

Earth Fault Location in Medium Voltage Power System Network

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ABSTRACT

Electric in power systems network is always exposed to failures that can be caused by natural phenomena or human errors. This paper focused on the fault localization method on medium voltage (MV) power system network. Faults that occurred in a power system network may damage the system which results in the components of the system failure. A network of MV power system network was constructed using ATP/EMTP software to simulate and analyse an earth fault transient signal for earth fault location purpose. The transient signal produced from the simulation of ATP/EMTP software was analysed using MATLAB software. All the data and the signal of the dominant transient frequency were collected and trained in Artificial Neural Network (ANN). The ANN model is used to locate an earth fault location in the simulated power system network. Based on the result, the system works as being expected.

Keywords: Earth Fault Location, Medium Voltage Network, Artificial Neural Network, Fast Fourier Transform, Linear Regression, ATP/EMTP Program.

1. INTRODUCTION

Fault location is not an uncommon thing in a power system network. There have been many faults occurred on the overhead line which consume a lot of time for troubleshooting and maintenance. In addition, if a fault takes too much time to be repaired, it requires investment of money and loss its ability. Along these lines, in order to settle this issue, a precise and brisk system is needed in order to locate the fault at medium voltage network. There are various strategies available based on post-fault circuit analysis with outside signal sources such as the bridge and travelling wave radar techniques, wherein many cases are not relevant. This is because they are moderate, require control by human, and non-permanent faults are not being detected. Consequently, the utilization of fault generated signals in the fault location is exceptionally acceptable.

This paper concentrates on the location of a single phase to earth fault medium voltage (MV) distribution network. Single-phase to earth fault is the most well-known type of fault that happened in power distribution networks. They are around 70% of permanent faults that happened in rural MV networks. The faults mostly caused by animals and climate conditions such as a thunderstorm, snow, fallen trees and strong wind. One of the ways to lessen an earth fault in overhead line feeders is by supplanting the bare conductor to protect the conductor type of overhead line. Nonetheless, the key to solving this problem is spending a large amount of money.

The initial transients of earth faults in MV distribution network are important especially for unearthing and compensated neutral networks. The earth fault transient signals consist of many different frequency components, which result from charging and discharging of the network capacitances. The transient components provide valuable information for fault location

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purposes. The charging component has a higher amplitude and lower frequency than the discharge component and hence is more suitable to be used for fault location purposes.

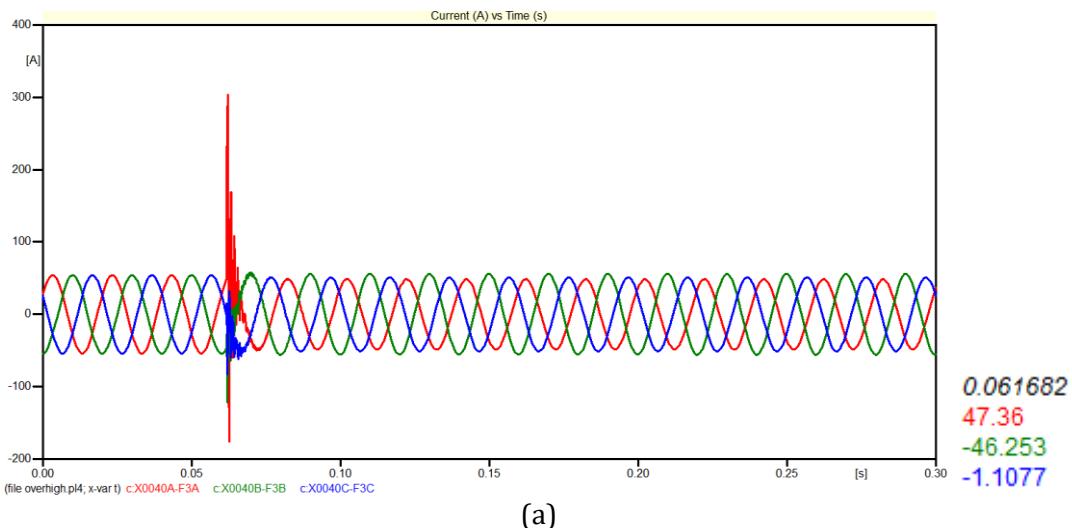
The algorithms to locate an earth fault in unearthing or an isolated neutral MV network has been discussed in this project by using the information of the measured transient signal. The network is modelled using Alternative Transient Program-Electromagnetic Transients Program (ATP-EMTP) software. There are many types of fault location algorithms that have been developed. However, in this project, the fault location algorithm is proposed based on the Artificial Neural Network (ANN).

2. RESEARCH METHODOLOGY

ANN is used to estimate the fault location. The identification of charge transient component is performed using a Fast Fourier Transform (FFT). The FFT has the capacity of pictorial the amplitude of FFT that contents the transient signal with respect to the frequency. FFT was plotted after all the data was collected to get the signal of the dominant frequency. The flow of the fault location algorithms steps based on ANN will be discussed in ANN simulation later.

