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Comparison between ANN and ANFIS-Based Algorithms for Detection and Classification of Fault on Transmission Lines

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ABSTRACT— This paper presents a comparison between relaying algorithm based on Artificial Neural Network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) technique for the protection of transmission line. A feed forward ANN with six inputs and eleven outputs has been developed for the detection and classification of faults. Data was generated by simulating a 400 kV, 50Hz, 100 km transmission line in PSCAD/EMTDC at a sampling frequency of 2 kHz. Three ANN and ANFIS configurations with different combinations of inputs have been attempted. Initially all the three ANN and ANFIS configurations were trained and tested using truncated data for their comparative performance. ANFIS configuration has been found to be the best one and different set of data have been used for training and testing with different number of epochs and membership function. 'gbell' membership function found to be the best membership function in performance for both training and testing with least error, been 100% accuracy and lesser number of epochs and faster than ANN.

KEYWORDS— artificial neural network, fault detection, phase selection, power system faults, transmission line.

INTRODUCTION

A transmission line is one of the main components in electric power system which provides a path to transfer power from generation to load. The transmission line is exposed to different types of faults namely phase-to-earth, two-phase-to- earth, phase-to-phase, three phase faults. The fault on the transmission line needs to be detected and then isolated quickly to prevent the disturbance in the line. It is important to detect, classify and clear the faults with high speed, selectivity and accuracy in order to prevent instability which can cause damage to the system. Several techniques have been reported in the literature for detection and location of faults on transmission lines [1,2]. The objective is to protect the transmission line in such a way that the power system is stable and only the faulty part is to be isolated leaving the rest part of the system in operation. Hence, it is essential to detect the fault quickly and separate the faulty section of the transmission line for safety, economy and power quality. A fault detector that uses artificial neural networks (ANN) has been described in [3]. It performs the fault defection problem as a pattern classification process. However it does not classify the faults. Back-propagation ANN has been used as a pattern classifier for a distance of 100 km with two sources at both ends in [4]. However, only one type of fault, phase to ground fault, was simulated varying the fault distance, fault resistance, fault inception angles, sources impedance, source capacities and power transfer angle. ANN used six inputs, namely normalized Ia, Ib, Ic and Va, Vb, Vc and had six nodes in the input layer, six nodes in the first hidden layer, two nodes in the second hidden layer and one node in the output layer.ANN was successfully trained to detect fault in protection zone only with accuracy at 78.82% of the protection zone. Fault detection and classification has been achieved in [5]. Two hidden layers with (30-20-15-11) have been used. However, it requires large memory as the number of inputs is more. Faults have been detected and classified using ANN with the relay operating time of 1 cycle in [6]. Single-line-ground faults have been classified with the relay operating time of 1 cycle in [7]. The prime motive behind the present work was an accurate fault classification as well as fault detection in such a way that the maximum accuracy is achieved with minimum relay operating time. Paper reports improved algorithm which does classification as well as detection and has accuracy of 100% and requires less memory with relay operating time of less than ¾ cycle which is an improvement over work achieved by the earlier researchers.

ANN has been trained and tested using Back-propagation algorithm with a large amount of data. The inputs to ANN were the rms values of phase voltages, line voltages, line currents and ratios of sequence components of currents in different combinations and the same data used for training and testing for ANFIS.

The transmission line was simulated using an electromagnetic transient program, EMTDC/PSCAD on a sample three-phase power system. The data has been generated for all the types of faults at two different locations with two values of fault resistance and eight values of fault inception angles at a sampling rate of 2 kHz. Three ANN configurations (ANN-1, ANN-2, ANN-3) with six inputs and eleven outputs have been attempted. The three configurations differ in the inputs. The inputs were Va, Vb, Vc and Ia, Ib, Ic to ANN-1, Vab, Vbc, Vca and

In/Ip, Io/Ip, Ip/Iload to ANN-2 and. Va, Vb, Vc and In/Ip, Io/Ip, Ip/Iload to ANN-3. The same configuration used for ANFIS.

All the three ANN and ANFIS configurations were attempted and compared. ANFIS has been found as the best configuration in terms of accuracy and performance as 100% accuracy has been achieved in both training and testing with a minimum delay.

