Artificial Neural Network-Based Transmission Line Fault Distance Prediction

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***Abstract*— In this paper, artificial neural network-based transmission line fault distance prediction model is presented. The study was based on a case study of a faulted three phase transmission line that was connecting two power sources. The measured phase current and voltages from the over were used for the training and validation of the ANN model. Further fault distance predictions were conducted for different fault types and fault locations. The results showed that for the given set of data, the actual fault locations and the ANN predicted fault locations haver^2value of 0.9982with maximum percentage prediction error of -1.51%. In all, the prediction results were impressive with very high coefficient of determination and low percentage prediction errors.**

Keywords — Artificial Neural Network, Transmission Line, Phase Current, Phase Voltage, Fault Distance, Fault Types, Fault Distance Prediction

I. INTRODUCTION

Fault incidents are regular occurrences in power systems and timely detection and location of the fault are essential for the restoration of the power system to acceptable working conditions [1,2,3,4,5]. The focus of this paper is on the determination of fault location on a large power system network. Different faults can occur on a transmission line and each category of fault present different characteristics which need to be factored in the procedure for determining the fault location [6,7]. Also, when fault occurs on one phase of a three phase transmission line, due to the coupling effect , the other phases are also affected by the fault [8,9,10,11].In all, there are intricate issues associated with transmission line faults that makes is quite difficult for the application of manual method of fault location estimation [12,13,14,15]. Also, simple methods of fault location estimation fails to achieve very high level of accuracy due to the complex issues associated with the transmission line faults and the ripple effect on the various line parameters. As such, in this paper, an Artificial Neural Network (ANN)-based transmission line fault distance prediction is adopted [16,17,18]. The ANN is an intelligent algorithm which can handle the uncertainties and complexities that are associated with transmission line faults.

In this paper, the ANN model is trained based on a dataset obtained from the case study transmission line. A different set of data from the case study line is used to validate the ANN model during the training period and also another set of data from the case study line is used to cross validate the ANN model after that model training process. This double validation is meant to ensure that the developed ANN model can give very high fault location prediction even when unprecedented fault scenario occurs on the line. Specifically, MATHLAB software was used for the model training, and validation as well as simulation of different fault categories and different fault locations on the case study transmission line. In each case, the prediction of the ANN model is noted and the prediction performance is assessed through percentage error in fault distance estimation and the R-squared value.

II. METHODOLOGY

Fault Detection and Location Prediction with Artificial Neural Network(ANN)

In this study, it is assumed that a three phase fault occurred along a transmission line connecting two power sources. Then, an artificial neural network (ANN)-based transmission line fault was developed and simulated using Simulink software to determine the location of the fault. In the Simulink neural network toolbox, the case study dataset for the transmission line was divided into three different sets namely the training data set, the validation data set and the testing data set. The training data set is used to train the ANN model by computing the gradient and updating the network biases and weights. The validation data set is provided to the ANN model during the training process (just the input without the outputs) and the error in validation data set is monitored throughout the training process.

When the network starts over-fitting the data, the validation errors increases and when the number of validation fails to increase beyond a particular value, the training process stops to avoid further over-fitting the data and the network is returned at the minimum number of validation errors. The test set was not used during the training process but was used to test the performance of the trained ANN model. The flow chart for the ANN model is shown in Figure 1.

