Asymmetrical Fault Recognition System on Electric Power Lines Using Artificial Neural Network

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Abstract – *The occurrence of faults on electric power lines reduce the efficiency and reliability of the whole power system network. Against this backdrop, this paper applied artificial neural networks in recognizing asymmetrical faults in electric power lines to improveelectric power line protection.The proposed artificial neural network based shunt fault recognition systems were trained using set of current and voltage data generated from simulating different asymmetrical faults states of the studied power system, modeled in MATLAB/Simulink environment. A comparative analysis of the three asymmetrical fault recognition modelswere done to establishwhich artificial neural network-based model/configurationleads tooptimal performance. The results show that the artificial neural network-based model that uses both current and voltagedata as input gave the best performance and hence,it may be employed in building asymmetrical faults detecting devices for electric power lines.*

***Keywords*:** Fault recognition, asymmetrical fault, artificial neural networks, power lines, power system

I. INTRODUCTION

Electric power lines are electrical power conductors designed to deliver electrical power from one substation to another substation in varying degrees of voltage[1]. In the cause of conveying electric power generated tothe gridand to different substations, the transmission lines encounter disturbances which may be due to broken cross-arms, opening of jumper cables, tree contact, bird or animal contact, lightning, etc. These disturbances are considered as faults. There are two main classes of faults on electric power lines namely; series faults and shunt faults [1][2].Series faults occur if there is an unbalanced series impedance condition in the lines which results when breakers that control the lines open one or two lines, when one or two electric power lines are broken, and/or when one or two jumper cables of power lines are opened[4]. On the other hand, shunt fault occurs when there is an insulation breakdown between the line conductors or between the line conductors and the ground. Shunt faults are further categorized as symmetrical and asymmetrical faults. The asymmetrical faults are faults with unbalanced fault currents and comprises single line-to-ground faults, line-to-line faults and double line-to-ground faults. These faults account for greater percentage of faults that occur on electric power lines [4] and may be caused by trees contact with lines, lightning strokes, salt spray on dirty insulators, vehicle colliding with the poles, birds short circuiting the lines, etc.

Fault recognition is the first line of action in power line protection and it promotes speedy clearance of faults on electric power lines. Furthermore, the time it takes a protective device to recognize the initiation of a fault along the lines also, affects the reliability of the entire power system.Consequently, in order to ensure uninterrupted transmission of electric power to end-users, the lines need to be protected with an intelligent, fast and accurate fault recognition system.Several research work have been done using ANN in recognizing shunt faults on electric transmission lines. Gowrishanka, *et al*[5] combined the capability of discrete wavelet Transform and artificial neural network to develop a fault detector and classifier in transmission lines. Leite, *et al*[6] developed a new technique for the detection and location of high-speed faults using neural networks. The review of different approach of fault detection was reviewed by[7]. Fault detection and classification for transmission line protection system using artificial neural network was proposed in [8]. Silva, *et al*. [9] employed Wavelet Transform and ANN for detection and classification of faults in power transmission lines. A fault detection and location system for high-speed protection in extra high voltage transmission lines using feed-forward neural network with the backpropagation algorithm based on supervised learning was applied by [10]. Seema, et al. [11] used ANN with gradient descent backpropagation algorithm to implement an intelligent fault identification system. A multilayer perceptron backpropagation neural network was used by[12] to develop a fault detector, classifier, and locator for a transmission line.

Therefore, this paper would employ the pattern recognition ability of an artificial neural network in developing an asymmetrical fault recognition systems and afterward carry out a comparative analysis of the models to determine the one that gives optimal performance.

II. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is inspired by the way biological neurons work. They are parallel computational systems and are made of several processing elements connected together in a specific way to perform a precise task it was designed for[13]. The processing elements have the ability to learn from training data and generalize to new situations. The ability of ANN to be configured to perform tasks comparableto biological neurons makes them more efficient and robust for real-world applications. The unique characteristics of ANN that gave it an edge over other artificial intelligence in fault recognition is that information processing can be carried out in a parallel distributed manner, problems that are inherently nonlinear is solved by it,prior knowledge functions relating the problem variables is not necessary, it is more tolerant to noise and has the ability to handle situations of incomplete information and corrupt data.ANN learns to produce an output based on a given input data using a set of training dataset[4].The process of accomplishing the learning may be done using supervised learning process or unsupervised learning process. The supervised learning process is the most preferred form of learning for asymmetrical faults recognition on electric power lines. In this method, the network weights are modified iteratively tominimize the error between the given input data and its corresponding target values [12]. Figure 1 illustrates the supervised learning approach for a feed-forward neural network.