2.1 Fault Location Algorithm

At the point when an earth fault occurs in MV feeder, the transient signal can likewise be identified from the secondary side of the HV/MV power transformer. Figure 1 shows an example of a simulated earth fault transient current signal recorded at the secondary side of the HV/MV power transformer. The transient signal that has been captured is analyzed using FFT. Figure 2 shows an example of extracted FFT of the simulated transient signal. In order to recognize the charge frequency of the simulated transient signal, the used of FFT is vital when earth fault happens.



(a)

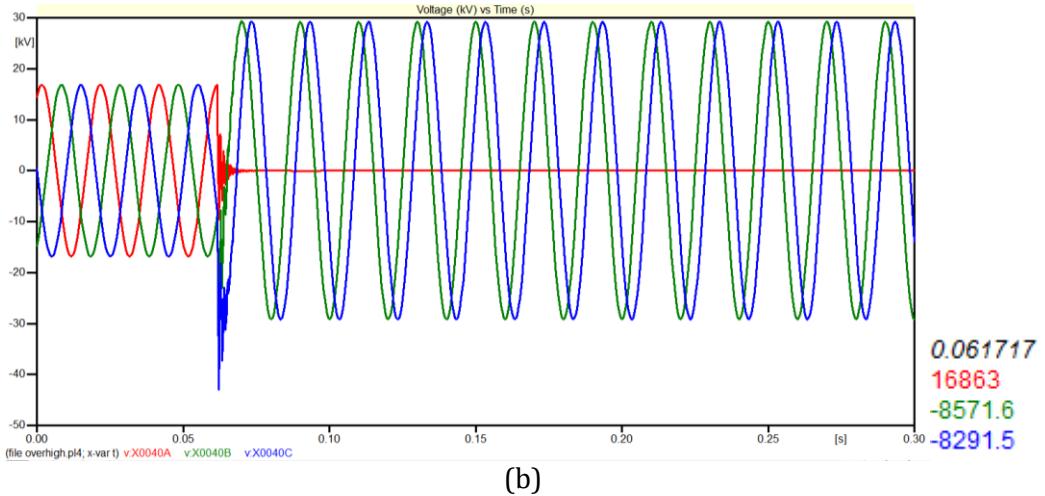


Figure 1. An example of an earth fault transient signal of current and voltage.

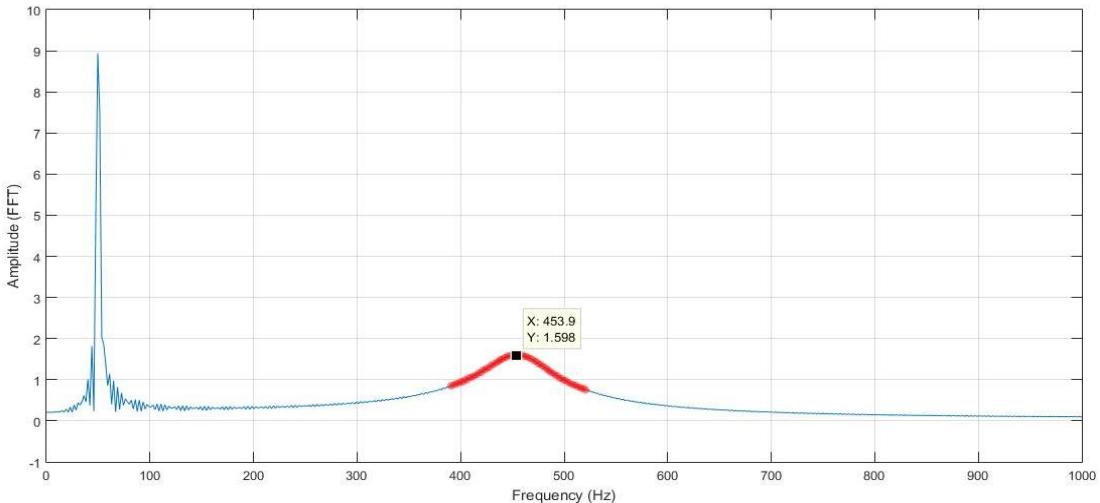


Figure 2. FFT of simulated transient signal when earth fault happens at the network.

The proposed algorithms are proven to utilize earth fault transient signal produced by a simulation model. The simulation of the voltage and current transient is compulsory and imperative in order to justify the proposed fault location algorithms. In this exploration, Alternative Transient Program (ATP/EMTP) been used as the transient simulator. The program was selected because it is standout amongst the most widely recognized simulation tools utilized by researcher and power engineers for simulation of transients. The program software consists of considerable modelling capabilities for transmission lines, cables, breakers, loads, converters, protection devices, non-linear elements, electromagnetic coupling, and dominant power electronics devices and equipment.

