International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V71I2P245

Volume 71 Issue 2, 440-449, February 2023

Original Article

Application of ANN-Based Approach for Fault Location in Extra High Voltage Networks

Saurabh S. Shingare[1], Prabodh Khampariya[2], Shashikant Bakre[3]

[1,2]Department of Electrical Engineering, School of Engineering, SSSUTMS, Sehore, M.P. India
[1,3]Department of Electrical Engineering, AISSMS, Institute of Information Technology, Pune, India

[1]Corresponding Author: saurabhgcek@gmail.com

Received: 21 September 2022 Revised: 10 February 2023 Accepted: 18 February 2023 Published: 25 February 2023

Abstract *- The present paper is related to the application of an ANN-based approach for fault location in extra high voltage networks. Finding faults in extra high voltage networks is the focus of this research, and an ANN-based approach will be used to accomplish this. Using Neural Networks to locate transmission line faults is a dependable and appealing method, especially given the complexity of today's power transmission networks. Before deciding on a neural network architecture and learning approach, it is important to explore and analyze their benefits for a certain application. Each training component and performance indicator needs to give and take. When given a vast quantity of data for training, back propagation neural networks excel; hence these networks are employed throughout the fault-finding process, from initial detection through classification to final placement.*

Keywords *- ANN, Reliable, Fault location, Detection, Complexity*.

1. Introduction

Over the last several decades, the global power grid has seen fast expansion, resulting in the construction of many new transmission and distribution lines. Thanks to this growth, more electricity is now accessible to more people in more places. In addition, there has been an increase in the demand of end users for a consistent and continuous electric supply. They do not prefer interruptions in their electric supply as a result of the spread of new marketing concepts such as deregulatory policies. End users are very sensitive to power supply disruptions due to the proliferation of new marketing concepts like these. This has led to an increase in the need for reliable, round-the-clock access to electrical power.

A breakdown in the power system is one of the most significant problems that might develop and impair the constant transfer of energy and electricity. Any situation in which the power system's components experience an abnormal current flow is regarded as a power system issue. Because many of these problems stem from the forces of nature, people often find themselves helpless in the face of them. This makes it difficult to eradicate these problems completely. As a result, it is of the utmost importance to have a well-coordinated safety system that can detect any sort of aberrant current inside the power network. It should correctly localize the fault issue within the power system. Obviously, this is crucial. Repairing power system problem often falls on fault-detecting devices. They then cut off the faulty part of the power grid from the rest of the grid.

Therefore, among the most important difficulties in ensuring a constant energy supply are the detection, categorization, and localization of problems. The most prevalent kind of defect is a temporary one, followed by persistent ones, then symmetric ones, and lastly, asymmetric ones.There is no one-size-fits-all solution to fault localization that can be used for all of these different kinds of defects since the fault detection process differs so much from issue to problem. High Voltage Transmission Lines are more prone to encounter failure than local distribution lines due to the lack of insulation around the transmission line wires. This is due to the direct connection between the High Voltage Transmission Lines and the High Voltage Substations.

This is due to the direct connection of the high-voltage transmission line cables to the high-power substations. The formation of a fault on a transmission line may have been caused by a number of different occurrences, including short contact with a tree, interaction with a bird or animal, or natural phenomena like lightning or thunderstorms. In order to find any problems with a transmission line, a physical inspection might take anything from a few minutes to many. This is because transmission lines may be rather lengthy at times and may go across locations with diverse topography. This contributes to this issue. Consequently, most studies on protective relaying for power systems centre on fault protection for transmission lines. This is because transmission lines may span a broad variety of terrain, and their lengths can be very considerable.

2. Literature Survey

For the literature study point of view, we have selected some closely related research articles to our research, and they are as follows:

Adhikari S. et al. (2016) [1] used Compact Reconfigurable I/O (CRIO) devices in control technology and programmable automation. Using fuzzy logic, they applied this automation technology to detect and classify transmission line faults online. When CRIO, along with the LabVIEW software, are used, the real-time data capture of transmission lines may be accomplished. When a problem develops in the system, current waveforms are distorted as a result of transients, and the pattern of the distorted waveforms varies depending on the fault. Through the CRIO-9067, LabVIEW generates three phases of ac zero and positive sequence currents data, which are then processed and sent to the appropriate device. The results demonstrate that the suggested approach can perform proper tripping action and classify the kind of fault at high speeds. As a consequence, it may be used in a real setting.

Anh, T. T. (2018) [2] presented a new method using the classical artificial neural networks MLP (Multi-Layer Perceptron) in parallel with distance relays to correct the fault location estimation of the relay. There will be no other inputs to the solution other than the voltage and current signals at the beginning of the lines. The Alternative Transients Program is abbreviated as ATP. Similarly, the Electromagnetic Transients Program is abbreviated as EMTP. Both are used to create the training sample signals of the transient states. The numerical results will demonstrate that the method has assisted in lowering the fault location error from 0.92 percent to 0.42 percent.

Aung, K. et al. (2017) [4] applied methodology based on ANN in Myanmar for fault finding. [3]It was used on double-circuit Transmission lines for fault location and classification. The suggested approach detects and classifies defects using voltage and current information from each sector. An ANN can characterize nonlinear relationships between observed data by detecting their patterns. The adaptive protection method using ANN is evaluated for fault resistance and fault initiation angle. Once trained, the neural network provides reliable answers for a variety of system characteristics and scenarios. The test results show that the suggested approach is suitable for detecting and classifying faults on teed transmission circuits. It can increase the performance of standard fault section methods.

Bhupatiraju R. K. V. et al. (2018) [5] presented a three-phase fault classifier. It was accurate and the first of its kind. The previous approaches using phasors cannot fulfill the high-speed needs of current power networks. Transient-based systems employ powerful signal-processing techniques to identify faults quickly. The suggested approach uses fault-transients to promptly and accurately identify the fault. Previous methods failed due to fault-induced transient patterns with relay-measured signals. An efficient classification system is built considering results shown by examining fault transients. The approach contains a probabilistic neural network hybrid procedure to deal with transient fluctuations in fault inception angle and fault resistance. It is meant to solve the double-line-to-ground fault categorization issue. The suggested method's effectiveness is shown by thorough simulation experiments and comparisons.

