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Deep learning based detection, classification, and location of power system faults

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ABSTRACT

The identification, categorization, and localization of faults play a crucial role in maintaining the smooth operation of power systems. Distance relays possess a significant capability to withstand power fluctuations, thereby minimizing inadvertent disruptions in transmission lines. Addressing these challenges involves the adoption of advanced fault analysis techniques to enhance the accuracy and speed of relay operations. While modern machine learning (ML) approaches are still nascent in fault analysis, the authors propose a novel deep learning (DL) based long short term memory (LSTM) method for precise fault detection, classification, and rapid fault location estimation. The proposed approach is applied to the Kundur two-area 4 machine 11 bus system covering a distance of 220 km. The LSTM fault detection (LSTM (FD)) module accurately detects and classifies faults, while the LSTM fault location (LSTM (FL)) module precisely estimates fault locations. The effectiveness of the proposed method is verified through a comparative assessment with various traditional ML and DL techniques. The protection modules are also tested under different fault locations, fault resistances, and noisy signals. The features taken into consideration for the operation of the protection modules are different bus voltages, bus currents, zero sequence voltage, zero sequence current, fault inception angle, and fault resistance.

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1. INTRODUCTION

Overhead transmission lines are the major parts of the power system. The possibilities of getting affected by faults are greater in transmission lines, as these are exposed to nature. Safeguarding these lines involves identifying faults, classifying them, and pinpointing their locations. Detecting and categorizing faults is crucial for relaying functions, while accurately determining fault locations aids in maintenance. Consequently, robust protection systems are essential for overhead transmission lines to function reliably under adverse conditions.

Once a fault occurs, the amount of time required to determine the fault location will definitely reduce the reliability of the power system. The fault location technique can do the job accurately and quickly without affecting the reliability of the system. Accurate fault classification and estimation of fault location can reduce the time needed to resume the service [1]. The motivation for the literature survey is to have a method that is very accurate, reliable, and sensitive. Neyestanaki and Ranjbar [2] reviewed and analyzed no such technique that works best for distinct fault scenarios. The method of fault identification encoding using grid topology is described [3]. The methods discussed above have very low generalizability. The detection and classification of faults are done using wavelet transform and support vector machine (SVM) [4]. The author uses the envelope spectrum correlation method of SVM. The methods of decision tree and k-nearest neighbor (KNN) are used for the identification of transmission line faults [5], [6]. A new method known as sparse auto encoder is introduced for the processing of fault parameters [7]. Different types of faults are classified using convolution neural network (CNN). The various faults are detected using automatic seismic fault detection method [8]. The most updated fault status can be obtained by using the online fault detection method. The spatiotemporal correlation method is an online method for the detection of faults [9], [10]. The voltage stability at each and every instant can be analyzed by using a variation auto encoder. But the issue with the spatiotemporal matrix is that it does not develop any correlation between the nodes. The location of the faults in the transmission line can be estimated by using the traveling wave technique [11]. This is done specifically by using both single and double ended techniques of traveling wave theory. Inaccuracy is the main factor in single ended techniques. This can be overcome by using double ended techniques but double ended techniques are highly expensive. High frequency electromagnetic waves emanate as a result of the faults. The authors have used the fast Fourier technique as a substitute for discrete wavelet transform technique [12]. However, the system's accuracy is impacted by the existence of source inductance. The alienation technique of wavelet theory can be used for transmission line fault analysis [13]–[15]. Some protective equipment, like relay get affected by the use of the fault location technique [16]. Hence, the reliability of the system is hampered.

Hence, it is crucial to embrace an approach that overcomes the constraints associated with traveling wave-based techniques. This research introduces a novel method for detecting, categorizing, and pinpointing faults on transmission lines. The newly proposed technique utilizes a deep learning (DL) model called long short term memory (LSTM) to carry out protective tasks during faults. A significant advantage of this approach is its independence from a communication link, use of low sampling frequencies, avoidance of intricate methodologies, compatibility with single-end measurements, resilience to noisy signals, and overall reliability and robustness. The primary objective of this research is to achieve precise and swift fault detection, classification, and fault location estimation. A comparative evaluation of performance, presented midway through the paper, contrasts the proposed DL model with other existing methods.

In section 2, the author has presented the proposed DL model. Section 3 explains about the power system under study. Section 4 explains about design of fault detection and classification algorithm. Section 5 presents the detailed function of fault location module. After the completion of both training and testing, the results thus obtained are discussed under section 6. Section 7 concludes the study.

