International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 5 Issue 12, December - 2021, Pages:123-136

Enhancement of Transmission Line Protection for MASHKOR and JEBAL AWLIA Line using Artificial Neural Networks

Ahmed Mohammed Alsayed Ibrahim(1), Elebaid Khalid Elsayed(2), Mohammed Hyder Musa(1), Sara Sideeg Elnow Ali(1)

Electrical Engineering Department
(1)Sudan University of Science and Technology
(2)Pamukkale University
Khartoum, Sudan

Email: alsaginy.ahmed@gmail.com , elebaid89.4@gmail.com , mohammedhyder222@gmail.com , sarasideegalnow@gmail.com

Abstract*— in this paper, a forward artificial neural network (FANN) architecture is designed and implemented for the purpose of improving transmission line protection, particularly in Sudan, using the transmission line connecting MASHKOR and JEBAL AWLIA as a case study, which is classified as a long transmission line. The substation holding this line provides a genuine dataset for training and testing the neural network, which comprises of three phase voltages and currents at varied measured zone distances. A Simulink model for the transmission line is created, and the parameters for the line are obtained from the substation administration. The training and testing processes are then carried out, and the results demonstrate the effectiveness and powerful effects of artificial neural networks in improving protection schemes over conventional methods.*

Keywords— Transformer, fault analysis, protection, transmission line, artificial neural networks (ANN), back propagation, Levenberg-Marquardt algorithm.

1. INTRODUCTION

Fault studies are an important part of the research of power systems, where numerous types of faults occur. Three phase balanced faults and unbalanced faults are the two types of power line defects. Unbalanced faults include single line to ground faults, line to line faults, and double line to ground faults. For the PID controller to function effectively, the proportional, integral, and derivative gains must be appropriately calibrated [1]. To get better outcomes than traditional tuning methods, such controllers can be tuned using artificial intelligence (AI) methodologies and optimization algorithms.

When transmission line errors take place, a large number of transient components of various frequencies are produced in the electrical power system. Much faults in the transient components are used. The ability to forecast, control and assess faults of machinery and electricity networks will thereby greatly increase the stability of the power grid. Although large quantities of different transient data can be collected correctly on time, the main challenge is how to detect and distinguish errors by using transitional signals [2].

If an electrical system is faulty, it causes a power flow interruption. It is absolutely vital to locate the problem site in order to repair and restore the electric flow. The location of problems in such power systems must be discovered fast and correctly in order to enhance the economy, safety, and dependability of such power systems.

2. PROBLEM STATEMENT

Faults in electricity systems cause significant harm. It disrupts the functioning of the power system, reduces system dependability, and damages power system components. Heavy currents cause overheating of lines, cables, and coils, which can end in a fire or explosion. Furthermore, system stability may be jeopardized, cascade tripping of power system components may occur, and a total blackout may result. If the problem is not resolved soon, an arc on over-head transmission lines may burn the conductors, forcing them to break and creating a long-term disruption in power delivery. If the fault is identified incorrectly, the fault will not clear and the aforementioned problem will remain unaddressed, hence it is critical to know the kind and zone of the fault in order for it to be cleared correctly. There are several issues with fault categorization systems. The fault detection approach, like the impedance method, is sluggish and produces erroneous findings. A erroneous fault report forwarded to control centers or straight to protective systems might exacerbate the situation. It may result in healthy components being tripped and defective portions being left behind.

3. MODEL OF THE TRANSMISSION LINE:

This project investigates a 220 KV transmission line system that connects MASHKOR and JEBAL AWLIA (146.7 Km) as a sample. This transmission line is used to develop and implement the proposed architectures and algorithms for this problem, as well as to demonstrate the work. Figure 1 depicts the testing system. Zone 1 is 30 kilometers from the source, zone 2 is 60 kilometers, zone 3 is 90 kilometers, and zone 4 is 120 kilometers. Table 1 contains more detailed information about transmission line parameters.

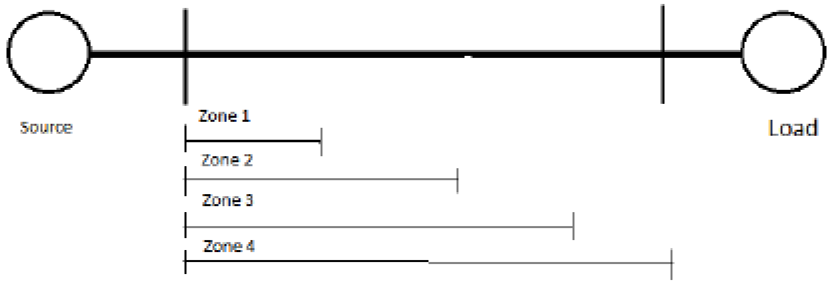

Fig. 1. A single line diagram of transmission line

Table 1: Transmission line parameters

No.	from	to	length (km)	No. of circuit	conductor type & size	nominal voltage kV	R1 (Ω/km)	X1 (Ω/km)	C1 (nf/km)	B1
55	mushkur	jebel aulia	146.72	2	2*240mm²ACSR	220	0.067	0.302	13.06	4.10
56	mushkur	rabak	106.31	2	2*240mm²ACSR	220	0.067	0.302	13.06	4.10
57	rank	roseires	172.54	2	2*240mm²ACSR	220	0.067	0.302	13.06	4.10
58	rabak	rank	163.46	2	2*240mm²ACSR	220	0.067	0.302	13.06	4.10
59	rabak	tandalti	112.26	2	2*240mm²ACSR	220	0.067	0.302	13.06	4.10

MATLAB2016a is used to model this transmission line, and in order to model this line the distributed parameters are used. Each line is 73.35 km long and is split into two lines 1 and 2 each. To simulate multiple types of failure, the tri-phase fault simulator model is used. The following simulation results comprise two categories: phase-by-phase failures, phase-by-phase failures, double-phase failures and three phase failures are considered.