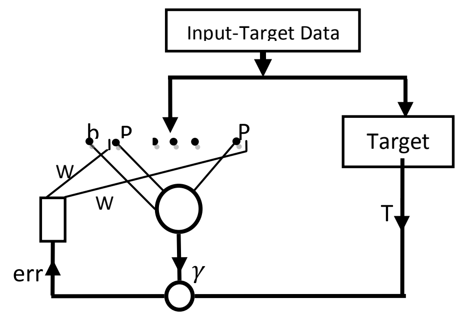

Figure 1: The supervised learning approach for a feed-forward neural network

The training of the network is accomplished by sequentially applying input vectors(P_1- P_n) while modifying network weights (W_o-W_n) accordingly[14]. The network weight converges gradually as the training (adjustment of different weights) progresses to values that will enable each input vector to produce the target[9]. The output of the neuron, γ is given as the weighted sum ($\sum W_i P_i + b$) of the input. Afterward, a nonlinear transfer function, $f$is applied to the weighted sum which produces the artificial neuron's output.The transfer function is one of the major key factors that determine the capability of an artificial neuron to approximate functions [15]. The commonly used types of activation functions are the linear activation function, sigmoid activation function, and radial activation function [16]. The appropriate transfer function is chosen based on the application's requirements. Moreover, since the study deals on nonlinear problem, the sigmoid transfer function is a preferred choice.

III. THE STUDIED POWER SYSTEM MODEL

The power line studied is 33-kV power system network spanning 140 km length. The conductor used is Aluminum Conductor Steel Reinforced (ACSR), which has the following properties:

1. Height of pole from ground surface = 28 ft = 8.5344 m
2. Normal cross-sectional areal Alu/Steel = 150/35 mm = 0.150/0.035 m
3. Approximate overall diameter = 18.1 mm = 0.0181 m
4. Calculated D.C Resistance at 20 ^{0}C = 0.1828 Ohm/km

The system is modeled in Simulink environment in MATLAB 2015a. The single line diagram of the studied power line and the snapshot of the Simulink model is shown in Figure 2 and Figure 3 respectively [17].

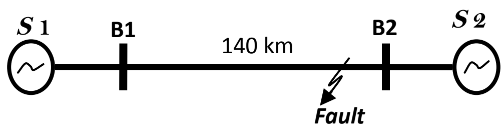

Figure 2: Studied Power System Single Line Diagram

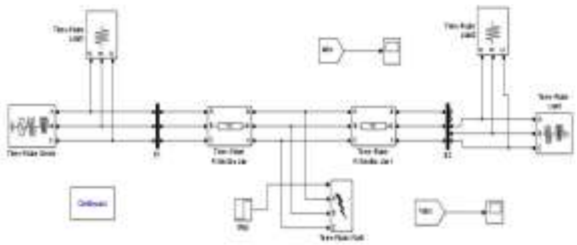

Figure 3: The Simulink model of the Studied Power System

A. Data Generation and Pre-Processing

The instantaneous voltage and current values were obtained through the three-phase measurement block.The 50 Hz signal is sampled at 1.5 kHz, thus having thirty (30) samples/cycle. To obtain sufficient training data, each category of asymmetrical fault is simulated at a varying resistance(0.25, 0.5, 0.75, 5, 10, 20, 30 and 50) Ohms and distance(140 km at an interval of 2 km). Consequently, 560 different fault situation are acquired for each of the asymmetrical faults simulated. The obtained data were pre-processed using these mathematical expressions:

$$V_i^{RYB} = \frac{V_s^{RYB}(n+12)}{V_s^{RYB}(n-12)}$$

$$I_i^{RYB} = \frac{I_s^{RYB}(n+12)}{I_s^{RYB}(n-12)}$$

Where, V_i^{RYB} = instantaneous voltage inputs to ANN; I_i^{RYB} = instantaneous current inputs to ANN; V_s^{RYB} = Sampled voltage phases; I_s^{RYB} = sampled current phases
n = Sample number corresponding to the instantaneous time where the faultoccurred.

Moreover, the data were normalized to reduce the size of the data to conform to neural network input pattern of 0's and 1's which will also help in minimizing the computational burden of the system. Table 1 shows the target truth table for the different types of asymmetrical faults considered while Table 2 depicts a sample of normalized input data.

