IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 6, December 2025, pp. 5096~5105
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i6.pp5096-5105

A smart grid fault detection using neuro-fuzzy deep learning algorithm

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Article Info

Article history:

Received Nov 8, 2024
Revised Oct 24, 2025
Accepted Nov 8, 2025

Keywords:

Deep learning
Fault detection
Long short-term memory
Neuro-fuzzy algorithm
Smart grid

ABSTRACT

This paper proposes a novel data analysis framework that integrates deep learning with a binary neuro-fuzzy algorithm to address the problem of fault localization in smart power grids. In the first stage, a long short-term memory (LSTM) network is employed to train data samples collected from smart meters. The resulting learned features are subsequently utilized by an adaptive neuro-fuzzy inference system (ANFIS) for accurate fault detection and classification. Through this intelligent hybrid approach, multi-phase faults can be efficiently identified using a limited amount of data. The proposed method distinguishes itself by its capacity to rapidly train and test large datasets while maintaining high computational efficiency. To evaluate the performance of the model, an advanced simulation of the IEEE 123-node test feeder is conducted. The robustness and effectiveness of the proposed framework are validated using multiple performance metrics, including precision, recall, accuracy, F1-score, computational complexity, and the ROC curve. The results demonstrate that the proposed deep learning–based model significantly outperforms existing approaches in the literature, achieving a fault detection and classification precision of 99.99%.

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1. INTRODUCTION

In the previous few years, there have been significant transformations in electrical networks, resulting in the emergence of a new generation of networks known as the smart grid. The rapid evolution of technology and the rising requirement for sustainable energy solutions have spurred the rise of smart grids. The incorporation of intelligent grid technologies in urban environments offers numerous advantages, including enhanced energy efficiency, reliability, and eco-friendliness [1]. Real-time bidirectional communication is readily available at each stage, encompassing power generation, and distribution systems in a smart grid [2]. The smart grid presents a significant chance for energy distributors to improve the system, guaranteeing uninterrupted access to electrical energy while simultaneously cutting down on field operation expenses [3]. Energy distributors have been actively installing numerous smart meters to utilize the collected data for efficient demand management and to develop such a system. To this day, the data is gathered every month through the meters. However, by incorporating advanced meter infrastructure (AMI), the meters are now capable of capturing data at intervals as frequent as every 15 to 30 minutes. As a result, this data can accumulate to the terabit scale [4]. Furthermore, the information is gathered from intelligent sensors, advanced meters, and the supervisory control and data acquisition (SCADA) system to guarantee the efficient transmission of data to energy consumers and distributors [5]. The gathering and examination of this data will enable the extraction of crucial information for the strategic planning of activities within the intelligent distribution system and the upkeep of essential electrical machinery [6]. The utilization of data analytic machine learning and deep learning techniques is imperative for the efficient training and testing of the substantial volume of data obtained from smart meters.

Numerous researches have been conducted on data analytics within intelligent power grids [7]. Bano *et al.* [8] employed smart electrical network data analysis techniques to detect disturbances using phasor measurement units (PMUs). The utilization of this algorithm could potentially lead to a decrease in data volume, resulting in the extraction of meaningful information from the dataset. Researchers introduced an Apache spark framework designed for embedded computing in the context of data analysis in smart power grid environments [9]. Ahmed *et al.* [10] created a bidirectional communication network connecting multiple residences using client agents within the transformer agents. The evaluation of the precision of these models was assessed through the utilization of error coefficients.

An *et al.* [11] employed a reinforcement deep learning model to identify instances of data attacks in AC electrical grids. The findings from the simulation indicate a limited ability to detect attacks when the model is being implemented. Liao and Anani [12] was developed a neural network for the purpose of identifying deficiencies in voltage sag. The complexity identification is constrained by this approach. The utilization of homomorphic encryption-based data aggregation and blockchain was suggested in [13] to enhance data security while maintaining a high level of training time efficiency. A machine learning algorithm has been used to identify the exposure of urban areas to specific seismic hazards [14], as well as to discriminate between different types of artificial seismic sources [15]. According to Abdalzaher *et al.* [16], a trust model based on a deep auto-encoder (AE) is employed to identify attacks in IoT systems with the assistance of cognitive radio. Furthermore, Moustafa *et al.* [17] presents the implementation of an optimized regression model to predict ground vibrations caused by blast-driven activities. In a smart grid, the prediction of solar generation is accomplished using an intelligent model, as demonstrated in [18].