4. AN OVERVIEW OF NEURAL NETWORKS:

The computer tools modeled after brains are Artificial Neural Networks. It has an integrated structure of neurons that are manufactured artificially and function as data transmission pathways. In order to solve a number of problems in design detection, estimation, optimization, associative memory, and regulation, researchers are building artificial neural networks (ANNs). As seen below [3], a treatment device called a perceptron is the easiest presentation of the neural artificial cell.

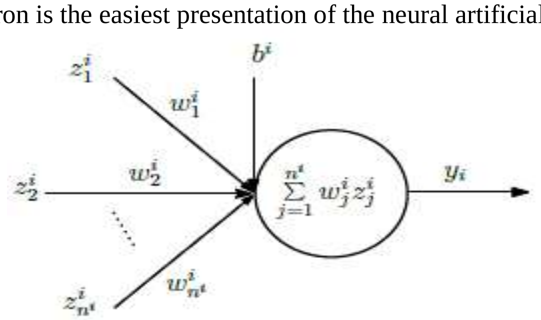

Fig. 2. Perceptron model of an ANN [4]

Feedforward networks are the most simplistic neural networks with no network input, and thus the information transfer is unidirectional, as shown by the following model.

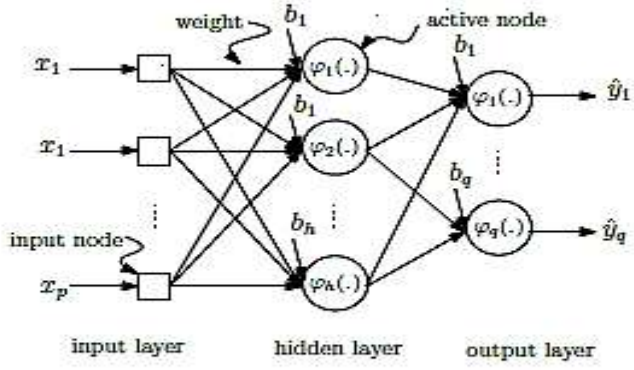

Fig. 3. Three-layers feedforward neural network [4]

The FNNs are computer models consisting of several neurons (nodes) linked by synaptic links (weights) and organized layer by layer. An FNN node is able to process relation weights for details. The y_i (excitation) output of the node (node indicated as I is determined mathematically by [5]:

$$y_i = \varphi_i\left(\sum_{j=1}^{n^i} w_j^i z_j^i + b^i\right) \tag{1}$$

The activation functions, referred to as φ(x), describe the neuron output with the input net x. Often it is referred to as a transfer function because its features restrict and correct the output signal. In the artificial neural network construction, the sigmoid function is the most common mode of activation, described by:

$$\varphi(x) = \frac{1}{1 + \exp(x)} \tag{2}$$

The underlying principle behind the efficient implementation of neural networks to all fields is to decide the weight to accomplish the desired goal. The two different learning processes are typically tracked and unmonitored. The weight of the network is adjusted with the primary objective of reducing the error between such inputs and their corresponding goal value while learning is supervised. Therefore, we know a set of training inputs which the neural network should preferably produce, and the corresponding goals.

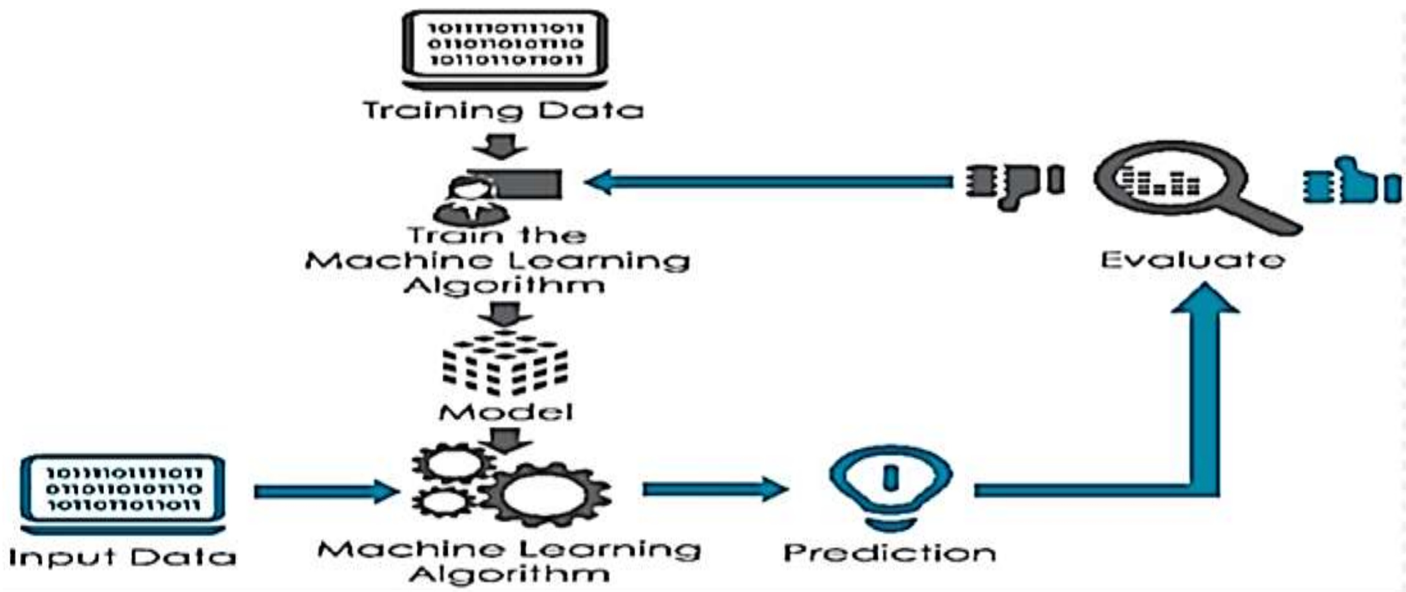

Fig. 4. Scheme of supervised learning [5]

A systemic step-by-step method is used to create an Artificial Neural Network, which optimizes a criterion also called the learning law. The training input / output data for these networks is important, since it offers information required to detect the optimum operating point. A neural network's non-linear nature flexibly renders computing elements of its system. An artificial neural network is a device that receives an input, processes the data, and produces an output. As the necessary target response to the neural network is shown, an error is made at the output and the discrepancy in the desired answer is obtained with the output of the actual machine. Error information is sent back to the system. In a sequential order widely known as the learn law, it makes several changes to the parameters. This is replicated until you have acknowledged the optimal performance.

