Artificial Intelligence Based Fault detection and classification in Transmission Lines

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Abstract -- Artificial neural networks and wavelet transform have been used to achieve fault Identification and classification on electric power transmission lines. This work proposed an improved solution based on wavelet transform and neural network back-propagation algorithm. The three-phase current and voltage waveforms measured during the occurrence of fault in the power transmission-line are pre-processed first and then decomposed using wavelet multi-resolution analysis to obtain the high frequency details and low frequency approximations. The patterns formed based on high frequency signal components are arranged as inputs of the neural network, whose task is to indicate the occurrence of a fault on the lines. The patterns formed using low frequency approximations are arranged as inputs of the second neural network, whose task is to indicate the exact fault type. The neural networks which can learn was trained to recognize patterns, classify data and forecast future events. Feed forward networks have been employed along with back propagation algorithm for each of the three phases in the Fault location process. An analysis of the learning and generalization characteristics of elements in power system was presented using Neural Network toolbox in MATLAB/SIMULINK environment. Simulation results obtained demonstrated that neural network pattern recognition and wavelet multi-resolution analysis approach are efficient in identifying and classifying faults on transmission lines as satisfactory performance was achieved especially when compared to the conventional methods such as impedance and travelling wave methods.

Indexed Terms: Pattern recognition, Feed forward back propagation algorithm, neural network, Liebenberg-Marquardt algorithm, Power system protection

I. INTRODUCTION

Occurrence of a fault in a power system is one of the most important factors that hinder the continuous supply of electricity and power [1]. Any abnormal flow of current in a power system’s components is called a fault in the power system. These faults cannot be completely avoided since a portion of these faults also occur due to natural reasons which are beyond the control of mankind. Hence, it is very important to have a well-coordinated protection system that detects any kind of abnormal flow of current in the power system, identifies the type of fault and then accurately locates the position of the fault in the power system. The faults are usually taken care of by devices that detect the occurrence of a fault and eventually isolate the faulted section from the rest of the power system.

As a result, some of the important challenges for the incessant supply of power are detection, classification and location of faults [2]. Most of the research done in the field of protective relaying of power systems concentrates on transmission line fault protection due to the fact that transmission lines are relatively very long and can run through various geographical terrain and hence it can take anything from a few minutes to several hours to physically check the line for faults [3].

Hence, many utilities are implementing fault classifying devices in their power quality monitoring systems that are equipped with Global Information Systems for easy location of these faults. Fault detection techniques can be broadly classified into the following categories [4]:

- Impedance measurement based methods
- Travelling-wave phenomenon based methods
- High-frequency components of currents and voltages generated by faults based methods
- Artificial Intelligence based method.

An overhead transmission line is one of the main components in every electric power system. The transmission line is exposed to the environment and the possibility of experiencing faults on the transmission line is generally higher than that on other main components. Line faults are the most common faults, they may be triggered by lightning strokes, trees may fall across lines, fog and salt spray on dirty insulators may cause the insulator strings to flash over, and ice and snow loadings may cause insulator strings to fail mechanically [5]. Fault classification and faulted phase selection play a critical role in the protection for a transmission line. Accurate and fast fault detection and classification under a variety of fault conditions are important requirements from the point of service restoration and reliability. Purposes of fault classification and faulted phase selection:

1. Identifying the type of fault, e.g., single-phase to ground fault, phase-to-phase fault, etc. Therefore, the relay can select different algorithm elements to deal with different fault situations.
2. Identifying the faulted-phase to satisfy single-pole tripping and auto reclosing requirements for operation.
3. Correct detection of the fault distance, the maintenance crew can find and fix the problem to restore the service as quickly as possible. Rapid restoration of the service reduces outage time and loss of revenue [6]. The speed and accuracy of protective relay can be improved by accurate and fast detection and classification.

