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

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ABSTRACT

Transmission lines suffer from unexpected failures due to various random causes which can lead to instability. The functions of protective systems are to detect, classify faults, locate and sent trip signal to circuit breaker for isolation. The main objective of this task is to study the available techniques and algorithms to develop improved relaying algorithm based on adaptive neuro-fuzzy inference system (ANFIS) which could have 100% accuracy and operate with minimum delay. The training , testing and validation data samples to be used by the ANFIS models were generated using sequence current components and line voltages under normal and fault conditions at various locations on a 400kv,50Hz, 100km transmission line. Simulations were performed using EMTDC/PSCAD, on a sample three-phase power system. The lines current were first processed using FFT algorithm and then the sequence components were derived from the same fundamental frequency. Various fault scenarios are considered in this work. The ANFIS's were trained and tested using the various sets of data in which six inputs were used in different combinations. The inputs to ANFIS's are rms line voltages and ratio of sequence currents was used. Different membership functions were used with different number of epochs and 'gbell' membership function was found to be the best in performance for both training and testing. Data was extended and the ANFIS was tested with 'gbell' membership function. The result obtained show 100% accuracy with lesser number of epochs than needed with ANN.

Keyword: Transmission lines, Faults, Circuit Breaker, Adaptive Neuro-Fuzzy Inference System (ANFIS), Membership Function.

INTRODUCTION

Adaptive neural fuzzy inference system (ANFIS) is based on fuzzy logic modelling and uses artificial neural network as the learning algorithm. The system can teach, change the data environment or respond to the remote stimulus for adapting to the change of data environment [7]. ANFIS produces constant and linear target by using respective zero and first-order polynomial equations and is also known as a Sugeno-type of fuzzy inference system (FIS). Fault occurs in the transmission line is expected to avoided, utility problems and equipment damage from effect of the arc and so on. These failures are disrupted the reliability operation of the power system. The different researchers to overcome in this problem have suggested many various schemes and algorithms. There are several techniques to detect fault in the transmission system, they are: time domain, frequency domain, and wavelet transform and hybrid intelligent technique. Lin et.al presented a detection of fault in power system by using Adaptive Probabilistic Neural Network architecture [1-3].This paper describes how to develop an improved relaying technique that can detect and classify the type of error by using a Hybrid Intelligent Techniques. It is also introduced the name of Adaptive Neuro Fuzzy Inference System (ANFIS). The main objective of this work is to study the available techniques and algorithms for develop improved relaying algorithm based on adaptive neuro-fuzzy inference system (ANFIS) which could have 100% accuracy and operate with minimum delay.

Data Generation for Training and Testing

This project involves a 400kV transmission line which has been used to develop and implement the proposed strategy using ANFIS. The training patterns to be absorbed by the Adaptive Neuro Fuzzy Inference System model were generated using sequence current components and line currents under normal and fault conditions at various locations along a transmission line. The model shown in Fig. 1:

Selection of Best Combination

The inputs are selected based on the best performance between the three set of inputs combination of ANFIS, the best among them was selected. The three combination of inputs include $(V_a, V_b, V_c \ and \ I_a, I_b, I_c)$, $(V_{ab}, V_{bc}, V_{ca} \ and \ I_n/I_p, I_o/I_p, I_p/I_{load})$ and $(V_a, V_b, V_c \ and \ I_n/I_p, I_o/I_p, I_p/I_{load})$.Where this combination found to be best combination i.e. $(V_{ab}, V_{bc}, V_{ca} \ and \ I_n/I_p, I_o/I_p, I_p/I_{load})$.

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. 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.

