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RESEARCH ARTICLE

Deep Learning Based Relay for Online Fault Detection, Classification, and Fault Location in a Grid-Connected Microgrid

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ABSTRACT In this article, a maiden attempt have been taken for the online detection of faults, classification of faults, and identification of the fault locations of a grid-connected Micro-grid (MG) system. A deep learning algorithm-based Long Short Term Memory (LSTM) network is proposed, for the first time, for the online detection of faults and their classifications of the considered MG system to overcome the issues that persist in the existing algorithms. Also, a combination of an LSTM network and feed-forward neural network (FFNN) with a back-propagation algorithm (BPA) is proposed to identify the exact locations of the faults since the identification of fault locations is more challenging than fault categorizations. To select a suitable deep learning network with multiple hidden layers for achieving the aforesaid objectives, a rigorous analysis has been done. To study the accuracy of the proposed techniques, different types of faults with different parameters are considered in this paper. An extensive simulation has been done in MATLAB/Simulink platform to study the performance of the system with the proposed techniques. To validate the effectiveness of the proposed techniques, the entire system is implemented in the real-time platform using the OPAL-RT digital simulator. Comparison has also been done for the results obtained using ANN and proposed techniques. The results show that the proposed techniques based on the deep learning network effectively detect, classify, and identify the location of different faults of an MG system with acceptable performances.

INDEX TERMS Fault detection, fault classification, deep learning algorithm, long short-term memory network, OPAL-RT.

I. INTRODUCTION

The demand for power from microgrids (MG) is increasing rapidly due to their reliability and ability to supply green energy [1], [2]. A MG consists of multiple distributed energy resources (DERs), communication devices, and variable loads which are always a reason for an electrical fault in the MG [3], [4], [5]. MG can operate both in islanded mode and grid connected mode. Unpredictable properties of MG components have negative impacts on the safety mechanism [6]. Therefore, the safety of an MG system is a significant matter before implementing this technique [7], [8], [9],

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[10], [11]. The faults in a power system are mainly two types; which are open circuit faults and short circuit faults. Open circuit faults occur in the system mainly due to the failure of one or more conductors. Asymmetrical and symmetrical faults are the two main types of short-circuit faults [12]. Some of the causes of these faults are weather conditions, equipment failures, human errors, etc.

The Fault in a microgrid can be unpredictable and require a focused strategy to fix the damaged parts [13]. There are different types of short circuit faults phase to phase, and phase to ground, which appear in the MG supply line and create an unstable current signal in the MG [14]. The presence of electrical faults makes the system unstable and the quality of the power is affected by it [15], [16], [17]. The appearance of these faults makes the operation of the system abnormal. It may be dangerous to personnel as well as animals and also affects the operating voltage actively. The abnormal currents due to faults can make the equipment overheat.

There are various safety devices such as circuit breakers, fuses, and relays which are commonly used for protection. Detection and classification of the faults is a big issue. Also, the location of the fault needs to be identified at the earliest possible so that faulty parts can be isolated from the main healthy system. Multiple fault analysis systems are studied to categorize the faults in the MG [18], [19], [20], [21]. In [22] and [23], a safety strategy built on transmission are presented. This method has a backup safety option when the core safety system fails to function. A mathematical morphology-based method was planned for a radial low-voltage DC distribution network [24]. A method based on abc-dq transformation is aimed at [25] to sense the type of fault. All these techniques only concentrate on the safety of a specific functioning system. In [26] phase angle, a positive voltage and zero sequences voltage-based fault identification method was planned. One more MG protection strategy based on harmonic analysis was proposed in [27]. An artificial neural network-based technique is proposed by Majid [28], where a feed-forward neural network is applied for the detection-classification of fault in the transmission line. The proposed technique was only tested with a three-phase transmission line in Simulink. Transmission lines are always connected with a main grid or with any microgrid and the response of the techniques can be different in these types of conditions. A sequential overlapping differential transform-based fault detection method is proposed by Haiyan in [29] for high-resistance ground faults. By using the initial current values, this method is tested with an AC microgrid. Zero-mode current values are used to identify the fault which is only suitable for single-phase to-ground faults. In the DC microgrid, for detecting the fault a superconducting fault current limiter is applied by Guangyang [30]. By comparing the currents of the healthy area with the faulty area currents it detects the fault. But sometimes it is difficult to know the location of the fault, so the collection of data for the comparison can become a big challenge. This method becomes slower when the fault is high resistance fault. For the detection of open circuit switch faults a method which is based on transistor logic is proposed by Godvin [31]. Transistor logic-based fault detection module is applied to detect the fault by analyzing the charge of the capacitor. An H-bridge inverter fault is detected with this technique. The operating efficiency of PV systems can be affected by unsymmetrical faults, and even can damage the system. For detecting various types of unsymmetrical faults in the PV system a voltage sensing-based method is investigated in [32]. Characteristics of the voltage signal of the system are analyzed to detect various unsymmetrical faults. But the techniques used for the detection, classification, and location of faults need to be updated and should be based on modern technology [33]. So, that the power system can easily handle these problems that are making it unstable in operation. Considering the above, there is a knowledge gap in the methods of fault detection and classification in microgrids. Deep learning-based networks have become very popular because of their accuracy and learning ability.

So, from the above mentioned survey, the contributions in the paper are as follows:

1) A maiden technique based Deep learning-based Long short-term memory (LSTM) network is proposed to classify the types of faults and to detect the presence of a fault of a grid-connected micro-grid system.
2) A combination of deep learning and artificial neural network is also proposed to detect the fault location of a grid-connected microgrid.
3) To study the effectiveness of the proposed techniques, different types of faults with different parameters are considered.
4) The study system with proposed techniques is implemented in real-time platform using OPAL-RT (OP4510) digital simulator for validation purpose.
5) Comparison has also been done for the results obtained using ANN and proposed techniques.

For the analysis of the proposed techniques, a grid-connected microgrid system is built in MATLAB/Simulink environment and different types of faults are created in the transmission line of the studied model. For every type of fault model, phase voltage and current data are collected to train the proposed LSTM network as well as the artificial neural network (ANN), FFNN. For the classification and detection of a fault, the proposed technique is compared with the ANN-based technique of detection classification of a fault. The proposed technique uses the phase voltage and current waveform data and zero sequence voltage-current data as key inputs for the fault analysis of the MG.

Based on the aforementioned objectives, the paper has been prepared as follows: the description of the studied microgrid model and methodologies are discussed in section II. Section III presents the system response and analysis. Finally, section IV draws a conclusion.

II. MODELING AND TECHNIQUES

A. MICROGRID SYSTEM CONFIGURATION AND MODELING

A grid-connected MG system is shown in Figure 1, comprising solar, diesel generator and battery, which are simulated to develop and implement the proposed method based upon ANNs. In the following sections, the mathematical formulation of the microgrid components is discussed.

Renewable energy generation contains solar PV and a wind energy source. A battery is added to maintain a constant power supply to load.

Solar: Solar PV power (P_{pv}) is produced by the PV array cells and define as,

$$P_{pv} = \eta AG(1 - \alpha(T - 25)) \tag{1}$$

where G, T, A, η, and$\alpha$are solar irradiation, temperature, panel area, efficiency, and power degradation respectively.

Wind: Wind power (P_w) produced by a wind system and formally defined as,

$$P_w = \frac{1}{2}\sigma A_b v^3 \tag{2}$$

where σ is the air density, A_b is the blade area and v is the speed of the wind.

Diesel Generator: The output power (P_G) of N numbers of diesel generators defined as,

$$P_G = \sum_{i=1}^{N} P_{Gi} \tag{3}$$

where P_{Gi} is the output of the n^{th} generator.

Battery storage: Voltage (output) and the State of Charge are analyzed as,

$$V_b = E_0 - R_{in}I_b - K\frac{Q}{Q - \int_0^t I_b(t)dt} + A\exp(-B\int_0^t I_b dt) \tag{4}$$

$$SOS = 100(1 - \frac{\int_0^t I_b dt}{Q}) \tag{5}$$

where V_b, I_b, E_o, R_{in}, K, Q, A, and B denote battery terminal voltage, battery terminal current, battery no-load voltage, internal resistance, polarization voltage, the capacity of the battery, zone amplitude, and inverse time constant respectively.

B. PROPOSED TECHNIQUE

ANN is useful for fault recognition and categorization efficiently because of its reliability to work in complex systems. For solving nonlinear as well as complex problems the ANNs are the best among other methods. The ANN can learn and update themself with involvements. They are usually accepted and applied in solving problems of different types of fault identification for the following properties:

- The condition of the power system changes after every single fault and a neural network (NN) can rearrange the system's dynamic changes.
- ANN can learn by experience and can make choices.
- They can perform more than one function at a time because of their numerical strength.

The ANN has many advantages, but it also has certain disadvantages with it. Some important features are the selection of network type, selection of the number of hidden layers, selection of the number of neurons, and learning algorithm parameters. There are some constraints like pre and post-fault values of line currents and voltages required for the detection of fault and categorization of fault. Pre and post-fault values of line current and voltage of the MG transmission lines are very different. So, the fault classification method required a NN that can able to sense and categorize the nature of faults from the pre and post-fault value patterns.

1) BACK PROPAGATION NEURAL NETWORK (BPNN)

In BPNN proper tuning of the weights reduce the rate of error. The output returned to the previous iteration to analyze any weight change. The weights are chosen randomly. After each step, the weights get updated and it is a repeated process. The most prominent advantages of BPNN are as follows:

- Backpropagation is easy, simple, and fast to program.
- Only the number of input parameters needs to tune.
- It can work without having proper knowledge of the network.

The algorithm of BPNN is shown in Figure 2.

2) DEEP LEARNING-BASED LSTM NETWORK

Neural network use neurons to transmit input data to get output responses, their deep learning system work with the transformation and extraction of features. Deep learning work with neurons that are interconnected and inspired by the human brain. LSTM is a deep-learning algorithm designed by Hochreiter and Schmidhuber. LSTM is an advanced type of Recurrent Neural Network (RNN). Power system load forecasting has been based on this method [34], for quick detection in power system LSTM is used [35], and so many other works [36], [37], [38] has shown the popularity of LSTM has increased in the field of power system because of having to multitask learning ability. To enable the storage and access of information over a long period, a memory cell is imported into the RNN structure and it runs straight down the entire chain. To add information to the memory cell, LSTM uses different optional gates. The output gate controls any entries from the cell. The input gate decides when to read data, while the forget gate is responsible for resetting the cell. A basic LSTM structure is given in the literature [39], [40].

3) DATA COLLECTION, TRAINING, AND TESTING

Neural networks and deep learning networks can be developed when input and output data are available for prediction and response. Therefore, training the network or developing the network is a very important part of it. To develop the

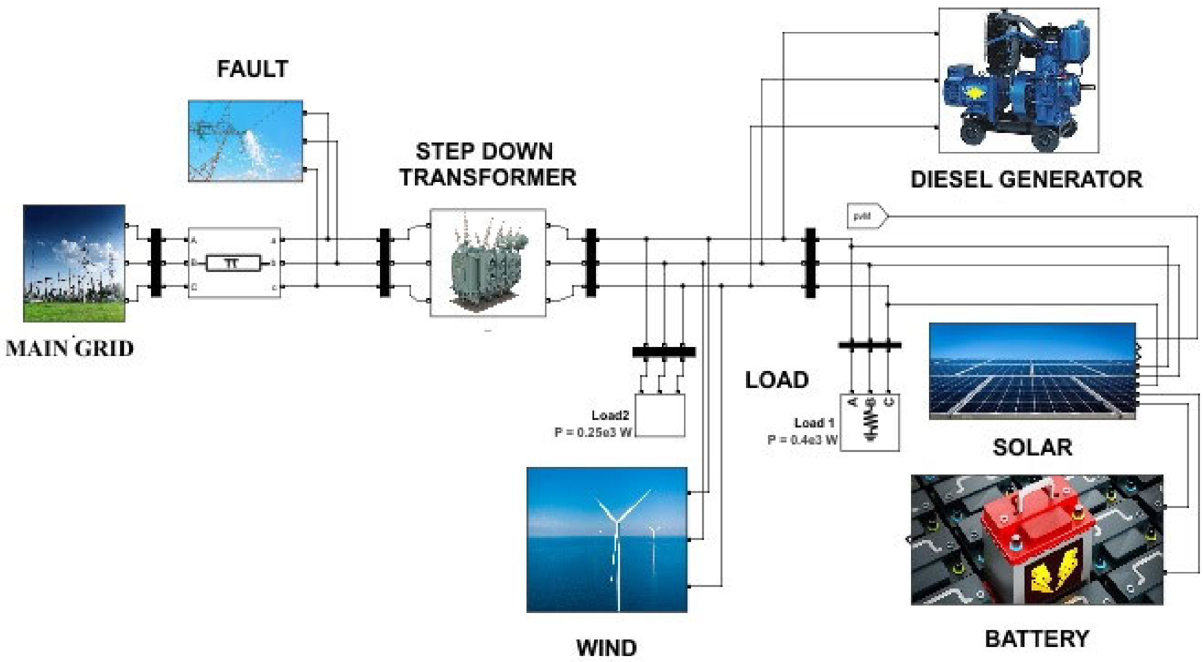


FIGURE 1. Microgrid model.