2.2 Description of the Simulation and the Network Model

A single-line diagram of typical 20 kV distribution network is shown in Figure 3. The overall length of the MV distribution network is about 157 km with 144 number of distribution substations. It has been used in this project as MV distribution test network. It is consisting of 6 feeders of overhead lines cable. The part that has been highlighted is the Feeder 3 which was used to test in this project. In ATP simulation, a single line to ground fault was simulated for every 2 km each in the fault distances.

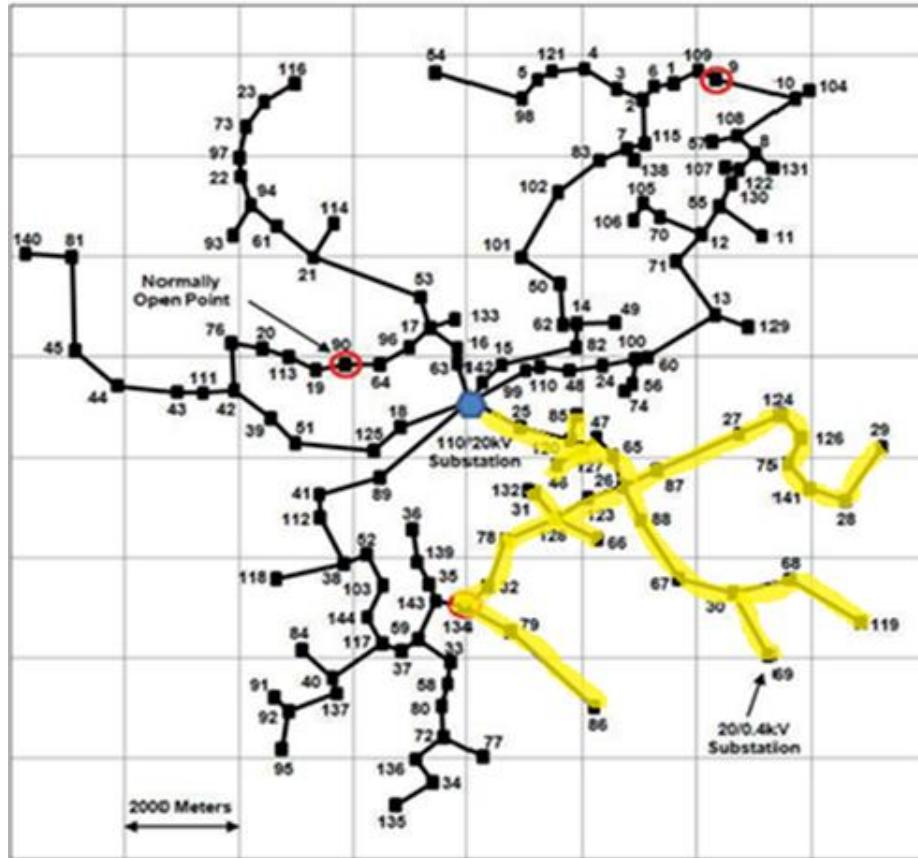


Figure 3. A Single-line diagram of 20kV distribution network.

3. RESULTS AND DISCUSSION

This section presents the results in this project. From the ATP-EMTP simulation, several earth fault signals were collected dominant frequency of the charge transient signal is obtained from the FFT result. The magnitude of each dominant frequency of the measured earth fault transient signals was different according to the location of earth faults in the network.

3.1 Result of ANN

Table 1 and Figure 4 show the samples, overall Mean Square Error (MSE), and Regression values (R). The total number of samples in every part is the difference due to the percentage that has been set before. Therefore, the total number of samples must be the same as what has been put in the data before it is about 513 samples of data were collected in this project. The Mean Square Error (MSE) represents the average squared error difference between actual output values and target. While for the Regression values (R), measures the correlation between the output and target values for training, validation, and testing sample.

Table 1 Mean Square Error and Regression values

	Samples	MSE	R
Training	359	0.21503	0.988654
Validation	77	0.209476	0.987908
Testing	77	0.2895	0.98594