Deep learning techniques such as convolutional neural network (CNN) have the capability to identify anomalies within electrical grids. In a study conducted by Diaba *et al.* [19], the implementation of CNN, gated recurrent unit (GRU), and long short-term memory (LSTM) models was carried out to detect physical cyber-attacks in the smart grid and SCADA metering infrastructure. This model must consider numerous parameters within a network environment. Simultaneously, the adaptive neuro-fuzzy inference system (ANFIS) model was studied to identify and categorize faults within a smart grid.

The primary contribution of this study can be outlined as follows:

– Various deep learning techniques for analyzing smart grid data have been consolidated in our research. We have outlined the capabilities and constraints of each method in detail.
– We have introduced an innovative integrated deep learning framework using ANFIS and LSTM to identify and categorize various faults within a smart grid by analyzing data collected from smart meters.
– The efficacy of the suggested model was also assessed through the examination of various metrics including accuracy, loss curve analysis, F1-score, ROC analysis, model complexity, precision-recall evaluation, and calibration assessment.

The rest of this work is organized as follows: section 2 outlines the experimental setup used and the deep learning methods employed. Section 3 gives the results and discussion using OpenDSS and MATLAB, along with the fuzzy rules employed for fault identification and classification. The conclusion of this paper can be found in section 4 with perspectives.

2. METHODOLOGY AND EXPERIMENTAL SETUP

2.1. Experimental setup

The experimental platform consists of a Dell computer equipped with an Intel Core i7 processor running at 2.20 GHz, 6 GB of RAM, and the Windows 10 operating system. The data analysis and algorithmic implementation were carried out using Python and MATLAB R2023. The electrical network simulations were performed with the OpenDSS software, which enables detailed modeling of distribution systems. The fault detection framework was deployed on the IEEE 123-node test feeder, augmented with virtual smart meters for data acquisition and monitoring. This configuration provides a realistic environment for validating the proposed detection model. The overall structure of the experimental setup is illustrated in Figure 1.

2.2. Proposed method for fault identification

The identification of malfunctions in an electrical grid enables the elimination of faults that arise within an electricity distribution system. The fault diagnosis procedure comprises three distinct stages.

i) Initially, abnormal voltage and current parameters in the impacted portion of the electrical grid can be detected and recognized.
ii) Subsequently, the determination of the occurrence and characteristics of the malfunction is essential to expedite accessibility and offer a dependable resolution for any issues that arise within the electrical grid.
iii) Ultimately, rectifying the error promptly is essential to prevent any harm to the unaffected sections of the network.

To accomplish this task, a unique integrated deep learning approach was used, incorporating the LSTM model and the ANFIS algorithm. This method incorporates fuzzy logic and neural network strategies to effectively diagnose faults within a smart electrical network using data from smart meters. Figure 2 depicts the flowchart of the proposed model for fault detection, which is constructed using the neuro-fuzzy deep learning approach. Initially, the attributes of the data obtained from the intelligent meters are extracted. Subsequently, the aforementioned data is set as the inputs for training the LSTM model. The smart meter data is then used for fault classification through the application of the neuro-fuzzy system. If a fault is identified, the hybrid system will promptly pinpoint and isolate the fault. Conversely, if no fault is detected, the system will proceed to retrieve data once more from the smart meters. Following the detection of the error, an assessment of its precision is conducted. If this level of accuracy meets the required standards, data is produced to facilitate decision-making to manage operations of restoration. In cases of low accuracy, adjustments are made to the weight, hyperparameters to enhance the reliability of the model. The LSTM hyper-parameters are determined using the dataset, the number of iteration and the accuracy expected.