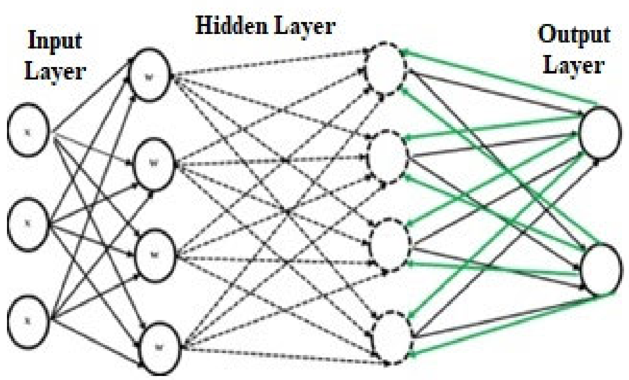


FIGURE 2. Back propagation algorithm.

neural networks and the deep learning-based LSTM network, data is collected from the considered model after creating different types of faults. A total of 11 types of faults (line A to ground fault, line B to ground fault, line C to ground fault, line AB to ground fault, line AC to ground fault, line BC to ground fault, line ABC to ground fault, line A to line B fault, line A to line C fault, line B to line C fault and line AB to line C fault) are considered to collect the training, testing and validation data. All these different types of faults are created in the model in three different locations (fault at 0 km end, fault at 5 km end, and fault at 10 km end) of the transmission line of the studied microgrid. For every different location of the transmission line, all 11 types of fault conditions are considered to collect the set of data.

For the training of ANN for the detection, classification, and detection of fault location, MATLAB neural network fitting toolbox is used. Where 10 hidden neurons are used with 70 % of training, 15 % of testing, and 15 % of testing data. After training the neural network, the trained network is exported as MATLAB/Simulink model and used in the studied model for fault detection, classification, and detection of location. The flow chart of the proposed deep learning-based LSTM network is given in Figure 3(a) and an LSTM cell structure is shown in Figure 3(b), where c and h represent the current state quantity and the current output of the LSTM unit respectively

For the training of the LSTM network fault voltage and current data of input as well as output is used, out of that 15% of data is used as testing data. A total of four layers have been utilized with 200 hidden units. The layers are the sequence input layer, LSTM layer, full connected layer, and regression layer. The number of epochs for training is 250. The LSTM network is built by MATLAB coding whose parameters are given in Table 1.

The NN toolbox and the LSTM network both use the whole dataset in three parts. The first part is the training dataset. This is responsible for the training of the NN by updating the network weights and computing the gradient till the error is zero. The second part of the dataset is validating the data set. The data set is validated, and it is used for the training. The third part is known as the testing set. The test set of data is different from training data which is not used to train. This test set of data examines the trained network. To achieve a good result large dataset is required. Therefore, different fault condition has been considered and observed at multiple locations of the transmission line. The process of fault detection, classification, and location are discussed below.

TABLE 1. **Lstm constraint values.**

Hidden Units	Optimizar	Initial Learning Rate	Drop Factor	Max Epochs
200	ADAM	0.005	0.2	250

4) FAULT DETECTION

The deep network detects the fault depending on the inputs. The inputs are three-phase voltage signals, three-phase current signals, and zero sequence voltage and current. The values of input currents and voltages are updated by the pre-fault values of the currents and voltages respectively. The output of the deep network is in binary form, i.e., 1 or 0, where 1 indicates the appearance of the fault and 0 indicates the no-fault condition.

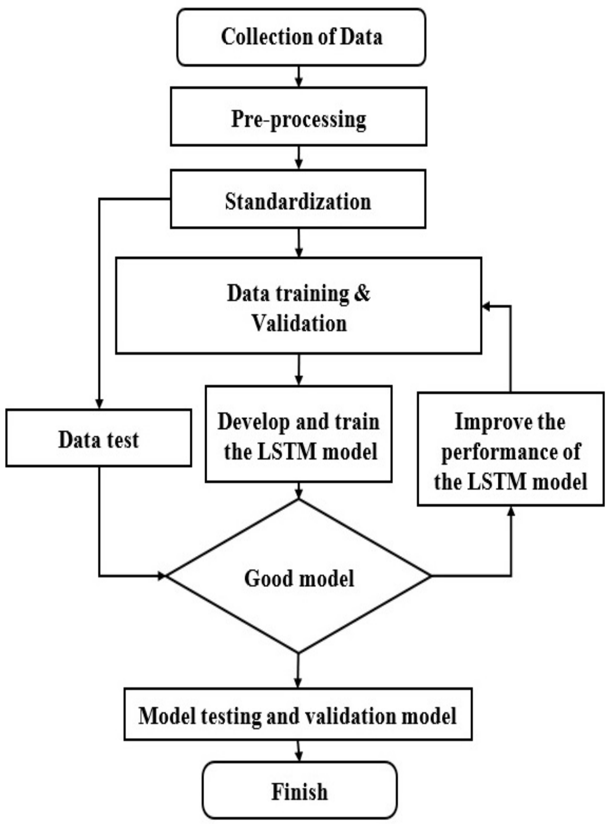
Figure 4 shows the MATLAB/Simulink block for the detection of a fault in the studied model. Where the deep network takes 8 inputs in the form of voltage and current from the location of the fault that is been created in the three-phase line of the studied model as shown in Figure 1. It provides an output in binary form. When the fault is detected successfully it gives output as 1.

The same process of fault detection is applied to detect the fault in the studied model with the ANN technique but a trained ANN network is applied in this case. The ANN is trained with the same data set that is been used to train the LSTM network and the deep network shown in Figure 4 is replaced by this trained ANN network.

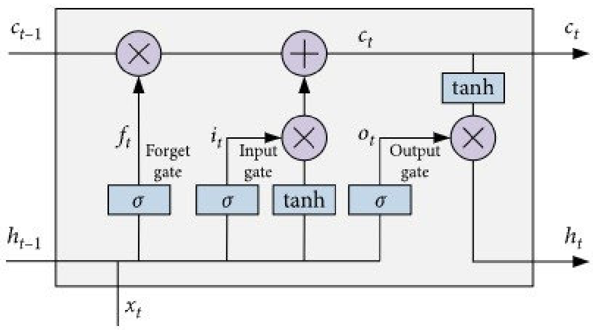
5) FAULT CLASSIFICATION

The same process is used for the development and design of the deep network for the classification of faults. The developed Network takes a set of eight inputs. Hence the deep network provides four numbers of outputs, one is for the ground line and the other corresponds to the three-phase line fault. The output result is in the binary form where 1 denotes the existence of fault on the corresponding line and 0 denotes the nonexistence of fault. The developed network with the connection of input and output ports is shown in Figure 4.

Also, for the classification of fault type by ANN-based technique same classification and the same model is applied. But the network that is used in this ANN-based technique is a trained neural network, trained in MATLAB neural network fitting toolbox with the help of pre-fault dataset, and the deep network shown in Figure 4 is replaced by this network.



(a) Flowchart of LSTM.



(b) The LSTM cell structure

FIGURE 3. **Flowchart of LSTM and the LSTM cell structure.**

6) FAULT LOCATION DETECTION

The MATLAB/Simulink neural network toolbox is utilized to detect fault locations in the line. For the detection of the location of various types of faults, two different NN are developed. The first one is used for the detection of line-to-ground and double-line-to-ground faults. Two inputs which are zero-sequence voltage and zero-sequence current are fed. The second one is used for location detection of double line fault, triple line fault, and triple line to ground fault as shown in Figure 5. The outputs depend on one input which is voltage. Figure 6 shows the structural diagram of the Simulink model for validation of the proposed method in OPAL-RT.

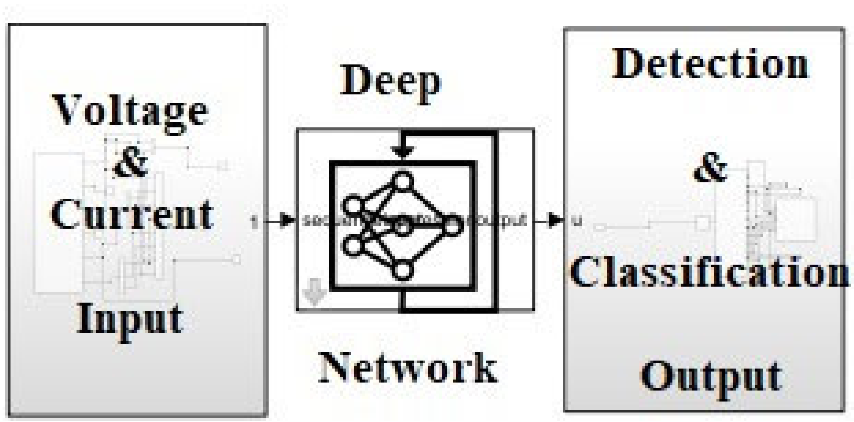


FIGURE 4. Fault classification and detection block in MATLAB/simulink.

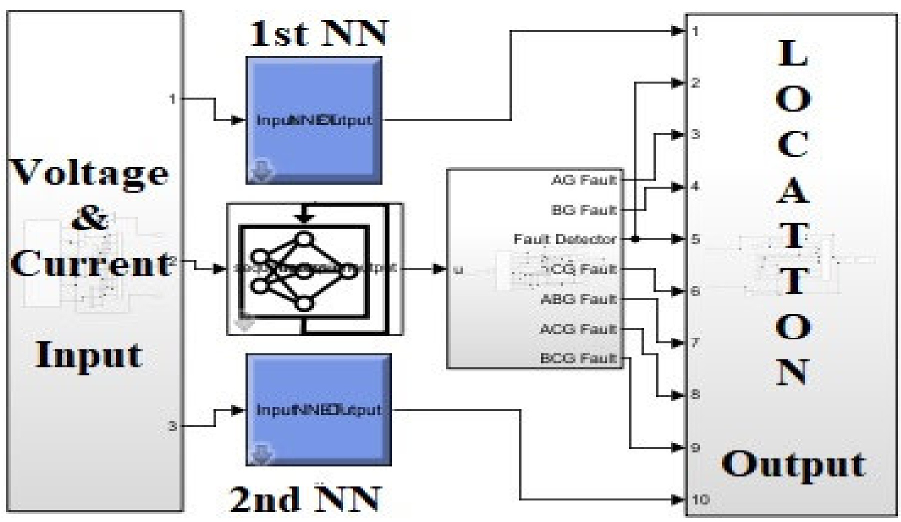


FIGURE 5. Detection of fault location MATLAB/simulink block.

III. RESULTS AND DISCUSSION

Various types of faults are created at different times of the simulation for the studied MG model at different lengths of the transmission line. A total of 13 cases are considered here in this section to analyze the performance of the proposed technique. Case-1 to case-11 are considered for the analysis of the detection and classification of the fault. Case 12 and case 13 are considered for the analysis of the fault location of the line in kilometers. For the real-time verification of the studied model for different types of faults, a real-time simulator (OP4510) is used with the OPAR-RT lab in the host system. The OPAL-RT lab setup is shown in Figure 7. In the OPAL-RT lab set up two systems, the host and target simulator are present. The host system included MATLAB and RT-lab. The real-time design of the Simulink model for real-time simulation is done in the host system of the OPAL-RT lab setup and the real-time result is been taken from this system. The other system of the setup is the target simulator which included the real-time simulator. Both these systems are connected to each other by an ethernet cable.

The proposed LSTM-based technique is compared with the ANN-based technique for fault detection and classification with their simulation results. All the cases are discussed in detail below.