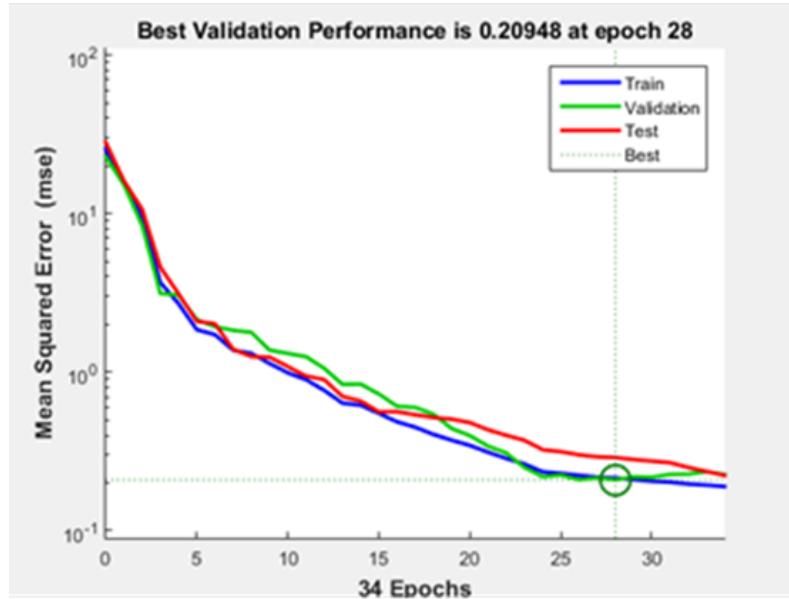


Figure 4. Mean Square Error vs Epochs number.

The plot shown in Figure 5 is the error histogram with 20 bins. The red bars represent testing data, the green bars represent validation data and blue bars represent training data.

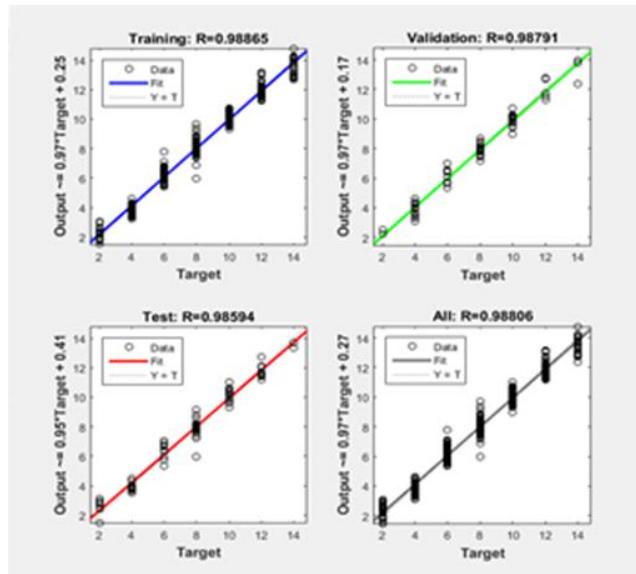


Figure 5. Regression plot in training data.

The regression plots in Figure 6 is the network outputs with recognition to the objectives or targets for training, validation, and test sets. The regression is used to validate network

performance. In this work, the fit is reasonably good for all data sets, with R values in each case of 0.98.

3.2 Testing Data

In order to test the performance of the ANN, several data from FFT processed earth fault transient signal were used to test the trained ANN model.

Figure 6 shows a retrained performance (MSE) graph of a neural network model that was created during its training. The training stopped after 14 epochs because the test error increased. The result here is reasonable because the training set error and the validation set error have similar characteristics. Hence, it does not appear of any significance overfitting has occurred. After initial training of the neural network model, it is retrained for 14 epochs and performance MSE is obtained 0.95415 at epoch 8 in training at its best of validation performance.

The circled point in Figure 6 also shows where the best validation of performance takes place. Compared to Figure 4, the Mean Square Error (MSE) value is lower than the Mean Square Error (MSE) value in Figure 6. The closer the Mean Square Error (MSE) value towards the better performance of the algorithm.

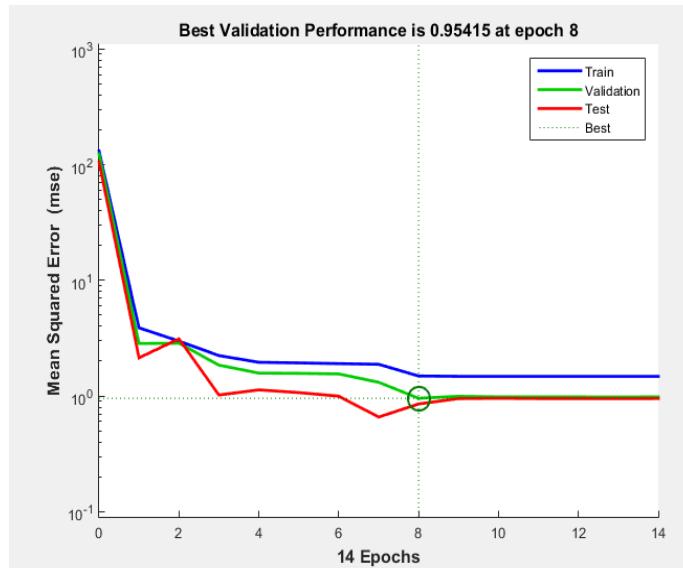


Figure 6. The validation performance graph.

