ARTIFICIAL NEURAL NETWORK BASED SMART SHUNT FAULT RECOGNITION SYSTEM FOR THE 33-kV NIGERIA POWER LINES

By

[1]Mbamaluikem, Peter O.; [2]Olabode, Olufemi R. and [3]Adedokun, Adedoyin G.

[123] Department of Electrical and Electronics Engineering, Federal Polytechnic, Ilaro, Ogun State, Nigeria

Corresponding Author E-mail: peter.mbamaluikem@federalpolyilaro.edu.ng

1st International Conference and Exhibition of the Federal Polytechnic, Ilaro, on the Technological Innovation and Global Competitiveness.

Theme: Knowledge & Technological Innovation for Global Competitiveness

Held at International Conference Centre, Federal Polytechnic, Ilaro, Ogun State, on November 5-8, 2018.

Abstract

The Nigeria 33-kV power lines are more exposed to the environment than 330-kV transmission lines and 132-kV sub-transmission lines, hence chances of occurrence of shunt faults in this power lines is very high. Such faults need to be recognized quickly at its occurrence to hasten its clearance in order to forestall power system damages and reduce the system downtime. Consequently, this paper presents a new approach to recognize shunt faults on the 33-kV Nigeria power line network using artificial neural network. The network is modeled and simulated in the MATLAB/Simulink 2015a environment. This study employed a feed forward neural network with back-propagation algorithm in training the system. The proposed system uses as inputs, instantaneous values of voltages and currents during normal and abnormal situations on the power lines to detect the presence or absence of shunt faults on a particular line. The artificial neural network based smart fault recognition system developed achieved an accuracy of 100% for all shunt fault conditions tested. The results presented show that this approach has the potential to recognize all shunt faults on electric power lines on the 33-kV Nigeria power lines with high level of accuracy.

Key words: Artificial neural network, fault recognition, shunt fault, power lines, MATLAB/Simulink, Back-propagation algorithm

1. Introduction

The functioning of today's complex society requires steady electric power supply. An attempt to meet up with the electrical energy need of the society has increased the size and complexity of power system likewise the power lines. Electrical overhead power lines are network of interconnected electrical conductors that convey electrical power from station to station in a varying degree of voltages in order to meet the extremely large number of load demands. In Nigeria, there are four levels of transmission voltages namely; 330kV, 132 kV, 33 kV and 11 kV. The 33 kV power lines links 132 kV to 11 kV and is characterized with very lengthy transmission lines which often pass through bushes, thus being more exposed to the environment. Consequently, the possibility of experiencing a fault is very high in this line (Saha, Izykowski, & Rosolowski, 2010). Faults on electric power lines may be seen as sudden disturbances that can cause abnormal flow of current in the lines. Faults on overhead transmission lines are broadly classified into open circuit fault and shunt circuit fault Williams, (2012). This paper considers the later which may be caused by trees falling across lines, trees growing up to the power lines, broken cross arms, bird shorting the lines, vandalism, etc., because its frequency of occurrence is very high (Patrick & Fardo, 2009; Akpojedje, Onogbotsere, Mormah, & Onogbotsere, 2016). Thus, for optimum utilization of power system and continuity of service, it is necessary to rapidly recognize these faults to enable utility operators to commence the process of faults clearance at a good time and hence prevent prolonged system downtime and minimize damage and perhaps prevent incipient fault from degenerating into severe faults (Saha, Das, Verho, & Novosel, 2002). Moreover, as the size and complexity of power system grows, the probability of faults occurrence becomes very high as such it becomes expedient to recognize such faults as soon as it occurs using faster and more reliable accurate systems.