A. CASE 1: AG FAULT CREATED AT 0.2 SEC

Phase A to ground fault (AG fault) is created in the Simulink model at 0.2 sec of simulation. The faulty model is simulated in MATLAB as well as in RT_LAB for 0.4 sec. The response of the model for classification and detection of fault with the ANN technique is shown in figure 8 and the proposed technique classification and the detection result are shown in

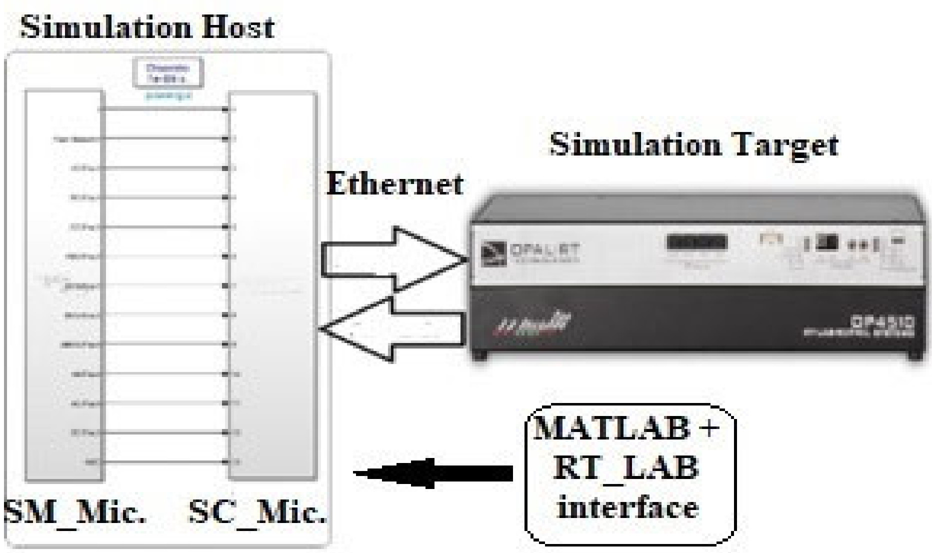


FIGURE 6. RT-Lab structural diagram.

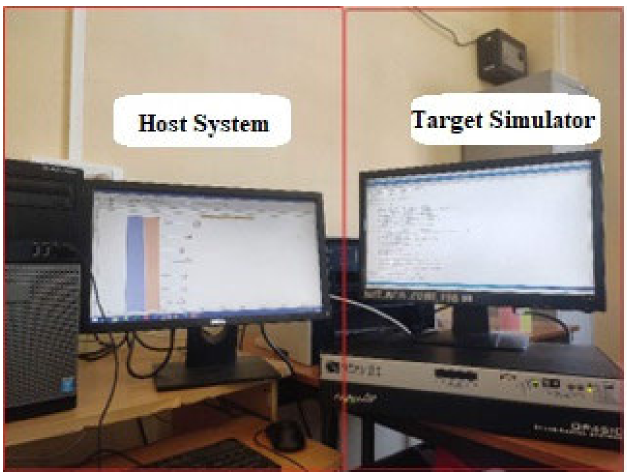


FIGURE 7. RT-LAB setup diagram with the host system and target simulator.

figure 9. In both figure 8 and figure 9, the Y axis represents the occurrence and presence of a fault in the line with the help of 0 and 1. Here the no-fault condition is denoted by 0 and 1 in the output signal denotes the presence of a fault. The X-axis represents the time of the simulation. From the fault detector graph of figure 8 and figure 9, it can be seen that the detector signal rises from 0 to 1 at 0.2 seconds of simulation which confirms that the fault occurred in the line and for the rest of the time of the simulation it stays at 1 which confirm that fault is present in the line from 0.2 to 0.4 second. For the classification of the fault total of 11 types of faults are considered in this studied model.

Figure 8 shows that other than the fault detector graph output signal rises from 0 to 1 and stays for the rest of the simulation time only in the AG fault graph, which conforms to the type of fault. But from figure 8 it can be seen that in the AG graph, it takes time to classify the fault type, the fault is detected at 0.2 sec by the fault detector graph but for classification, it takes some time. So, there is some delay in classifying the fault by the ANN-based classification technique. Also, the ABG fault graph of figure 8 rises from 0 to 1 between the time duration of 0.2 sec to 0.3 sec. At the same time, the AG graph of figure 9 shows that LSTM based technique can classify the fault at exactly 0.2 sec when the fault occurs in the line. In figure 9, the fault signal rises from 0 to 1 and stays at 1 for the rest of the time only for the fault detector and AG fault graph at 0.2 sec, which conforms to the occurrence, presence, and type of the fault. So, both the techniques are accurate for AG fault detection, but the proposed technique is more accurate in detecting the type of fault.

B. CASE 2: BG FAULT CREATED AT 0.2 SEC

For case 2 of the simulation phase B to ground fault is created in the three-phase line of the studied microgrid model. In both detector and BG fault graph of figure 10 and figure 11, the fault signal rises from 0 to 1 at 0.2 sec time it stays for the rest of the simulation time. This confirms that fault has occurred and the fault is present in the line also it conforms to the type of the fault which is BG fault.

However, in figure 10, along with the fault detector graph, some disturbances can be seen in the AG graph, ABG graph, BCG graph, and ABCG graph. For the fault detector graph of figure 10, the fault detection signal rises at 0.2 sec of simulation time but also before that it rises from 0 to 1 in between the time duration of 0 to 0.1 sec. But the fault detector graph of the proposed technique shows fault is first detected at 0.2 sec

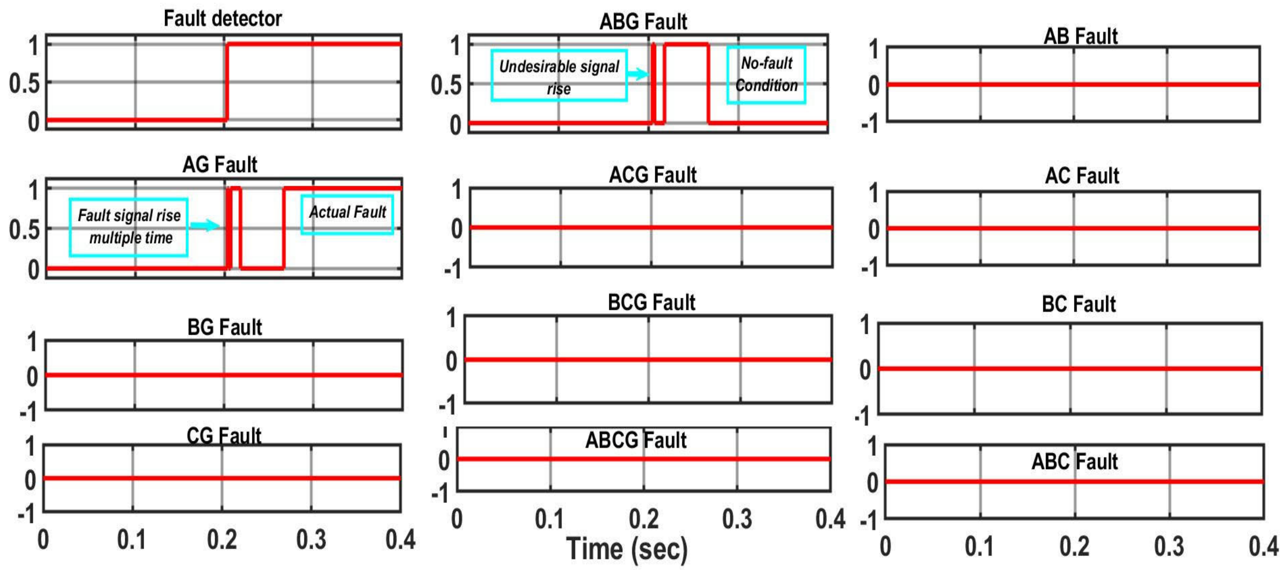


FIGURE 8. ANN fault detection and classification of AG fault (Case - 1).

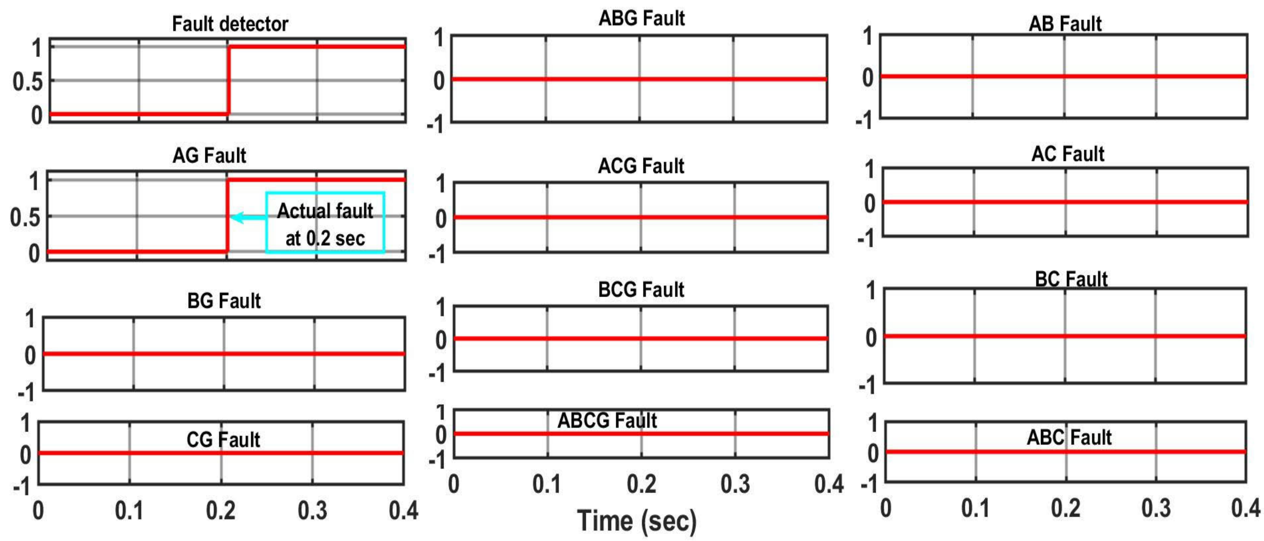


FIGURE 9. LSTM fault detection and classification of AG fault (Case - 1).

of simulation time in figure 11 and the fault detection signal stays at 1, which tells about the presence of a fault in the line. The ANN-based technique can classify the type of fault but the BG fault graph of figure 10 shows it takes some time to classify because the BG fault signal did not rise from 0 to 1 at exactly 0.2 sec of simulation time. But the BG fault graph of the proposed technique in figure 11 shows it classifies the fault at exactly 0.2 sec of simulation time when a fault occurs and there is no disturbance in any other fault graph of figure 11. So, case 2 of simulation results shows that the proposed technique is better than the ANN-based technique in classifying the type of fault as well as in detecting the fault.

C. CASE 3: CG FAULT CREATED AT 0.2 SEC

CG fault is created at 0.2 sec of simulation time in case 3 and the fault signal graph for detecting the fault as well as for classifying the fault is given in figure 12 with ANN-based technique and figure 13 with LSTM-based technique. The X-axis represents the presence of the fault and Y axis represents the time of the fault. From the fault detector graph of figure 12 and figure 13 it can be seen that at 0.2 sec of time fault signal rise from 0 to 1 and stays for the rest of the simulation time. Response of the fault signal for the CG graph of figure 13 also follows the same but the fault signal of the CG graph of figure 12 rise at 1 with a little bit of delay. The rise of the fault signal from 0 to 1 denotes that fault occurs and

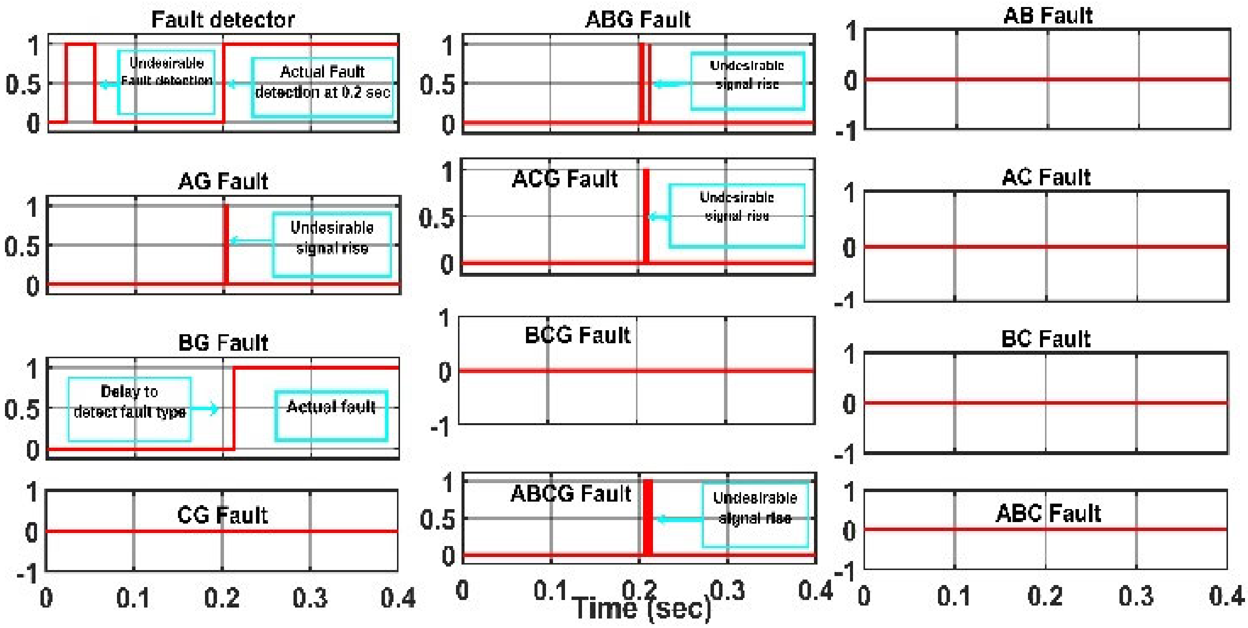


FIGURE 10. ANN fault detection and classification of BG fault (Case - 2).

