ANN Based Location of Fault for 500KV Transmission Line in Sudan from Merowe to Atbara

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Abstract

Today, transmission lines have become one of the important core components in systems of electrical power that are used to transport energy. Since transmission lines are prone in nature, the probability of failures in transmission lines is generally higher than that of other major components. This paper presents the fault of the transmission line from Merowe to Atbara in northern Sudan using artificial neural networks. A transmission line model was created in MATLAB R2014a using SIMULINK and SIMSCAPE with the SIMPOWERSYSTEM toolbox. The current and voltage values obtained from the transmission line model have been used as an entry for artificial neural networks. The results obtained from the proposed artificial neural networks were acceptable and the networks were found to be practically practicable for implementation. The significance of picking the most proper artificial neural network, to get the best performance from the neural networks.

Key words-*Transmission line, Artificial Neural Networks, Fault location*

I. Introduction

Transmission line is considered one of the important core components in systems of electrical power for transporting energy [15][23][10][16], which connects the station of generation energy with the station of customer distribution and consumption [23][26][1][9]. Since transmission lines are prone in nature, the probability of failures in transmission lines is generally higher than that of other major components [10][14][25]. Fault is any unnatural condition in transmission lines [15][23]. There are many reasons for faults can be prompted through lightning strokes, bushes may also fall throughout lines, storms, birds shorting the lines, salt spraying on unclean insulators and fog, and snow loading may also lead insulators chains to fail [23][10][1][9][24][8]. It is very important to find out the fault and find its location in order to make vital maintenance and to repair energy as quickly as possible, if faults occur in transmission lines [23][25]. In order to develop transmission line models for power system analysis, transmission line parameters such as resistance, capacitance and inductance must be considered [14]. Subsequently, accurate location of issues on the transmission line is a fundamental necessity to a long-lasting shortcoming [23]. Location of fault, classification of fault and detection of fault play a critical role in the safety and protection of a transmission line [10][5][27]. In systems of electrical power, the room of control contains an enormous number of approaching cautions because of different kinds of faults [13][18]. The kinds of faults can be characterized [15][23][26][8][13][21][22][4] as:

- Fault in three phases (3L), which as a percent of occurring represents approximately 2-3%.
- Faults in two lines to ground (LLG), which as a percent of occurring represents approximately 15%.
- Faults in two lines (LL), which as a percent of occurring represents approximately 10%.
- Faults in line to ground (LG), which as a percent of occurring represents approximately 70%.

To secure these frameworks, shortcomings should be recognized and detached precisely. For quite a few years, intelligent techniques have been used in the process of fault location [1][8][11][17][20][6][2]. To determine on the transmission line the position faults, these techniques are used, such as artificial neural networks [3][19][7][12]. Within an artificial neural network, there are certain layers that contain neurons. The neurons number in the layers is determined to be sufficient to provide the desired problem-solving quality. It is required that the number of layers be few to reduce the time to solve the problem [13]. The feedforward back propagation algorithm has been decided as the ideal topology to use for the location of faults on 500KV transmission line using voltage and current values [11][20]. This paper aims to discover where faults are located in the 500KV transmission line from Merowe (Source 1) to Atbara (Source 2) in northern Sudan using artificial neural networks. The system studied is composed of 500KV, 50Hz with a length of 236.7Km transmission line. In this work the results of had been taken at different locations for fault on length of transmission line with different resistances to fault. Through many checks of synthetic neural networks, the overall performance of the proposed plan became verified.

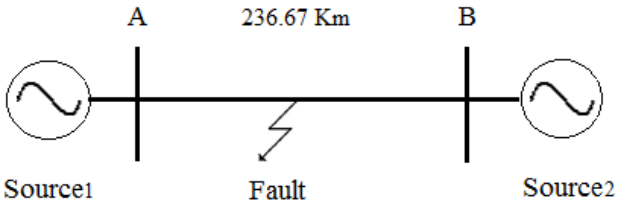


Fig. 1. Model of power system from Merowe to Atbara

II. Modeling And Simulation

The considered system consists of $500KV, 50Hz$ with a transmission line of 236.7Km length from Merowe to Atbara.

TABLE I
PARAMETERS OF TRANSMISSION LINE

Parameters	Set Value
Base voltage	500 KV
Frequency	50 Hz
Positive sequence resistance	0.028 Ohm/Km
Positive sequence Capacitance	0.3445 Ohm/Km
Positive sequence Inductance	0.8785e-3 Ohm/Km
Zero sequence Inductance	3.1226e-3 Ohm/Km
Zero sequence resistance	13.083e-9 Ohm/Km
Zero sequence Capacitance	9.99e-9 Ohm/Km
Length of line	236.67 Km
X/R	15

The power system modeling in Fig.1. By using distributed parameters line in Table I simulate The transmission line that using MATLAB R2014a software shown in Fig.2.

