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FAULT LOCATION FOR TRANSMISSION LINES BASED ON ARTIFICIAL NEURAL NETWORK

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Abstract : This article focuses on using artificial neural networks to detect and classify faults in power lines. Detection, classification and error detection using neural networks. Each of the three steps in the error localization process uses network forward and backward propagation algorithms. A neural network analysis with different hidden layers and different numbers of neurons per hidden layer is provided to illustrate the use of the neural network at each level. The simulation results show that this method fits the characteristics of neural networks well and gives good results in transmission error detection..

KEY WORDS: **ANN, Feed-forward network, back-propagation algorithm, Levenberg-MaB-Rquardt algorithm, root-mean-square error.**

I.INTRODUCTION

Over the last several decades, there has been a tremendous expansion of the global power grid, which has resulted in the installation of a massive number of new transmission and distribution lines. Furthermore, the advent of new marketing ideas such as deregulation has raised the requirement for a consistent and uninterrupted supply of electricity to end consumers who are extremely sensitive to power disruptions [1]. A power system malfunction is one of the most significant problems impeding the continuous delivery of energy and power [2]. A power system fault is defined as any aberrant flow of current in the components of a power system. These flaws cannot be totally prevented since some of them are caused by other factors. These flaws cannot be totally prevented since some of them develop due to natural causes that are beyond mankind's control. As a result, it is critical to have a well-coordinated protection system that detects any aberrant flow of current in the power system, determines the kind of problem, and properly locates the fault in the power system. Devices that detect the existence of a problem and subsequently isolate the defective portion from the rest of the power system handle the faults.
Therefore, one of the most important problems in continuous power is the detection, classification and operation of faults [3]. Faults can be continuous, continuous, symmetrical, or asymmetrical, and the diagnostic process is different for each fault, as there is no single fault location that applies to all.

II. ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network (ANN) is a collection of primitive neurons that are often linked in biologically inspired topologies and organized in layers [39]. Figure 3.1 depicts the structure of a feed-forward ANN, also known as a perceptron. Each Ith layer contains Ni neurons, and the inputs of these neurons are coupled to the neurons of the previous layer. The excitation pulses are fed into the input layer. To put it simply, an elementary neuron is a processor that generates an output by performing a basic non-linear operation on its inputs [40]. Each neuron has a weight linked to it, and training an ANN is the act of modifying different weights based on the training set. By altering the node weights, an Artificial Neural Network learns to provide a response based on the inputs provided. As a result, we require a set of data known as the training data set, which is utilised to train the neural network.

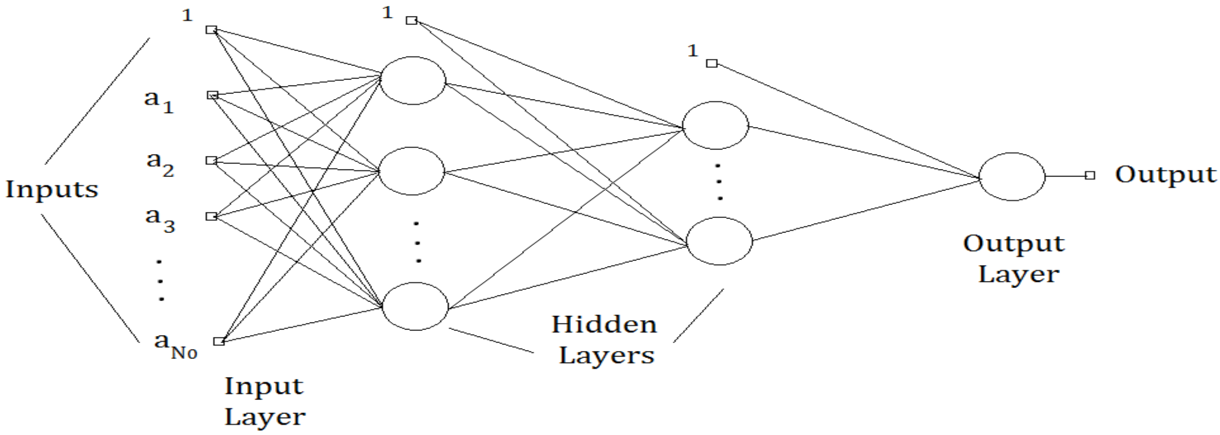

Figure 3.1 A basic three-layer architecture of a feedforward ANN

The input set of ANN is shown in Fig. 3.1 a1, a2,...aN0. ANNs are used for a variety of purposes in various industries, including signal processing, computers, and decision-making, due to their excellent pattern recognition capabilities. Here are some key points about artificial neural networks. [41]:

• A raw sample of the input signal or signal function, extracted using a specific measurement method, is fed into the ANN.

• The most recent signal sample and some previous samples are sent to the INS.

• The output of the neural network is correlated with the choice under consideration, which can be the type of defect, the presence of the defect, or the location of the defect.

• The learning scheme used in an ANN is the most important component determining its function.

• Pre- and post-processing techniques can also be used to improve the learning process and minimize ANN training time. One of the most significant drawbacks of using artificial neural networks in applications is the lack of well-defined guides to help select the optimal number of hidden layers to use and the number of neurons per hidden layer. On the other hand, it is beneficial because of its ability to generalize [39]. ANN's commitment to parallel computing is an important aspect. As a result, it can provide correct outputs for all inputs even if they are not passed to the ANN during the training phase. Another challenge in the development of ANN-based applications has been the synthesis of adaptive learning algorithms. This approach is based on error backpropagation where neuron weights are sequentially changed to minimize the error between the actual and desired outputs. to get a specific result. This is called supervised learning. Unlabeled training data with no recommendations. This allows AI solutions to identify patterns and correlations that, when applied to data, produce results. This is called supervised learning. You can also use a set of algorithms to extract patterns and make decisions from large data sets. This is called unsupervised learning.

III. ANN BASED FAULT DETECTION

Artificial Neural Network (ANN) based fault detection refers to the use neural networks to identify and detect faults or anomalies in a system or process. ANN is a machine learning model inspired by the biological structure of the human brain, consisting of interconnected artificial neurons.