2. PROPOSED LONG SHORT TERM MEMORY MODEL

DL falls within the realm of machine learning (ML), which in turn is a subset of artificial intelligence. Its remarkable ability to extract features autonomously has established its superiority across various domains. Within DL, the system autonomously trains and comprehends data through numerous concealed layers. Its effectiveness is particularly pronounced when dealing with extensive datasets. The model under consideration is a variation of the recurrent neural network (RNN), outperforming other RNNs, especially in tasks involving prolonged temporal dependencies [17]. As shown in Figure 1, DL models are of two types: supervised learning and unsupervised learning. Our proposed LSTM model is a supervised type, and it is also one of the RNN models. The proposed LSTM is part of RNN. Three different layers, like input, forget, and output, are used to represent the current, prior, and output data [18]. The hidden layers of the LSTM network use memory blocks instead of memory units. Each memory block consists of only one memory cell. These memory cells carry regulatory gates. The flow of information is completely controlled by these gates. If any information is no longer required, it will be automatically reset by using the forget gate. All these gates use a simple sigmoid function [19]. The major advantage of this network is that it can take any length of data as input and generate any length of data due to the availability of the hidden layers that travel across time. All layers of LSTM cells are evaluated by using activation functions element-wise [20]. The input gates are responsible for storing the elements, while the forget gates are responsible for forgetting or eliminating the unwanted elements [21]. The updates of the elements are done by the input modulation unit. The output gates determine the selection of output elements. The update of information in all the gates is done by the learning rate. The main purpose of the network is to minimize the cost function. The LSTM network is capable of doing n-way classification. Both classification and regression modules are employed by the DL network. The detection and identification of faults is done by the classification module. The fault location is estimated by the regression network. The fault location estimation is also done by He *et al.* [22] with an accuracy of 90%. The fault location performance of our proposed LSTM methodology can be studied better from the basic flow diagram in Figure 2. It depicts how data moves through an LSTM network. The data from the LSTM cell passes to the dense layer. The output of the dense layer either classifies different types of faults or estimates the location of the faults.

Figure 3 depicts the architecture of the LSTM model, which serves dual purposes: fault classification and fault location estimation. The input layer transfers data to the LSTM hidden layer comprising multiple LSTM cells. The LSTM cell outputs are then forwarded to a fully connected dense layer, where multi-class classification is performed using the softmax activation function. For regression tasks, data from the LSTM layer bypasses the softmax layer and directly connects to the fully connected layer. However, for classification, the data must traverse through the softmax layer subsequent to the fully connected layer.

