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Artificial Neural Network Based Fault Detection, Classification and Location in Transmission Lines

OLUROTIMI OLAKUNLE AWODIJI[1], IROAKAZIE TOCHUKWU JOHN[2]

[1, 2] Department of Electrical and Electronics Engineering Faculty of Engineering University of Jos, Plateau State Nigeria

Abstract- In response to the escalating demand for electrical power, increasingly complex electrical power systems have emerged, with transmission lines spanning substantial distances to link power generators and consumers. However, these lines are susceptible to faults due to environmental exposure, demanding swift and accurate detection and diagnosis for network reliability and security. This paper presents a contemporary solution for fault detection and diagnosis in overhead transmission lines, employing an Artificial Neural Network (ANN) algorithm within the MATLAB/Simulink environment. .This paper underscores the ANN's efficacy in enhancing fault detection and diagnosis in transmission lines, thereby fortifying electrical power system reliability and security while highlighting the ANN's distinct advantages in this context.

Indexed Terms- Artificial Neural Networks (ANN), Back propagation Algorithm, Electrical Power Systems, Fault Diagnosis, Fuzzy Logic, MATLAB/Simulink, Mean Square Error (MSE)., Transmission Lines, Wavelet Transforms.

I. INTRODUCTION

In the electric power system, faults are inevitable, and their occurrence can significantly impact the reliability and stability of the system. Effective fault detection, classification, and location techniques are critical for maintaining the reliability and stability of the power system. Traditional methods of fault detection, classification, and location have limitations in terms of accuracy, speed, and robustness. Therefore, there is a need to develop more advanced and effective techniques to address these limitations. In this context, the use of artificial neural networks (ANN) has shown significant promise for fault detection, classification, and location in the power system. ANN-based approaches can provide accurate and reliable results, even in the presence of noise and uncertainties. MATLAB is a widely-used platform for implementing ANN-based approaches for fault detection, classification, and location in power systems.

The problem addressed in this paper is to develop and validate an ANN-based approach for fault detection, classification, and location in the power system using MATLAB. The project aims to address the limitations of traditional methods and provide a more accurate, faster, and robust technique for fault detection, classification, and location. The proposed approach will be validated using simulations and experimental data to demonstrate its effectiveness in real-world scenarios.

Artificial Neural Networks (ANNs) have made substantial contributions to fault detection, classification, and location in transmission lines, as follows:

1) Pattern Recognition: ANNs excel at discerning intricate patterns within data, rendering them invaluable for fault detection in transmission lines through the analysis of electrical signals and voltage/current waveforms to identify anomalies.
2) Fault Classification: ANNs proficiently categorize various fault types, such as short-circuits, open-circuits, or transient faults, predicated on acquired knowledge from historical datasets, thereby expediting the swift identification of fault nature.
3) Location Estimation: ANNs are adept at estimating the precise location of a fault along a transmission line by amalgamating data from multiple sensors and sources, essential for precise fault localization and rapid response.
4) Fault Diagnostics: ANNs yield comprehensive fault information, encompassing fault severity,

facilitating the prioritization of maintenance and repair tasks.

5) Real-time Monitoring: ANNs can be implemented for continuous, real-time monitoring of transmission lines, continuously scrutinizing data and delivering alerts upon fault detection, thereby enabling prompt responses to mitigate potential damage.
6) Reduced False Alarms: ANNs can be fine-tuned through training with historical data to curtail false alarms, thereby enhancing fault detection accuracy and minimizing unwarranted disruptions.
7) Adaptability: ANNs are amenable to adaptation in response to shifting conditions and evolving fault patterns, achieved by recurrent retraining with new data, ensuring efficacy in dynamic environments.
8) Data Fusion: ANNs are proficient at fusing data from diverse sources, encompassing sensors, SCADA systems, and communication networks, to heighten fault detection precision.

II. POWER SYSTEMS

The process of converting mechanical energy to electrical energy is accomplished by the power station generator, which then supplies energy to substations via transmission lines. This energy is then transmitted to distribution substations before it is ultimately transferred to domestic, commercial, and industrial consumers [1]. Transmission lines are characterized by resistances, capacitances, and inductances which vary with the length of the line and play a critical role in the dynamic behavior of the system. Furthermore, transmission lines are often modeled as PI-sections, enabling their efficient modeling as the aggregation of many PI-sections [2].

