities. The remaining load power, not supplied by DER in the grid-connected mode, is supplied by the main grid. In grid-connected mode, the diesel generator operates off-line; in island mode, it supplies the remaining load not covered by the wind generator and solar PV system. Three-phase voltages and currents at bus B1 for typical islanded mode operation are displayed in Fig. 5. These voltages and currents, as can be observed, exhibit transients from the MATLAB/Simulink simulation because of the initial transients. Once the transients settle, they virtually become symmetrical and match the load. The ANN-based protection technique for the microgrid is trained and tested using these voltages and currents.

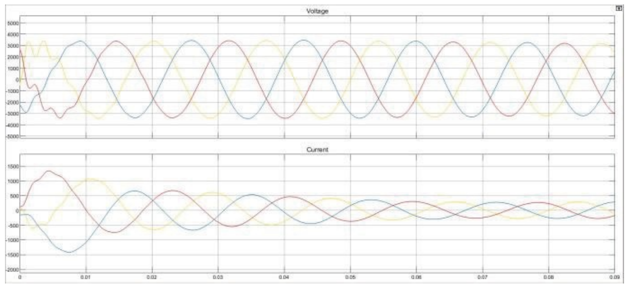

Fig. 5. Voltages/currents at relay location - normal operation.

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A. Faults and Protection:

The main goal of establishing and running microgrid-based electrical power systems is to provide consumers with uninterrupted electricity as much as feasible. Voltage surges, dips, and over currents brought on by physical mishaps, human mistake, or uncontrollable natural occurrences like lightning will inevitably create periodic power outages [17]. Faults are characterised as accidental, unintentional contacts or connections, as well as flashovers between various phases of wires and/or phase wires to ground, when some of these occurrences occur [17]. Determining the nature of the flaws, classifying them, and clearing them as quickly as feasible are all excellent maintenance practices. A fault detection system that consists of circuit breakers and protection relays guarantees a quick, safe, and dependable fault clearing process [17].

Four types of faults (single-phase-to-ground, two-phase, two-phase-to-ground, and three-phase) occur in a three-phase electrical power system that uses overhead lines, and they are mostly caused by insulation failure. Protective relays are used to guard against defects in the power system equipment. Microprocessors are used in the design and construction of the industrial protective relays used today to safeguard power systems against problems [18]. The microprocessor carries out two primary tasks. Estimating the parameters of the fundamental and other frequency voltage and current phasors is the first function. For this, the Discrete Fourier Transform (DFT) technique is typically employed. Implementing the relay logic is the microprocessor's second job. The relay logic computes extra parameters using the phasors.

If an abnormal operating state is detected in the protected microgrid component, a decision is made based on these criteria. The relay logic makes use of many computing approaches. In order to identify the defects, the logic is developed in this article utilising ANN.

activation function receives the outcome of (1) after a weighted (w) sum of inputs (x) with a bias (b) is assessed. The linear, step, sign, and sigmoid functions are the most often used activation functions. The sigmoid function seen in many applications is represented by equation (2) below.

An

$$y = f\left(\sum_{j=1}^{m} w_j x_j + b\right) \quad (1)$$

$$f(v) = \frac{1}{1+e^{-v}} \quad (2)$$

An uneven number of neurones with weighted connections make up each layer of an artificial neural network (ANN). Furthermore, every layer is made up of several nodes, or neurones, with connections between every node in a layer and every other layer. The number of nodes in the input and output layers of any ANN is determined by the input and output data dimensions. Heuristic approaches are used to determine the number of hidden layers and nodes inside them [19]. There is an ideal number of hidden layers and nodes for an ANN; anything more than that causes the classifier to overfit. Training the ANN to identify patterns in a particular data set is facilitated by adjusting the weights in accordance with the learning rule. Levenberg-Marquardt and backpropagation are two well-liked training techniques. The following is the Levenberg-Marquardt method for changing weights, w, during the kth iteration:

$$w(k+1) = w(k) - [\,J(k)^T J(k) + \mu I\,]^{-1} J(k)^T e(k)$$

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(3)

3.ARTIFICIAL NEURAL NETWORKS:

Researchers have been paying close attention to the field of artificial intelligence in recent years due to deep learning techniques that have demonstrated promise real-world applications in autonomous cars and visual systems. Support Vector Machines (SVM) and artificial neural networks are two examples of AI approaches. ANNs are more well-liked by data scientists due to their potent capacity to identify patterns in vast and intricate datasets.