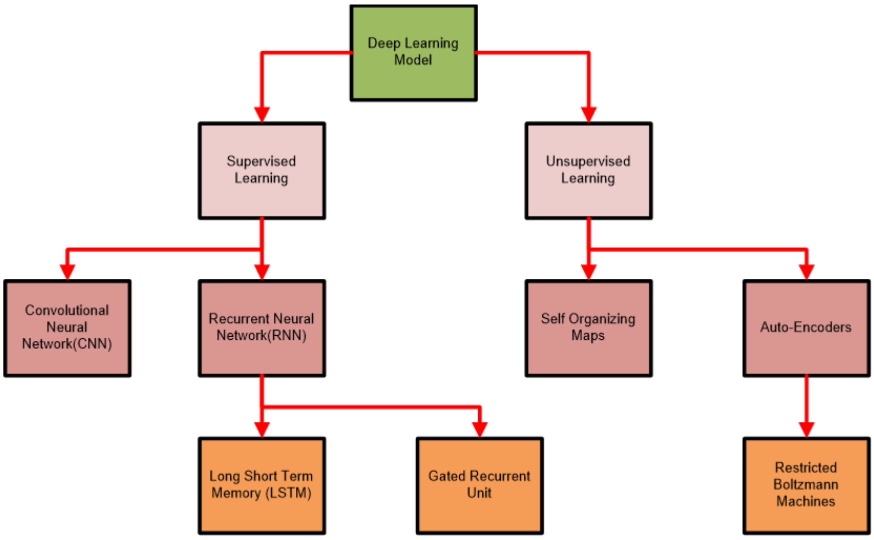


Figure 1. Types of DL

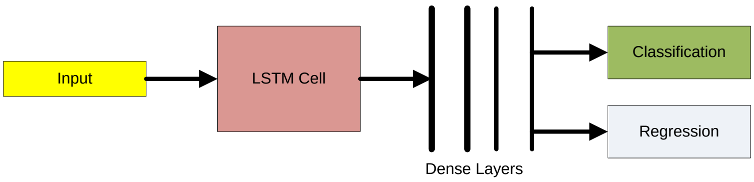


Figure 2. Basic flow diagram of LSTM

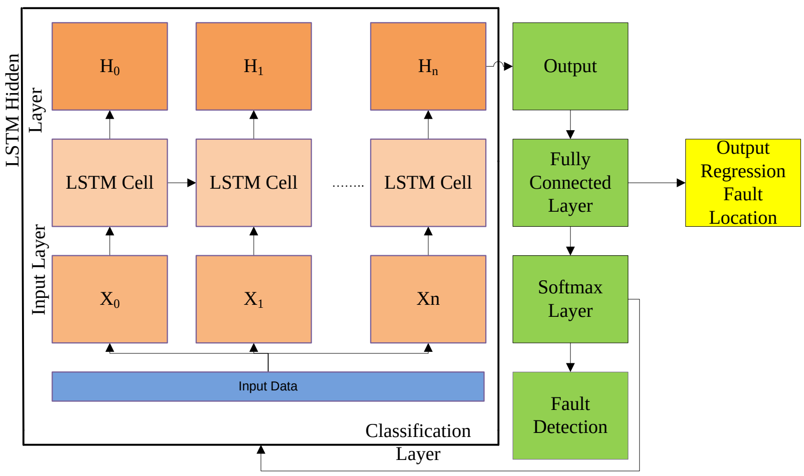


Figure 3. LSTM architecture

The proposed approach for addressing faults in transmission lines is outlined in the flowchart depicted in Figure 4. This diagram illustrates a three-stage process. The initial stage focuses on fault detection, where the LSTM fault detection (LSTM (FD)) module determines whether a fault is present or not. A fault is indicated by the condition "1," while the absence of a fault is denoted by "0." If no fault is detected, the process concludes at this point. However, if a fault is detected, the process proceeds to the second stage, which involves fault classification using the same LSTM (FD) module. Subsequently, the third stage, following the second one, entails estimating the fault's location with assistance from the LSTM fault location (LSTM (FL)) module.

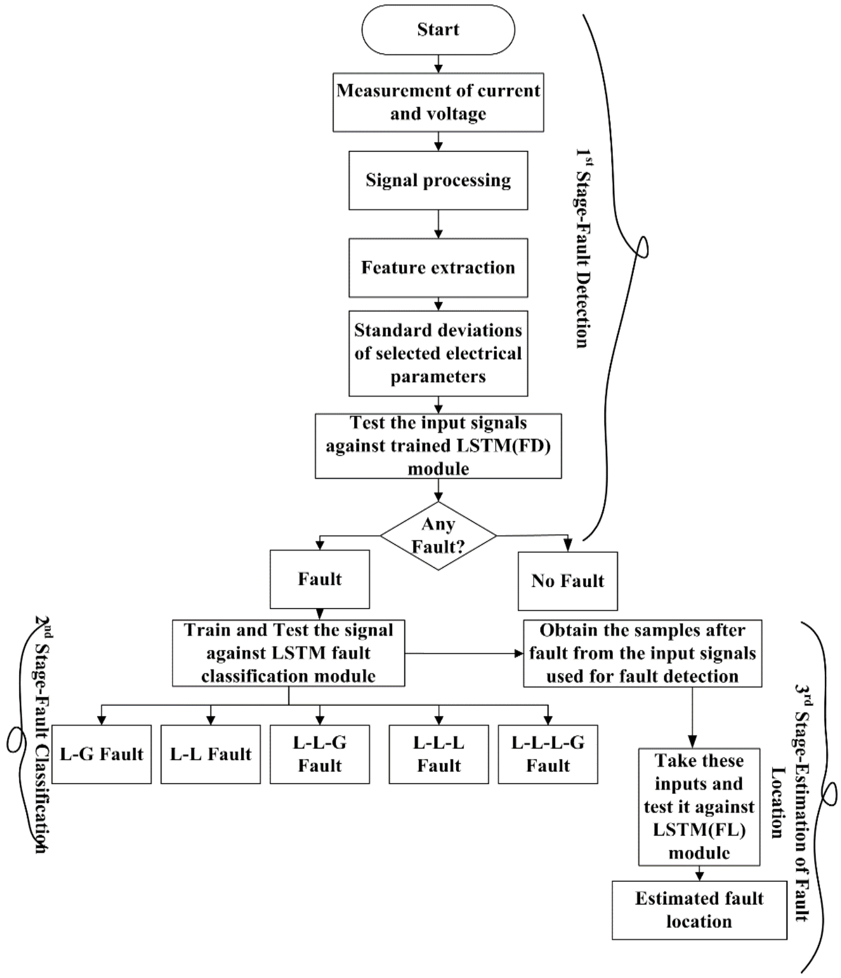


Figure 4. Flow chart of proposed LSTM model

3. PROPOSED POWER SYSTEM

The Kundur test system, consisting of 11 bus 2 area and 4 machines, is used for our proposed model [23]–[25]. As depicted in Figure 5, buses 7 and 9 are interconnected via a weak tie line, serving as links between two distinct areas. Loads are distributed across buses 7, 8, and 9, with both buses 7 and 9 featuring connections to two shunt capacitors. The system's frequency is rigorously maintained at 60 Hz. Table 1 details the essential parameters of this proposed power system. Given that these modules consist of RNNs, they exhibit superior performance when dealing with complex systems and extensive datasets. Kundur's proposed power system, comprising 4 machines, two areas, and 11 buses, generates 500001 data points for classification and regression tasks. The data is sampled at a frequency of 1 kHz. The accuracy and precision of LSTM models are thoroughly analyzed. Two distinct modules of LSTM are employed: LSTM (FD) for fault classification and detection, and LSTM (FL) for fault location estimation. The classifier effectively categorizes various fault scenarios, including 3 single-line-to-ground (L-G) faults, 3 double-line faults, 3 double- L-G faults, 1 triple-line fault, 1 triple- L-G fault, along with 1 instance of no fault condition. Additionally, it identifies both the fault type and the specific phase in which the fault has occurred.