II. MATERIALS AND METHODS

AI is a subfield of computer science that investigates how the though and action of human beings can be mimicked by machines [7]. Both the numeric, non-numeric and symbolic computations are included in the area of AI. The mimicking of intelligence includes not only the ability to make rational decisions, but also to deal with missing data, adapt to existing situations and improve itself in the long time horizon based on the accumulated experience.

From quite a few years, intelligent based methods are being used in the process of fault detection and location. Three major families of artificial intelligence based techniques that have been widely used in modern power system are [8]:

1) Expert System Techniques (XPS),
2) Artificial Neural Networks (ANN),
3) Fuzzy Logic Systems (FLS).

1) EXPERT SYSTEMS:

The first systems included a few heuristic rules based on the expert's experience. In such systems, the knowledge takes the form of the so-called production rules written using the *If … then …* syntax (knowledge base). The system includes also the facts which generally describe the domain and the state of the problem to be solved (data base). A generic inference engine uses the facts and the rules to deduce new facts which allow the firing of other rules. The knowledge base is a collection of domain-specific knowledge and the inference system is the logic component for processing the knowledge base to solve the problem. This process continues until the base of facts is saturated and a conclusion has been reached as shown in Figure 2.1. To guide the reasoning and to be more efficient, these systems may incorporate some strategies known as met knowledge. Rule based systems represent still the majority of the existing expert systems.

There are few applications of XPS to power system protection reported, but all of them solve the off-line tasks such as settings coordination, post-fault analysis and fault diagnosis [8]. As yet there is no application reported of the XPS technique employed as a decision-making tool in an on-line operating protective relay. The basic reason for this is that there is no extensive rule base that describes the reasoning process applicable o protective relaying. Instead, only a few rules or criteria are collected [9].

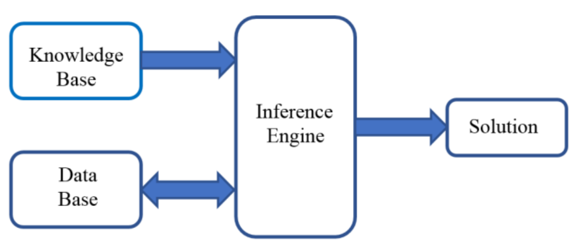

Fig. 2.1: Simplified block diagram of an XPS

2) ARTIFICIAL NEURAL NETWORKS:

The ANNs are very different from expert systems since they do not need a knowledge base to work. Instead, they have to be trained with numerous actual cases. An ANN is a set of elementary neurons which are connected together in different architectures organized in layers of what is biologically inspired. An elementary neuron can be seen like a processor which makes a simple non-linear operation of its inputs producing its single output. The ANN techniques are attractive because they do not require tedious knowledge acquisition, representation and writing stages and, therefore, can be successfully applied for tasks not fully described in advance. The ANNs are not programmed or supported by knowledge base as are Expert systems. Instead, they learn a response based on a given inputs and required output by adjusting the node weights and biases accordingly. The speed of processing, allowing real time applications, is also advantage.

Since ANNs can provide excellent pattern recognition, they are proposed by many researchers to perform different tasks in power system relaying for signal processing and decision making [10].

3) FUZZY LOGIC SYSTEMS:

Fuzzy logic (FL) can be defined as a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. Fuzzy based classification technique employs a simple, rule-based IF X AND Y THEN Z approach to a solving control problem rather than attempting to model a system mathematically.

With reference to Figure 2.2 the fuzzy approach to protective relaying assumes that [11]:

- The criteria signals are fuzzified in order to account for dynamic errors of the measuring algorithms. Thus, instead of real numbers, the signals are represented by fuzzy numbers. Since the fuzzification process provides a special kind of flexible filtering, faster measuring algorithms that speed up the relays may be used.
- The thresholds for the criteria signals are also represented by fuzzy numbers to account for the lack of precision in dividing the space of the criteria signal between the tripping and blocking regions.
- The fuzzy signals are compared with the fuzzy settings. The comparison result is a fuzzy logic variable between the Boolean absolute levels of truth and false.
- Several relaying criteria are used in parallel. The criteria are aggregated by means of formal multi-criteria decision-making algorithms that allow the criteria to be weighted according to their reasoning ability.
- The tripping decision depends on multi-criteria evaluation of the status of a protected element. Additional decision factors may include the amount of available information, or the expected costs of the relay mal-operation.