5. GENERAL MODEL OF ANN FOR THE TRANSFORMER, THE DATASET, AND THE WAVEFORMS:

The neural network used here is a feedforward neural network with the use of Levenberg-Marquardt algorithm as a learning algorithm which is shown in Figure 5 [6].

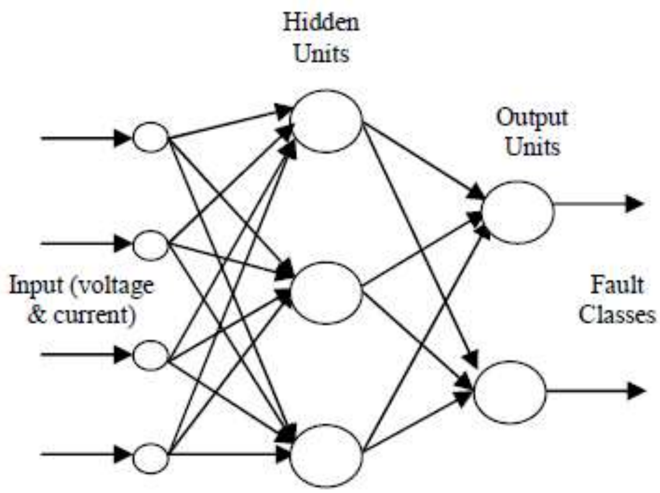

Fig. 5. Genral model of the used ANN

The data set necessary for training the neural networks created below is generated using MATLAB/SIMULINK from various fault circumstances and fault locations, as shown in tables 2, 3, 4, 5, and 6:

Table 2: Voltage and Current results for various fault cases far of 15 Km from the source

Type of fault	V a (KV)	V b (KV)	V c (KV)	I a (A)	I b (A)	I c (A)
Normal	127.5	127.5	127.5	302.53	302.53	302.53
A-G	56.25	127.2	127.6	13410.7	280	358.7
B-G	127.6	56.25	127.2	358.9	13410.7	280
C-G	127.2	127.6	56.25	280	358.9	1310.7
AB	72.7	71	127.5	14612.9	14322.8	302.6
BC	127.5	72.7	71	302.6	14612.9	14322.8
AC	71	127.5	72.7	14322.8	302.6	14612.9
AB-G	47.5	48	127.3	15704.7	15314.9	330
BC-G	127.3	47.5	48	330	15704.7	15314.9
AC-G	48	127.3	47.5	15314.9	330	15704.7
ABC	38.8	38.8	38.8	16705	16705	16705

According to the numbers in table 2, in the event of a single line-to-ground fault, the value of the current at the defective phase was more than its nominal value and the voltage value was low. In the instance of a line-to-line failure, the current values at the problematic phases were equal and big when compared to another phase. The voltage levels of the problematic phases were all the same magnitude and took the smallest value.

Table 3: Voltage and Current results for various fault cases far of 30 Km from the source

Type of fault	V a (KV)	V b (KV)	V c (KV)	I a (A)	I b (A)	I c (A)
Normal	127.5	127.5	127.5	302.53	302.53	302.53
A-G	77.9	127.11	127.7	9300.56	289.65	374.15
B-G	127.7	77.9	127.11	374.15	9300.56	289.65
C-G	127.11	127.7	77.9	289.65	374.15	9300.56
AB	82.484	81.36	127.5	11230	10939	302.5
BC	127.5	82.48	81.36	302.5	11230	10939
AC	81.36	127.5	82.48	10939	302.5	11230
AB-G	67.7	68.13	127.4	11845	11487	334.9
BC-G	127.4	67.7	68.13	344.9	11845	11487
AC-G	68.13	127.4	67.7	11487	344.9	11845
ABC	59.4	59.4	59.4	12799	12799	12799

Table 4: Voltage and Current results for various fault cases far of 60 Km from the source

Type of fault	V a (KV)	V b (KV)	V c (KV)	I a (A)	I b (A)	I c (A)
Normal	127.5	127.5	127.5	302.53	302.53	302.53
A-G	96.67	127.03	127.78	5765.9	298.9	387.7
B-G	127.78	96.67	127.03	387.7	5765.9	298.7
C-C	127.3	127.78	96.67	298.9	387.7	5765.9
AB	95.06	94.5	127.5	7693.5	7401.9	302.59
BC	127.5	95.06	94.5	302.59	7693.5	7401.9
AC	127.5	95.06	94.5	7401.09	302.05	7693.5
AB-G	87.26	87.68	127.4	7997	7691	356.6
BC-G	127.4	87.26	87.68	356.6	7997	7691
AC-G	87.68	127.4	87.26	7691	356.6	7997
ABC	80.99	80.99	80.99	8715	8715	8715

Table 5: Voltage and Current results for various fault cases far of 90 Km from the source