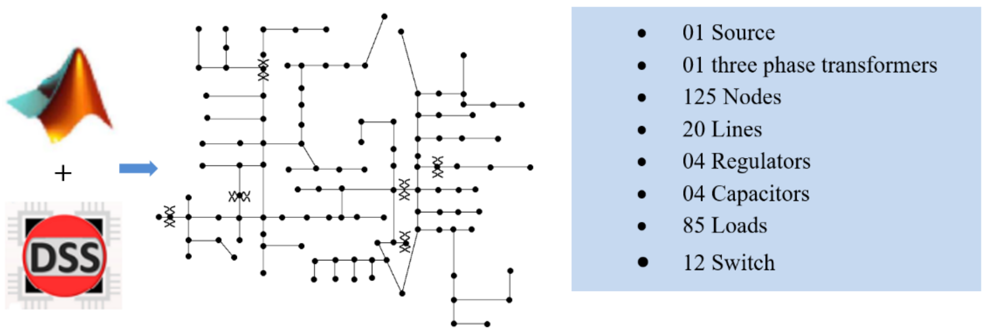


Figure 1. Experimental setup

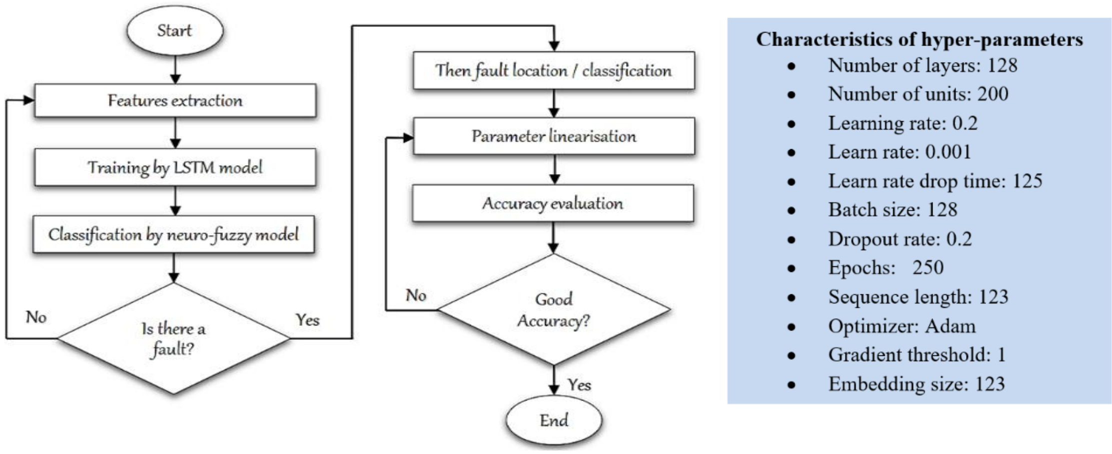
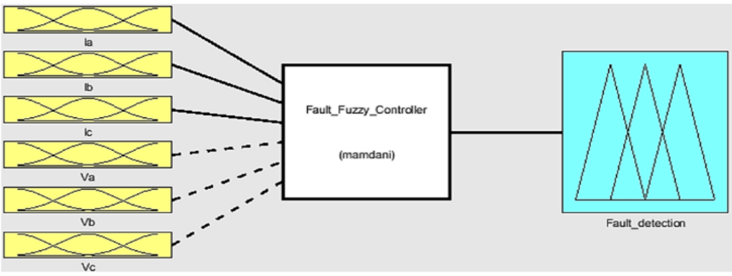


Figure 2. Flow chart of proposed model

Therefore, a study case is conducted using an IEEE 123-bus test network. This testing system consists of three distinct phases: phase A, phase B, and phase C. Therefore, when the current deviates from its usual path, it indicates a fault. This testing system consists of three distinct phases: phase A, phase B, and phase C. Therefore, when the current deviates from its usual path, it indicates a fault. A single-phase fault is characterized by the occurrence of a fault between phase A and ground, phase B and ground, or phase C and ground. Furthermore, a two-phase fault refers to a fault occurring between A and B, or A and C or B and C. The fault occurring between phase A and phase B, as well as phase C, is classified as a three-phase fault. Deviations from the normal voltage range can lead to overvoltage and voltage dips. Figure 3 illustrates the neuro-fuzzy controller model. This model considers six input parameters that correspond to the phase currents and voltages, specifically: I_a, I_b, I_c, V_a, V_b, and V_c. The controller calculates the inputs. The result is a numerical value that signifies a specific occurrence of a malfunction within the electrical distribution system. The result is a numerical value that signifies a specific occurrence of a malfunction within the electrical distribution system.