Meanwhile, a number of systems have been developed for fault recognition over the years but in the recent times the artificial intelligent based systems are more reliable. Notwithstanding, research is still ongoing in these areas to advance and offer better viable solutions. Fault detection and classification for transmission line protection system using artificial neural network was proposed in (Phyo, 2016). The capacity of discrete wavelet Transform and artificial neural network was used by Gowrishanka, et al. (2016) to develop a fault detector and classifier in transmission lines. Leite, et al (Leite, et al. 2009) developed a new technique for the detection and location of high-speed faults using neural networks. Silva, et al. (2006) employed Wavelet Transform and ANN for detection and classification of faults in power transmission lines. Singh, et al. (2014) used ANN with gradient descent backpropagation algorithm to implement an intelligent fault identification system. A fault detection and location system for high-speed protection in extra high voltage transmission lines using feedforward neural network with the backpropagation algorithm based on supervised learning was applied by (Bouthiba, 2004). However, this study is intending to use the model of 33-kV Nigeria power line which would be build in Matlab/Simulink to simulate shunt faults and use Artificial Neural Network (ANN) to design a smart shunt fault recognition system that can detect all shunt faults in the power lines.

2. Artificial Neural Network

Artificial Neural Network (ANN) may be considered as interconnected parallel computational machine modeled after biological neurons. It consists of collection of parallel processing elements called neurons, joined collectively to acquire a unique result (Chakraborty, 2010). This makes them popular for real-world applications. In addition, its functionality in processing data in a parallel distributed manner, remedy troubles that are naturally nonlinear without having prior knowledge features pertaining to the problem variables and its capability in handling incomplete statistics and corrupt data, gave it an edge over other classes of artificial intelligence in fault recognition in power lines (Singh, et al., 2014).

An artificial neural network learns to produce a preferred output based totally on a given input data through training. Hence, a training data set is required to train any artificial neural network to perform a unique operation (Haque & Kashtiban, 2007). The training of the network is performed by sequentially making use of input vectors whilst adjusting network weights accordingly and passing the same via an activation function. The network weights converge gradually as weights adjustment progresses to values that will enable every input vector to produce the goal (Santos & Senger, 2011)(Yadav & Dash, 2014). Figure 1 is a simple structure of a feed forward multilayer perceptron artificial neural network.

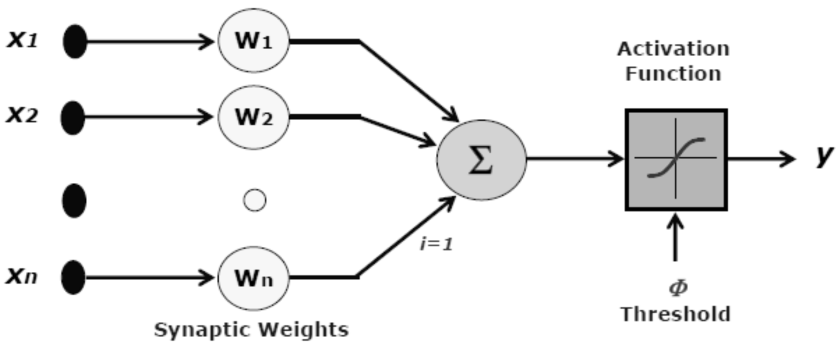

Figure 1: Simple Structure of a feedforward Multilayer Artificial Neural Network

3. The modeled Power System

The single line diagram of the 33-kV power line studied is shown in Figure 2. The network length is 140 km and Source 1 as indicated in the diagram has a reference voltage of 33 kV, while Source 2 has a reference voltage of 11 kV. This network is modeled in MATLAB 2015a.

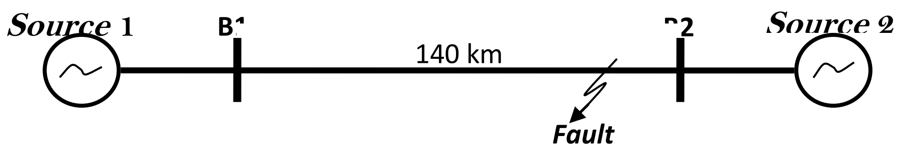

Figure 2: Studied Power System Single Line

The Pi model was used to model the studied 33-kV power line in Simulink/MATLAB 2015a environment. The power line characteristics and parameters used for the model are shown in Table 1 and the Simulink model of the 33-kV Nigeria power line is shown in Figure 3