In fault detection, ANNs can be trained to recognize patterns and behaviors within a system that indicate the presence of faults. The process typically involves the following steps.

- Data collection.
- Data preprocessing.
- Model training.
- Fault detection
- Performance evaluation.

As illustrated in Fig 3.2, any basic neuron model may be characterised by a function that calculates the output as a function of N0 inputs. The core concept underlying the complete neuron model, including the activation functions described below, is based on [5].

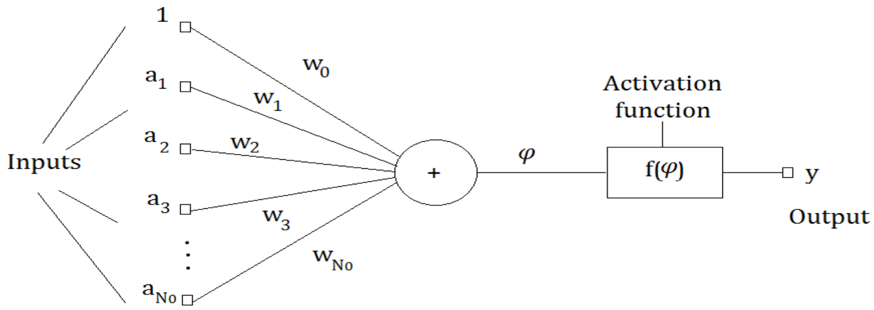

Figure 3.2 Typical model of a neuron.

The output of the neuron is given by $y = f(\varphi) = f(\sum^{N0} w_i a_i)$

Where: $w_0 a_0$ is the threshold value (polarization), f (φ) is the neuron activation function, φ is the summation output signal and y is the neuron output.

$$\varphi = W^T A$$

Where: $W = \lfloor w_0\, w_1 \ldots\ldots w_{K_0} \rfloor$, $A = \lfloor a_0\, a_1 \ldots a_{N0} \rfloor^T$.

An activation function decides how powerful the output from the neuron should be, based on the sum of its inputs. Depending upon the application's requirements, the mostappropriate activation function is chosen.

The activation function f (φ) can be in different forms a few of which are described below:

- Step function

$$f(\varphi) = \begin{cases} 1 & \text{if } \varphi \geq 0 \\ 0 & \text{if } \varphi < 0 \end{cases}$$

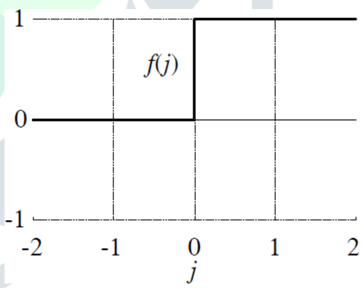

Figure 3.3 Step activation function

- Piece wise linear function

$$f(\varphi) = \begin{cases} 1 & \text{if } \varphi > 1 \\ -1 & \text{if } \varphi < -1 \\ \varphi & \text{if } |\varphi| < 1 \end{cases}$$

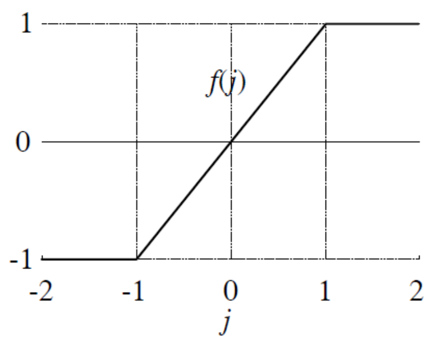

Figure 3.4 Piece wise linear activation function

- Sigmoid unipolar function

$$f(\varphi) = \frac{1}{1 + e^{-\beta\varphi}}$$

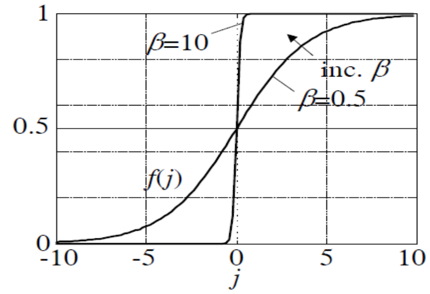

Figure 3.5 Sigmoid unipolar activation function.

- Sigmoid bipolar function

$$f(\varphi) = \tanh(\beta\varphi) = \frac{1 - e^{-2\beta\varphi}}{1 + e^{-2\beta\varphi}}$$

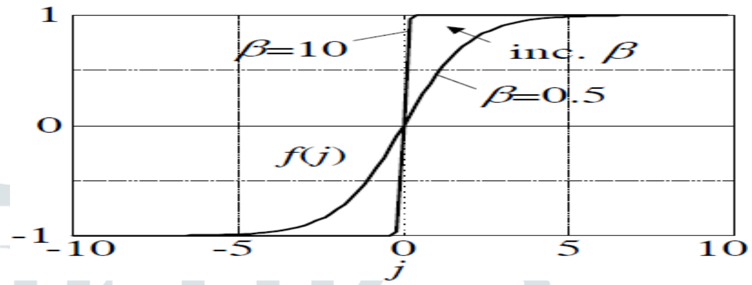

Figure 3.6 Bipolar activation function.

Depending on how the neurons are connected to each other in the model, neural networks can be divided into two types: feedforward networks and feedback networks. As the name implies, feedback networks differ from feedforward networks in that they have feedback connections that feed back into the network along with the inputs. Because of their simplicity and the existence of well-defined learning algorithms, only feedforward networks are used in this paper for simulations, which are briefly discussed in the next section**.**

IV. FEEDFORWARD NETWORKS AS FAULT LOCATOR.

The feedforward network is the simplest neural network, there is no connected feedback in the network, so the information propagation is one-way [40]. The feed forward network with input N0 and output signal KR is shown in Figure 3.7. The calculation process of layer i can be explained by the following equation: (16)

$$p(i) = f(i)(W(i)g(i-1)) \qquad (16)$$

Where $p^{(i)} = [p_1^{(i)} \; p_2^{(i)} \; \dots \; p_{N_i}^{(i)}]^T$ is the signal vector at the output of the i^{th} layer.