Neurones in feedforward artificial neural networks are stacked in layers with only weighted forward connections to layers below them [19]. As seen in Fig. 6, these neural networks consist of three different sorts of layers: input, hidden, and output.

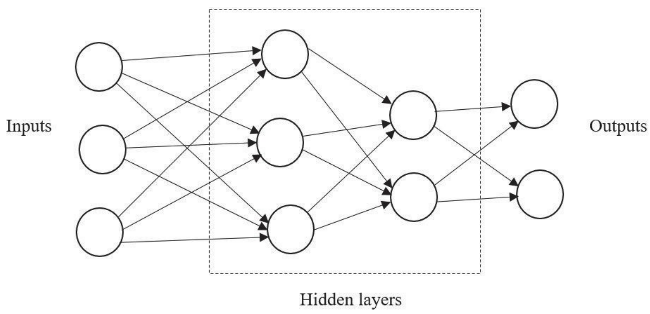

Fig. 6. Multilayer feedforward neural network.

A mathematical model of a neuron (perceptron) is given in (1).

where the damping factor, denoted by μ, is modified after each iteration until the total square error is reduced. The Jacobian matrix J contains the mistakes' e first derivatives. A feedforward network with Levenberg-Marquardt training is used in this study. The suggested microgrid protection approach makes use of a two-layered network with seven neurones in the first hidden layer and five neurones in the second. The ANN is implemented using MATLAB software. A snapshot of the MATLAB-based ANN used to identify problems is shown in Fig. 7.

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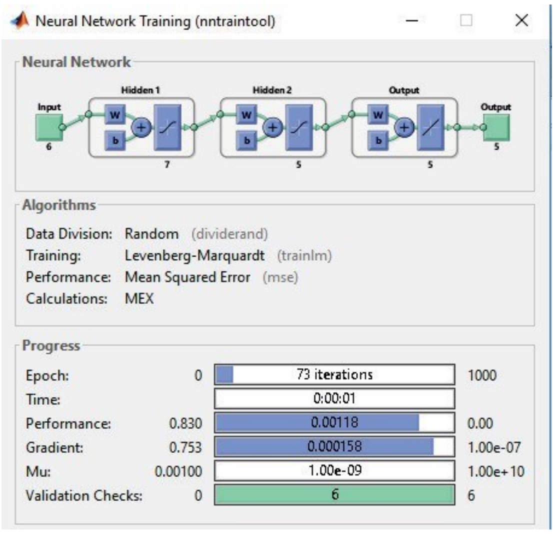
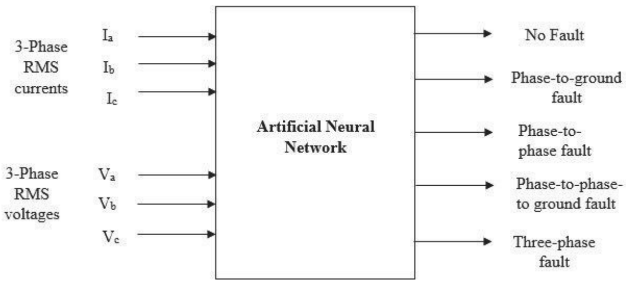


Fig. 7. A screenshot of the MATLAB ANN-based fault identification method.

4. ANN FOR THE IDENTIFICATION OF MICROGRID FAULTS:

There are four phases involved in using an ANN-based technique for microgrid protection [20]:

1. Selection of proper inputs and outputs
2. Selection of the ANN structure
3. Training of the ANN
4. Testing of the ANN
5. As in previous research, the inputs are chosen as the relay location's RMS values of three-phase voltages and currents [20]. The results show several fault scenarios as well as no problem. The output goes to 1 if that condition occurs, else the output goes to 0. The ANN displayed in Figure 8 illustrates the choices made for inputs and outputs that determine the network's topology. There are six input neurones and five output neurones in the network. Three-phase voltage and current RMS measurements are sent into the input neurones. The five output neurones represent four specified kinds of defects and one instance of no fault or normal operation. To make training easier, the number of hidden layers and the neurones within each hidden layer are chosen.



