Fault Detection and Classification in Transmission Lines: An ANFIS Approach

Noopur Pandey(1) , PROF. Arti Bhandakkar (2)

(1) *Research Scholar, SRIT Jabalpur*

(2) *Associate Professor, Department of Electrical Engineering, SRIT, Jabalpur (M.P)*

Abstract: **An overhead transmission line is one of the main components in electric power system. The transmission line is exposed to different types of faults such as phase-to-earth fault, two-phase-to-earth fault, phase to-phase fault, three phase fault. The fault detection and classification for the transmission line is an important issue since identifying accurate fault detection can facilitate repairing the damage and restoring the transmission line rapidly. The time needed to detect the fault will affect the quality of the power delivery. Therefore, accurate fault detection on the line is an important requirement for a permanent fault. This paper presents an application of ANFIS approach for automated fault disturbance detection and classification in transmission lines using measured data from one terminal of the transmission line. The ANFIS design and implementation are aimed at high-speed processing which can provide selection real-time detection and classification of faults. The Training and Testing of ANFIS is done using MATLAB version7, R2010a.**

Key words **- ANFIS technique, fault detection, classification, digital protection, transmission line**

1 INTRODUCTION

Transmission lines are open-air wires or insulated cables that carry electric power from one place to another. In the context of this book, ‘transmission lines’ are consider for not only the very high voltage lines which are considered to as ‘transmission’ by electrical engineers, but also the lower voltage (but still high) lines considered to as ‘sub transmission’ and ‘distribution’. They all carry electric power and they all behave in roughly the same way. Transmission lines operate at high voltage to reduce losses, because loss is proportional to the square of current, and for a given amount of power carried, current is inversely proportional to voltage. [1]

Transmission lines, being current carrying wires, produce magnetic fields and therefore exhibit inductance that can be described as being in series with the terminals of the line. Since they carry high voltage, they also produce electric fields that are terminated on the conductors, so that transmission lines also exhibit capacitance that is generally described as being in shunt with the terminals of the line.

The Electric Power System is classified into many different parts. One of which is the system, in which power is supplied from generating stations and substations via transmission lines to the end users called consumers, is transmission system. All the methods could encounter various types of inefficient functioning which is usually called “Fault”.
The fault detection and classification for the transmission line is an important issue since identifying accurate fault detection can facilitate repairing the damage and restoring the transmission line rapidly. The times needed to detect the fault will affect the quality of the power delivery.

Taharbouthib et. al. deals with the application of artificial neural networks (ANNs) to fault detection and location in extra high voltage (EHV) transmission lines for high speed protection using terminal line data.

They proposed an neural fault detector and trained locator using various sets of data available from a selected power network model and simulating different fault scenarios (fault types, fault locations, fault resistances and fault inception angles) and different power system data (source capacities, source voltages, source angles, time constants of the sources). [10]

2. LITERATURE REVIEW

Recent applications in protection have covered fault diagnosis for electric power systems, transformer protection and generator protection.The fault location algorithm being a key element in the digital relay for power transmission line protection, ***G.K Purushothamaet. al***. discusses the potential applicability of ANN techniques for determination of fault location and fault resistance on EHV transmission lines with remote end in-feed. Most of the applications make use of the conventional Multi-Layer Perception (MLP) model based on back propagation algorithm.Recent applications in protection have covered fault diagnosis for electric power systems ***E.A. Mohamed et. al***. describes the development of a fast, efficient, artificial neural network (ANN) based fault diagnostic system (FDS) for distribution feeders. ***A. L. Orille-Fernandez et. al***. presents a novel approach to fault detection, faulted phase selection and direction estimation based on Artificial Neural Networks (ANN). The suggested approach uses the Finite Impulse Response Artificial Neural Network (FIRANN) with the same structure and parameters in each relaying location. ***A.H. Osman, T. Abdelazim, and O.P. Malik*** discusses a transmission line distance relaying technique using an on-line trained neural network (NN) is developed. Results of numerical simulation and experimental studies show very good accuracy and fast estimation of distance to fault for various faults under different operating conditions, high fault resistance, and remote-end feed.

