Fault Detection, Classification And Location In Power Distribution Smart Grid Using Smart Meters Data

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Fault detection and location give to smart grid the ability to self-healing and isolating the fault in order to limit the negative consequences. In the literature, several techniques are proposed for detection and classification of faults using artificial intelligence algorithms. This paper proposes a novel method using fuzzy logic and neural networks for detection, classification, characterization and location of faults based on data from sensors and smart meters installed in the smart grid. The proposed technique in this paper, use simultaneously the OpenDSS-Matlab platform, makes it possible to detect and classify the fault in the network. The IEEE 37-bus system is used to verify the proposed method. The obtained precision using the proposed strategy is 99.9% which is good value in the literature. This method can be useful for network operators in detection, classification, characterization and location of faults.

Keywords: fault classification, fault detection, fuzzy logic, smart meter data, smart grid

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1. Introduction

The smart grid was developed with the objective of integrating intelligence into the power grid through communication devices. Smart grids are complex networks that include many devices to allow control, monitoring and supervision of the network based on energy demand [1]. The smart grid can be defined as an intelligent system using information and data collected from sensors, servers, intelligent electronic devices and smart meters in order to make the network more flexible, efficient and reliable [2, 3]. The smart grid offers several advantages for production, transmission, distribution operators and consumers, in particular: demand management because the smart grid allows consumers and operators to manage electricity consumption; ensuring reliability of the network because it makes it possible to anticipate and locate remotely, faults and outages detection in order to allow energy recovery; providing grid stability because the smart grid helps to maintain the balance between production and consumption despite variations of energy demand [4, 5]. In order to migrate to the smart grid across the world, some countries already started to establish roadmaps that would allow them to move towards a smart grid in the next years [6, 7]. In Souhe et al. [6], the authors estimated a deployment of 4 million of smart meters in Cameroon for the next 20 years. Fig. 1 shows the structure of a smart grid.

In addition, with the integration of renewable energies and intelligent communication and control devices, the smart grid becomes interactive in order to allow reconfiguration of the system and self-repair of the network when a fault occurs. Several challenges have emerged with these new configurations including: power flow, grid voltage and frequency balance. Under these conditions, a fault can occur in the network, moreover, it is difficult to con-

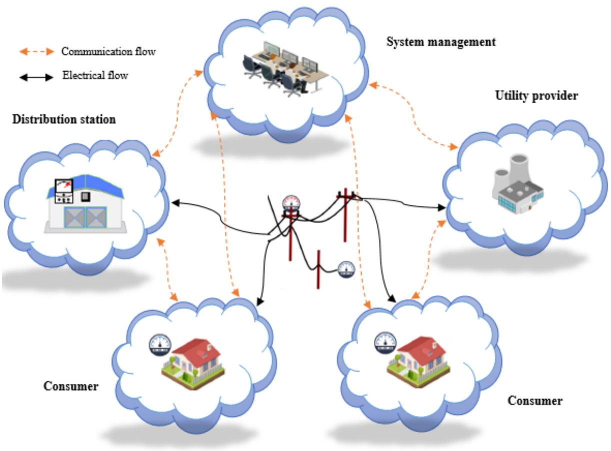

Fig. 1. Structure of a smart grid

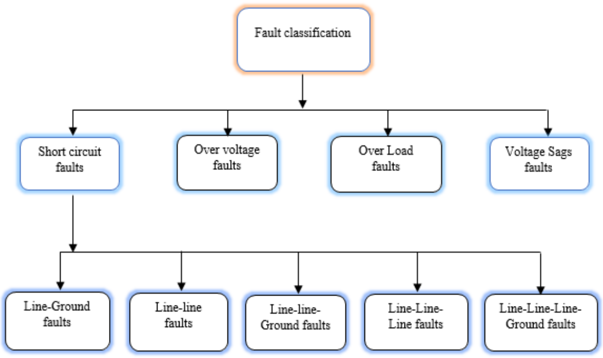

Fig. 2. Classification of faults in the distribution network

trol or detect these faults. With increasing of the number of faults in different areas of the smart grid, it is a rather complicated problem that requires considering the power generation and distribution infrastructure. In addition, faults can appear through various outages which would lead to a permanent interruption of energy in the network. If maintenance is not carried out as soon as possible, these faults can cause instability in the network and increase technical losses. It is therefore important to identify the faults, their causes and their effects, to develop techniques for detecting and classifying them to allow restoration operations [8, 9]. A classification of faults in the distribution network is given in Fig. 2.