As power plants are typically situated far from electrical consumers for safety reasons, electricity must be transmitted to consumers via long transmission and distribution lines. Prior to supply to consumers, voltage must be stepped down through the use of transformers [3]. Substations play an integral role in power system operation and control. Step-up substations utilize operating voltages of 22kV, 400kV, or 500kV, depending upon the operating parameters of the transmission line [4], [5]. Therefore, electrical power systems are composed of a number of components, including generation units, transmission lines, distribution lines, and substations, all of which function together to form a complete Electrical Power System (EPS). Electrical power generated is typically rated at 11kV to 25kV, which is stepped up to 220kV or 500kV using a generator transformer, depending upon the rated transmission voltage parameters and the requirements of long distance transmission lines. Prior to feeding into the grid, power must be transmitted through high voltage lines.

A. CONVENTIONAL FAULT DETECTION MECHANISMS

In order to improve fault detection on the transmission line, various advanced fault detection methods have been developed that can detect faults more accurately and quickly. These methods utilize advanced digital signal processing techniques and sophisticated algorithms that can analyze the power system behavior in real-time and detect faults based on the unique characteristics of fault signatures.

One such advanced fault detection technique is based on wavelet transform analysis which can detect and classify faults based on the characteristics of waveforms generated during a fault. Another technique is based on artificial intelligence and machine learning algorithms that can analyze the power system behavior and detect faults with high accuracy and speed.

Furthermore, with the increasing complexity of power systems and the integration of renewable energy sources, the traditional fault detection techniques may not be sufficient to detect all types of faults. Hence, there is a need to develop new fault detection techniques that can take into account the unique characteristics of power systems with renewable energy sources. Overall, the goal of improving fault detection techniques is to enhance the reliability and stability of power systems and prevent major power outages.

Another advanced fault detection technique is the Fuzzy Logic Controller (FLC). FLC is a powerful tool that has gained significant attention in the field of high-speed digital relaying, owing to its ability to accurately detect faults within a single cycle of the fault incident [24]. The FLC is capable of processing real-time data and making quick decisions based on the information it receives. It uses a mathematical approach that allows for the analysis of complex systems and is particularly wellsuited for situations where the relationship between input and output is not well-defined.

The use of FLC for fault detection has been found to provide high accuracy and reliability. It is capable of detecting faults even in situations where traditional detection techniques may fail, such as during power swings. In addition, FLCs are capable of handling large amounts of data and can be easily programmed to suit different fault detection scenarios [25].

III. ANN FAULT DETECTORS

In recent years, Artificial Neural Network (ANN) has emerged as a promising tool for fault detection in power transmission systems. A study was conducted to test the effectiveness of ANN in detecting various types of faults, classifying them, and locating them, while also considering different fault resistances. Based on the results, it was recommended that the ANN technique can be applied to power transmission lines for fault detection.

The ANN fault detector is capable of detecting faults, locating them, and classifying them on the transmission lines. The ANN's effective structures and capabilities for learning make it a reliable and accurate tool for fault detection. With its ability to handle complex data and process large amounts of information, ANN has the potential to improve fault detection accuracy and speed, resulting in improved system reliability and reduced downtime.

A. TESTING OF ANN

Artificial Neural Networks (ANNs) have been proposed as an effective approach to fault detection and classification on transmission lines. To evaluate the performance of ANN-based fault detection and classification techniques, various types of faults, including fault resistances, fault locations, and other fault characteristics, have been used in testing.

Fault resistances are one of the important parameters that are used to evaluate the effectiveness of fault detection and classification techniques. The resistance of a fault can vary depending on the type of fault and the location of the fault on the transmission line. By testing ANN fault detection and classification techniques using fault resistances, researchers can evaluate the accuracy and reliability of the network in identifying and classifying different types of faults.

In addition to fault resistances, fault locations are another important parameter used in testing ANN fault detection and classification techniques. The location of a fault can have a significant impact on the overall performance of the power system, and accurate fault location is critical for maintaining system reliability and safety. By testing ANN-based fault detection and classification techniques using fault locations, researchers can evaluate the accuracy and reliability of the network in identifying the location of faults on the transmission line.

