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Efficient Fault Detection and Location in Extra High Voltage Networks: An Artificial Neural Network (ANN)-Based Approach

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Abstract: This paper focuses on the use of ANN to detect and locate faults in Extra High Voltage (EHV) network. For each phase in the fault location process, backpropagation algorithms and feedforward networks have been used. Many ANNs have been proposed for each of the many types of faults that might occur, including LG, LL, LLG, and 3ϕ faults. To support the selection of the neural networks in each phase, analysis on neural networks with different numbers of hidden layers and neurons per hidden layer has been provided. The simulation results show that the ANN-based strategy was effective in finding transmission line problems and achieving good outcomes.

Keywords: *ANN, EHV, Fault Location, Detection, Backpropagation*

1. Introduction

The fast development of the world power grid in recent decades has necessitated the building of numerous distribution and transmission lines. Due to this expansion, end consumers now need an uninterrupted and reliable supply of electricity. These customers are very sensitive to power supply outages because of the advent of deregulatory policies. Consequently, need for continuous and reliable electrical power supply is growing. It is challenging and difficult to eliminate power system breakdowns completely. Therefore it is very important to develop a super safety system with capability of detecting and classifying faults in power networks. Many faults require specialized localization method which different detection devices are not capable for. Failure in case of EHV transmission lines are due to nonexistence of insulation around the transmission lines and also these lines are directly connected to substations. Various factors such as contact with trees, animals, lightning, or thunderstorms are responsible for faults on transmission lines. Physical inspections of transmission lines are time-consuming due to diverse geographical locations and their lengthy nature. In recent times, neural networks approach proves their importance in abnormalities on transmission lines. In the late 1980s and early 1990s, application of neural networks ongoing attractive widespread. Typically, neural networks are applied to enhance defect detection, classification, and localization processes.

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2. Literature Survey

Leh, N. A. M., et al. (2020) [1] presented a designed method based on an Artificial Neural Network (ANN) to enhance power system quality. This method detected and categorized the faults accurately. In their study the tested a 14-bus system in MATLAB by executing a feed-forward ANN with the backpropagation algorithm. MSE, confusion matrix and linear regression are used to evaluate the system performance. Impressively this achieved 100% accuracy rate in fault detection. Also 70% accuracy achieved in classification of fault with suitable correlation values.

Tayeb, E. B. M. (2013) [2] introduced a novel distance protection scheme in power lines to detect fault with the framework featured zones of neural network. In this method backpropagation (BP) algorithm is used to analyze the faults, including LG, LL, and LLG faults. For experimentation different softwares like Neuroshell software, Power System Block Set and MATLAB simulation was used. The scheme gives the very accurate and fast results to give support to use of BPNN architecture.

Ben Hessine, et al (2014) [3] introduced specific algorithm based on ANN for location and classification of fault. This involved design and development of modular ANN based fault locator. Evaluation under various fault location conditions with wide range of fault resistances and inspection angles are done with this algorithm. This shows its superiority and high performance over remaining algorithms by 0.0175% and 0.3041%. The response time is reduced to one cycle from occurrence of fault. This proved that, the presented modular AMM-based algorithm to detect the fault location is very accurate.

Nag, A., & Yadav, A. (2016) [4] focused on overhead transmission lines and underground cable fault detection with ANN. For fault analysis they considered zero sequence current component, sending end current and voltage, cable parameters. Levenberg Marquardt algorithm was utilized to supervise ANN training with collected data. Variation in fault inception angles and fault resistance are explored for different fault conditions. The simulation results proved high accuracy and performance in classifying faults in overhead transmission lines and underground cable.

Gayathri, K., & Kumarappan, N. (2015) [5] designed an innovative algorithm for double circuit transmission lines fault detection. This algorithm focused on considering two circuit mutual coupling during faults. Support Vector Machine (SVM) and measured single-end positive sequence current and voltage system signals are utilized in proposed algorithm. The hybrid combination of SVM based on Radial Basis Function (RBF) with reconstructed input and NN method based on Scaled Conjugate Gradient (SCALCG) utilized for EHV lines fault location. In MATLAB testing of a 400kV and 150km line average fault location error was done. In worst case maximum error of 1.852km and in best case error of 7.874e-003 km occurred in fault location in double circuit. A 4% error occurs with outperforming SVM fault location. An efficient and highly accurate hybrid approach of combining SVM and neural network methods was demonstrated effectively.

Karić, A., et al. (2018) [6] focused on modeling the WSCC 9-bus test system in Matlab/Simulink for fault analysis with ANN. In this investigation they utilized backpropagation algorithm with trained feed-forward neural networks. The researchers experimented with the number neurons per hidden layer and hidden layer number in the network to enhance network performance. It is found that neuron numbers in the hidden layer was varying with fault types. Hidden layer with 5 neurons was enough for LG faults. However, hidden layer with a minimum of 10 neurons gives acceptable results for two-phase and two-phase-to-ground faults. In case of three-phase faults, the hidden layer with 30 to 35 neurons was sufficient. The results did not get any noteworthy improvement for further increase in neurons per hidden layer. It gives idea about alteration in network architecture for optimal performance in fault detection.