The scenarios that can occur on the voltage depend on the amplitude and the duration, so we can have: voltage drop, over-voltage or voltage sag. Short circuit faults can be: line fault, line-line fault or line-line-line fault. In order to limit the occurrence of these faults, smart meters can collect data in the smart grid through communication infrastructures in order to prevent faults by analyzing data in real time using intelligent flows. In the literature, several intelligent methods and algorithms have been proposed for the purpose of detection, classification and eliminating faults by protective devices. In [10], the authors proposed a fuzzy logic algorithm using the discrete wavelet transform to identify faults in the distribution network. This technique is able to identify the occurrence of faults and their negative effects. In addition, this method makes it possible to calculate changes in energy levels. The energies calculated by the discrete transform are used as input linguistic variables of the fuzzy logic inference system. The proposed method was applied in IEEE 13 bus test network and the real Indian network to verify the methodology. The obtained results show that this method is better in fault detection that those in the literature. A neural network technique was employed in [11], in order to classify and detect faults in transmission network lines. Specifically, the neural network is used as a tool for recognizing, identification and detection of faults. The algorithm considers dynamic changes in the system to achieve reliable, fast and accurate output. The neural network therefore shows its capacity to be able to identify and classify the faults in the smart grid through its reliability and its efficiency in the detection and classification of faults. The accuracy of this technique is evaluated using the correlation coefficient. The results of simulation give 0.93788 correlation coefficient which is better than the previous methods. In [12], the authors adopted a method of fault identification based on voltage fluctuation. In this paper, the authors used neural networks as a technique for identification and classification of fault. This method is implemented on real network with the aim to detect and identify the fault. From the simulation results, the detection error is 0.2%. This method is efficient for detection and identification of faults because using of artificial intelligence algorithms. In [13], a platform for fault detection in a smart grid was proposed. In this paper, the authors used the Kalman filter estimator and a Euclidean detector. The Kalman filter is able to consider the nonlinear variations of the network by using the state equation and measurement equation. This detector makes it possible to measure the relationships between the dependent variables and the time series of prediction variables. The results obtained show that this method effectively makes it possible to detect faults and attacks in the system. However, it has been proven that the detector is unable to statistically detect faults by injecting erroneous data.

In a smart grid, faults are detected by analyzing the shape of voltage, current and phases. That is why in [14], the authors presented a theoretical adaptation and control platform for the level of security of the smart grid. This system uses state estimation technique to estimate data from remote devices and analysis tools to detect faults in the smart grid. So, after the simulation in real grid, a 25% overload is observed for a long period. This fault can be detected efficiently by using the proposed method. In [15], the authors developed a two-step classification strategy for voltage drops. This typical classification technique consists of a selector and classifier to achieve efficient classification. The authors tested their methods on three causes of voltage drops to obtain simulation results to prove the efficiency, robustness and accuracy of the proposed method. In terms of precision in the fault detection and classification, the proposed strategy outperforms the previous methods.

In [16], the authors proposed an evaluation of signal processing tools based on the Hilbert transform and the linear Kalman filter to estimate and detect voltage drops. This tool allows a recent detection of the degradation of the voltage quality and allowing a rapid response. Hilbert transform and Kalman filter can be used for analysis and estimation of nonlinear scenarios in the network. The performances of these methods have been validated on a simulated network. The obtained results show that the Hilbert transform and the Kalman filter can be used for the detection of voltage drops. Despite this, it would be necessary to prolong the investigations in order to have all the parameters of the network in order to effectively assess the performance of these methods. The work in Nadeem et al. [17] proposed a scheme for the protection of high voltage direct current terminal networks based on a voltage source converter for the interconnection of renewable sources and fault analysis. The method used for fault detection is the successive data window technique which is an effective method for implementation of intelligent operations in the network. In [18], the authors developed a method of faults location in a loop micro grid using a hybrid algorithm based on the wavelet transform and the multi-class support vector machine (M-SVM). In this paper, the fault is located in a reduced search area using this hybrid algorithm. This hybrid algorithm is a combination of deep learning techniques for network applications. The simulation results make it possible to validate and demonstrate the efficiency and the precision estimation of the proposed method. However, this method does not consider the possibility of some various and different faults that may occur in the distribution network.