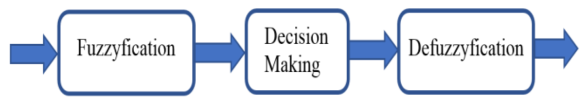

Fig. 2.2: Simplified block diagram of the fuzzy logic approach

The Fuzzy BasedFault Classification is based on Angular differences among the sequence components of the fundamental during fault current as well as on their relative magnitudes. The phasor diagram of a phase "a" to ground fault is shown in the Figure 2.3.

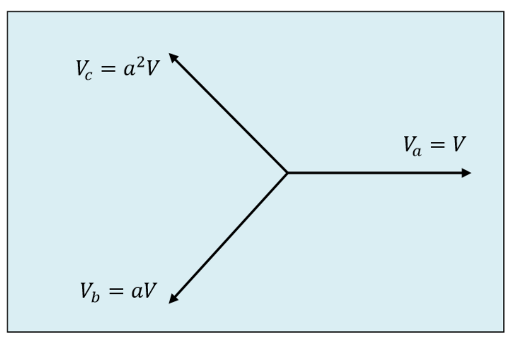

Fig. 2.3: Phasor diagram for a-g fault

The zero, positive and negative sequence components of the post fault currents relative to phase "a" are denoted as I_{aof}, I_{a1f} and I_{a2f} respectively. The angles between the positive and negative sequence components of phase a, b and c are given as

$$arg\_A = |Arg(I_{a1f}) - Arg(I_{a2f})| = 0^0$$

$$arg\_B = |Arg(I_{b1f}) - Arg(I_{b2f})| = 120^0$$

$$arg\_C = |Arg(I_{c1f}) - Arg(I_{c2f})| = 120^0 \quad (1)$$

The magnitudes of I_{aof}, I_{a1f} and I_{a2f} are related by

$$R_{of} = |I_{aof}/I_{a1f}| = 1 \text{ and } R_{2f} = |I_{a2f}/I_{a1f}| = 1 \quad (2)$$

Similarly, the magnitudes and angle between the positive and negative sequence components are obtained for other types of asymmetric faults.

For every type of fault, there exists a unique set of these five parameters. So it is possible to formulate simple logic base for determining the fault type from the values of the five inputs. The different inputs are represented by a corresponding fuzzy variable. Now a fuzzy rule was developed using these five variables to detect the type of fault. For example:

If arg_A is "approximately 30^0" and arg_B is "approximately 150^0" and arg_C is "approximately 150^0" and R_{of} is "high" and R_{sf} is "high" then fault type is "a-g"

In this method, only 3 parameters are sufficient and it identifies 10 types of short-circuit faults accurately. But the main disadvantage with this method is that it is applicable to only asymmetric faults and it is not very effective if you are looking to classify not just by the type of fault.

In conclusion, the XPS, ANN and FLS approaches have their own advantages and limitations but XPS and FLS methods require a knowledge base, that is, an expertise body of coded information of any particular system under consideration before they could be applied. This makes them ill-disposed to generalized application. ANN on the other hand does not require a knowledge base hence it is well suited to generalized and rapid deployment. This is the reason for the choice of ANN in this dissertation for fault identification and location on electric power transmission lines.

- OUTLINE OF THE PROPOSED SCHEME:

Firstly, the entire data is extracted and collected from the model of a power transmission line after simulation. The data is decomposed and filtered into low frequency bands & high frequency bands. Both are then subdivided into two sets namely the training and the testing data sets. Then, the excellent pattern recognition and classification abilities of neural networks have been cleverly utilized in this dissertation to address the issue of transmission line fault location on the adopted Nigerian Transmission line. The second step in the process is fault detection using neural networks. Once it is known that a fault has occurred on the transmission line, the next step is to classify the fault into the different categories based on the phases that are faulted. Then, the final step is to pin-point the position of the fault on the transmission line.