Whei-Min Lin et. al. presents a new approach to identify fault types and phases. A transmission line fault classification method based on a radial basis function (RBF) neural network with orthogonal-least-square (OLS) learning procedure was used to identify various patterns of associated voltages and currents. The RBF neural network was also compared with the back-propagation (BP) neural network in this paper. It is shown that the RBF approach can provide a fast and precise operation for various faults. The simulation results also show that the proposed approach can be used as an effective tool for high speed relaying. [13]

P. K. Dash, A. K. Pradhan, and G. Panda present a new approach for the protection of power transmission lines using a minimal radial basis function neural network (MRBFNN). This type of RBF neural network uses a sequential learning procedure to determine the optimum number of neurons in the hidden layer without resorting to trial and error. ***R.N. Mahanty and P.B. Dutta Gupta*** presented the application of radial basis function (RBF) neural networks for fault classification and location in transmission lines. Instantaneous current/voltage samples have been used as inputs to artificial neural networks (ANNs). Whereas, for fault classification, pre fault and post fault samples of only the three-phase currents are sufficient, for fault location, post fault samples of both currents and voltages of the three phases are necessary.

3. FAULT DETECTION & CLASSIFICATION

The Simulated Power System under Study. A 1000 MW hydraulic generation plant (machine M1) is associated to a load center from end to end a long 500 kV, 400 km transmission line. The load center is demonstrated by a 5000 MW resistive load. The load is served by the remote 1000 MW plant and a local generation of 5000 MW (machine M2). The arrangement has been modified so that the line carries 950 MW which is close to its surge impedance loading (SIL = 977 MW). The Simulink diagram is shown in figure 4.1

ANFIS apply the theory of fuzzy sets and fuzzy if-then rules to originate outputs. The outputs removed from ANFIS used not only in discerning between transmission line healthy and/or faulty states but also used in categorizing fault type. The ANFIS's were trained and tested in this work to provide fault detection and classification for the transmission line.

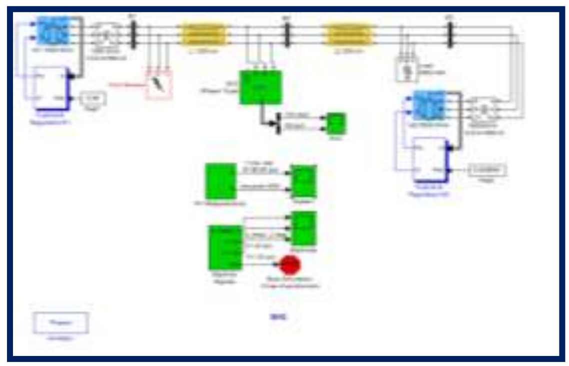

Figure 1 Fault Detection & Classification Methodology Using ANFIS

4. THE FIRST ANFIS USED FOR FAULT DETECTOR (FD)

The value of 1 is indexed for the presence of fault and the value of 0 is indexed for the non-faulty conditions. The second ANFIS is used to find out the type of location of fault in the first protection zone of the transmission line layer 100% of the line length from the sending end data merely and also for classification of the fault.

5. RESULTS & DISCUSSION

5.1 Case-1 Fault Detection

a) Fault Detection Unit:

The fault detection unit is built by using various training data at fault and no fault conditions. After that, it is tested using different situations of the simulated power system.

b) Training Data for Fault Detection Unit:

The training data accustomed train the ANFIS of the fault detection unit are taken in account at the no fault conditions and fault conditions.

The fault conditions are conceded out as follows:

All dissimilar fault types (single line to ground, double lines, double lines to ground and three lines fault).