Initially, the data is acquired through fault simulation using the OpenDSS software on the IEEE 123 bus network. Subsequently, the aforementioned data is gathered through the utilization of intelligent meters and subsequently subjected to analysis by MATLAB's advanced fuzzy system. This sophisticated system enables the detection and precise localization of various faults within the distribution network. Moreover, Figure 3 presents the data collected from the smart meters installed in the IEEE 123 bus network. This data includes the measurements of voltage and current characteristics during instances of phase faults. The current and voltage can be classified as "Low" when their magnitudes fall within the range of 0 to 0.1 per unit (pu). On the other hand, they are considered "High" when their values exceed 10% of the base value.

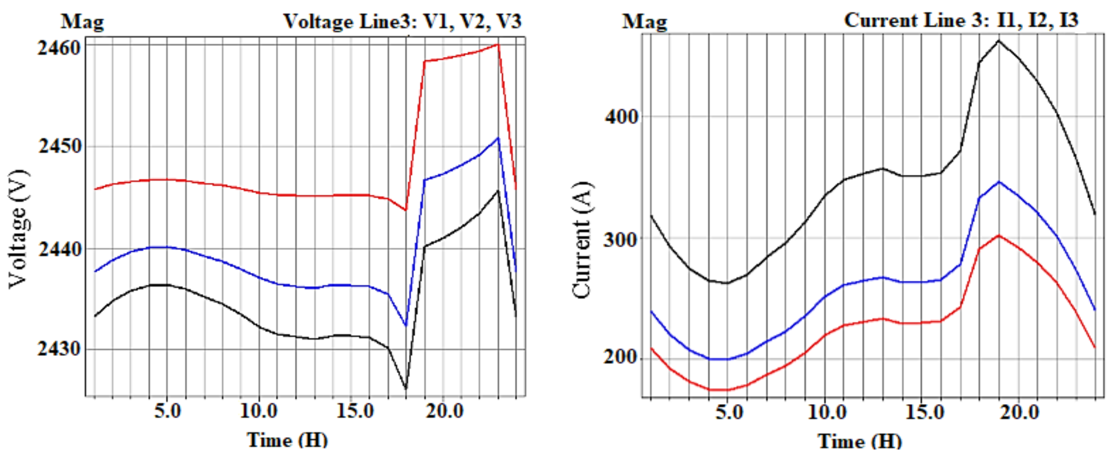


I_a	I_b	I_c	V_a	V_b	V_c	Fault
1	0	0	0	1	1	Ph A
0	1	0	1	0	1	Ph B
0	0	1	1	1	0	Ph C
1	1	0	1	1	0	Ph A-B
1	0	1	0	1	0	Ph A-C
0	1	1	1	0	0	Ph B-C
1	1	1	0	0	0	Ph A-B-C