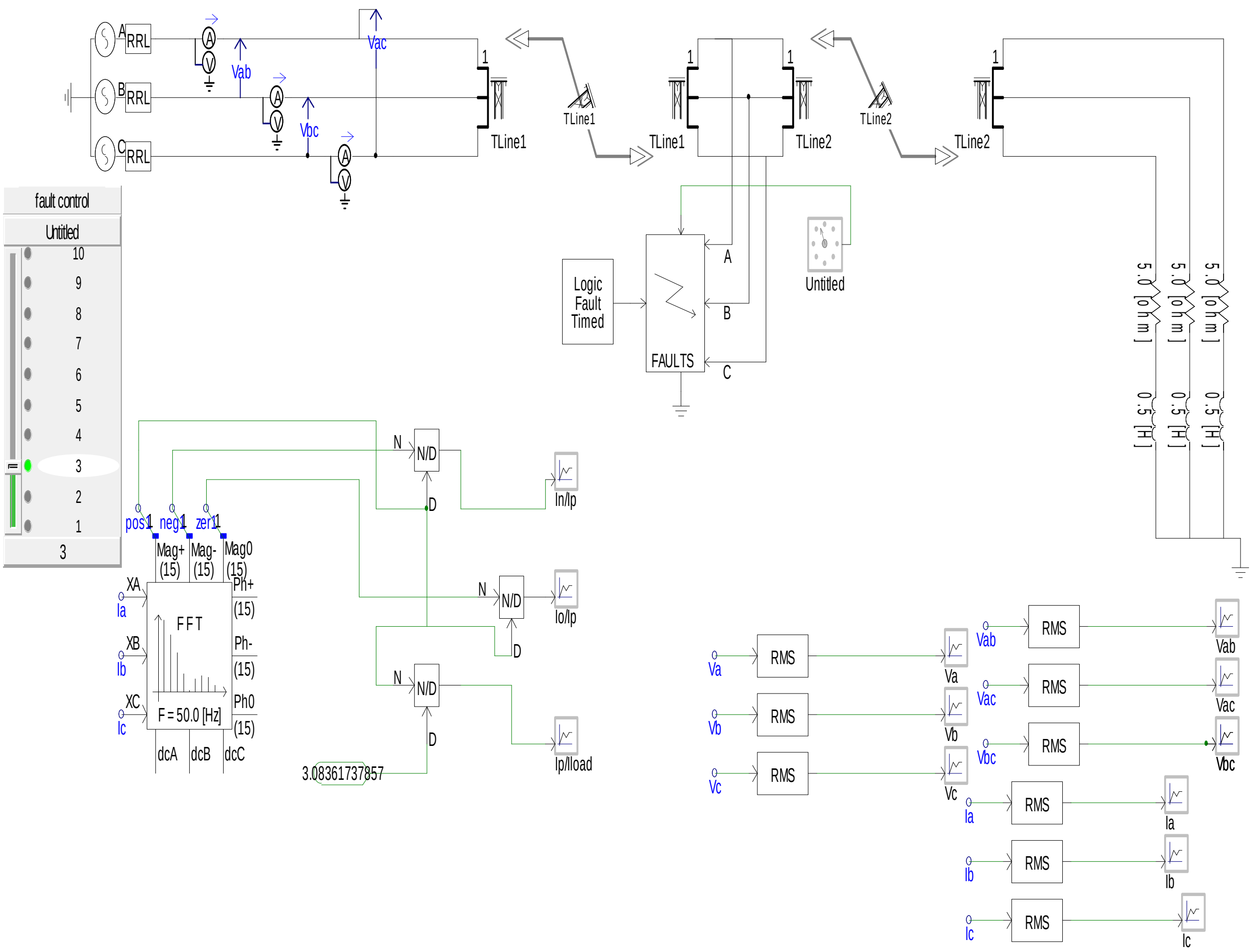

Fig. 1 Training process with different numbers of epochs using Gaussian membership function

Gaussian Membership Function

The Gaussian membership functions was used by default for the six inputs $(V_{ab}, V_{bc}, V_{ca}$ and $I_n/I_p, I_o/I_p, I_p/I_{load})$ in both testing and training. The optimum number of epochs for both training and testing of gauss membership function is 20.

Rule Viewer and Surface Viewer

Fig. 3 shows how the rules are arranged using IF THEN for the six inputs and based on this conditions the ten outputs is produced.