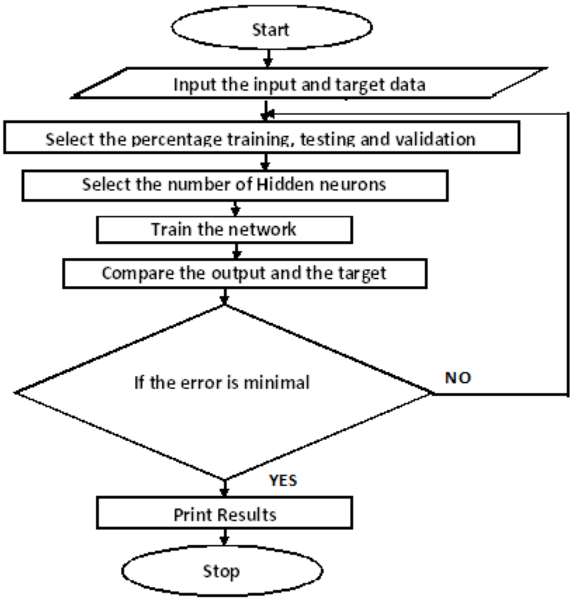

Figure 1. Flow chart for ANN model prediction

A portion of the data input data (the phase current and phase voltage) used in the ANN simulation is shown in Table 1. Specifically, the simulation, the phase current and phase voltage measured with time are the input data and the fault location is the output. In all, about 1631 data samples are used in the simulation process, as shown in Figure 2. The percentage of the data set used for the training, the testing and the validation are shown in Figure 2. Also, Figure 2 shows that the training, validation and testing percentage were 70 %, 15 % and 15 %of the respectively.

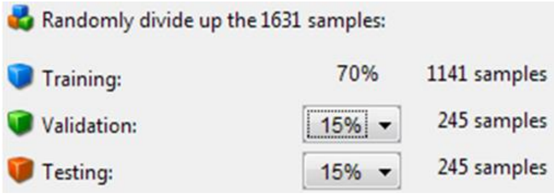

Figure 2. The portions of the dataset used for training, validation and testing of the ANN model

The ANN architecture is shown in Figure 3. The ANN architecture comprises of the input, hidden and the output neurons. Figure 3 shows that the input neuron has two inputs (current and voltage), the hidden layer has ten neurons with each of the neurons having the log sigmoid model in Equation (1) and the output layer has on neuron which is the fault location.

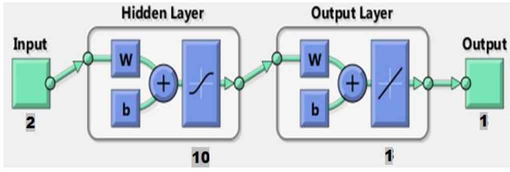

Figure 3. ANN architecture

In each of the hidden neurons, a log sigmoid model was used which is given as;

$$logsig(n) = 1/(1 + e^{-n}) \quad (1)$$

Where n is the input.

III. RESULTS AND DISCUSSION

The ANN fault location model was simulated using Simulink software. A portion of the data set used for the training, validation and testing of the model for the different types of faults at different fault locations is shown in Table 1. The percentage error prediction errors for the different types of faults at different fault locations are shown in Table 2. The results in Table 2 show that for the given set of data, the actual fault locations and the ANN predicted fault locations have $\boldsymbol{r}^2$ value of 0.9982with maximum percentage prediction error of-1.51%.Furthermore, the ANN predicted data for the fault current is plotted against time , as shown in Figure 4.

Table 1. The voltage and current data with fault location used for training, testing and Validation of the ANN model

Fault type	Voltage		Current		Fault location
	Magnitude	Phase	Magnitude	Phase	
A-G	26.03	309.99	985.41	702.83	23.16
B-G	41.81	250.21	1155.71	736.80	20.38
BC	79.50	218.22	1143.36	726.67	41.40
ABC	93.47	192.29	1472.54	781.19	41.40

Table 2. The percentage error in fault distance using the ANN method

Fault type	Actual distance (km)	ANN method (km)	% error with ANN method
A-G	23.16	24.23	-1.51
B-G	20.38	21.20	-1.15
AB-G	41.40	42.42	-1.44
ABC-G	41.40	40.44	1.35

