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Detection and Analysis of Faults in Power Distribution Network Using Artificial Neural Network

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ABSTRACT: Early detection and location of faults in networks has been a major challenge in power systems engineering as it results in loss of energy, revenue and damage to equipment and facilities. The reason for this delay in detection is because, in most cases operators of these network rely mainly on information/complaint provided by customers without actually having a scheme to check and verify the information whether it is misleading or correct. This work developed an Artificial Neural Network(ANN) based program written in mat lab 7.5 environment to detect various kinds of faults in the network. The results obtained when compared to exiting results from power holding companies were found to be satisfactory.

1.0 INTRODUCTION

Distribution and utilization of electrical energy is the final stage in electricity delivery to end users with voltage levels of 11kV and 0.415kV at the distribution substation and consumer end respectively. Fault occurrences in power distribution systems are almost unavoidable and when it occurs, results to major challenges such as waste of time, stress, increase cost required to locate and diagnose fault, and then do the necessary repair before returning the line to service. In typical power distribution systems, various kinds of faults occur at different times for different reasons/causes such as insulation failures, short circuit conditions etc. In Nigeria, fault location is estimated by trial and error method and in most cases is dependent on the information provided by customer(s).These information in some cases result in energizing the line, section by section until the protective relay trips the circuit breaker tied to the line and the faulty section is identified and then isolated. This procedure may be repeated severally, thus subjecting these equipment to stresses and time wastage most especially if the customers report is/are technically wrong. It is therefore, vital that fault analysis and identification be carried out quickly for quick system restoration through various improved intelligent techniques. A better approach to fault detection and diagnosis in distribution network is the use of Artificial Intelligent (AI) technique such as Artificial Neural Network (ANN), due to its following characteristic properties such as: fast learning, fault tolerance, ability to produce correct output when fed with partial input and recognize various learning patterns and behaviors where exact functional relationships are neither well defined nor easily computable. This paper presents a method of fault detection and diagnosis in power distribution system using ANN. The detection and diagnosis of faults in power distribution network could be time consuming. The aim of using ANN is to provide faster, easier and less costly means of fault detection and diagnosis in order to increase system reliability and security. Rumuola distribution network in Rivers state, Nigeria is used as a case study. Real-time line parameters were obtained and various fault computations were analyzed.

2.0 REVIEW OF FAULT LOCATION METHODS FOR DISTRIBUTION SYSTEMS

Faults in power systems results to outages, thus affecting power quality in terms of service continuity and disturbance propagation and in most cases, cause high economic losses, equipment damages etc. Fault location includes the determination of physical location of the fault (Mora-Flürez *et al.*, 2009). Some strategies for fault location in distribution systems have been developed to estimate the relative distance to the fault from data acquisition provided by the protection devices. The performance of these techniques can be affected due to some particular characteristics of the respective system, such as unbalanced system, non-homogeneous conductors, etc (Ziolkowski *et al.*, 2007). Researchers have done considerable work in the area of fault diagnosis particularly in radial distribution systems. Traditional outage handling methods were based on customers calls and with the use of GPS technology, their location is determined, thus knowing the actual location/ of the fault in the network. there are also cases were these faults occurs, yet no calls made by customers, resulting in difficulty in locating such faults by power providers. In recent years, some techniques have been discussed for fault location particularly in radial distribution systems. These methods use various algorithmic approaches, where the fault location is iteratively calculated by updating fault current. Researchers have also used mathematical equations to estimate fault location that requires information such as circuit breaker status, fault current waveforms, and fault indicator status

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for non-radial system (Zhu *et al.*, 1997; Senger *et al.*, 2007). In this approach, fault types and faulted phases are identified and used to compute the apparent impedance based on selected voltages and currents. Girgis (1993) presented equations to calculate all kinds of faults occurring at the main feeder and a single-phase lateral. Loads were considered as constant impedance though its dynamic nature was not considered. Performance assessment of cables used could also pose a major challenge. Saha *et al.*, (2007) proposed method is devoted for estimating location of faults on radial systems, which could include many intermediate load taps. In this method non homogeneity of the feeder sections was also considered.