6. Fig. 8. ANN inputs/outputs for microgrid faults identification.

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On the distribution line that links buses B1 and B2 of the microgrid depicted in Figure 1, faults are simulated. At bus B1, the relay site, data is gathered. The faults are replicated at various line lengths, ranging from the relay point to the other end (100%) of the line in 10% steps. Single-phase-to-ground, phase-to-phase, phase-to-phase-to-ground, and three-phase-to-ground faults are the four categories into which these faults fall. Faults are simulated for every 10% distance on the line; the ANN is trained using the data corresponding to these faults. To test the trained ANN, faults are also generated at different distances, such as 45%.

Fig. 9 displays the three-phase voltage and current statistics for the single-phase to ground fault, taking into account the islanded mode of operation.

Instantaneous numbers taken straight out of MATLAB/Simulink make up this data. Using one cycle of data samples, fundamental frequency RMS values are calculated from these values. The DFT equation found in equation (4) [18] is used for this:

$$X = \frac{2}{N} \sum_{k=0}^{N-1} x_k \, e^{-j2\pi k/N} \qquad (4)$$

where N is the number of samples per cycle, X is the RMS value, and is the signal's sample value. The RMS values in this research are calculated using 36 samples (N=36) each cycle. Figures 10 and 11 provide the RMS values of the three-phase voltages and currents that are displayed in Figure 9. The ANN-based defects detection approach is trained and tested using the RMS values.

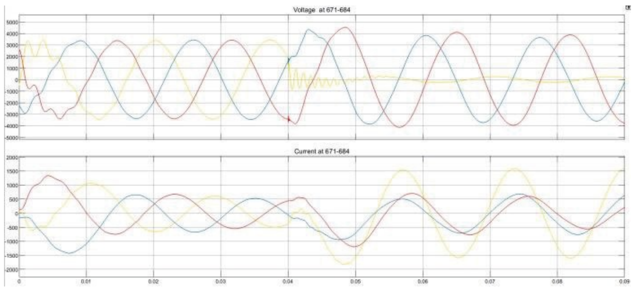

Fig. 9. Voltages and currents at relay location for phase-to-ground fault.

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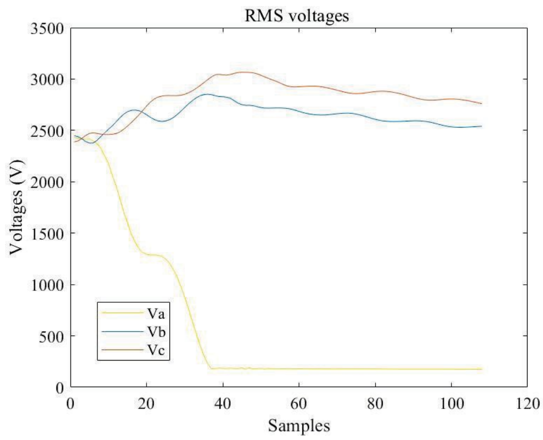

Fig. 10. RMS values of voltages at relay location for phase-to-ground fault.

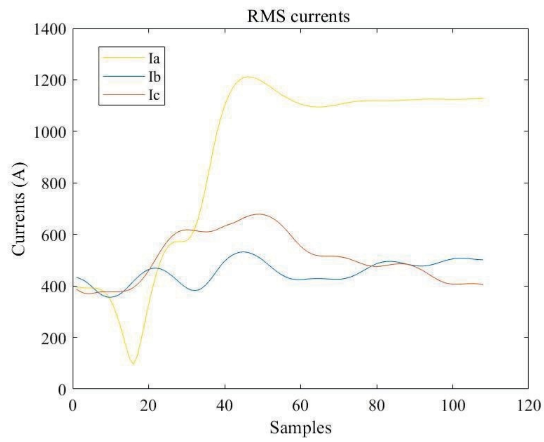

Fig. 11. RMS values of currents at relay location for phase-to-ground fault.