Pattanayak, R. et al. (2019) [7] introduced ANN to achieve reliable and rapid detection and classification of fault in a hybrid power system. Here they used a feed-forward neural network with the backpropagation algorithm. They trained network with instantaneous current and voltage values. The developed intelligent system was effectively classify faults through simulation with performance assessment based on MSE. The results gave the accuracy with enhanced features and training the network with more fault classification cases. It gave quick and specific fault classification for power supply stability and maintenance.

Asbery, C. W., & Liao, Y. (2020) [8] focused on classification and location of fault with ANN on single two-terminal transmission lines. This study introduced approach of utilizing multiple single hidden layer neural networks in suggested modular ANN to estimate the fault type. For reliable fault type and fault location estimation it determined the essential amount of training data. Simulated results highlight the specific neural network structures for most accurate results. 24 neurons for fault classification and 27 neurons for fault-location ANNs For voltage phasors, ANN produced reliable results. Each fault location ANN has 33 neurons, while the fault classification ANN has 24 neurons. This achieved most accurate results with current phasors. It showed reliability and effectiveness in fault analysis power transmission systems.

Halim, H. (2015) [9] demonstrated ANN application for location of fault in extra high voltage (EHV) series compensated transmission lines. The network was thoroughly tested using MATLAB software on a 400-kV, 300-km transmission line. Various power system data such as voltages, currents, capacitances, time constants, angles are incorporated in this algorithm. Experimental results gave 0 to 0.016% error which was very low in most cases. The outcomes of the proposed fault locator algorithm showcased robustness and precision.

Sousa, J. C., et al. (2019) [10] introduced Traveling Waves based fault location technique for Smart Grid. MATLAB is used to process the data obtained from the Grid using a bench oscilloscope. This algorithm utilized identified peak signals and analyze fault regions to calculate distance of fault. Wavelet transform was used to arrest frequencies of the relevant Traveling Wave. Moreover, to identify the fault occurred they measured a Clarke transformed signal mode delays. The researchers empirically determined various parameters such as Wavelet decomposition levels, ground thresholds, and peak detection constants in the method. The proposed method was fully automated and accurate.

Bhupatiraju, R. K. V., et al. (2018) [11] introduced a new innovative approach to classify fault in three-terminal transmission circuits. This effective and rapid fault classification algorithm involves transient patterns thorough analysis. Wavelet transform was used to process post-fault voltage signal’s quarter-cycle. In targeting double-line-to-ground fault classification, a probabilistic neural network to handle the impact of fault resistance (Rf) and fault inception angle (FIA) on transient variations was employed in this approach. Accuracy of 100% was achieved for LG, LL, and LLL faults, and for LLG faults accuracy was 99.59%. The influence of FIA and Rf was effectively addressed by this method.

Khoudry, E., et al (2020) [12] introduced a real-time intelligent SFDS to provide rapid transmission line protection. To achieve its objectives effectively, SFDS integrates machine learning algorithms with traveling wave theory and advanced signal processing techniques. This accurately differentiate between external and internal faults with fault type identification. It also specify location of faults and estimate fault inception time within the system. To identify fault signals, it used a differentiator-smoother filter with peak detection and it utilized impedance angle estimation for discrimination of fault. Traveling wave theory principles was used to estimating the fault inception time. The K-Nearest Neighbors (KNN) algorithm and the Genetic Programming (GP) algorithm were used to fault classifier and fault locater respectively. The significant advantage of this method is its rapid fault diagnosis and performance with low test error.

Alashter, M. A., et al. (2020) [13] introduced an intelligent approach to detect, classify and locate faults on transmission lines using ANN based simulation model of distance relay. In this a three layer FF network with BP algorithm design was employed. Most suitable network was provided for fault identification block, fault classification block and fault location block of distance relay. Considering different fault types, phase currents and voltages were used as inputs to the neural networks. Prominent advantage of ANN based relay model is that it need not require impedance calculation, current, and voltage for setting, ease to implement and use. Also it is more accurate in fault analysis.

Kapoor, G. (2020) [14] proposed a novel application for determination of location of fault using discrete wavelet transform (DWT) in three-phase transmission lines. At both ends of the transmission line current measurements were taken. From this measurements DWT coefficients was obtained. MATLAB simulation was used to study behavior of transmission line under fault condition. A 50Hz, 400kV, 3ϕ line with a 300km distance was considered for simulation. This study discovered the outcomes of varying fault parameters to cover different system situations. The proposed DWT-based technique showed accurate determination of fault location and proved durability against variations in fault types.

