Detection and Classification of Faults in High Voltage Transmission Line using Artificial Neural Network

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***Abstract*—The problem of recognising and classifying transmission line faults has existed for a very long time. This one was among the main difficulties of the power engineering. Typically, the protective relay device, tape and distinct control and safety of software systems liable for sensing the fault and isolate the damaged unit as of the system. This article is about identifying and classifying problems on high voltage transmission lines. Using artificial neural networks, defect detection and classification were accomplished. The back-propagation process algo works with a network of direct distribution for every of the 3-phases of the process of fault detection and classification. The investigation of neural networks with varied sums of unseen layers and neurons in the hidden layer was under the condition that the neural network selection be verified at each stage. In MATLAB/ SIMULINK, this model for a typical transmission line is used to generate the voltage and current settings. A simple network was chosen to mimic all conceivable scenarios of failures and test creation. The ANN is trained and tested for defect detection and classification using produced test data sets. The simulation results show that an artificial neural network-based model for effective detecting and arranging of faults on transmission lines also achieves performance satisfaction.**

Keywords: Faults, Neural Networks, Feedforward, Simulation, Backpropagation, Algorithm.

I. Introduction

The transfer of energy network utilities is a complicated operation that involves several power plants, transmission lines, and substations. Electricity is usually generated at 11-25kV at a power plant and subsequently for long-distance transmission, then stepped to EXT/ storeys EHV/UHV in line with the demand. Power is supplied via the transmission network with high voltage lines [1]. The main function of the network is receiving electrical energy from a three phase source and distribute it to various types of consumers in the desired voltage levels and high reliability. Most transmission systems are used in a radial configuration, predominant because of the simplicity of their operation and the economy of the overcurrent protection. In such transmission systems, the protection needs only to sense current, and there is no need to determine the direction. High voltage power lines are commonly used in current power systems to enhance power transfer capability, steadfastness and safety of transmission of electric power. Different configurations designed for dual-ckt lines joint with the influence of reciprocal links, making security of them a puzzling task. 0-sequence mutual imp. can reach 50-70% of its Impedance. Hence, mutual communication, especially under earth fault, creates problems for old protection orders distance. The great majority of faults (more than 75%) are single line to ground type [2]. The proper proportion of numerous faults occurring is listed below:

1. Single LG fault -70-80%
2. LL- to- ground fault - 10-17%
3. L-L-fault – 8-10%
4. 3-phase fault – 2-3%

Lightning, conductors that cook in the wind, tree branches that fall through the conductors and subsequently fall or burn, and insulator failure caused by pollution are all temporary issue sources. Mistakes are typically transitory, but they might lead to permanent failures. If the fault cannot stay too long, the arc can cause irreparable damage to conductors, insulators, and other equipment. Recovery may be accelerated in case detected fault is either identified or may be predictable with equitable precision. Hence, the deficiencies in the transmission system must be discovered immediately, regardless of whether they are permanent or temporary.

The purpose of this work is to create a proposed 5-bus transmission system model in order to obtain data sets for the Ann technique in stationary and various faulty states such as the LLG fault, double LG fault, 3-phase fault, and so on, as well as to create artificial neural network (ANN) models of data sets received by the transmission model. The method employed in this work makes use of the major components of voltage or current data. To

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produce training datasets for the ANN, the transmission line model 250 is constructed and run in MATLAB/ Simulink. The ANN makes it easier to categorize flaws in a straightforward and practical manner.

II. System Configuration

To evaluate the efficiency of the proposed neural network-centered fault detector and classifier, a 250 kV, 100 kilo meter transmission spreading line between two sources was used in the following study, as shown in figure 1.

The lines indicate the non-concentrated characteristics, and the frequency of the line parameters has been examined [3]. Values of three-phase voltages or currents are monitored at a five-bus system, and the resulting data set is then sent into the neural network as input. Figure 2 depicts a Simulink-model transmission line that was used to generate the whole collection of neural network testing and training data. There were ten distinct fault situations generated for the purposes of fault detection and categorization.

The main phase in the procedure of fault identification. When we recognize that the failure happened on a power line, the following phase is to check identification of the weather or what was done in this work.