Table 1: The Target Truth Table for the asymmetrical faults

Fault Type	R-G	Y-G	B-G	R-Y-G	R-B-G	Y-B-G	R-Y	R-B	Y-B	R-Y-B	No-Fault
Line State	1	1	1	1	1	1	1	1	1	1	0

Table 2: Sample of the scaled Voltage and Current values for ANN

S/N	V_R	V_Y	V_B	I_R	I_Y	I_B
1	0.0326	0.7932	0.6076	0.0177	0.0105	0.0083
2	0.0902	0.8032	0.5883	0.0175	0.0107	0.0083
3	0.1498	0.8077	0.5697	0.0171	0.0109	0.0084
4	0.2444	0.8020	0.5444	0.0161	0.0111	0.0086
5	0.3115	0.7872	0.5317	0.0152	0.0111	0.0088
6	0.3966	0.7528	0.5248	0.0139	0.0109	0.0091
7	0.0389	0.7898	0.6116	0.0176	0.0105	0.0083
8	0.0418	0.7905	0.6104	0.0176	0.0106	0.0085

IV. PROPOSED ANN-BASED ASYMMETRICAL FAULT RECOGNITION SYSTEM

ANN-Based asymmetrical fault recognition system (AFRS) is aimed to recognize the presence or absence of a fault on an electric power lines. In this paper three ANN-Based AFRS are presented. The first AFRS (AFRS1) uses only the instantaneous current values, the second AFRS (AFRS2) uses the instantaneous voltage value only and the third AFRS (AFRS3) uses both the instantaneous current and voltage values.The configuration of each AFRS corresponds to the number of input, hidden and output neurons and layers. To this end, the input variables determine the number of neurons in the input layer, the number of hidden layers and hidden layer neurons is determined by experimentation while the output neurons corresponds to the target. AFRS1 and AFRS2 contains three neurons each in the input layer corresponding to the input variables and AFRS3 contains six neurons in the input layers. The output layer of each consists of one neuron to recognize the presence or absence of a fault.In this paper only ANN structures with single hidden layer was considered. Figure 4 shows the block diagram representation of the proposed system.

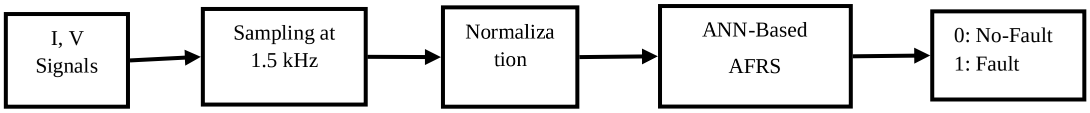

Figure 4: Block Diagram of ANN-BASED AFRS

Moreover, the segments involved in the developmental processof the ANN-BASED AFRS is as follows:

1. Acquisition and Pre-Processing of input Data set
2. Preparation of appropriate target data set suitable for the ANN to learn
3. Choosing of ANN configuration
4. Train the ANN
5. Calculate the performance MSE
6. Evaluate the trained ANN using the Performance MSE, confusion matrix, Regression Plot and a new set of data outside.

V. Results

Several ANN configurations with single hidden layer were selected and trained extensively.It was found that these configurations 3-14-1, 3-8-1 and 6-6-1 for AFRS1, AFRS2 and AFRS3 respectively gave the optimal performance amidst other configurations. The results of the performance MSE, confusion matrix, regression plots which was used as a performance test are presented. Figure 5 to Figure 8 shows the structure, performance MSE, confusion matrix and regression plot for AFRS1