In [19], the authors developed a method of linear approximation relation for the location of faults. This method is based on linear regression relations considering the variability of the electrical network. However, this method is not applicable for fault location and classification in a looped micro grid. In [20], the authors proposed a method consisting in the detection of hidden faults using devices consisting of a protective relay system. In this paper, the combination of nonlinear operations allows to develop a decision criteria for the detection of hidden faults in the smart protective system. The protective devices can be useful to eliminate the faults when they occur. The effectiveness of this method is demonstrated by applying it in IEEE 39 bus system. The results show that this method can detect hidden faults with 98% accuracy by sending alarm information, and ensuring safe operations of the smart grid. In [21], the authors developed a state estimation algorithm using data from smart meters for network load analysis and estimation in order to limit power losses. Single-phase and three-phase state estimation algorithms are compared through simulations on a real distribution network using measurement data from smart meters. For this purpose, the three-phase state estimation algorithm has shown its highest precision for estimating the state of the lines. The method proposed in this paper has shown its usefulness for distribution network operators to analyze the power flow in the smart grid in order to carry out all the necessary operations in the network.

An intelligent system for identifying and managing faults is also proposed in [22]. In this paper, intelligent identification, monitoring and suppression systems have an important role for self-healing of smart grid. Monitoring and identification systems can operate independently and exchange data records from the same database. In addition, eight types of overvoltage are presented and analyzed, the transform algorithm is used to extract the elements of the overvoltage. From these eight types of overvoltage, the six different characteristics are proposed. The accuracy of the identification system is verified through a succession of records, the results show that the system is operational for real world applications.

A wavelet approach based on deep neural networks has been proposed in [23] to develop an intelligent fault detection scheme. To this end, some works have developed methods for identifying electrical disturbances in smart grid [24] and Decision Tree (DT) techniques and Variational Decomposition Mode (VDM) for the classification of disturbances in the quality of energy [25]. Likewise, an automated identification of disturbance waves in a smart grid is developed in [26].

The need for fault protection has led to the development of a protection scheme for high voltage multi-terminal networks for the interconnection of decentralized production. The works in [27] allowed to develop a method of consecutive data and harmonics of high voltage systems to avoid circuit breaker malfunction without communication. The position of these faults is classified and a faulty part is isolated from the rest of the general network using hybrid circuit breakers. The hybrid circuit breakers with protective scheme can be used for fault diagnostic and network healing. Likewise, other methods for the protection of high voltage networks are characterized by revealing their advantages and disadvantages [28, 29]. For the development of modification operations in the network, a review on network reconfiguration, fault detection, location and isolation is presented in [30].

Line fault classification models from deep learning can be used for training from a sample of simulated fault. The work in [31] make it possible to propose a new fault classification model for power lines in smart grid using machine learning. First, a conditional generative network is applied for increasing the fault sample; subsequently the loss function of the convolutional neural network is designed in order to provide a framework for fault classification on the improved convolutional neural network. A fault detection and classification in smart grid is studied in [32]. In this paper, the most common fault are described and classified with their characteristics and data analysis requirements. Several other works have been carried out in the field of classification and detection of faults using the reflective wave method [33], the combination of wavelet singular entropy theory and fuzzy logic [34]. In addition, some researches have been carried out for the diagnosis of faults in the smart grid [35]. In [36], the authors have studied the faults in smart grid networks for Monitoring, detection and classification with the aim to prevent the occurrence of the faults in the long term. Bansal and Sodhi [37] made a review on Micro-grid fault detection methods by providing issues, implementation and future applications. A novel fault location method for distribution networks using smart meters has been proposed in [38]. In [39], authors presented a general review on faults classification and identification on smart grid considering possible instability of network. Moreover, a technical review on classification of various faults in smart grid systems has been presented in [40]. Trindade et al. [41] presented a fault location technique in distribution systems based on smart meters for the monitoring, detection and classification of these faults. Other researches have been developed through various methods of recording data on low voltage [42] and on the characterization of spatio-temporal data of synchrophasors and analysis in the smart grid [43] A new method for faults location in transmission lines by voltage measurements considering measurement errors has been presented in [44]. Using the controlled data calculation method, the research in [45] made it possible to detect, identify and locate faults in smart grid. A method of classification of fractional order by the color relation has been proposed in [46] for the detection of faults in a photovoltaic energy conversion system in a smart grid. This method can detect the faults in photovoltaic power plants and to prevent any disturbance in the network. Using a convolutional, unsupervised auto-encoder learning tool, the work in [47] allowed for the detection and classification of faults in transmission lines. The authors used this new generation deep learning model for the smart grid operations and requirements.