III. IMPLEMENTATION OF ANN IN THE FAULT DISTANCE LOCATION

Following is a basic description of how to implement an artificial neural network-based fault locator method in a single circuit transmission line from Merowe city to Atbara city.

A. Architecture and Learning Rule Selection

It has been determined that feedforward backpropagation would be the ideal topology to use for the location of faults on the 500KV transmission line from Merowe to Atbara in Sudan. There are various factors involved in determining the ideal topology, such as the size of the network, the learning strategy, and the size of the training data set. Using samples of voltage and current values, which were obtained from a simulation model of the transmission line as inputs to the neural network to training. The output of the artificial neural network is the location of fault from terminal A (Source) of the transmission line. Using TANSIG and PURELIN transfer functions for limiting the amplitude of the output. By modifying the weights and biases of neural networks using backpropagation learning, one can improve the accuracy and speed of back propagation. The following figures (Fig.3, Fig.4, Fig.5 and Fig.6) describe the ANN that can be used to locate faults based on their type.

- Fig.3 shows an architecture of a neural network with six input neurons, twenty-five hidden neurons, and the output of one neuron that was chosen to locate the location of the line to ground faults (LG).
- The neural network in Fig.4 has six input neurons, two hidden layers with twenty-five and five neurons respectively, and the output of one neuron to locate the position of two-line faults (LL).
- The neural network in Fig.5 has six input neurons, two hidden layers with thirty-five and five neurons respectively, and the output of one neuron to locate the position of two-line to ground faults (LLG).
- Fig.6 shows an architecture of a neural network with six input neurons, twenty-five hidden neurons, and the output of one neuron to locate the position of a three-line fault (3L).

TABLE II
LOCATION AND PERCENTAGE ERRORS OF A.G FAULT

No	Actual Location (km)	Fault Resistance Rf=10 ohm		Fault Resistance Rf=75 ohm	
		Estimated Location (km)	Error (%)	Estimated Location (km)	Error (%)
1	15	14.9982	0.0008	15.0019	0.0008
2	30	29.9960	0.0017	30.0018	0.0008
3	45	44.9938	0.0026	44.9974	0.0011
4	60	59.9932	0.0029	59.9949	0.0022
5	75	74.9912	0.0037	74.9931	0.0029
6	90	89.9897	0.0044	89.9926	0.0031
7	105	104.9901	0.0042	104.9932	0.0029
8	120	119.9923	0.0033	119.9941	0.0025
9	135	134.9950	0.0021	134.9948	0.0022
10	150	149.9967	0.0014	149.9953	0.0020
11	165	164.9965	0.0015	164.9961	0.0016
12	180	179.9947	0.0022	179.9976	0.0010
13	195	194.9935	0.0027	194.9990	0.0004
14	210	209.9961	0.0016	209.9958	0.0018

B. Training Process for Location of Fault

After the end of the process of training, the performance of the neural network has been checked by validation performance and regression to choose the best Artificial Neural Network (ANN) to locate the fault location. The following figures illustrate the performance of training according to the type of fault:

- The best validation performance in Fig.7 is 7.0734e-05, and the best linear regression (the relationship between the targets and the outputs of the ANN, which is indicated by the correlation coefficient $R = 1$) in Fig.8 of the developed locator for LG.
- The best validation performance in Fig.9 is 8.6718e-06, and the best linear regression (the relationship between the targets and the outputs of the ANN, which is indicated by the correlation coefficient $R = 1$) in Fig.10 of the developed locator for LL.
- The best validation performance in Fig.11 is 1.2888e-05, and the best linear regression (the relationship between the targets and the outputs of the ANN, which is indicated by the correlation coefficient $R = 1$) in Fig.12 of the developed locator for LLG.
- The best validation performance in Fig.13 is 8.4885e-06, and the best linear regression (the relationship between the targets and the outputs of the ANN, which is indicated by the correlation coefficient R = 1) in Fig.14 of the developed locator for 3L.