The goal of this dissertation is to propose an integrated method to perform each of these tasks using wavelet multi-resolution analysis tool and pattern recognition capability of artificial neural networks. A back-propagation based neural network has been used for the purpose of fault detection and another similar one for the purpose of fault classification. For each of the different kinds of faults, separate neural networks have been employed for the purpose of fault location.

III. RESULTS AND DISCUSSION

1) SIMULATION RESULTS OF TRAINING THE FAULT IDENTIFICATION NEURAL NETWORK:

In the first stage which is the fault identification phase, the network takes in three inputs (W_a, W_b, and W_c) at a time, which are the summation of the detail coefficients for all three phases. The entire input data set (3047x3 vector matrix) is subdivided into three; 60%, 20%, 20% for the training set, validation set and testing set respectively giving a set of three inputs and one output in each input-output pair. The output of the neural network is just a yes or a no (1 or 0) depending on whether or not a fault has been detected. After extensive simulations it has been

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decided that the desired network has five hidden layers with 8 neurons in the first hidden layer, 10 neurons in the second hidden layer, 20neurons in the third hidden layer,15 neurons in the fourth hidden layer and 6neurons in the fifth hidden layer.

Fig 3.1 shows the training process of the neural network with (3.8.10.20.15.6.1) configuration (3 neurons in the input layer, 5 hidden layers with 8, 10, 20, 15 and 6 neurons in them respectively and one neuron in the output layer).

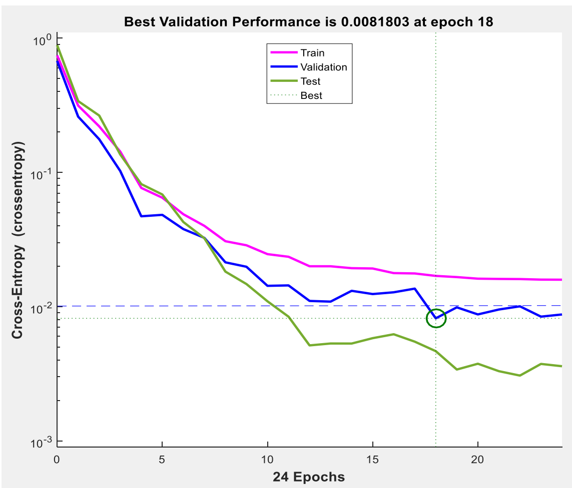

Fig. 3.1: Mean-square error performance of the network (3.8.10.20.15.6.1).

From the above training performance plots, it is to be noted that very satisfactory training performance has been achieved by the neural network with the (3.8.10.20.15.6.1) configuration (3 neurons in the input layer, 5 hidden layers with 8, 10, 20, 15 and 6 neurons in them respectively and one neuron in the output layer). The overall Cross-Entropy of the trained neural network is way below the value of 1e-2 and is actually8.18036e-3 by the end of the training process. Hence this has been chosen as the ideal ANN for the purpose of fault detection.

2) SIMULATION RESULTS OF TESTING THE FAULT IDENTIFICATION NEURAL NETWORK:

Once the neural network has been trained, its performance has to be tested by three different factors. The first of these is by plotting the best linear regression that relates the targets to the outputs as shown in Fig 3.2.