Fault distance (Df) 5%, 40% and 80% of the line Inception fault time (Tf) 5 msec IV) Fault resistances (Rf) 0 and 100 ohms.

The feedback data to the FNN detection unit are the impedances of the three phases (magnitude and phase i.e. 6 input) later distributing them by their non-fault values. They are taken from the essential standards of the voltage and current measurements after making Fourier transform every 10 msec.

Although the output data from FNN are:

$-1 \leq$ output $<0.5$for no fault conditions.

$0.5\leq$ output<3 for fault conditions

c) The ANFIS detector:

The ANFIS detector consists of six neurons in the input layer i.e. N=6,(Zapu, Zaph, Zbpu, Zbph, Zcpu, and Zcph) and three triangular membership functions for each input i.e. F=3(low , medium and high values) and constant membership function for the output.

d) Testing Data for Fault Detection Unit:

The testing data are preferred at unlike fault and no fault situations. The fault conditions are done at dissimilar fault detachments, different fault resistances, different fault initiation times and dissimilar fault types which are not preferred for the training data. Some of these testing data are shown in Table 1. In table 1, the first four columns are Fault inception time (Tf), Fault resistance (Rf), Fault distance (Dfp.u) and Fault type respectively.

Now the next six columns are impedances (magnitude and phase) of the three phases and these six values are used as input to the ANFIS detector. In conclusion the output of the ANFIS detector is shown in the last column to define the condition if it is fault or not. The testing is done in 25 epochs.

FOR FAULT CONDITIONS:

Fig. 5.1 Shows FIS Editor for fault conditions. There are six inputs, (Zapu, Zaph, Zbpu, Zbph, Zcpu, and Zcph) and sugeno type FIS Editor is used.

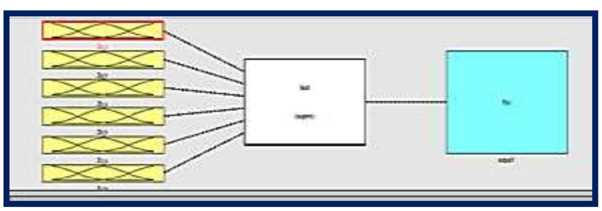

Fig.5.1 FIS Editor

Fig. 5.2 shows different membership function of inputs. In this work three Triangular membership function is used for every inputs.

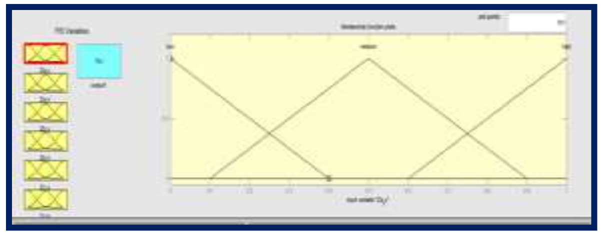

Figure 5.2 Membership Function

Figure 5.3 shows Test FIS plot against training data.

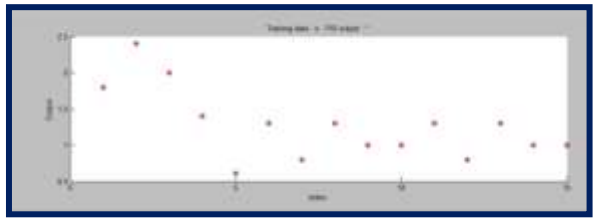

Figure 5.3 Test FIS plot against training data

Figure 5.4 shows graph between testing data and FIS output.