IV. TESTING RESULTS OF ANN BASED FAULT LOCATION

- To test artificial neural network performance, 14 different line A to ground (A.G) faults were tested in different phases with an increased fault distance of 15 km and different fault resistance $Rf = 10 and Rf = 75$ ohm in Table II. It can be seen that the maximum error is 0.0071% and the average error at fault location is

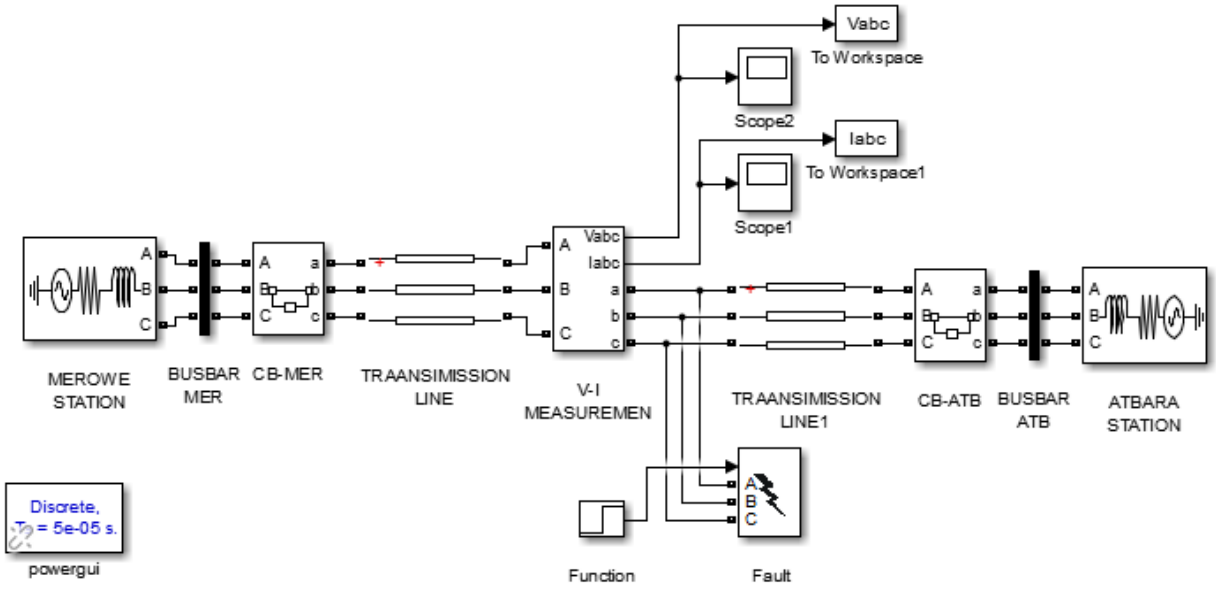


Fig. 2. Simulation of 500KV transmission line system

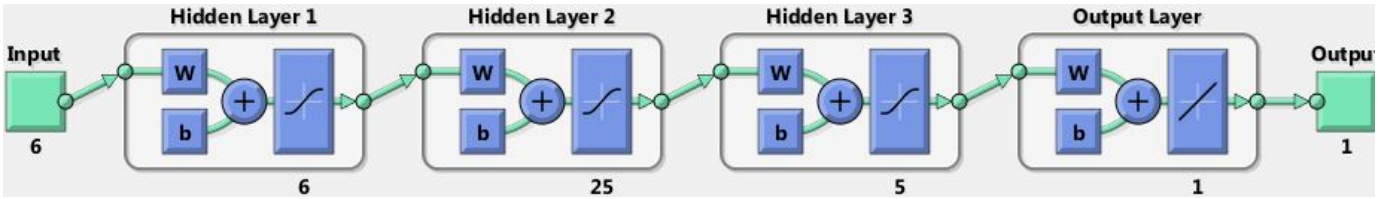


Fig. 3. The neural network of fault location of (LG)

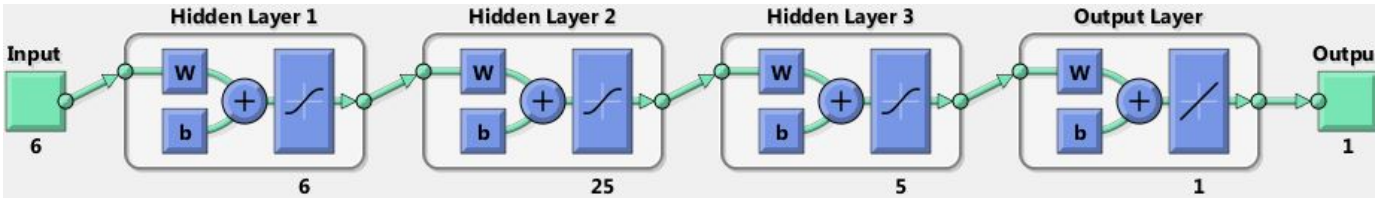


Fig. 4. The neural network of fault location of (LL)