Figure 7 shows the regression plot of testing the data. In order to have perfect results, the solid line of the plots should be on the same phase with the dotted lines. The dotted lines represented the target data which is the perfect results subtracted with the outputs. When the solid lines totally in a phase with the dotted lines, the R-value which equals to 1 indicates the relationship between outputs and targets is exactly linear. Based on Figure 7, it can be concluded that the results of the training tool are in a good condition as the value of R is nearest to 1, which is 0.91 and above. Then, the data should be in 45 degrees in a line for a perfect fit which means the network outputs are equal to the targets. The results clearly show that the Neural Networks have been tested with sufficient data and proper inputs so that it can predict better.

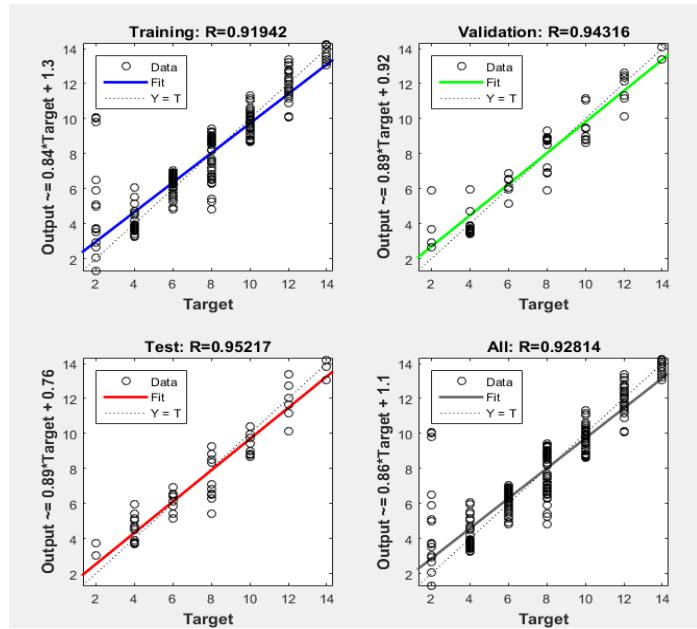


Figure 7. Regression plot of testing the data.

Figure 8 shows the result of earth fault location ANN model. The red line shows the prediction of ANN and it shows that the fault is about to happen at 6.7 km. While in Figure 9, the actual fault distance is at 6.2 km. Therefore, this result can be concluded that it is in an error-free or in an accurate order to detect the distance of the fault because the actual and the prediction of the distance is small.

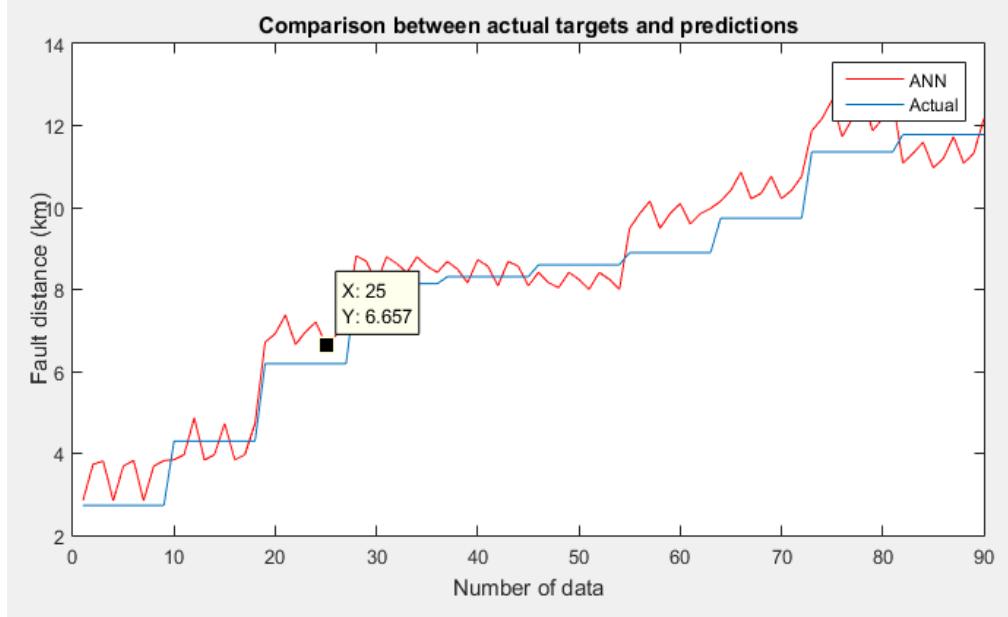


Figure 8. Comparison graph between ANN and actual targets.