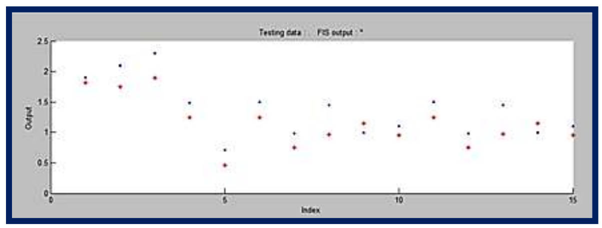

Figure 5.4 Graph between testing data and FIS output

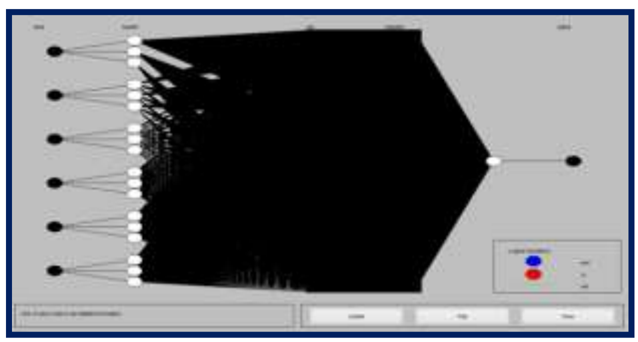

Figure 5.5 Structure

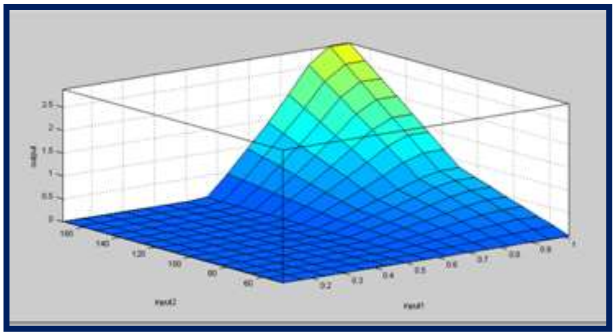

Figure 5.6 Surface

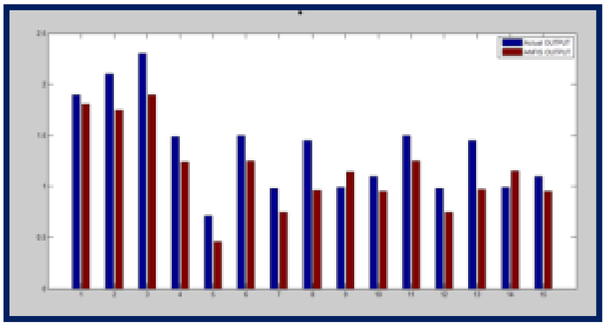

Figure 5.7 Actual vs ANFIS Output

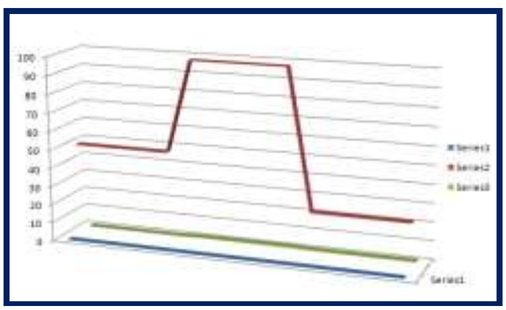

Figure 5.8 Plot between R_f ,T_f and D_f .

b) For No Fault: The ANFIS detector consists of six neurons in the input layer i.e. N=6,(Zapu, Zaph, Zbpu, Zbph, Zcpu, and Zcph) and three triangular membership functions for each input i.e. F=3 (low , medium and high values) and constant membership function for the output.

The no fault conditions are accomplished at dissimilar states of variations in the voltage and the frequency of the two generators within the acceptable limits to imitate the deviations in the feeding and the loading situations in the power systems. Some of these fault conditions (different states of variations) are presented in Table 5.2.

The variations in the voltage and the frequency of the two generators are introduced in Table 5.2.The process is completed in 3 epochs and 729 rules are generated. Figure (5.9) shows FIS Editor for no fault conditions.

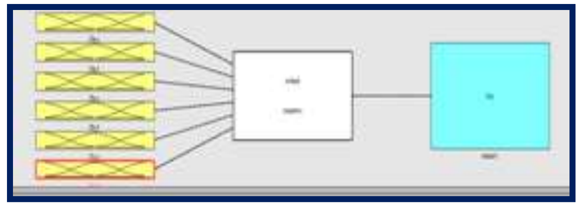

Figure 5.9 FIS Editor for no fault conditions.