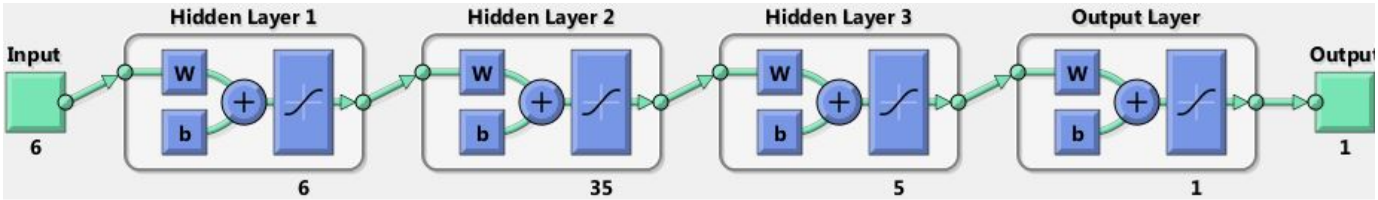


Fig. 5. The neural network of fault location of (LLG)

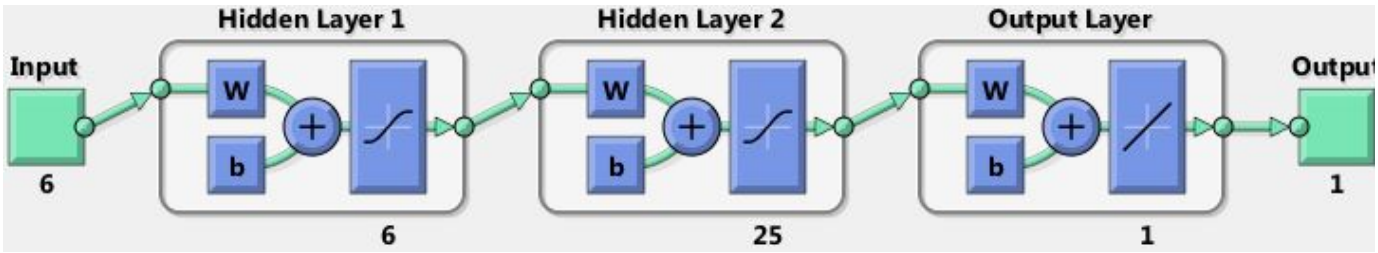


Fig. 6. The neural network of fault location of (3L)

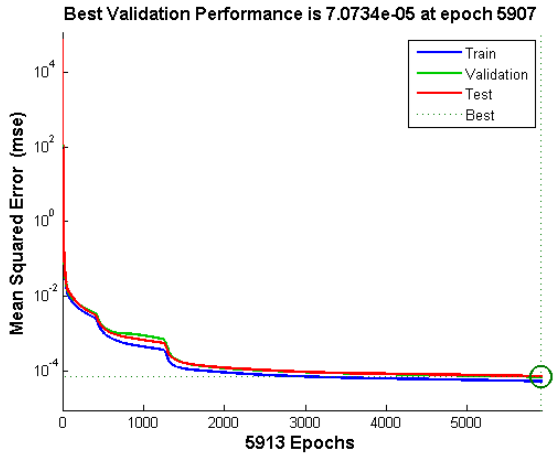


Fig. 7. Best validation performance (LG)

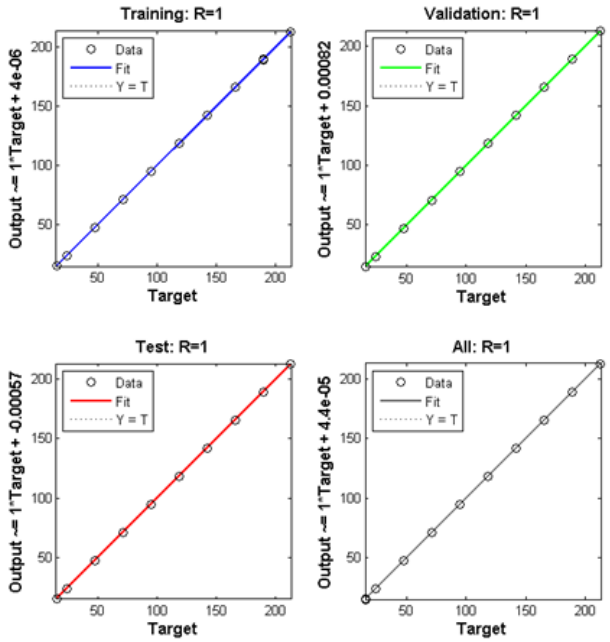


Fig. 8. Best linear regression of the outputs vs. targets (LG)