Type of fault	V a (KV)	V b (KV)	V c (KV)	I a (A)	I b (A)	I c (A)
Normal	127.5	127.5	127.5	302.53	302.53	302.53
A-G	96.67	127.03	127.78	5765.9	298.9	387.7
B-G	127.78	96.67	127.03	387.7	5765.9	298.7
C-C	127.3	127.78	96.67	298.9	387.7	5765.9
AB	95.06	94.5	127.5	7693.5	7401.9	302.59
BC	127.5	95.06	94.5	302.59	7693.5	7401.9
AC	127.5	95.06	94.5	7401.09	302.05	7693.5
AB-G	87.26	87.68	127.4	7997	7691	356.6
BC-G	127.4	87.26	87.68	356.6	7997	7691
AC-G	87.68	127.4	87.26	7691	356.6	7997
ABC	80.99	80.99	80.99	8715	8715	8715

Table 6: Voltage and Current results for various fault cases far of 120 Km from the source

Type of fault	V a (KV)	V b (KV)	V c (KV)	I a (A)	I b (A)	I c (A)
Normal	127.5	127.5	127.5	302.53	302.53	302.53
A-G	109.8	126.9	127.8	3273.2	306.5	398.04
B-G	127.8	109.8	126.9	398.04	3273.2	306.5
C-C	126.9	127.8	109.8	306.5	398.04	3273.2
AB	106.9	106.9	127.5	4739	4447	302.6
BC	127.5	106.8	106.9	302.6	4739	4447
AC	106.9	127.5	106.8	4447	302.6	4739
AB-G	102.9	103.5	127.4	4871	4604.9	365.1
BC-G	127.4	102.9	103.5	365.1	4871	4604.9
AC-G	103.5	127.4	102.9	4604.9	365.1	4871
ABC	99	99	99	5303.5	5303.5	5303.5

It was clearly show that the value of the current reduces when the fault occurs far from the source. The following waveforms show the currents waveform at various cases: Note that, the measured values that listed in above tables are represented the Vrms value and the value from the plot is a line value. The current waveform at normal condition on transmission line is shown in Figure 6.

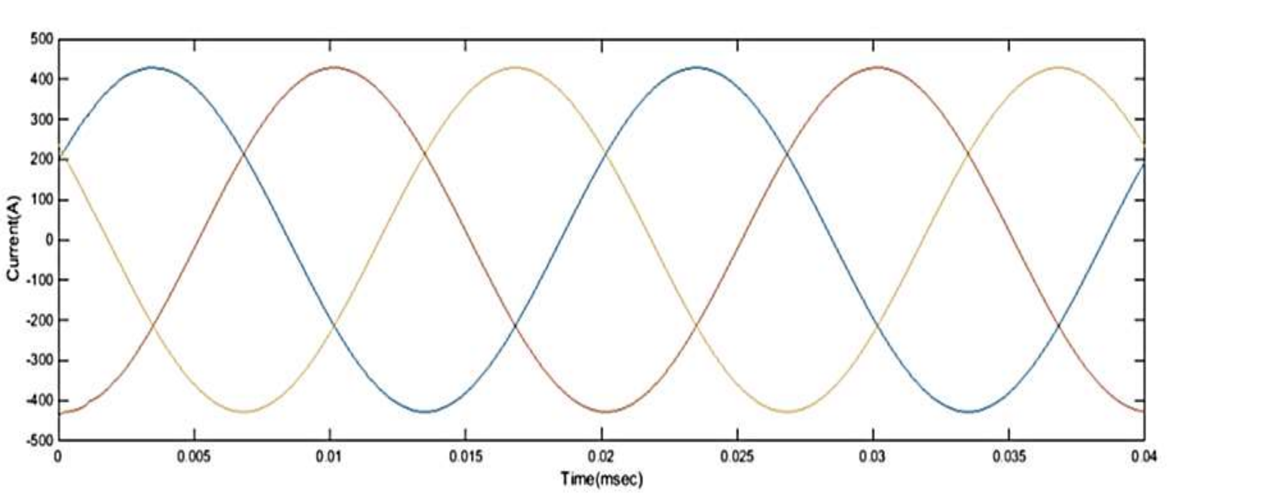

Fig. 6. Current waveforms at normal condition

As seen from above Figure, the value of currents (greater than 400 A) was taken from the scope but the value in the table (302.5 A) describe the momentary value of it.

In case of a single line to ground fault, the current waveforms are as follows:

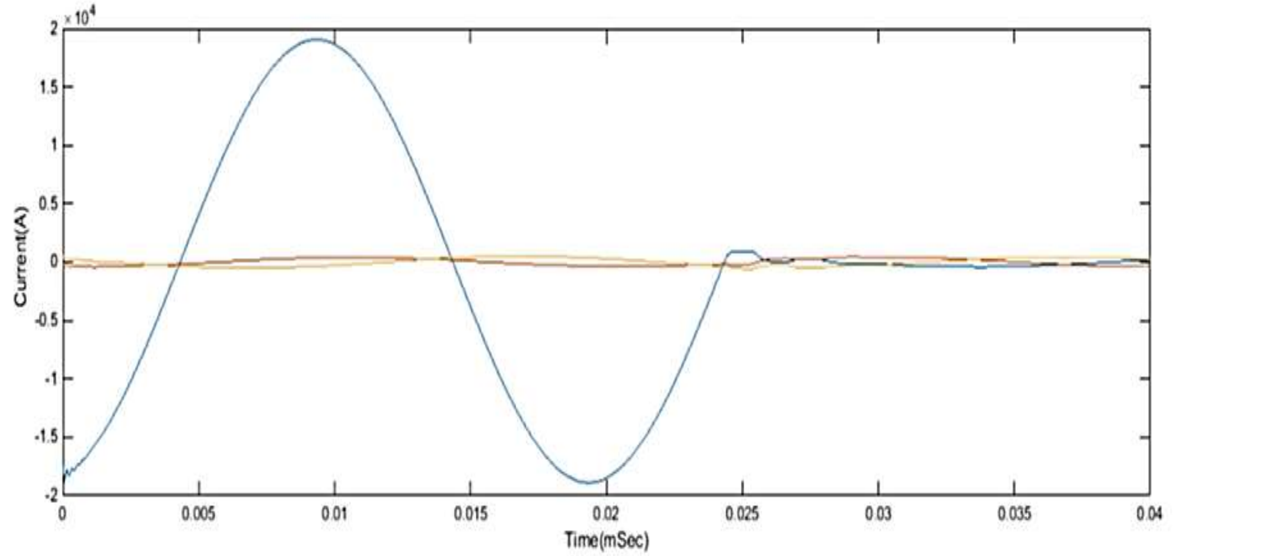

Fig. 7. Current waveforms at single line to ground fault

From above Figure, and when a single line-to-ground fault occurs the value of the current at these phase became greater than of normal condition value. From the scope, the faulty current value is (13410.7A), and its momentary value is greater than (15000 A).