Figure 3. Architecture of neuro-fuzzy system with six inputs

3. RESULTS AND DISCUSSION

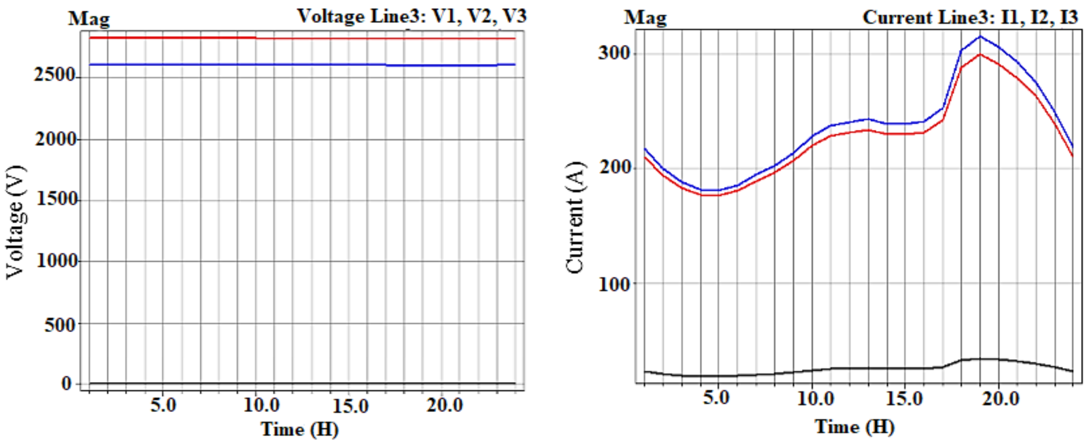
Figures 4 to 9 show the simulation results respectively for normal conditions, single-phase fault, two-phase fault, and three-phase fault. It can be illustrated that the results vary according to the cases considered. Figures 4(a) and Figure 4(b) give a constant evolution of the current and voltage in the electrical network. In normal condition, the voltage is comprised between 2420 V and 2460 V. In the same time, the current is comprised between 100 A and 500 A.



(a) (b)

Figure 4. Simulation results under normal conditions (a) voltage and (b) current

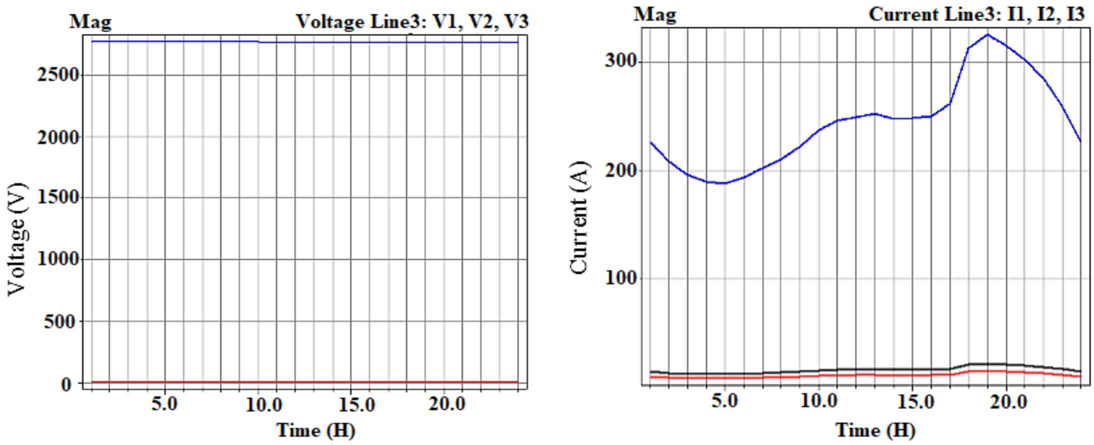
In Figure 5, a single-phase fault has been implemented to evaluate the ability of the system to train the measurement data while considering the fuzzy rules. Figure 5(a) gives the voltage curve; it can be seen that the voltage of phase A is under the normal range. In same time, the current of phase A is over the normal range as illustrated in Figure 5(b).



(a) (b)

Figure 5. Simulation results during a single-phase fault (a) voltage and (b) current

Figure 6 gives the implementation results for a two-phase fault. It should be observed that the appearance of this fault leads to a drastic drop of the voltage in the phases, in particular phase A and phase B as illustrated in Figure 6(a). In same time, the current of phase A and phase B evolves inversely to the voltage between critical values as shown in Figure 6(b). Moreover, the greatly affected buses are 45, 46, and 52.