Figure (5.10) shows different membership function of inputs. In this work three Triangular membership function is used for every inputs.

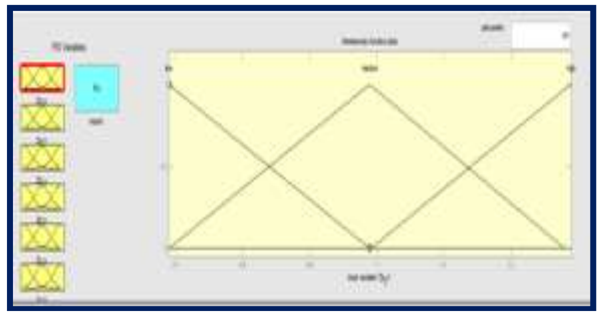

Figure 5.10 Membership function

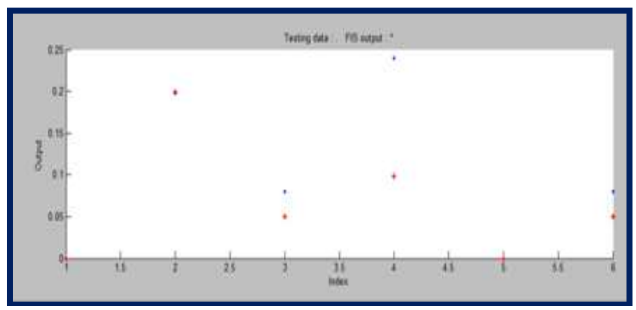

Figure 5.11 Test fis plot against testing data

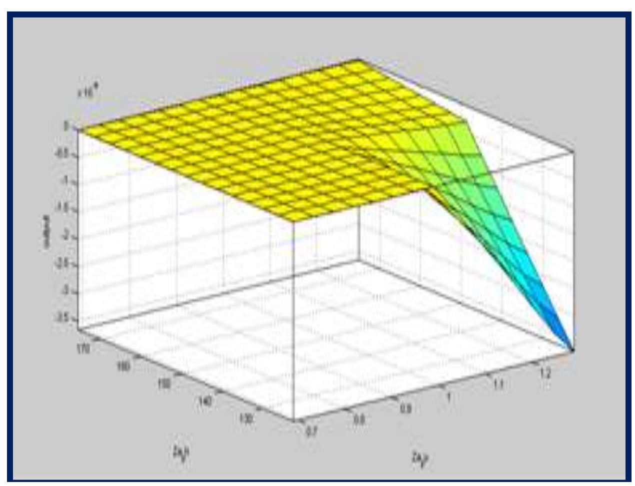

Figure 5.12 Surface

TABLE- 5.1 FOR FAULT CONDITIONS

Tf	Rf	Df	Fault type	Zapu	Zaph	Zbpu	Zbph	Zcpu	Zcph	Output	ANFIS Output	Absolute Percentage Error
.007	50	0.1	BG	0.98	161	0.48	-268	1.06	157	1.9	1.81	4.737
.007	50	0.1	BC	0.94	157	0.41	-268	0.12	161	2.1	1.75	16.667
.007	50	0.1	BCG	0.91	171	0.12	-256	0.26	189	2.3	1.9	17.391
.007	50	0.1	ABC	0.38	69	0.26	-273	0.95	143	1.49	1.24	16.779
.007	50	0.1	ABCG	0.18	69.1	0.16	-265	0.74	83.1	0.71	0.463	34.789
.002	100	0.6	AG	1.02	158	0.98	-247	0.58	121	1.5	1.25	16.667
.002	100	0.6	AB	0.41	104	1	-248	0.88	73.4	0.98	0.747	23.778
.002	100	0.6	ABG	0.27	126	0.99	-246	0.24	98.9	1.45	0.963	33.586
.002	100	0.6	ABC	0.21	49.1	0.11	-323	0.19	108	0.99	1.14	15.152
.002	100	0.6	ABCG	0.19	57.8	0.18	-321	0.22	101	1.1	0.954	13.273
.004	25	0.35	CG	1.02	158	0.98	-247	0.58	121	1.5	1.25	16.667
.004	25	0.35	CA	0.41	104	1	-248	0.88	73.4	0.98	0.748	23.673
.004	25	0.35	CAG	0.27	126	0.99	-246	0.24	98.9	1.45	0.97	33.103
.004	25	0.35	ABC	0.21	49.1	0.11	-323	0.19	108	0.99	1.15	16.162
.004	25	0.35	ABCG	0.19	57.8	0.18	-321	0.22	101	1.1	0.954	13.273