II. DATA GENERATION FOR TRAINING AND TESTING OF ANNS AND ANFIS

A. Simulation

Simulations were performed using an electromagnetic transient program, EMTDC/PSCAD, on a sample three-phase power system. Fig. 1 shows the three phase model of the system that has been studied. The system consists of a generator of 400 kV located on one side of the transmission line. The transmission line (line-1 and line-2 together) is 100 km long. The line has been modeled using distributed parameters. A three phase fault module is used to simulate different types of faults with different inception angles, different fault resistances, and different source and load impedances at various locations on the transmission line.

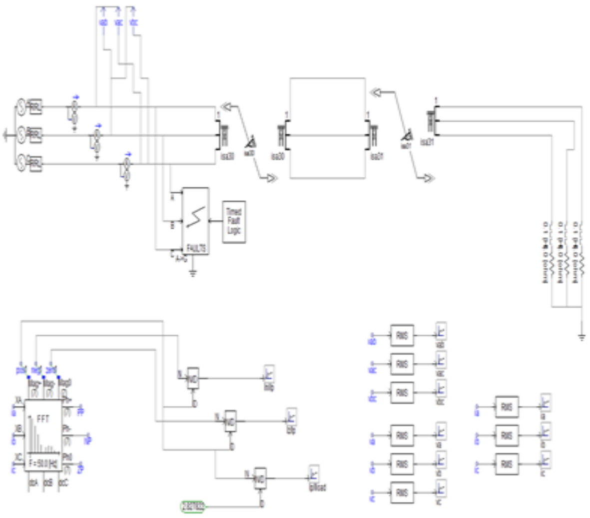

Fig. 1. Model simulated in PSCAD (fault location at 0km)

B. Dataset

As the input signals to the protective relay are currents and voltages. In the same way these inputs have to be fed to the ANN. However, some other parameters are needed to differentiate between the types of faults. Those parameters are zero sequence currents (Io), positive sequence currents (Ip) and negative sequence currents (In). Twelve quantities are needed to select the best set of input combinations for the neural network. The quantities include Ia, Ib,I c, Va, Vb, Vc, Vab, Vbc, Vca and In/Ip, Io/Ip, Ip/Iload. Balanced faults and unbalanced faults are differentiated by the ratio of negative sequence current to positive sequence currents (In/Ip), the ratio of zero sequence currents to positive sequence currents (Io/Ip) is used to differentiate between the ground faults to phase faults and the balanced fault and no fault condition is differentiated by the ratio of positive sequence currents to load currents (Ip/Iload). C. Generated Data The values of three-phase rms voltages and currents are measured. The rms voltages include the rms line to line voltages and rms phase voltages. The line components are first processed using FFT algorithm and then the sequence components at the fundamental frequency are derived.

Fig. 2 shows the graphs obtained during single line-to-ground fault of the system.

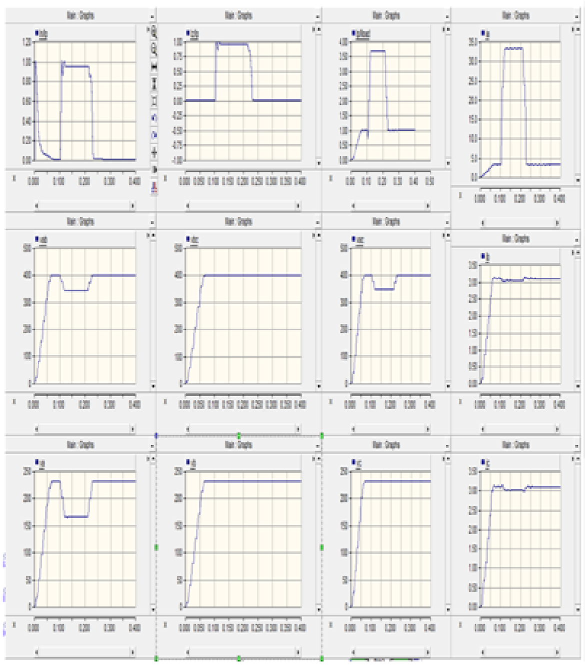

Fig. 2. Rms graphs of 12 parameters during single-line-to-` 1ground fault.

III. ANN INPUTS AND CONFIGURATION

Three ANN configurations have been attempted. The configurations differ in the input signals applied. The three combination of inputs include (Va, Vb, Vc and Ia, Ib, Ic) for ANN-1, (Vab, Vbc, Vca and In/Ip, Io/Ip, Ip/Iload) for ANN-2 and (Va, Vb, Vc and In/Ip, Io/Ip, Ip/Iload) for ANN-3. but the combination of ANN-2 have better accuracy compare ANN-1and ANN-3, due to this ANN-2 will be consider.