Table 1: The Characteristics and Parameters used for the Power line modeling

Line Length	140 km
Type Conductor	ACSR
Positive- and zero-sequence resistances (Ohms/km)	[0.18446 0.39072]
Positive- and zero-sequence inductances (H/km)	[0.0010981 0.0024668]
Positive- and zero-sequence capacitances (F/km)	[1.0865e-08 6.6177e-09]
Fault Starting	0.020 seconds
Duration in fault	0.03 Seconds

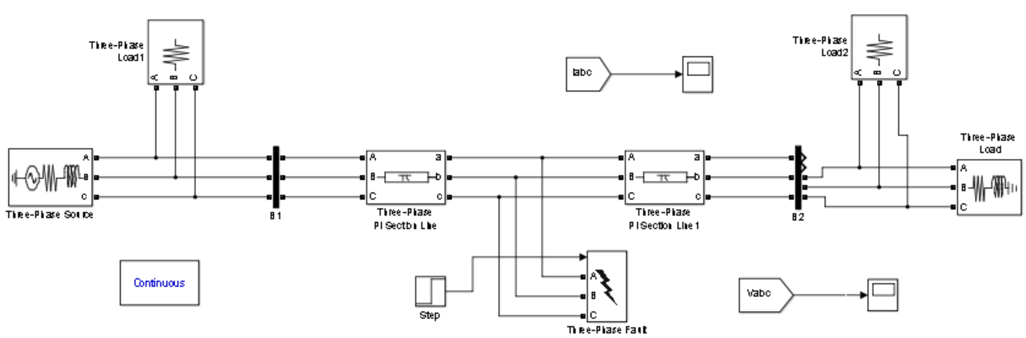

Figure 3: Snapshot of the modeled 33-kV Power line in Simulink/Matlab environment

In the model, information regarding current and voltage are obtained at bus B1 using the three-phase V-I measurement block. The instantaneous values of voltages and currents acquired are used for fault recognition. The pi-section line 1 and 2 together is 140 km long. Ten different shunt faults plus no fault condition are simulated between 1 km and 140 km at a step of 2 km (Peter, Oluwaseun, & Ayokunle, 2018). The values of resistances and fault inception angles used are shown in Table 2.

Table 2: Parameter Values used in Generating the Training and Test Dataset

Training Dataset	
Fault distance (km)	1, 3, 5, …, 140
Fault inception angle (^{0})	30, 60
Fault Resistance (Ohms)	0.25, 0.5, 0.75, 5, 10, 20, 30 and 50
Test Dataset	
Fault distance (km)	8, 16, 24, …, 138
Fault Resistance (Ohms)	15, 25
Fault Resistance (Ohms)	5,15, 25 and 35
Fault inception angle (^{0})	20, 90

3.1 Data Preprocessing/Normalization

This study resorted to obtaining the input data (instantaneous values of currents and voltages) for training the ANN model by simulation due to insufficient real-time data. The simulation time is set to 0.02 second. These shunt faults are simulated one after another and the three phase voltage and current waveforms generated are sampled at a frequency of 1.5 kHz. Hence, there are thirty (30) samples per cycle. These samples are preprocessed to obtain an appropriate input data set for the ANN (Swarup & Chandrasekharaiah, 1991). Meanwhile, the fault was created at 0.04s which corresponds to the 55th sample. The scaling was done using the 12th sample before and after the occurrence of the fault. Hence, the inputs to the ANN are the ratios of the post-fault and pre-fault instantaneous voltages and currents in each of the phases, which correspond to the 67th sample and 43rd sample after and before the occurrence of the fault respectively. The scaling can be done mathematically, using the following generalized expression: $V_i^{abc} = \frac{V_s^{RYB}(n+12)}{V_s^{RYB}(n-12)}$ and $I_i^{abc} = \frac{I_s^{RYB}(n+12)}{I_s^{RYB}(n-12)}$

Where, V_i = instantaneous voltage inputs to ANN; I_i = instantaneous current inputs to ANN; V_s^{RYB} = Sampled voltage phases; I_s^{RYB} = sampled current phases, n = Sample number corresponding to the instantaneous time where the fault occurred.

