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Revolutionizing Fault Detection: A Neural Network Approach for Transmission Lines

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Abstract *:*This research concentrates on Artificial Neural Networks (ANN) application in identifying and categorizing faults within Extra High Voltage (EHV) networks. The process entails employing backpropagation algorithms and feedforward networks for individual phases. Diverse ANNs are suggested to handle different types of fault, encompassing LG, LL, LLG, and 3-phase faults. The paper conducts an analysis of networks with diverse configurations, involving varying numbers of layers which are hidden and neurons in it, to guide the selection of NN for each phase. The simulated outcomes illustrate the efficacy of the ANN-based approach in recognizing transmission line issues, producing favorable outcomes.

Keywords: *ANN, EHV, Fault classification, Fault detection, Backpropagation*

1. Introduction

In the preceding few years, there has been a significant global expansion of the power grid, characterized by the widespread installation of numerous transmission and distribution lines. This growth has been further accelerated by the adoption of innovative marketing concepts like deregulation, highlighting the growing demand for a dependable and continual electric supply to consumers [1]. A crucial impediment to the consistent delivery of electricity is a power system (PS) fault [2]. An unusual current drift within the components of a PS is referred to as a fault. These faults, partly arising from natural causes beyond human control, necessitate a well-coordinated protection system. This system should not only identify abnormal current flows but also determine the fault type and quite trace its position within the PS. Devices responsible for managing faults detect their occurrence and detach the faulty segment from the remaining PS. Therefore, the primary tasks in ensuring continuous power supply revolve around detecting, classifying, and localizing faults [3]. Faults manifest in various types such as transient, persistent, symmetric, or asymmetric, each requiring a specific detection process. For these many types of defects, there isn't a single fault location method that works for all of them. HV Transmission Lines are extra susceptible to faults than local distribution lines. This vulnerability arises because cables lack insulation, disparate distribution lines. Research in protective relaying in PS primarily focuses on fault protection due to the length and varied geography of transmission lines (TL), making physical inspection time-consuming [4].

The automated location of faults significantly enhances system reliability, as swiftly restoring power translates to cost and time savings. Consequently, several efficacies are incorporating fault locating campaigns with Global Information Systems into their power quality monitoring systems for efficient fault location [2]. There are several types of fault position techniques that may be distinguished, such as methods based on impedance measurement, methods based on traveling wave phenomena, methods based on I and V which have high frequency, created by faults, and intelligence based methods [5].

In recent years, intelligent-based methods, particularly Artificial Neural Networks (ANN), have played a crucial role in fault recognition and position. In the realm of power and automation, three prominent artificial intelligence techniques—Expert System Techniques, ANNs, and Fuzzy Logic Systems—have been widely applied [6]. Among these, ANN-based methods, as highlighted for fault location on TL, stand out for not requiring a knowledge base compared to other artificial intelligence methods [7].

2. Methodology

While the foundational principles governing relays remain constant, the advent of digital technology has substantially altered their functioning, offering several enhancements compared to traditional electromechanical relays [8]. The primary goal is to formulate, cultivate, evaluate, and appliance a comprehensive approach for fault analysis, as explained in Figure 1. Primarily, the collected data is segregated into training and testing datasets. The initial phase involves fault detection. Once the identification of a fault on the TL is established, the subsequent stage is to categorize the fault into distinct phases [9]. The third step is to precisely determine the fault's location on TL. This aims to recommend cohesive technique that employs artificial neural networks to perform each of these tasks. For fault detection, a backpropagation based NN is utilized, and a similar one is employed for fault classification. Separate neural networks for fault location are employed for each type of fault. The flowchart in Figure 1 outlines each of these sequential steps [10].

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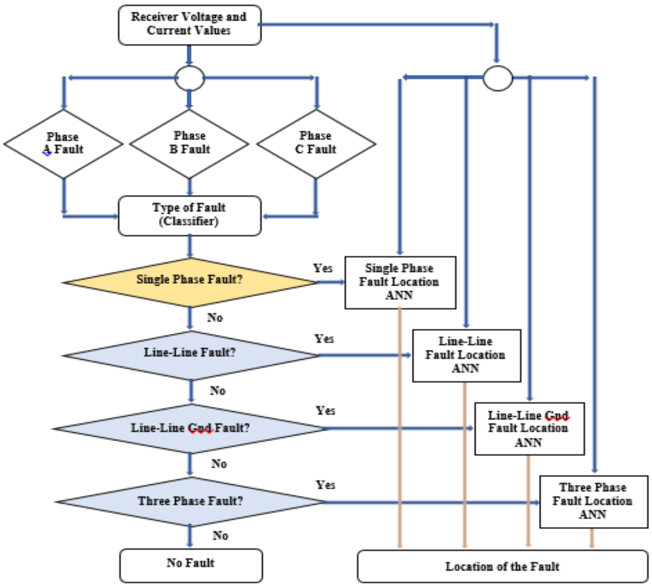

Fig. 1 Fault diagnosis strategy

3. Modeling the Power Transmission Line System

The proposed approach, which employs ANN, has been implemented and tested on a 500 kV TL system. Simulations of this power system were conducted, and Figure 2 shows a simulation model which creates datasets. On both sides of model, generator impedances ZP and ZQ are shown in figure. In order to record V and I samples at terminal A, a V-I measuring block is utilized. The TL, consisting of line-1 and line-2, spans 300km, and fault-simulator introduces various fault types at different positions alongside the line, each with distinct fault resistances. The three-phase V and I are restrained, adjusted as needed, and then input into the NN. Faults are broadly categorized into symmetrical and unsymmetrical faults.