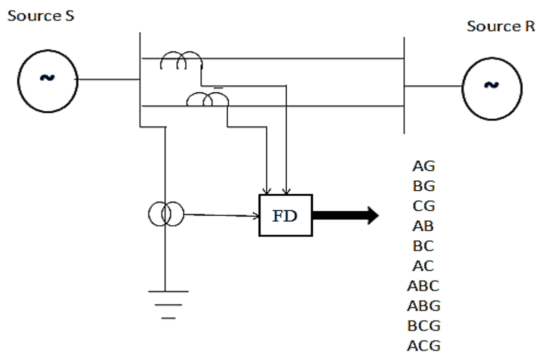

Fig. 1: The System Under Consideration

A. Network Simulation

The network will be skilled by using a “znntrain”. That function calls MATLAB NN elements Ann functions. Functions are named “newff” and “nftool”. The function “newff” generates a direct distribution network and returns network object. The function “train” train the created network. The arrangement of the function “newff” will be recited from MATLAB help. Used in this work are merely certain of its arguments, namely the “newff” (input [N1, N2, ... NJ], {F1, F2, ... FJ}, the learning algorithm). This function generates a feedforward network of J layers (input layer is not involved). In Tolal number of nodes in every layer N1, N2, NJ every layer with triggering function F1, F2, and FJ, respectively.

B. Data Pre-Processing

Reducing the neural network size advances the results and that will be accomplished by execution of feature-extraction. Thus entirely significant and important data in the o/p-waveforms of the signals of current and voltage can be used successfully. Current and voltage were obtained and sampled at the sampling frequency of 50 Hz. The voltage and current of entirely 3-phases is taken beside its matching wine. In Fig. 3 displays the signal of current phase fault of B-G at 100 km distance from the terminal and the transmission line. A signal is a plan of the samples taken at the frequency of sampling of 50 Hz.

Now once we are done with this, the neural network inputs are the values of each of the 3-phases of the currents and voltages in for no fault case and for the cases of occurrence of various fault [4].

C. Backpropogation Algorithm

The unseen layer permits ANN to create its personal interior functions of mapping between input and output. Consider a 3-layer network of input level “l” with six signal inputs, a hidden layer, having “ m “ layer and output layer-and-roll, the four output signals. We consider a sigmoidal activation function of the unseen and layers at response and activation function being linear in the input layer. The steps in the algorithms of back propagation is shown below:

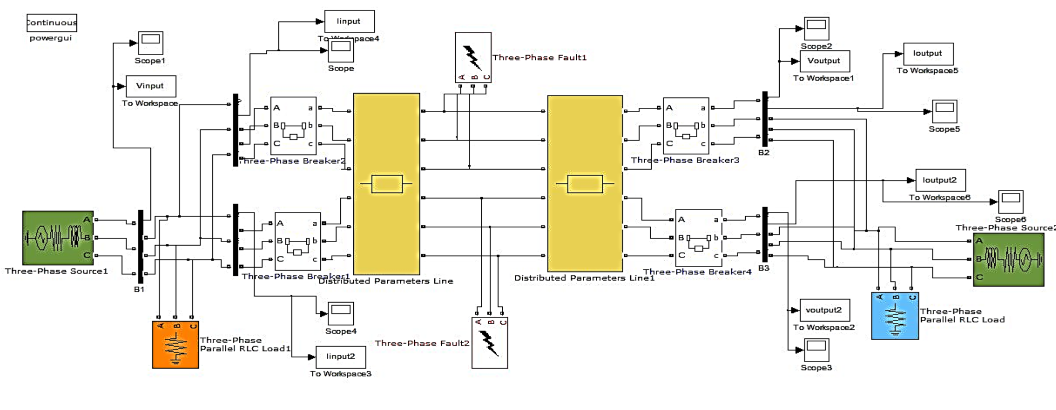

Fig. 2: MATLAB/ Simulink Based System Model

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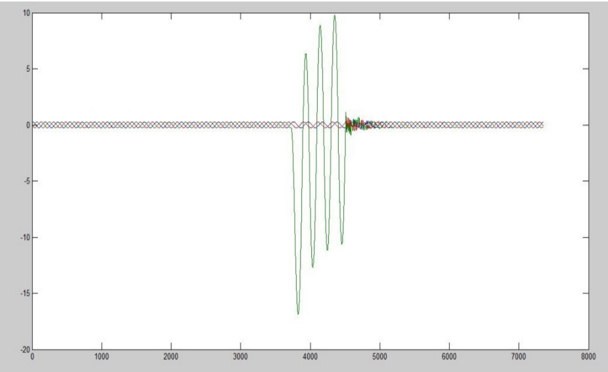