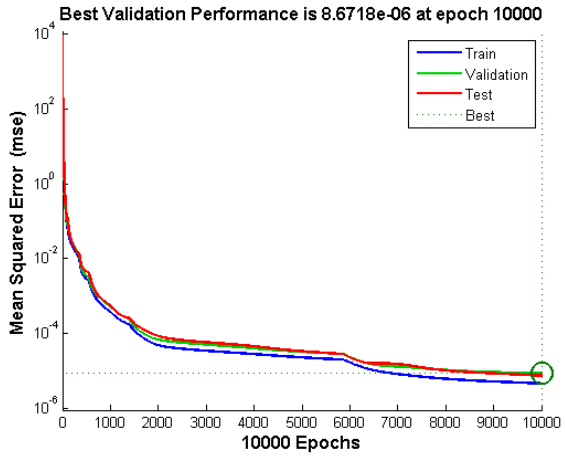


Fig. 9. Best validation performance (LL)

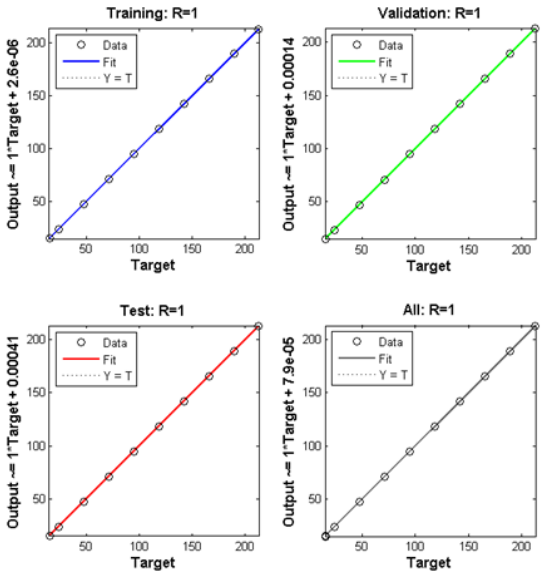


Fig. 10. Best linear regression of the outputs vs. targets (LL)

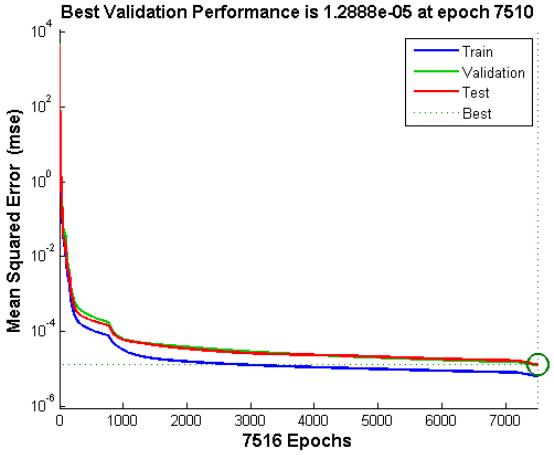


Fig. 11. Best validation performance (LLG)

TABLE III
LOCATION AND PERCENTAGE ERRORS OF A.B FAULT

No	Actual Location (km)	Fault Resistance Rf=10 ohm		Fault Resistance Rf=75 ohm	
		Estimated Location (km)	Error (%)	Estimated Location (km)	Error (%)
1	15	14.9982	0.0008	15.0019	0.0008
2	30	29.9960	0.0017	30.0018	0.0008
3	45	44.9938	0.0026	44.9974	0.0011
4	60	59.9932	0.0029	59.9949	0.0022
5	75	74.9912	0.0037	74.9931	0.0029
6	90	89.9897	0.0044	89.9926	0.0031
7	105	104.9901	0.0042	104.9932	0.0029
8	120	119.9923	0.0033	119.9941	0.0025
9	135	134.9950	0.0021	134.9948	0.0022
10	150	149.9967	0.0014	149.9953	0.0020
11	165	164.9965	0.0015	164.9961	0.0016
12	180	179.9947	0.0022	179.9976	0.0010
13	195	194.9935	0.0027	194.9990	0.0004
14	210	209.9961	0.0016	209.9958	0.0018