Other works have been done on fault diagnosis in smart grids [48]. Fault diagnostics review in micro-grid is done in [49]. In [50], a fault location framework is presented in distribution networks with distributed generations using SVM and data from smart meters located in the networks. In this paper, the SVM was trained with voltage values measured from the generation substation and smart meters located in households. This method is validated on an IEEE 34-bus system, which has made it possible to locate, classify and characterize 11 different faults; moreover, the accuracy of the localization of these faults is above 87%. Using SVM, other authors have located faults in the distribution system by considering variations in distributed generations [51]. The works in Amer et al. [52] allowed the development of a new method of discrete wavelet transform for the detection and location of faults in smart grid. This method is implemented on an IEEE 14-bus system to confirm its effectiveness. The simulation results show satisfactory performance making it possible to classify faults and noisy signals and to precisely locate the location of these faults. In [53], the authors presented a fault detection scheme with photovoltaic panels thanks to the monitoring of the output power of these photovoltaic panels. In this work, the proposed scheme makes it possible to classify line-line, line-ground faults from climatic disturbances. The results obtained show the high precision of the proposed fault detection scheme. Moreover, the accuracy of this technique shows that the proposed model outperforms those in literature. Likewise, an adaptive fault identification scheme for microgrid using a scenario using classification is proposed in [54]. This method is implemented in Matlab Simulink to verify its effectiveness for identification and detection of faults with the aim to isolate the fault in order to ensure fast restoration of the network.

Other authors have worked on the detection of voltage drops using an empirical decomposition ensemble approach [55] and instantaneous element extraction [56]. On the other hand, in [57], research focused on strategies ensuring voltage stability in the smart grid. Still for stability problems, the work in [58] focused on monitoring using an Adaboost classifier. Adaboost classifier is a deep learning technique based on artificial intelligence algorithms which is useful for data analysis and training. Other events can appear in a smart grid, so in [59] the authors classified these events using supervised learning using PMU data. Regarding the prediction of real-time voltage stability in a smart grid, work in [60] uses data from smart meters and thevenin's improved estimator.

In this paper, the detection and classification of faults were implemented in IEEE 37-bus system is proposed using a Neuro-fuzzy algorithm implemented through the OpenDSS-Matlab platform. The contribution of this paper concern a novel OpenDSS-Matlab framework for fault detection, classification and location. Considering that, OpenDSS makes it possible to simulate the operation of the electricity distribution network, the network data is then stored in smart meters, Matlab can then extract the data coming from OpenDSS and implemented a Neuro-fuzzy algorithm in order to identify faulty scenarios in the network. The novelty of this paper concerns the implementation of OpenDSS-Matlab platform where OpenDSS is used for network simulation and data collection then Matlab help for data training and testing using artificial intelligence algorithms.

This paper is structured as follows: section 2 presents the material and method, including, OpenDSS and Matlab software respectively for network simulation and the fault detection algorithm. Section 3 gives the results obtained in terms of detection accuracy. The conclusion is presented in section 4.

2. Material and method

2.1. Material

2.1.1. OpenDSS

The simulation of the electrical distribution network was carried out using OpenDSS (Open Distribution System Simulator) simulator. OpenDSS works through command lines with its own console. It was also designed to be used with tools such as: Matlab, Excel, Python, OMNet ++ and many others software through the COM interface [61, 62].

2.1.2. OpenDSS-G

OpenDSS-G is a new step in the evolution of simulation tools for planning and operations based in OpenDSS. This interface has adopted the functionalities of OpenDSS for making easier to the user to use the advance features of the platform. This version includes the parallel processing features included in OpenDSS. In this paper, OpenDSS-G allows us to locate geographically the fault in the power network.