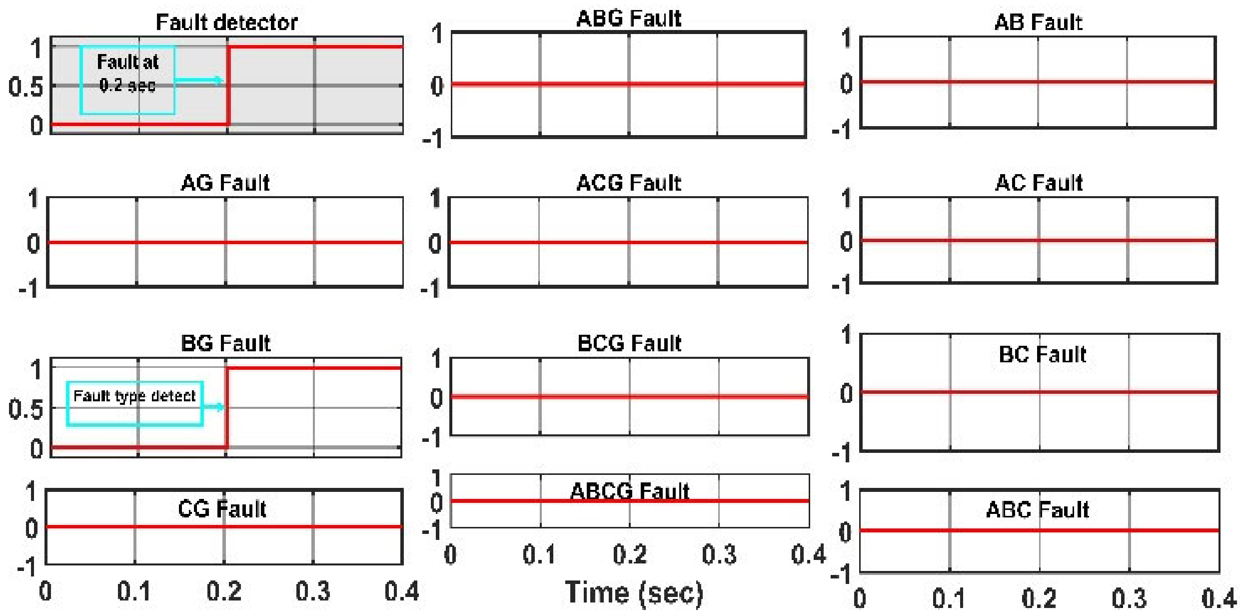


FIGURE 11. LSTM fault detection and classification of BG fault (Case - 2).

for CG graph also it confirms that specific that type of fault occurs. The time duration of 0.2 to 0.4 sec of the time fault signal stays at 1 which confirms that the fault is still in the line. So, the fault detector graph and CG graph of figure 12 and figure 13 confirms that a fault occurred at 0.2 seconds and it is a line-to-ground fault on line C. The fault persisted from 0.2 seconds to 0.4 seconds.

So, from figure 12, it is clear that the ANN based technique is capable of detecting and classifying the CG fault however, when it comes to classifying the type of fault, the technique shows a delayed response. Also, some disturbances like when the fault classifying signal of CG fault rises from 0 to 1 can be seen in some other fault graphs in figure 12. Where figure 13 shows, LSTM based technique detects the fault as well as

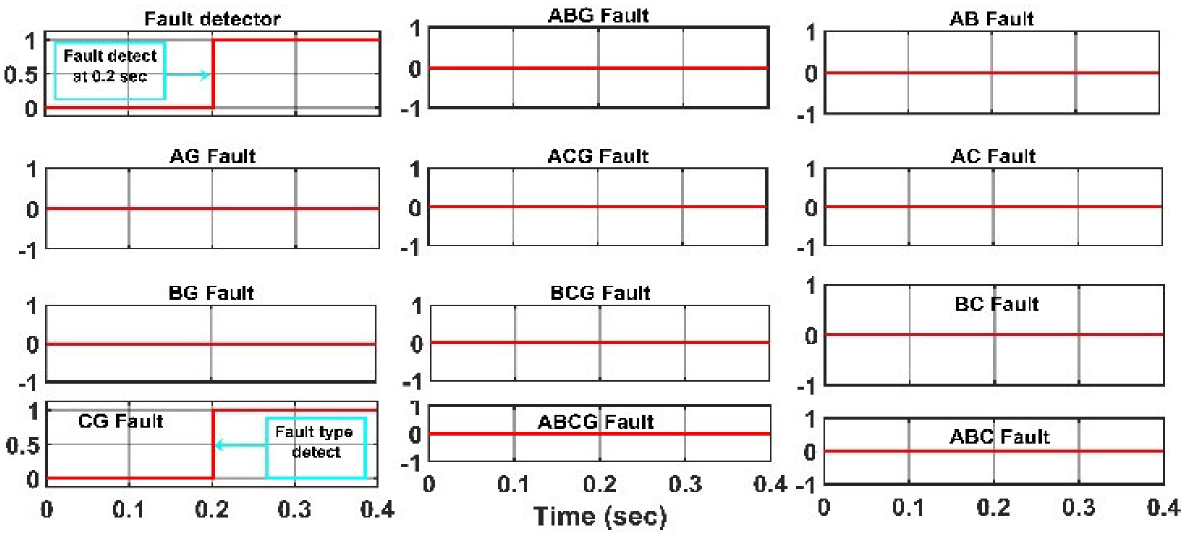


FIGURE 12. ANN fault detection and CG fault (Case - 3).

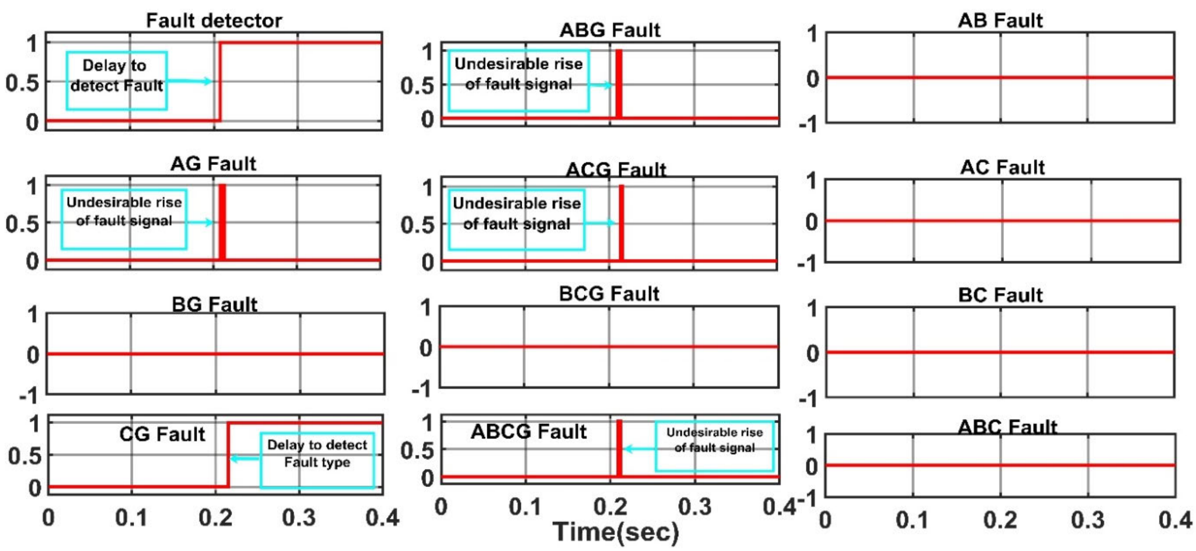


FIGURE 13. LSTM fault detection and CG fault (Case - 3).

classifies the fault at an exact 0.2 sec time of the simulation, and in the process of classifying the type of fault it gives a response only at the CG fault graph. Therefore, to classify the CG fault LSTM based technique is more precise although for detecting the presence of fault both techniques give almost the same response.

D. CASE 4: ABG FAULT CREATED AT 0.2 SEC

In case 4 phase AB to ground fault is created for the time duration of 0.2 sec to 0.4 sec. The fault classification and detection graph with fault signal are shown in figure 14 and figure 15 for classifying the type of fault and for the detection of fault when it occurs in the line. In the Y axis of figure 14 and figure 15, point 0 denotes the no-fault condition, and point 1 denotes the fault condition, when a fault occurs and is present in the line. From the fault detector graph of figure 14, it can be seen that the fault signal rises from 0 to 1 after 0.2 sec and it stays at 1 for the rest of the simulation time.

So, the fault is created at 0.2 sec that is successfully detected by the fault detector and the fault signal in the fault detector stays at 1 for the rest of the simulation time which confirms that fault is present in the line from 0.2 sec to 0.4 sec. Also, LSTM based fault detector signal in figure 15 shows that fault is detected at exactly 0.2 sec. For classifying the types of faults there are a total of 11 types of faults are considered as shown in figure 14 and figure 15. It can be seen from figure 15 that fault signals rise from 0 to 1 only for the ABG fault graph, which conforms to the types of faults that

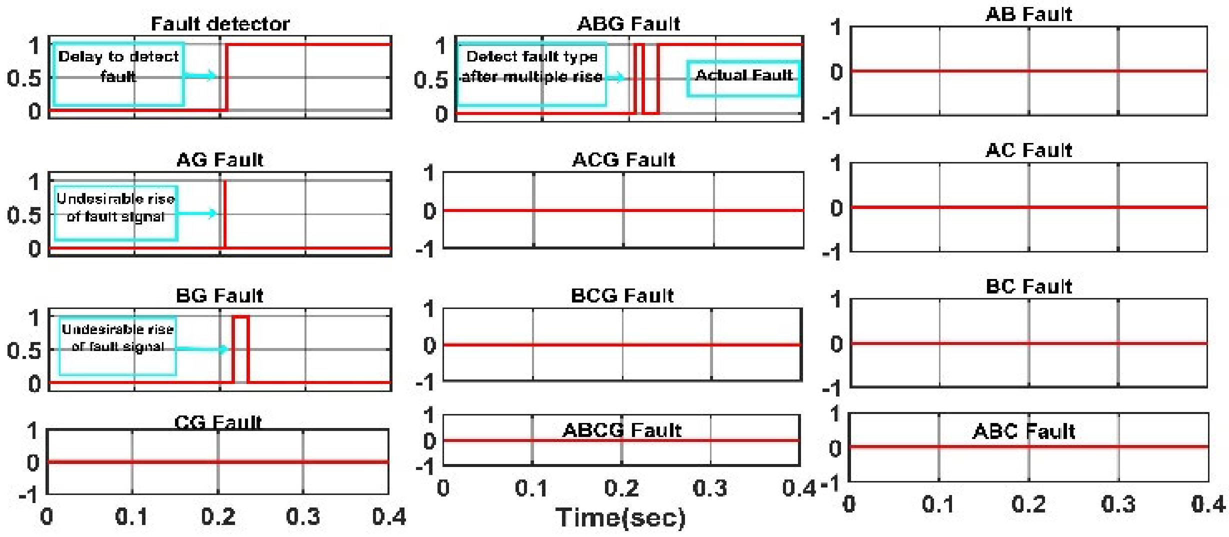


FIGURE 14. ANN fault detection and ABG fault (Case - 4).