For fault detection, 1100 unique fault conditions were replicated, and an equivalent number of cases were generated for fault classification. The fault location simulation involves varying case numbers based on the specific fault type under consideration.

4. Result Interpretation

4.1 Fault Detection

Several Multi-Layer Perceptron configurations have been examined for fault detection purposes. Critical factors, including system extent, learning policy, and training dataset size, play a crucial part in defining the optimal topology. Following a thorough investigation, the backpropagation process has been identified as the preferred choice. Even though it is inherently sluggish because of small erudition rates, there are ways to make it work much better, including using the Levenberg-Marquardt optimization approach. Choosing an appropriate network size is crucial, not only for reducing training time but also for enhancing the NN's ability to effectively characterize the given problem. Regrettably, there is no universal rule specifying the perfect number of layers which are hidden and hidden-layer neurons for this.

4.1.1 Neural Network Training for the Detection of Fault

In initial phase, dedicated to fault discovery, the system processes six-inputs concurrently. These inputs correspond to scaled V and I of all phases concerning pre-defect values, encompassing ten diverse faults and a normal scenario. Consequently, the training set comprises approximately 1100 input-output pairs, distributed among ten faults (each with 100 instances) and the normal case, with each pair containing six-inputs and one-output. The NN's output is binary, representing a "yes" or "no" (1 or 0) based on fault detection. Following extensive simulations, it was determined that the optimal system structure consists of a 1 hidden-layer with 10 neurons. To illustrate, various neural networks with diverse hidden layer configurations achieving satisfactory performance are presented. The most effective neural network is detailed further, depicted in Figure 9, with error performance plots showcased in Figures 5 – 9.

Figure 3 displays performance graph of the 6-10-1 NN configuration, which comprises 6, 10, 1 neurons in the input, hidden and the output layer respectively. The graph indicates that the network fell short of reaching the targeted Mean Square Error (MSE) outcome of the training progression.