Chang, H. H. et al. (2020) [6] proposed a novel nonintrusive fault-monitoring (NIFM) based method. They use the Hyperbolic S-transform (HST) to extract fault signals before identifying them. [7] This research uses power-spectrum-based HST to quantitatively modify HST coefficients reflecting transient fault signals and minimize input size for recognition algorithms (HSTCs). After feature selection, SVMs detect the fault-location indication (SVMs). The transient electromagnetic software simulates different failure types in a sample power system (EMTP). The simulation results show that the suggested approaches successfully locate faults in power transmission networks for NIFM applications.

Dwivedi, A. et al. (2019) [8] implemented a real-time algorithm. It can avoid the malfunctioning of distance relays during load increments. This supervisory method manages zone-3 of distant relays with the help of phasor data from PMUs spread throughout the power system network. Since PMUs convey information to the central control center more slowly than Zone-3 elements, the algorithm is suited for transmission line protection. In the System Protection and Control Centre, the suggested solution is validated by extensive real-time tests on a 400 km EHV transmission line laboratory model using an algorithmic approach. It uses NI Compact Reconfigurable Input-Output embedded controllers and LabVIEW field-programmable gate array software to implement PMUs. The experimental findings support the suggested algorithm's practicality for real-time implementation.

Ferreira V. H. et al. (2020) [9] proposed the autonomous neural model. This worked on the transmission line's one terminal electrical signals and information of fault on it. This model may give inference uncertainty. The detection model yields a false positive probability if a problem is probable. It offers probabilities for each class and an error margin around the projected short-circuit spot. Their study also extracts important information from oscillography to feed neural networks. Essai proposes a fast voltage and current. The experiments simulate real-world transmission line failures in Brazil's electrical grid. The approach works well with multi-terminal and series-compensated lines.

Gayathri, K., & Kumarappan, N. (2015) [11] developed a new algorithm as a highly flexible solution for problems by integrating two circuits under error conditions related to double-circuit transmission lines. The method was founded on six-line circuit currents and three-line voltages. It uses SVM with the recorded frequency characteristics of a +ve sequence voltage and current data. Pre-error conditions and error resistance are tested. The exactness of the method is checked using an error correction tool. The method's accuracy was assessed using SVM reconstruction in the first step. The next step uses single-line common-end current and voltage data. Their research introduces a new hybrid EHV error detection method that combines a SCALCG-based neural network algorithm and RBF-based SVM with recreated inputs. The proposed method minimizes error in the short term using both SVM-based RBF inputs and SCALCG-based sensor networks.

George N. et al. (2019) [12] proposed a novel machine learning-based reach element for zone-1 transmission line distance protection. The challenge is tackled using artificial neural networks as binary classification. The suggested approach uses voltage and current signals from the protected transmission line's local terminal. The superimposed three-phase voltages and currents are derived using a power cycle window moving average. The slope of the first rising edge and the rise time of the first peak following the fault are utilized for training the model and therefore predict the fault reach. In addition to fault kinds, pre-fault load flows, and source impedance-to-line impedance ratios, the suggested solution is evaluated for different fault scenarios. Zone-1 detection is accurate to 98.4% within 10 ms of a fault.

Ghorbani A. et al. (2020) [13] introduced a communication-assisted system to improve calculations of detection and location of fault for a transmission line compensated with TCSC. Only the remote end's current data is synchronously transmitted to the local end. The suggested technique requires less data transmission bandwidth than existing pilot impedance-based protection methods. In the proposed approach, the pre-fault situation and fault resistance are irrelevant. This technique does not use TCSC parameters in the resulting formula of the location of the fault. Hence TCSC parameter fluctuations do not influence the outcomes of the proposed method. Power swing circumstances and measurement errors are used to evaluate the suggested method's accuracy. The simulation shows the suggested scheme's great accuracy and speed in all fault conditions.

Hessine, M. B. et al. (2015) [15] provides an accurate high-speed protection algorithm based on ANN for estimating fault location on EHV transmission lines. This technique was developed using disrupted transmission line models. The suggested protection employs just 3-ϕ current signals at one end of the wire. The suggested approach includes fault detection, classification and fault localization. The samples of 3-ϕ, zero-sequence current components of pre and post-fault conditions are used for the process of detection and classification of the fault. Four ANN networks are used to locate faults. 3-ϕ current pre and post-fault magnitudes are employed. They are tested for several malfunctions, such as various fault sites, resistors and installation angles, using MATLAB software to validate their performance. The ANN-based classification and location of fault are very accurate for all tests. The simulation outcomes suggest that the given ANN-based technique may be employed for transmission line fault prevention.

Hessine, M. B. et al. (2015) [16] presented a novel algorithm for fault location in EHV transmission lines. Voltage and current at both ends of the post-fault are necessary to calculate the synchronization angle. In the first part, the synchronization angle is valued mathematically. Then the balanced and unbalanced fault locations are established. The suggested approach is unaffected by pre-fault measurements or fault states. The suggested algorithm's performance is evaluated using digital simulation in MATLAB. The suggested algorithm's simulation results show remarkable accuracy.

Jana, S., & De, A. (2017) [18] presented waveform provides an analysis-based approach for detecting and classifying short-circuit faults. The new zone identification system will be used to divide the large power network into ideal zones with various buses and lines. This reduced the computational stress of dealing with large amounts of waveform data. [17]The first module of ANN-based taxonomy was designed to achieve an "exploratory world search" for a faulty area, which was further enhanced by the second module of taxonomy to determine the exact "local search" in the zone. Wrong conditions and the like. Disturbance recorders installed at selected bus stops called "monitoring points" collect basic wave data. The extended Kalman filter feature implements abstraction, which is often the basic idea of any waveform analysis-based error-finding system. The indicated technology has been effectively verified with positive results on the IEEE 57 bus network.

Jiang, J. A. et al. (2018) [19] used long-term wind speed history data to determine types of areas that may be at risk for incorrectly measuring the temperature of the line in the DTR model. The researchers then developed a model to predict line temperature accurately. The case study shows that the projected model can efficiently measure wind speed in a particular region of the EHV network. The line temperature predicted by this technique may be used as a dependable orientation for the energy transfer approach, which is consistent with the findings.