And $W^{(i)} = \begin{bmatrix} w_{10}^{(i)} & w_{11}^{(i)} & \cdots & w_{1N_{i-1}}^{(i)} \\ w_{20}^{(i)} & w_{21}^{(i)} & & w_{2N_{i-1}}^{(i)} \\ \vdots & & & \vdots \\ w_{N_i0}^{(i)} & w_{N_i1}^{(i)} & \cdots & w_{N_iN_{i-1}}^{(i)} \end{bmatrix}$ is the weighing matrix between the $(i$-1)th and the i^{th} layer.

$$g^{(i-1)} = \begin{cases} A & for \ i = 11 \\ [p^{(i-1)}] & for \ i = 2,3,\ldots,R \end{cases} \quad (17)$$

A is the vector containing the input signal, f(i)(.) is the function performed by the neurons in layer i, and R is the standard set. All neurons in a given layer must be comparable in every sense, and the overlying layer can be more than one and is usually determined by the configuration reasons of the neurons. The yield of nervous tissue is represented by the yield vector:

$$y = p^{(R)} = [y_1 \quad y_2 \ \ldots y_{N_R}]^T \quad (18)$$

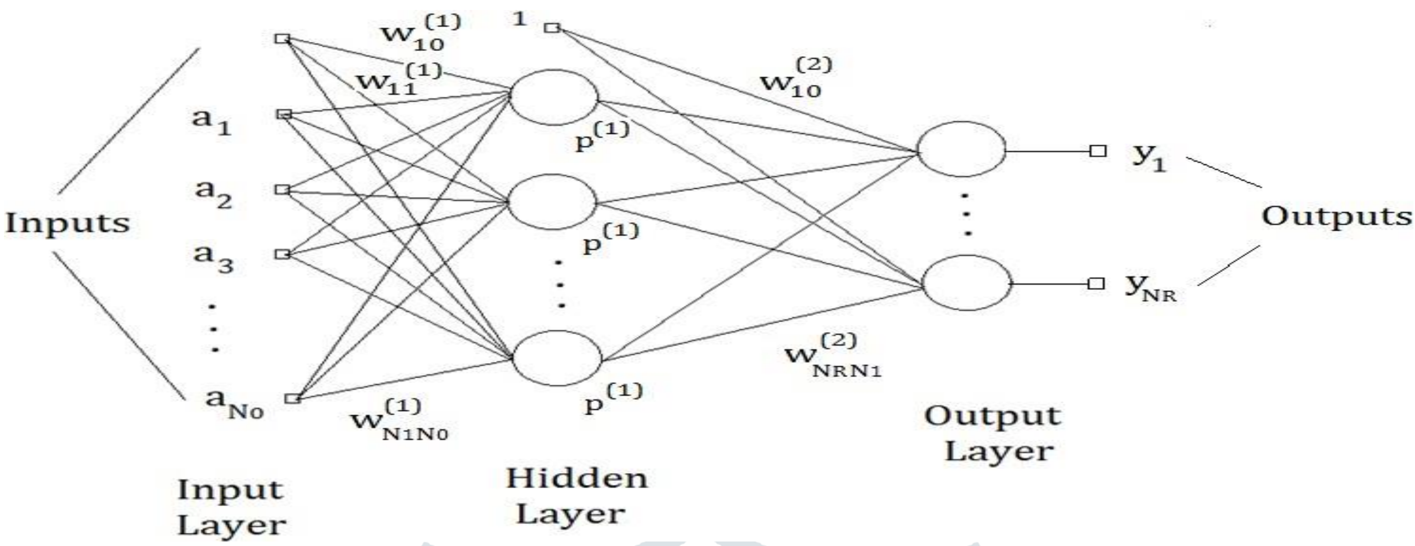

Figure 3.7 Structure of a two-layered feedforward network.

Minimization of equation (23) above is a non-linear problem, as function functions are generally non-linear. There are many methods that can handle nonlinear functions efficiently and follow the cheapest method. The steepest descent is an extension of the Laplace approximation, where the contour integral in the complex plane deforms to the stop in the direction of the steepest descent so it does not hurt [42]. The back-error propagation learning method is based on steepest descent, most commonly used in a version called the Levenberg-Marquardt algorithm [42].

V. BACK-ERROR-PROPOGATION.

The error backpropagation algorithm selects the weights for the neural network nodes, feeds the input pairs, and gets the result. Then we calculate the error for each of the final stages and report the error back. When this is done we adjust the weights and repeat the process using all the input-output methods available in the data. This process continues until the network converges to the desired destination. The error regression technique is widely used for many purposes, including analysis of errors (other than error sums of squares) and Jacobian and Hessian matrices.The correction factor is calculated as a function of the minimum estimation error according to equation (23). This is done layer by layer back and forth across the network. The algorithm is shown in Figure 3.9.