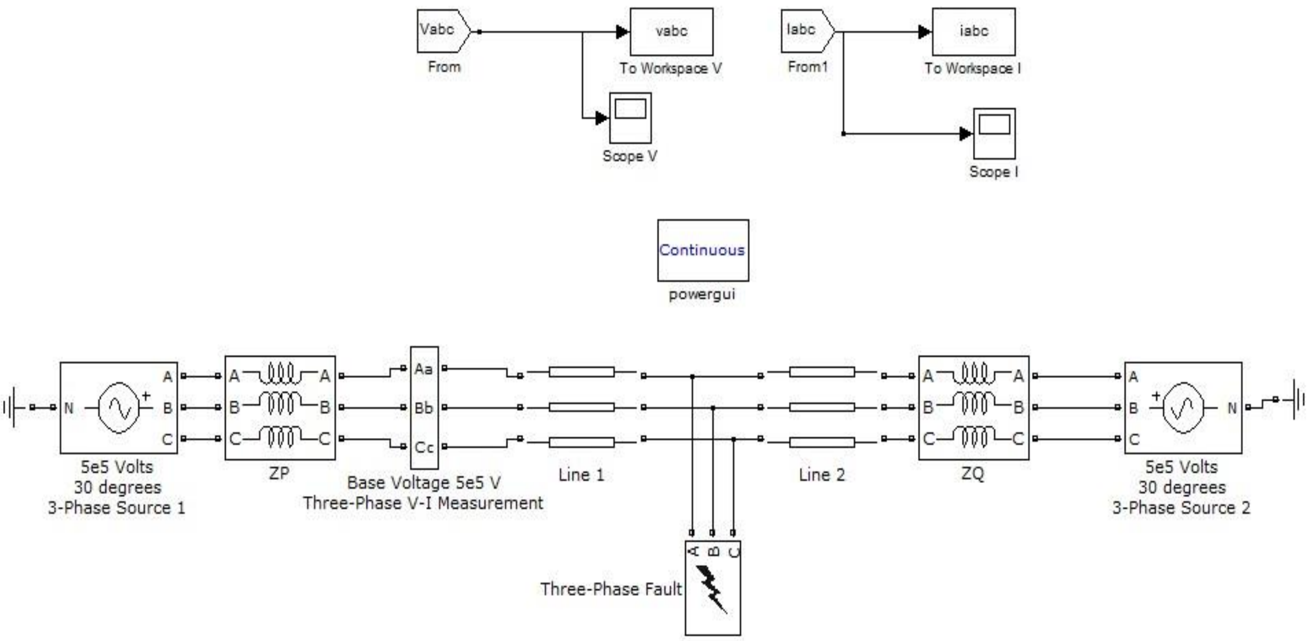

Fig. 2 Simulation Model of Transmission Line

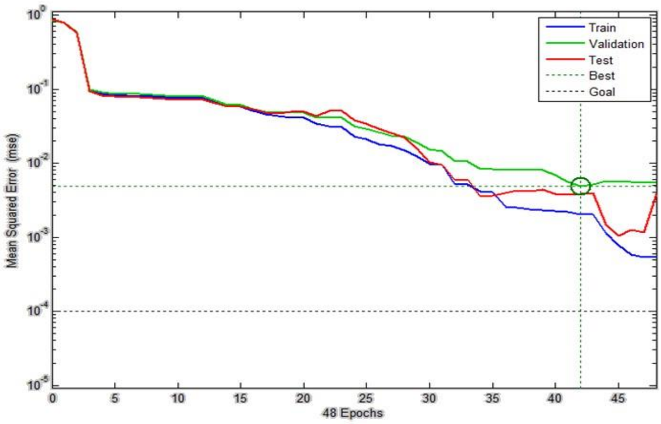

Fig. 3 (6-10-1)NN MSE performance

Figure 4 demonstrates the preparation enactment graph of the NN configured as 6-10-5-1. The neuron in the input, two hidden, and output layer are 6, 10 and 5, 1 respectively. It's important to highlight that the NN fell short of attaining the targeted Mean Square Error of 0.0001 by the conclusion of the training.

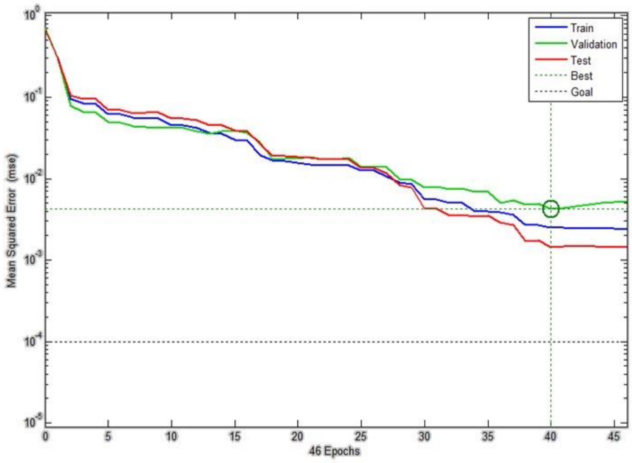

Fig. 4 (6-10-5-1)NN MSE performance

Figure 5 illustrates the training progression of the NN configured as 6-10-5-3-1, featuring neurons in input, three hidden and output layers respectively.

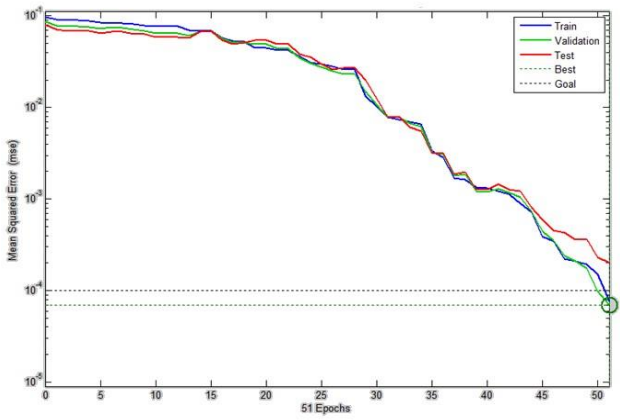

Fig. 5 (6-10-5-3-1)NN MSE performance

Based on the performance graphs above, it is important to highlight the exceptionally satisfactory results obtained by NN configured as 6-10-5-3-1. This particular configuration, characterized by neurons in input, 3 hidden and output layers respectively, achieved whole Mean Square Error significantly below the specified threshold of 0.0001. Specifically, the MSE at the conclusion of the training process is 6.9776e-5. This configuration has been selected as the optimal ANN for purposes in detection of fault.

4.1.2 Neural Network Testing for the Detection of Fault

After training the NN, its outcome is assessed through three distinct factors. The initial evaluation involves plotting the most effective linear regression, depicting the relationship between the outputs and targets, as exemplified in Figure 6.

The correlation-coefficient (r) serves as a metric for assessing in what way effectively the NN's targets align with deviations in the outputs, ranging from 0 (indicating no correlation) to 1 (representing complete correlation). In this instance, the r is determined to be 0.99967, signifying an outstanding level of correlation.