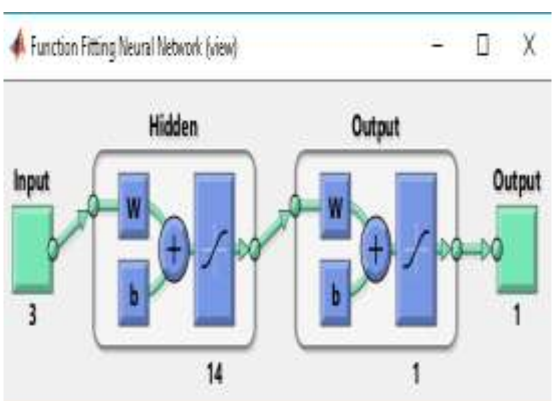

Figure 5: The Structure of AFRS1

Figure 6: Confusion Matrix for AFRS1 with 3-14-1 Structure

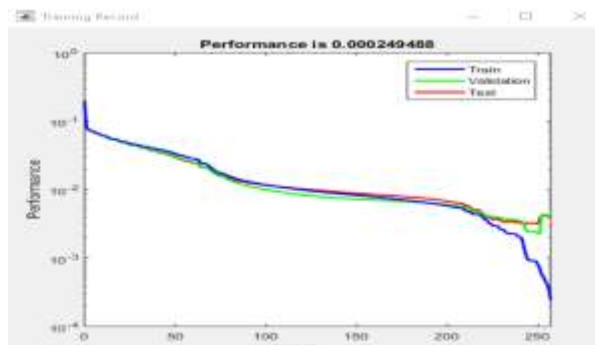

Figure 7: Performance Plot for AFRS1 with 3-14-1 structure

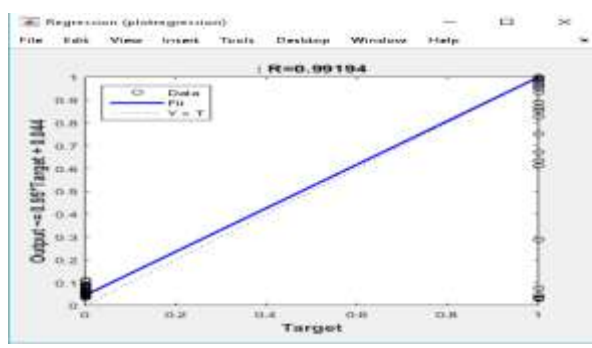

Figure 8: Regression Plot for AFRS1 with 3-14-1 structure

Figure 9 to Figure 12 shows the structure, confusion matrix, validation performance plot, and linear regression plot respectively for AFRS2.

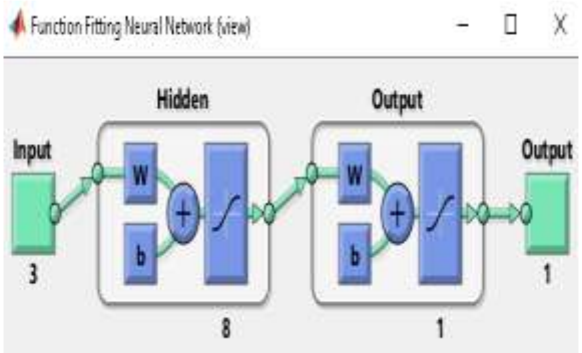

Figure 9: The Structure of AFRS2

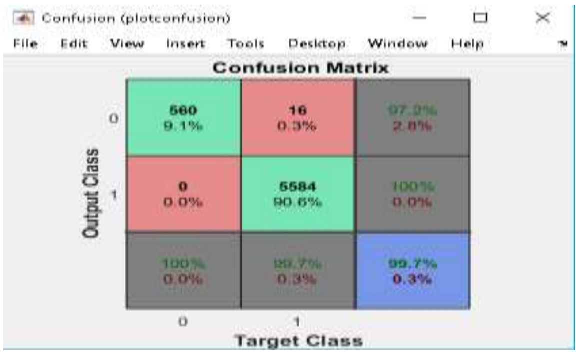

Figure 10: Confusion Matrix for AFRS2with 3-8-1 Structure

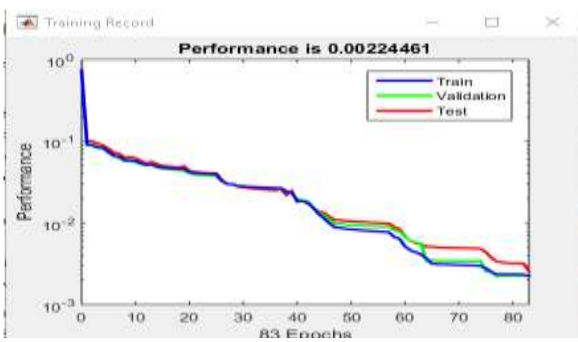

Figure 11: Performance Plot for AFRS2with 3-8-1 Structure

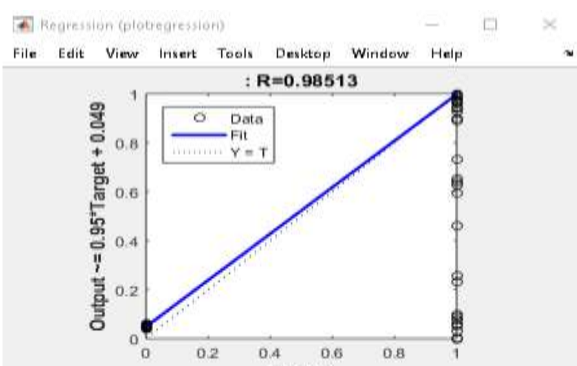

Figure 12: Regression Plot for AFRS2with 3-8-1 Structure

Figure 13 to Figure 16 respectively shows the structure, confusion matrix, performance plot, and linear regression plot for AFRS3.