A. ANN-2

1) Inputs Line voltages and sequence current ratios were used as inputs to ANN-2. The six inputs used include Vab, Vbc, Vca and In/Ip, Io/Ip, Ip/Iload. The outputs were eleven which consists of AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABCG and no-fault. One hidden layer was used with different number of neurons for optimization.

2) Results The numbers of iterations required for the training process were 48. The mean square error in fault detection achieved by the end of the training process was 4.57e-07 and the number of validation check fails was zero by the end of the training process. Fig. 3 shows the training performance plot of the neural network.

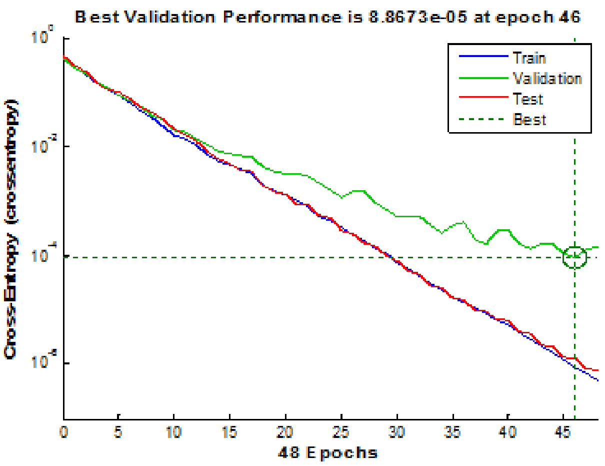

Fig. 3. Mean-square error performance of ANN-2 (6-20-11)

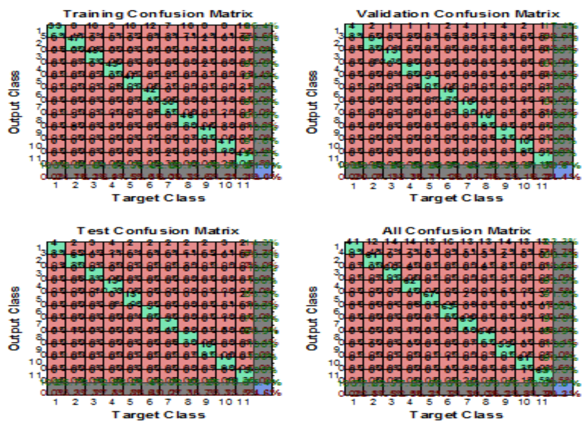

Fig. 4. Confusion matrices for Training, Testing and Validation Phases of ANN-2 (25 sample delay)

The accuracy of training for ANN-2 for fault classification with no delay was 79.8%. In order to increase the accuracy 5 samples were removed and the accuracy was still 83.2%. Then the accuracy reached a value of 94.1% at a delay of 10 samples, 99.4% at a delay of 15 samples, 99.2% at a delay of 20 samples. The accuracy of 100% was obtained at a delay of 25 samples as shown in Fig. 6. Further delay would make no sense. Confusion matrices for a delay of 25 samples (12.5 ms) are shown in Fig. 4. Similarly ANN-2 was tested and the accuracy of testing for ANN-2 for fault classification with no delay was 81.3%. In order to increase the accuracy 5 samples were removed and the accuracy was still 84.9%. Then the accuracy reached a value of 93.5% at a delay of 10 samples, 98.0% at a delay of 15 samples, 98.8% at a delay of 20 samples. An accuracy of 100% was obtained at a delay of 25 samples as shown in Fig. 5.