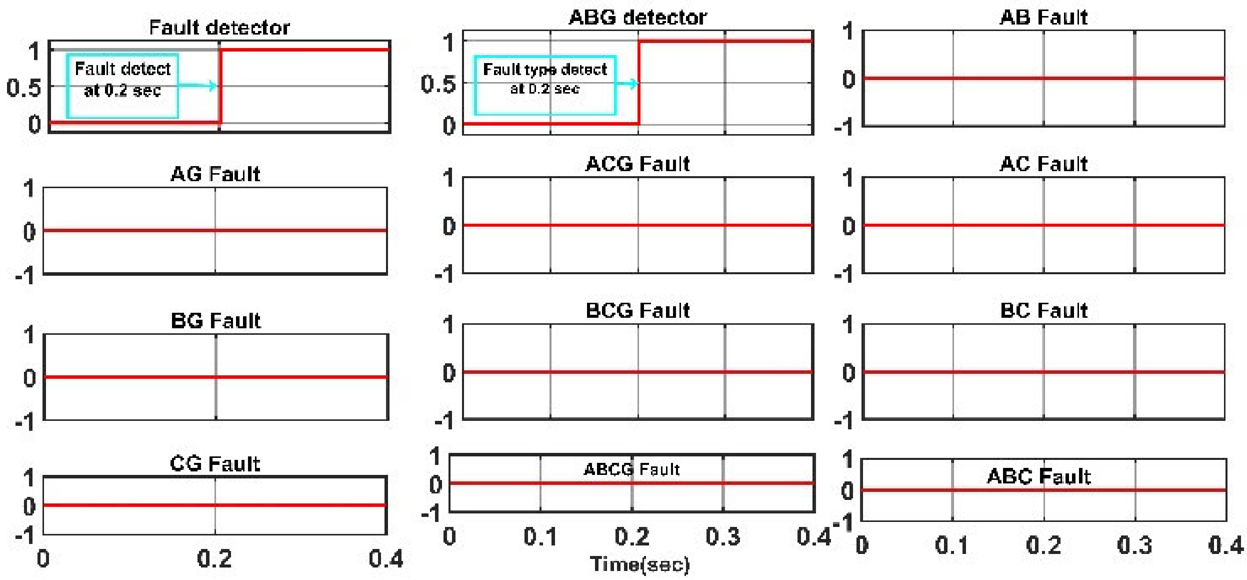


FIGURE 15. LSTM fault detection and ABG fault (Case - 4).

occur in the line and that is phase AB to ground fault. But, for ANN based technique, figure 14 shows along with the ABG fault graph, the fault signal rise from 0 to 1 for the AG graph and BG graph. Although it is clear from figure 14 that, the fault signal for classifying the type of fault stays up only for the ABG fault graph which conforms to the type of fault.

So, from figure 14 and figure 15 it is clear that both ANN and LSTM-based techniques can detect and classify the fault. But an ANN based detection method takes some time to detect the fault whereas the LSTM based technique detects the fault at the exact time of occurrence. Also, in classifying the type of fault LSTM-based technique gives accurate results without any disturbance compared to the ANN-based technique.

E. CASE 5: ACG FAULT CREATED AT 0.2 SEC

In case 5, phase AC to ground fault is created and both the NN-based technique and LSTM-based technique outputs for fault detection and classification are analyzed and compared. ANN technique-based detection and classification results are shown in figure 16 and LSTM-based outputs are given in figure 17. The fault detector graph of both techniques (figure 16, figure 17) shows, the fault detection signal rises from 0 to 1 at the exact time of fault creation which is 0.2 sec

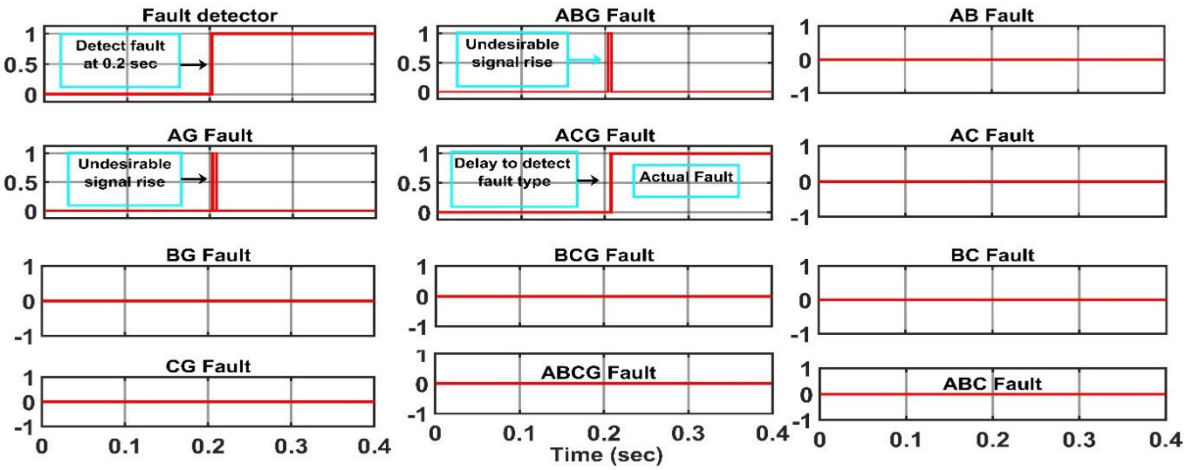


FIGURE 16. ANN fault detection and ACG fault (Case - 5).

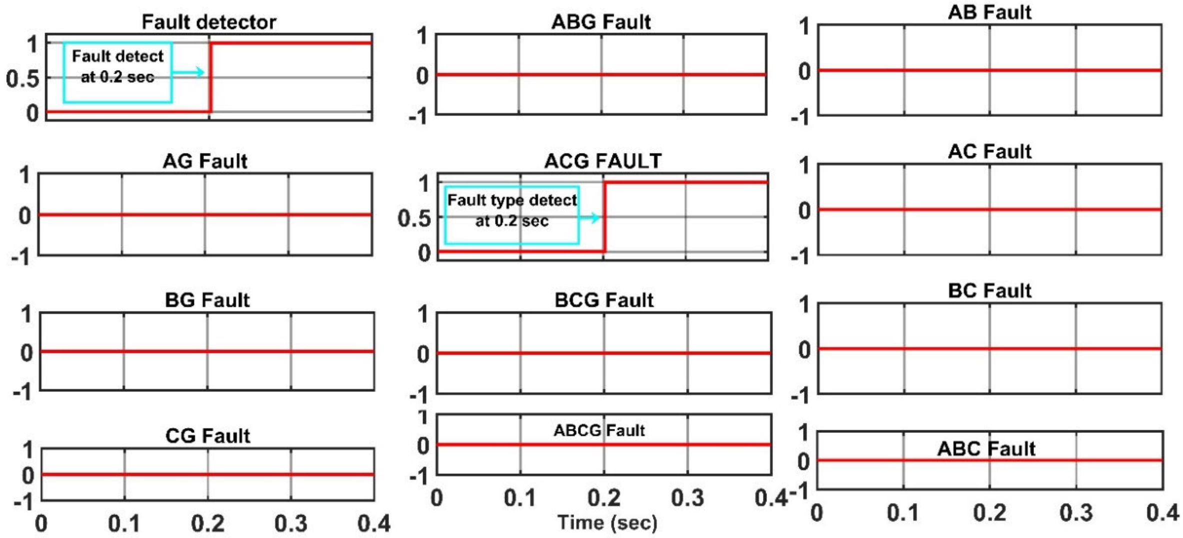


FIGURE 17. LSTM fault detection and ACG fault (Case - 5).

and it stays at 1 for the rest of the simulation time, which conform about the occurrence of fault and presence of a fault in the line. From figure 16 it can be seen that in the ACG graph, the signal rises from 0 to 1 not exact at 0.2 sec but just after 0.2 sec of simulation time, and it stays at 1 for the rest of the time which confirms that it is an ACG fault, it occurs in the line after 0.2 sec and fault stays in the line for the rest of the time. Also, the rise of fault signal can be seen in the AG fault graph and the ABG fault graph, but in these cases, the signal did not stay at 1 for the rest of the time. To eliminate these disturbances and the time delay LSTM based technique is proposed and the detection-classification results of the proposed method are shown in figure 17 for ACG fault. From figure 17 it can be seen that in the fault detector graph signal detect fault at exactly 0.2 sec of simulation time and for classifying the fault type fault signal rise at the ACG graph only without any disturbance present in the other fault signal graph.

So, to detect the fault both ANN and LSTM-based technique is accurate but to categorize the types of fault LSTM is much better. Because the LSTM-based technique classifies the fault without any delay in the process of classifying and there are no disturbances or rise of fault signal from 0 to 1 present in any other fault graph.

F. CASE 6: BCG FAULT CREATED AT 0.2 SEC

In case 6, Phase BC to ground fault is created in case 6 and both ANN-based and LSTM-based technique is tested under this condition. The detection and classification result of both techniques is analyzed and compared in this case for BCG fault at 0.2 sec of faut creation time. Figure 18 and figure 19 shows the detection and classification result of ANN based

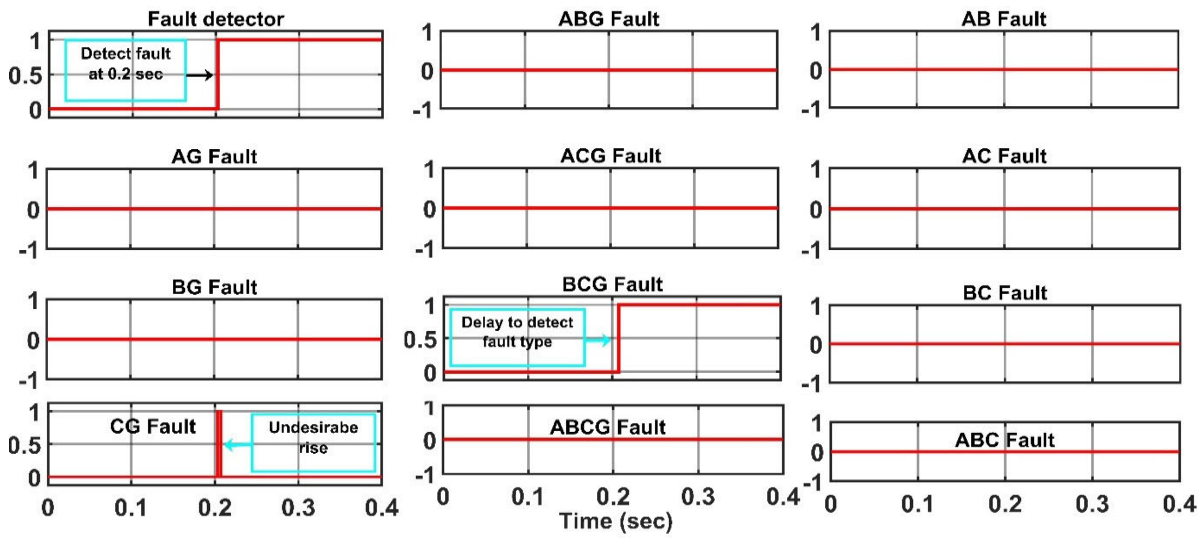


FIGURE 18. ANN fault detection and BCG fault (Case - 6).

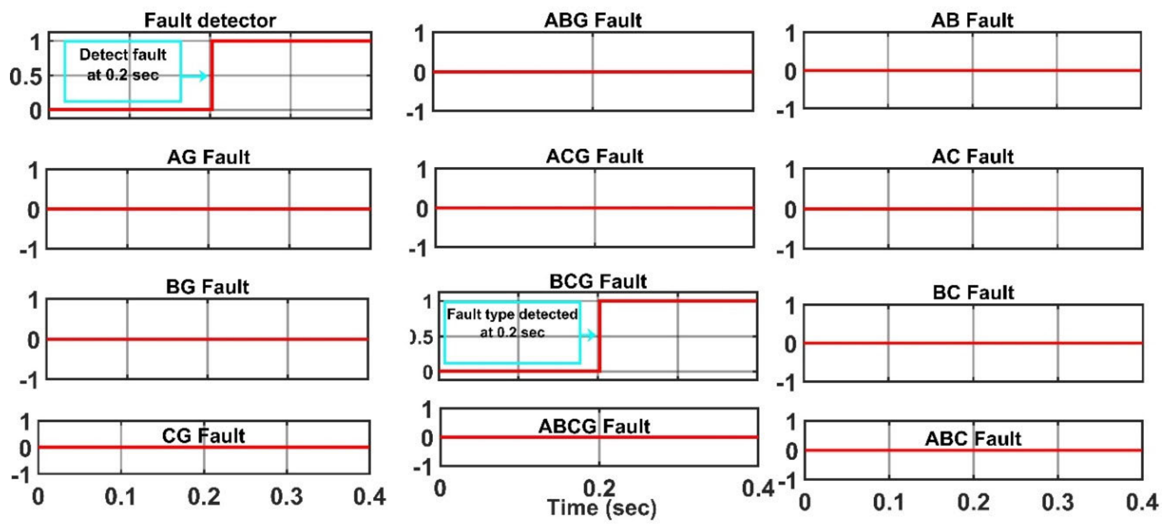


FIGURE 19. LSTM fault detection and BCG fault (Case - 6).

method and LSTM-based method respectively. From the fault detector graph of figure 18 and figure 19, it can be seen that the detector signal rises from 0 to 1 at the exact time of fault creation which is 0.2 sec for both techniques. There is no delay in detecting the fault and the detector signal stays at 1 for the remaining time which tells that fault is still present in the line. For classification, figure 18 shows ANN based technique successfully classify the type of fault because the fault signal rises from 0 to 1 and stays at 1 for the remaining time only for the BCG fault graph but with a bit of delay in this process that can be seen in the BCG fault graph of figure 18 and only disturbance can be seen in CG fault graph. In this classification process, LSTM based technique performs better as seen in figure 19. In figure 19 fault signal rises from 0 to 1 only at the BCG fault at exactly 0.2 sec of simulation time and there is no disturbance present in any other fault graph.