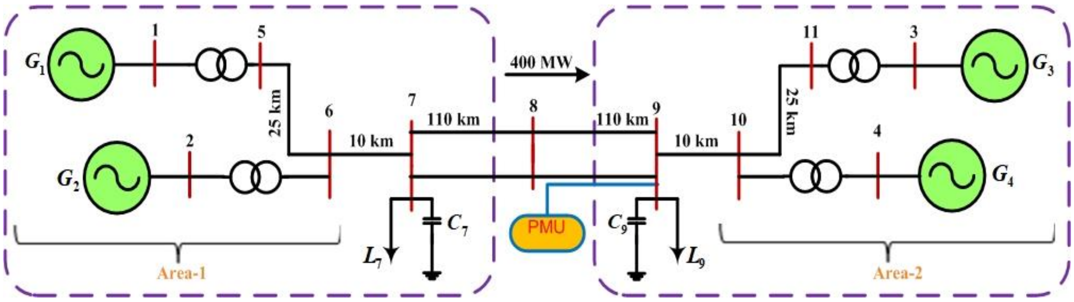


Figure 5. Kundur's two area system

Table 1. System parameters

Synchronous generator			
Machines	Rated power	RMS ph-ph voltage	Frequency
M1 M2 M3 M4	900 MVA	20 kV	60 Hz
Transformers			
Machines	Rated power	RMS ph-ph voltage (primary)	RMS ph-ph voltage (secondary)
T1 T2 T3 T4	900 MVA	20 kV	230 kV
Loads			
Load	Active power	Reactive power (inductive)	Reactive power (capacitive)
C1	967 MW	100 MVAR	187 MVAR
C2	0 MW	0 MVAR	200 MVAR
C3	1767 MW	100 MVAR	187 MVAR
C4	0 MW	0 MVAR	350 MVAR
Lines			
Lines	Length	RMS voltage	
L1 L2 L3 L4	220 km	230 kV	

4. DESIGN OF FAULT DETECTION AND CLASSIFICATION MODULE

The module responsible for the detection and classification of different types of transmission line faults is LSTM (FD). A total of 500001 samples are automatically extracted, of which 80% are used for training purposes and 20% are used for testing and validation purposes. The features thus extracted are used to prepare the LSTM training module for classification and detection purposes. The target values assigned with "0" define a non-faulty condition, while "1" defines a faulty condition. There are 64 storage units in the LSTM network. The non-linear activation function used here is rectified linear unit (ReLU). Different gates, like the forget gate, input gate, and output gate, are used to perform various functions. The input gate is responsible for adding information with the help of the tanh function, as shown in Figure 3. The sigmoid function used in the regulatory filter multiplies the information. The significance of the forget gate is important as it removes all unwanted information and hence improves the efficiency of the network. The LSTM network is followed by three dense layers. The last layer is used for classification purposes. Once the training module is designed, 20% of the total data is used for both testing and validation purposes.

There's a possibility that fault resistance might increase during a fault event. It's important for the recommended comprehensive protection strategy to remain dependable despite variations in fault resistance. The performance of the proposed LSTM (FD) and LSTM (FL) modules has been assessed across various fault resistances. Table 2 showcases multiple test results for fault detection, indicating the accurate fault detection capability of the proposed method. Regardless of the fault scenarios, the detection time remains consistently at 0.001 seconds.

Table 2. Effect of fault resistance in fault detection and fault classification performance

Fault resistance (ohm)	Sensitivity	Specificity	F1 score	Accuracy	Maximum time (sec)
<20	100	100	100	100	0.001
<40	100	100	100	100	0.001
<100	100	100	100	100	0.001

5. DESIGN OF FAULT LOCATION ESTIMATION MODULE

This research employs a DL approach utilizing LSTM techniques to identify faults within Kundur's power system. The method for fault detection is verified using training and testing datasets containing instances of faults. The training of the LSTM-based fault location module LSTM (FL) involves using specific methods to extract current and voltage features, which are then utilized to create the input for the LSTM (FL). The target output comprises the corresponding fault location values. The LSTM (FL) model is developed by adjusting various parameters of the LSTM architecture to tackle the regression problem, with optimal parameter values determined through iterative experimentation. The proposed model comprises three dense layers with 32, 16, and 8 units respectively, with the LSTM network tailored for regression to determine fault locations. Unlike classification tasks, the final dense layer in the proposed model operates without an activation function, and the loss function is computed using mean square error (MSE). During the regression process, the LSTM model uses a batch size of 5 over 6,000 epochs. Details regarding the parameters utilized in the LSTM (FD) and LSTM (FL) modules are outlined in Table 3. After the training phase, the LSTM (FL) module is assessed on unknown test samples to evaluate its performance in fault location. The configuration remains unchanged except for the final layer, which doesn't utilize an activation function to assist with regression.