In all, 6 x 6,160 sample information set is extracted, scaled and used as input data for training the ANN-based model. Hence, the complete training set comprises of 6 x 6,160 input data set and 1 x 6,160 target output data. Table 3 shows the truth table of the fault state of the lines.

Table 3: The input and Target Truth Table for the ANN-based SSFRS

V_a	V_b	V_c	I_a	I_b	I_c	Target	Fault Type
0.3253	0.2693	0.3471	0.4805	0.4861	0.4835	1	A-G
0.3979	0.3383	0.3955	0.4336	0.4385	0.4362	1	B-G
0.4472	0.3923	0.4380	0.3868	0.3912	0.3891	1	C-G
0.5715	0.5604	0.5677	0.1104	0.1114	0.1109	1	A-B-G
0.5755	0.5720	0.5748	0.0604	0.0608	0.0606	1	A-C-G
0.5765	0.5759	0.5765	0.0340	0.0342	0.0341	1	B-C-G
0.5766	0.5767	0.5769	0.0252	0.0253	0.0252	1	A-B
0.5768	0.5771	0.5772	0.0183	0.0184	0.0183	1	A-C
0.4765	0.4397	0.4906	0.3339	0.3377	0.3361	1	B-C
0.4964	0.4599	0.5039	0.3080	0.3115	0.3100	1	A-B-C
0.5767	0.5768	0.5769	0.0247	0.0247	0.0247	0	NO FAULT

4. The Proposed Smart Shunt Faults Recognition System

The smart shunt fault recognition system (SSFRS) proposed is designed to detect the presence (1) and the absence (0) of a fault in 33-kV Nigeria power line using the preprocessed/normalized instantaneous current and voltage data set. Figure 4 shows the block diagram representing the proposed SSFRS.

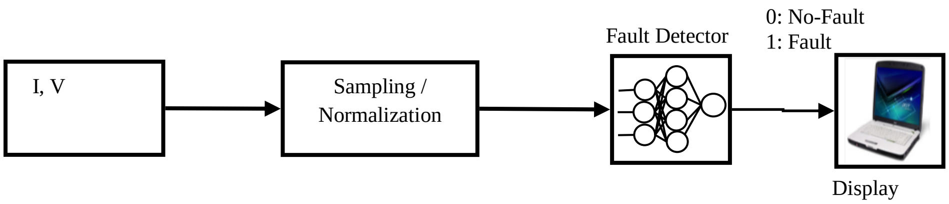

Figure 4: The block diagram of SSFGS

The implementation stages involved in the developmental process are as follows:

1. Power line modeling, simulation, sampling and Pre-Processing of the input Data set
2. Preparation of appropriate target data set suitable for the ANN to learn
3. Selection of the ANN configuration
4. Training of the ANN configuration selected
5. Calculation of the performance MSE
6. Performance evaluation and validation of the trained ANN configuration using the Performance MSE, confusion matrix, Regression Plot and a new set of data outside the one used for training.
7. Generate and save a Simulink Model for the best performed ANN.

4.1 Results

The supervised learning was employed in training extensively several configurations of the ANN with varying number of hidden layers, hidden layers neurons and activation functions. It is observed after series of training and testing of various combinations of hidden layers and transfer function that the ANN with configuration 6-5-1 gave the best satisfactory performance among several configurations considered in each case. The performance MSE, confusion matrix and regression plot are used as performance indicators for the trained ANN. Moreover, Figure 5 to Figure 7 show the performance MSE, confusion matrix and regression plot for SSFRS.