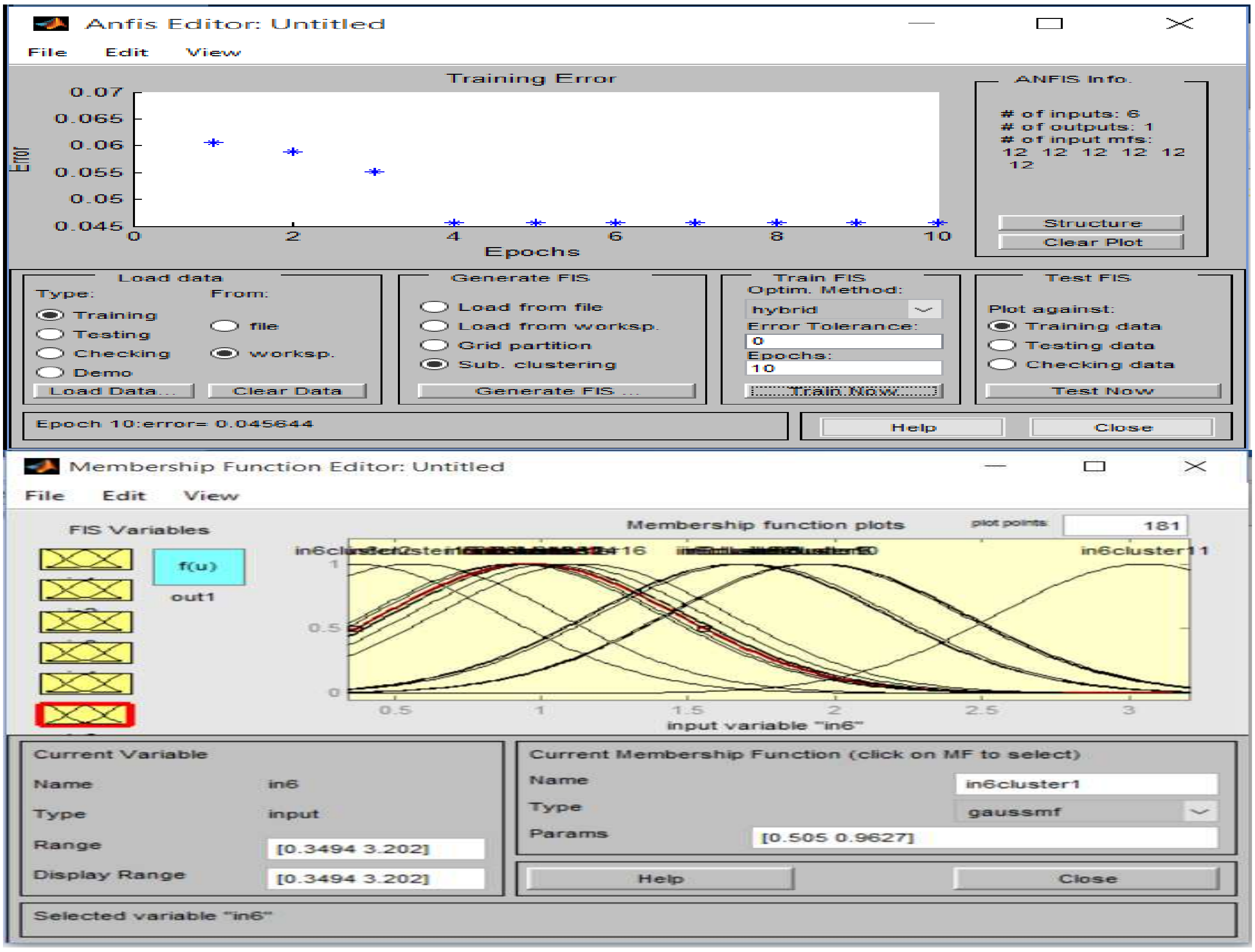

Fig. 2 Gaussian membership functions

Comparison of Membership Functions

Table -1 Comparison of Different Membership Function with their Performance for Training and Testing