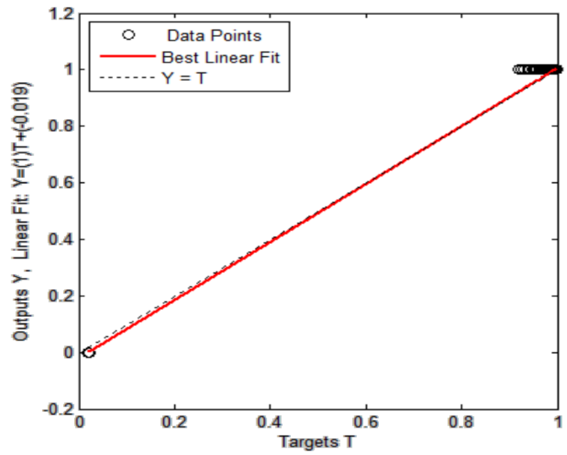

Fig. 3.2: Regression fit of the outputs vs. targets for the network (3.8.10.20.15.6.1).

The correlation coefficient (r) is a measure of how well the neural network's targets can track the variations in the outputs (0 being no correlation at all and 1 being complete correlation). The correlation coefficient in this case has been found to be 0.99967 which indicates excellent correlation.

The second means of testing the performance of the neural network is to plot the confusion matrices for the various types of errors that occurred for the trained neural network. Fig 3.3 plots the confusion matrix for the three phases of training, testing and validation. The diagonal cells in white colour indicate the number of cases that have been classified correctly by the neural network and the off-diagonal cells which are in pink indicate the number of cases that have been wrongly classified by the ANN.

The last cell in blue in each of the matrices indicates the total percentage of cases that have been classified correctly in green and the vice-versa in red. It can be seen that the chosen neural network has 98.7% accuracy in fault detection. Hence the neural network can, with utmost accuracy, differentiate a normal situation from a fault condition on a transmission line.

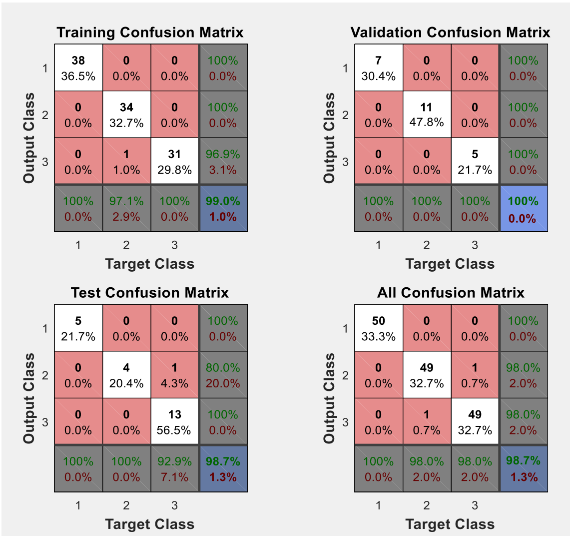

Fig. 3.3: Confusion matrices for Training, Testing and Validation Phases.

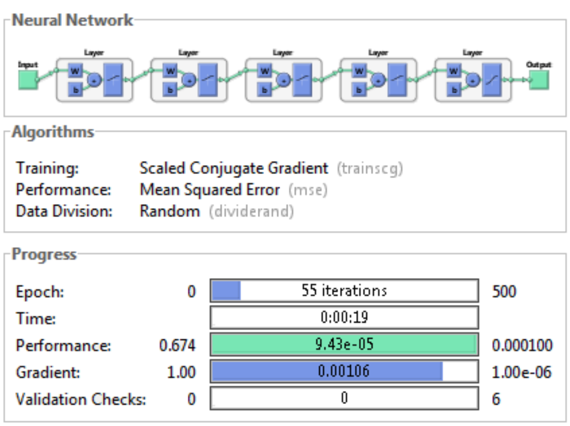

Fig. 3.4: Overview of the ANN (3.8.10.20.15.6.1) chosen for fault detection.

Figure 3.4 presents a snapshot of the trained ANN with the (3.8.10.20.15.6.1) configuration and it is to be noted that the number of iterations required for the training process were 55. It can be seen that the mean square error in fault detection achieved by the end of the training process was 9.43e-5 and that the number of validation check fails were zero by the end of the training process.