2.1 AI and Statistical Analysis Based Methods

Artificial Intelligent is one of the categories which falls under knowledge based methods. There are several artificial intelligent methods such as Artificial Neural network (ANN), Fuzzy Logic (FL), Expert System (ES) and Genetic Algorithm (GA). These methods help operators or engineers to do less laborious work as time spent in diagnosing technical tasks/challenges is substantially reduced and human mistakes are avoided. Therefore, many researchers used artificial Intelligence based methods in distribution system fault locations. Al-Shaher *et al.*, (2003) developed fault location method for distribution systems using ANN. The researcher used feeder fault voltage, circuit breaker status, real power of feeders during normal condition, and real power of feeders during short circuit, etc, to train the ANN. A Refined Genetic Algorithm (RGA) was adopted to solve the problem, based on the "natural selection, best survival" theory. The RGA found the most reasonable hypothesis or hypotheses based on the evaluation result of each hypothesis evaluated by set covering theory. Thukaram *et al.*,(2002) offered a method which estimated the voltage magnitude and phase angle at all load buses through state estimation. A threshold was used to detect the fault path. Chen *et al.*,(2002) used a cause-effect network to represent causality between faults and the actions of protective devices. The cause effect network's features of high-speed inference and ease of implementation made it feasible to implement an on-line fault section estimation system. Based on the actions of protective devices, the network could quickly find faulted sections. Lee S.J *et al* .,(2009) presented an alternative solution to the problem of power service continuity associated to fault location. A methodology of statistical nature based on finite mixtures is proposed. A statistical model was obtained from the extraction of the magnitude of the voltage sag registered during a fault event, along with the network parameters and topology. The approach is based in the statistical modeling and extraction of the sag magnitude from voltage measurements stored in fault data bases. The determination of groups of well-defined characteristics allows an optimization in the classification of data thus ensuring good model accuracy.

2.2 ANN

ANNs are composed of simple elements operating in parallel inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. Typically, ANNs are adjusted/trained, so that a particular input leads to a specific target output based on comparison of the output and target, until the network output matches the target. Feed-forward NN based on supervised back propagation learning algorithm is used to implement fault detector and locators. It consists of an input layer representing the input data to the network, some hidden layers and an output layer representing the response of the network. Each layer consists of a certain number of neurons, each neuron is connected to other neurons of the previous layer through adaptable synaptic weights w and biases. Feed-forward NN of three layers is considered (input, hidden and output). Once the network is trained with the algorithm and appropriate weights and biases are selected, it is then used in the test to identify the output pattern given an appropriate input pattern. The training is performed off-line resulting in reduced on-line computations. ANNs have considerable advantages in terms of knowledge acquisition based on trained data, performance, speed etc. An important feature of fault diagnosis using ANN is their ability to interpolate trained data to give an appropriate response for most cases of input data. Fault diagnosis is conceptualized as a pattern classification problem which involves the association of patterns of input data representing the behavior of the power system to one or more fault condition. The design process of ANN fault detector/locator goes through the following steps:

- ❖ Preparation of a suitable training data set that represents cases the NN needs to learn.
- ❖ Selection of a suitable NN structure for a given application.
- ❖ Training the NN.
- ❖ Evaluation of the trained NN using test patterns until its performance is satisfactory.

3.0 METHODOLOGY

The following method was adopted in this work:

- ✓ Obtain one line diagram of Rumuola power distribution system, fault current and voltage values
- ✓ Develop a functional NN program in Matlab 7.5 environment to detect and diagnose faults including flow chart of the fault analysis.
- ✓ Test run the software for different fault values.

This is achieved by inputting patterns which contain root mean square (rms) values of voltages and currents in the

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instance of fault before operation of circuit breakers are fed into the ANN program using Matlab7.5. These data is then used for detection and location of faults. ANN is trained off-line with different fault conditions and used on-line. The diagnostic system is able to detect and diagnose the faulted locations corresponding to input pattern consisting of switching status of relays and circuit breakers.