Table 3. Parameter details during training of different modules

Name of LSTM module	Parameters of the module	Values
Fault detection and classification	Epochs	400
	Batch size	100
	Layers and neurons	LSTM-64, Dense-32, Dense-16, Dense-8, Dense-1
		Adam
	Optimizer	Sigmoid
	Activation function	
Fault location	Epochs	6,000
	Batch size	5
	Layers and neurons	LSTM-64, Dense-32, Dense-16, Dense-8, Dense-1
		Adam
	Optimizer	Inner layer–ReLu
	Activation function	

The method for estimating fault location was also evaluated under different resistance conditions. Analysis of Table 4 indicates that the method maintains an error rate of less than 1% across all fault scenarios tested. Therefore, it can be concluded that the proposed LSTM-based approach remains resilient to changes in fault resistance.

Table 4. Variation of fault location performance with fault resistance

Fault resistance	Actual fault location (km)	Predicted fault location (km)	Absolute error	Percentage error
1	23.3	24.012	0.712	0.0297
	112.2	113.032	0.832	0.0074
	224.5	223.89	0.61	0.0027
31	255.1	254.78	0.32	0.0013
	305.3	304.89	0.41	0.0013
	344.5	345.85	1.35	0.0039
61	465.2	464.706	0.494	0.0011
	551.2	552.068	0.868	0.0016
	621.2	621.852	0.652	0.0010
91	751.2	752.48	1.28	0.0017
	851.2	852.32	1.12	0.0013
	912.3	912.491	0.191	0.0002

6. RESULT AND DISCUSSION

Experiments employing various symmetrical and asymmetrical fault scenarios have been carried out to evaluate the proposed method. The LSTM model demonstrates exceptional accuracy, particularly in fault localization. The LSTM (FL) model accurately predicts the locations of diverse fault types. Detailed performance metrics of the LSTM (FL) model are presented in Table 5, showcasing minimal absolute error and strong correlation between actual and estimated fault locations. Table 6 outlines the performance of the LSTM fault detection model, presenting mean squared error (MSE) and R values across different stages such as training, validation, and testing.

The parameters shown in Table 6 define the close correlation between output and target value. The accuracy of the detection system is clearly visible from the regression value as shown in Figure 6. The regression values assess the association between outputs and targets. An R value of 0 indicates a random connection, while a value of 1 signifies a strong correlation.

Table 5. Variation of fault location performance with different fault condition

Type of the fault	Actual fault location	Estimated fault location	Absolute error	Percentage error
L-G	13.18	13.4	0.22	1.642
	23.45	23.94	0.49	2.047
	23.62	24	0.38	1.583
L-L	29.51	30.13	0.62	2.058
	31.49	31.54	0.05	0.159
	46.65	47.19	0.54	1.144
L-L-G	49.51	49.7	0.19	0.382
	55.65	56.32	0.67	1.190
	67.24	67.31	0.07	0.104
L-L-L-G	81.28	81.41	0.13	0.160
	131.52	132.11	0.59	0.447
	158.19	158.52	0.33	0.208

Table 6. Performance analysis of the fault detection

Parameter	Sample	MSE	R value
Training	400001	$9.66543e^{-19}$	1.0
Validation	50000	$8.04176e^{-17}$	1.0
Testing	50000	$2.12887e^{-18}$	1.0