S/no	MBF	EPOCHS	Training Error	Testing Error
1	Gaussmf	10		
		14	0.021942	0.2144
		20	0.021942	0.2144
2	Trimf	0.2	0	3.1014
		10	0	3.1014
		20	0	3.1014
3	Tripmf	10	NaN	3.1014
		15	NaN	3.1014
		20	NaN	3.1014
4	Gbellmf	10	0.017927	0.23384
		15	0.007128	0.10751
		20	0.007128	0.10751
5	Gaussmf2	10	0.011809	0.39615
		15	0.011809	0.39615
		20	0.011809	0.39615
6	Sigmf	10	0.057081	0.67929
		15	0.057081	0.67929
		20	0.057081	0.67929
7	Dsigmf		Nil	Nil
8	Psigmf		Nil	Nil
9	pimfZ	10	NaN	NaN
		20	NaN	NaN
		30	NaN	NaN
10	Zimf		NaN	NaN

Findings: gbellmf is the best membership functions

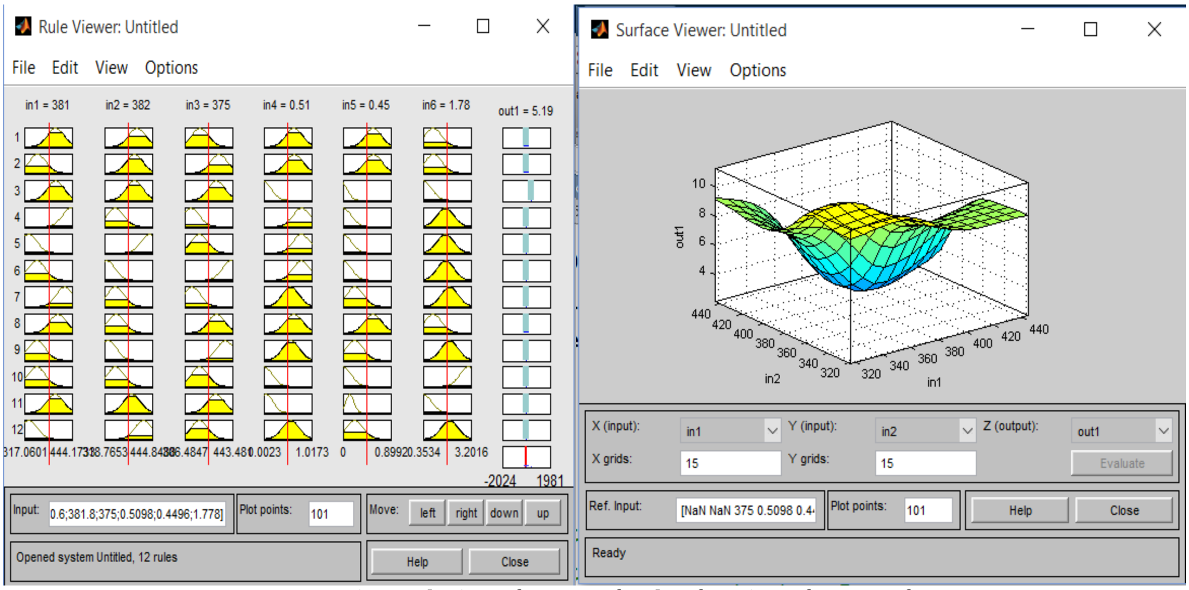

Fig. 3 Rule viewer for gaussmf and surface viewer for gaussmf

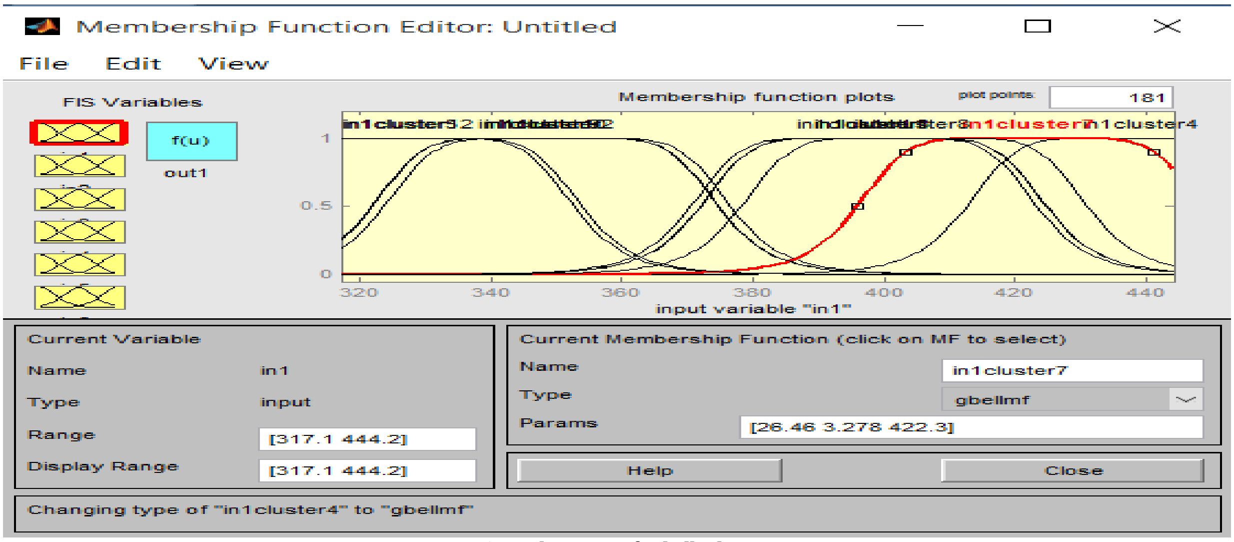

Fig.4 The curve of 'gbell' shape

ANFIS with 'gbell' Membership Functions

In hybrid learning algorithm, MF parameters are adjusted to identify the best prediction value. The parameters determine the size of MF curve as shown in Fig.4. The curve of 'gbell' shape has been selected in the learning process due to its high performance as shown in the comparisons Table -1.

Number of Epochs

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. The numbers of epochs are updating starting from 10 epochs to 20 epochs and the optimized number of epochs was found to be 15.

Rule

In this part, an ANFIS model has been developed with 17 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 structure ANFIS model is shown in Fig.5 for that purpose. There are five stages of ANFIS operational process that includes fuzzification, 'IF-THEN' rules, normalization, defuzzification and neuron addition.

Training and Testing

In the training the 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 90 degree fault inception angle and 50km fault location. While for testing the same inputs were used with 45 degree inception angle. The figures 6 & 7 shows the training and testing results starting from 10 epochs to 20epochs of the gbellmf.