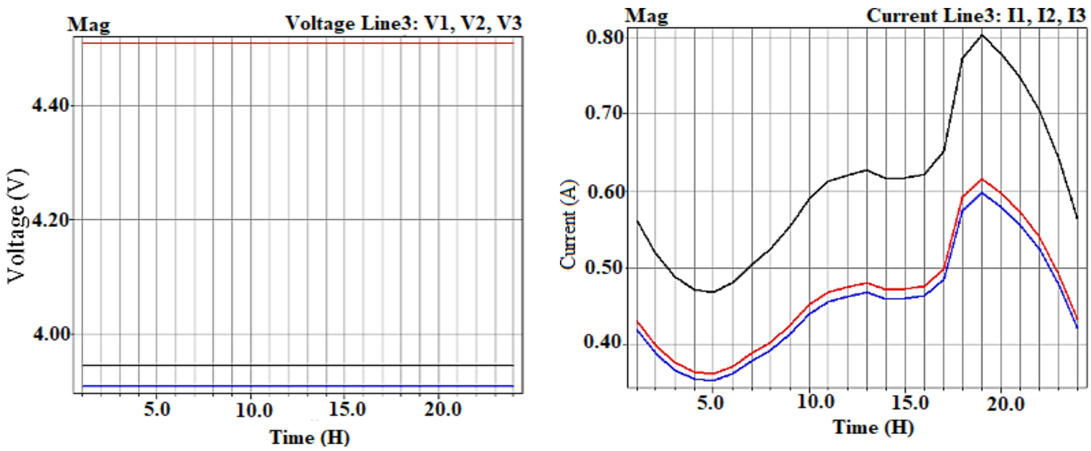


(a) (b)

Figure 6. Simulation results during a two-phase fault (a) voltage and (b) current

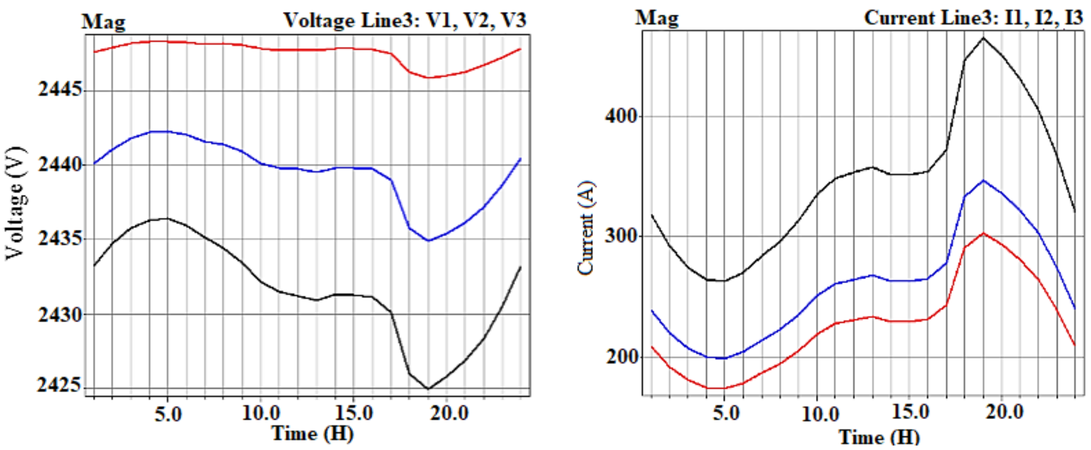
Figures 7(a) and 7(b) respectively illustrate the behavior of the voltage and current magnitude for a three-phase fault. The collected data show that this fault causes a collapse of all phases. This fault caused an increase in the phase currents and a progressive drop in the voltages. Moreover, around all buses are affected by the three-phase fault. The greatly affected buses are 34, 71, 92, 75, 11, 52, 70, 80, and 84.

Figure 8(a) illustrates the evolution of voltage while Figure 8(b) gives the current during an overvoltage. These results show an increase in voltage compared to normal conditions. The data acquired demonstrates the instability of the network when this fault appears and the need to locate it in order to act effectively. In Figure 9, a voltage drop illustrates the impact of this fault on the voltage as shown in Figure 9(a) and current characteristics in Figure 9(b). These phases are dramatically affected by the occurrence of this kind of fault.