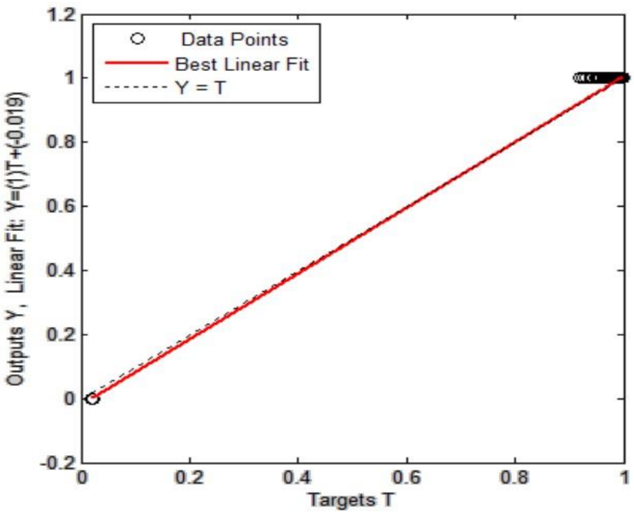

Fig. 6 (6-10-5-3-1)NN outputs vs. targets

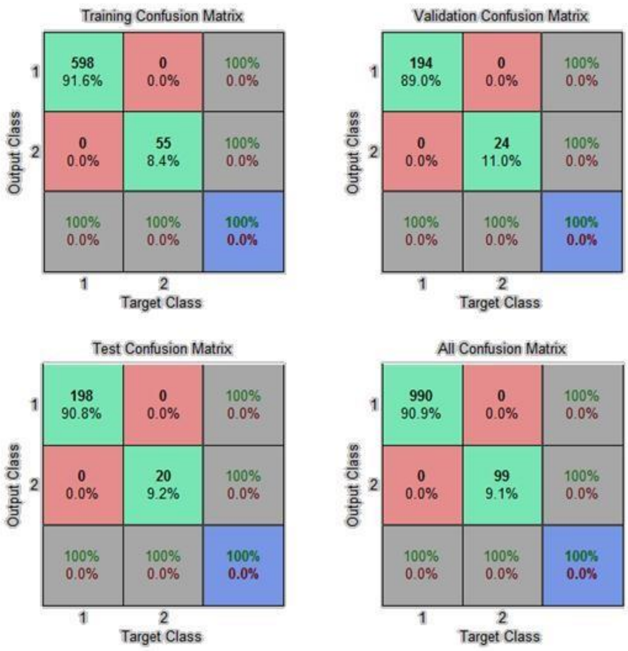

Fig. 7 Various Phases Confusion Matrices

Second step employed to evaluate the neural network's performance involves plotting confusion matrices to depict different error types that occurred during training, testing, and validation. Figure 7 explains the confusion-matrix for these 3phases. Green diagonal cells represent instances correctly classified by the NN, while red off-diagonal cells indicate misclassifications. The blue cell in each matrix denotes the overall percentage of correctly classified cases in green-color and vice versa in red-color. Notably, the selected NN demonstrates 100% fault detection accuracy.

The next testing phase procedure involves generating a distinct dataset known as test-set. This assesses enactment of the trained-NN. 300 diverse test-cases were simulated, encompassing 200 related to various fault types. For every fault, there are around twenty instances (each with a different fault resistance and position). The remaining 100 cases represent scenarios without faults. After analyzing the NN's results, it was observed that it achieves 100 percent efficiency in detecting the occurrence of a fault. Accordingly, the NN can accurately discriminate between a normal state and a fault state on a TL.

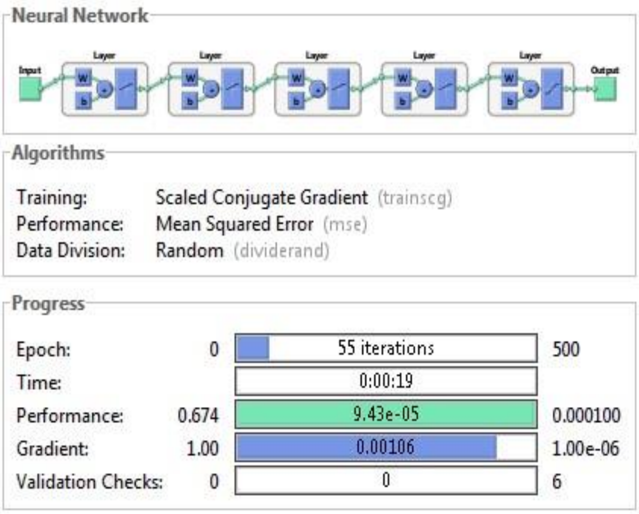

Fig. 8 Snapshot of (6-10-5-3-1)NN

Figure 8 provides a trained ANN configured as 6-10-5-3-1, indicating Fifty-five iterations. Notably, there were no validation check failures at the end of the training procedure, and the attained MSE in defect detection was 9.43e-5.

The layers which are in input, hidden and output of the NN that was chosen for defect detection are shown in Figure 9.