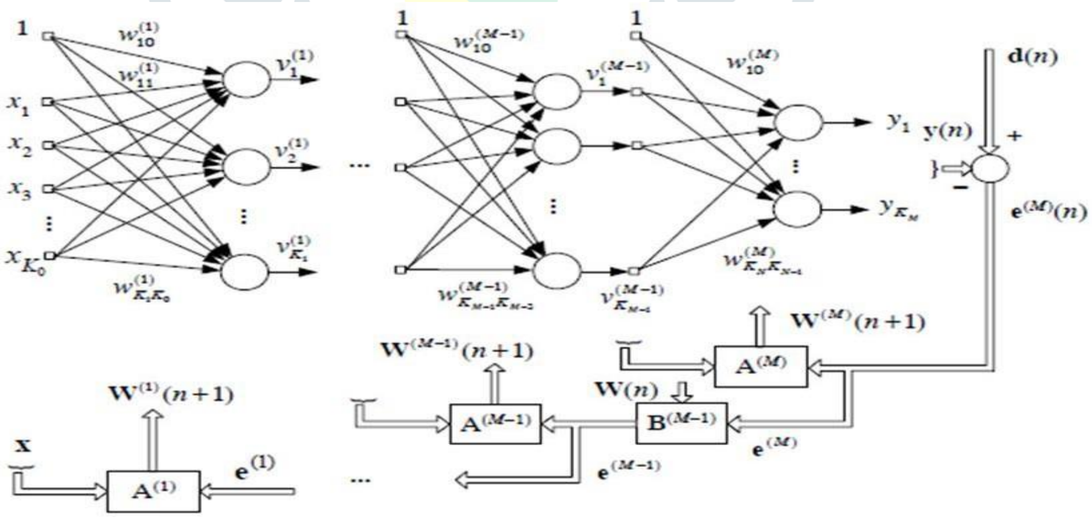

Figure 3.9 Structure of back-error-propagation algorithm [adopted from [5]]

The weight vectors are contained in blocks A(M), A(M-1), ..., A(1) and the error spread over the layers is calculated and B(M-1), B(M-2), ..., B(2). The reverse error propagation algorithm has been used in many ways, but the basic idea has remained the same. The only change in these implementations is the method used to calculate the updated weights when returning from one layer to the next in the neural network. Relevant changes are also used in the training process of the partnership. The value of the resulting learning process can be estimated by examining the correction factor for the level of achievement.

The total number of iterations required to achieve satisfactory convergence depends on

- size of the neural network
- structure of the network
- problem under investigation
- learning process
- size of network training / learning set

Determines the performance of the selected ANN and the known can predict the learning strategy adopted using a network trained in some tests with results. These tests are also part of the learning process.

Therefore, the entire dataset consists of a training dataset and a test dataset. The first is used to train the neural network and the se cond is used to evaluate the effectiveness of neural network training.

VI. FAULT DETECTION AND CLASSIFICATION SYSTEM

The design process of proposed fault detection and classification approach is as follows:

- Training of artificial neural network and validation of the trained ANN using test patterns to check its correctness and generalization. Domain knowledge and techniques such as statistical analysis, signal processing, or time frequency analysis can be used to identity informative features that help in fault location and classification.
- Creating data acquisition of current and voltage signals in power system. Combining multiple ANN models into an ensemble can improve the overall accuracy and robustness of the fault detection system.
- Data Augmentation using techniques like data resampling, noise injection, or perturbation can be employed to augment the training data and improve the generalizing ability of the ANN models.
- Change system parameters, collect current and voltage waveform data, sort and analyze results. Combining ANNs with Support Vector Machines (SVMs), Random Forests, etc. can leverage the strengths of different algorithms and improve overall performance
- Choosing the right INS topology for a given application.

Create different learning models by modifying failure resistance, failure location, and failure type.

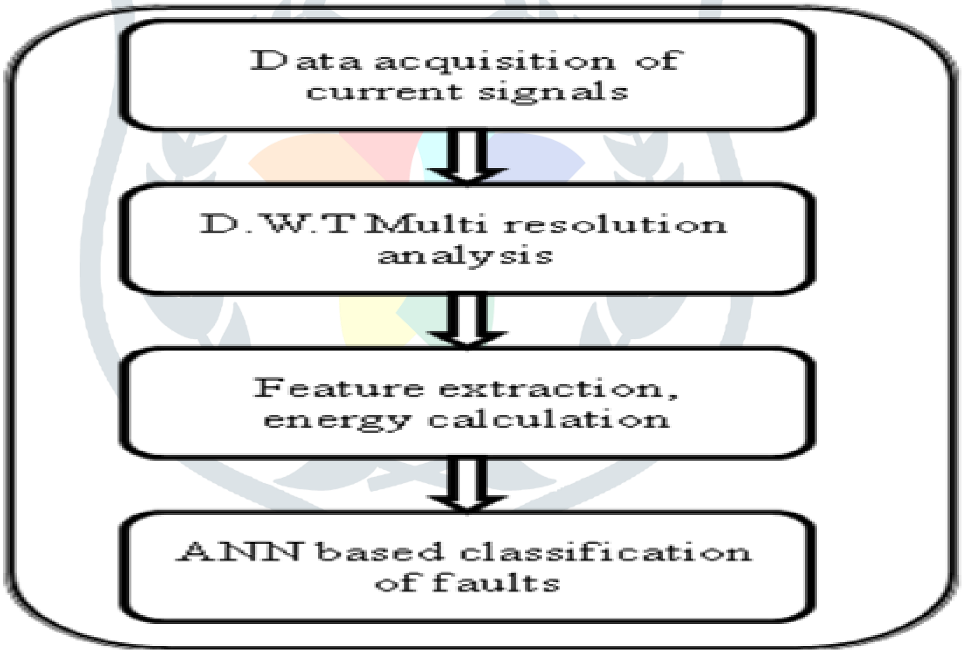

Fig: 3 Process of fault detection and classification.