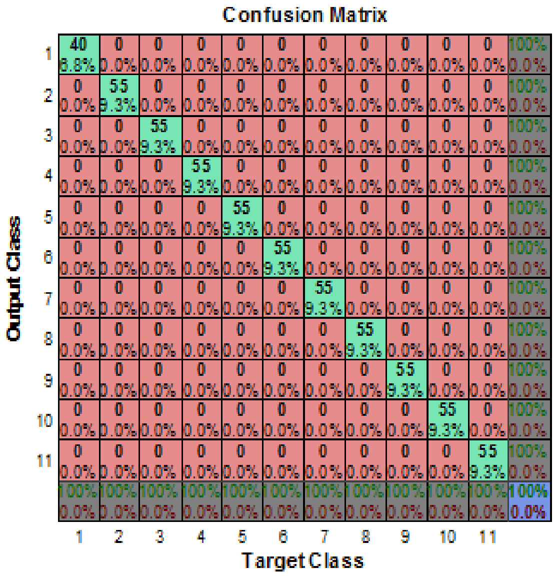

Fig. 5. ANN-2 Confusion matrix for testing of ANN-2 with 25 sample delay

IV. ANFIS INPUTS AND CONFIGURATION

Three ANFIS configurations have been attempted. The configurations differ in the input signals applied. The three combination of inputs include (Va, Vb, Vc and Ia, Ib, Ic) for ANFIS-1, (Vab, Vbc, Vca and In/Ip, Io/Ip, Ip/Iload) for ANFIS-2 and (Va, Vb, Vc and In/Ip, Io/Ip, Ip/Iload) for ANFIS-3. but the combination of ANFIS-2 have better accuracy compare ANFIS-1and ANFIS-3, due to this ANFIS-2 will be consider.

A. ANFIS-2

1) Inputs Line voltages and sequence current ratios were used as inputs to ANFIS-2. The six inputs used include Vab, Vbc, Vca and In/Ip, Io/Ip, Ip/Iload. The outputs were eleven which consists of AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABCG and no-fault.

B. ANFIS DATA TRAINING AND TESTING

The data is classified as training data and testing data in ANFIS's learning process. Testing data should be in the range of training data for the purpose of testing procedures. The number of training epoch also gives a good result in predicting the target. Accurate targets consider a minimum prediction error from the result of ANFIS training. The error can be reduced by adjusting the variable membership function (MF) and epoch parameters. With increasing in number of MF and epoch, the error will reduce accordingly. Sometimes, no reducing in error can be noticed even though the epoch was increased up to 5000 and above. This is due to the way the data is assembled. Therefore effective input data assembly will result good prediction. For this work, effective configuration of the data has been reached by preparing a wide data range between their elements and arranging the data from small to large values.

During the training process, MF parameters are varied so as to yield the ANFIS's output as target values. The minimum error percentage is a small difference between target and prediction values and it is used to measure the success level of a training process.

C. TESTING AND TRAINING OF ANFIS WITH GBELLMF WITH EXPANDED DATA SET

I. In this part the number of samples data increased for both training and testing,in the training similarly six inputs were used i.e. V_{ab}, V_{bc}, V_{ca} *and* $I_n/I_p, I_o/I_p, I_p/I_{load}$ together with the 0 and 90 degree faults inception angles and 50km fault location. While for testing the same set of inputs were used with 45 and 135 degree inception angles. The figures below show the training and testing results starting from 10 epochs to 20epochs of the gbellmf.

D. RULE

In this part, an ANFIS model has been developed with 12 fuzzy ‘IF-THEN’ rules for the task of determining the ten faults and no-fault condition. Since, the number of block functions represents the rules for every input data, it is difficult to describe the operational process of the model due to lack of space. However, a rule viewer is shown in Fig.5.1.8 for that purpose. There are five stages of ANFIS operational process that includes fuzzification, ‘IF-THEN’ rules, normalization, defuzzification and neuron addition. Figure 5.4.1:show the rule viewer of gbellmf with 12 rules

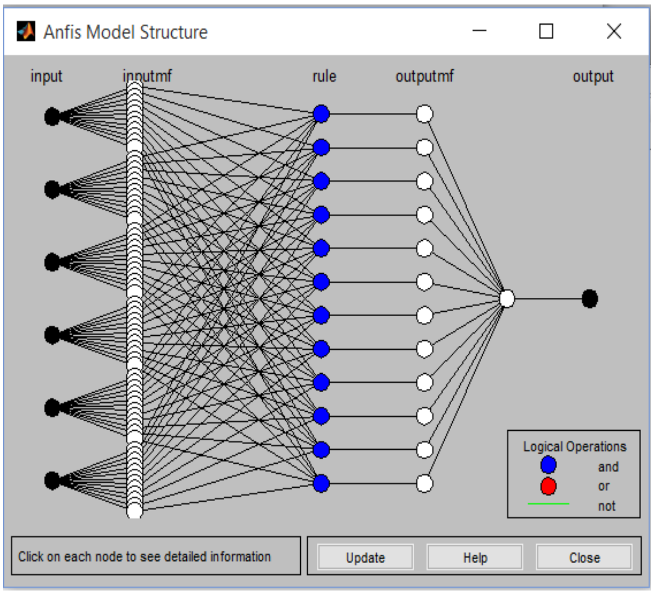

Fig. 6: An ANFIS model structure for the task of identifying ten fauts and no-faults condition