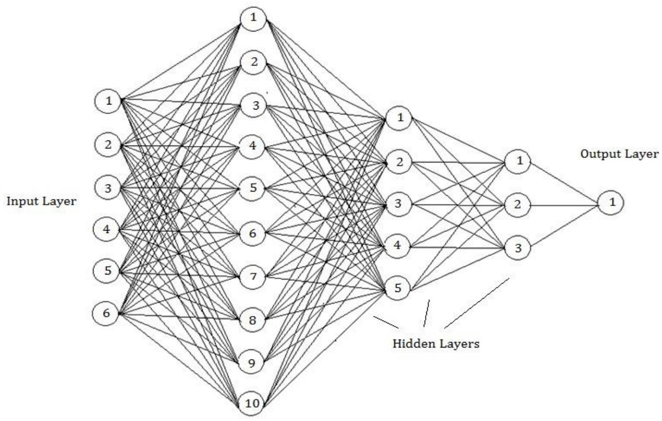

Fig.9 Chosen (6-10-5-3-1)ANN for Fault Detection

4.2 Sorting of Fault

Upon detecting a burden on the TL, the subsequent phase involves identifying the specific fault type. It begins with a assessment of various NN that underwent examination, followed by the selection of a specific network. In the realm of fault classification, NN have been widely proposed. The majority of these classifiers leverage multilayer perceptron networks and adopt the backpropagation strategy. Despite the inherent slowness and challenges in determining the optimal network size associated with this strategy, it remains the preferred approach when dealing with extensive training sets. This is because the suggested algorithm excels in providing a concise distributed representation for intricate datasets.

4.2.1 Neural Network Training for the Fault Classifier

Six sets of inputs are sent to the planned network, which are the 3phase V and I scaled to match their respective pre-fault values. The outputs are binary (0 or 1) and indicate whether a fault is present or absent on line (A, B, and C represent the 3phases P1, P2 and P3 respectively of TL and G i.e. Gnd denotes the ground).

Consequently, the several conceivable arrangements are used to accurately represent each of the ten distinct fault categories. The offered NN aims to effectively separate between these categories. Table 1 clarifies the truth-table depicting the faults and the corresponding ultimate fault output.

Table 1 Fault classifier ANN outputs for several faults

Type of	Network Outputs			
Fault	P1	P2	P3	Gnd
P1-Gnd	1	0	0	1
P2-Gnd	0	1	0	1
P3-Gnd	0	0	1	1
P1-P2	1	1	0	0
P2-P3	0	1	1	0
P3-P1	1	0	1	0
P1-P2-Gnd	1	1	0	1
P2-P3-Gnd	0	1	1	1
P3-P1-Gnd	1	0	1	1
P1-P2-P3	1	1	1	0

The training set consisted of about 1100 IO pairs, with 100 pairs for each defect and 100 pairs for the normal situation. Each set included 6 inputs and 1 output. An exploration of back-propagation networks involved analyzing various combinations of layers which are hidden and neurons in it. Among these, networks demonstrating suitable recital are offered, followed by an in-depth description of the most effective neural network. Figures 10 to 15 display error performance plots for NN with various layers which are hidden. The selected network is exemplified in Figure 19, with its error presentation plots shown in Figures 15 to 19.

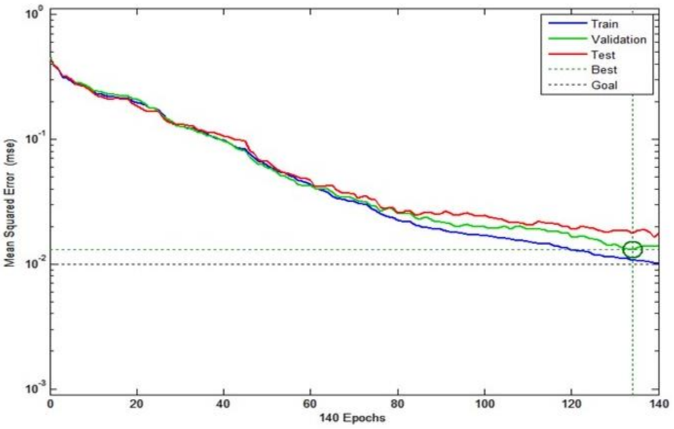

Fig. 10 (6-5-5-31-4)NN MSE performance

The training performances plot of NN 6-5-5-31-4 in Figure 10 shows the best MSE performance, which is noted as 0.01289. The NN has neurons six, five, five, 31 neurons and four in the input, 3 hidden and output layers respectively.