In case of line to line fault the waveforms are shown in Figure 8.

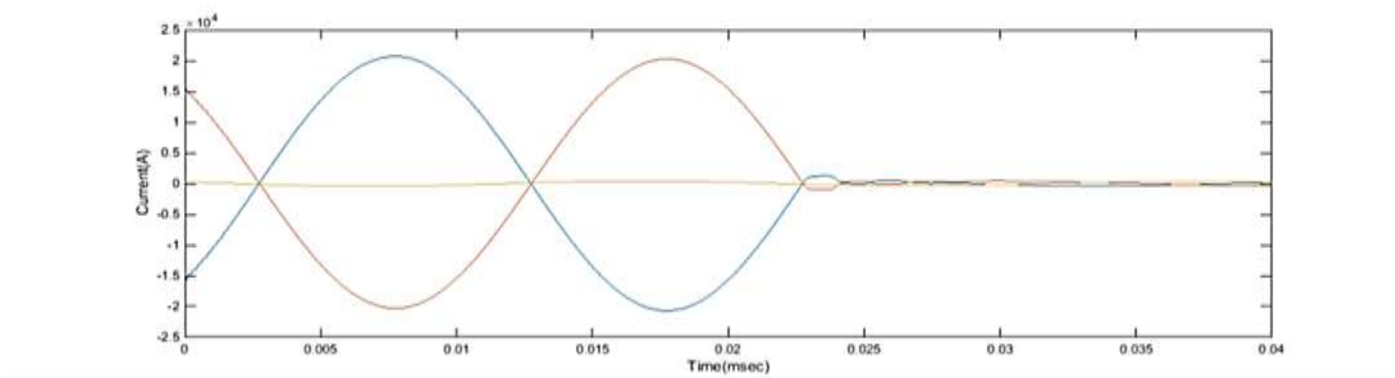

Fig. 8. Current waveforms at line to line fault

And from figure, when double line fault occurs the fault current value was became (14612.9 A), and the momentary value is less than (20000 A).

International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 5 Issue 12, December - 2021, Pages:123-136

In case of double line to ground fault, the waveforms are shown in Figure 9.

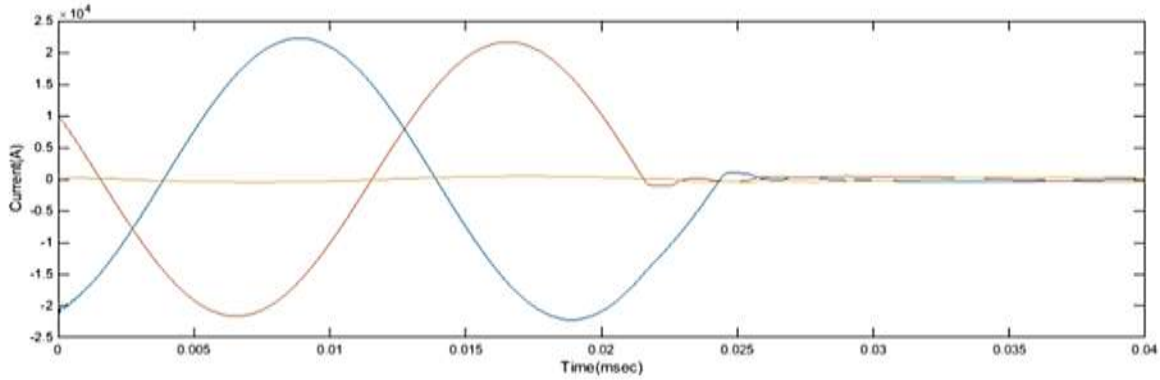

Fig. 9. Current waveforms at double line to ground fault

When a double line-to-ground fault occurs, the defective current measured by the scope is (15704.7A), and its instantaneous value is more than (20000 A).

In case of three lines fault, the waveforms are shown below.

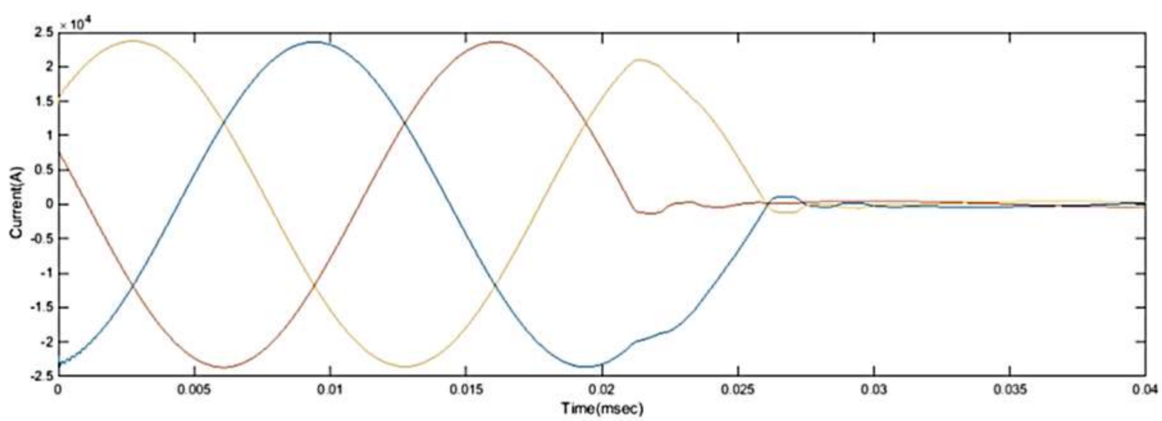

Fig. 10. Current waveforms at three lines fault

6. FAULT DETECTION ANN SIMULATION MODEL:

The simulation model for the fault detection by ANN is shown in Figure 11.