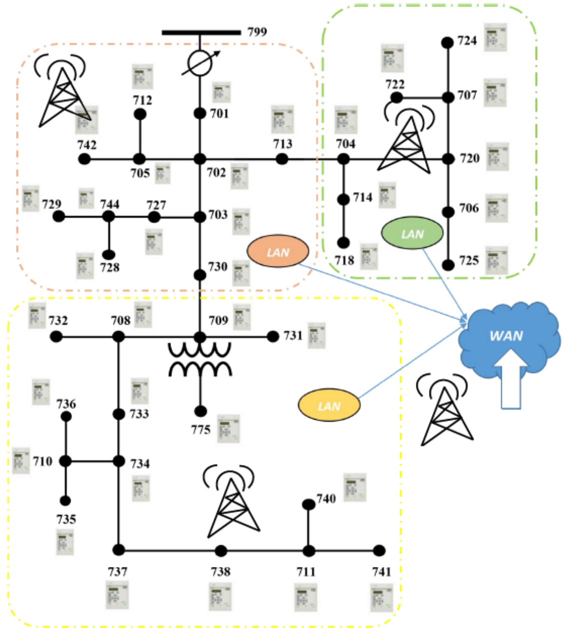

Fig. 3. IEEE 37-bus system

2.1.3. Matlab

In this paper, the simulations were carried out using the Matlab R2020b 64 bit version. It is used for matrix calculations to analyze data and classify it. Matlab helps for the implementation of Neuro-Fuzzy Algorithm.

2.1.4. Computer

All the simulations of this work were done on a DELL computer with following characteristics: core I5, 3.1 GHz processor, 8 GB RAM, Windows 10/64 bits.

2.1.5. IEEE 37-bus System

Fig. 3 shows the intelligent electrical system used in this work. This system is a smart IEEE 37-bus system. The IEEE 37-bus system is characterized by 33 KV substation voltage, two transformers, 37 buses under 4.8KV, 32 lines and 65 loads. Smart meters are located on each of the network nodes in order to retrieve data and improve accuracy in fault detection. This network is simulated using OpenDSS time series software in which the various faults were simulated on the nodes. In addition, it was necessary to perform thousands of simulations of these different types of faults using the OpenDSS-Matlab platform in order to obtain fault location and classification data.