Other types of faults, such as single-phase-to-ground faults, double-phase-to-ground faults, and three-phase faults, have also been used in testing ANN-based fault detection and classification techniques. These faults represent real-world scenarios that power system operators may encounter, and by testing the network using these types of faults, researchers can evaluate the effectiveness of the network in identifying and classifying these types of faults.

IV. DATASET OF FAULT DATA

In this research, a dataset was used to train and test the models developed. The dataset comprised of measurements or signals from a system or process, which included different types of faults.

The dataset was divided into three subsets: the training set, validation set, and testing set. The training set is used to train the model, while the validation set is used to optimize the model's hyper parameters and prevent over fitting. The testing set is then used to evaluate the model's performance and generalization ability.

The division of the dataset into these subsets is a crucial step in the machine learning process as it helps ensure that the model's performance is not solely based on the training data. This approach provides a more accurate assessment of the model's performance on new and unseen data.

The dataset used in this project was carefully selected to ensure that it was representative of real-world scenarios and contained a range of different faults. This approach enabled the models to be trained and tested on a variety of fault types, leading to a more robust and accurate fault detection and classification system.

V. TRANSMISSION LINE SIMULATION

The transmission line used in this project was modeled using the Pi model in the Simulink/MATLAB 2016a environment, with the SimPowerSystems toolbox. Figure 1 depicts a snapshot of the modeled transmission line network, which was used as the basis for this project. The models composed of a three-phase fault simulator, three-phase loads, transformers, PI section transmission lines and load buses.

To simulate the behavior of the transmission line, the model was simulated in Simulink, with voltage and current signals measured using the three-phase V-I measurement block. The transmission line was composed of two lines, line 1 and line 2. An 11kv source was modeled and also Egbim transmission line network was also modeled to test the efficacy of the developed ANN model.

The generated data was used to train the neural network for the development of the Artificial Neural Network (ANN) fault diagnosis model. For the purpose of fault detection and classification, ten (10) fault cases, as well as a no-fault case, were simulated. Sample data were obtained from the three-phase voltage and current waveforms generated by the simulation.

VI. SELECTION OF ANN CONFIGURATION

The Back Propagation Feed Forward Neural Network (BP-FFNN) with the Levenberg Marquardt algorithm has been selected to develop a fault detection model. This decision was based on a series of experiments conducted to determine the appropriate algorithm, activation functions, number of hidden layers, and hidden neurons required for the model. The model takes in eight (8) inputs at a time, which are the scaled instantaneous voltages and currents for all three phases for ten (10) different fault cases and a no-fault case. The training set consists of a total of six thousand, one hundred and sixty (6,160) input-output data sets, comprising five hundred and sixty (560) data sets for each fault case. The neural network utilizes the instantaneous voltage and current values extracted from the input data to detect the presence of a fault and classify it accordingly.

TABLE I
The truth table of the Detector-Classifier for various Fault Conditions

Fault type	Network target A	Network target B	Network target C	Network target G
A-G	1	0	0	1
B-G	0	1	0	1
C-G	0	0	1	1
A-B-G	1	1	0	1
A-C-G	1	0	1	1
B-C-G	0	1	1	1
A-B	1	1	0	0
A-C	1	0	1	0
B-C	0	1	1	0
A-B-C	1	1	1	0

A. CONVENTIONAL BACKPROPAGATION ALGORITHM

This algorithm is an iterative gradient based algorithm proposed to minimize an error between the actual output vector of the network and the desired output vector. The term back propagation refers to the manner in which the gradient is computed for nonlinear multilayer neural networks [16]. The output of all hidden layers and the output layer are obtained by propagating the training patterns through the network. Let us define the matrix:

$$O^l = A^l W^l \dots\dots\dots\dots\dots\dots\dots\dots (1)$$

The entries of A^{l+1} for all layers ($l = 1,2,\dots\dots, L-1$) are evaluated as:

$$a_{p,j}^{l+1} = f\left(O_{p,j}^l\right) \dots\dots\dots\dots\dots\dots (2)$$

Where; $p = 1, \dots., P$ and j = 1, 2,……n_{l+1}

An algorithm is required to adjust the weights so that the network learns how to map the input patterns to the output patterns. The most widely used algorithm for training feed forward neural networks is the BP algorithm. Learning is achieved by adjusting the weights such that the network output, A^L is as close as possible or equal to the target, T^L. The error is given as:

$$E = \frac{1}{2P}\sum_{p=1}^{P}\sum_{j=1}^{n_L}(t_{p.j} - a_{p,j}^L)^2 \ldots\ldots\ldots..(3)$$