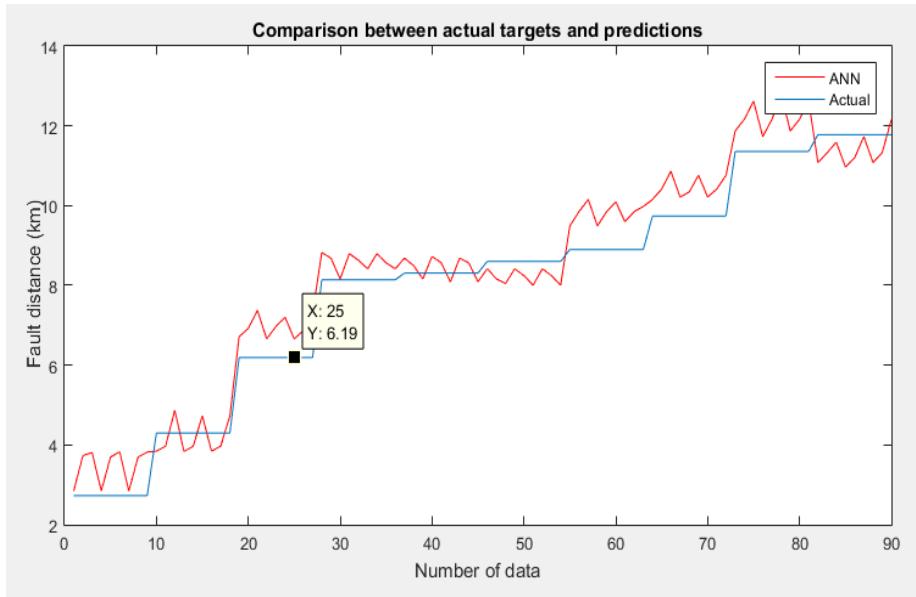


Figure 9. Comparison graph between the actual targets and ANN.

The test data in Figure 10 shows that the solid line is slightly moving from the dotted line. However, it is acceptable because the R-value indicates of 0.99; nearest to 1.

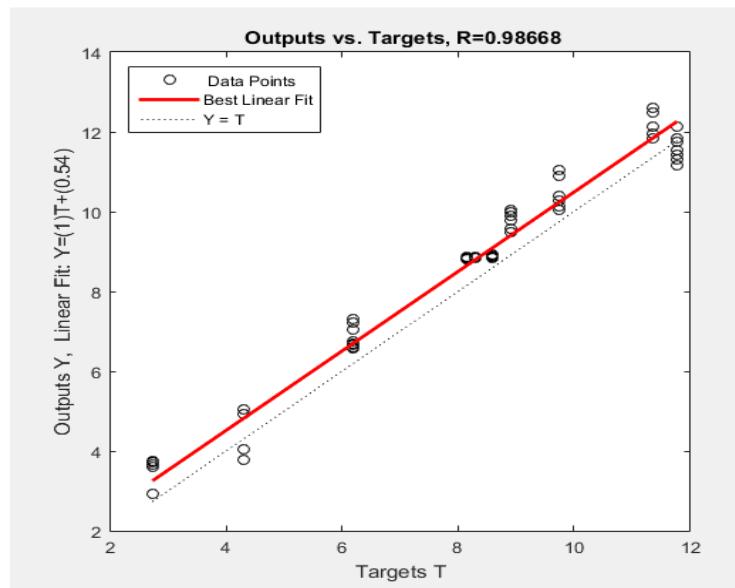


Figure 10. Test data result.

3.3 Linear Regression Result

Linear regression is a method to find the best fitting straight line through the points from the data collected and the best-fitting line is called a regression line. If the dotted point is very near to the regression line means its error of prediction is small but if the dotted point is much higher than the regression line, its error of prediction is large. Figure 11 shows a negative linear relationship. It has a regression equation with slope of -0.0269 and y-intercept, 23.194. Right underneath is the R-squared value of 0.9573 or in percentage is about 96%. This means, it is in a very highly correlated that is nearest to 1 or 100%. This explained that the relationships are

exactly linear. From the graph, it shows that the higher the fault distance, the lower the frequency obtained.

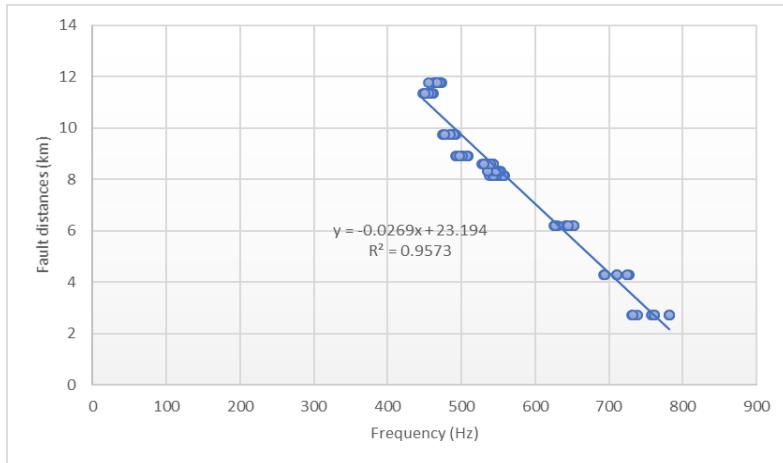


Figure 11. Negative linear relationship of a regression line.