G. CASE 7: ABCG FAULT CREATED AT 0.2 SEC

In case 7, phase ABC to ground fault is created at 0.2 sec of simulation time and the fault is present in the line for the rest of the time. ANN-based technique and LSTM-based technique output result is shown in figure 20 and figure 21 respectively for the detection and classification of ABCG fault. The fault detector graph of figure 19 rises from 0 to 1 with a bit of delay and stays at 1 for the rest of the time which tells the fault is created after 0.2 sec of simulation time

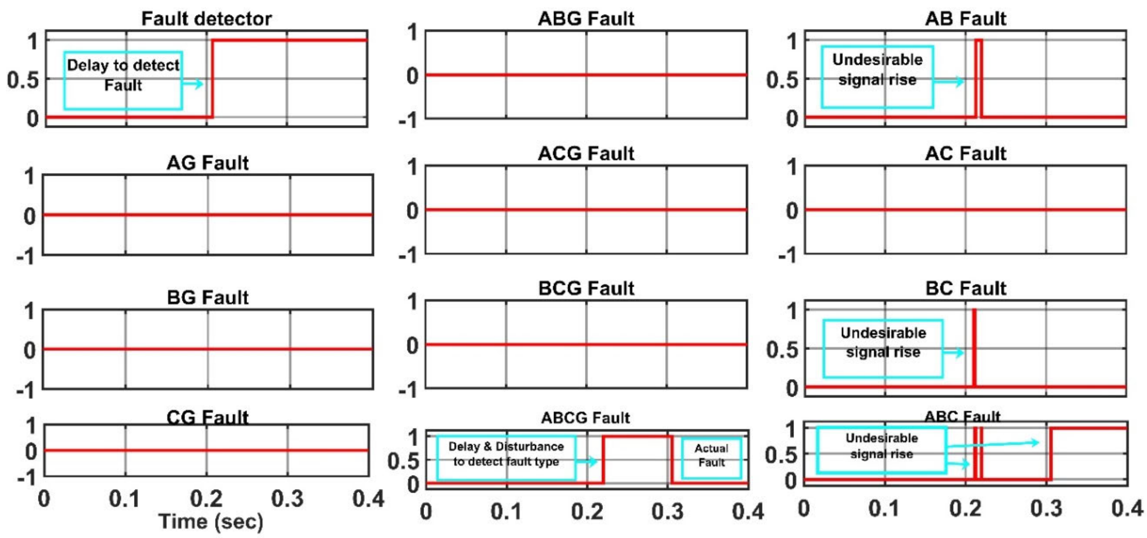


FIGURE 20. ANN fault detection and ABCG fault (Case - 7).

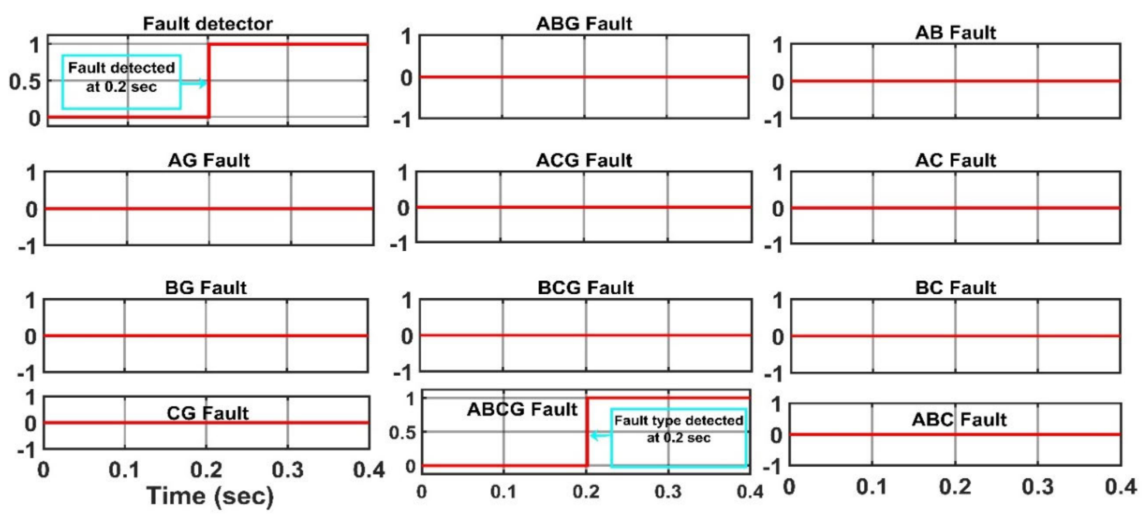


FIGURE 21. LSTM fault detection and ABCG fault (Case - 7).

and the fault is present in the line. But for the LSTM-based technique, figure 21 shows that the detector signal of the fault detector graph rises from 0 to 1 at exactly 0.2 sec of simulation time. In the process of classification ANN base output in figure 20 shows, the fault signal rise from 0 to 1 and stays at 1 for some time duration for both the ABCG fault graph and the ABC fault graph. That tells that ANN based technique is not able to classify the type of fault. Some other disturbances can be seen in the BC fault graph and the AB fault graph of figure 20. But figure 21 shows that LSTM based technique successfully classifies the type of fault because the fault signal rises from 0 to 1 only for the ABCG fault graph.

So, in both classifying and detecting the fault LSTM based technique gives a better response than ANN based technique. Although ANN-based technique can detect the fault with some delay in the detection process.

H. CASE 8: AB FAULT CREATED AT 0.2 SEC

In case 8, line A to line B fault is created at 0.2 sec of simulation time and the fault is present in the line for the remaining time. Figure 22 shows the ANN-based output and figure 23 shows the LSTM-based output for the detection and classification of line AB fault. In the fault detector graph of figure 22, the detector signal rises from 0 to 1 after 0.2 sec with some delay in it, not at exactly at 0.2 sec of simulation time, and stays at 1 for the rest of the simulation time. So, the ANN technique can detect the fault but with some delay in the process. But the fault detector graph of figure 23 shows that

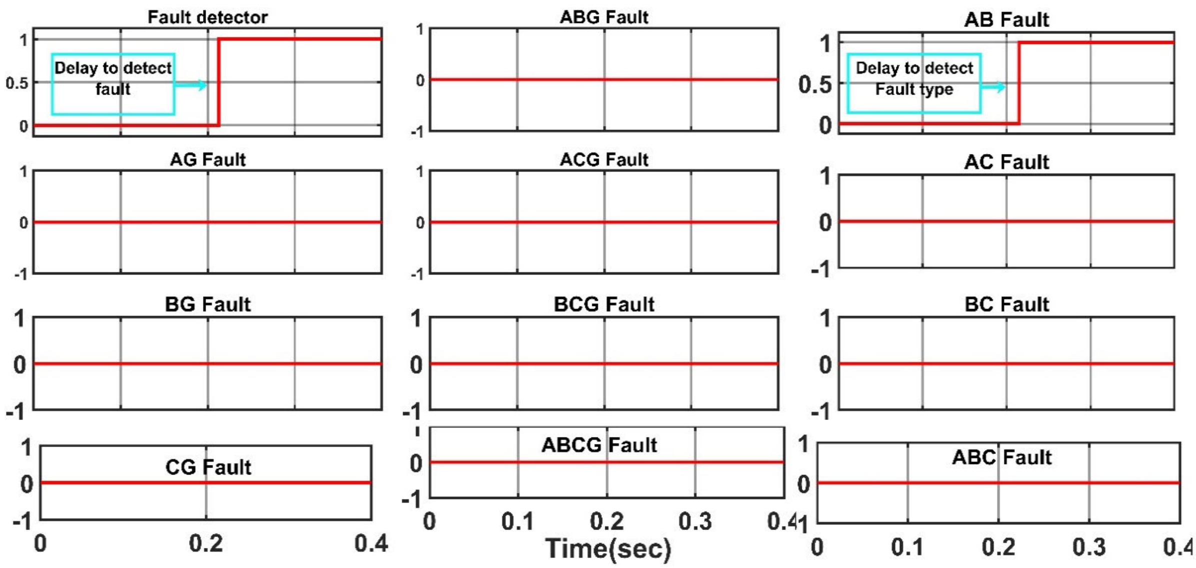


FIGURE 22. ANN fault detection and AB fault (Case - 8).

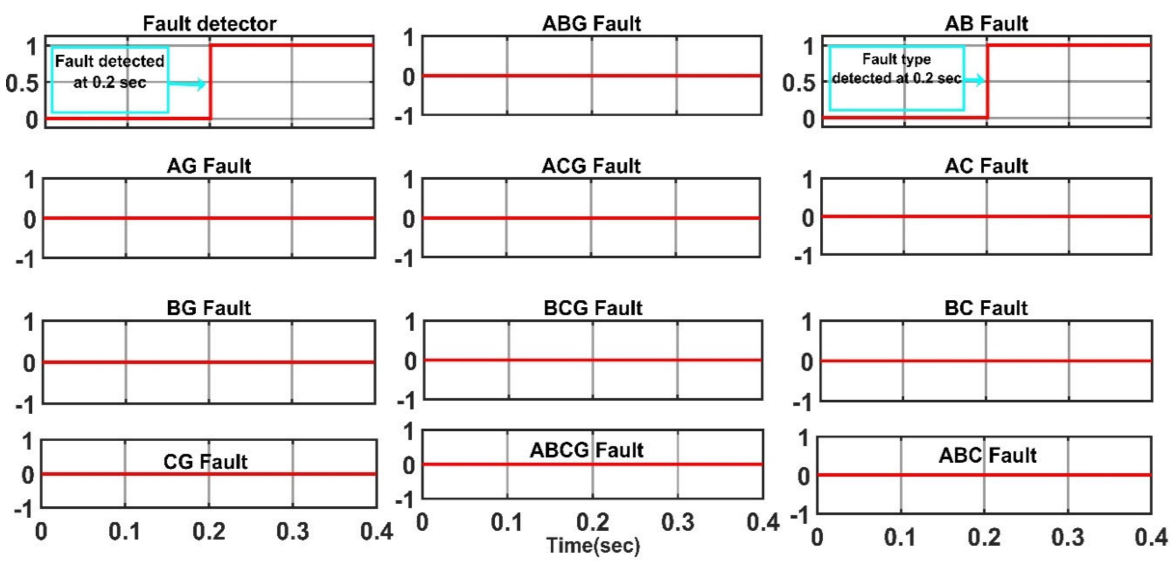


FIGURE 23. LSTM fault detection and AB fault (Case - 8).

the fault detector signal rises from 0 to 1 at exactly 0.2 sec of simulation time and stays at 1 for the rest of the time. So, the LSTM technique gives a better response to detecting the AB fault. To classify the type of fault, the AB fault graph of figure 22 shows a fault signal rise from 0 to 1 with some delay and stays at 1 for the rest of the simulation time. But the AB fault graph of figure 23 for the LSTM-based technique shows that the fault signal rises from 0 to 1 at exactly 0.2 sec time.

So, both techniques can classify and detect the AB fault without any disturbance but ANN based technique gives its response with some delay.