So, we need to minimize the error E, with respect to the weight changes $W_{i,j}$. We follow the delta rule to incorporate the learning rate ɳ, along with the gradient descent algorithm techniques to define the weight change. The changes of weights are proportional to the error gradient mathematically,

$$\Delta W_{ij}^l = -ɳ.\frac{\delta E}{\delta W_{ij}}; \quad 0 < ɳ \leq 1 \ldots\ldots\ldots\ldots(4)$$

If the gradient $\frac{\delta E}{\delta W_{i,j}}$ is positive then the weight change should be negative and vice versa. Hence, a minus sign is added at the right hand side of (4).

The weight changes $\Delta W_{i,j}^{L-1}$ for the weights connecting to the final layer are obtained by:

$$\Delta W_{i,j}^{L-1} = -\frac{ɳ}{2P}\sum_{p=1}^{P}\sum_{j=1}^{n_L}\frac{\delta}{\delta W_{i,j}^{L-1}}(t_{p,j} - a_{p,j}^L)^2 \ldots.(5)$$

Notice that for a given j, only $a_{p,j}^L$ has a relation with $W_{i,j}^{L-1}$, we get:

$$\Delta W_{i,j}^{L-1} = \frac{ɳ}{P}\sum^{P}\left(t_{p.j} - a_{p,j}^L\right)\frac{\delta a_{p,j}^L}{\delta W_{i,j}^{L-1}} \ldots\ldots..(6)$$

The partial derivative $\frac{\delta a_{p,j}^L}{\delta W_{i,j}^{L-1}}$ can be evaluated using the chain rule. From equations (5) and (6)

$$\Delta W_{i,j}^{L-1} = \frac{ɳ}{P}\sum_{p=1}^{P}\left(t_{p.j} - a_{p,j}^L\right)f'\left(O_{p,j}^{L-1}\right)a_{p,i}^{L-1}$$

$$= \frac{ɳ}{P}\sum_{p=1}^{P}\delta_{p,j}^{L-1}a_{p,i}^{L-1} \ldots\ldots\ldots.(7)$$

Where; $\delta_{p,j}^{L-1} = \left(t_{p.j} - a_{p,j}^L\right)f'\left(O_{p,j}^{L-1}\right)$ and $f'\left(O_{p,j}^{L-1}\right) = \frac{\delta a_{p,j}^L}{\delta O_{i,j}^{L-1}}$

By analogy the weight change for other lower layers of weights are:

$$\Delta W_{i,j}^l = \frac{ɳ}{P}\sum_{p=1}^{P}\delta_{p,j}^l a_{p,i}^l \quad l = 1,\ldots..,L-1$$

And

$$\delta_{p,j}^l = \sum_{k=1}^{n_{l+1}}[\delta_{p,k}^{l+1}\,w_{j,k}^{l+1}]F'\left(O_{p,j}^l\right) \quad l = 1,\ldots\ldots,L-1$$

The learning procedure therefore consists of the network starting with a random set of weight values, choosing one of the training patterns and evaluating the output(s) using that pattern as input in a feedforward manner. Using the BP procedure, all the weight changes for that pattern are evaluated. This procedure is repeated for all the patterns in the training set so that for all the weights ($\Delta W_{i,j}$) are obtained. Then corrections to the weights are made.

It has been proven that BP learning with sufficient hidden layers can approximate any nonlinear function to arbitrary.

VII. TRAINING OF THE ANN

The ANN Classifier used in this research is depicted in Figure 2 and 3. It consists of eight (8) inputs, namely, Voltages (Va, Vb, Vc, V0) and Currents (Ia, Ib, Ic, I0), which have been processed through filtering and normalization techniques. The ANN architecture comprises 10 hidden layers and 1 output layer.

The primary objective of the ANN is to identify Faults on Phases A, B, and C. To achieve this, the output is trained to give a response to any of the fault conditions presented, representing a Common Fault Alarm or Trip. By leveraging its training, the ANN is able to accurately identify and classify various fault conditions in transmission lines.