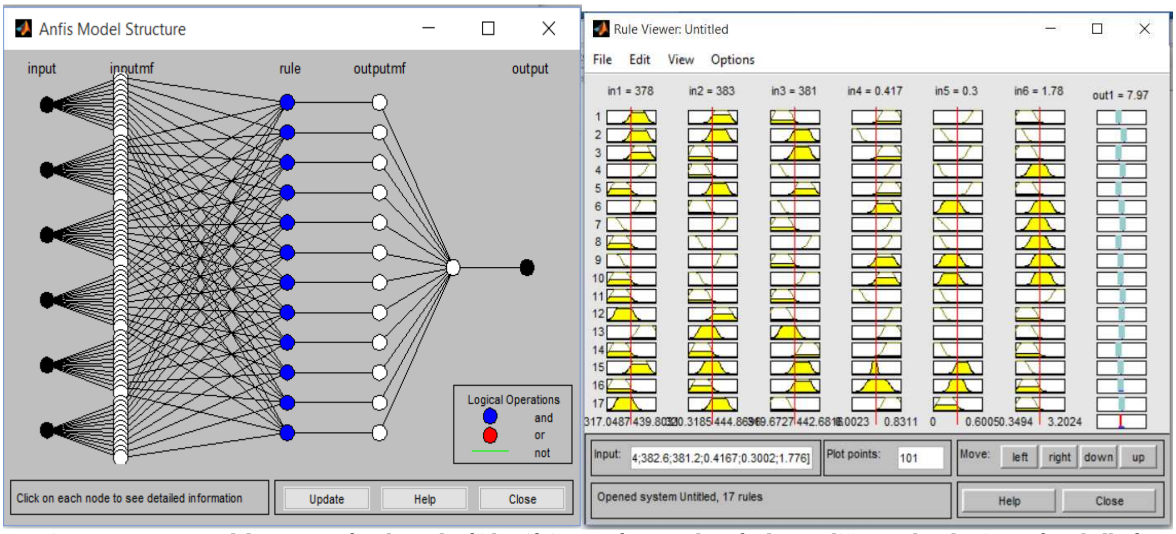

Fig. 5 An ANFIS model structure for the task of identifying ten fauts and no-faults condition and Rule viewer for gbellmf