Sahoo, B. K., et al. (2020) [15] proposed a deep learning model to identify symmetrical and unsymmetrical faults in transmission lines. MATLAB Simulink model used to collect phase currents. Python programming language was employed to use this data for training and testing of ANN. They got impressive fault detection technique as a result of this algorithm. The authors recommended Convolutional Neural Network (CNN) for better outcome. This technique provide easier cost effective maintenance of transmission line. Also this model provides more accuracy in detection of symmetrical and unsymmetrical faults.

Liu, X. W. (2021) [16] introduced a new approach to enhance the accuracy of location of traveling wave fault on transmission lines. The proposed method of fault verification and analysis combined the ant colony algorithm and the Radon transform algorithm. This approach addressed the limitations of traditional traveling wave fault location methods such as low accuracy. In addition with this the approach point out different challenges posed by various factors that can impact on identification of fault in power transmission systems. As an outcome, a more robust and dependable fault location technique is provided by the proposed approach. This improved fault identification accuracy.

Wadi, M., & Elmasry, W. (2021) [17] introduced an anomaly-based approach as a technique to detect a fault in electrical power systems. Principal Component Analysis (PCA)-based model and One-Class Support Vector Machine (SVM) model was employed by this approach. The Technical University of Ostrava recorded the VSB Power Line Fault Detection dataset from Kaggle. This real-time waveform data is used to train and test the models. There was limited access to real-time datasets of detection of electrical faults as the samples can be rare and costly. So an anomaly-based technique that creates a profile for normal samples and then detects any deviations from this profile was proposed to overcome this limitation. The experimental results of proposed technique in detection of fault provided approximately 80% for both PCA-based models and one-class SVM. This results further validated with Receiver Operating Characteristic (ROC) curve analyses and performance metrics.

Raval, P. D., & Pandya, A. S. (2017) [18] presented a methodology for fault analysis in Extra High Voltage (EHV) transmission lines with multiple series compensations. To detect and classify faults the proposed protection depend on single-end current data from the three phases of the transmission line. A Multiresolution Analysis (MRA) wavelet transform used to decomposes the signals up to the 8th level. After this signal processing, statistical features are extracted. Classification accuracy was improved by using ANOVA F-test statistics to choice related features. This is then used as input for Hybrid Wavelet-ANN structure for classification of fault. Then ANN is trained and tested. The proposed algorithm performance accessed using the Support Vector Machine (SVM) classifier with a quadratic kernel function. As compared to SVM the proposed method provide high accuracy and reliability in identifying and classifying fault patterns.

Maheshwari, A., et al. (2019) [19] proposed an ANN based fault locator (FL) that was trained using several data sets from a selected PS model. A backpropagation neural network algorithm was used to detect and locate fault. This approach introduced two ANN-based fault locators and compare it with a traveling wave-based fault locator. The results of proposed FL provide more accurate fault location as compared with the traveling wave-based FL. This is more highlighted in single-line-to-ground faults. Discrete wavelet transform (DWT) with ANN was used for the efficient results. However, the authors recommended that the ANN-based FL could possibly be used for other types of faults with the same level of accuracy.

Yadav, A., et al. (2012) [20] provided ANN based fault classification and distance location in Teed transmission circuits. In this three-end transmission line configuration, measurements of current and voltages are taken at one end of the circuit. Through offline tests and investigations of various fault scenarios are carried out. Proposed algorithm offers an efficient solution for detecting and locating faults in Teed transmission circuits to maintain stability.

3. Methodology

As shown in Fig.1, the main aim is to find the effective method to identify the faults. In this method first step is to design, followed by testing and in last the implement to check its results. In initial stage data collection and division will be performed. After that separate this into training and testing data sets. Procedural first step is to identify faults and then divide them according to phases which are affected. For detecting, classifying, and locating transmission line problems investigation will use neural network as its potential works as alternative to traditional methods. Pre-fault phase voltages and currents values will be inserted as input in neural network to detect fault. LG, LL, LLG and 3ϕ faults in EHV line will be considered and it is suggested to do analysis with ANN for the issues. The back-propagation neural network algorithm will give satisfactory results. The simulation results will validate all the planned neural networks mutually attain satisfactory performance.