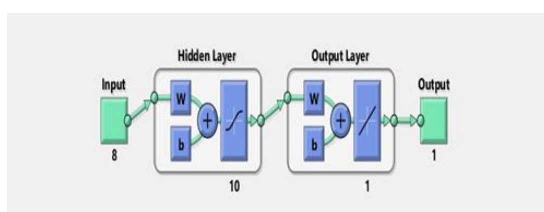

Figure 1 The ANN Classifier for Fault Detection.

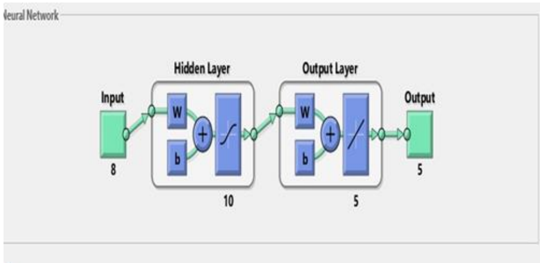

Figure 2 The ANN Classifier for Fault Classification and Location.

The design of the neural network architecture is critical to achieving accurate and reliable results. The number of hidden layers and the number of neurons in each layer should be chosen based on the complexity of the problem being solved. The more complex the problem, the greater the number of inputs and outputs required, and therefore the greater the number of hidden layers that are needed.

To ensure that the inputs and outputs of the neural network have the appropriate magnitude and correlations, it is necessary to train the ANN. The selection of the inputs is based on the size and complexity of the problem. The higher the number of inputs and outputs, the more detailed the complexity of the ANN. As a result, a larger number of hidden layers are needed to capture the complexity of the data and make effective decisions.

In this specific case, the inputs to the neural network are based on 50Hz and three-phase voltages and currents, which are normalized to DC. This allows for a more simplified representation of the input data and ensures that the ANN can make accurate predictions.

VIII. PERFORMANCE EVALUATION

The correlation between the Training Data Set and the Validation Data Set is an important factor in evaluating the performance of the ANN in fault diagnosis. The Training Data Set is used to train the ANN, while the Validation Data Set is used to evaluate the performance of the trained ANN. A good correlation between these two data sets indicates that the ANN has learned the patterns in the training data well and can generalize to new data accurately.

Figures 4 and 5 shows the correlation between the Training Data Set and the Validation Data Set, and as can be seen, the correlation is good. This indicates that the performance of the ANN in identifying faults correctly is good. Furthermore, Figures 6 and 7 shows the Error Histogram, which also indicates acceptable performance.

It is important to note that the accuracy of the training data greatly affects the performance of the ANN. The training data used in this project is composed of Fault Data, which was obtained through a number of Matlab Simulink simulations. Detailed graphs of the training data and simulations performed to obtain the training data are shown in the appendix.

It is crucial to prepare and curate the training data carefully to obtain the best possible performance from the ANN. Any errors or inaccuracies in the training data can result in poor performance of the ANN.

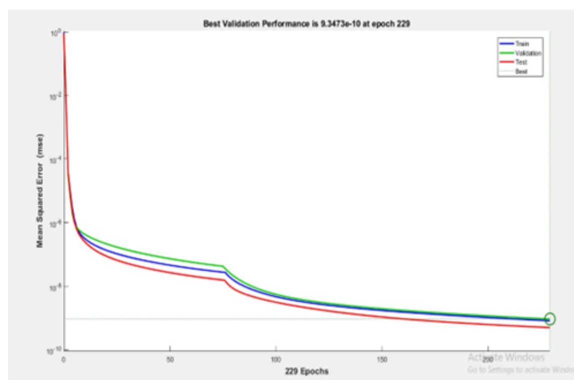

Figure 3 Performance of the Fault Classification and Location Training Process.

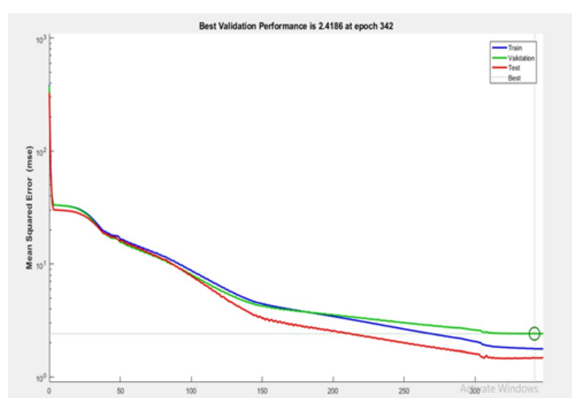

Figure 4 Performance of the Fault Detection Training Process.