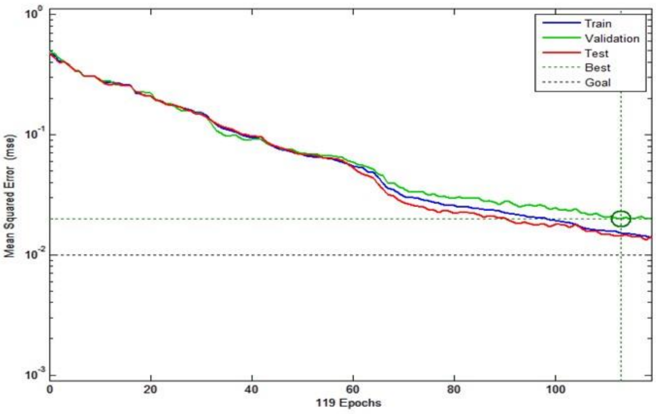

Fig. 11 (6-5-31-4)NN MSE performance

A NN plot with the configuration 6-5-31-4 is shown in Fig. 11. The MSE at the end phase indicates that 0.019773 is the finest authentication enactment. The training enactment plot of NN with the 6-5-4 configuration is presented in Figure 12. After the training procedure, the best validation performance for this scenario is 0.029578 in terms of MSE.

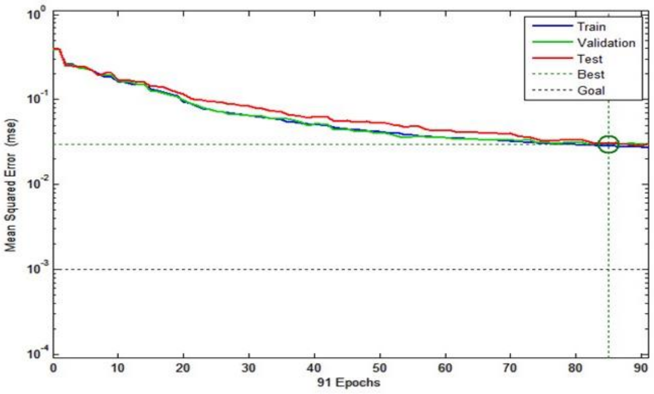

Fig. 12 (6-5-4)NN MSE performance

The NN set up as 6-10-4 is shown in Figure 13's training performance plot. The MSE of 0.0077 at the training phase indicates the ideal justification enactment.

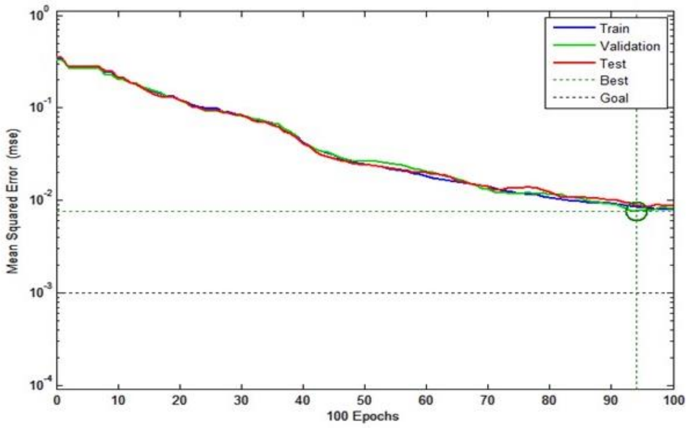

Fig. 13 (6-10-4)NN MSE performance

The NN set up as 6-20-4 (with 6 neurons in the input-layer, 1 hidden-layer with 20 neurons, and 4 neurons in the output-layer) is shown in Figure 14's training presentation plot. The MSE at the end of the training procedure indicates the best validation performance, which is 0.0093975.

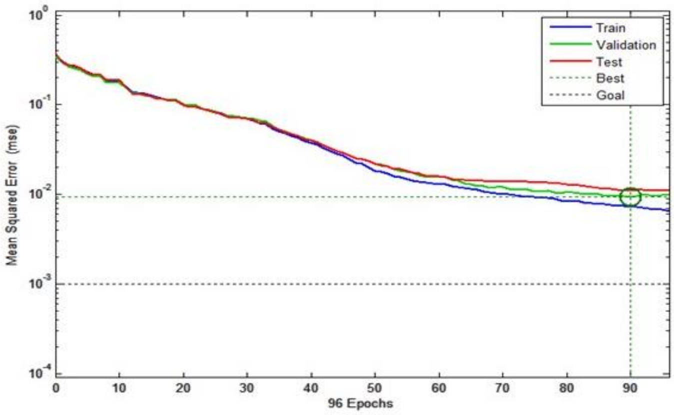

Fig. 14 (6-20-4)NN MSE performance

The NN set up as 6-35-4 (six neurons in the input-layer, one hidden-layer with thirty-five neurons, and four neurons in the output-layer) is shown in Figure 15's plot. At the end of the training procedure, the MSE indicates the ideal validation performance, which comes out to be 0.00359.