Kalam, M. A., & Jamil, M. (2018) [20] proposed a new way to protect the EHV-AC transmission system by innovative use of DWT and abstract thinking via the discrete

Fourier transform (DFT) in the frequency-phasor. [10] As a result of the maintenance of this method in both the basic components and the current defective signals' high frequency, it is possible to obtain greater reliability and selective protection. Using an EHV-AC transmission system mathematical model, the findings were tested against the original data. It has been found that the planned procedure is more precise, humbler computerized, quicker, and legal in more general cases of error than in the literature.

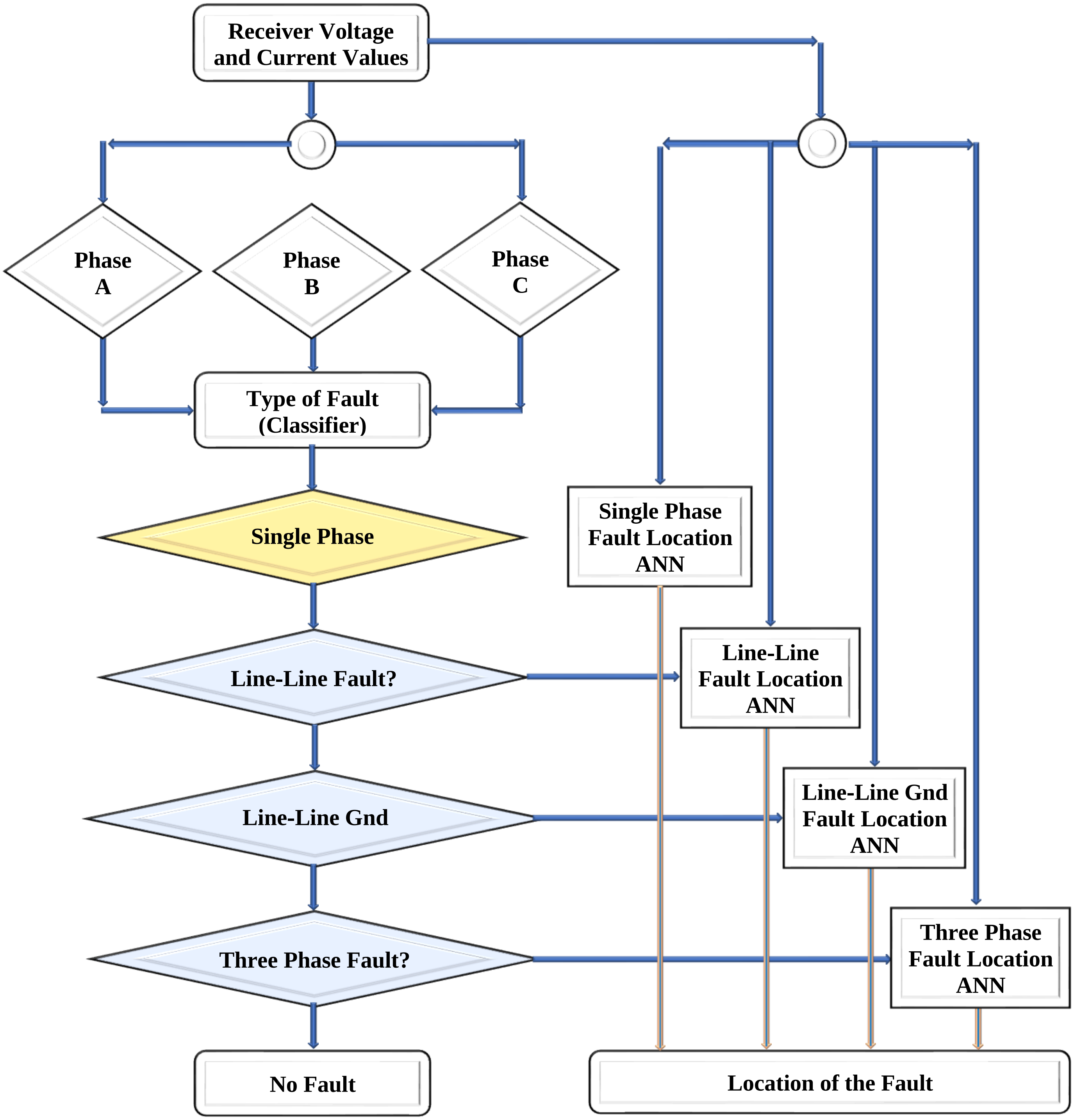

Fig. 1 Fault diagnosis strategy

3. Methodology

As shown in Fig.1, in this study, the primary objective is to design and develop a comprehensive method for fault identification. After this, we will test the method and finally implement it. Initial data collection and subdivision will be carried out on the full dataset. This set will be separated into the training and testing data sets. The initial phase in the procedure will be the identification of faults. The next step will be to categorize the problem depending on the phases that have been affected by the issue.

Neuronal networks will be used in this research to investigate if they can substitute traditional methods for detecting, classifying, and locating transmission line problems. Neuronal networks will be fed information on the pre-fault values of phase voltages and currents. This will be used to detect faults.

Many different types of faults may occur, including single line-to-ground faults, the line-to-lines, double-line-to-ground faults, and 3ϕ faults that should be considered in this study, and various for each of these issues, it has been recommended that ANNs be used. All of the neural networks explored in this study are based on the backpropagation neural network design described in detail below. With the help of artificial neural networks, it will be possible to design a fault location scheme for the transmission line system that will operate successfully from the point of detection of problems on the line to the point of fault placement. The simulation results produced will demonstrate that all of the suggested neural networks, taken as a whole, have attained sufficient performance.

4. Result and Discussion

4.1. Training the Neural Network to Locate Faults that Involve Three Phases

The feed-forward-back propagation method was used to locate three-phase faults in transmission lines. As was previously said, when provided with a large quantity of training data, these networks function well. In order to educate the neural network, numerous three-phase faults were included in the simulated transmission line. The fault distance (in 3 km increments) and the resistance were both modified. For each of the eight possible resistances, the simulation was executed a hundred times (0.25, 0.5, 0.75, 1, 5, 10, 25, and 50 ohms). That is why 800 transmission line issues were simulated. In each illustration, information about voltage and current is sent into the neural network from each of the three phases. Terminal A's neural network output is the fault distance value. Each input-output pair in a neural network consists of six inputs and one output. Numerous permutations of hidden-layer count and neuron density were tested in order to determine the optimal parameters for evaluating neural networks. First, the reader is presented with a selection of neural networks that exhibit acceptable error performance. Comparison of Outputs and Goals via Mean Square Error, The best-performing ANN model, is chosen using regression.