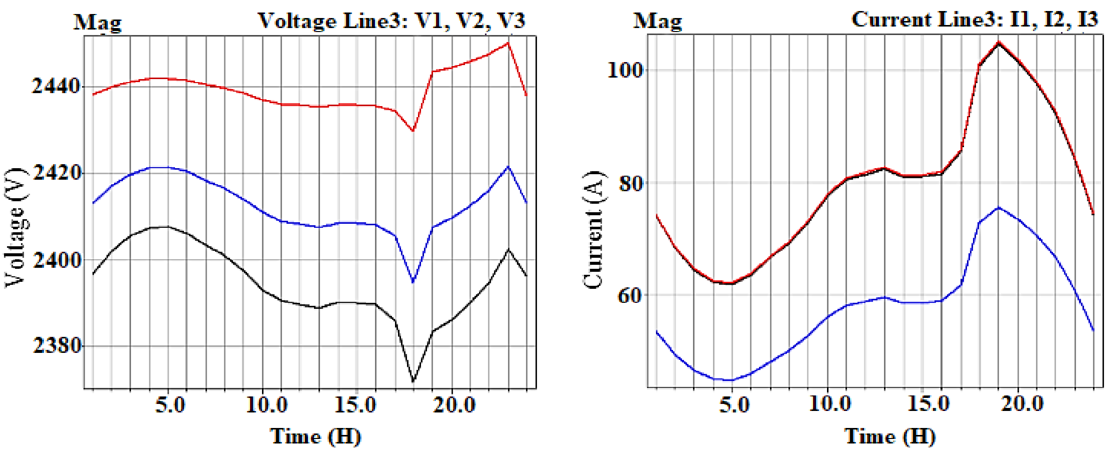
(a) (b)

Figure 7. Simulation results during a three-phase fault (a) voltage and (b) current



(a) (b)

Figure 8. Simulation results during an overvoltage (a) voltage and (b) current

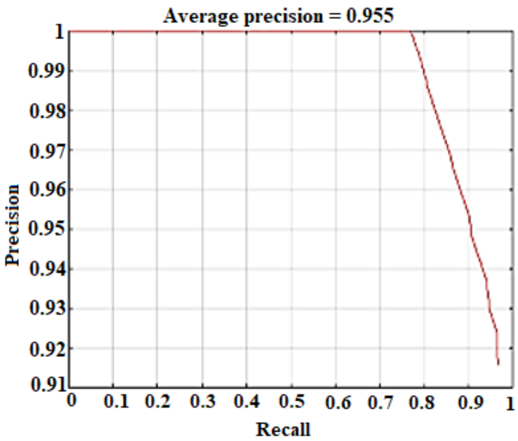


(a) (b)

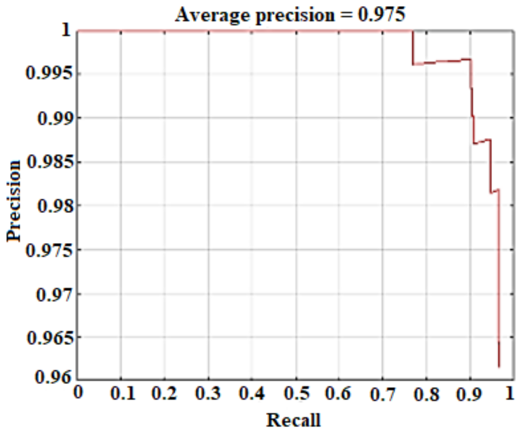
Figure 9. Simulation results during a voltage drop (a) voltage and (b) current

The training results reveal that the ANFIS-based fault detection system accurately identifies several types of faults: single-phase faults on phases A and B, two-phase faults on A–B, B–C, and A–C, as well as the three-phase fault on A–B–C. These fault types correspond respectively to rules 36, 22, 15, 50, 29, 43, and 57 of the fuzzy inference systems. The training of the ANFIS fault detector was conducted over 100 epochs, during which the training error exhibited a continuous decrease up to the final iteration, demonstrating effective model convergence. Model validation was subsequently performed to assess the fault detection capability of the trained system. The validation phase involved testing the neuro-fuzzy model with unseen input data, and the results indicate that the ANFIS model achieves a high level of performance, detecting, identifying, and classifying faults with an accuracy of 0.999. Furthermore, the precision–recall metrics for the ANFIS model, the LSTM model, and the proposed hybrid model are depicted in Figure 10, where Figures 10(a) to 10(c). The comparative analysis clearly demonstrates that the hybrid model proposed in this study exhibits superior precision–recall performance relative to the other models.