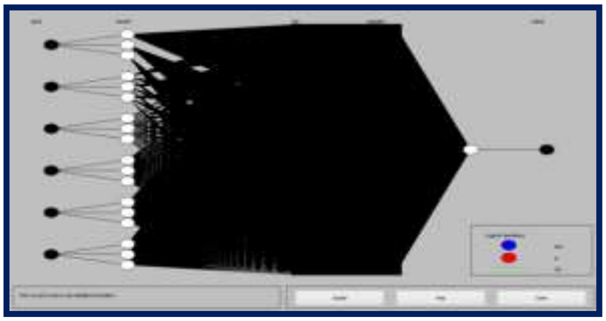

Figure 5.13 Structure

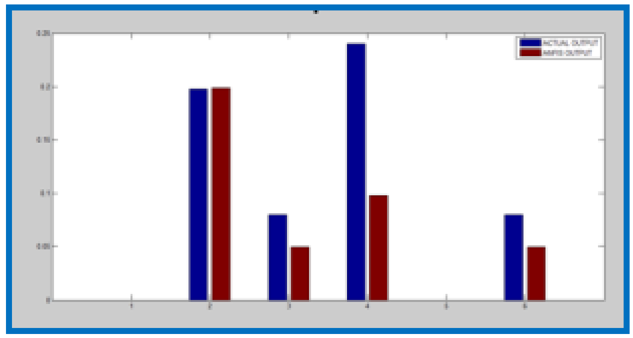

Figure 5.14 Actual vs ANFIS Output

Table-5.2 No Fault

V_1	V_2	f_1	f_2	Zapu	Zaph	Zbpu	Zbph	Zcpu	Zcph	Output	Anfis Output	Absolute Percentage Error
-5	0	-0.02	-0.02	0.69	175	0.69	-190	1.12	184	0	0	0
0	-5	-0.02	-0.02	1.29	122	0.64	-289	0.81	140	0.198	0.199	0.5050
-5	-5	0.02	0.02	1	157	1	-248	1	158	0.08	0.0499	37.625
5	0	-0.02	-0.02	1.24	124	0.61	-284	0.78	150	0.24	0.0982	59.0833
0	5	-0.02	-0.02	0.69	174	0.74	-190	1.09	183	0	0	0
5	5	0.02	0.02	1	157	1	-248	1	158	0.08	0.0499	37.625