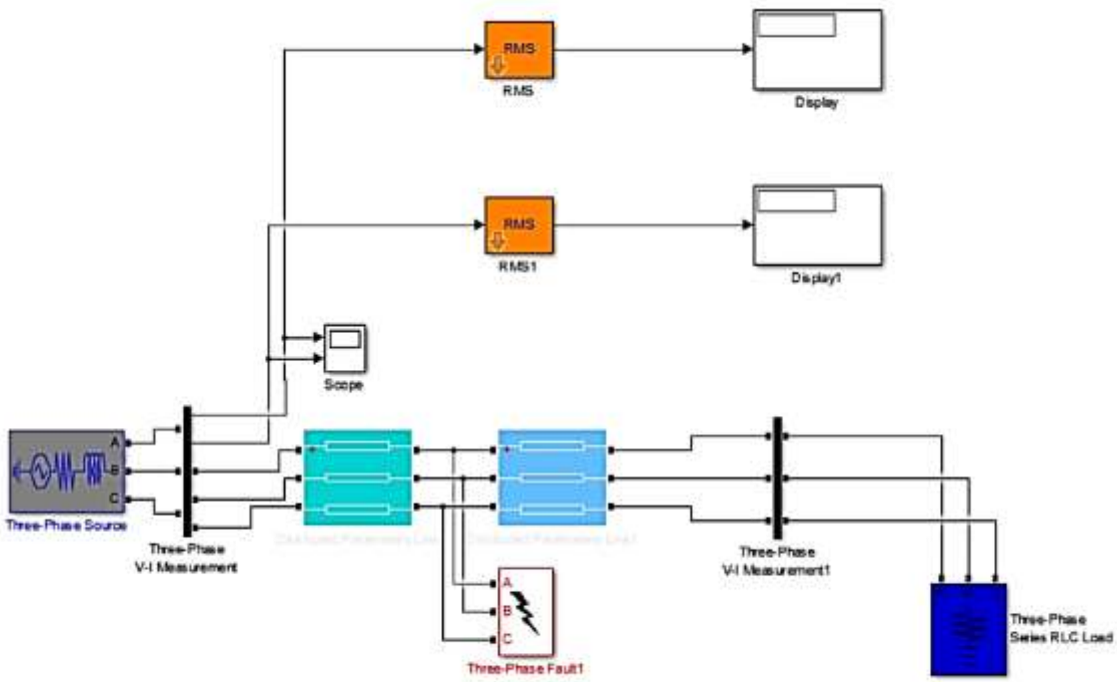

Fig. 11. Simulation model of ANN for fault detection

The network receives six inputs at a time in the first step of fault detection, which reflect voltages and currents for every three phases (scaled to pre-fault values) for ten different issues and no troubles at all. Depending on whether or not an error is detected, the neural network's output is a yes or no (1 or 0). After lengthy simulations, the ideal network was determined to include a hidden layer of 10 neurons. The training success plot is depicted in Figure 12.

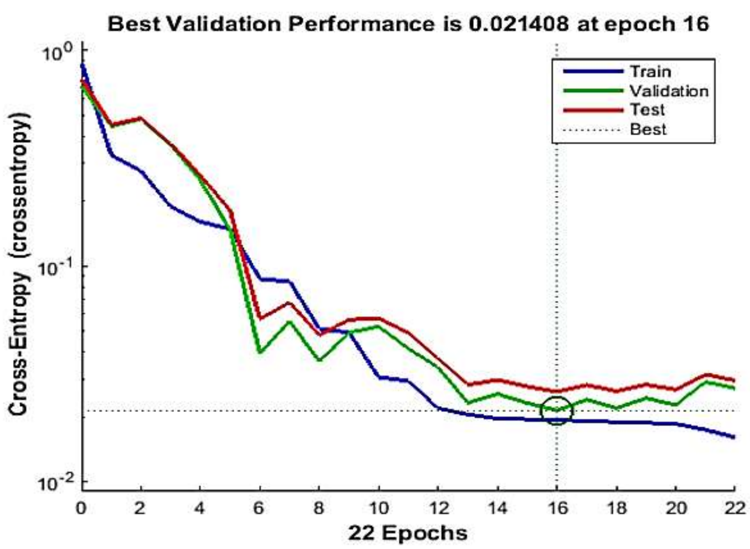

Fig. 12. Training performance plot

From the figure above, and after training the network for more time, it observes that the best performance is 0.021408 occurs at epoch 16.

International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 5 Issue 12, December - 2021, Pages:123-136

To validate the network, the following procedure was used: Following training, the neural network's output was examined for several types of mistakes for qualifying neural networks using a plot of the confusion matrices. Figure 13 depicts the uncertainty matrix for the three phases of preparation, testing, and validation. The number of instances successfully recognized by the neural network is shown by the green diagonal cells, whereas the number of cases wrongly categorized by the ANN is represented by the red off-diagonal cells. The average proportion of instances properly recognized in green is displayed in the final blue cell of each matrix, and vice versa in red. It is feasible to show that the neural network of choice has 100% detection accuracy.