The ANN is trained using the MATLAB ANN toolkit. As input for ANN training in MATLAB, the data corresponding to various faults caused at 10% increment distances from the line's relay position, as well as no fault case, are organised in the necessary manner. In MATLAB, the ANN output for training is generated to indicate 1 in the event of a fault situation and 0 otherwise.

There were 4,446 samples in total in the training data for the islanded mode. For every fault, this correspond to 108 samples, or three cycles of fault data. A total of 40 fault cases, or 10 fault distances and 4 types of defects, are present. A total of 126 samples, or 3.5 cycles of regular operation, are used for the no-fault instance. The two hidden layers of the ANN, seen in Fig. 7, consist of five neurones in the second hidden layer and seven neurones in the first hidden layer. The Levenberg-Marquardt technique is used to train the network. After 73 iterations, the network was trained. Figure 12 displays the training's regression plot, while Figure 13 displays the error histogram.

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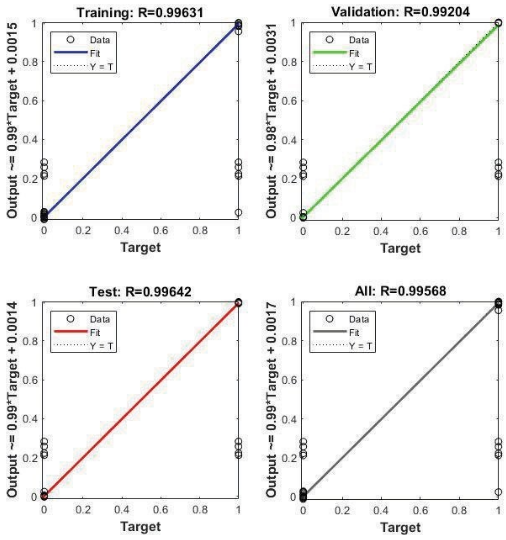

Fig. 12. Regression plot of ANN training.

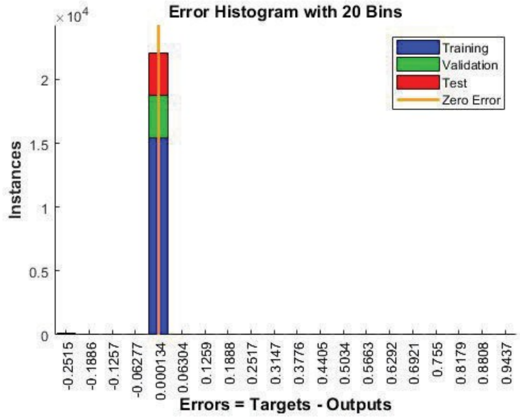

Fig. 13. Error histogram of ANN training.

Both trained and untrained data are used to test the trained ANN. The untrained data test verifies that the suggested ANN approach is appropriate for fault identification in microgrid protection, while the trained data test validates the efficacy of the training. Using the same training set of data, the trained ANN is initially evaluated. There are 4,446 samples altogether in this data set, including 40 fault instances that reflect 10 fault lengths, four different types of faults, and no problem at all. If the input voltages and currents match that fault, the ANN output is close to 1, else it is close to 0. An output of a phase-to-ground fault ANN is shown in Fig. 14.

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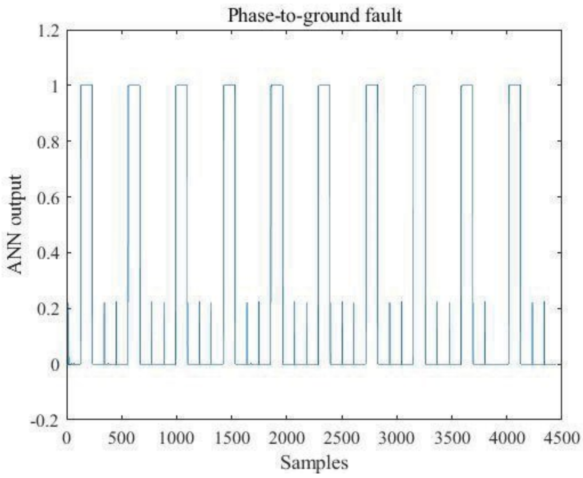

Fig. 14. ANN output for trained phase-to-ground fault data.