r^2=0.9982

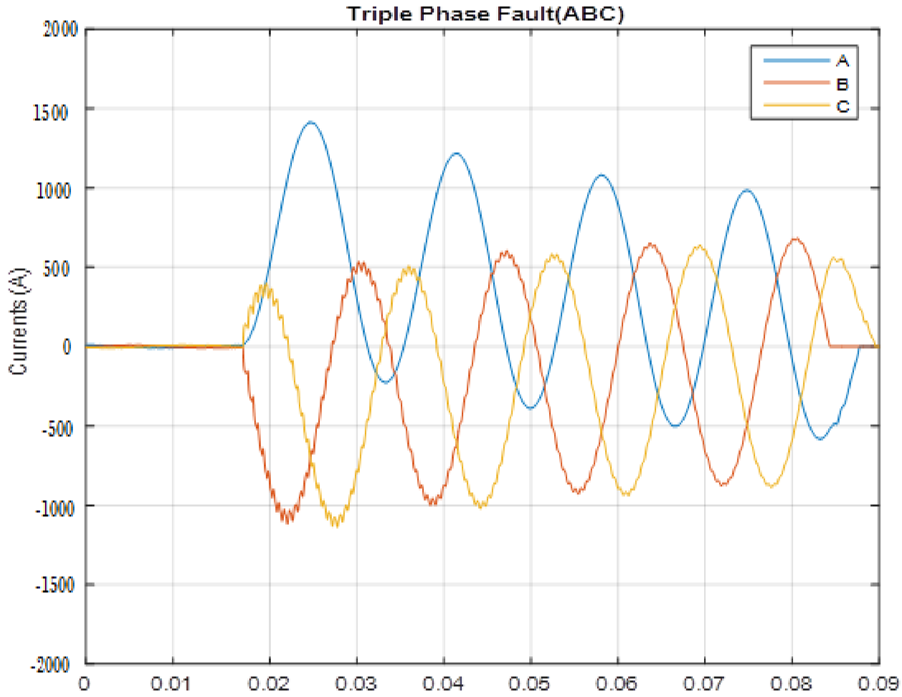

Figure 4. The triple phase ABC-ground fault

The current waveform at bus A during a triple phase to ground fault (ABC-G) is shown in Figure 4 and Table 1 (in row 4, column 4). According to Figure 5 and Table 2, fault occurred on the three phases at 41.40 km from bus A, the current wave form was stable until the fault occurred at 0.018 sec then the current increase to 1472.54A.

Furthermore, the R-square values between the outputs and the targets of the ANN model are shown in Figure 5. The results in Figure 5 show that the R-square values are above 0.998 for the training dataset, the validation dataset, the testing dataset and for all the dataset. Knowing that the closer the value of R-square is, to 1, the better the performance of the neural network, the values ofR-square in this cases are above 0.998 which is very close to 1. Essentially, the ANN model has good prediction accuracy for the case study transmission line fault locations.

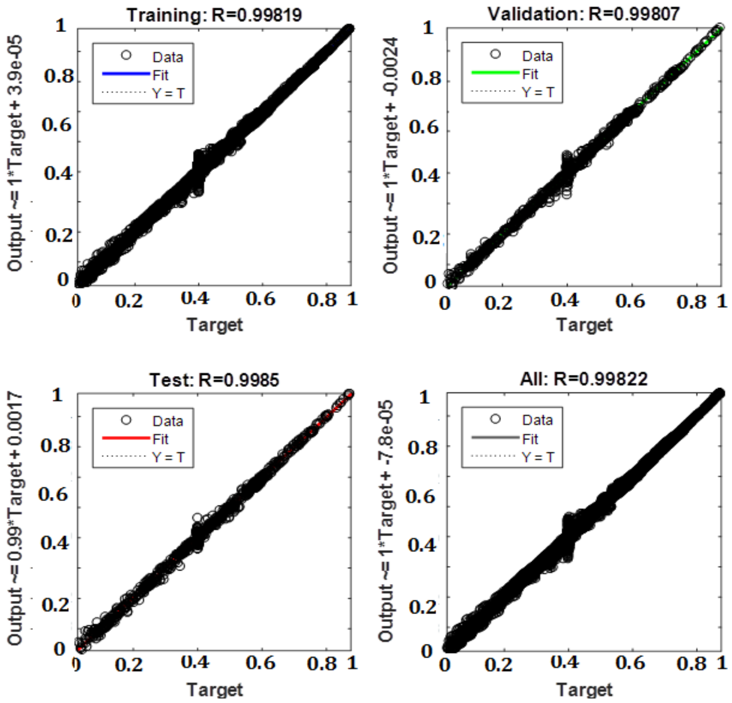

Figure 5. The R-square values between the outputs and the targets of the ANN model

IV. CONCLUSIONS

Artificial neural network (ANN) model for fault location on a three phase transmission line is presented. The ANN flowchart is also presented along with the description of the model training and validation. The model uses phase voltage and current during fault incidence to determine the location of the fault. Sample data set from a three phase transmission line were used to assess the ANN model's fault location prediction capability. In all, the prediction results were impressive with very high coefficient of determination and low percentage prediction errors.