TABLE 5.3 Testing Data

T(secs)	Rf	Df	FAULT TYPE	Ir	Zapu	Zaph	Zbpu	Zbph	Zcpu	Zcph	OUTPUT	ANFIS OUTPUT	Abs. Percentage Error
0.004	0	0.15	PG	326	0.02	48.5	1.35	192	1.48	-238	1.4	1.3	7.143
0.004	0	0.15	PP	1.69	0.02	-5.8	0.02	84.2	0.83	-182	1.9	2.47	30
0.004	0	0.15	PPG	197	0.02	3	0.02	83	1.47	-159	3	2.72	9.333
0.01	25	0.25	PPP	194	0.04	33.2	0.19	27.3	0.09	41	3.9	3.58	8.718
0.01	25	0.25	PG	31.3	0.7	132	1.46	58.2	0.92	-201	1.4	1.4	0
0.01	25	0.25	PPP	203	0.14	17.9	0.19	15.6	0.16	18.8	3.5	4	14.286
0.012	50	0.35	PG	24.9	0.82	141	0.93	138	1.11	68.2	0.9	0.579	35.667
0.012	50	0.35	PP	1.5	0.58	61.8	1.2	141	1.18	-16.6	2.2	2.29	4.091
0.012	50	0.35	PPG	13.9	0.02	84.1	0.88	142	0.05	10.1	2.6	2.94	13.077
0.012	50	0.35	PPP	0.12	0.074	31.3	0.12	29.2	0.08	81	3.8	4.2	10.526
0.008	100	0.45	PP	1.5	1.43	141	3.87	108	1.18	-288	2.2	1.52	30.909
0.008	100	0.45	PPG	5.9	0.04	88.7	0.93	139	0.12	-0.16	2.7	2.62	2.963
0.008	100	0.45	PPP	1.8	0.86	55.6	1.21	49.8	1.48	39.2	4.2	3.51	16.429

5.2 CASE-2 FAULT CLASSIFICATION

(a) Fault Classification Unit:

The fault classification unit is built at dissimilar circumstances of all fault types (i.e. single line to ground, double lines, double lines to ground and three lines fault). Now the unit is tested by means of testing data dissimilar from those of the training phase.

(b) Training data for Fault Classification Unit:

The training data used to train the FNN of the fault classification unit are taken at:

a) Fault distance (Df) about 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70% and 80% of the line

b) All type of faults

c) Inception fault time (Tf) 2 msec

d) Fault resistances (Rf) about 0, 25, 50 and 100 ohms.

The input data to the ANFIS Classification are the impedances of the three phases (magnitude and phase) and the zero sequence element of the currents (i.e. 7 inputs) later dividing them by their non-fault values. They are taken from the essential values of the voltage and current quantities after making Fourier transform every 20 msec.

While the output data from FNN are:

$0.5 \leq$ output <1.5 for single phase to ground fault

$1.5 \leq$ output < 2.5 for phase to phase fault

$2.5 \leq$ output <3.5 for double phase to ground fault

$3.5 \leq$ output < 4.5 for three-phase fault.

(c) The ANFIS Classifier:

The ANFIS classifier contains of seven neurons in the input layer i.e. N=7, three triangular membership functions for each input i.e. F=3 and relentless membership function for the output.

(d) Testing data for Fault Classification Unit:

The testing data are selected at different fault conditions which are carried out at unlike fault conditions.

These unlike fault conditions are: Different fault spaces, Different fault resistances, Different fault inception times and Different fault types which are not selected for the training data. Certain of these testing data are shown in Table 5.3.

Table 5.3 can be described as follows; the first four columns are fault inception time, fault resistance, fault distance and fault type correspondingly. Then and there the next seven columns are zero sequence current in per unit and impedances (magnitude and phase) of the three phases and these seven values are used as input to the ANFIS classifier. Lastly the output of the ANFIS classifier is presented in the column to define the fault type and last column shows the absolute percentage error.