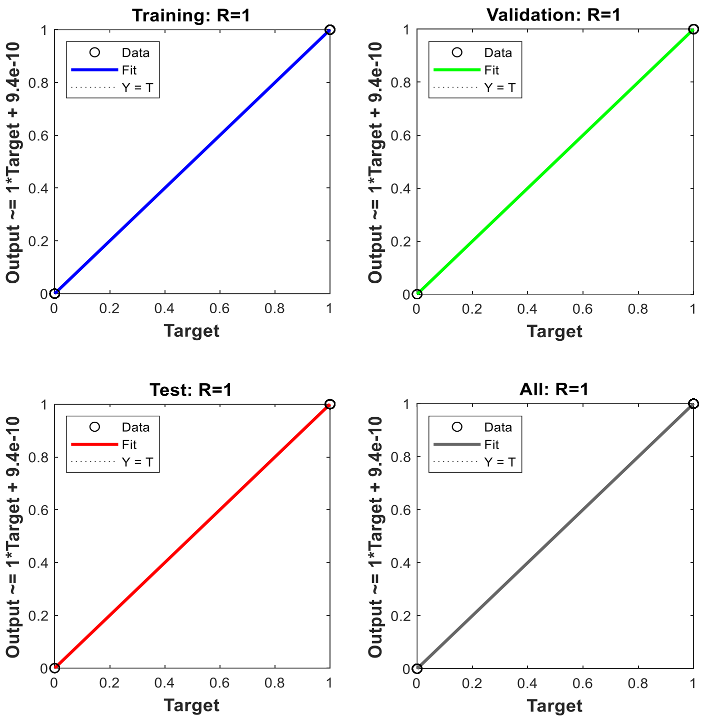


Figure 6. Regression values of fault detection defining accuracy of the system

The classification of fault varieties is also conducted using an LSTM classifier in real-time. The performance of the classification model is depicted in Table 7 and Figure 7. A multistage fault is induced between bus 1 and 2 to initiate an L-L-G fault by the author, as illustrated in Figure 8, which displays the voltage and current waveforms during the L-L-G fault. The fault is initiated for very short duration i.e., 0.03 seconds only. Figure 9 showcases eleven different fault conditions and an overall fault detection. Figure 9(a) shows the response of fault detector. Figure 9(b) shows the fault at specific line. It shows that the fault persists for 0.03 seconds only. Figures 9(c) and (d) indicate absence of AB and AG fault respectively. Figures 9(e), (f), and (g) indicate the absence of ACG, AC and BG fault. The fault BCG, BC, CG, ABCG, ABC are also not available as indicated in Figures 9(h), (i), (j), (k), and (l) respectively. The average error rate is remarkably low, standing at a mere 0.25%. Table 8 provides a comparison between the actual and predicted fault detection values, offering a comprehensive insight into the performance of our classification model. The LSTM (FL) model is responsible for estimating fault locations, with Figure 10 demonstrating a close correlation between actual and estimated fault locations spanning a distance of 220 km.

Table 7. Performance analysis of the fault classification

Parameter	Samples	MSE	R value
Training (80%)	400001	$1.00431e^{-2}$	$9.79121e^{-1}$
Validation (10%)	50000	$9.53323e^{-3}$	$9.80371e^{-1}$
Testing (10%)	50000	$1.44694e^{-2}$	$9.89969e^{-1}$