3.1 Training the NN

This involves development of algorithm as shown in section 3.1.P are the various fault voltage values(training pattern) and T their corresponding distances (training target). Tansig and purelin are both symbolic linear transfer functions respectively, Y = sim(net,X) are network output. All other parameters are defined. Using the NN tool box in matlab 7.5 as shown in figure 1.0 and the flow chart in figure 2.0

```
P = [fault voltage values]; %Training pattern
T = [distance values]; %Training Targets
net = newff([min max],[5 1],{'tansig' 'purelin'});
%Plot the original data points and the untrained output
Y = sim(net,P);
figure(1)
plot(P,T,P,Y,'o')
title('Data and Untrained Network Output')
%Train the network and plot the results
net.trainParam.goal=0.01; %0 is the default-too small!
net.trainParam.epochs=100; %For this program, don't train too long
net = train(net,P,T);
X = linspace(0,10); %New Domain Points
Y = sim(net,X); %Network Output
figure(2)
plot (P,T,'ko',X,Y)
```

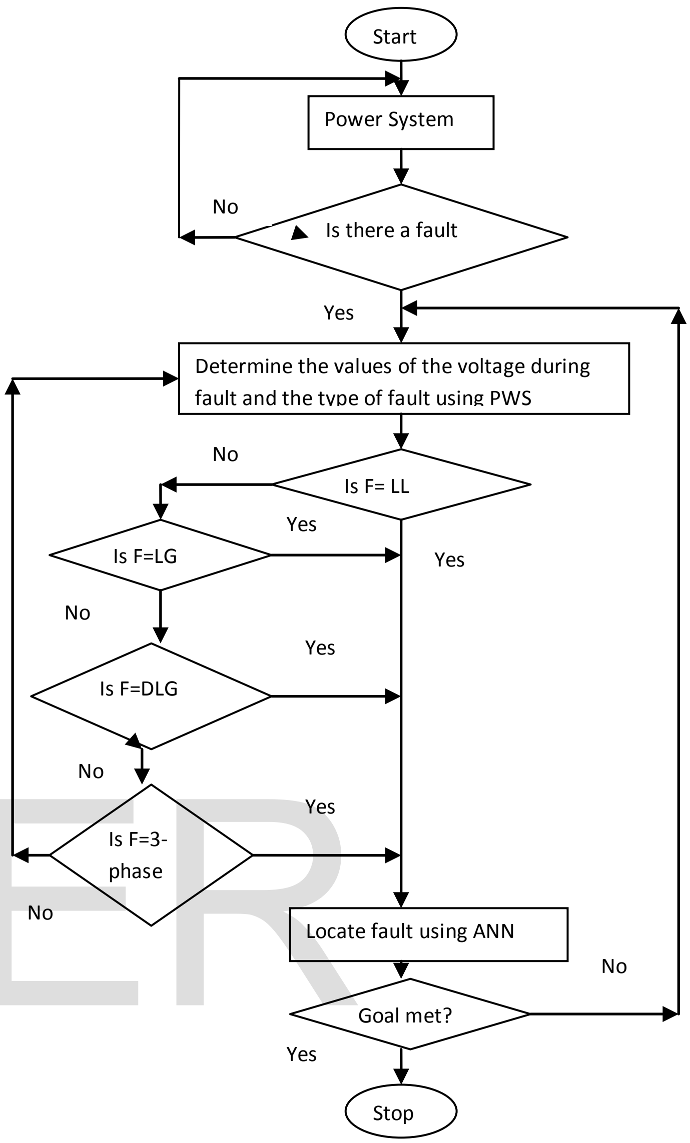



Figure 2.0 Flow chart of Fault Detection and Diagnosis

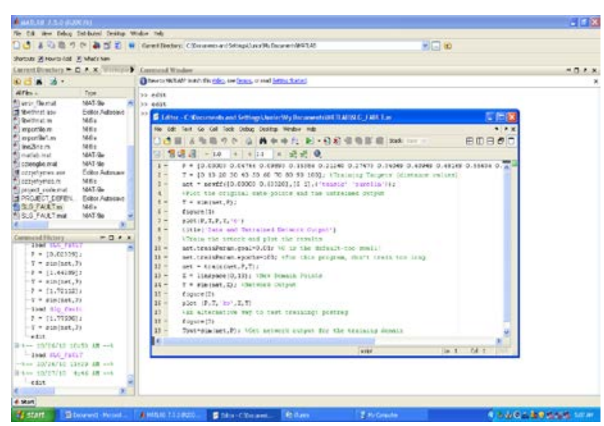


Figure 1.0 User Interface Showing the Training Algorithm

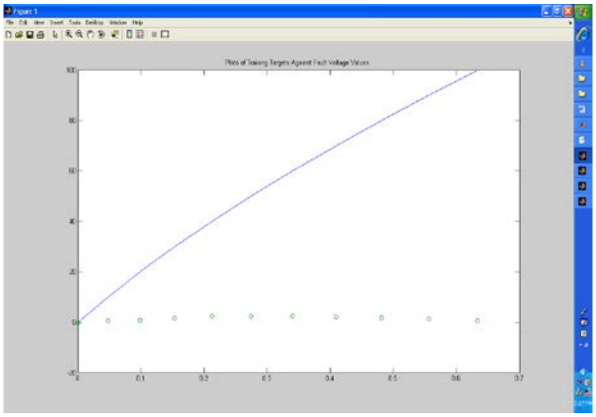


Figure 4.0 Data and Untrained Network Output Plot

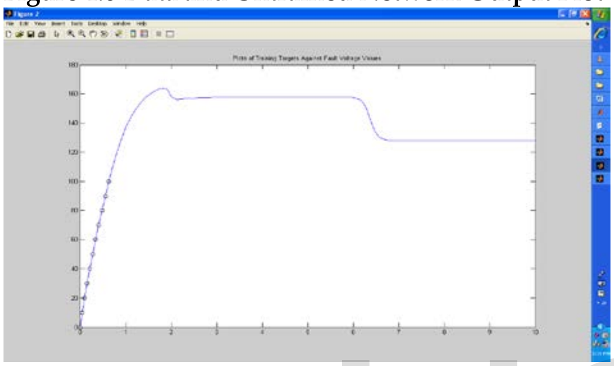


Figure 5.0 New Domain Points of the Trained Network

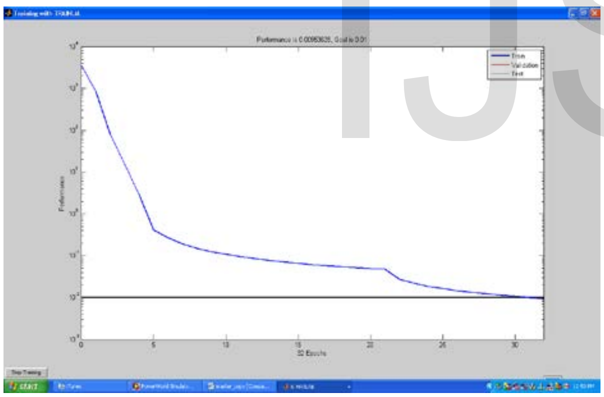


Figure 7.0 Training Pattern of SLG Fault

Figure 6.0 gives a Regression (R). It measures correlation between outputs and targets. R value of 1 means a close relationship, 0 a random relationship**.** Figure 7.0 shows that the performance goal of the network was met after 32 epochs. Actual fault location is obtained by multiplying ANN fault location by feeder distance as shown one-line diagram shown in figure 8.0.

Further training showed better domain points as represented in the trained network in figure 5.0 and applying linear regression analysis results in figure 6.0 and further training give figure 7.0.