I. CASE 9: AC FAULT CREATED AT 0.2 SEC

Here in this case line A to line C fault is created at 0.2 sec of simulation time and the fault is present in the line for the rest of the simulation time. Figure 24 and figure 25 show the AC fault detection and classification results for ANN based technique and LSTM-based technique respectively. If the detector signal or the fault signal rises from zero to 1 that denotes the presence of fault and type of fault. In figure 24, the fault detector signal in the fault detector graph rises from 0 to 1 but not exactly at 0.2 sec, after 0.2 sec with some delay that conforms to the occurrence of a fault, and the signal

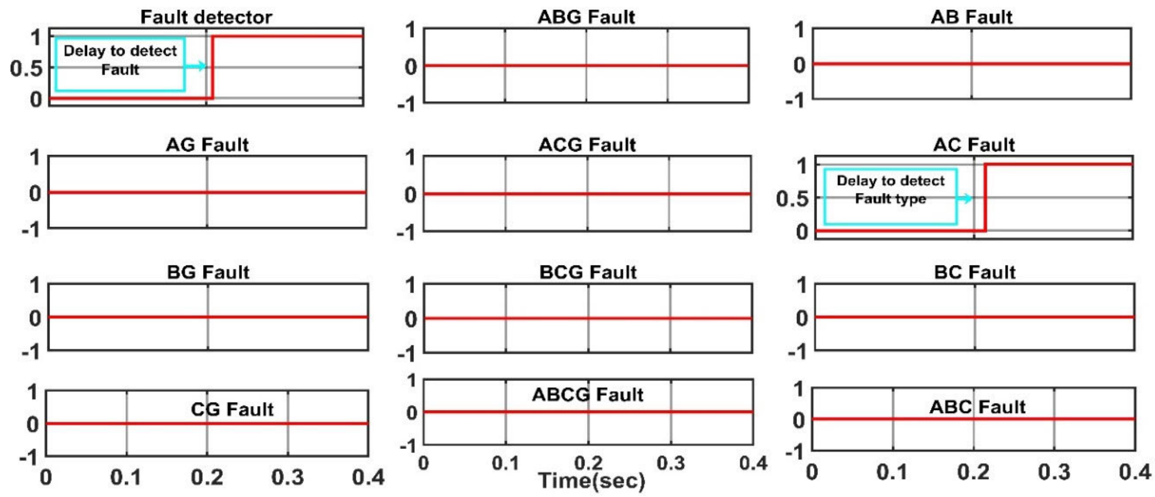


FIGURE 24. NN fault detection and AC fault (Case - 9).

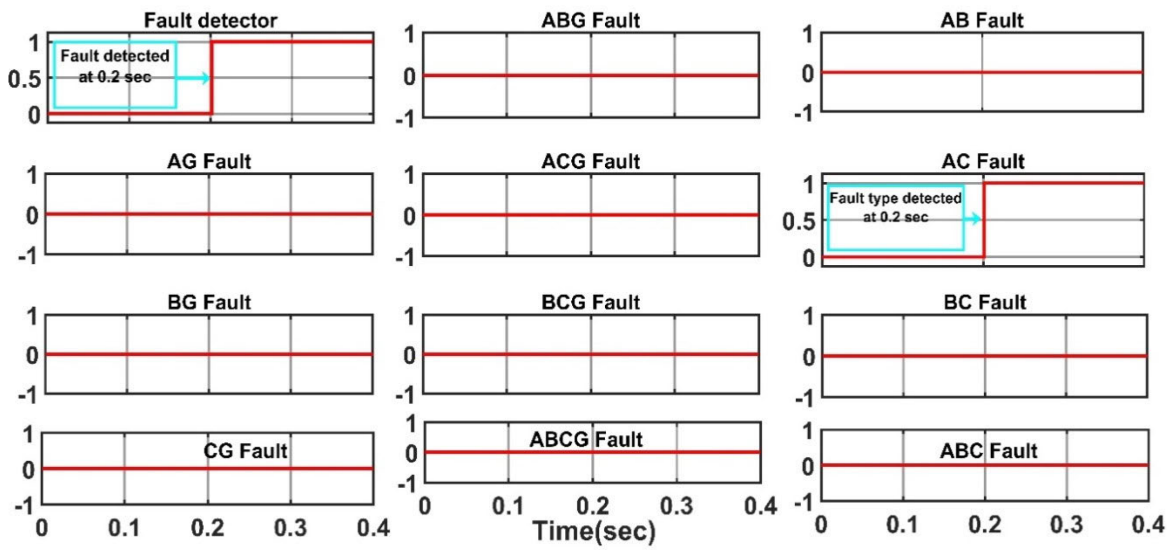


FIGURE 25. LSTM fault detection and AC fault (Case - 9).

stays at 1 for the rest of the time which means the fault is present in the line up to 0.4 sec of the simulation. But the fault detector graph of figure 25 shows that the detector signal rises from 0 to 1 at exactly 0.2 Sec and stays at 1 for the rest of the time. So, the LSTM base technique can detect the fault without any delay. Same in classification, the AC fault signal rise from 0 to 1 after 0.2 sec with some delay with the ANN-based technique that can be seen in figure 24 but in figure 25 with the LSTM-based technique fault signal for AC fault graph rises from 0 to 1 at an exact 0.2 sec time.

So, both LSTM and ANN-based technique is successfully detecting and classifying the fault type but the LSTM-based technique gives a much better result compared to ANN based technique because the ANN-based technique may not respond immediately.

J. CASE 10: BC FAULT CREATED AT 0.2 SEC

Line B to C fault is created at 0.2 sec and both LSTM and ANN-based fault detection-classification outputs are analyzed in this case. Figure 26 shows the ANN technique-based results and figure 27 shows LSTM technique-based results for BC fault detection classification. The fault detector graph of figure 26 and figure 27 shows the detection of fault results for ANN based technique and LSTM-based technique respectively. The fault detector graph of figure 26 detects

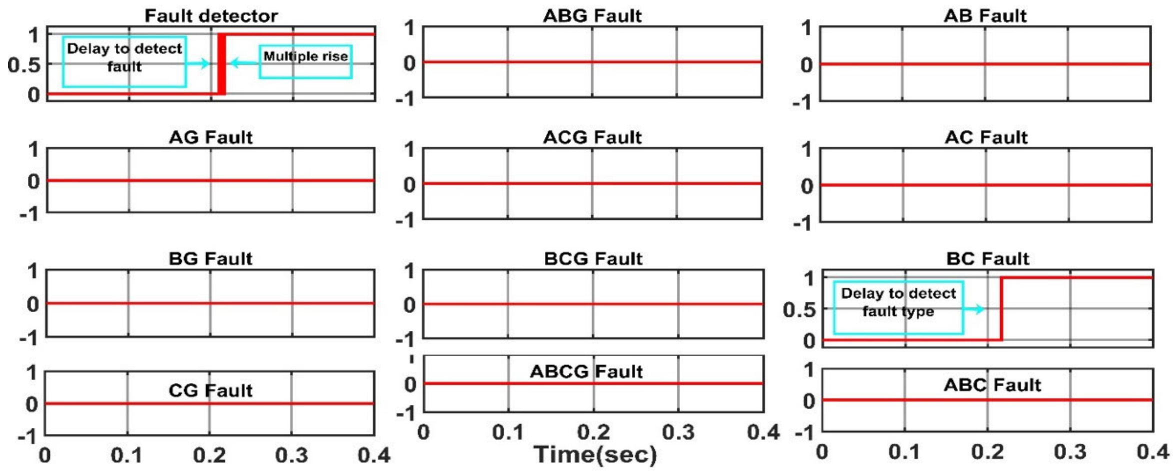


FIGURE 26. ANN fault detection and BC fault (Case - 10).

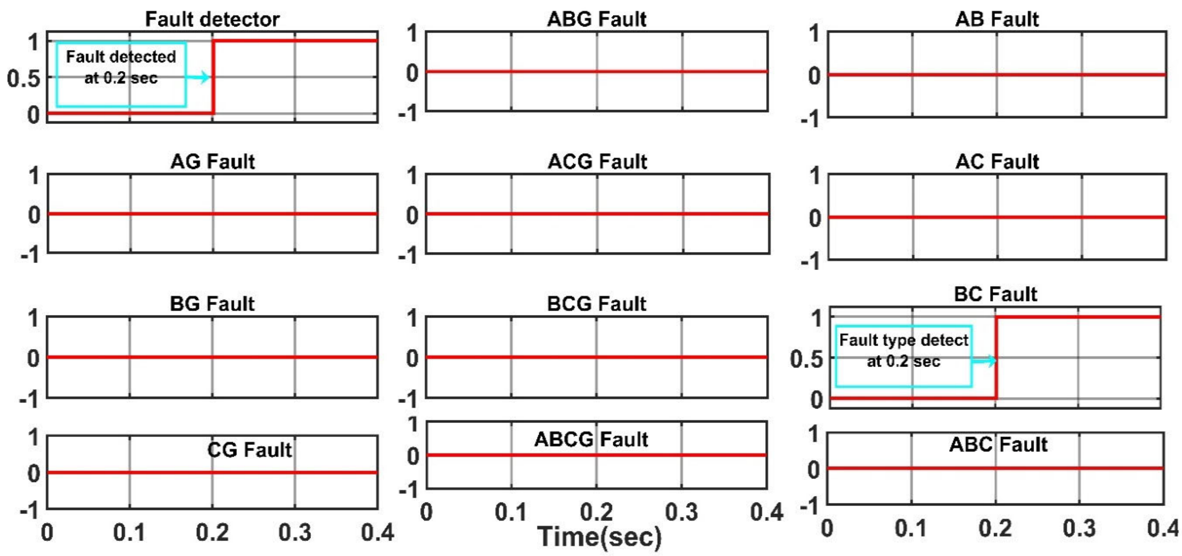


FIGURE 27. LSTM fault detection and BC fault (Case - 10).

the fault after 0.2 sec with some delay because the detector signal of it rises from 0 to 1 after 0.2 sec with some delay but the detector signal for figure 27 in the fault detector graph rises from 0 to 1 at exactly 0.2 sec. So, both techniques can detect the fault. For classification, the fault signal rises from 0 to 1 after 0.2 sec with some delay in the BC fault graph of figure 26 but in figure 27 it rises at exactly 0.2 sec.

So, ANN based technique can classify and detect the fault but there is some delay in the detection process as well as in the classification process of it. The proposed LSTM-based technique can classify and detect the BC fault without any delay, it detects the fault and classifies the type of fault exactly when a fault occurs in the line.

K. CASE 11: ABC FAULT CREATED AT 0.2 SEC

In case 11 three phase fault ABC is created at 0.2 sec of simulation time in the studied model to analyze the performance of the ANN-based technique and LSTM-based technique for the detection-classification of ABC fault. Figure 28 and figure 29 show the detection-classification result for the ANN-based technique and LSTM-based technique respectively. In both the fault detector graph of figure 28 and figure 29 fault detector signal rise from 0 to 1 at exact 0.2 sec which describes that fault occurred in the line at 0.2 sec and in both case fault detector signal stays at 1 up to 0.4 sec of simulation time which tells about the presence of a fault in the line. So, both ANN based technique and LSTM-based technique can detect the fault accurately. For the classification of the ABC fault,

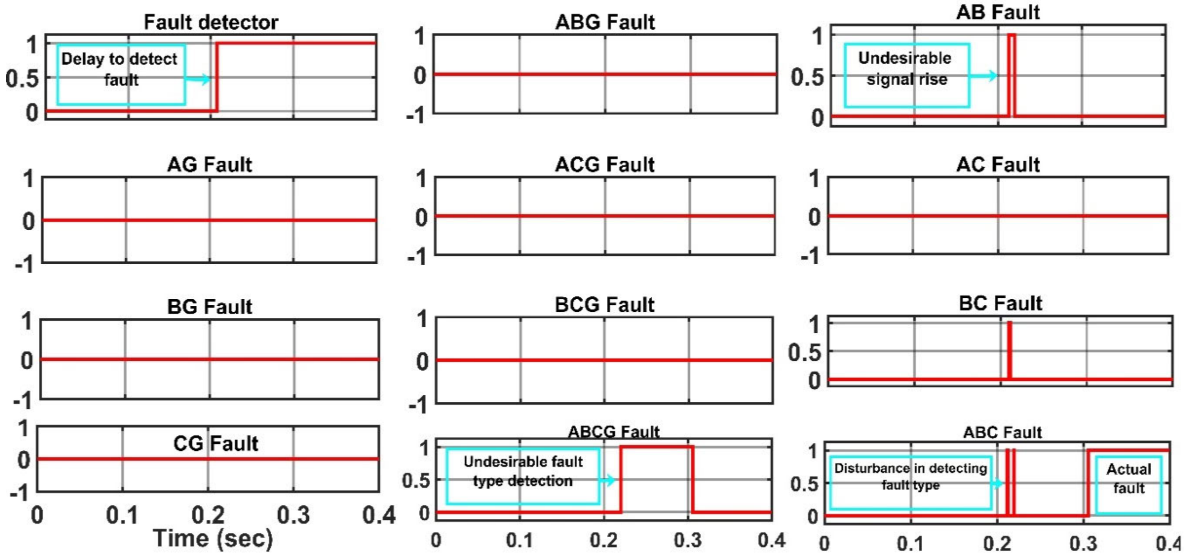


FIGURE 28. ANN fault detection and ABC fault (Case - 11).