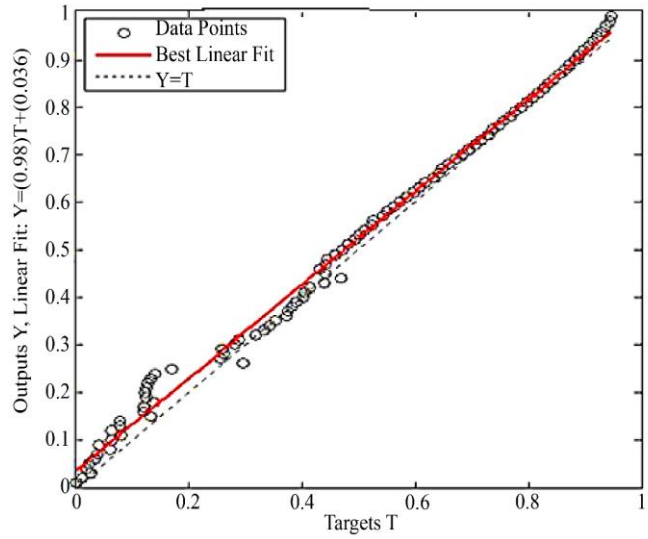

Fig. 2 Regression: ANN's Output versus Targets with Configuration (6-21-10-1)

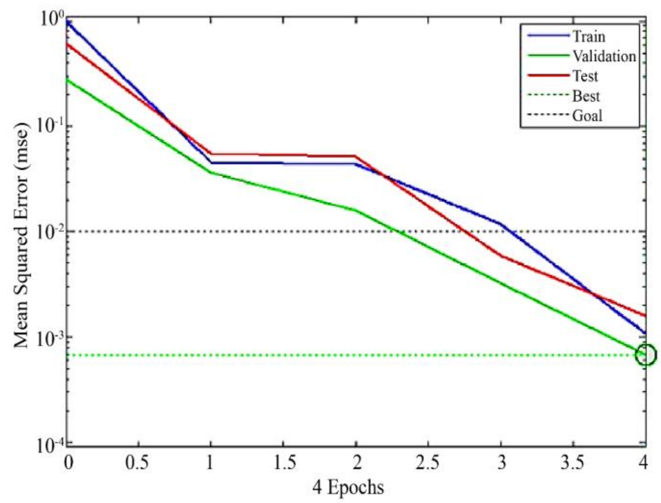

Fig. 3 MSE Neural Network Performance with Configuration (6-21-10-1)

As shown in Fig.2, with 6 neurons in the input layer, 21 neurons in the 1st hidden layer, 10 neurons in the 2nd hidden layer, and 1 neuron in the output layer, the best linear regression fit between the outputs and the targets. One may count twenty-one neurons in the network (6 - 21 - 10 - 1). The correlation coefficient, also known as r, is a statistic that represents the degree to which the outputs and the objectives of the neural network are connected to one another. As was said before, the correlation coefficient may also be written as r. As the value of r approaches 1, it is hypothesized that the effectiveness of the neural network will improve. The correlation coefficient, r, was calculated to be 0.9970 in this study.

Fig.3 illustrates the training, testing, and validation outcomes for a neural network that had the following configuration: There are ten neurons in the output layer, six neurons in the input layer, and a total of twenty-one neurons throughout the two hidden layers (6 - 21 - 10 - 1). The dashed green line in the graph clearly demonstrates that the best possible MSE performance can be achieved with this neural network. The MSE target was set at 0.01. Thus, this value is below that to indicate a lesser standard error (denoted by the black line).

In order to assess the transmission line's reliability, a series of twelve simulated three-phase faults were introduced into the system. Each time the simulations were repeated with an increment in the distance of the fault higher by 25 kilometres. The error rate of the ANN was calculated. Here (Fig.4), you can see the outcomes of the neural network analysis (6-21-10-1). The greatest margin of error is clearly more than 3%, which is probably considered pretty good. Nonetheless, more sophisticated neural networks are much sought.

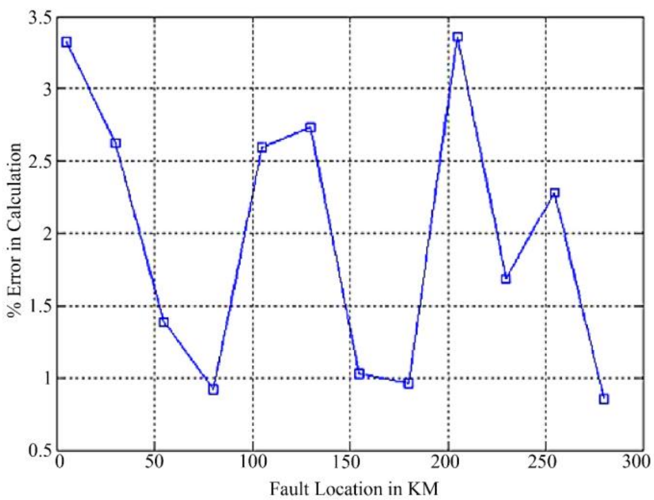

Fig. 4 (6-21-10-1) Configuration ANN Test Phase Performance

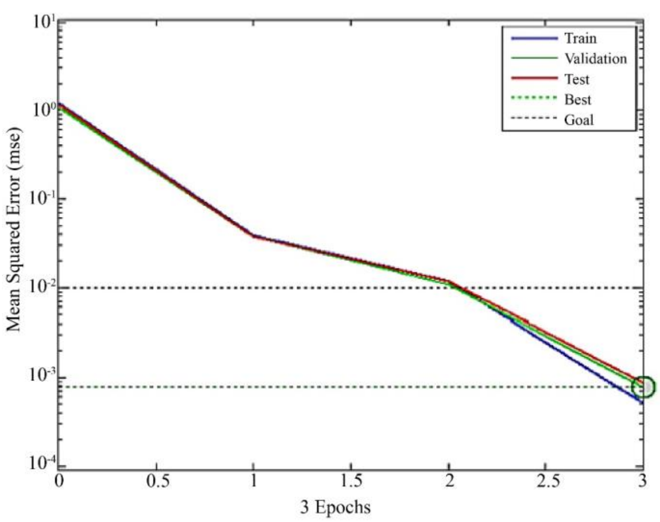

Fig. 5 MSE Neural Network Performance with Configuration (6-21-1)

Fig.5 displays the outcomes of our training, testing, and validating the neural network using the below configuration. Six neurons are found in the input layer. Another 21 in the hidden layer and a single in the output layer. This (6-2-1) neural network has a maximum mean squared error performance of 0.00075875 (shown by the dashed green line). This is much lower than the target MSE value of 0.1. (denoted by the black dotted line).