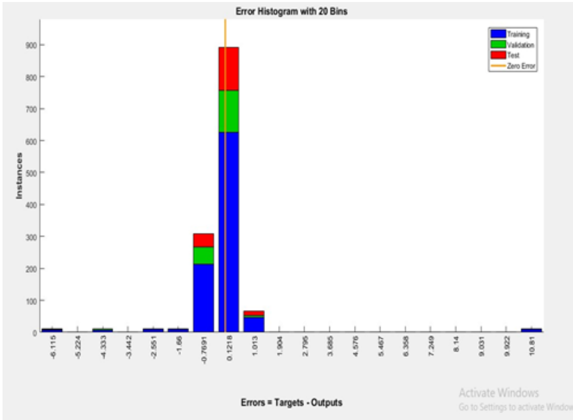

Figure 5 Performance of Classification and Location ANN, showing Error Histogram.

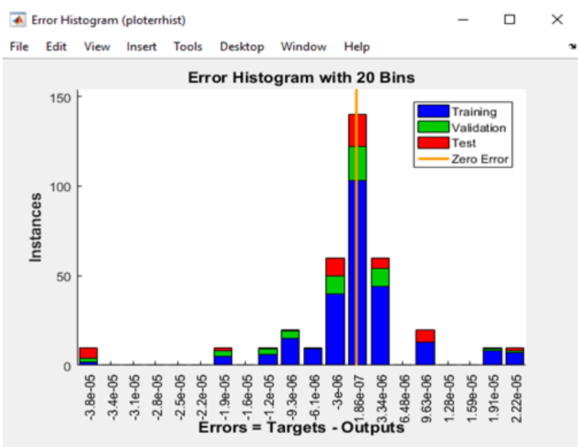

Figure 6 Performance of Fault Detection ANN, Showing Error.

IX. RESULTS

The results of the developed model are thoroughly presented and analyzed. The ANN-based approach demonstrates its effectiveness in detecting, classifying, and locating faults in transmission lines. The presented results provide valuable insights into the performance and efficacy of the developed model, offering a comprehensive understanding of its capabilities in addressing the challenges associated with fault detection, classification, and location in transmission line systems.

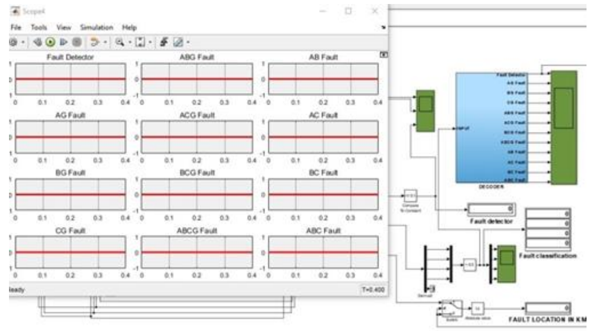

Figure 7 No Fault Response of the Developed System.

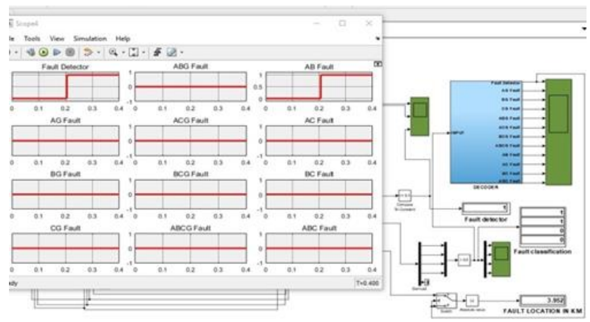

Figure 8 AB Fault Response of the Developed System.

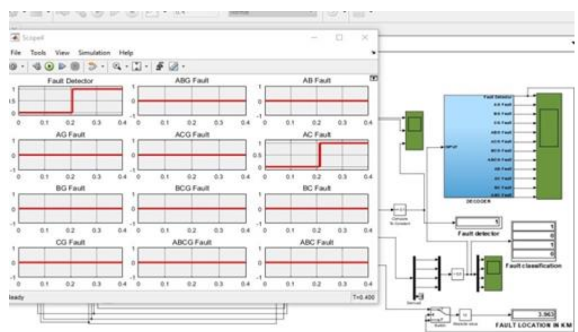

Figure 9 AC Fault Response of the Developed System.