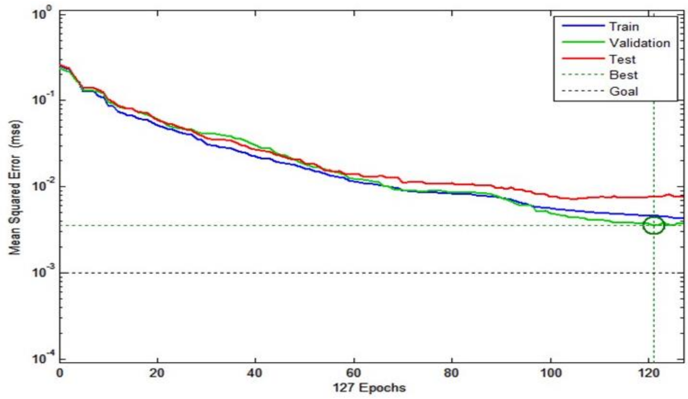

Fig. 15 (6-35-4)NN MSE performance

Based on the performance plots above, it is evident that the NN with the 6-35-4 has achieved satisfactory training performance. The MSE is 0.0035986, and the similar characteristics observed in the testing and validation curves, as depicted in Fig. 15, indicate efficient training. Therefore, this configuration has been selected as the optimal Artificial Neural Network for classification of faults.

4.2.2 Neural Network Testing for the Fault Classifier

After training the NN, its performance has been assessed by considering three distinct factors. The initial evaluation involves plotting the most effective linear regression, demonstrating the relationship among the targets and outputs, as depicted in Figure 16. In this instance, the correlation coefficient was determined to be 0.98108, indicating suitable relationship between the targets and outputs. The figure includes a dotted line representing the perfect regression fit. In NN a solid-red line depicting the actual fit. Notably, both lines closely follow each other, signifying excellent performance by the NN.

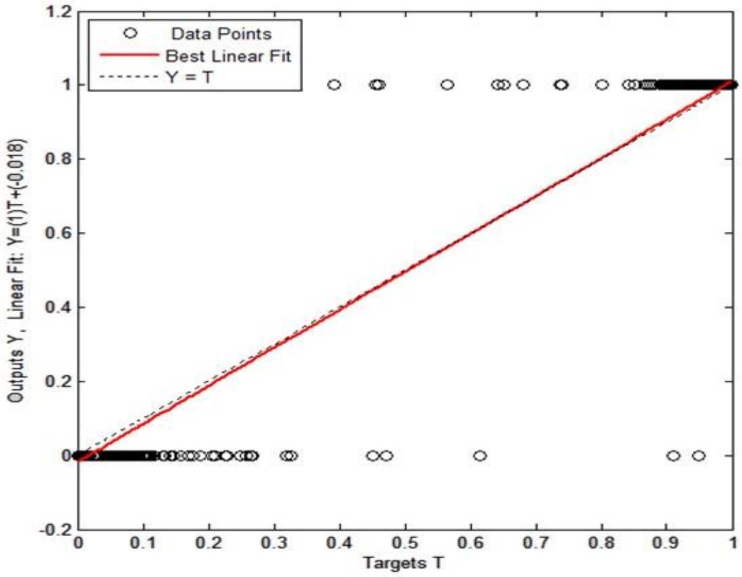

Fig. 16 (6-35-4)NN Outputs vs. Targets

Making the Receiver Operating Characteristics curve (ROC) is the second step in the testing procedure. Figure 17 illustrated ROC of several stages. The connection between NN classifier's accurate positive classification rate and the rate of wrong classification is effectively represented by these graphs. Consequently, a perfect ROC would only include upper-left corner points, denoting a classification with 100% genuine positive and 0% false positivity. Notably, all of the lines in Figure 17's ROC curves are located in the upper-left corner, making them almost perfect.