3) SIMULATION RESULTS OF TRAINING THE FAULT CLASSIFIER NEURAL NETWORK:

The same process that was employed in the previous section (section 3.1) is also followed in this section in terms of the design and development of the classifier neural network. The designed network takes in sets of three inputs (W_a, W_b, and W_c). The neural network has four outputs, each of them corresponding to the fault condition of each of the three phases and one output for the ground line. Hence the outputs are either a 0 or 1 denoting the absence or presence of a fault on the corresponding line (A, B, C or G). Where A, B and C denote the three phases of the transmission line and G denotes the ground). Hence the various possible permutations can represent each of the various faults accordingly. The proposed neural network should be able to accurately distinguish between the ten possible categories of faults. The truth table representing the faults and the ideal output for each of the faults is illustrated in Table 3.1.

Table 3.1 Fault classifier ANN outputs for various faults.

Type of Fault		Network Outputs			
		A	B	C	G
L-G	A-G Fault	1	0	0	1
	B-G Fault	0	1	0	1
	C-G Fault	0	0	1	1
L-L	A-B Fault	1	1	0	0
	B-C Fault	0	1	1	0
	C-A Fault	1	0	1	0
L-L-G	A-B-G Fault	1	1	0	1
	B-C-G Fault	0	1	1	1
	C-A-G Fault	1	0	1	1
3 -Phase	A-B-C Fault	1	1	1	0

Hence the training set consisted of about 2090 input output sets (19 for each of the ten faults and 19 for the no fault case) with a set of three inputs and one output in each input-output pair. Back-propagation networks with a variety of combinations of hidden layers and the number of neurons per hidden layer have been analysed.

Fig 3.5 shows the training performance plot of the neural network 3.12.35.24.4 (3 neurons in the input layer, 3 hidden layers with 12, 35 and 24 neurons in it respectively and four neurons in the output layer). It can be seen that the best validation performance in terms of the Cross-Entropy by the end of the training process in this case is 7.3899e-3 which is below the Cross-Entropy goal of 1e-2.

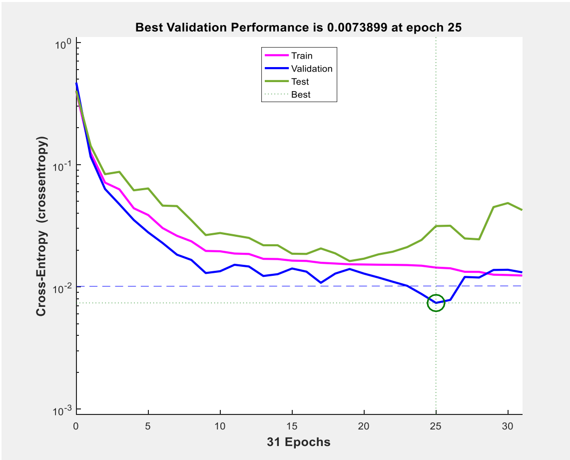

Fig. 3.5: Mean-square error performance of the network with configuration (3.12.35.24.4).

From the above training performance plots, it is to be noted that satisfactory training performance has been achieved by the neural network with the 3.12.35.24.4 configuration (3 neurons in the input layer, 12, 35 and 24 neurons in the hidden layers respectively and four neurons in the output layer). The overall Cross-Entropy of the trained neural network is 7.3899e-3 and it can be seen from Fig 3.5 that the testing and the validation curves have similar characteristics which is an indication of efficient training. Hence this has been chosen as the ideal ANN for the purpose of fault classification.

4) SIMULATION RESULTS OF TESTING THE FAULT CLASSIFIER NEURAL NETWORK:

Once the neural network has been trained, its performance has been tested by taking three different factors into consideration. The first of these is by plotting the best linear regression that relates the targets to the outputs as shown in Fig 3.6. The correlation coefficient in this case was found to be 0.98108 which indicates satisfactory correlation between the targets and the outputs. The dotted line in the figure indicates the ideal regression fit and the red solid line indicates the actual fit of the neural network. It can be seen that both these lines track each other very closely which is an indication of very good performance by the neural network.