Fig.3: Data Pre-Processing Illustration

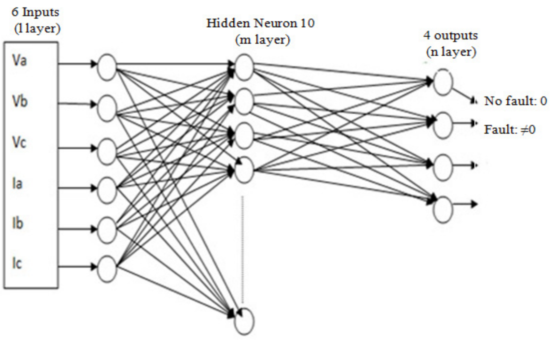

Fig.4: A (6-10-4) Neural Network

Step I: The inputs besides outputs with respect to its highest values. This is known as the neural networks acts well if the input and outputs lie between 0-1and -1 to +1. In case of each pair of training, consider that nearby are 'l' inputs assumed by $\{I\}_I$ and 'n' outputs $\{O\}_O$ in a form of current and voltage.

Step II: Consider that the quantity of neurons in the unseen layer to be ranging from 1<m<30.

Step III: $[V]$ Shows the weight of synapse joining the input neurons to the unseen layer neurons and [W] signifies the weight of synapse connecting the hidden layer neurons to the response neurons. Now set the weights of the slight arbitrary values.

Step IV: In case of the present data set training, single set of inputs as well as outputs too. Present the pattern to the input layer $\{I\}_I$ as input to the input layer and via taking linear activation function, the input layer output is calculated as

$$\{O\}_O = \{I\}_I \tag{1}$$

Step V: Calculate the inputs to the unseen layer by multiplying matching weights of synapses as

$$\{I\}_H = [V]^T \{O\}_I \tag{2}$$

Step VI: If the unseen layer units calculate the o/p using the sigmoidal functions as:

$$\{O\}_H = \left\{\frac{1}{1+e^{-I_{Hi}}}\right\} \tag{3}$$

Step VII: Calculate the inputs of the response layer by product of matching weights of synapses as

$$\{I\}_O = [W]^T \{O\}_H \tag{4}$$

Step VIII: If the response layer units calculate the output by sigmoidal function as follows:

$$\{O\}_O = \left\{\frac{1}{1+e^{-I_{Oj}}}\right\} \tag{5}$$

The overhead is the output of network.

Step IX: Compute the error and the alteration between the output of network and the preferred output like in case of the i^th^ set of training as,

$$E^P = \sqrt{\frac{\Sigma (T_j - O_{Oj})^2}{n}} \tag{6}$$

Step X: Find $\{d\}$ as

$$\{d\}\_\{(T_K - O_{OK})O_{OK}(1 - O_{OK})\} \tag{7}$$

Step XI: Find [Y] matrix as

$$[Y] = \{O\}_H \langle d \rangle \tag{8}$$

Step XII: Find

$$[\Delta W]^{t+1} = \alpha[\Delta W]^t + \eta[Y] \tag{9}$$

Step XIII: Find {e} = [W]{d} (10)

$$\{d^*\} = \{e_i O_{Hi}(1 - O_{Hi})\} \tag{11}$$

Find [X] matrix as

$$[X] = \{O\}_I < d^* >= \{I\}_I < d^* \tag{12}$$

Step XIV: Find $[\Delta V]^{t+1} = \alpha[\Delta V]^t + \eta[X]$ (13)

Step XV: Find

$$[\Delta V]^{t+1} = [V]^t + [\Delta V]^{t+1} \tag{14}$$

$$[\Delta W]^{t+1} = [W]^t + [\Delta W]^{t+1} \tag{15}$$

Step XVI: Find the error rate as

$$\text{Rate of Error} = \frac{\sqrt{E_p}}{nset} \tag{16}$$

Step XVII: Repeat steps IV-XVI until the convergence in the error rate is less than the tolerance value.