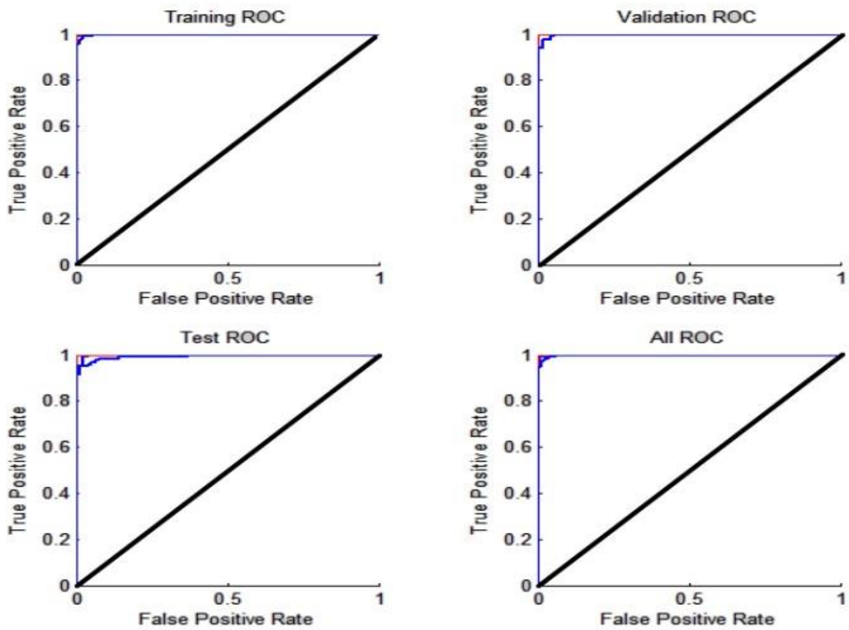

Fig. 17 (6-35-4)ANN Gradient and Validation performance

In order to assess how well the trained NN performs, a unique collection of data known as the test set is created during the third testing phase. Three hundred different test cases in all were simulated, with five hundred instances corresponding to different kinds of faults (about fifty examples for every ten faults, differing in fault resistance and position for every case). The remaining 50 cases represent scenarios without any faults. After analyzing the results, it was observed that the efficiency of the NN, particularly in accurately identifying the fault type, reached 100%. The NN can separate among the fault types on a TL with utmost accuracy.

Figure 18 shows a simulated training window. It is noteworthy that the training progression met in approximately 144 iterations, and the recital, as measured by MSE, attained a value of 6.26e-3 by the conclusion of the training.

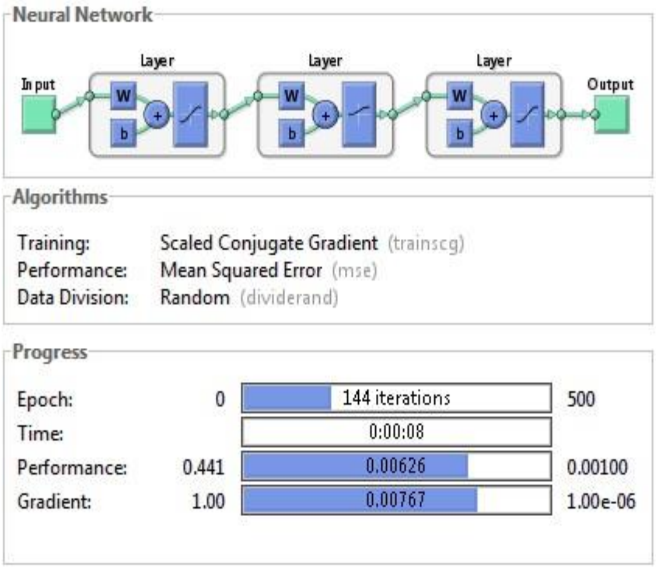

Fig. 18 Chosen (6-35-4)ANN fault-classifier

Figure 19 shows the ANN fault classification architecture. Each neuron in layer which is output represents the burden state for the 3phases (P1, P2 and P3), and the 4th neuron is dedicated to ground fault identification. A value 0 in the output indicates no fault, while a value of 1 signifies a fault in the respective phase.

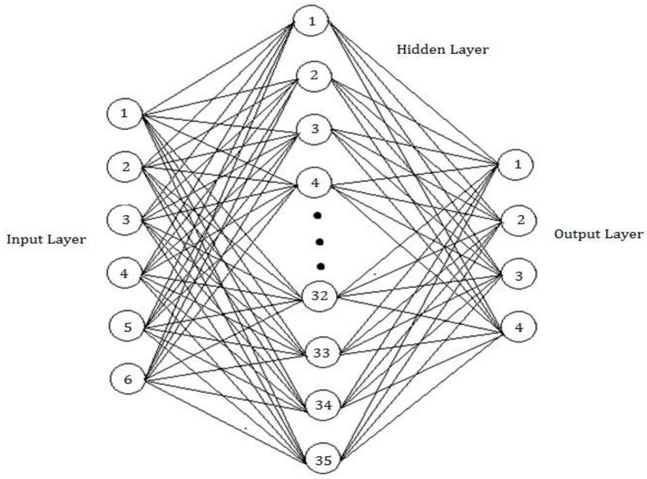

Fig. 19 Chosen (6-35-4)ANN for Fault Classification

5. Conclusion

In this study, an alternate method for identifying and categorizing TL faults, based on ANN, is presented. The simulation results obtained demonstrate that the proposed neural networks have achieved satisfactory overall performance. The paper emphasizes the importance of selecting the most suitable neural network configuration to optimize network performance. Interestingly, this method uses 720 Hz as a very low sampling frequency to sample the V and I waveforms, in contrast to the higher frequencies commonly used in the literature (typically 2 kHz – 5 kHz).

Neural networks emerge as a trustworthy and appealing solution for an effective TL fault detection system, particularly given the growing intricacy of modern power systems. Before applying certain neural network topologies and learning algorithms, it is important to carefully research and evaluate their benefits since training features and performance aspects must be balanced. Back Propagation NN proves to be highly effectual when adequately more training dataset is offered in all stages.

In comparison to numeric relays and traditional layouts, such as Taurus fault detection and Event Sequence Recorders, the proposed technique excels in fault recognition. This innovative, straightforward, cost-effective, precise, efficient, and economical approach outperforms conventional methods. Adjusting the training dataset size, varying the layer numbers which are hidden, and modifying the neurons number in each of them can result in enhancements to the performance of the proposed approach.

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