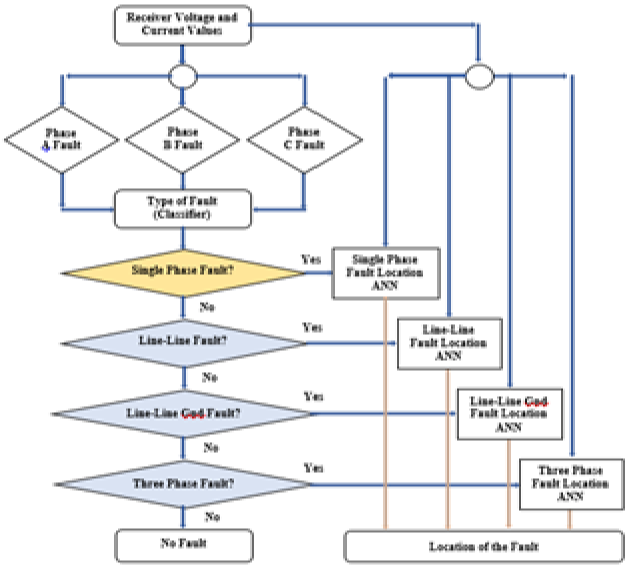

Fig. 1. Fault diagnosis strategy

4. Simulation Studies for EHV Transmission Line

To improve the transmission capacity in existing systems, the double circuit transmission line is widely used. Now a days it is popular due to its advantages over single circuit lines. In the two parallel lines, the mutual inductance between the conductors induces emf in the conductor of other line. That's why when apply traditional methods to parallel lines, the mutual coupling between then affects their performances.

Fig.2 shows a simulation model of an Extra High Voltage (EHV) double circuit transmission line. It have two transmission lines each of 150 km length and operating at 400 kV with generators at both ends. It is considered that both mutual lines runs in same right way. The each transmission line is characterized with three Pi sections. To consider mutual coupling effects, line parameters which are dependent on frequency are considered. From this we got the voltage and current values.

5. Result Interpretation

5.1 The Neural Network Training to Identify Three Phase Faults Location

For locating three phase faults in transmission line the feed-forward-back propagation algorithm was used. These networks with a large amount of data gave well performance. Simulation included various faults to train the neural network. Also the resistance was modified with increment of 3km in the fault distance. For each of 0.25, 0.5, 0.75, 1, 5, 10, 25, and 50 ohms resistances, hundred times simulation was conducted. This results in a total 800 situations of transmission line. Input to the neural network was the simulated results about voltage and current from each of three phases. At terminal A the output of the neural network was the value of fault distance.

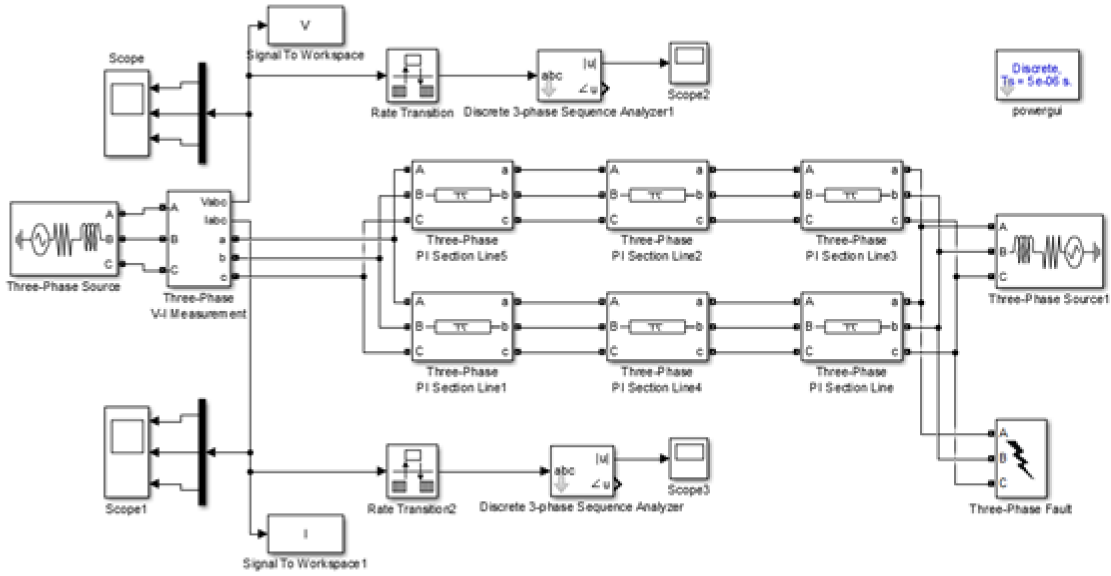

Fig.2. EHV transmission line simulation model

In the neural network each I/O pair contains of six I/Ps and one O/P. For assessing neural networks to obtain optimal parameters, various combinations of different number of hidden layer and neuron in that were tested. The goal is to obtain the acceptable error performance giving neural network configuration. After comparing goals using the Mean Square Error and the outputs, using regression the best-performing ANN model was selected.