IV. Proposed ANN Based Fault Detector

Figure 5 depicts the major functioning components of the proposed fault detector. The relay will acquire 5 current and voltage signals from the transmission end s (relay site) through the bus. Following preprocessing, they will feed the detector (FD) to identify any faults, and if a fault is detected, the detector will assess the transmission line defect. The proposed fault detection (FD) method is designed to demonstrate the presence or lack of culpability. The occurrence of a breakage is discovered by determining the system state directly from immediate current (I) and voltage (V) data. The detector (FD) is designed to approximate the fault in the transmission line using the fundamental magnitude of the vector voltage signals. The detector only makes use of one data line on the terminal [5].

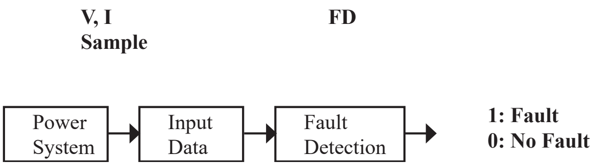

Fig. 5: Block Diagram of Fault Detection

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A. ANN Fault Detector-Design Process

The procedure of designing the fault detector based on ANN is based on the subsequent phases:

1. Grounding of a appropriate data sets of training that characterizes conditions whichare required by the ANN to be learnt.
2. Choice of a appropriate ANN arrangement for a specified requirement.
3. The ANN training while waiting for its performance being acceptable.
4. Assessment of the ANN that was trained by test arrangements.

B. Fault Detector

In order to create the Ann, inputs and outputs corresponding to neural network fundamentals must be separate for pattern cleaning. The network's inputs should provide an accurate picture of the situation. The process of developing designs based on the defect sensor's information using ANN (FD) [6].

C. Inputs and Outputs

Input signal (Voltage) models are created as a sequence of trials matching to the rate of sampling. Those signals how to simulate the process of sampling (62 samples each period at 50 Hz). The output of Ann is noted with either a value other than zero (fault) or 0 (without fault situation).

D. Neural Fault Detector's Structure and Training

The input layer offers three current and voltage phases. The responses of the unseen layer, as well as the activation function of the sigmoid, are measured and sent to the response layer, which is made up of only one neuron. The transmission line status is provided by the response value of the neuron corresponding to the layer of output with sigmoid activation function: 0 (failure) or 0. (non-faulty situation) [7].

V. Proposed Fault Classifier Based on ANN

Major functional blocks for constructing the figure of the suggested fault classifier is displayed in Fig. no. 7 signals of voltage or current of end of transmission line s (location of relay) is attained through relay via the bus. After preprocessing, they will feed sensor (FD) to identify any faults and in case fault is noticed, the classifier of fault evaluates to the transmission line's fault Type.

Task of recognition of fault can be expressed in form of a a organized case pattern. Direct 3-layer fully connected neural network was applied to categorize faulty and non-faulty data groups and the algorithm of error back-propagation was applied for exercise. The number of neurons in input and hidden layers were choosed specially based on simulations and numerous network arrangements were skilled and verified in directive to create an suitable network with acceptable results, that was tolerance of fault, time response and generalization abilities [7]

A. Neural Fault Classifier's Structure and Training

Lines 50-62 consecutive data samples with a signal frequency of 2 kHz are the neural network's matching inputs in order to construct a better neural network system for learning and testing. The Ann is trained using a variety of input models representing various sorts of fault (A–G, B–G, s–G, A–B–G, A–C–G). B–C–d, A–C, A–C, B–C, and A–B and C, where A, B, and C are connected to the phases and G is the ground) at various classes for different faults (error producing angles, fault resistance) and varied system data energy (power source, voltage source, source angles, time regular sources).

B. Proposed ANN Structure for Fault Classification

For processing the provided input data, multilayer feed forward networks are used. A network is chosen initially, and also to create a defect classification based on neural networks, a network with three inputs and one output was examined. The network architecture was decided empirically which involves exercise and verifying dissimilar sum of networks. 3-layer network was obtained suitable for a selector fault. The TRANS-sigmoidal function was used as a function of activation of unseen layer neurons in all networks, and the same was done for the response layer [8]. Figure 8 depicts the fault classifier.