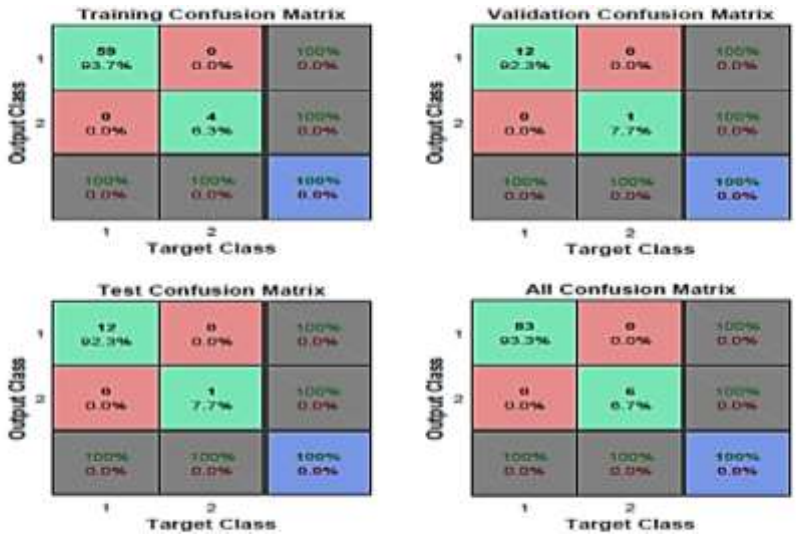

Fig. 13. Confusion matrices for Training, Testing and Validation

As can be observed, the selected neural network exhibits perfect error detection accuracy.

7. RESULTS AND DISCUSSION:

Six input sets made up the network (the three-phase voltage and current values scaled with respect to their corresponding pre-fault values) with four outputs, corresponding to each of the three phases of the fault and one for the ground line. The outputs are either 0 or 1, denoting the safety of the connection (A, B, C or G). As a result, each mistake will produce unique permutations where each mistake will produce unique permutations. The proposed neural network should be able to appropriately distinguish between faults. The truth table for each issue, as well as the best solution for each problem, are shown in Table 7.

Table 7: Fault classifier ANN outputs for various faults

Type of Fault	A	B	C	G
No Fault	0	0	0	0
A-G Fault	1	0	0	1
B-G Fault	0	1	0	1
C-G Fault	0	0	1	1
A-B Fault	1	1	0	0
B-C Fault	0	1	1	0
A-C Fault	1	0	1	0
A-B-G Fault	1	1	0	1
B-C-G Fault	0	1	1	1
A-C-G Fault	1	0	1	1
A-B-C Fault	1	1	1	0

As a result, the training set had around 88 output sets, each with six inputs and one output. Backpropagation nets with different hidden layer combinations and number of neurons per hidden layer were investigated. The best neural networks are those that have been properly defined and have achieved sufficient efficiency. The output graphs of a single hidden layer neural network are shown in Figure 14.

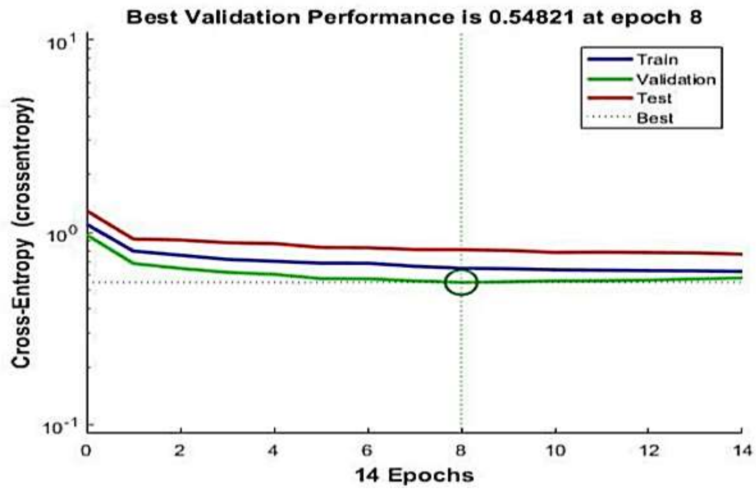

Fig. 14. Performance plot of one hidden layer

From the figure above, and after training the network for more time, it observes that the performance is 0.54821 occurs at epoch 8.

The receiving feature curve is drawn during the classifier data set testing phase (ROC). Figure 15 shows the ROC curves for each preparation, testing, and validation phase, as well as the total ROC curve. In reality, the ROC curves are diagrams of the neural network classification's true positive rates (positive classification rate) and false positive rates (incorrect classification rate).

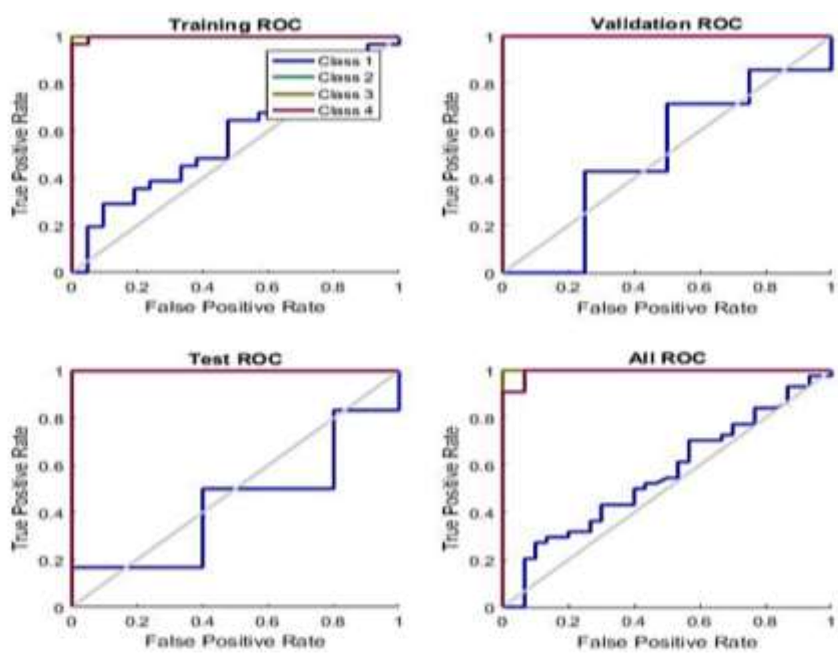

Fig. 15. The Receiver Operating Characteristics curve (ROC)

From the curves plotted in Figure 15, the test of the data set didn't classify carefully. It will be perfect classification when it has a large number of samples.