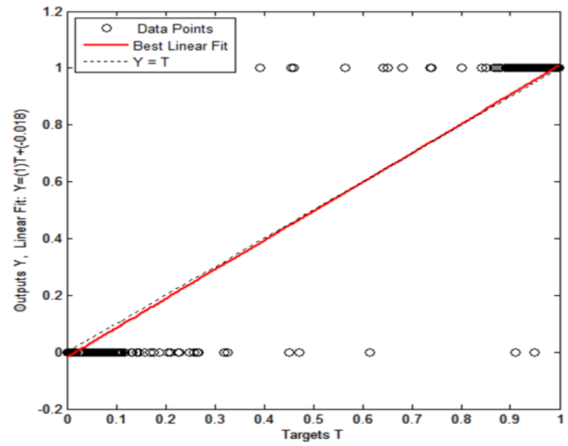

Fig. 3.6: Regression fit of the Outputs vs. Targets of ANN with configuration (3.12.35.24.4).

The second approach of testing the performance of the neural network is to plot the confusion matrices for the various types of errors that occurred for the trained neural network. Fig 3.7 plots the confusion matrix for the three phases of training, testing and validation. The diagonal cells in white colour indicate the number of cases that have been classified correctly by the neural network and the off-diagonal cells which are in pink indicate the number of cases that have been wrongly classified by the ANN. The last cell in blue in each of the matrices indicates the total percentage of cases that have been classified correctly in green and the vice-versa in red. It can be seen that the chosen neural network has 98.7% accuracy in fault detection. Hence the neural network can, with utmost accuracy, differentiate between the ten possible types of faults on a transmission line.

Fig. 3.7: Confusion matrices for Training, Testing and Validation Phases of the ANN with configuration (3.12.35.24.4).

Fig 3.8 provides an overview on the neural network and is a screen shot of the training window simulated using the Artificial Neural Network Toolbox in Simulink. Important things to be noted are that the training process converged in about 144 iterations and that the performance in terms of mean square error achieved by the end of the training process was 6.26e-3.

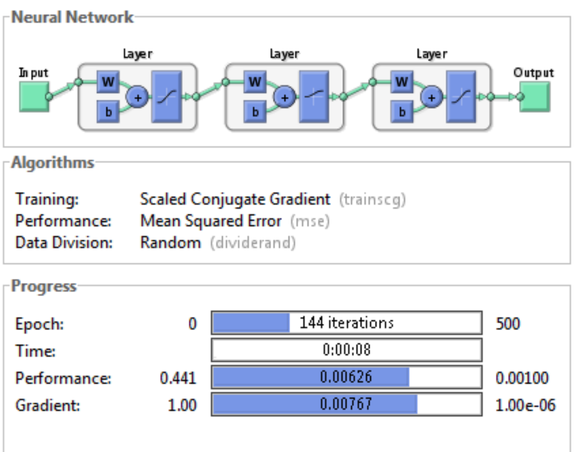

Fig. 3.8: Overview of the ANN with configuration (3.12.35.24.4), chosen as fault classifier.

IV. CONCLUSIONS

To simulate the entire power transmission line model and to obtain the training data set, MATLAB R2016a has been used along with the SimPowerSystems toolbox in Simulink. In order to train and analyze the performance of the neural networks, the Artificial Neural Networks Toolbox has been used extensively. Some important conclusions that can be drawn from this thesis are:

- Neural Networks are indeed a reliable and attractive scheme for an ideal transmission line fault location scheme especially in view of the increasing complexity of the modern power transmission systems.
- It is very essential to investigate and analyze the advantages of a particular neural network structure and learning algorithm before choosing it for an application because there should be a trade-off between the training characteristics and the performance factors of any neural network.
- Back Propagation neural networks are very efficient when a sufficiently large training data set is available and hence Back Propagation networks have been chosen for all the three steps in the fault location process namely fault detection, classification and fault location.

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