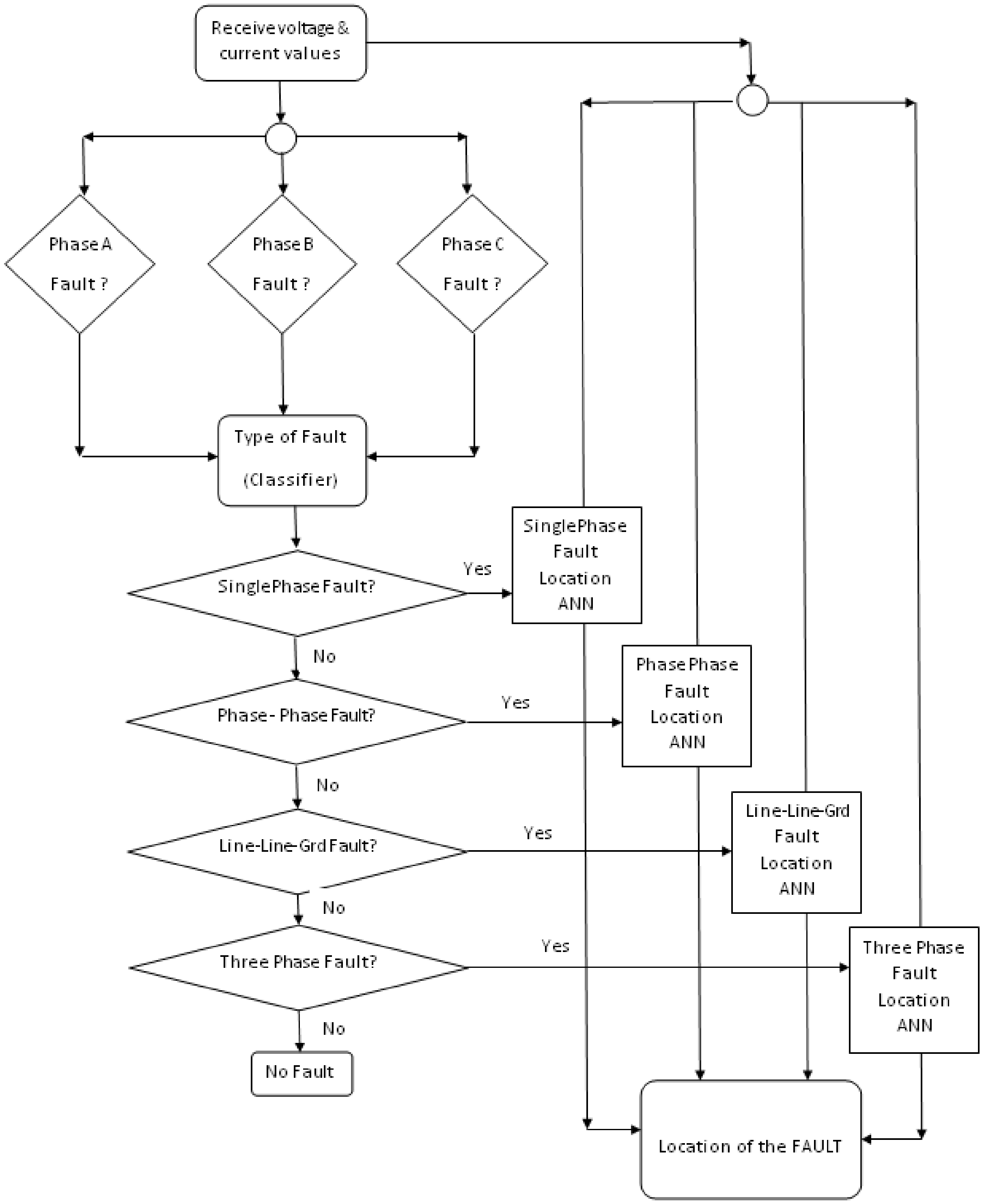

Figure 4. Flowchart depicting the outline of the proposed scheme

VII. RESULTS AND DISCUSSION

The proposed power system was simulation model using the SimPower toolbox in Simulink by The MathsWorks shown in fig 4.2. The three-phase fault simulator is used to simulate various types of faults at varying locations along the transmission line with different fault resistances.

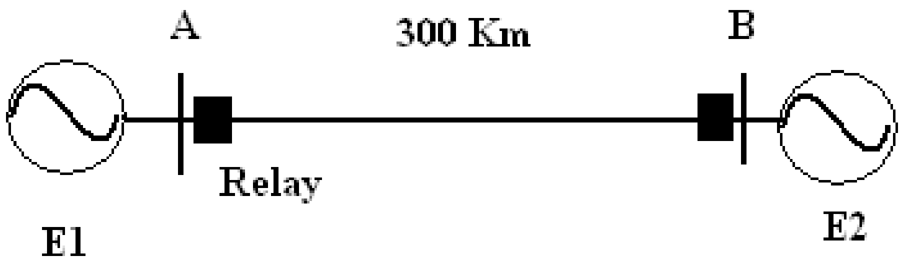

Figure 4.1 One-line diagram of the studied system.

The power system was simulated by MathWorks using the SimPowerSystems toolbox in Simulink. The model used to obtain the training and testing data is shown in Figure 4.2. In Figure 4.2, ZP and ZQ are the impedances of the generator on both sides.

A three-phase V-I test block is used to measure terminal A voltage and current patterns. The transmission line (line 1 and line 2) is 300 kilometers long and a three-phase fault simulator is used to simulate various faults with different fault resistances at different locations in the transmission line.

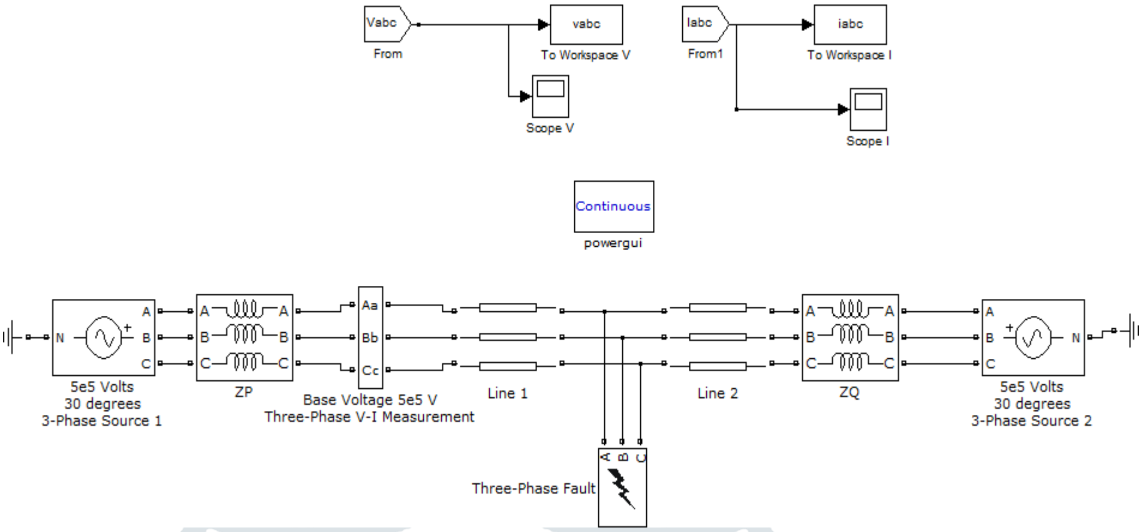

Figure 4.2 Studied model in SimPower Systems.