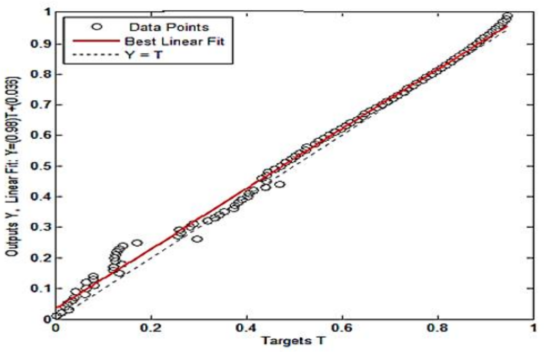

Fig. 3. Configuration (6 – 21 – 10 - 1): Output versus Targets

As shown in Fig.3, using NN, the finest regression among the targets and outputs was input layer of 6 neurons, 1st hidden layer of 21 neurons, 2nd hidden layer of 10 neurons and output layer of 1 neuron. The correlation-coefficient "r" is a statistical measure which characterizes the relationship strength between the objectives and the outputs of the NN. A higher value of r indicating better performance. This shows a stronger connection among the NN's outputs and the preferred objectives. The calculated value of r was 0.9970. This value indicates a very high degree of correlation between the desired objectives and the neural network's outputs. This suggest effective performance of neural network in fault distances predication in transmission line. More accurate results of predictions are expected with the value of r equal to 1.

The presentation of NN architecture as shown Fig.4 consists of six, twenty-one, ten and one neurons in the input,1st hidden, 2nd hidden and output layer respectively i.e. (6 - 21 - 10 - 1). The gap among the actual target values and the predicted outputs is Mean Square Error (MSE). The graph shows this dashed line with green color which obviously indicates the finest presentation of neural network. The black line on the graph shows the 0.01 as set MSE target. In the graph as the dashed green line is below the black line, it shows that of low standard error and the neural network has perform accurately in prediction of fault distance.

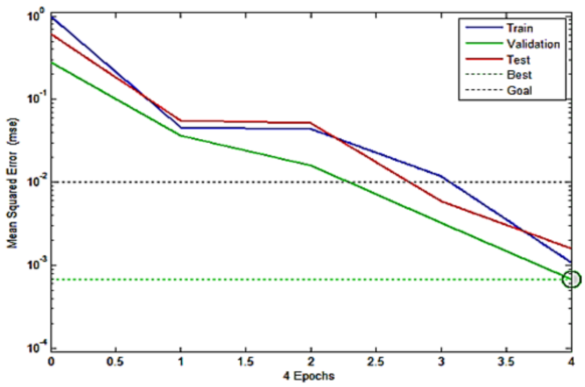

Fig. 4. Configuration (6 – 21 – 10 - 1): MSE Performance

In the simulation a set of 12, 3ϕ faults was hosted. An increment in the fault distance of 25 kilometers was repeated in each simulation. The error rate of the ANN was calculated with the analysis of the neural network results.

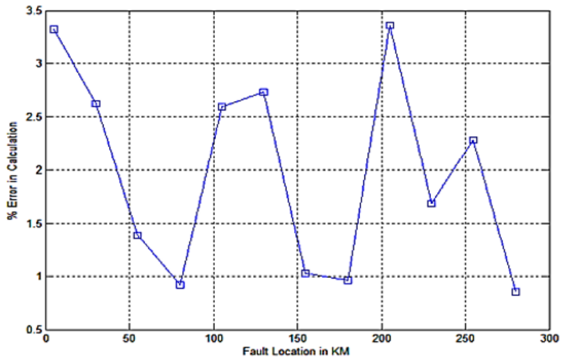

Fig. 5. Error versus fault distance with (6 – 21 – 10 - 1) Configuration

Fig.5 shows the performance of this assessment. The obtained error rates during the simulations are shown in the graph. The greatest margin of error was slightly above 3% which indicates accurate performance of the neural network (6-21-10-1). Generally this level of error is considered to be good for prediction of fault distance in transmission lines.

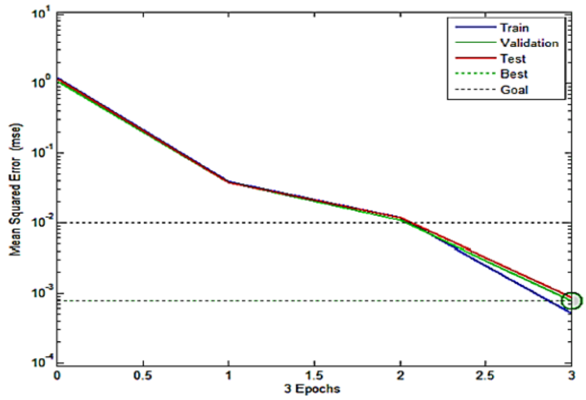

Fig. 6. MSE Neural Network Performance with Configuration (6-21-1)

Fig.6 shows the configuration (6-21-1) as output of training, testing and validation of a neural network. This neural network, number of neurons was single, twenty-one and six in output, hidden and input layer. MSE performance of the NN was shown by the graph. The dashed green line in the graph represents 0.00075875 MSE which is the maximum calculated performance. The black dotted line represents target MSE of 0.1. The green line was very close to the black which shows the high accuracy in the prediction of fault distance.