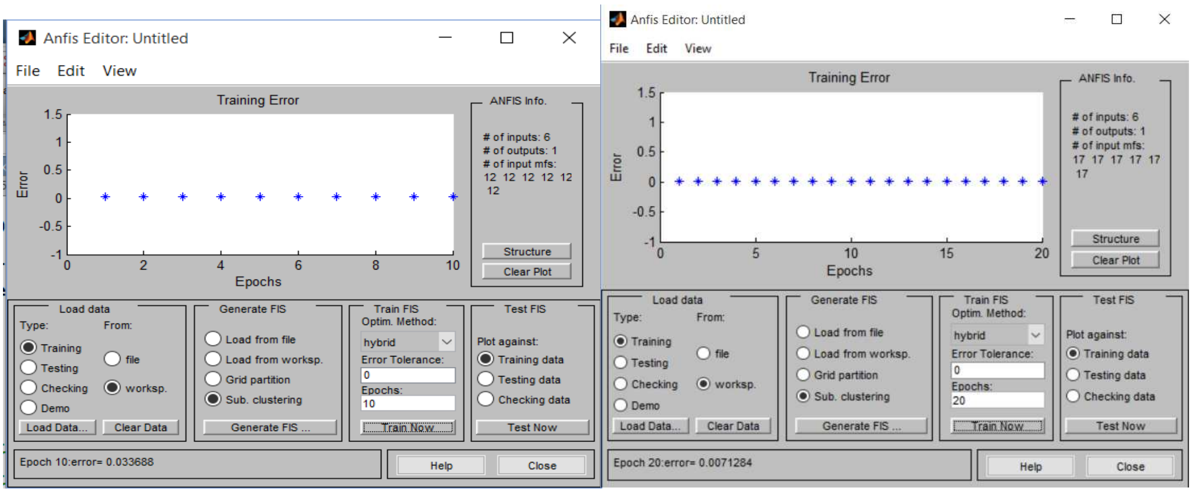

Fig. 6 Training with 10 epochs and Training with 20 epochs

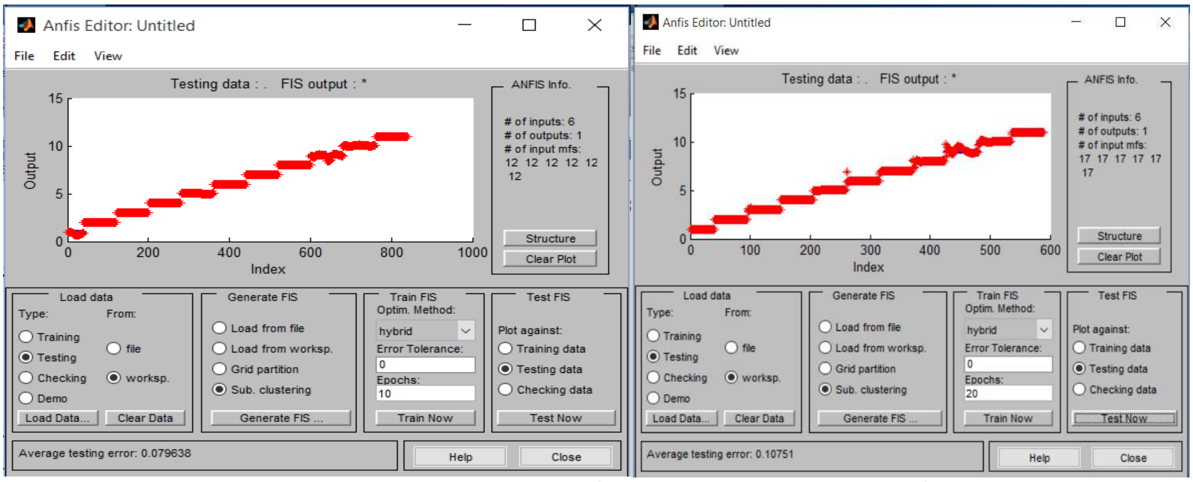

Fig. 7 Testing with 10 epochs gbellmf and Testing with 20 epochs gbellmf

Testing and Training of ANFIS with gbellmf with Expanded Data Set

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.

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.8 for that purpose. There are five stages of ANFIS operational process that includes fuzzification, 'IF-THEN' rules, normalization, defuzzification and neuron addition.

Training Results

About 1640 samples of data set ware trained 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 some of the results are show in the Fig. 9.