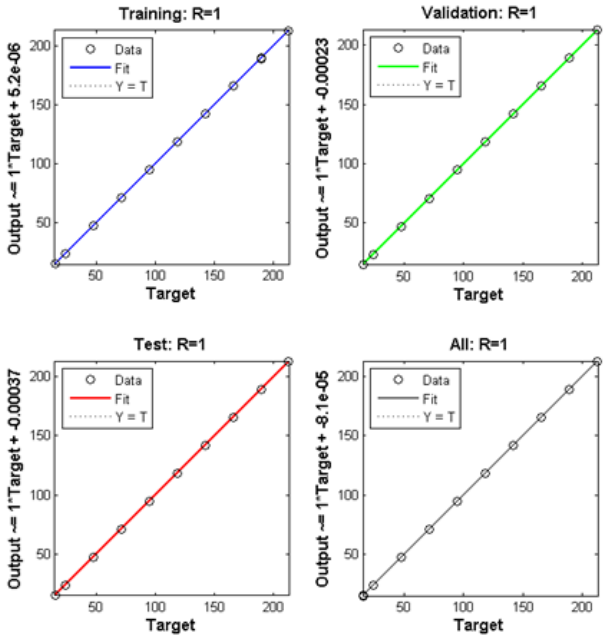


Fig. 12. Best linear regression of the outputs vs. targets (LLG)

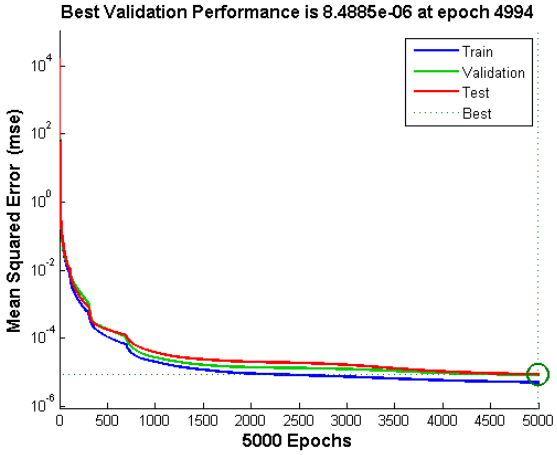


Fig. 13. Best validation performance (3L)

0.001712%. The accuracy of the above algorithm is measured by the percentage error calculated as:

$$\%Error = \frac{EstimatedLocation - ActualLocation}{TotalLength} \times 100 \quad (1)$$

- To test artificial neural network performance, 14 different line A to line B (A.B) faults were tested on different phases with an increased fault distance of 15 km and different fault resistance Rf = 10 and Rf = 75 ohm in Table III. It can be seen that the maximum error is 0.0044 %, and the average error at fault location is 0.002157%.
- To test artificial neural network performance, 14 different line A to line B to ground (A.B.G) faults were tested on different phases with an increased fault distance of 15 km and different fault resistance $Rf = 10 and Rf = 75$ ohm in Table IV. It can be seen that the maximum error is 0.0035% and the average error at fault location is 0.00144%.
- To test artificial neural network performance, 14 different three-line A.B.C faults were tested on different phases with an increased fault distance of 15 km and different fault resistance $Rf = 10 and Rf = 75$ ohm in Table V. It can be seen that the maximum error is 0.0025%, and the average error at fault location is 0.00134%.

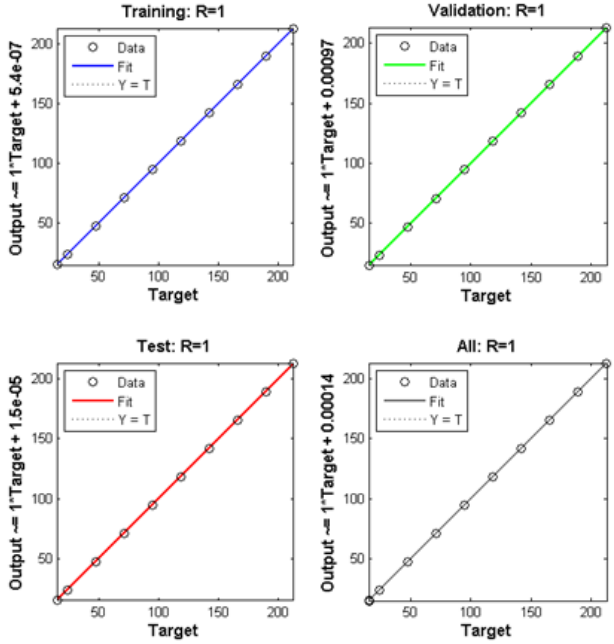


Fig. 14. Best linear regression of the outputs vs. targets (3L)