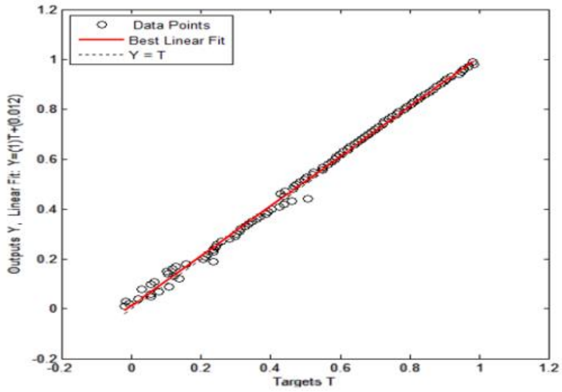

Fig. 7. (6 – 21 - 1) Configuration: Output versus Targets

Fig.7 represented (6-21-1) neural network with number of neurons six, twenty-one and one in input hidden and output layer respectively. The calculated correlation coefficient (r) is 0.98904 with is neural network configuration. This is more advanced as compare with previous configuration (6-21-10-1) value. It gives the best performance in prediction of fault compared to previous one. In the simulated system a succession of 12, 3ϕ faults were hosted. For each simulation fault distance was increased by 25 km and the error rate was calculated.

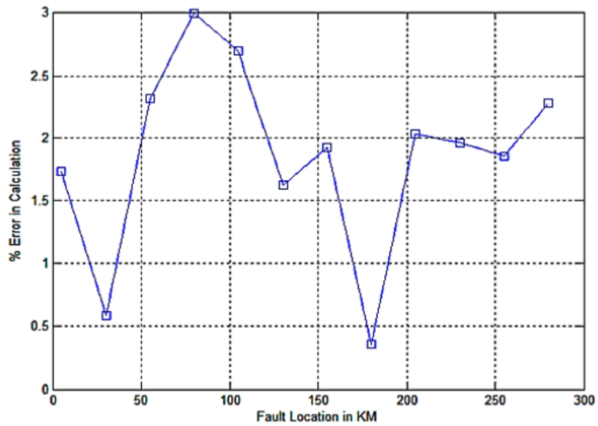

Fig. 8. (6-21-1) Configuration ANN Test Phase Performance

Fig.8 shows the results of the neural network (6-21-1) configuration consisting of six neurons in the input layer, twenty-one neurons in the hidden layer and one neuron in the output layer. The graph shows the error rates of 3 percent gained during the simulations. This is advantageous over the previous configuration. This can be easily illustrated with 90-degree rule.

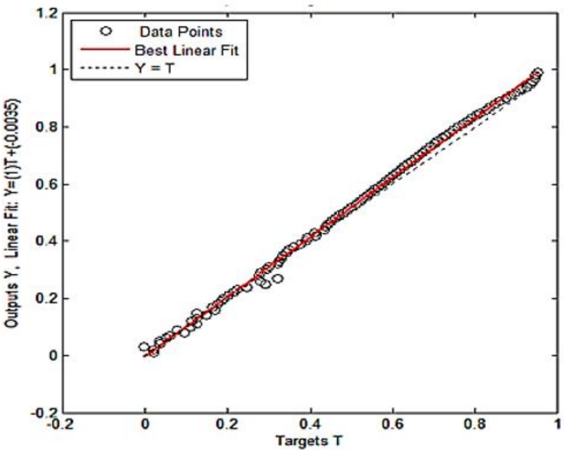

Fig. 9. (6-6-21-16-1) Configuration: Output versus Targets

Fig.9 shows a graph for NN architecture indicating number of neurons 6 in 1st, 21 in 2nd and 6 in 3rd hidden layers, 6 in input and one in output layer. The graph shown in Fig.9 gives suitable regression among the NN's outputs and its goals. In this configuration value of r is nearly equal to 1 which is 0.99897. This indicates high degree of r which gives accurate results in prediction of fault distance.