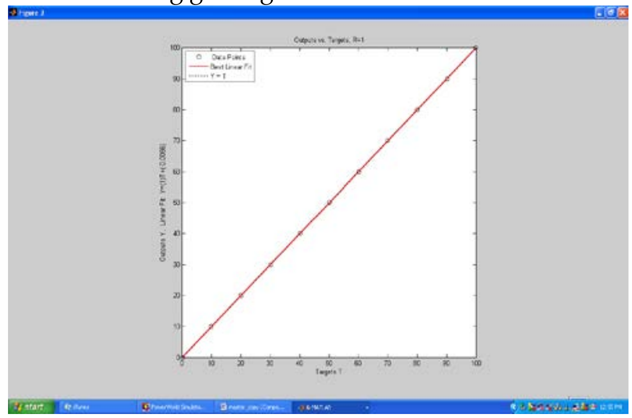
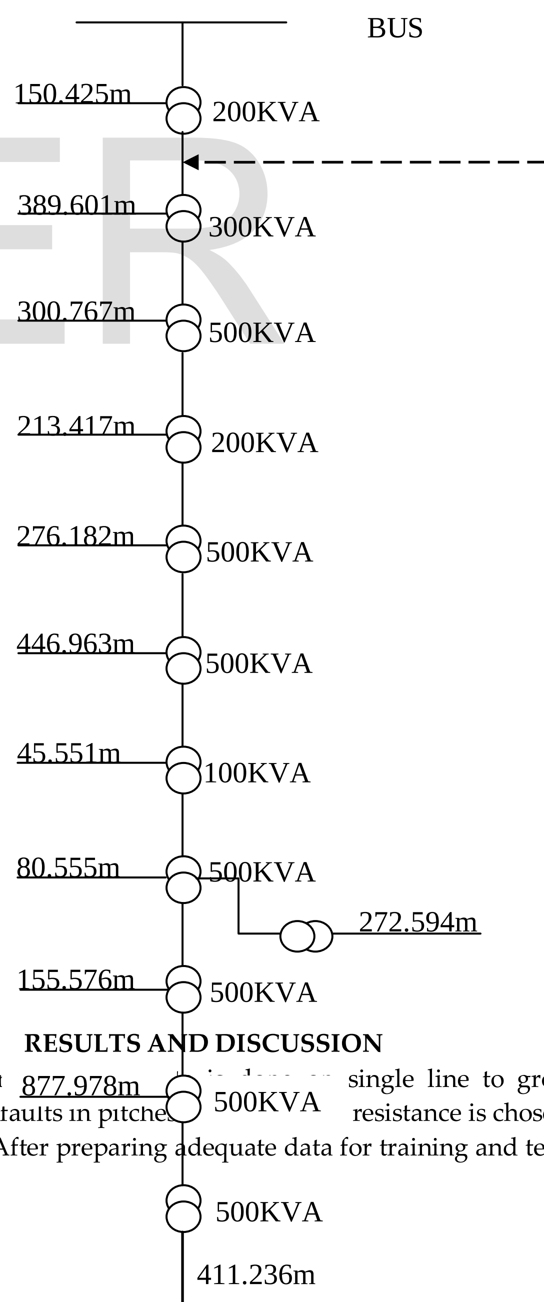


Figure 6.0 Linear Regression for SLG Fault



4.0 RESULTS AND DISCUSSION

Traini ... single line to ground (SLG) faults in pitche ... resistance is chosen as zero. After preparing adequate data for training and testing of NNs, selecting the number of neurons in the hidden layer of the networks such that the exactness of network at maximum is obtained using 100 epochs and adopting Mean Squared Error (MSE) criterion for selecting best structure. Four steps were taken in the training process: Assembling of the training data (i.e. fault voltage values and -Line fault locations, Creating the network object parameters, Training the network and Simulating the network response to new ult studies (double line to ground, three phase to ground faults etc) were also obtained using same approach