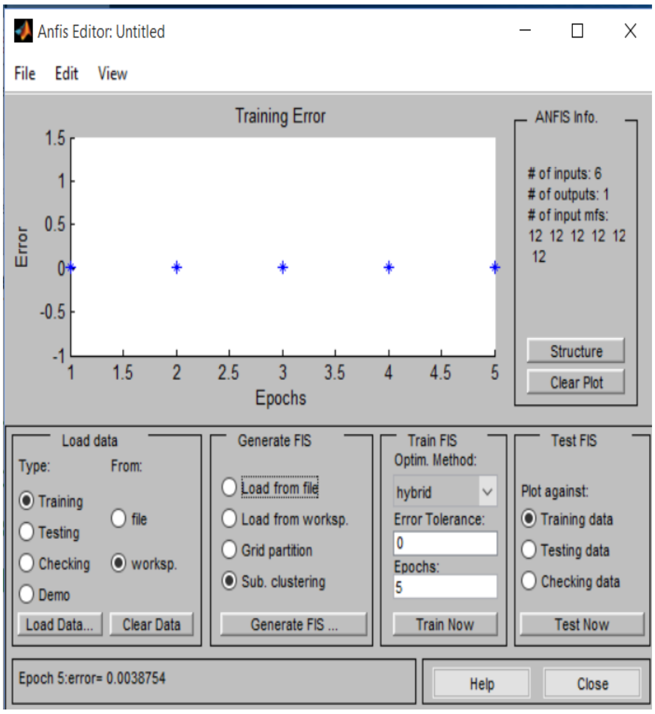

Figure 7:train result of gbellmf with 5 epochs

E. Testing results

About 1640 samples of data set were tested with six inputs i.e. V_{ab}, V_{bc}, V_{ca} *and* $I_n/I_p, I_o/I_p, I_p/I_{load}$ and ten faults and no-fault condition used as output with different fault inception angles and epochs. The results are show in the figures below;

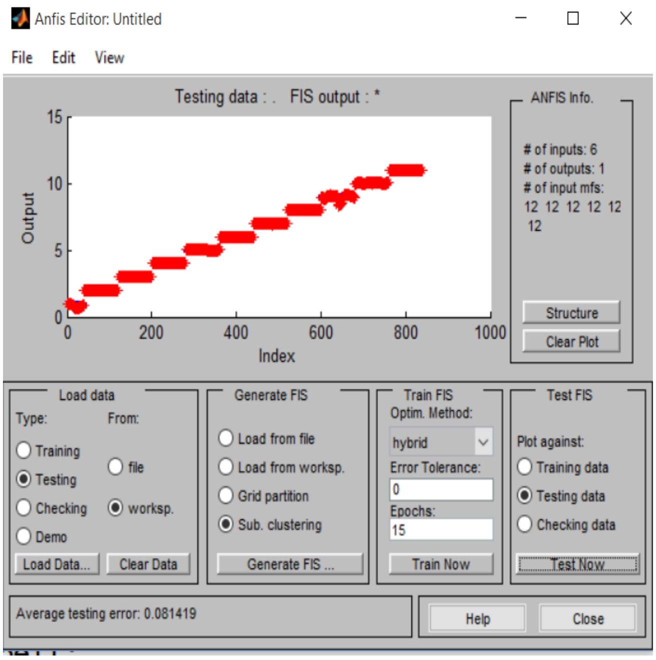

Figure 8:test result of gbellmf with 15 epochs

V. FINDINGS

A. ANFIS

- Gbellmf has the best performance for both training and testing data.
- The error are reduced with increased the number of epochs
- The optimum number epochs for both testing and training was found to be 5epochs
- Training error = 0.0038754
- Testing error =0.0814
- Faster than ANN

B. .ANN

- 20 neurons is the optimums number for training
- 22 neurons is the optimum number for testing
- The optimum delay is 25 samples i.e.12.5ms

VI. CONCLUSION

ANFIS technique involves more computation, but it provides better accuracy for detection and classification all types faults in transmission lines than ANN .Different set of data had been trained and tested with different number of epochs and membership function and gbellmf was found to be the best membership function in performance for both training and testing with least error, high accuracy and less number of epochs and faster than ANN with less delay.

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