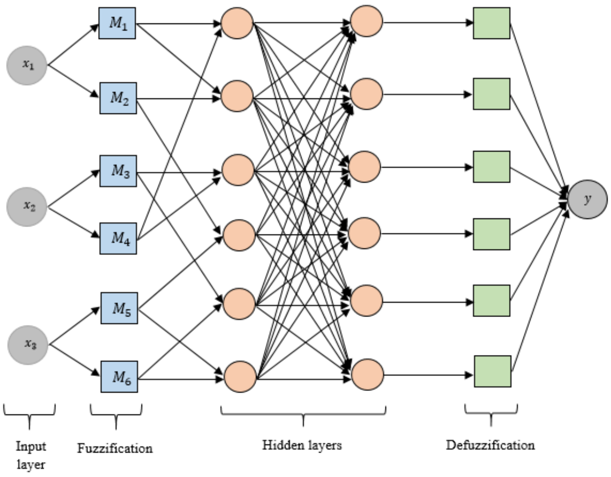

Fig. 4. Proposed ANFIS model

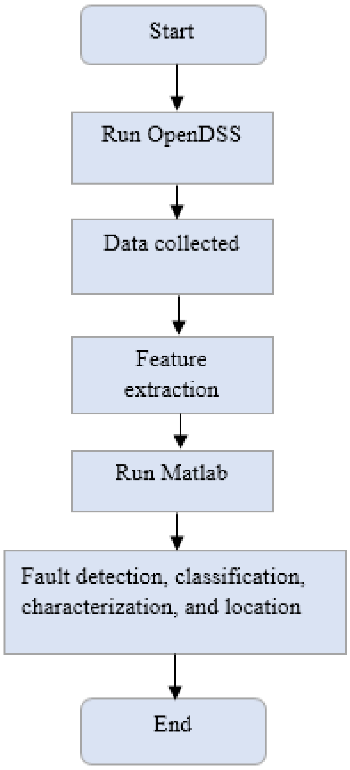

Fig. 5. Fault detection, classification and location flowchart

2.2. Method

2.2.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Neuro-Fuzzy Inference System is a combination of fuzzy logic and neural networks. In a fuzzy inference system, the member functions used are chosen arbitrarily. With an adaptive Neuro-Fuzzy Inference System (ANFIS), the limb functions are adapted to the database. The modeling of the fuzzy inference system allows the interpretation of the relationships between the inputs and the outputs of the fuzzy algorithm. The ANFIS algorithm also improves the system by adapting the member functions of the inputs and outputs of the sample database. This adaptation is achieved through Neuro-Fuzzy learning. Fig. 4 presents the ANFIS model used in this work.

The learning process consists of calculating the parameters of the member functions that would allow the fuzzy inference system to optimally follow the input and output data by following steps: structuring the models of the member functions of the inputs and outputs based on Sugeno's Fuzzy Inference System; introduction of ANFIS training data; training the model; testing the model and the calculation of the error criteria.

2.2.2. Proposed Strategy

The method consists of the detection, classification, characterization and location of faults using data from smart IEEE 37-bus network that we have built. This method is implemented through the following steps, which the flowchart is given in Fig. 5.

First the OpenDSS software is launched in order to simulate the operation of the network for the different types of faults that occur in the network. The simulation data obtained from the OpenDSS software is contained in a csv file. These data being collected, a preprocessing makes it possible to extract the important characteristics for the model. Next, Matlab software will be launched for the implementation of the Adaptive Neuro-Fuzzy Inference System algorithm. Using this algorithm, the faults simulated in the OpenDSS software will be detected, classified, characterized and located at the various points.

The implementation of the neuro-fuzzy algorithm with Matlab makes it possible to classify and geographically locate faults in the network. The neuro-fuzzy algorithm will be able to classify and characterize faults from the membership functions of the voltage and current input variables. The fault location can be achieved by the geographical representation of the network in OpenDSS-G. The position of the faults will be located in a precise and reliable operation. TTable 1 shows the types of faults that can occur in the system using the proposed method.

Fig. 6 shows the ANFIS model for fault detection using current and voltage data from smart meters. Depending on the values of the currents and voltages, faults can be detected and classified. The fuzzy controller has six inputs: the voltages V_1, V_2, V_3 and the currents I_1, I_2, I_3. These inputs are trained in the ANFIS controller in order to identify the type of fault and obtain their positions.

Table 1. Description of fault

Faults type	Description
Fault 1	Line fault on phase 1
Fault 2	Line fault on phase 2
Fault 3	Line fault on phase 3
Fault 4	Line-line fault on phase 1-2
Fault 5	Line-line fault on phase 2-3
Fault 6	Line-line fault on phase 1-3
Fault 7	Fault on phase 1-2 and ground
Fault 8	Fault on phase 2-3 and ground
Fault 9	Fault on phase 1-3 and ground
Fault 10	Line-line-line fault
Fault 11	Line-line-line fault and ground

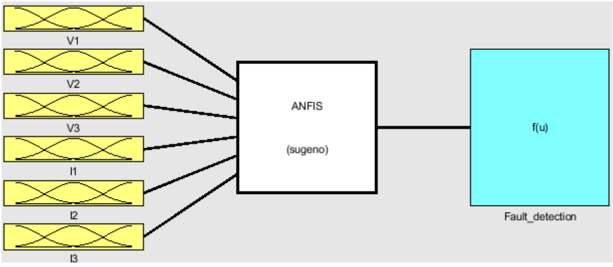

Fig. 6. ANFIS model for fault detection

3. Result discussions

A succession of simulations were carried out on the IEEE 37-bus system in the OpenDSS software. Using the OpenDSS software, the operation of the IEEE 37-bus network in normal mode and in mode with line-ground, line-line and line-line-line fault is shown in Fig. 7.

The simulation is carried out using OpenDSS for analyzing of distribution network during the faults. The accuracy of the proposed method is validated by applying it in Matlab using the data of simulations. In addition, the simulation of overvoltage faults, voltage drop and voltage dips allows to obtain Fig. 8.