Following training, network enactment was validated using testing data. Finally, the most suited network that produced acceptable results was picked. The carefully selected network contains 6 inputs and 4 outputs. The sum of the neurons in the buried layer of ten neurons is chosen. The output must be between 0 and 1 depending on the sort of problem that happens in the system. Table I shows the fault categorization Ann outputs for various faults.

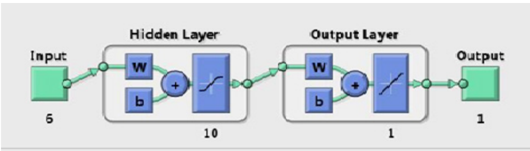

Fig. 6: ANN Fault Detector Structure

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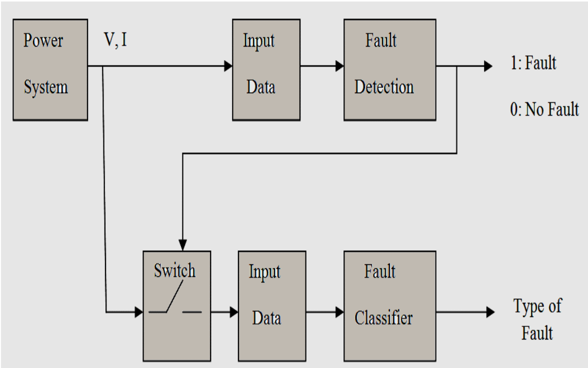

Fig. 7: Block Diagram of Fault Classifier

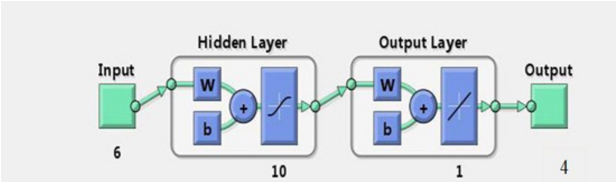

Fig. 8: ANN Fault Classifier Structure

TABLE 1: FAULT CLASSIFICATION ANN OUTPUTS FOR SEVERAL FAULTS

Type of fault 1	**Network Output**			
	A	B	C	G
AG fault	1	0	0	1
BG fault	0	1	0	1
CG fault	0	0	1	1
AB fault	1	1	0	0
BC fault	0	1	1	0
AC fault	1	0	1	0
ABG fault	1	1	0	1
BCG fault	0	1	1	1
CAG fault	1	0	1	1
ABC fault	1	1	1	0

VI. RESULTS AND DISCUSSION

The proposed Neural network was tested with test data and results were analyzed. The method of back propagation is considered for recognition and grouping for faults on lines of transmission. Various practical constraints are considered in the fault recognition and grouping problems. Work in a broad sense covers:

"Development of a technique for fault detection and grouping of transmission systems using a neural network and a neural network as a classifier, using measurements at the substation"

The specification parameters used in simulation are as follows:

A. Two Source Power Model

TABLE 2: SOURCE DATA AT BOTH ENDS

PARAMETER	**VALUE**
Three Phase Voltage Frequency Phase Angle	250 kV 50Hz 0,10,25,30,50
Base Voltage(Short circuit level)	100e6
Base Voltage (Phase to Phase)	25kV
X/R Ratio	7

B. Transmission Line Data

Double Circuit Line Parameter
Length = 100 km
+ive seq. resistance R_1= 0.01809 Ω/KM
0-seq. resistance R_0= 0.2188 Ω/KM
0-seq. mutual resistance R_{0m}=0.20052 Ω/KM
+ive seq. inductance L_1=0.00092974 H/KM
0-seq. inductance L_0= 0.0032829 H/KM
0-seq. mutual inductance L_{0m}=0.0020802 H/KM
+ive seq. capacitance C_1=1.2571e-008 F/KM
0-seq. capacitance C_0 = 7.855e-009 F/KM
0-seq. mutual = -2.0444e-e009 F/KM

C. Pattern Generation

Fault Type = AG, BG, CG, ABC, AB, BC, AC, ABG, BCG, ACG
Inception angle of Fault = 0, 10, 30 deg
Fault resistance = 0, 5, 10, 20 Ω