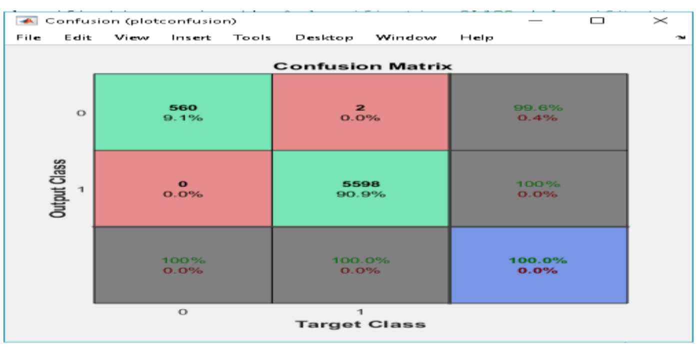

Figure 5: Confusion Matrix for SSFRS with 6-5-1 configuration

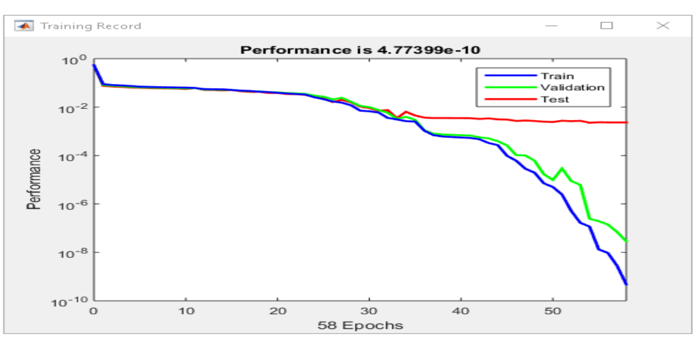

Figure 6: Performance Plot for SSFRS with 6-5-1 configuration

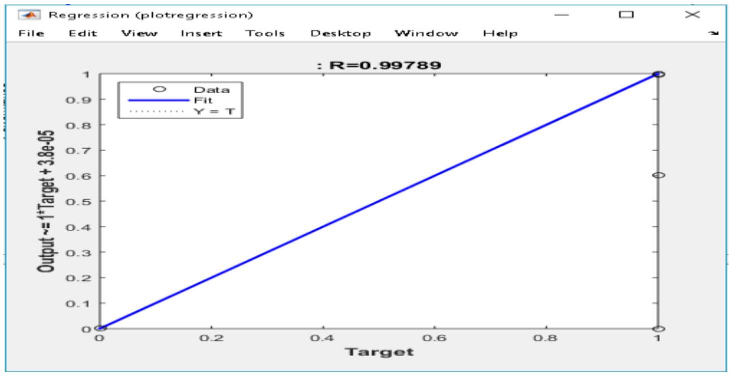

Figure 7: The ROC for SSFRS with 6-5-1 Configuration

4.1.1 Testing with a New Set of Data

Furthermore, the developed SSFRS capability to generalize was tested after training, with 10 new fault cases for each fault type amounting to 110 new fault scenarios. Table 4 presents the results of the developed smart shunt fault recognition system for a selected fault type.

Table 4: Result of the SSFRS with New Data set

Km	**SSFRS OUTPUT**				**TARGET**				**SSFRS OUTPUT**				**TARGET**				**SSFRS OUTPUT**				**TARGET**			
	A-G								**B-G**								**C-G**							
8	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
16	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
24	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
32	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
40	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
	A-B-G								**A-C-G**								**B-C-G**							
48	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
56	1	1	0	0.9	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
64	1	1	0	0.9	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
72	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
	A-B								**A-C**								**B-C**							
80	1	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
88	1	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
96	1	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
104	1	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
	A-B-C								**No-Fault**															
112	1	1	0.9	0	1	1	1	0	0	0	0	0	0	0	0	0								
120	1	1	0.9	0	1	1	1	0	0	0	0	0	0	0	0	0								
128	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0								
136	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0								

4.2 Discussion

It can be seen from the blue square box of the confusion matrix (Figure 5) that the accuracy of the developed SSFRS is 100%, showing that there is no confusion in recognizing all the faults tested. In addition, the performances plot (Figure 6), shows that the errors are in the range of 0.0001 which is below the preset MSE goal of 0.001 and more so, the linear regression fit shows that the relationship between the actual SSFRS output and the desired targets are satisfactory as the correlation coefficient is very close to the ideal value (1). Thus, indicating an excellent correlation. Finally, Table 4 shows the results of the SSFRS outputs with the corresponding targets for different shunt faults and No-fault condition. The results in Table 4 shows that all the three lines short-circuit faults and No-fault condition were accurately detected. This is a proof of the accuracy of the developed SSFRS in detecting all shunt faults on 33-kV Nigeria power lines.