TABLE IV
LOCATION AND PERCENTAGE ERRORS OF A.B.G FAULT

No	Actual Location (km)	Fault Resistance Rf=10 ohm		Fault Resistance Rf=75 ohm	
		Estimated Location (km)	Error (%)	Estimated Location (km)	Error (%)
1	15	14.9991	0.0004	15.0018	0.0008
2	30	29.9918	0.0035	29.9923	0.0033
3	45	45.0077	0.0033	44.9999	0.00004
4	60	59.9951	0.0021	60.0001	0.00004
5	75	74.9941	0.0025	74.9999	0.00004
6	90	90.0048	0.0020	90.0041	0.0017
7	105	104.9980	0.0008	105.0029	0.0012
8	120	119.9986	0.0006	120.0033	0.0014
9	135	135.0042	0.0018	135.0082	0.0035
10	150	149.9965	0.0015	150.0057	0.0024
11	165	164.9954	0.0019	165.0013	0.0005
12	180	180.0008	0.0003	180.0013	0.0005
13	195	195.0022	0.0009	194.9980	0.0008
14	210	210.0005	0.0002	209.9945	0.0023

V. CONCLUSION

In this paper,an artificial neural network based location of the fault system for a 500KV transmission line from Merowe to Atbara in northern Sudan has been developed. The backpropagation algorithm is used for multilayer feedforward networks. In transmission lines, a technique is designed to

TABLE V
LOCATION AND PERCENTAGE ERRORS OF A.B.C.G FAULT

No	Actual Location (km)	Fault Resistance Rf=10 ohm		Fault Resistance Rf=75 ohm	
		Estimated Location (km)	Error (%)	Estimated Location (km)	Error (%)
1	15	14.9991	0.0004	14.9998	0.00008
2	30	29.9945	0.0023	29.9982	0.0008
3	45	44.9943	0.0024	44.9960	0.0017
4	60	59.9953	0.0020	59.9947	0.0022
5	75	74.9966	0.0014	74.9940	0.0025
6	90	89.9979	0.0009	89.9941	0.0025
7	105	104.9988	0.0005	104.9947	0.0022
8	120	119.9990	0.0004	119.9956	0.0019
9	135	134.9986	0.0006	134.9963	0.0016
10	150	149.9980	0.0008	149.9965	0.0015
11	165	164.9982	0.0008	164.9964	0.0015
12	180	179.9995	0.0002	179.9962	0.0016
13	195	195.0009	0.0000	194.9959	0.0017
14	210	209.9988	0.0005	209.9940	0.0025

TABLE VI
COMPARISON OF THE PRESENT WORK WITH THE PREVIOUS WORKS

Author & Year(reference)	Algorithm Used	Inputs	Line configuration	Fault Type Line configuration	Error
Gaurav Kapoor, 2018 [17]	Discrete Wavelet Transform (DWT)	Current Signals	Double Circuit	Three phase	Maximum error 2.4666%
Ayokunle A, et al. 2017 [6]	Artificial Neural Network (ANN)	Voltage & Current Signals	Single Circuit	LG, LLG, LL	Maximum error 0.0679% Average error 0.056933
Atul A, et al. 2016 [3]	Artificial Neural Network (ANN)	Current Signals	Double Circuit	Three phase	Maximum error 1.3623%
Sushma Verma, 2015 [9]	Discrete Wavelet Transform (DWT)	Current Signals	Single Circuit	LG, LLG	Average error <0.2588km
Ashish N. Kakde, 2015 [7]	Distributed Parameter Line Model	Voltage & Current Signals	Single Circuit	LG	Maximum error 0.075%
Present work	Artificial Neural Network (ANN)	Voltage & Current Signals	Single Circuit	LG, LL, LLG, LLLG	Maximum error 0. 0071% Average error 0.001662%

locate the fault high accurately and true. Finally in general, it found the maximum error for all different faults of location is around 0. 0071 percent. A very satisfactory value is the average error of 0.001662 percent in the fault location, which is very low.

REFERENCES

[1] A. A. Awelewa, P. O. Mbamaluikem, and I. A. Samuel, "Artificial neural networks for intelligent fault location on the 33kv nigeria transmission line," *International Journal of Engineering Trends and Technology (IJETT*, pp. 147155,.

[2] K. V. Babu, M. Tripathy, and A. K. Singh, "Recent techniques used in transmission line protection," *International Journal of Engineering, Science and Technology*, p. 18.

[3] K. M. Bukkur, K. B. A, and M. Shukri, "Dynamic scheduling of assembly line using neural networks for saria industrial complex - sudan," *Journal of Karary University for Engineering and Science*, vol. 1, no. 2.