D. Fault Detection

With aim of fault recognition, several methods of Perceptron of multi-layer have been considered. Several features that show a part in determining the perfect ways is the dimension of the network used training approach and the exercise data of a given size. Subsequently exhaustive research, back-propagation algorithm was selected by way of the perfect method. Although a simple back-propagation algorithm is comparatively sluggish because of running at low speeds learning, several methods can expressively improve the result of the algorithm. One of these strategies is the use of levenberga-Marquardt optimization method. The selection of network size is critical since it not only reduces training time but also enhances a neural network's capacity to represent an issue. Regrettably, no thumb rule exists to command the number of invisible layers and neurons in the unseen layer to the difficulty.

To identify network problems, six inputs are required, which are the voltages and currents on all three phases for 10 different faults and the no fault condition. The neural network's answer is a simple Yes or No (1 or 0) depending on whether or not the error was found. Following many

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simulations, it became clear that the selected network contains one unseen layer with 60 neurons in the hidden layer. For example purposes, multiple neural networks (with varying numbers of hidden layers and neurons in the hidden layer) were proven to yield acceptable results, and the best neural network was specified in further detail. A different view error plots were shown in figures 9-13.

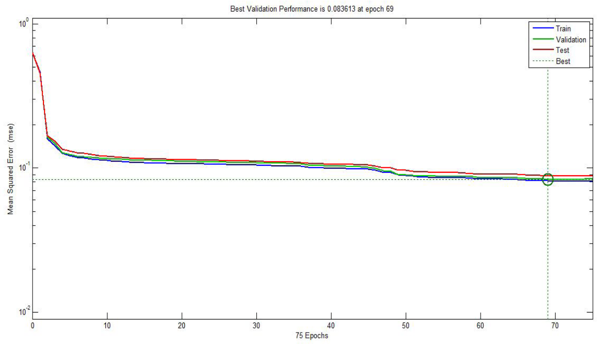

Fig. 9 Mean-square Error Performance of the Network (6-05-1)

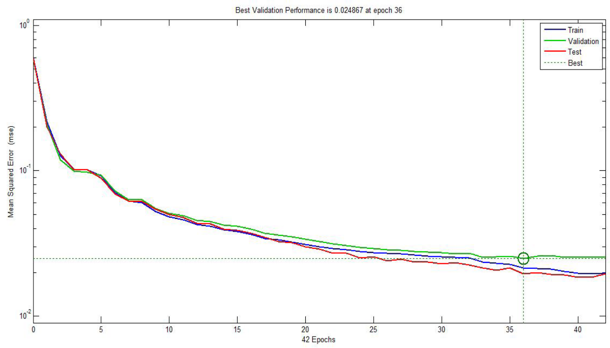

Fig. 10: Mean-square Error Performance of the Network (6-15-1)

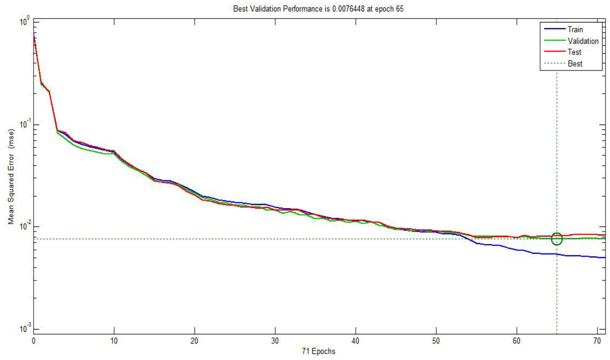

Fig. 11: Mean-square Error Performance of the Network (6-25-1)

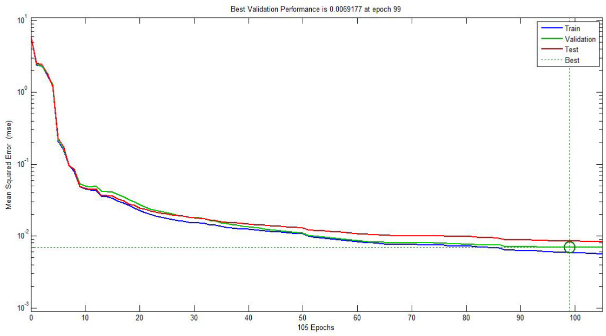

Fig. 12: Mean-square Error Performance of the Network (6-45-1)