This network has an input layer consisting of 6 neurons. A hidden layer has twenty-one neurons. An output layer has a single neuron. The top linear regression fit between the network's outputs and objectives is shown in Fig.6. (6-21-1). As was previously noted, the correlation coefficient, also known as r, is a statistic that reflects the extent to which the neural network is related to the outputs and the goals. It is hypothesized that when the value of r gets closer to 1, the neural network's performance would improve in a directly proportional way. Specifically, r was calculated to be 0.98904, which is more advanced than the prior value (6-21-10-1).

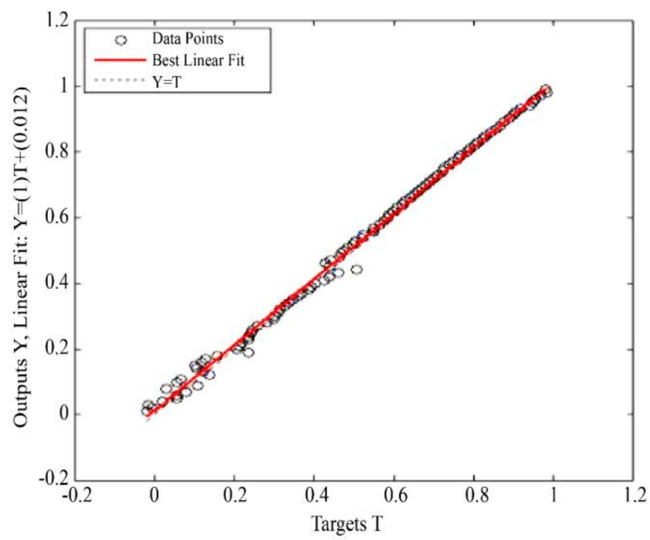

Fig. 6 Regression for ANN's Output versus Targets with Configuration (6-21-1)

In order to assess the transmission line's reliability, a series of twelve simulated three-phase faults were introduced into the system. The simulations were run many times, and on each iteration, the distance of fault being raised by 25 kilometres. The ANN's error rate was determined after each run. The outcomes of the neural network study are shown in Fig.7, which may be viewed here (6-21-1). A 3 percent mistake rate, a huge improvement over the previous case, is clearly visible. To illustrate this, a 90-degree rule may be quite helpful.

With one neuron in the output layer, six in the input layer, and three hidden layers consisting of a total of six, twenty-one, and sixteen neurons, respectively, as shown in Fig.8, the top linear regression fit may be achieved between the network's outputs and its goals (6 - 6 - 21 - 16 - 1). As was previously noted, the correlation coefficient, also known as r, is a statistic that reflects the extent to which the neural network is related to the outputs and the goals. It is hypothesized that when the value of r gets closer to 1, the neural network's performance would improve in a directly proportional way. In this case, r was calculated to be 0.99897, which is quite near the value of 1.

The performance of this network was evaluated by simulating a total of 100 distinct three-phase failures on the transmission line. All situations in the simulation had the fault distance increased by 10 km, and the ANN's accuracy was measured after each iteration. Fig.9 for an illustration of the neural network study findings (6-6-21-16-1).

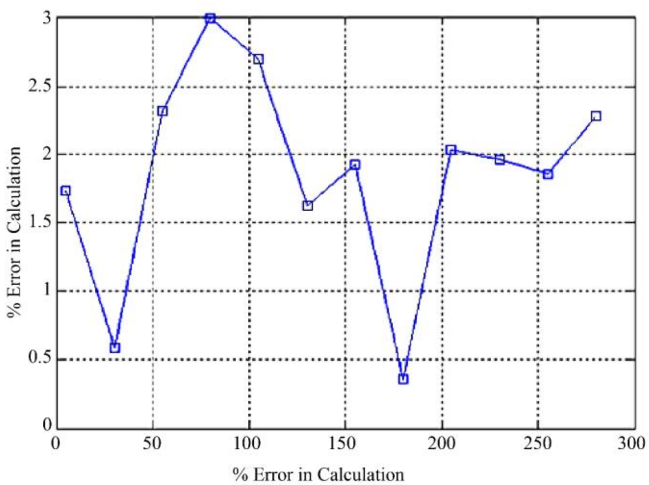

Fig. 7 (6-21-1) Configuration ANN Test Phase Performance

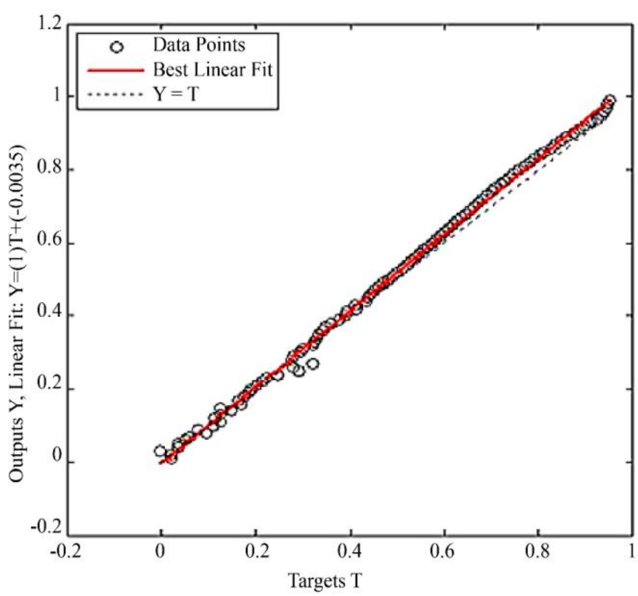

Fig. 8 ANN's Output versus Targets (6-6-21-16-1)