3.4 Comparison and analysis of ANN and Linear Regression

Neural networks are faster than other methods inclusive of regression due to the fact they are executing parallel and tolerate many errors and additionally these networks can make rules with none implicit formulation. Artificial neural network method is better than linear regression method in estimation and neural network method is more descriptive than the linear regression method. From the past research of theory also state that the neural network method is better than the linear regression method and is proved in this study [20]. The next logical step for the studies is to enhance in addition to the performance of Neural Networks, for this approach, perhaps through better training methods, better architecture selection, and better input.

Table 2 shows the result of ANN for the fault distances testing measured at ten fault locations for every 2 km. The errors are shown in Table 2. From the results obtained, the percentage errors for all compounds were lower than +/- 7% with an average percentage error of 7.17%.

Table 3 presents the table form of Linear Regression method. From the table, it can be seen that the percentage errors were lower compare to the ANN result in Table 2 with an average percentage error of 4.68%.

Table 2 ANN result of testing the fault distances

Fault distances (km)			
No.	y-actual (data)	y-estimate (ANN)	Δy (error)
1	2.73	3.86	1.13
2	4.3	4.61	0.31
3	6.19	7.04	0.85
4	8.14	8.64	0.5
5	8.31	8.47	0.16
6	8.6	8.48	0.12
7	8.9	10.16	1.26
8	9.74	10.6	0.86
9	11.36	12.6	1.24
10	11.78	11.04	0.74
Average error (%)			7.17

Table 3 Linear Regression table form

No.	Actual data		Estimate data		Δy (error)
	x-axis	y-axis	x-axis	y-axis	
	Frequency (Hz)	Fault distance (km)	Frequency (Hz)	Fault distance (km)	
1	782	2.73	782	2.16	0.57
2	694.3	4.3	694.3	4.52	0.22
3	650.4	6.19	650.4	5.7	0.5
4	551.2	8.14	551.2	8.37	0.23
5	536	8.31	536	8.78	0.47
6	543.6	8.6	543.6	8.57	0.03
7	509.3	8.9	509.3	9.49	0.6
8	490.2	9.74	490.2	10.01	0.27
9	459.7	11.36	459.7	10.83	0.53
10	471.1	11.78	471.1	10.52	1.26
Average error (%)					4.68

Table 4 Comparison between the Mean Average Error (MAE) of ANN and LR

No.	Δy (error) ANN	Δy (error) Linear Regression
1	1.13	0.57
2	0.31	0.22
3	0.85	0.49
4	0.5	0.23
5	0.16	0.47
6	0.12	0.03
7	1.26	0.59
8	0.86	0.27
9	1.24	0.53
10	0.74	1.26
ΔMAE	0.72	0.47

Absolute error (Δx) is the amount of error in the measurements. It is the difference between the estimated value (x_0) and the actual value (x). It is written as in the following equation:

$$\Delta x = x_0 - x \quad (1)$$

For example, if a distance state happened at 10 km but the actual distance is 9.5 km, then the distance has an absolute error of $10 \text{ km} - 9.5 \text{ km} = 0.5 \text{ km}$. Mean Average Error (MAE) is the average of all absolute errors.

4. CONCLUSION

A network of medium voltage (MV) power system is well modelled and was simulated using ATP/EMTP software. Besides, an earth fault transient signal has been analyzed for earth fault location purpose. In this work, the faults were located at a different branch in the medium voltage distribution network. The fault location was located by analyzing the earth fault transient signal that was captured at the secondary side of the HV/MV transformer. In this work, it concludes that the system works as being expected. The accuracy of the estimated distance and the test results indicate the effectiveness of the method and are demonstrated properly. The ANN training can be executed offline with the available system parameter. Based on the present of communication technology and computer, the fault information can be transferred to a remote place for decision and analysis.

