Simulation Experiments for Faults Location in Smart Distribution Networks using IEEE 13 Node Test Feeder and Artificial Neural Network

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Abstract
The security and reliability of supply is often affected due to fault occurrence in electrical power Distribution Networks (DN). In the conventional DN, faults location takes more than the expected time, which results in economic losses to power utility companies as well as consumers. However, the advent of Intelligent Electronic Devices (IEDs) and recent advances in Information and Communication Technology (ICT) has made DN better, safer and smarter. In this paper, we present the outcome of simulation experiments carried out to locate faults in a DN. The IEEE 13 Node Test Feeder was simulated in SIMULINK with different fault conditions and the fault data acquired were utilized to develop an ANN classification model. The outcome of the experiments shows that the ANN based classification model is effective in locating faults on distribution lines with satisfactory performances.

Keywords: Smart Distribution Grid, Fault, ANN, Backpropagation, Intelligent Electronic Device

1. Introduction
Smart Grid (SG) is a power system that is safe, secure, cost-effective, more dependable, and eco-friendly. It is an upgraded system of power grid for its advanced energy efficacy, outlined demand, controlled emission, reduced cost and enhanced utility [1]. It is defined as “a network of electricity which could professionally mix the performance and activities of all users associated with it – consumers, generators and those who operate both – so as to guarantee economic efficiency, low losses power system that is sustainable, and high levels of security and quality of safety and supply” [2]. Smart grid is renowned for its outstanding capability of self-healing by embracing the skills of self-recognition, identification, decision and restoration. Isolation from the main grid under dangerous fault condition is realizable via self-healing [3].

Power Quality (PQ) issues, momentary and sustained interruptions, outages and increased operational costs are the effects of faults in DN [4]. The management of faults has been an established problem in power DN. The electrical Power Distribution Lines (PDLs) faults are expected to be recognized first; its type identified appropriately and be cleared as fast as possible. A good recognition system for faults provides reliable, effective, secure and fast approach of a relaying procedure. Notably, the advent of ICT and IEDs integration into the DN has resulted in a safer, better and smarter system. ICT provides the capability for unified communications and the
integration of telecommunications, software, middleware, computers, audio-visuals and storage systems, which allow users to access, manipulate, transmit and store data [5].

Various researchers have made several efforts to find solutions to the problems of fault location in power systems. Hybrid fuzzy-genetic method (i.e. a combination of fuzzy set methods, genetic algorithm and real-time measurement) led to the fault detection of a time-effective and high-quality large-scale system as reported in [6-8]. In [9-11], fault confirmation and location knowledge-based systems were designed by pooling numerous kinds of information – Advance Metering Infrastructure (AMI), Supervisory Control and Data Acquisition (SCADA) and customer calls. The experimental outcomes of hybrid Artificial Neural Network (ANN) and Support Vector Machine (SVM) considered in [12, 13] show lower accuracy when the ANN and SVM classifier were trained on data from a simulated network and tested on data collected from the real power network but high accuracy when the ANN and SVM classifier were trained on data from a real power network and tested on data collected from simulated network.

Methods on distance metric dependent similarity measure and transient voltage stability and voltage sag were debated in [14-16]. In [17, 18], Dynamic Time Warping (DTW) was employed on the range of events for similarity estimation. The analysis of dynamic array is subject to the reality that process signals’ representation could be made at diverse stages of details and that comparable actions lead to qualitatively comparable trends. The simulated outcomes revealed that the suggested methods can precisely differentiate between voltage sag and transient voltage stability in power system protection [19, 20].

Other techniques for the different segments of the power system have been recommended in the literature. Expert system techniques are studied in [21-23]; a smart supervisory coordinator in dynamic physical systems and a mode identification technique for hybrid system were proposed in [24-26]. Experimental results proved that these methods could function in the real-time industrial environments. Discrete Wavelet Transforms (DWT), Bayesian selectivity, artificial intelligence and harmonics for High Impedance Fault (HIF) detection approaches and other automated techniques in power systems have been proposed in [27-29, 33-36].

In this paper, we simulated different fault conditions using IEEE 13 Node Test Feeder and develop a classification model to detect and classify fault locations in the distribution subsystem.

2. Materials and Methods
2.1 Distribution System Model
A generic architecture for intelligent fault detection, classification and location in smart grid was evolved in [32]. The architecture comprises of three layers, which are the Power Grid Components Layer (PGCL), the Fault Data Acquisition Layer (FDAL) and the Machine Intelligence Layer (MIL). The FDAL encompasses Digital Signal Transmission (DST) unit, the microcontroller and the Power Generation, Transmission, Distribution and Consumption Sensors or Devices (PGTDCS). The study at hand focuses on fault location using ANN in the distribution system unit of the generic architecture.