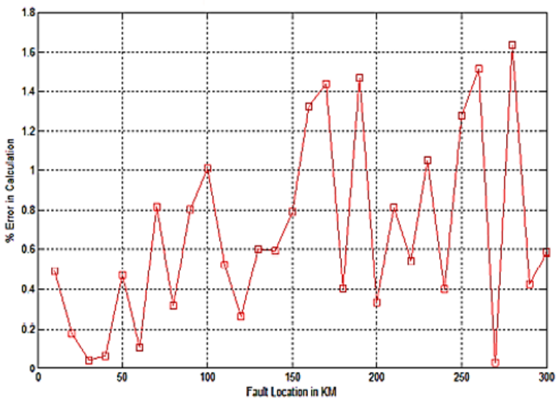

Fig. 10. (6-6-21-16-1) Configuration: Test results

Total hundred different 3ϕ defect cases were simulated under neural network performance. By increment of 10 km in fault distance in each simulation accuracy of ANN was measured. Fig.10 shows the graph of the neural network configuration (6-6-21-16-1). Relatively high percentage of error 1.62 was observed. The typical abnormality doesn't account for the error rate of 0.677 percent presented in estimate. With various considerations this neural network (6-6-21-16-1) is considered the ideal option for detecting three-phase faults in transmission lines.

Fig.11 shows the process of ANN training based on method, Levenberg Marquardt. To help the process of training, the stand-in selected function was MSE improves network's accuracy.

Fig.12 shows the graph of configuration (6 - 6 - 21 - 16 - 1) of NN for experimentation and validation. The graph shows the MSE presentation of the neural network throughout the training and testing stages. Comparting results of these stages are crucial for validating performance of the model. Black dotted line indicates 0.1 as a MSE target. The dotted line with green color shows maximum MSE performance of 0.00060607.

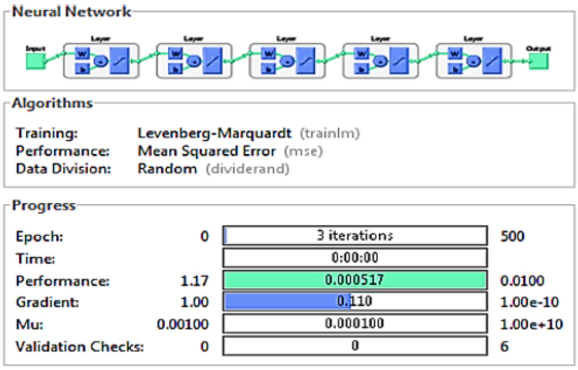

Fig. 11. Overview of Three-Phase Fault Location Neural Network

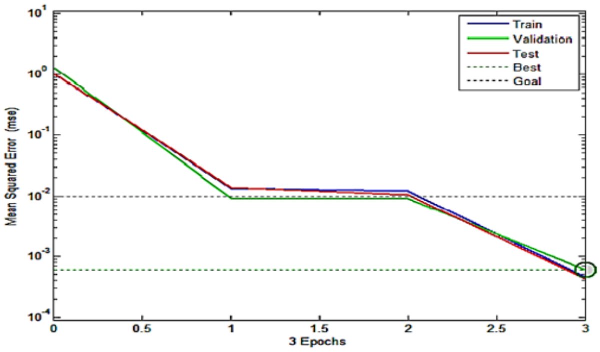

Fig. 12. (6-6-21-16-1) Configuration: MSE

This shows the neural network's predictions are very close to the actual target values. So is confirms about its high accuracy and effectiveness in predicting fault distances in the transmission line.

5.2 Testing of three-stage neural network for fault localization

After completion of training phase of ANN next phase is the testing of it. In this stage evaluation performance of networks output was examined. The methods and procedures used to systematically test the neural network was discussed in this section. Fig.12 shows the test phase performance plot, which plays a vibrant role in judging the network's capabilities. The investigation into the problem told that the percentages of maximum and average fault error fall comfortably within an acceptable range. These two rates of error are lower than the targeted one. This observation points out that both error rates lies within the reasonable considerable boundaries. This showed satisfactory network's performance testing results.

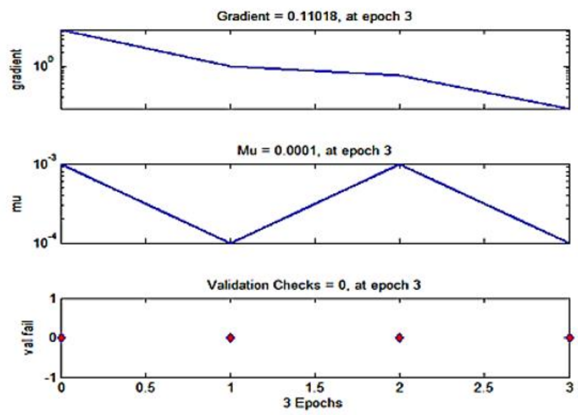

Fig. 13. (6-6-21-16-1) Configuration: Gradient and Validation

A Fig.13 shows graphical representation plot of performance gradient and validation for measuring performance of NN. This strategy is of highest importance and should not be overlooked. Fig.14 illustrates this graph. After completion of training, this graph shows zero instances of failed validations. Also the gradient shows a consistent and smooth decline. This indicates successful training. The number 95 serves as evidence to support this observation.