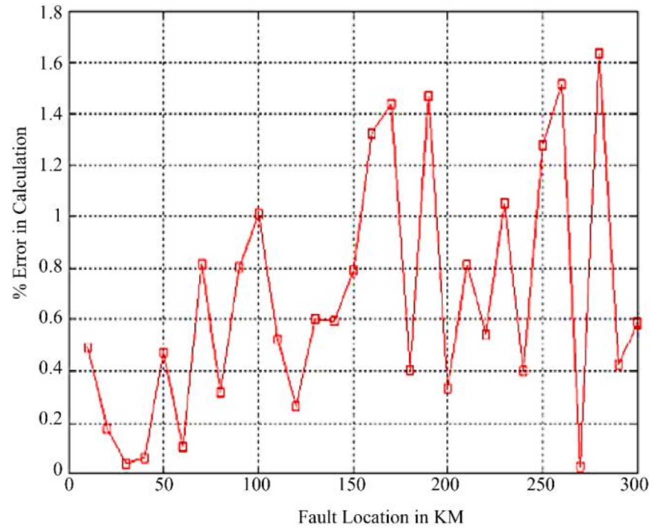

Fig. 9 Test Phase Performance of the ANN (6-6-21-16-1)

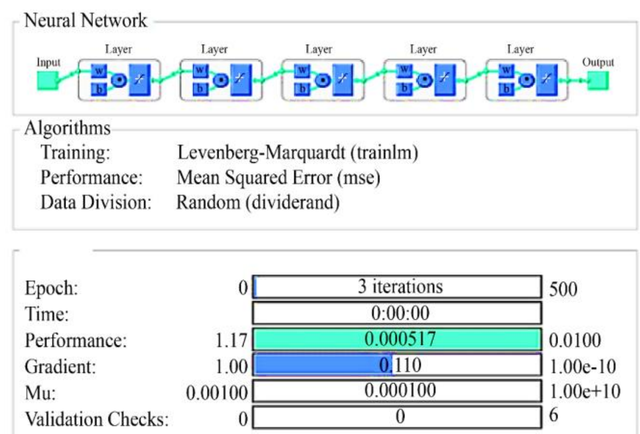

Fig. 10 Overview of Three-Phase Fault Location Neural Network

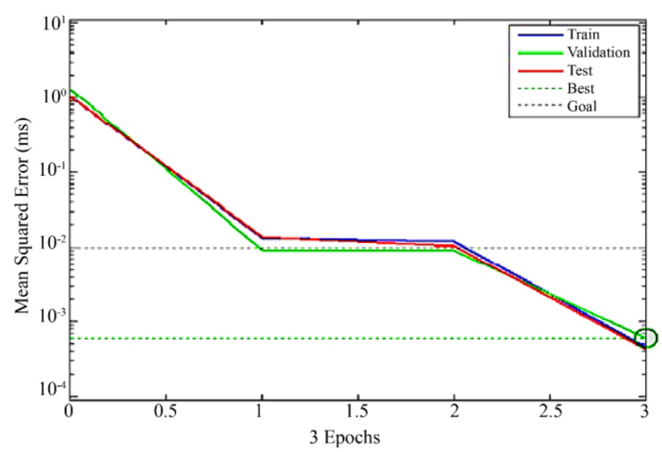

Fig. 11 Neural Network Mean Square Error (6-6-21-16-1)

Sentence 92 reveals that the range of the most important inaccuracy is 1.62 percent, which is quite a high percentage. It is worth noting that the standard deviation does not even include the 0.677% error introduced by the fault location estimate. You are being made aware of this fact. This is why this neural network is ideal for detecting three-phase faults in transmission lines. The following considerations led to the selection of this option: Fig.10 presents an overview of the trained ANN, and it can be observed that the Levenberg-Marquardt approach was used for the training process. The data-derived mean square error was chosen as the performance function for the training process.

The results of training, testing, and validating the neural network with the following configuration are shown in Fig.11: six neurons in the input layer, one hidden layer comprising twenty-one neurons, and one neuron in the output layer (6 - 6 - 21 - 16 - 1). Comparing the outcomes of the training and testing stages were used to validate the model. The maximum MSE performance of this neural network is 0.00060607, which is well below the target MSE value of 0.1, as shown by the green dotted line (denoted by the black dotted line).

4.2. Three-stage neural network testing for defect localization

After the neural network has been competent, we go on to the testing phase, where we look at the network's output to see how well we did. In this section, we will go through the methods and procedures that were used to put this neural network through its paces during testing. The test phase performance plot is shown in Fig.11 and is an integral aspect of the network testing process. This diagram helps assess the network's performance. The network's performance is adequate since both the average and maximum fault percentages in pinpointing the source of the problem are well within the acceptable range. Both of these error rates are much below what would be considered problematic. This may be deduced by observing that both of these error rates are well within the range of what is deemed to be reasonable.

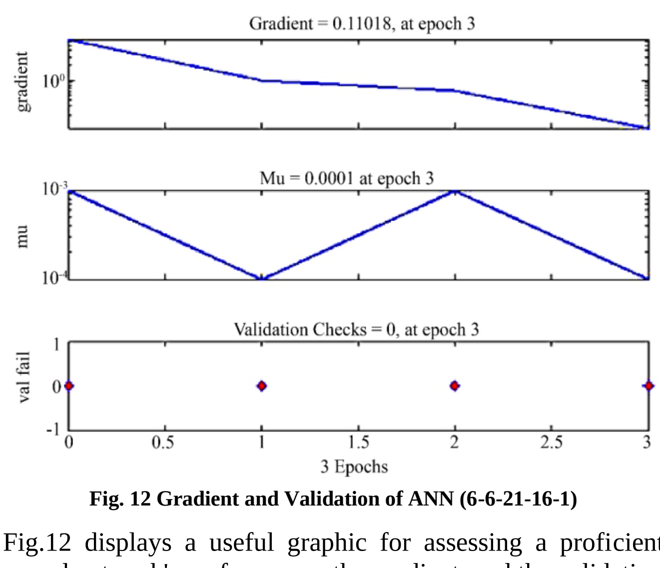

Fig. 12 Gradient and Validation of ANN (6-6-21-16-1)

Fig.12 displays a useful graphic for assessing a proficient neural network's performance, the gradient, and the validation performance plot. This is a crucial strategy that must not be disregarded. Observe this graph in Fig.14. When training is complete, the largest number of failed validations is zero, and the gradient is shown to be lowering consistently and smoothly. Both of these findings may be seen with the naked eye. One needs to look at the number 95 to see that this is true. Since the validation step immediately follows the test phase, any validation failures indicate a job well done during training. The validity of this reasoning is further supported by the data shown in Fig.13, which compares test and validation curves. This bolsters the argument that the neural network can generalize more of the fresh data being fed into it.