Considering the description of IEEE 37-bus system the voltage at buses is 2800 V. In Fig. 8, in normal condition the voltage is 2800 V, this value is the same with the voltage description. In case of a drop in voltage, the voltage drops to 2600 V. In case of an overvoltage, the voltage increases to 3000 V. A voltage dip is observed for a few milliseconds.

The data obtained from the OpenDSS software are trained in the Matlab software in order to detect the position of faults that occur in the network. In addition, using deep learning in Matlab, the precision of fault detection is obtained. So, the identification of fault is successfully achieved for all kinds of faults.

Table 2 presents the results of the fault location implemented in the IEEE 37-bus system as well as the detection precision in the ANFIS model from Matlab.

Table 2. Results of fault detection

Fault	Line	Precision of detection
Line short circuit	711-740	99.9%
Line-line short circuit	709-730	98.9%
Line-line-line short circuit	729-744	97.8%
Voltage drop	706-720	96.1%
Over voltage	701-799	95.2%
Voltage sags	714-718	94.4%

Fig. 9 gives the geographical localization of fault in IEEE 37-bus system. The fault are located in buses 799, 720, 709, 711, 718 and 729.

A comparison of our technique with the literature is presented in Table 3.

4. Conclusions

This paper presented a new method for the detection, classification, location and characterization of faults in smart grid. To this end, the adopted approach is based on Adaptive Neuro-Fuzzy Inference System (ANFIS) for diagnosis in the distribution system. For this, we used the OpenDSS software for the simulation of faults in the electrical distribution network. In addition, Matlab software was used to implement the neuro-fuzzy approach to detect and classify faults that were simulated in OpenDSS. The data collected was used for training the neuro fuzzy system to identify and locate faults. To validate the proposed method, we used an IEEE 37-bus system which single-phase, two-phase and three-phase short-circuit faults were detected respectively in lines 1, 5 and 31. In addition, the overvoltage and voltage drop were simulated in this test network using OpenDSS software. Then, using the algorithm implemented in Matlab, these overvoltage faults and voltage drops were identified. Precision values in the identification of fault were obtained showing the reliability of the neuro-fuzzy method for the detection and classification of all kind of fault. In terms of precision, the proposed method gives better results comparing with the literature. Moreover, the obtained results show the effectiveness of this method for power grid operators to detect faults and prevent them in order to avoid the consequences that could appear.

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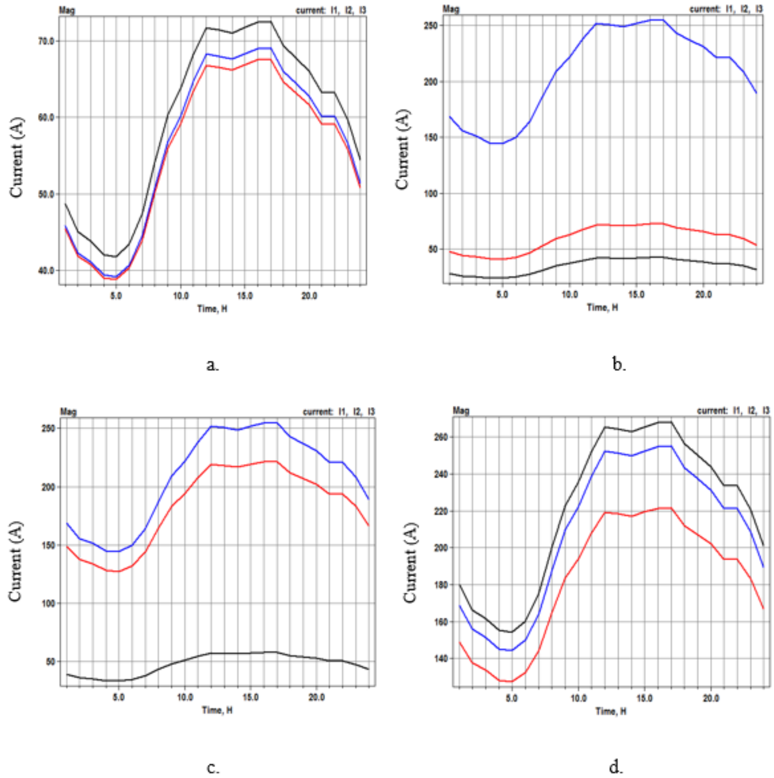