The 13 Node IEEE test feeder was selected as the distribution system model in this study based on its reputation for the evaluation of generic attributes of electric power distribution system, operating at 4.16 kV. It is short, relatively loaded and consists of a voltage regulator, which could
be found at the substation and possesses an inline transformer. It comprises of two shunt capacitors, nine unbalanced loads and various overhead and underground lines [30]. Figure 1 shows the Single-line diagram of the model.

Figure 1: One-line Diagram of the 13 Node IEEE Test Feeder [30]

The distribution system’s model simulation was done in MATLAB Simulink using SimPowerSystems toolbox. Figure 2 shows the Simulink block diagram of the model. To obtain the datasets for this study, the 3-phase currents and voltages samples were measured using the 3-phase V–I measurement blocks. On the model, several types of fault at diverse locations and different fault resistance values were simulated.
2.2 Fault Data Acquisition and Machine Intelligence

The different fault resistances utilized include 0.001Ω, 0.0025Ω, 0.005Ω, 0.0075Ω, 0.01Ω, 0.025Ω, 0.05Ω, 0.075Ω and 0.1Ω at strategic locations on the 3-phase distribution branches of 631-671, 632-633, 671-680 and 692-675 containing respective lengths of 0.6096km, 0.1524km, 0.3048km and 0.1524km. The frequency for this study is 50Hz and 11 fault types were considered while forty eight occasions of faults were simulated for every fault type. The simulated fault dataset serve as features that were fed as inputs to the ANN, which is the adopted machine intelligence technique for this study. The four three-phase lines of IEEE 13 Node Test Feeder were divided into four zones as illustrated in Table 1. The ANN takes-in 6 inputs (i.e. 6 input layer neurons) comprising the 3-phase currents & voltages computed as ratios of their respective post-fault & pre-fault values and gives out 4 outputs (i.e. four output neurons). Each of the outputs corresponds to the fault circumstance of each of the four zones. Therefore, the outputs are either a 1 or 0 signifying the presence or absence of a fault on the equivalent line.
Table 1. Target output of the MLP-ANN for Fault Location

| Fault Location | Line   | Network Output |
|----------------|--------|----------------|
| Zone 1         | 632-633| 1 0 0 0        |
| Zone 2         | 632-671| 0 1 0 0        |
| Zone 3         | 671-680| 0 0 1 0        |
| Zone 4         | 692-675| 0 0 0 1        |

3. Results and Discussion

The overview of the trained Feed Forward ANN (FFANN) with the most satisfactory performance for fault location classification is shown in Figure 3, having topological configuration of 6-30-15-5-4 i.e. 6 neurons in the input layer, 3 hidden layers with 30, 15 and 5 neurons respectively and 4 neurons in the output layer. Several backpropagation ANN configurations were analyzed out of which the lowest MSE of 5.4033e-11 at Epoch 17 was selected (see Figure 4).

Figure 3. FFANN with configuration (6-30-15-5-4) chosen for fault location
The performance of the trained FFANN model were tested using four evaluation tools; first is the regression curve, which relates the targets and the outputs for the training, validation and testing stages (see Figure 5). The correlation coefficient (R) obtained is 0.94485 - signifying acceptable correlation between the targets and the outputs. The second is the Receiver Operating Characteristics curve (ROC) as shown in Figure 6. The ROC curves are plots of the rates of positive sorting (true positive rates) and rate of incorrect sorting (the false positive rates) of the neural network fault location. An ideal ROC curve would therefore, display points only in the upper-left corner because that is what indicates an excellent true positivity in the location. Figure 6 shows an ROC curve for this network, which is nearly perfect because it has all the lines in the upper-left corner. The third factor in the testing procedure is the gradient and validation performance plot. It can be seen in Figure 7 that there is a steady decrease in the gradient and also that the number of validation failures are 0 during the entire process which indicates smooth and efficient training. The fourth factor is the confusion matrix, with 71.8% as the best training accuracy for the FFANN model as shown in the confusion matrix in Figure 8. The foregoing indicates that the FFANN location model has the ability to isolate faults from any zone on the modeled distribution system.
Figure 5: The Training, Validation and Testing Phases’ Regression Fit.

Figure 6. ROC curve of the FFANN (6-30-15-5-4).
Figure 7. Gradient and validation performance of the FFANN (6-30-15-5-4).

Figure 8: Confusion Matrix for the Best FFANN Model
4.0 Conclusion

In this paper simulation experiments were performed to demonstrate the application of FFANN (a machine intelligence technique) for the location of faults in a 3-phase lines power distribution system. The neural network inputs are the 3-phase voltages and currents obtained through fault simulations on the IEEE 13 Node Test Feeder in Simulink. Our results demonstrate that FFANN is acceptable in detecting and locating faults in an electrical distribution system. In the future, more simulation data will be explored towards improved performance. Furthermore, recent advances in machine intelligence technique such as deep learning will be explored towards real-time implementation of the approach in a complex smart grid.

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