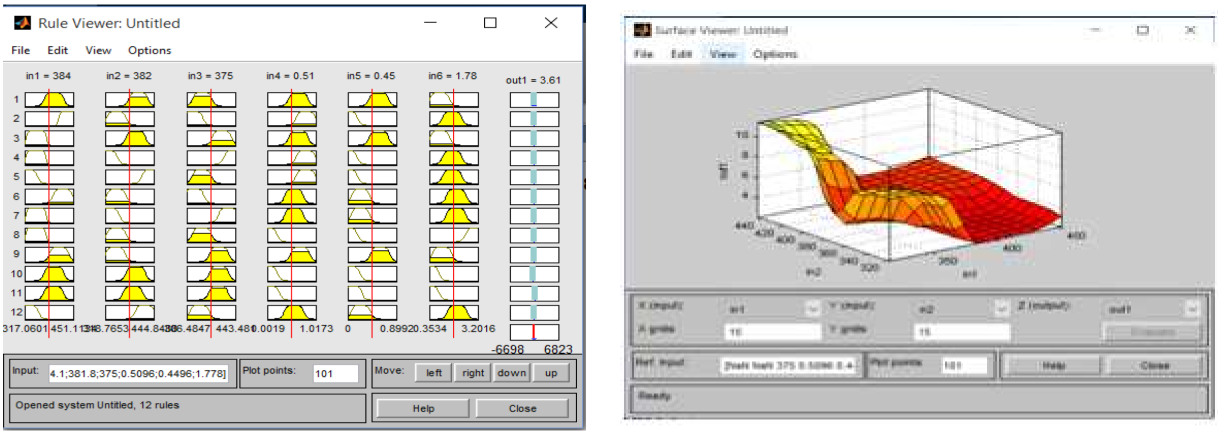

Fig. 8 Rule viewer of gbellmf and show the surface viewer of gbellmf

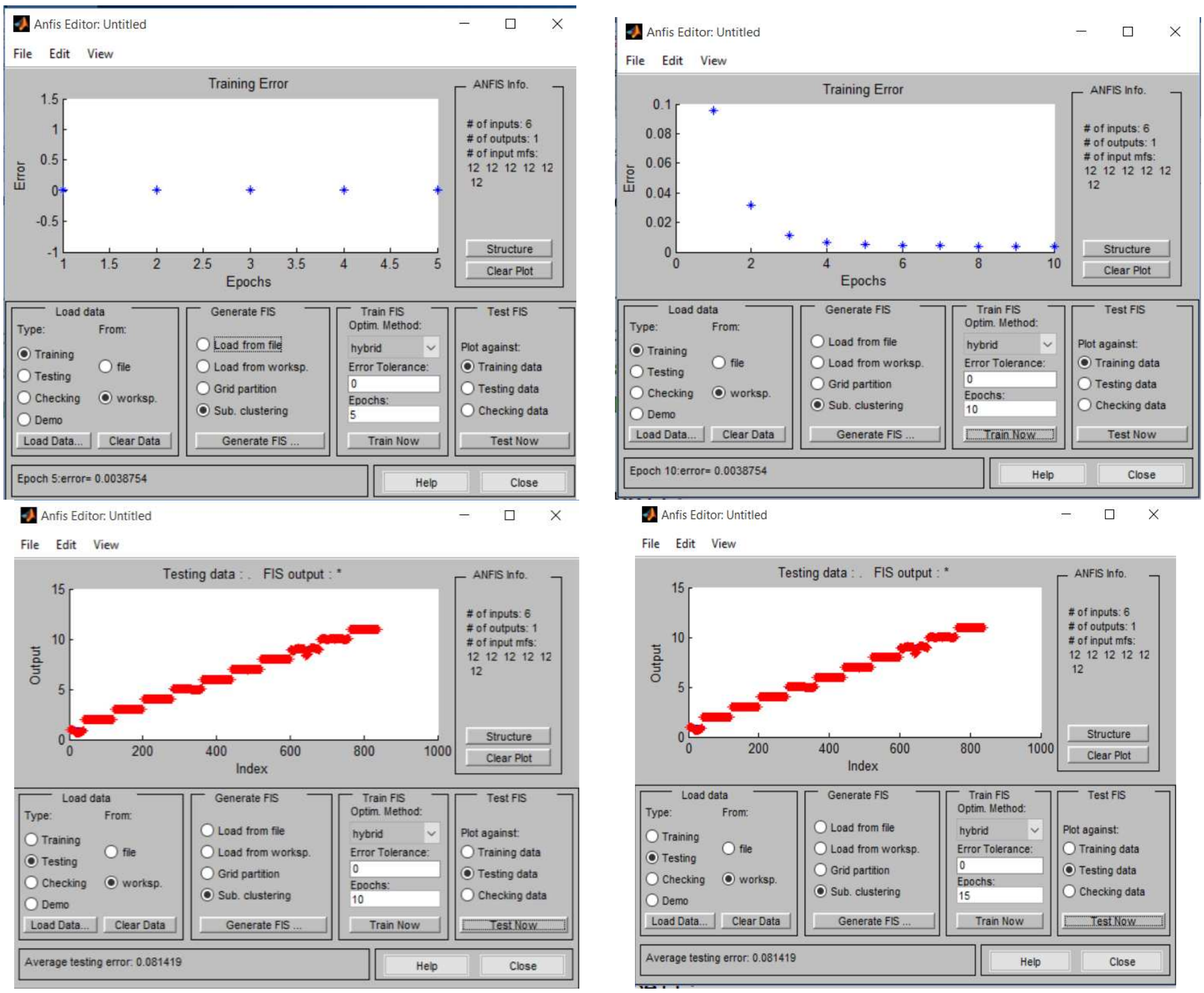

Fig. 9 Train result of gbellmf with 5 epochs and train result of gbellmf with 10 epochs

CONCLUSION

This work has studied the usage of adaptive neuro-fuzzy inference systems (ANFIS) as an alternative method for the detection and classification of faults. The methods employed make use of rms values of the phase voltages, line voltages, ratio of sequence currents phase currents and load current. The 100km transmission line (400kv, 50Hz) was model in PSCAD. The data generated was used as inputs for training and testing of ANFIS in MATLAB. All kinds of faults namely single line-ground, line-line; double line-ground and three phase faults, have been simulated on PSCAD in this work. Investigation has been made with the use of adaptive neuro-fuzzy inference system (ANFIS) as an accurate method for detection and the classification of transmission line. ANFIS technique involves more computation, but provides 100% accuracy of detection and classification. Different set of data have been used for training and testing with different number of epochs and membership functions. '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 than ANN.

The algorithms developed can be further trained and tested with larger data, to be generated through PSCAD for more inception angles, multiples location of faults and multiple value of source, load and fault impedance. Relaying algorithms using other artificial intelligence techniques, like genetic algorithms, can be developed.

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