The values of the three-phase voltages and currents are measured and modified accordingly and are ultimately fed into the neural network as inputs. The SimPowerSystems toolbox has been used to generate the entire set of training data for theneural network in both fault and non-fault cases.

Table 4.1 Sample of Inputs to the neural network for various fault cases.

Case No:	Input Vector						FaultType
	V_a/V_a(pf)	V_b/V_b(pf)	V_c/V_c(pf)	I_a/I_a(pf)	I_b/I_b(pf)	I_c/I_c(pf)	
1	0.6204	0.9719	1.0425	1.6840	0.5056	0.8775	A to Ground
2	0.6573	0.7351	0.8289	0.4024	27.6875	1.7453	B to Ground
3	1.2580	0.9141	0.7924	1.4994	-1.5179	-4.7497	C to Ground
4	-0.1882	0.6041	1.0001	4.9014	20.6762	0.9994	A to B
5	1.0000	0.5516	0.3276	1.0000	33.8158	-7.1187	B to C
6	1.1586	1.000	0.9208	-1.6037	1.0025	-2.2493	C to A
7	-0.1276	0.5841	0.9042	2.9694	30.4194	1.4733	A to B to Ground
8	0.9359	0.5145	0.3833	0.9257	35.3006	-6.7506	B to C to Ground
9	0.9864	0.9147	0.8350	0.6229	-1.2876	-5.0284	C to A to Ground
10	0.3135	0.4373	0.4991	1.8649	35.9958	-6.5793	A to B toC
11	1.0000	1.0001	1.0001	1.0000	1.0007	0.9998	No Fault