5. CONCLUSION

The proposed method uses artificial neural networks to develop fast and reliable fault recognition system for the 33-kV Nigeria electric power line. The performance of the proposed scheme is evaluated using various fault types and encouraging results were obtained. The preprocessed instantaneous value of voltages and currents sampled at a frequency of 1.5 kHz was used as inputs data to the ANN-based SSFRS. Moreover, all the single line-to-ground faults, double line-to-ground faults, and line-to-line faults tested were accurately recognized. More so, results presented for the ten (10) different fault cases analyzed showed that the developed recognition system is efficient and reliable enough to be implemented on the 33-kV Nigeria electric power line.

References

Akpojedje, F. O., Onogbotsere, M. E., Mormah, E. C., & Onogbotsere, P. E. (2016). A Comprehensive Review of Nigeria Electric Power Transmission Issues and Rural Electrification Challenges. *International Journal of Engineering Trends and Technology (IJETT), 31*(1).

Bouthiba, T. (2004). Fault Location in Ehv Transmission Lines Using Artificial Neural Networks. *Int. J. Appl. Math. Comput. Sci.*, *14*(1), 69–78.

Chakraborty, R. C. (2010). *Fundamentals of Neural Network: Soft Computing.* Retrieved from http://www.myreaders.info/html/softcomputing.html

Das, R., & Novosel, D. (2000). *Review of fault location techniques for transmission and sub-transmission lines.* Georgia: Proceedings of 54th Annual Georgia Tech Protective Relaying Conference.

Leite, D. F., Hell, M. B., Costa, P., & Gomide, F. (2009). Real-time fault diagnosis of nonlinear systems. *Nonlinear Analysis, Theory, Methods and Applications*, *71*(12). https://doi.org/10.1016/j.na.2009.06.037

Patrick, D. R., & Fardo, S. W. (2009). *Electrical Distribution Systems* (2nd ed.). The Fairmont Press, Inc.

Peter, O., Oluwaseun, S., & Ayokunle, A. (2018). FAULT IDENTIFICATION SYSTEM FOR ELECTRIC POWER TRANSMISSION LINES USING ARTIFICIAL NEURAL NETWORKS, *9*(2), 678–685.

Phyo Thwe, E. (2016). Fault Detection and Classification for Transmission Line Protection System Using Artificial Neural Network. *Journal of Electrical and Electronic Engineering*, *4*(5), 89. https://doi.org/10.11648/j.jeee.20160405.11

Saha, M. M., Das, R., Verho, P., & Novosel, D. (2002). Review of Fault Location Techniques for Distribution Systems. *Proceedings of Power Systems and Communications Infrastructure for the Future Conference.* Beijing.

Saha, M. M., Izykowski, J., & Rosolowski, E. (2010). Fault Location on Power Networks. *Springer publications*.

Santos, R. C. Dos, & Senger, E. C. (2011). Transmission lines distance protection using artificial neural networks. *International Journal of Electrical Power & Energy Systems, 33*(3), 721–730. https://doi.org/10.1016/j.ijepes.2010.12.029

Singh, S., K R, M., & S, T. (2014). Intelligent Fault Identification System for Transmission Lines Using Artificial Neural Network. *IOSR Journal of Computer Engineering*, *16*(1), 23–31. https://doi.org/10.9790/0661-16112331

Swarup, K. S., & Chandrasekharaiah, H. S. (1991). Fault detection and diagnosis of power systems using artificial neural networks. *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems*, 3442–3446. https://doi.org/10.1109/ANN.1991.213505

Tarafdar Haque, M., & Kashtiban, A. (n.d.). Application of Neural Networks in Power Systems; A Review.

William, P. D. (2012). *Analysis of Faults in Overhead Transmission Lines. Masters Theses.* Sacramento: Electrical and Electronic Engineering Department, California State University.

Yadav, A., & Dash, Y. (2014). An Overview of Transmission Line Protection by Artificial Neural Network : Fault Detection , Fault Classification , Fault Location , and Fault Direction Discrimination, *2014*, 1–20. https://doi.org/10.1155/2014/230382