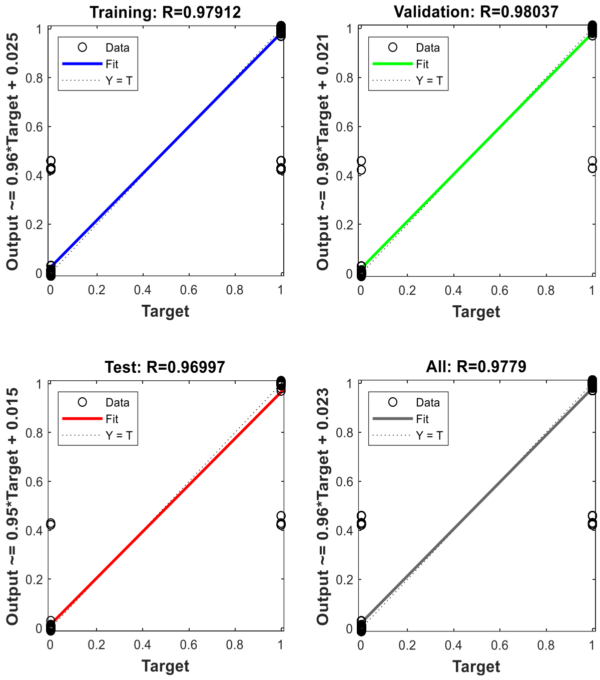


Figure 7. Accuracy of fault classification system

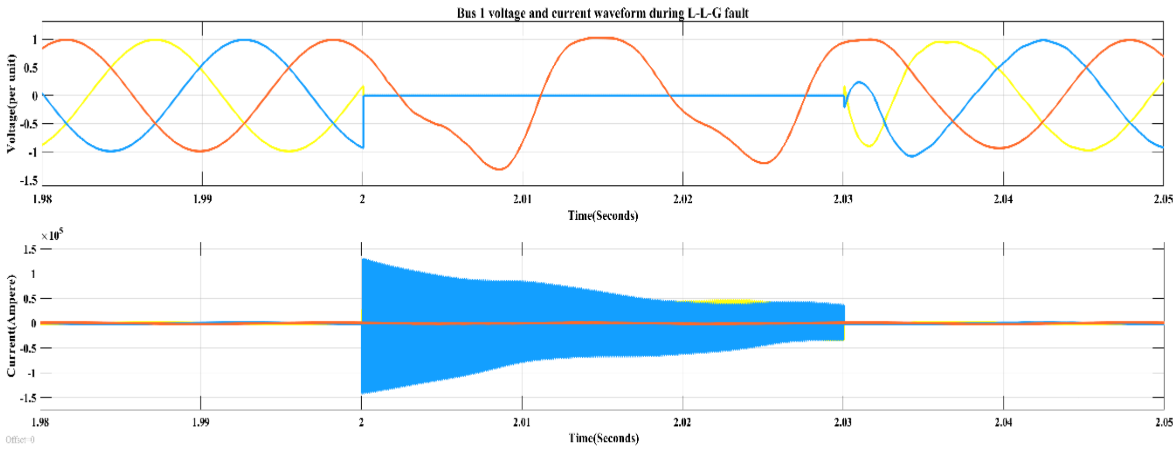
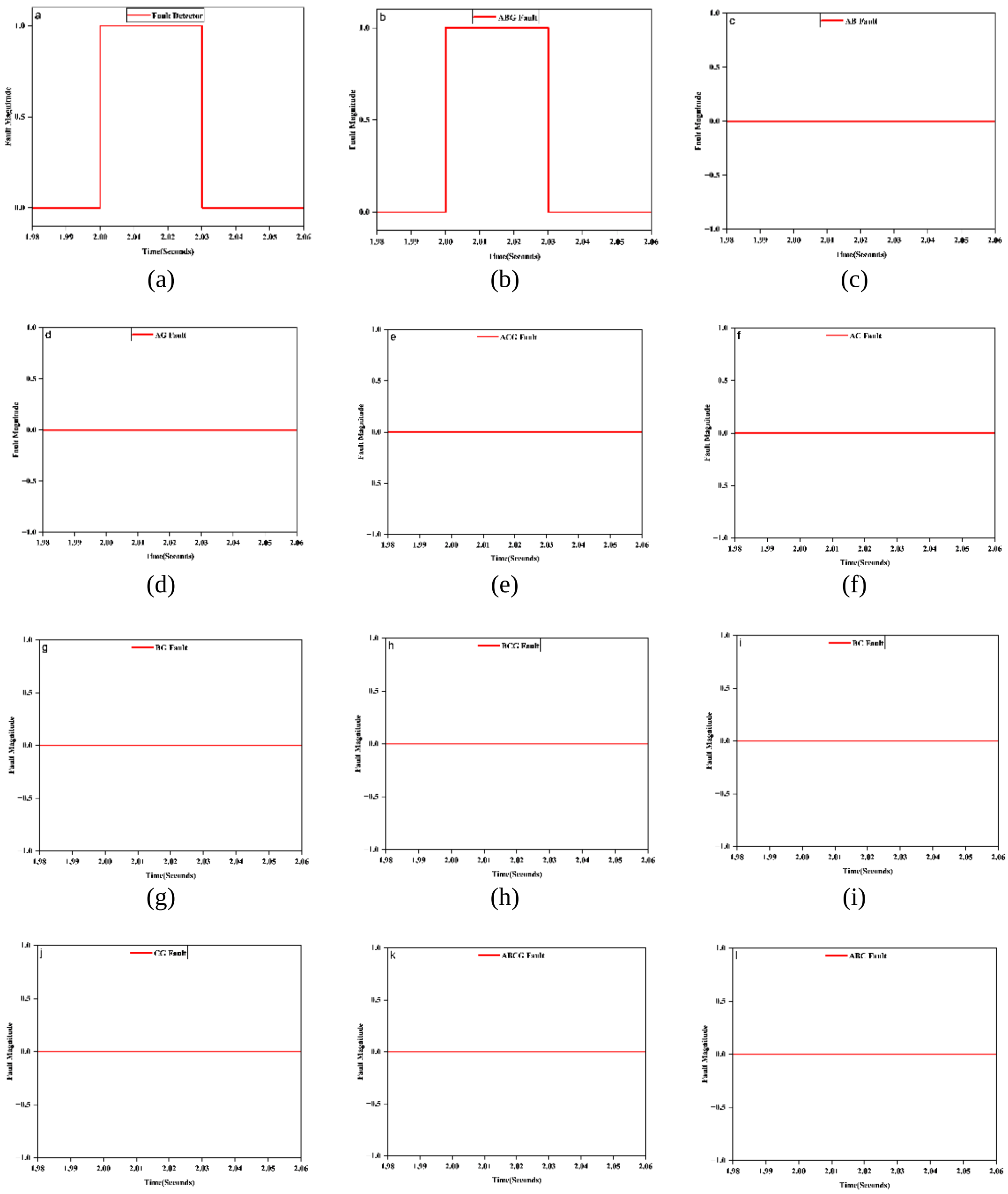


Figure 8. Three phase voltage, current waveform during double line to ground fault

Conventional protection techniques for transmission lines predominantly rely on traveling wave-based methods. To overcome the limitations of traditional protection methods, this study employs a DL approach known as LSTM for fault localization in Kundur's expansive transmission lines. A comparative evaluation is conducted between the proposed method and existing approaches based on parameters such as employed methods, types of measurements utilized, sampling frequencies, accuracy of reach setting, and performed protection tasks. Table 9 presents a comparison of different methods recommended for transmission lines alongside the proposed approach.