Thirdly, the correlation coefficients between the various training, validation, and testing phases are considered while evaluating the network's efficiency. In order to gauge the network's efficiency, this is done. Fig.13 shows the regression plots produced throughout the procedure's training, testing and validation stages. With a correlation value of 0.99329, the best linear fit is very congruent with the model case. This may be demonstrated by calculating the total correlation value of the linear fit. This is something that can be seen in real life. Fig.14 depicts the ANN architecture used for the investigation of three-phase faults. The input layer of this ANN consists of 6 neurons, the hidden layer of this ANN contains 21, and the output layer consists of 1 neuron.

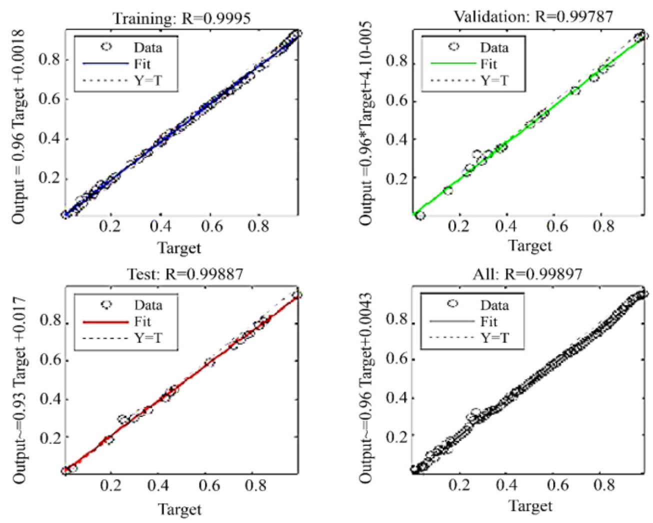

Fig. 13 Regression Plots of ANN's Various Learning Phases (6-6-21-16-1)

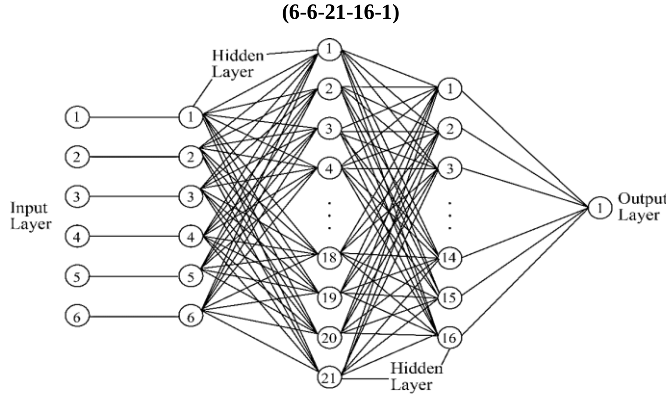

Fig. 14 (6-6-21-16-1): Chosen ANN's Structure

Table 1. ANN Chosen Percentage Errors as a Function of Fault Distance and Fault Resistance for Three-Phase Fault Location

Sr. No:	% Error vs. Fault Distance (Fault Resistance = 20Ω)			% Error vs. Fault Distance (Fault Resistance = 60Ω)		
	Fault Distance (km)	Measured Fault Location	Percentage Error	Fault Distance (km)	Measured Fault Location	Percentage Error
1	25	25.51	0.17	50	51.41	0.47
2	75	75.17	0.057	100	103.03	1.01
3	125	125.52	0.28	150	152.37	0.79
4	175	175.69	0.23	200	201.99	0.63
5	225	225.46	0.1533	250	253.84	1.28

Table 1 shows the proportion of inaccuracy in fault localization as a function of fault distance and fault resistance. The table contains these errors.

Next to each other in the table are columns that show data for two different fault resistance values-20, ohms and 60 ohms. It is important to note that 20-ohm resistance was included in the training data set. This directly contributes to the fact that the mean percentage of mistakes in fault detection is just 0.178 percent in this instance. In the second example, the same thing occurs, except this time, the fault resistance is set to 60 ohms. This resistance is not included in the training plan, but it is exceedingly challenging in comparison to the rest of the program. Because of this, the results achieved by the neural network in this scenario illustrate its adaptability and generalizability. To be clear, even with a standard deviation of 0.836%, this result is still within the realm of possibility when it comes to being deemed acceptable. Due to this, the neural network's performance has been deemed adequate, making its usage for defect identification within a three-stage procedure a real possibility.

5. Conclusion

This paper presents a novice Artificial Neural Network (ANN) based approach for fault detection and location in EHV transmission networks. For this purpose, the measured values of fault distance are compared with standard values or targeted values. In order to achieve the accurate value of fault distance, the ANN model is developed using which number of iterations are undergone. Initially, as the ANN is not trained, the execution is slower. However, as the network gets trained, it becomes faster. The error between the standard value and the predicted value is found. The error is minimized through backpropagation through the number of iterations. The methods used in backpropagation are Gradient Descent and Chaining. The convergence is obtained when the error approaches zero. The method is superior to conventional fault detection methods such as numeric relay, Event Sequence Recorders (ESR), Tauras fault detection and conventional layouts. The proposed method is novel, feasible, simple, accurate and cost-effective.

Acknowledgment

The author would like to express his gratitude to his research guides, Professor Dr. Prabodh Khampariya of the Department of Electrical Engineering at the Satya Sai University of Technology and Medical Sciences in Sehore, M.P., and Professor Dr. Shashikant M. Bakre of the AISSMS Institute of Information Technology, Pune for their technical assistance.