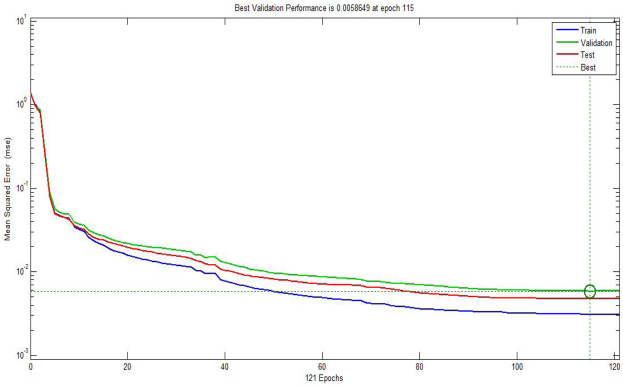

Fig. 13: Mean-square Error Performance of the Network (6-60-1)

1. *Testing of Fault Detection Neural Network*

As soon as the neural network becomes proficient, its outcomes are validated by several factors. The most important of these is by showing the best linear regression after the neural network has been trained; its efficacy has been validated by several variables. The first of these is to create a better linear regression that connects the indicators to the outputs, as illustrated in figure 14. The correlation coefficient (R) measures how well the neural network's goals can track changes in outputs (0 being no correlation and 1 for full correlation). In this example, the correlation coefficient was determined to be 0.98909, indicating an excellent connection.

2. *Fault Classification*

Even though the error back propagation learning strategy is inherently slow and makes determining the optimal network size difficult, it is without a doubt the best strategy to use when a large training set is available because the back-propagation algorithm can provide a very compact distributed representation of complex data sets.

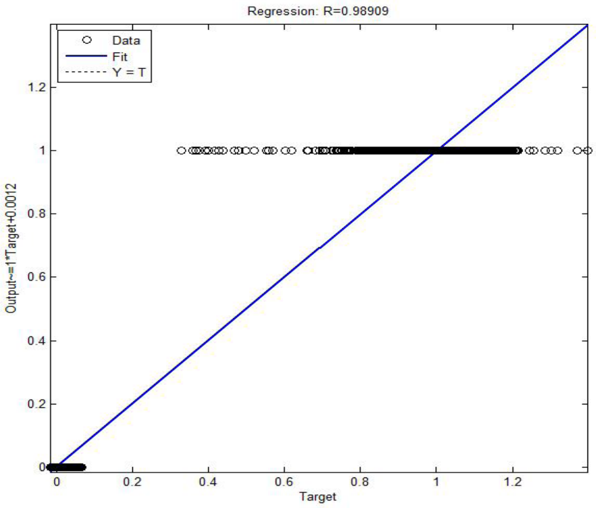

Fig. 14: Regression Fit of the Outputs vs. Targets for the Network (6-60-1)

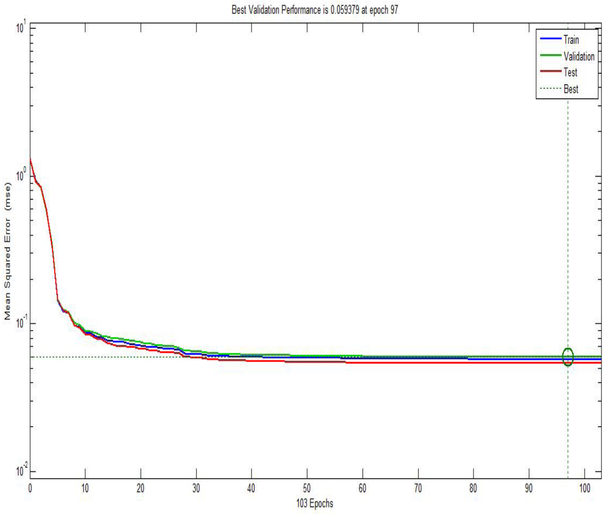

Fig. 15: Mean-square Error Performance of the Network with Configuration (6-15-4)

Back-propagation networks with various hidden layer combinations and number of neurons in the hidden layer were investigated. Those that performed satisfactorily are displayed. Figures 15–18 depict the error plots of neural networks with hidden layers.