The untrained data, which represents four different types of faults at a distance of 45% of the line from the relay station, is then used to evaluate the trained ANN. For every situation, there are three fault cycles represented by the 108 samples that make up this data. If the input voltages and currents match that fault, the ANN output is close to 1, else it is close to 0. Fig. 15 displays the single-phase-to-ground fault ANN output for the phase-to-ground fault input RMS voltages indicated in Fig. 10 and currents shown in Fig. 11. It is evident that the output is almost 1 in the event of a malfunction and nearly 0 in the absence of one.

Similar test results with untrained data were also shown by the ANN output for the islanded data for phase-to-phase, phase-to-phase-to-ground, and three-phase faults. The untrained data findings of the ANN for one instance of each fault and no-fault condition are summarised in Table I. The ANN output is near to 1 when the RMS values of the voltages and currents match that criteria, as can be seen from the data; otherwise, it is close to 0. Therefore, the viability of applying AI approaches for the detection of microgrid defects is confirmed by the successful fault identification by the ANN for both trained and untrained data in this article.

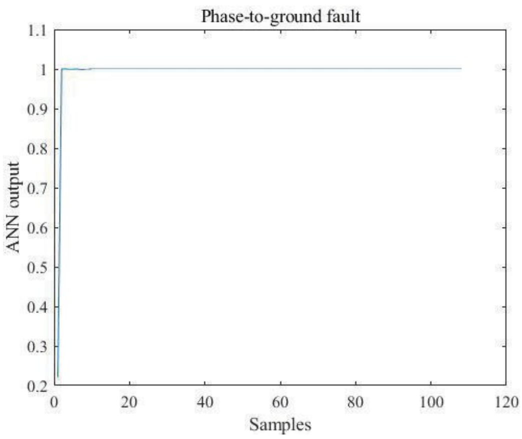

Fig. 15. ANN output for untrained phase-to-ground fault data.

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Inputs						Outputs				
Va	Vb	Vc	Ia	Ib	Ic	NF	PG	PP	PPG	3PG
2417.5	2461.5	2388.9	391.9	438	405.7	1.0010	-0.0006	-0.0002	-0.0003	0.0002
174	2540.2	2759.7	1128.7	501.5	405.2	-0.0000	1.0000	-0.0000	-0.0000	-0.0000
2084.3	1032.8	1077.8	42.7	1176.9	1139.2	-0.0000	0.0000	1.0000	0.0000	-0.0000
2576.2	122.1	141.3	271.8	1261.1	1288.5	0.0000	-0.0000	-0.0000	1.0000	-0.0000
83.4	86.8	92.4	1341.7	1335.2	1327.9	-0.0000	0.0000	-0.0000	0.0000	1.0000

Table I. Input voltages and currents and ANN outputs for untrained data.

5. CONCLUSION:

This study describes an ANN application for microgrid fault identification. MATLAB/Simulink was used to model the solar PV system, wind generator, and diesel generator for the microgrid. A modified IEEE 13 node test feeder model incorporates these DERs. In the simulations, four distinct fault types—phase-to-ground, phase-to-phase, phase-to-phase-to-ground, and three-phase—at various distribution line lengths were included in addition to normal operation. When operating in the islanded mode, the steady-state fault currents are typically smaller than when operating in the grid-connected mode. The ANN is trained and tested using the RMS values that are calculated using the DFT approach.

The single hidden layer network could not train well with the data. Two hidden layer network performed better during training. The trained ANN detects four categories of faults and a no-fault condition experienced by the islanded mode microgrid by the relay located at bus B1. The traditional overcurrent protection schemes set for grid connected mode may have difficulty in detecting faults in islanded mode because of low fault currents. Work is in progress to use ANN for detecting faults for both grid- connected and islanded modes. The paper used RMS values of voltages and currents as inputs to ANN. Other signals that may be considered in future studies include instantaneous values of voltages and currents.

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