REFERENCES

[1] Wischkaemper, J. (2011). *Electrical characterization of arcing fault behavior on 120/208V secondary networks* (Doctoral dissertation). Available at https://scholar.google.com/scholar?um=1&ie=UTF-8&lr&q=related:6Ze3lP66QoriMM:scholar.google.com/ Accessed on 12th November 2018

[2] Pinto Moreira de Souza, D., da Silva Christo, E., & Rocha Almeida, A. (2017). Location of faults in power transmission lines using the ARIMA method. *Energies*, *10*(10), 1596.

[3] Wei, W., & Tao, Z. (2018, March). Occurrence and countermeasures of urban power grid accident. In *IOP Conference Series: Earth and Environmental Science* (Vol. 128, No. 1, p. 012187). IOP Publishing.

[4] Picard, S. D., Adamiak, M. G., & Madani, V. (2015, March). Fault location using PMU measurements and wide-area infrastructure. In *2015 68th Annual Conference for Protective Relay Engineers* (pp. 272-277). IEEE.

[5] Blaabjerg, F., Yang, Y., Yang, D., & Wang, X. (2017). Distributed power-generation systems and protection. *Proceedings of the IEEE*, *105*(7), 1311-1331.

[6] Ngaopitakkul, A., Apisit, C., Bunjongjit, S., & Pothisarn, C. (2013). Identifying types of simultaneous fault in transmission line using discrete wavelet transform and fuzzy logic algorithm. *International Journal of Innovative Computing, Information and Control*, *9*(7), 2701-2712.

[7] Wang, L. (2016). The fault causes of overhead lines in distribution network. In *MATEC Web of Conferences* (Vol. 61, p. 02017). EDP Sciences.

[8] Suljanović, N., Mujčić, A., & Zajc, M. (2017). Communication Characteristics of Faulted Overhead High Voltage Power Lines at Low Radio Frequencies. *Energies*, *10*(11), 1801.

[9] Hänninen, S. VTT PUBLICATIONS 453. *VTT PUBLICATIONS*, *4*(5), 3.

[10] Patne, N. R., & Thakre, K. L. (2008). Factor affecting characteristic of voltage sag due to fault in the power system. *Serbian Journal of Electrical Engineering*, *5*(1), 171-182.

[11] Huang, Q., Zhen, W., & Pong, P. W. (2012). A novel approach for fault location of overhead transmission line with noncontact magnetic-field measurement. *IEEE Transactions on power delivery*, *27*(3), 1186-1195.

[12] Bouloutas, A. T., Calo, S., & Finkel, A. (1994). Alarm correlation and fault identification in

communication networks. *IEEE Transactions on communications*, *42*(234), 523-533.

[13] Katzela, I., & Schwartz, M. (1995). Schemes for fault identification in communication networks. *IEEE/ACM Transactions on networking*, *3*(6), 753-764.

[14] Jan, S. T., Afzal, R., & Khan, A. Z. (2015, February). Transformer failures, causes & impact. In *International conference data mining, civil and mechanical engineering* (pp. 49-52).

[15] Popović, L. M. (2014). Determination of actual reduction factor of HV and MV cable lines passing through urban and suburban areas. *Facta Universitatis, Series: Electronics and Energetics*, *27*(1), 25-39.

[16] Ekici, S. (2008). CLASSIFICATION of TRANSMISSION LINE FAULTS by USING WAVELET TRANSFORM and PROBABILISTIC NEURAL NETWORKS. *Technological Applied Sciences*, *3*(2), 200-210.

[17] Chen, K., Huang, C., & He, J. (2016). Fault detection, classification and location for transmission lines and distribution systems: a review on the methods. *High voltage*, *1*(1), 25-33.

[18] Upendar, J., Gupta, C. P., Singh, G. K., & Ramakrishna, G. (2010). PSO and ANN-based fault classification for protective relaying. *IET generation, transmission & distribution*, *4*(10), 1197-1212.