3. *Testing the Fault Classifier*

As illustrated in Figure 19, the best linear regression connecting the indicators to the outputs was constructed. In this example, the correlation coefficient was 0.93236, indicating a reasonable connection between aims and results.

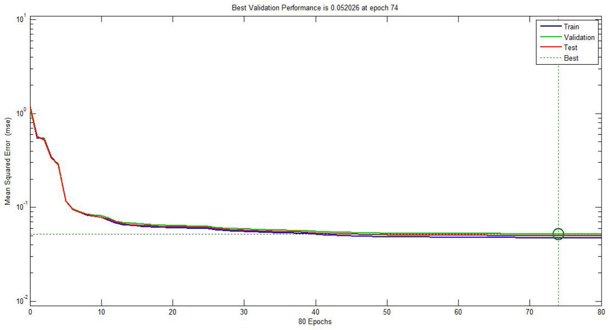

Fig. 16: Mean-square Error Performance of the Network with Configuration (6-25-4)

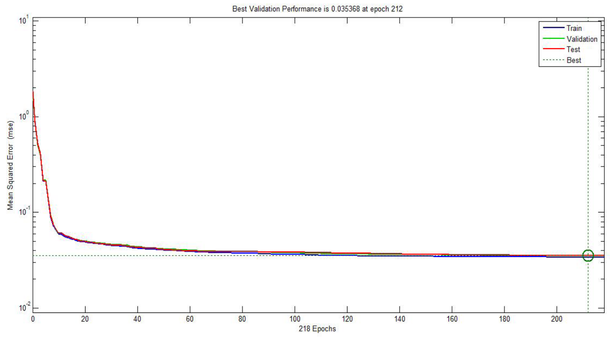

Fig. 17: Mean-square Error Performance of the Network with Configuration (6-45-4)

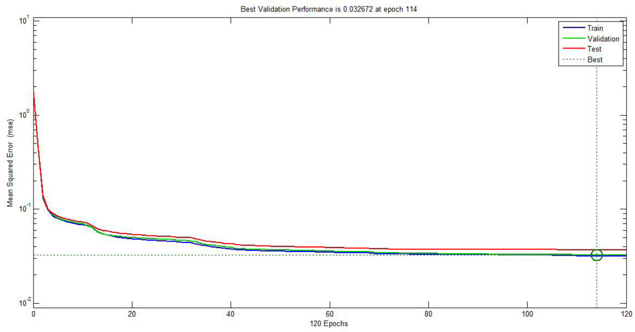

Fig. 18: Mean-square Error Performance of the Network with Configuration (6-60-4)

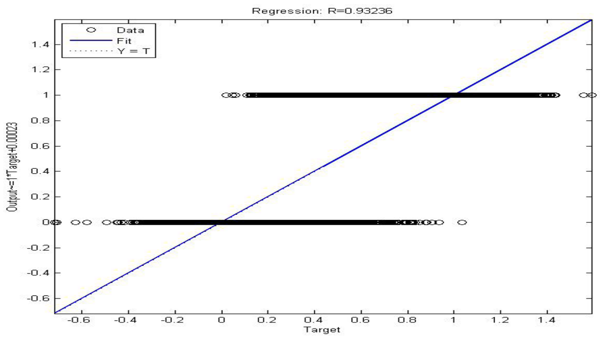

Fig. 19: Regression fit of the Outputs vs. Targets of ANN with Configuration (6-60-4)

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IV. Conclusions

The goal of this work is to provide a new strategy for detecting and classifying faults in High Voltage Transmission Line systems using the ANN technique while taking into account different practical restrictions. The transmission line model for a power system was created using the MATLAB/SIMULINK platform. The suggested Neural Network may be utilised for real-time power system analysis. Based on the findings, it is possible to conclude that the observations performed during a failure in a high voltage transmission system include essential information concerning fault identification and classification. Measurements taken at the substation are used to detect and categorise faults in transmission networks. The research conducted in this study indicate that the same structure of the neural network may be used for multiple network configurations, and only the weights of the neural networks are updated for various configurations.

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