[4] A. Y. EbhaKoley and A. Thoke, "Artificial neural network based protection scheme for one conductor open faults in six phase transmission line," *International Journal of Computer Applications*, p. 4246.

[5] M. Elhassan, I. Z, A, and O. Hassan Abdalla, "Approach control of dfig rotor side converter based on grid frequency coordinated control," *Journal of Karary University for Engineering and Science*, vol. 1, no. 1.

[6] A. Hadabi, E. Elsamani, A. Abdallah, and R. Elhabob, "An efficient model to detect and prevent sql injection attac," *Journal of Karary University for Engineering and Science: JKUES*, vol. 1.

[7] A. Jain, Moses, and Beaulah, "Soft computing based fault detection & classification for transmission lines," *International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT*, p. 40614064.

[8] M. Jamil, S. K. Sharma, and R. Singh, "Fault detection and classification in electrical power transmission system using artificial neural network," *springer open journal*, p. 113.

[9] A. N. Kakde, "Fault location in transmission line using distributed parameter line model based on unsynchronized measurement at two ends of line," *International Journal of Computer Applications*, vol. 2015, p. 1822.

[10] A. A. Kale and N. G. Pandey, "Ann based fault classifier and fault locator for double circuit transmission line," *International Journal of Computer Sciences and Engineering*, p. 1 6.

[11] G. Kapoor, "A discrete wavelet transform approach to fault location on a 138kv two terminal transmission line using current signals of both ends," *ICTACT Journal on Microelectronics*, p. 625629.
[12] M. Noraldain Alamin, "Detection and tracking of uav targets using deep learning," *Journal of Karary University for Engineering and Science*, vol. 1, no. 2.
[13] M. Patel and R. Patel, "Fault detection and classification on a transmission line using wavelet multi resolution analysis and neural network," *International Journal of Computer Applications*, p. 2733.
[14] A. G. Phiske and A. Ranjan, "Double circuit transmission line protection using line trap and artificial neural network matlab10 approach," *International Research Journal of Engineering and Technology (IRJET*, p. 30153020.
[15] A. Prasad, J. B. Edward, and K. Ravi, "A review on fault classification methodologies in power transmission systems: Parti," *Journal of electrical systems and information technology*, vol. 5, no. 1, pp. 48–60, 2018.
[16] S. Sahu and A. Sharma, "Detection of fault location in transmission lines using wavelet transform," *International Journal of Engineering Research and Applications*, p. 149151.
[17] S. Shahmordi, "Detection of fault location on transmission systems using wavelet transform," *International Academic Journal of Science and Engineering*, p. 23 32.
[18] P. Sharma, D. Saini, and A. Saxenain, "Fault detection and classification in transmission line using wavelet transform and ann," *Bulletin of Electrical Engineering and Informatics*, p. 456 465.
[19] A. Swetapadma and A. Yadav, "A novel single-ended fault location scheme for parallel transmission lines using k-nearest neighbor algorithm," *Computers & Electrical Engineering*, vol. 2018, p. 4155.
[20] E. B. M. Tayeb, "Faults detection in power systems using artificial neural network," *American Journal of Engineering Research (AJER*, p. 6975.
[21] D. D. Taywade and A. Ghute, "Detection and classification of transmission lines faults using discrete wavelet transform and ann as classifier," *International Journal of Engineering Sciences and Research Technology*, p. 924933.
[22] C. Tharani, "Matlab based simulations model for three phases power system network," *International Journal for Research in Applied Science & Engineering Technology (IJRASET*, p. 502509.
[23] E. P. Thwe and M. M. Oo, "Fault detection and classification for transmission line protection system using artificial neural network," *Journal of Electrical and Electronic Engineering*, p. 89 96.
[24] H. M. Umran and M. A. Hameed, "The faults detection and categorization for a part of iraqi electricity power transmission grid based on neural network techniques," *Journal University of Kerbala*, p. 190200.
[25] S. Verma, "Most suited mother wavelet for localization of transmission line faults," *International Journal of Sciences and Technology Research*, p. 286293.
[26] N. S. Wani, R. Singh, and M. U. Nemade, "Detection, classification and localization of faults of transmission lines using wavelet transform and neural network," *International. Journal of Applied Engineering Research*, vol. 2018, p. 98106.
[27] E. T. A. Yousif, O. A. Elnour, and M. A. Ibrahem, "Design and simulation of pitch optimizer and stall protection for a typical uav," *Journal of Karary University for Engineering and Science: The 1st Scientific Conference for Aerospace Researches & Applications Sudan*, p. 1.



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