The fault position must be discovered in order to isolate the defective section of the system. Table 8 shows the isolation FNN training set for the different zones.

Table 8: Isolation NN Training Set

Fault Location	Z1	Z2	Z3	Z4
Zone 1	1	0	0	0
Zone 2	0	1	0	0
Zone 3	0	0	1	0
Zone 4	0	0	0	1

The data of the zones fed into the neural, and after the classification ended the performance of the network is become 0.26792 at epoch 1as shown in Figure 16. It noted that when train the network more, the performance will be more accurate.

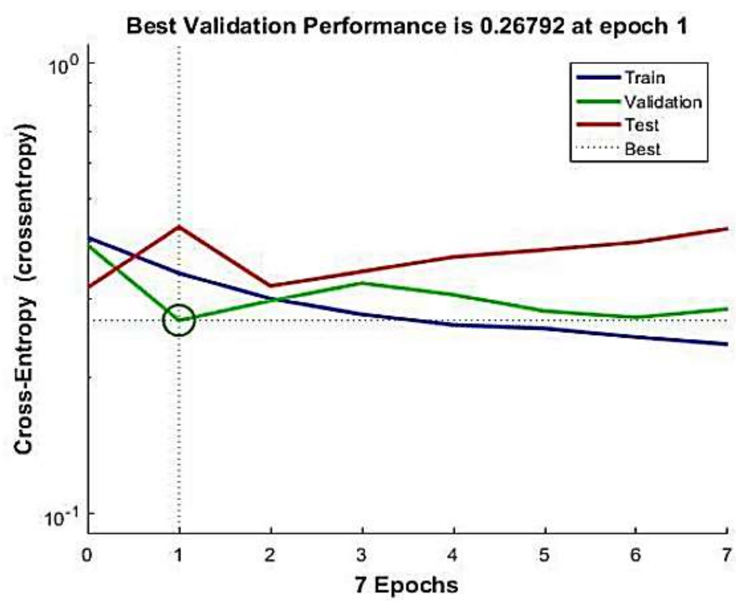

Fig. 16. Performmance plot of the location of the network

From the figure above, and after training the network for more time, it observes that the performance is 0.26792 occurs at epoch 1.

8. Conclusion:

This research looks at the use of neural back propagation networks to detect, identify, and quantify transmission line defects. As inputs, the neural network receives RMS phase voltages and phase currents. ANNs were proposed for each of the following potential faults: single-line, line-line, double-line-ground, and three-phase faults. The number of hidden layers and neurons per hidden layer of the ANN are controlled by the neural network design and the size of the training data set. The findings of ANNs that accept actual data (highly correlated) as inputs were very satisfying due to their adaptability. ANNs provide a viable and appealing alternative choice for constructing a safety relay system in a power transmission system.

9. References

[1] M. C. R. Paz, R. G. Ferraz, A. S. Bretas, and R. C. Leborgne, "System unbalance and fault impedance effect on faulted distribution networks," *Comput. Math. with Appl.*, vol. 60, no. 4, pp. 1105–1114, 2010, doi: 10.1016/j.camwa.2010.03.067.

[2] P. Jose and V. R. Bindu, "Wavelet-Based Transmission Line Fault Analysis," vol. 3, no. 8, pp. 55–60, 2014.

[3] M. Puri, A. Solanki, T. Padawer, S. M. Tipparaju, W. A. Moreno, and Y. Pathak, *Introduction to Arti fi cial Neural Network (ANN) as a Predictive Tool for Drug Design , Discovery , Delivery , and Disposition : Basic Concepts and Modeling*. Elsevier Inc., 2016.

[4] V. K. Ojha and A. Abraham, "Metaheuristic Design of Feedforward Neural Networks : A Review of Two Decades of Research," vol. 60, no. 2017, pp. 97–116.

[5] S. Hanif, T. Ilyas, and M. Zeeshan, "Intrusion Detection In IoT Using Artificial Neural Networks On UNSW-15 Dataset," *2019 IEEE 16th Int. Conf. Smart Cities Improv. Qual. Life Using ICT IoT AI*, no. October, pp. 152–156, 2019, doi: 10.1109/HONET.2019.8908122.

[6] A. N. M. E. Kabir, "A Learning System for Detecting Transformer Internal Faults," 2013.

[7] A. M. Alsayed and E. K. Elsayed, "Social Ski-Driver Algorithm Based Optimal Design of a PID Controller for a Linear BLDC Motor," vol. 4, no. 12, pp. 162–167, 2020.

Authors

Ahmed Mohammed Alsayed Ibrahim, Received the B.Eng. in Electrical engineering from Sudan University of Science and Technology, interested on control engineering especially optimal, nonlinear and robust as well as the new trend of fractional order control. Also, He interested in Artificial Intelligence especially machine learning and deep learning and currently he worked as a junior machine learning engineer as well as an instructor for machine learning and natural language processing (NLP) workshops.

Elebaid Khalid Elsayed, Received the B.Eng. in Electrical engineering from Sudan University of Science and Technology, he interested on control engineering especially nonlinear and robust with applied in drone vision. Also, he interested in Artificial Intelligence especially machine learning and deep learning and currently, applied computer vision for drone and developed algorithm for this application.

Mohammed Hyder Musa, Received the B.Eng. in Electrical engineering from Sudan University of Science and Technology, he is a teaching assistant in Sudan university of Science and Technology. He interested in power system analysis, distribution substation grid analysis, special machines, power quality, and renewable energy.