(a) (b) (c)
(d) (e) (f)
(g) (h) (i)
(j) (k) (l)

Figure 9. Fault detection visualization for double line to ground fault; (a) detects the presence of fault, (b) ABG fault, (c) AB fault, (d) AG fault, (e) ACG fault, (f) AC fault, (g) BG fault, (h) BCG fault, (i) BC fault, (j) CG fault, (k) ABCG fault, and (l) ABC fault

Table 8. Correlation between actual and predicted value

Random sample number	Actual status	Predicted status
26,881	0	0
3,045	1	1
5,247	0	0
13	1	1
87,954	1	1

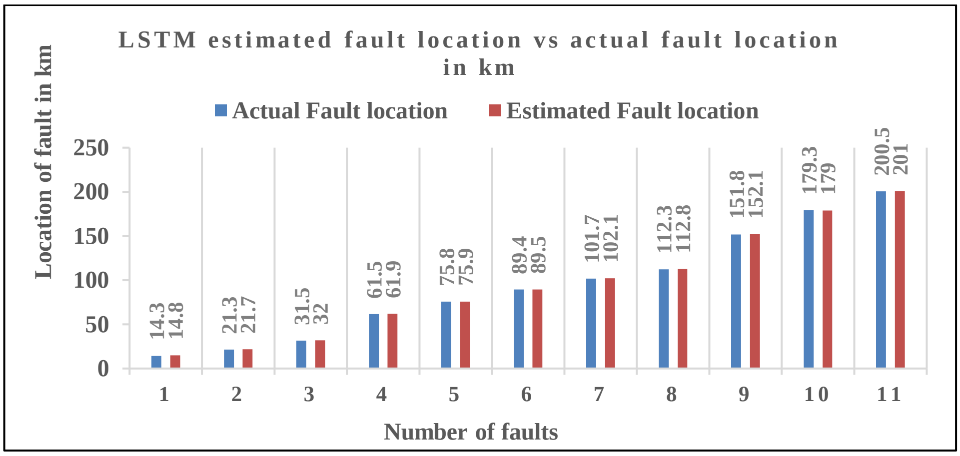


Figure 10. LSTM estimated fault location vs actual fault location

Table 9 emphasizes that the traveling wave method necessitates a high sampling rate, whereas methods utilizing measurements from both ends of the line require a communication link, unlike the proposed method. Furthermore, the proposed method offers superior reach setting capabilities compared to other existing methods. While conventional methods solely detect or locate faults, the proposed method not only detects and locates faults but also classifies them, thereby providing a comprehensive protection scheme. Consequently, the proposed method is better suited for safeguarding against faults in long transmission lines. Upon comparison with conventional methods, it becomes evident that the proposed approach offers numerous advantages.

Table 9. Comparative analysis with other existing methods

Author name and reference no.	Method implemented	Measurement required	Sampling frequency (kHz)	Type of protection done	Reach setting (%)
Zhang *et al.* [26]	Electromagnetic time-reversal technique	Both end	50	Fault location	-
Livani and Evrenosoglu [27]	DWT and SVM	Single end	More than 100	Fault location	-
Li and He [28]	Phase frequency	Single end	4	Fault location	-
Song *et al.* [29]	PRONY algorithm	Single end	50	Fault location	90
Yuansheng *et al.* [30]	Travelling wave theory with the Bergeron method	Both end	1000	Fault location	-
He *et al.* [22]	Travelling-wave	Single end	100	Fault location	90
Our proposed method	LSTM method	Single end	1	Fault location, fault detection, and fault classification	99

7. CONCLUSION

The paper introduces a novel approach aimed at enhancing the operational reliability and stability of power systems through data-driven methods. It proposes utilizing LSTM networks for predicting line trip faults. Additionally, the method suggests extending the network with LSTM subnetworks to leverage additional fault-related data. Experiments conducted on IEEE 11 bus 2 area 4 machine systems demonstrate improved accuracy through the fusion of multiple data sources. Similar to other DL models, LSTMs are prone to overfitting when the training data is insufficient. To address this concern, regularization methods such as dropout can be employed to alleviate the problem. Compared to existing data mining techniques, the proposed method exhibits significant enhancement, achieving an overall fault prediction accuracy of 99%. The reach setting is also 99%. This advancement holds substantial importance for power system operational reliability and stability. Moreover, the hardware requirements align with those commonly found in power systems, rendering the proposed method practical and valuable for real-world application.

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