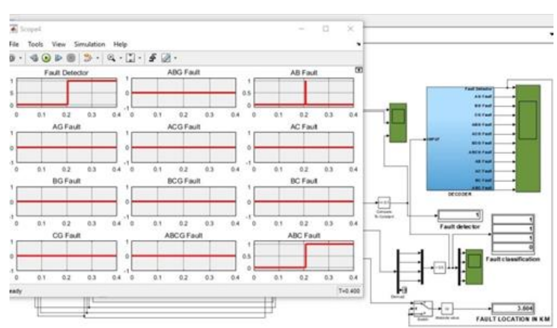

Figure 10 AC Fault Response of the Developed System.

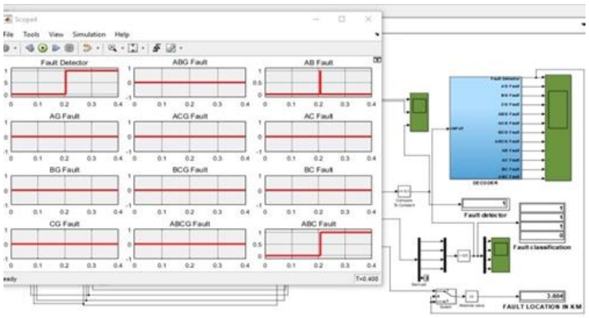

Figure 11 ABC Fault Response of the Developed System.

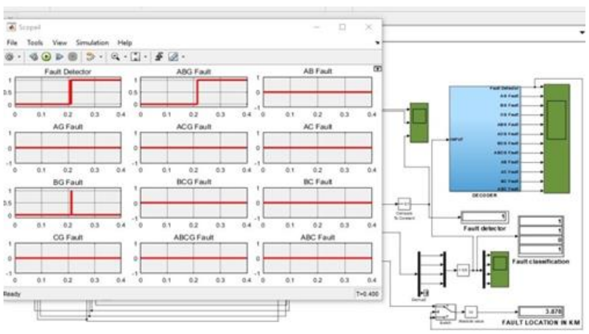

Figure 12 ABG Fault Response of the Developed System.

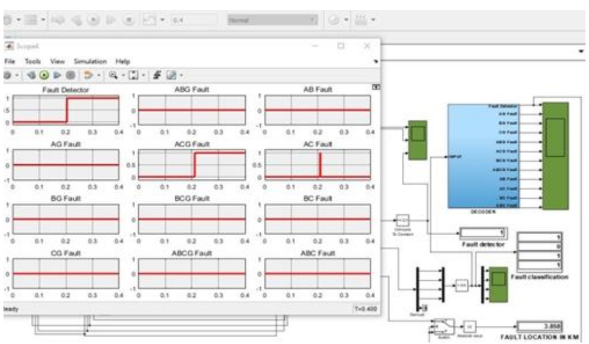

Figure 13 ACG Fault Response of the Developed System.

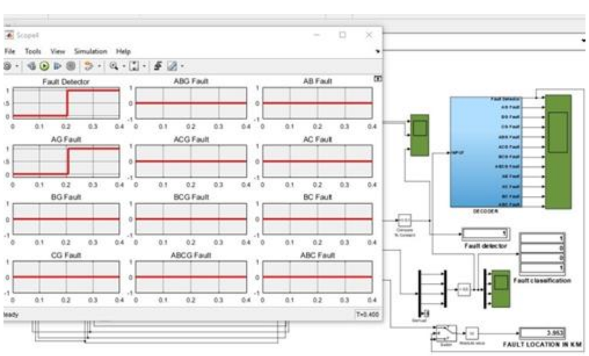

Figure 14 AG Fault Response of the Developed System

CONCLUSION

The research proposes a solution for detecting and diagnosing faults in transmission lines using an Artificial Neural Network (ANN) algorithm. The results obtained shows that the system is capable of detecting fault, classifying their fault and adequately determining their locations. This model can be extended to complex real situation where accuracy is highly desired.

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