Figure 5.15 FIS Editor

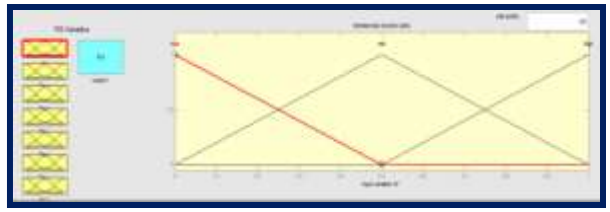

Figure 5.16 Membership function

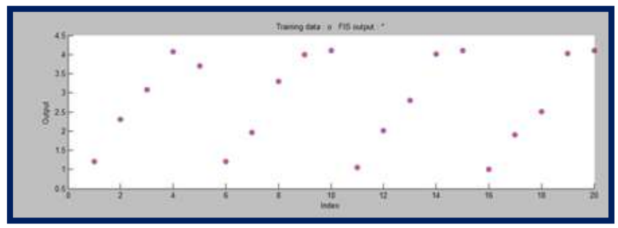

Figure 5.17 Test Fis Plot Against Training Data

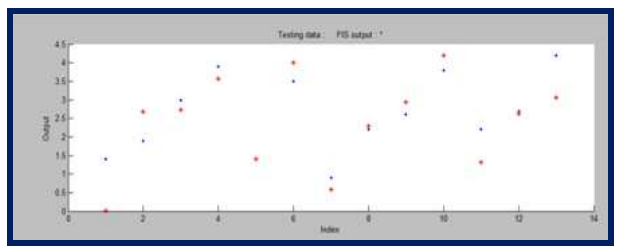

Figure 5.18 Test Fis Plot against Testing Data

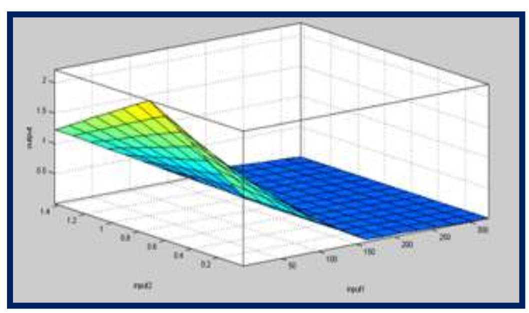

Figure 5.19 Surface

Figure 5.20 Rule viewer

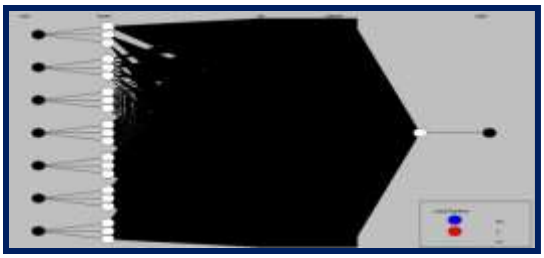

Figure 5.21 Structure

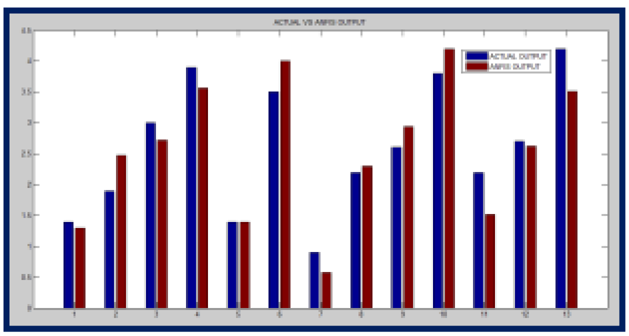

Figure 5.22 Actual vs ANFIS Output

CONCLUSION

An well-organized protective relaying scheme founded on ANFIS is projected in this thesis work. Moreover that a white noise is presented in the testing data to model the faults in the voltage and current measurements. The trained networks are proficient of so long as robust and specific detection and classification of fault for a variety of system circumstances, different inception time, fault locations, fault types and fault resistances.

In this thesis work present an application based on ANFIS for fault detection and classification for a transmission line protective scheme.

ANFIS technique includes more computation, but it delivers better accuracy for detection and classification all shunt faults.

The ANFIS has the succeeding design parameters for the configuration for fault detecting and fault classification are: Sugeno Type, Triangular membership functions and constant membership function for the output.

Simulations by ANFIS shown that the actual values generated by proposed method fit the desired values. The proposed methodology for output based on ANFIS can be used for protective scheme of transmission line.

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