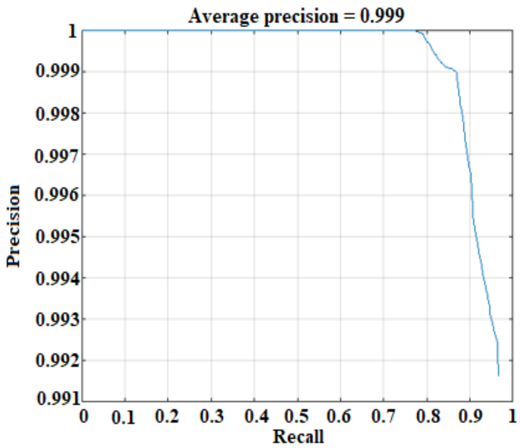
The model we put forward achieved a superior score of 0.9999 at the 100th epoch. Furthermore, the proposed model exhibits a notable enhancement in accuracy, attributed to its ability to optimize for extended training periods. Additionally, Table 1 presents a comparison with techniques used in literature. The proposed method demonstrates superior precision in comparison to alternative methods, while also effectively classifying and pinpointing all faults. The findings indicate that the suggested method surpasses the ones found in existing research.



(a)



(b)



(c)

Figure 10. Precision-recall comparison (a) ANFIS, (b) LSTM, and (c) proposed model

Table 1. Comparison with literature

Ref	Method	Is training dataset required?	Is fault classified?	Is fault located?	Precision
[20]	Deep learning framework	Yes	No	Yes	0.952
[21]	SVM	No	No	No	0.912
[22]	ANFIS	Yes	Yes	No	0.984
[23]	ANFIS	Yes	Yes	No	0.763
[24]	Temporal model	No	No	Yes	0.889
[25]	Fractional classifier	No	No	Yes	0.855
Writers	Proposed model	Yes	Yes	Yes	0.999

4. CONCLUSION

This study introduces an innovative approach to data analysis utilizing deep learning in conjunction with a neuro-fuzzy algorithm to effectively detect and identify faults. The utilization of LSTM in this study enables the training of data obtained from system. The neuro-fuzzy strategy is employed to identify and detect faults based on the analysis of trained data. To achieve this goal, a model is acquired utilizing deep learning techniques that merge two top-performing artificial intelligence algorithms. Our deep learning method was tested on an IEEE 123-bus network containing smart meters and nodes with faults to assess its capability in data analysis and fault detection. The findings of the suggested model demonstrate its superior performance in precision when compared to existing models in the literature. To the best of our understanding, this research paper represents the initial exploration of a deep learning framework with neuro-fuzzy strategy in the existing research literature, specifically for data analysis within a smart power grid. Future studies can be employed for the optimization of deep learning architectures and extending the framework to real time implementation using advanced sensor networks.

ACKNOWLEDGEMENTS

The authors express their gratitude towards the electrical engineering department at ENSET of the University of Douala for providing access to the laboratory facilities.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Etienne François Mouckomey	✓	✓	✓		✓	✓		✓		✓	✓	✓	✓	✓
Jacques Bikai	✓			✓		✓	✓		✓			✓	✓	
Camille Franklin Mbey		✓	✓		✓	✓		✓		✓		✓		✓
Alexandre Teplaira Boum	✓	✓		✓	✓		✓			✓	✓		✓	✓
Felix Ghislain Yem Souhe	✓		✓			✓		✓	✓			✓	✓	✓
Vinny Junior Foba Kakeu		✓	✓	✓		✓		✓		✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

No conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [EFM].

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