Fig. 7. (a) Normal conditions (b) line-ground fault (c) Line-line fault (d) Line-line-line fault

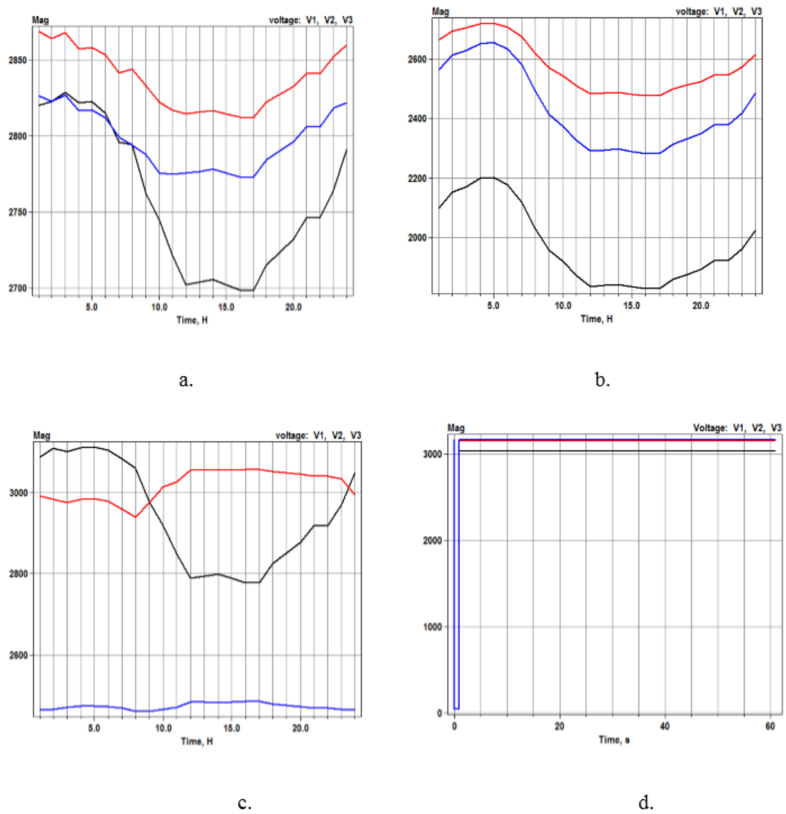

Fig. 8. (a) Normal conditions (b) Voltage drop (c) Over voltage (d) Voltage dip

Table 3. Comparison with the literature

Refs.	Method	Precision
[31]	Deep-Adversarial-Transfer Learning	98.05%
[43]	Spatial-Temporal Synchrophasor Data Characterization	94.26%
[46]	Fractional-Order Color Relation Classifier	95.85%
[50]	Support Vector Machines	90%
[60]	Improved Thevenin estimator	87.52%
This work	Proposed strategy	99.9%

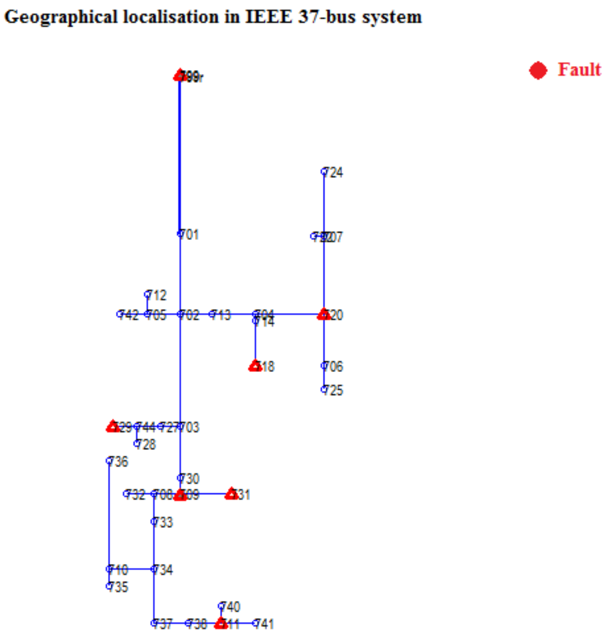

Fig. 9. Geographical localization of fault

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