References

[1] Shuma Adhikari, Nidul Sinha, and Thingam Dorendrajit, “Fuzzy Logic Based on-Line Fault Detection and Classification in Transmission Line,” *Springer plus*, vol. 5, no. 1, pp. 1-14, 2016. *Crossref*, https://doi.org/10.1186%2Fs40064-016-2669-4

[2] Tuan Anh Truong, “Integration of Neural Network and Impedance Based Relay to Improve the Shortage Fault Localization on a Transmission Line,” *Journal of Science and Technology,* vol. 185, no. 8, 2018.

[3] Tripathi Atuldev Ashok, and S. R. Deshmukh, "Comparative Study of Methods of Identification of Fault Location in Transmission Line," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 4, no. 7, pp. 32-36, 2017. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V4I7P107

[4] Koko Aung, Soe Soe Ei Aung, and Zeya Oo, “Fault Location: Classification and Detection of Extra High Voltage Transmission Line in Myanmar by Using Artificial Neutral Network Application,” *International Journal of Industrial Electronics and Electrical Engineering,* vol. 5, no. 5, pp. 25-30, 2017.

[5] Ravi Kumar Varma Bhupatiraju et al., “Transient-and Probabilistic Neural Network-Based Fault Classification in EHV Three-Terminal Lines,” *Turkish Journal of Electrical Engineering & Computer Sciences*, vol. 26, no. 2, pp. 974-986, 2018. *Crossref*, https://doi.org/10.3906/elk-1611-172

[6] Hsueh-Hsien Chang, Chuan-Choong Yang, and Wei-Jen Lee, “Fault Location Identification in Power Transmission Networks: Using Novel Nonintrusive Fault-Monitoring Systems,” *IEEE Industry Applications Magazine*, vol. 27, no. 2, pp. 76-89, 2021. *Crossref*, https://doi.org/10.1109/MIAS.2020.3024493

[7] N. Priya et al., "Fault Detection and Location in Power Transmission Lines Using Labview," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 8, no. 9, pp. 1-4, 2021. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V8I9P101

[8] Anmol Dwivedi et al., “A Real-Time Synchrophasor-Based Zone-3 Supervision of Distance Relays Under Load Encroachment Condition,” *IEEE Systems Journal*, vol. 13, no. 14, pp. 4227-4235, 2019. *Crossref*, https://doi.org/10.1109/JSYST.2018.2890475

[9] Vitor H. Ferreira et al., “Probabilistic Transmission Line Fault Diagnosis Using Autonomous Neural Models,” *Electric Power Systems Research*, vol. 185, p. 106360, 2020. *Crossref*, https://doi.org/10.1016/j.epsr.2020.106360

[10] K. Pranathi, G. Ravi Kumar, and J. S. S. Aditya, "Fault Analysis on Multi-Terminal System Using Wavelet Transform and Wavelet Morphing Technique," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 8, no. 6, pp. 28-37, 2021. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V8I6P105

[11] Gayathri, K, and Kumarappan, N, “Double Circuit EHV Transmission Lines Fault Location with RBF Based Support Vector Machine and Reconstructed Input Scaled Conjugate Gradient Based Neural Network,” *International Journal of Computational Intelligence Systems*, vol. 8, no. 1, pp. 95-105, 2015. *Crossref*, https://doi.org/10.1080/18756891.2014.967007

[12] Neethu George et al., “Machine Learning Based Setting-Free Reach Element for Zone-1 Distance Protection,” *2019 8th International Conference on Power Systems (ICPS)*, pp. 1-5, 2019. *Crossref*, https://doi.org/10.1109/ICPS48983.2019.9067658

[13] Amir Ghorbani et al., “A Pilot Protection Algorithm for TCSC Compensated Transmission Line with Accurate Fault Location Capability,” *International Journal of Electrical Power & Energy Systems*, vol. 122, p. 106191, 2020. *Crossref*, https://doi.org/10.1016/j.ijepes.2020.106191

[14] M. Usharani et al., "An Optimized Deep Learning Model Based PV Fault Classification for Reliable Power Generation," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 9, pp. 23-31, 2022. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V9I9P103

[15] Moez Ben Hessine, Houda Jouini, and Souad Chebbi, “Neural Network Approach to Fault Location for High Speed Protective Relaying of Transmission Lines,” *Computational Intelligence Applications in Modeling and Control*, vol. 575, pp. 283-314, 2015. *Crossref*, https://doi.org/10.1007/978-3-319-11017-2_12

[16] Moez Ben Hessine, Sahbi Marrouchi, and Souad Chebbi “An Accurate Fault Location Algorithm for Transmission Lines with Use of Two-End Unsynchronized Measurements,” *2015 IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC)*, pp. 1345-1350, 2015. *Crossref*, https://doi.org/10.1109/EEEIC.2015.7165365

[17] Jyothi.Remidala, and Neelima, "ANN Based Hybrid TCSC for Damping Inter-Area Oscillations," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 1, no. 9, pp. 5-10, 2014. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V1I9P108

[18] Subhra Jana, and Abhinandan De, “A Novel Zone Division Approach for Power System Fault Detection Using ANN-Based Pattern Recognition Technique,” *Canadian Journal of Electrical and Computer Engineering*, vol. 40, no. 4, pp. 275-283, 2017. *Crossref*, https://doi.org/10.1109/CJECE.2017.2751661

[19] Joe-Air Jiang et al., “Impact Assessment of Various Wind Speeds on Dynamic Thermal Rating of the Terrain-Located EHV Power Grids: A Case of Valley in Taiwan,” *IEEE Access*, vol. 6, pp. 48311-48323. *Crossref*, https://doi.org/10.1109/ACCESS.2018.2866593

[20] Md. Abul Kalam, and Majid Jamil, “Wavelet-Fuzzy-Based Protection Scheme of EHV-AC Transmission System and Efficacy of Discrete Fourier Transform,” *Journal of Electrical Systems and Information Technology*, vol. 5, no. 3, pp. 371-387, 2018. *Crossref*, https://doi.org/10.1016/j.jesit.2018.02.006