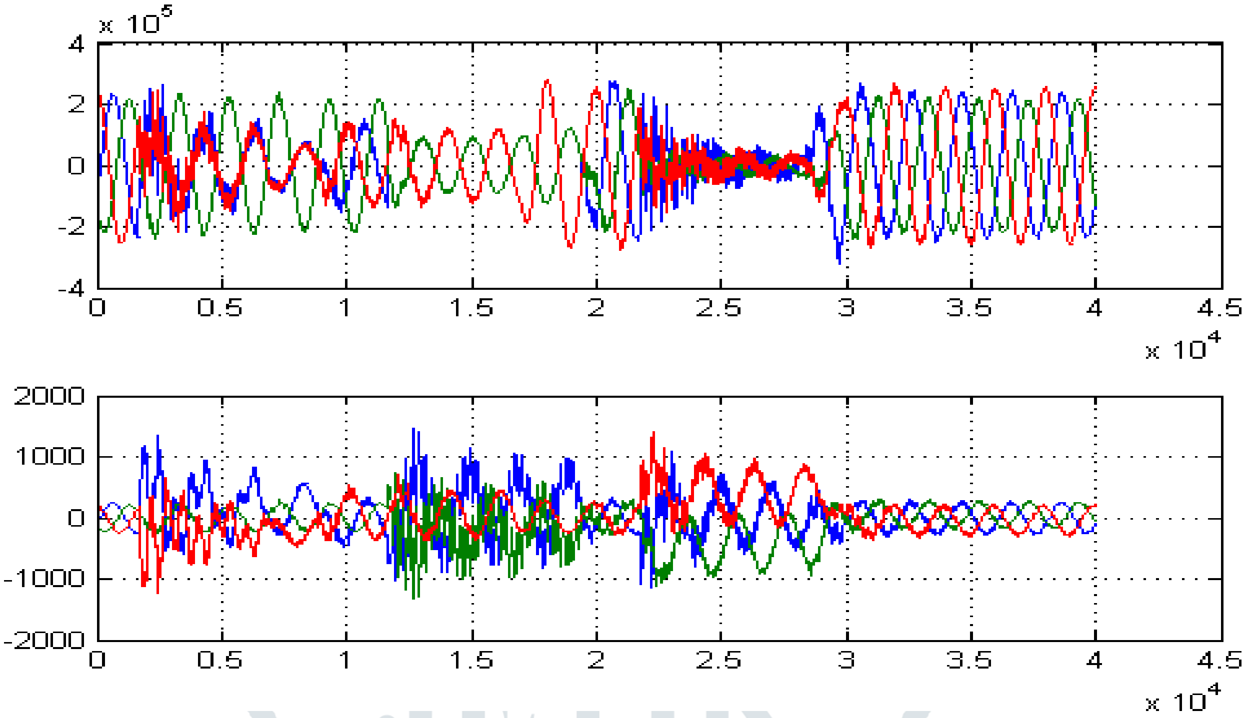

Fig:5 Shows the current waveform of a Phase A and B

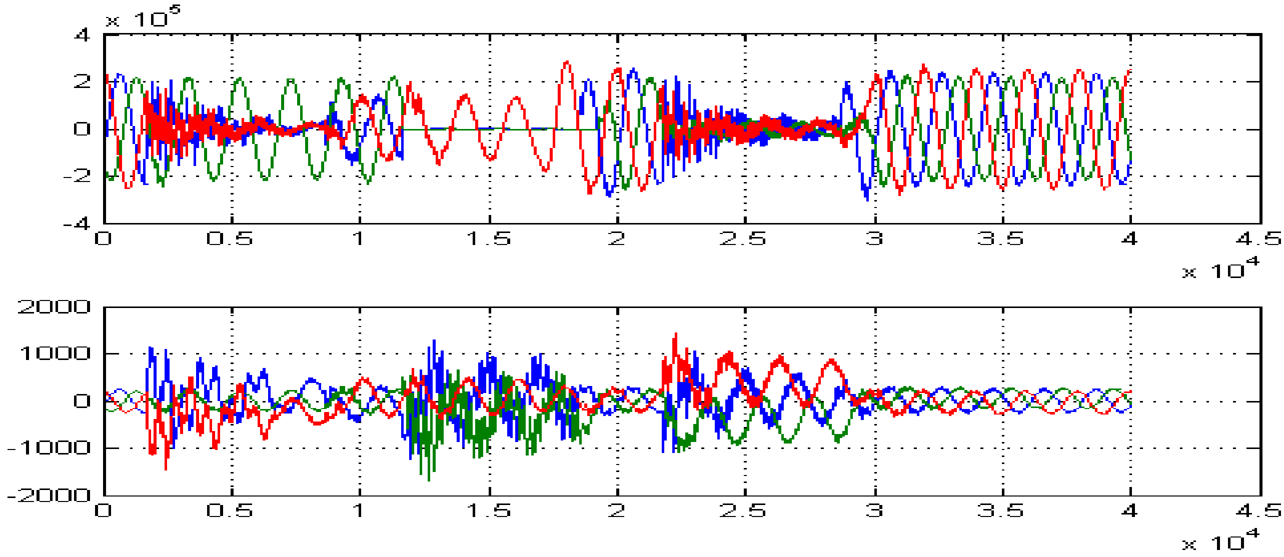

Fig:6 Shows the current waveform of Ground to Line

Case-1, Single Line Fault detection

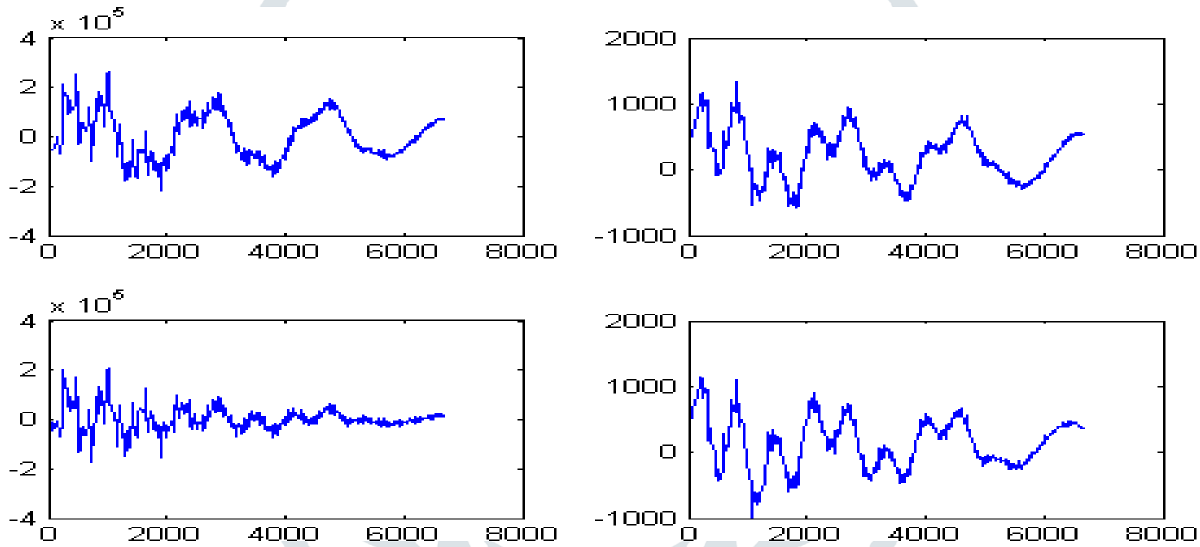

Fig: 7 Single Line Phase A and B fault detection

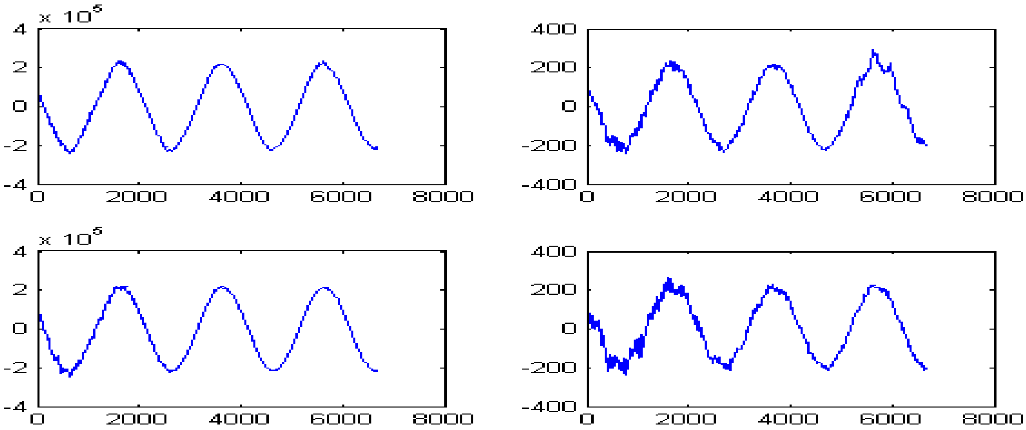

Fig: 8 Single Line Phase B and C fault detection

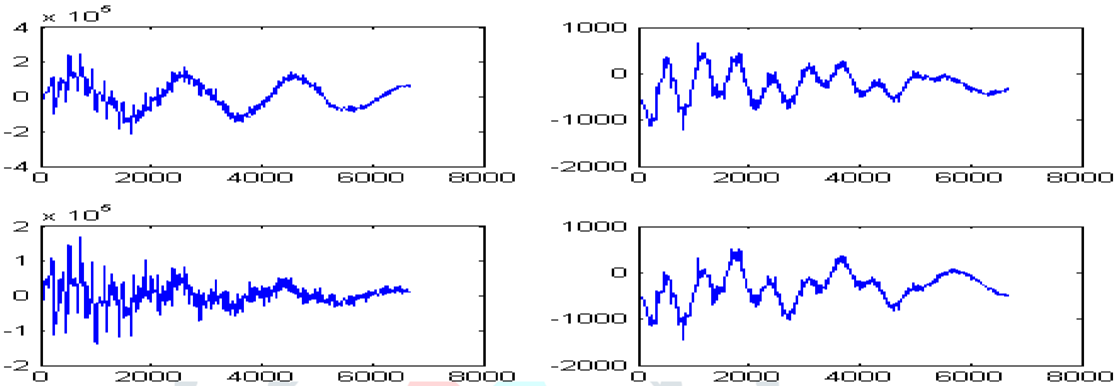

Fig: 9 Single Line Phase B and C fault detection

Case-2, Ground to Line Fault Detection

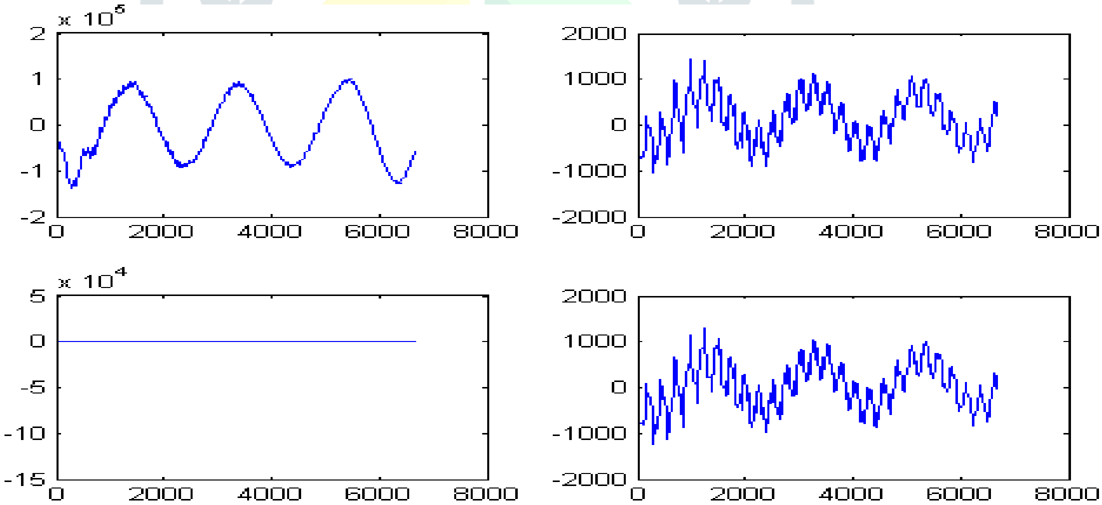

Fig. 10 Fault detection for Single line to ground fault in phaseA

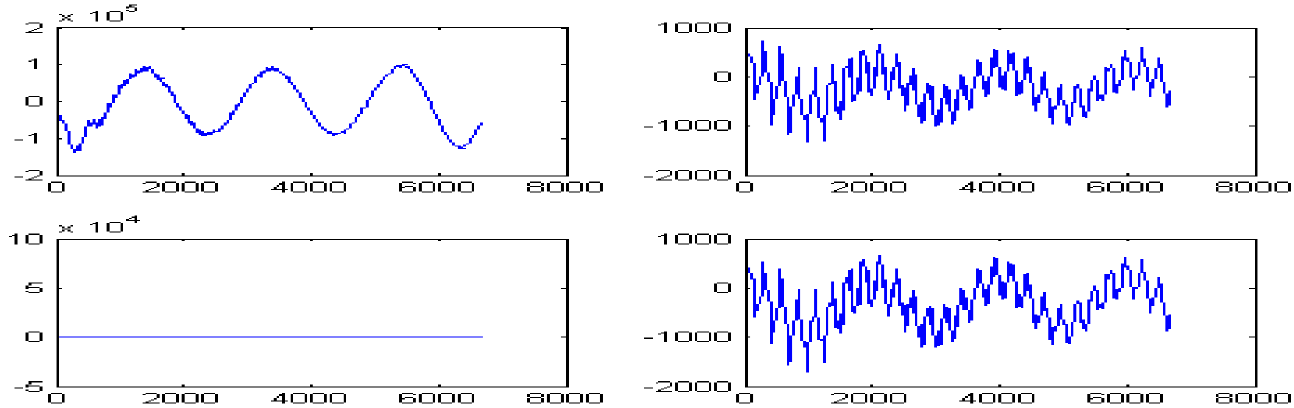

Fig. 11 Fault detection for Single line to ground fault in phaseC

VI. CONCLUSIONS.

The use of neural networks as an alternate way for detecting, classifying, and locating transmission line defects. The methods used for phase voltages and phase currents (scaled with respect to their pre-fault values) as neural network inputs.

All of the neural networks investigated in this thesis are back-propagation neural networks. A fault location method for the transmission line system was successfully built using artificial neural networks, from the identification of flaws on the line through the fault localization stage.

This is essential because the lower the sample frequency, the less computing load on the industrial PC running the neural networks. This entails significant energy savings because a continuous online detection technique of this type requires a significant amount of energy, a considerable percentage of which is due to constant waveform sampling. The enhancements listed above are some of the main advantages that this thesis provides over previous neural network-based systems for transmission line fault identification.

The simulation results reveal that all of the proposed neural networks have achieved satisfactory overall performance. As previously stated, the ANN's size (number of hidden layers and neurons per hidden layer) changes depending on the neural network's application and the size of the training data set. The importance of selecting the best ANN configuration to get the best network performance has been underlined in this study. The sample frequency chosen in this thesis for sampling the voltage and current waveforms is 720 Hz, which is extremely low in comparison to previous research (a huge percentage of the studies in the literature used 2 Hz). MATLAB R2010a was used in combination with Simulink's SimPowerSystems module to simulate the whole power transmission line model and get the training data set. The Artificial Neural Networks Toolbox has been widely used to train and assess neural network performance.

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