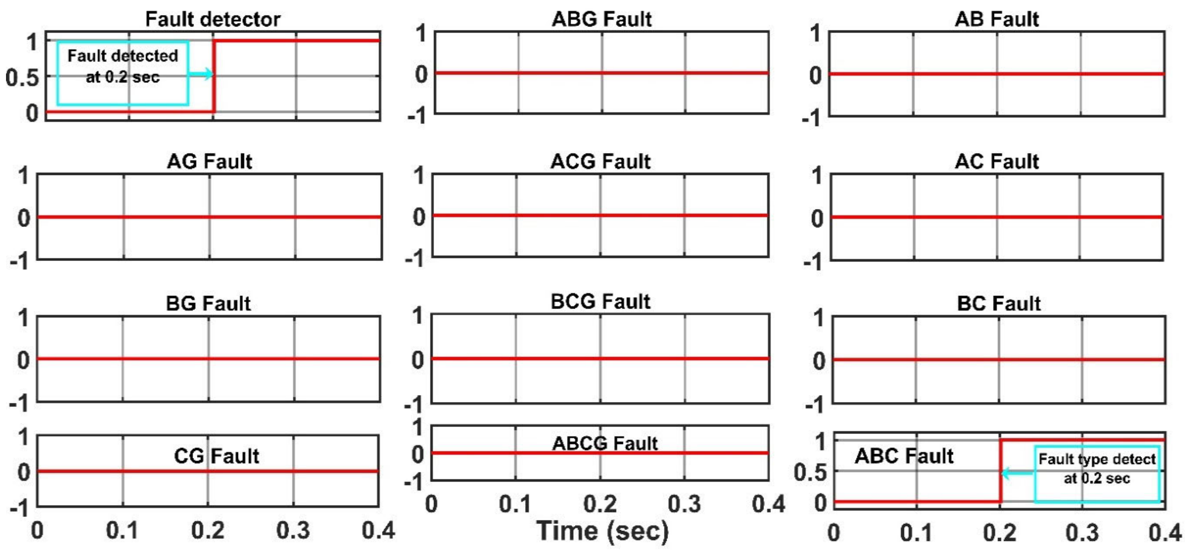


FIGURE 29. LSTM fault detection and ABC fault (Case - 11).

figure 28 shows the fault signal rise from 0 to 1 for the ABCG graph, AB graph, BC graph, and also for the ABC graph. So, the ANN base technique for classification of ABC fault is not able to classify the ABC fault. But in figure 29, for the classification of ABC fault, the fault signal rises from 0 to 1 only in the ABC graph at the exact 0.2 sec time of simulation and it stays at 1 for the rest of the simulation time. Which confirms that the type of fault is ABC fault.

So, to detect the fault in the line both ANN and LSTM technique is accurate but ANN based technique is not able to classify the ABC fault, whereas the proposed LSTM-based technique gives a better and more accurate response.

L. CASE 12: FAULT LOCATION AT 10 KM LENGTH

Other than the detection and classification of fault, the ANN-based technique also detects the location of the fault, and at what length of the transmission line it occurs so that the faulty place can be repaired or isolated from the main line in minimum time. For the detection of the fault, case 12 and case 13 conditions were considered.

In case 12, fault is created in the Simulink model at the 10 km end of the transmission line to detect the location of the fault. Figure 30 shows the fault location detection result for the 10 km end when the fault occurs in the line at 0.25 sec. The X and Y axis of figure 30 represents the simulation time

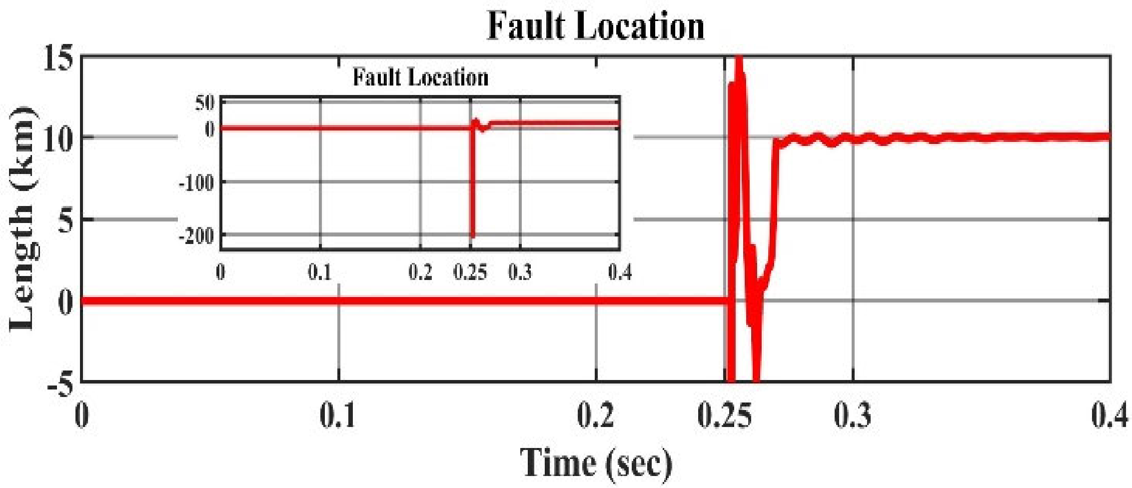


FIGURE 30. Fault location at 10km (Case - 12).

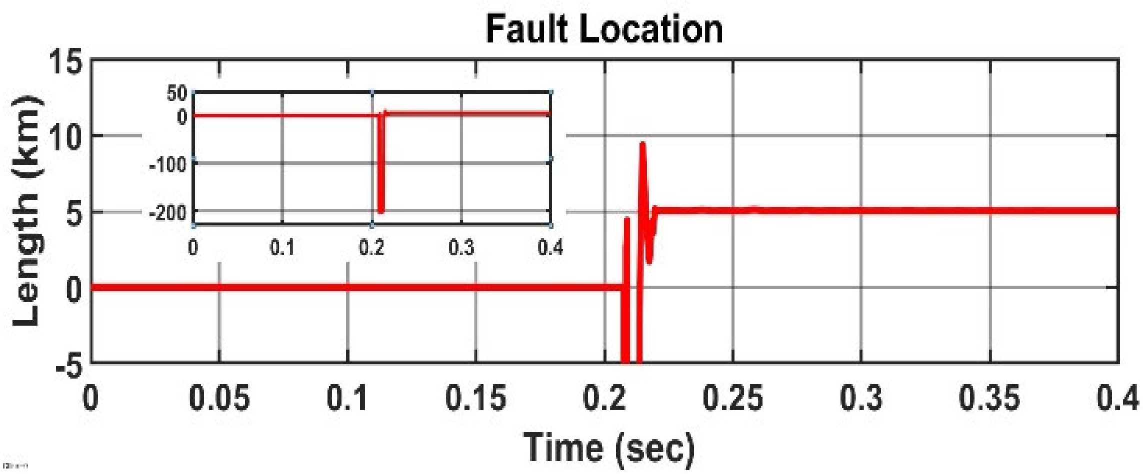


FIGURE 31. Fault location at 5km (Case - 13).

and length of the transmission line respectively. In figure 30 it can be seen that the output signal of the fault location detector rises from 0 to 10 at 0.25 sec and 10 denotes the location of the fault in kilometers. So, it confirms that the fault is at the 10 km end of the transmission line. The detector signal stays at 10 for the time duration of 0.25 second to 0.4 sec, which conforms that for that time duration fault is present in the line at 10 kilometers.

M. CASE 13: FAULT LOCATION AT 5 KM LENGTH

In case 13, the fault is created in the studied model of Simulink at a 5-kilometer end at 0.2 sec and the output of the location detector is given in figure 31. Where the Y-axis represents the length of the transmission line and X-axis represents the simulation time. It can be seen in figure 31 that the detector output is at the 0-kilometer end for the time duration of 0 to 0.2 sec. After that, it rises from 0 kilometers to 5 kilometers point at 0.2 sec of simulation time and stays at it for the rest of the time. So, figure 31 shows that the fault occurs at 0.2 sec of simulation time at 5 kilometers end of the transmission line, and for the rest of the simulation time fault is at 5 kilometers end.

For the detection and classification of different types of faults ANN based technique and LSTM based is applied and their results are discussed in cases 1, case 2, case 3, case 4, case 5, case 6, case 7, case 8, case 9, case 10, and case 11. After a complete analysis and comparison of the results of these two techniques, it has been found that the proposed LSTM-based technique is better at classifying the type of fault as well as detecting the fault. In some cases, like case 1, case 5, case 6, and case 11 both techniques can detect the fault accurately when a fault occurs in the line but in other cases like, case 2, case 3, case 4, case 7, case 8, case 9 and case 10 the proposed LSTM based techniques is

TABLE 2. Comparison between ANN-based and LSTM-based fault detection-classification techniques.

Fault type	ANN-based technique (BG fault created, case 2 [Figure 10])	LSTM-based technique (BG fault created, case 2 [Figure 11])	Remarks
Fault detector	The actual fault was created at 0.2 sec but it detects the fault with some disturbance. In the fault detection signal output, some undesirable signal rise present.	The fault is detected at exactly 0.2 seconds of simulation time when the fault was created. At the time of fault detection there is no disturbance present in the detection indication signal.	The LSTM-based technique detects the fault present in the line without any disturbance. The LSTM technique is more accurate than the ANN-based technique.
AG fault	This technique gives undesirable signal rise. At 0.2 second of simulation fault type detection signal rise and again come down to 0.	Here in this method, fault type detection signal did not rise throughout the simulation.	LSTM technique gives better and accurate response.
BG fault	Fault type is detected with some delay. BG fault is created in the model at 0.2 second to 0.4 second of simulation time. Here in this technique fault type detection signal rise but not exact 0.2second, it rises after 0.2 sec after taking some time.	Here, fault type detection signal rise at exact 0.2 sec, that indicates that BG fault is created in the model at exact 0.2 second of simulation time and stays at 1 up to 0.4 seconds of simulation.	Both the techniques are able to detects the fault type but ANN-based technique is slower than the LSTM-based technique to detect the type of fault.
CG fault	Fault type detection signal did not rise.	Fault type detection signal did not rise.	Both the techniques give accurate result.
ABG fault	Undesirable signal rise presents at 0.2 second of simulation.	Fault type detection signal did not rise.	LSTM technique gives better output.
ACG fault	Undesirable signal rise presents in the fault type detection signal during the simulation of the model.	Fault type detection signal did not rise.	LSTM technique gives better result.
BCG fault	Fault type detection signal did not rise.	Fault type detection signal did not rise.	Both the techniques give accurate result.
ABCG fault	Undesirable signal rise presents in the fault type detection signal during the simulation of the model.	Fault type detection signal did not rise.	LSTM technique gives better output.
AB fault	Fault type detection signal did not rise.	Fault type detection signal did not rise.	Both the techniques give accurate result.
AC fault	Fault type detection signal did not rise.	Fault type detection signal did not rise.	Both the techniques give accurate result.
BC fault	Fault type detection signal did not rise.	Fault type detection signal did not rise.	Both the techniques give accurate result.
ABC fault	Fault type detection signal did not rise.	Fault type detection signal did not rise.	Both the techniques give accurate result.

much better and accurate. For classifying the type of fault proposed technique to better for all the cases from case 1 to case 11. A details comparison of ANN based technique with the LSTM technique is given in table 2 where case 2, BG fault is considered for the comparison.

For the detection of the location, a combination of deep learning and ANN-based technique is applied and a complete analysis of location detection is given in case 12 and case 13. In both cases, it has been found that the combination technique can detect the location of fault accurately.

IV. CONCLUSION

In this study, deep learning-based LSTM network is applied for the detection and classification of the faults and a combination of LSTM and ANN is applied for the detection of the fault location where the fault occurred in MG. Three-phase voltages, three-phase currents, and zero sequence voltage and current are applied as input signals for both networks. The inputs are normalized concerning their pre-fault values. At different times various types of power system faults are created in the model and results for every condition are studied with the proposed method. For the classification and detection of a fault, the proposed technique is compared with the ANN-based classification and detection technique. After a complete analysis of results for different types of faults, it has been found that the proposed LSTM-based technique is much more accurate and better in classifying and detecting the fault. The proposed system has been effectively implemented in the real-time platform of simulation using the OPAL-RT digital simulator. The results show that the proposed technique successfully detects the fault and classifies their types in the MG. Furthermore, the combination successfully detects the location of the fault that occurred in the MG.

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