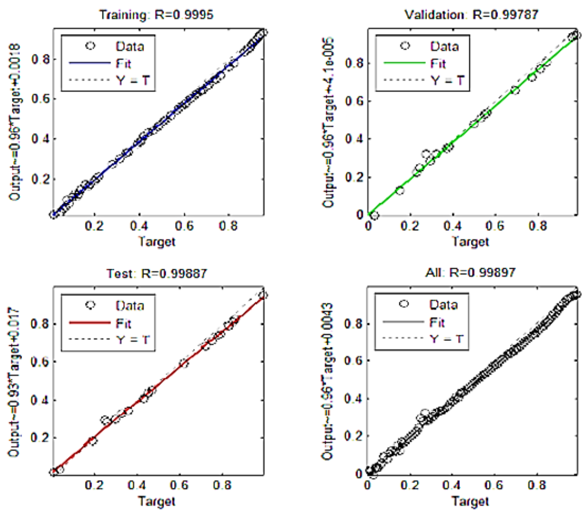

Fig. 14. (6-6-21-16-1) Configuration: Regression Plots

In support to the argument that the neural network can effectively generalize with new data inputs, Fig.14 shows the additional data that compares test and validation curves. While evaluating the network's efficiency different regression plots in Fig.14 was generated throughout the various stages with 0.99329 as the value of r. This strong value proves the effectiveness of the neural network. This is evident in real-life observations.

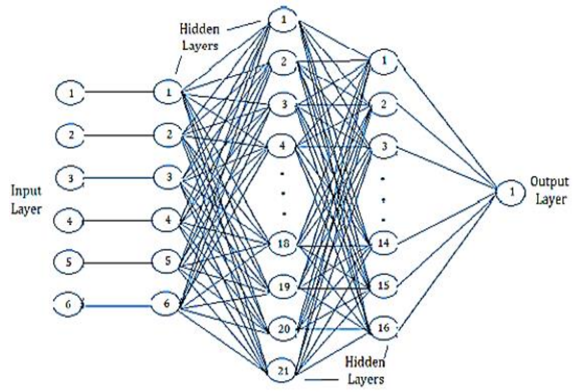

Fig. 15. (6-6-21-16-1): Chosen ANN's Structure

Table 1 presents the percentage errors in fault localization based on resistance and distance for location of 3ϕ fault. The table displays the measured fault locations and the corresponding errors for two different fault resistances (25 Ω and 60 Ω).

The table shows the findings on the exactness of fault localization concerning different fault distances and resistances along with the corresponding percentage errors. The data in table shows consistently low % errors which indicates the perfection of the selected ANN for detecting three-phase faults. The table includes two columns containing data for fault resistance values of 25 ohms and 60 ohms.

Table 1: Percentage Errors in Fault Localization

Sr. No.	% Error vs Fault Distance (Fault Resistance = 25 Ω)			% Error vs Fault Distance (Fault Resistance = 60 Ω)		
	Fault Distance (Km)	Measured Fault Location	% Error	Fault Distance (Km)	Measured Fault Location	% Error
1	25	25.51	0.17	50	51.41	0.47
2	50	50.34	0.09	75	75.23	0.73
3	75	75.17	0.057	100	103.03	1.01
4	100	100.28	0.13	125	125.17	0.87
5	125	125.52	0.28	150	152.37	0.79
6	150	150.43	0.262	175	175.45	0.71
7	175	175.69	0.23	200	201.99	0.63
8	200	200.27	0.2	225	225.5	1.03
9	225	225.46	0.1533	250	253.84	1.28

The ANN was trained using the 25-ohm resistance data which gave 0.178 percent low mean error in detection of fault. Also the ANN was tested with a fault resistance of

60 ohms which was not part of its training data. Still the neural network still performed exceptionally well, demonstrating its adaptability and ability to handle new conditions effectively. It is important to highlight that even with a standard error of 0.836 percent, the neural network's performance remains well within acceptable limits. This shows networks capability to reliably identify faults within a three-phase system.

6. Conclusion

This paper presents EHV power transmission fault prediction and location based on ANN approach. To reach the proposed goal ANN model was developed using MATLAB simulation. This ANN model is developed with several number of iterations to get the fault distance value. The measured fault distance value then compared with targeted value to get accurate value of fault distance. The percentage error between the predicted value and targeted value is calculated. Gradient Descent and Chaining methods are used for back propagation algorithm to minimize error. MSE obtained is much lower than the target which indicates the network's reliability and makes it as appropriate choice for precisely detecting three-phase faults. As compared to numeric relay, conventional layouts, Tauras fault detection and Event Sequence Recorders (ESR) like conventional methods, the projected method is best in detection of fault. The projected method is innovative, simple, reasonable, precise, efficient and economical. Modifying the dataset size for the training, adjusting hidden layer’s number, and changing layer’s neuron number can lead to enhancements in the performance of the suggested approach.

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