The distance which spans over length of 389.601 meters between the 300KVA and 500KVA transformers servicing Ikwere road and Anele close in Rumuokwuta is used to determine the actual NN fault locations for three Phase fault as shown in table 1.0. For Double Line to Ground fault, a distance of 213.417 meters between a 200KVA and a 500KVA transformer by Ebony/Orazi road in Rumuola was used to determine the actual NN fault locations at various fault voltages as shown in table 2.0. ANN Line to Line fault location was determined using the two 500KVA transformers located on Rumuola road, which are 446.963 .

fault voltage inputs. Both Tan-Sigmoid and linear Transfer Functions were used in the hidden and output layer respectively. Also, the default Levenberg-Marquardt algorithm (trainlm) was adopted to achieve a better training speed. Figures 4.0 and 5.0 shows plot of data versus network output untrained and trained values respectively for a single line to ground (SLG) fault. Other fa

meters apart at different fault voltage values as shown in table 1.0. Also, a distance of 877.978 meters between two 500KVA transformers located on Rumuola road were used to determine the NN fault location at various Single Line to Ground fault voltages. If any fault phase voltage values results in the network (S-L-G,L-L-G,D-L-G, or 3-Phase Fault) as shown in table 1.0,its fault position is located within the distances as shown. For instance, when S-L-G fault occurs and results to a phase voltage value of 0.0003kV,locating/tracing it along the line will almost exactly be at 0.3055m and same applies for every other kinds of fault in the network

S-L-G FAULT		**L-L FAULT**		**D-L-G FAULT**		**3-PHASE FAULT**	
Phase (kV)	Fault Location(m)	Phase (kV)	Fault Location(m)	Phase (kV)	Fault Location(m)	Phase (kV)	Fault Location(m)
0.0003	0.3055	0.86682	0.6159	1.40451	0.3099	0.40024	0.0701
0.04	87.7890	0.87768	44.0840	1.43312	21.1221	0.36522	38.9095
0.09	176.7273	0.88915	88.8133	1.46376	42.3799	0.32917	78.5549
0.15	262.2880	0.90122	134.1832	1.49670	63.9246	0.29206	116.5164
0.21	351.2211	0.91388	179.5289	1.53227	85.5860	0.25385	155.3024
0.27	440.0197	0.92695	223.6996	1.57034	106.9273	0.21453	194.7206
0.34	526.6174	0.94062	267.5543	1.61177	128.1428	0.17404	234.2472
0.40	613.3045	0.95479	313.1476	1.65682	149.2493	0.13236	273.2603
0.48	702.2516	0.96938	357.4180	1.70561	170.5014	0.08950	311.1541
0.55	791.5472	0.98445	402.3297	1.75899	192.3207	0.04538	350.6358

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0.63	877.03 51	0.99 994	446.94 96	1.81 722	213.32 52	0.00 005	389.57 65

It can be inferred from the plot that the NN program possesses learning ability and it was able to adapts to the data presented to it, to ensure an almost accurate fault location.the results also show that the error of the Neural Network predicted fault location for each fault type when compared to real life cases was less than 0.2 percent. This shows some degree of accuracy which ensures the quick restoration of the distribution network in the occurrence of a fault.

5.0 CONCLUSION AND RECOMMENDATIONS

This research finding will assist utility company in ensuring more accurate means of detection and diagnosis of faults as well as minimizing damages and reduction in waste of man-hours during the process of fault location in distribution network. The results obtained demonstrate NN effectiveness and high precision in determination and detection of fault location over different sections of the feeder under various kinds of faults. From the results obtained, it can be concluded that ANN is a more time and cost efficient method of fault detection when compared to the conventional trial and error method presently used in Nigeria. Although the simulation was done off-line, the work can be adapted for a real power system and the algorithm used for fault location on an energized system. Thus, the uses of ANN quickly give accurate prediction of fault location. It can be inferred from tables 4.0-7.0 that the trained NN can adapt to recognize learned patterns of behavior in the electric power system, where exact functional relationships are neither well defined nor easily computable. The NN is trained with in-line fault locations with their corresponding fault voltages to ensure a fast learning rate and ability to produce correct output when fed with a different input.

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