REFERENCES

- [1] P. Imriš, "Transient based earth fault location in 110kV sub-transmission networks," PhD dissertation, Helsinki University of Technology, (2006).
- [2] M. R. Adzman, D. Topolánek, M. Lehtonen, & P. Toman, "An earth fault location scheme for isolated and compensated neutral distribution systems," Int. Rev. Electr. Eng. **8**, 5 (2013) 1520–1531.
- [3] G. Achleitner, L. Fickert, C. Obkircher, & M. Sakulin, "Earth fault distance protection," in IET Conference Publications, (2009) 550 CP.
- [4] L. Prikler, "ATPDRAW Users' Manual," Norway, (2009).
- [5] Adzman, M. R., & Lehtonen, M. (2012). Estimation of single line to ground fault location in unearthing medium voltage distribution network. Proceedings of the 13th International Scientific Conference Electric Power Engineering 2012, EPE 2012, 1(January 2012).
- [6] Jiguparmar. (2012. Feb 9). Types of neutral earthing in power distribution. Available: <http://electrical-engineering-portal.com/types-of-neutral-earthing-in-power-distribution-part-1>
- [7] S. Hänninen & M. Lehtonen, "Earth fault distance computation with fundamental frequency signals based on measurements in substation supply bay," VTT Tied. - Valt. Tek. Tutkimusk., 2153, 3–40, 2002.
- [8] J. W. Cooley, P. A. W. Lewis, & P. D. Welch, "Historical notes on the fast Fourier transform," Proc. IEEE **55**, 10 (1967) 1675–1677.
- [9] S. H. S. Barakat, "Fault Detection, Classification and Location in Underground Cables," Egypt, (2014).
- [10] S. Kazemi, "Reliability evaluation of smart distribution grids," PhD dissertation, Aalto University, (Oct 2011).
- [11] S. Hänninen, "Single-phase earth faults in high impedance grounded networks Characteristics, indication and location," VTT Publ., 453 (2011) 2–78.
- [12] Z. C. Huang *et al.*, "Study of Earth-Fault Location Method for Distribution Network Based on Transient Signal", Applied Mechanics and Materials, **105-107** (2012) 742-746.
- [13] Mendenhall, W., & Sincich, T. Statistics for Engineering and the Sciences (3rd ed.), New York, NY: Dellen Publishing Co, (1992).
- [14] S. S. Gururajapathy, H. Mokhlis, H. Illias, A. A. Bakar, & L. Awalin, "Fault identification in an unbalanced distribution system using support vector machine," J. Electr. Syst. **12**, 4 (2016).
- [15] Anderson, D. R., Sweeney, D. J., & Williams, T. A. Essentials of Statistics for Business and Economics (3rd ed.) Mason, Ohio: Southwestern, Thompson Learning, (2003).
- [16] Amos Gilat, MATLAB an Introduction with Applications, (2012).
- [17] Khamis & N. K. K. Kamarudin, "Comparative Study on Estimate House Price Using Statistical and Neural Network Model," Int. J. Sci. Technol. Res. **3**, 12 (2014) 126–131.

- [18] O. S. Maliki, A. O. Agbo, A. O. Maliki, & C. O. Agwu, "Comparison of Regression Model and Artificial Neural Network Model for the prediction of Electrical Power generated in Nigeria," *Adv. Appl. Sci. Res. B*, 5 (2011) 329–339.

APPENDIX

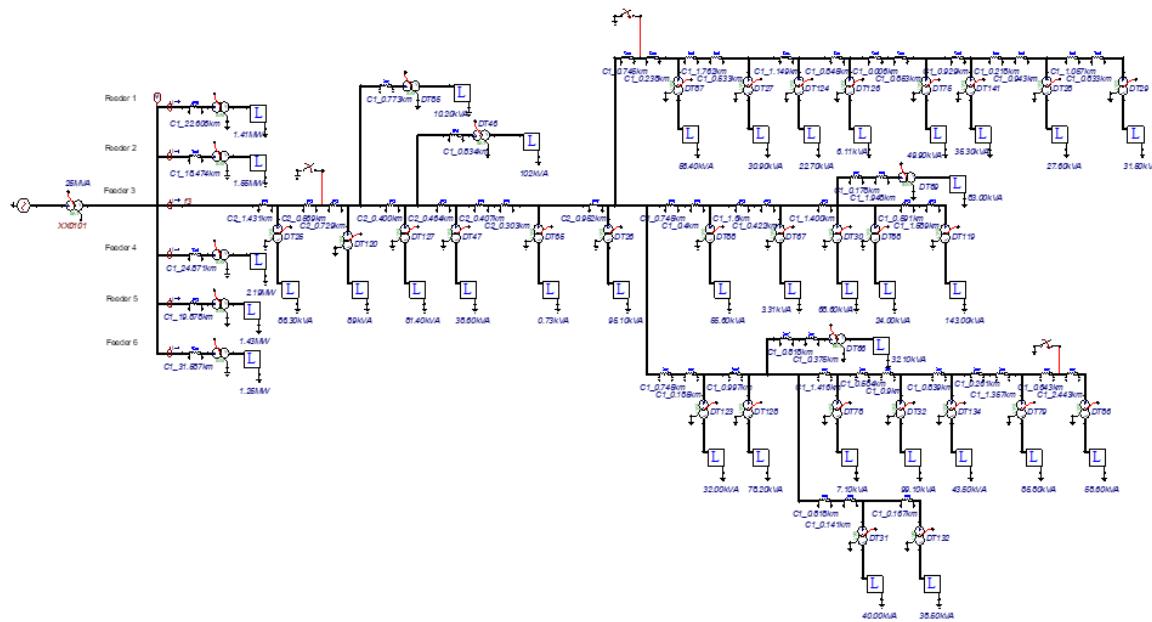


Figure 5. A circuit design of a medium voltage (MV) power system network using ATPDraw.