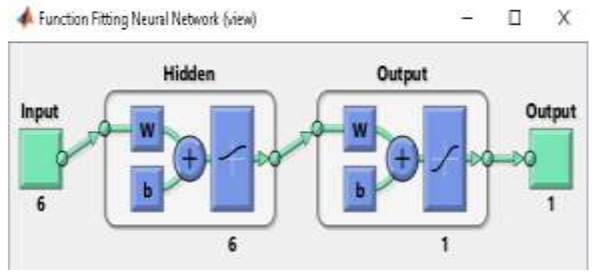

Figure 13: The Structure of AFRS3

Figure 14: Confusion Matrix for AFRS3with 6-6-1 configuration

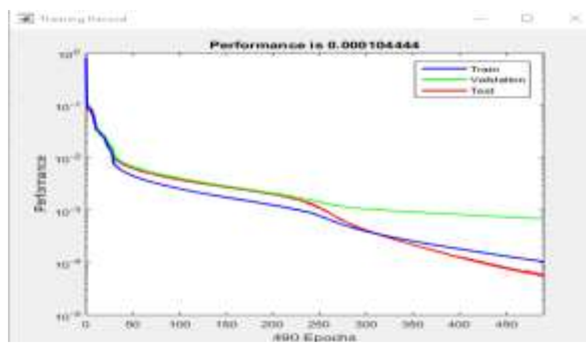

Figure 15: Performance Plot for AFRS3 with 6-6-1 configuration

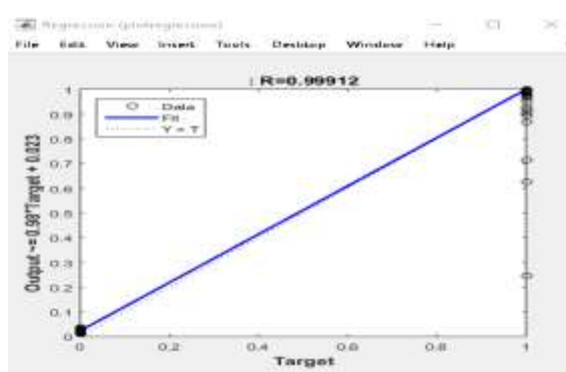

Figure 16: The regression plot for AFRS3 with 6-6-1 Configuration.

VI. DISCUSSION

The performance plots (Figure 7, Figure 11 and Figure 15)show that the developed AFRS1, AFRS2 and AFRS3 respectively achieved a significant mean square error (MSE) of $2.49488e^{-4}$, $2.24461e^{-3}$and $1.04444e^{-4}$. More so, from the confusion matrix (Figure 6, Figure 10 and Figure 14), the models, AFRS1, AFRS2 and AFRS3 achieved accuracy of 99.9%, 99.7% and 100% respectively.Furthermore, the correlation coefficient (r) plots (Figure 8, Figure 12 and Figure 16) which illustrate how well the neural network's targets track the deviations in the outputshave correlation coefficientof 0.99194, 0.98513, 0.99912 for AFRS1, AFRS2 and AFRS3 in that order. Since the values of the correlation coefficient are near the ideal value (1), the models are said to have good training, testing and validation. These result is an indicator that the trained systems are very efficient. Meanwhile, the results of the trained models indicate that the model (AFRS3) that uses instantaneous current and voltage values as input had a better capability in recognizing asymmetrical faults on electric power lines since it achieved the best performance MSE, accuracy and correlation coefficient and is therefore adjudged by this paper to be more suitable for real-time applications.

VII. CONCLUSION

The pattern recognition capability of neural network was employed in this study to develop an efficient artificial neural network-based models for asymmetrical fault recognition on electric power lines in this study. The models were developed using the pre-processed values of currents and voltages. Thus, AFRS1 uses current data only, AFRS2 uses voltage data only while AFRS3 uses both current and voltage data. Moreover, for faster implementation on hardware like FPGA, a single hidden layer network was considered. The results presented which shows that all the asymmetrical faults tested is accurately detected demonstrates the accuracy and efficiency of the developed asymmetrical fault recognizing system. The AFRS3 which gave the best performance and AFRS1 may be deployed for asymmetrical fault recognition on real-time situations.

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