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ACCURACY DETERMINATION AND FAULT IDENTIFICATION OF MULTITERMINAL TRANSMISSION LINE USING SOFT COMPUTING TECHNIQUES

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ABSTRACT
This paper presents soft computing-based techniques for diagnosis of fault in multiterminal transmission line of 3MNBS (Three Machine, Nine Bus System) using voltage and current samples. It is a completely unique approach of fault classification in multiterminal line 3MNBS considering simultaneous and zonal faults in a line using fuzzy logic system, ANN, and binary classifier techniques. The simulated sample using MATLAB software is employed to seek out the fault data of 3MNBS of line. Artificial neural network- based fault classification of 3MNBS has been presented. The binary classification technique (KNN, RF, LR, and Deep learning) proposes in this paper need the consideration of the samples of three -phase voltages and currents at all buses of 3MNBS. By comparing the results, it has been observed that the proposed method is excellent in terms of accuracy for fault classification of 3MNBS.

Keywords:
AI, ML, FLS, KNN, ANN, Binary classifier.

I. Introduction
This paper presents a novel approach for fault classification of 3MNBS with the help of soft computing techniques. In the previous paper of fault classification, the authors used fuzzy logic system to check the accuracy of types of fault but there was some error in line to ground fault as well as for non-ground fault, for some value of voltage and current fuzzy logic system is confused to perfectly classify the type of fault to minimize the error involved in fuzzy logic system the author presents multi-training of sample data again and again for minimization of error and to improve the accuracy. The fuzzy logic-based fault classification techniques are comparatively simpler because it requires just some linguistic rules. In (Ferrero et al. 1995) identified the character of fault (whether LG or LLG), but the involved phases within the fault couldn't been identified and phase fault isn't considered. In (Wang and Keerthi Pala 1998) reported the improved technique supported fuzzy-neural approach and thought of both the symmetrical and unsymmetrical fault. But this method required extra effort to get training of ANN. These soft techniques used some input value and target data, then 70 percent of sample be trained and remaining 30 percent samples are tested to validate the types of faults in multi-terminal transmission line(3MNBS). Almost 1200 of samples fault data are used for training and testing. The sample data is collected by MATLAB Simulink results. Same sample data of voltage and current obtained during simulation 3MNBS standard IEEE model is created in MATLAB Simulink environment. The confusion matrix is used to classify the accuracy efficiency and precision in results. With the help of NN tools the author tried to validate the sample of approximately1200 data gave good accuracy and also less error as well and to design best protective device as per fault classification. In this paper author proposed 3MNBS (Three machine nine bus system) i.e. multi-terminal line. Fault classification in transmission line for reliable supply of power to the consumers. It used fault voltage and current data in all three phases i.e. both un-symmetric and symmetric faults (11 types) in different effects or attributes have been taken like fault inception angle (0-360degree), fault resistance (0.001-5000ohm), different location and on the basis of simultaneous fault in different lines as well. Both fault voltage and current are considered for best classification of fault. Almost 130 different faults in different location and on the basis of fault resistance have been considered to get sample of voltage and current

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in all three phases. Previous researchers have not given fault classification by taking voltage and current in all three phases as input variable and out -put as types of faults. Also, none has guaranteed the accuracy of fault diagnosis. R. N. Mahanty et.el. [1]and [6] both have given radial basis function for fault classification in only two terminal and taken instantaneous voltage and current as input for neural network. R. K. Aggarwal et. el [2] described fault classification in multi-circuit line using fuzzy ARTmap (adaptive resonance theory) neural network, but it has drawn- back of accuracy as well as interfacing issue was major problem. In [3] author described the s-transform for fault classification and protection system but it has not discussed the issues involved in frequency determination. In [4] fault detection and classification were described using wavelets transform but the issue of filtering the high frequency and distorted signal was there. [5] Described the fault direction determination only using ANN, but not discussed the zonal and location study. [7] Described the comparative analysis of short circuit fault classification using KNN, ANN, SVM for single circuit line and not discussed mutual capacitance effect between various zones. [8] Described the symmetrical components and fault classification using fuzzy neuro network but only in single circuit lines. [9] ART with fuzzy rule is applied in the out-put of neural network for accuracy and fault determination in transmission line. [10] Given discrete wavelet transform (DWT) is used to extract high-frequency components of the two aerial modal currents. [11] Described signal processing and wavelets-based method for protection of single circuit transmission line, not discussed about multi-terminal as well as effect of mutual capacitance. In [12] a novel hybrid framework that is able to rapidly detect and locate a fault on power transmission lines is presented but it is not efficient in simultaneous fault operation. In [13] an adaptive convolution neural network (ACNN)-based fault line selection method is proposed for a distribution network. But not described for multi-terminal and simultaneous fault in lines. In [14] the use of an artificial neural network as a pattern classifier for a distance relay operation is discussed the scheme utilizes the magnitudes of three phase voltage and current phasors as input, but not given idea about zonal effect. ANN based fault classification described in single generator only and not focused about fault classification in 3MNBS [15- 23][24][27][30][33][37][40]. In [36] PMU based fault detection has been discussed. In [28, 41] wavelets-based method has been described. In [40-43] fuzzy and soft computing-based fault detection and classification techniques has been discussed. From the above literature survey author found that none has discussed effectively regarding fault classification in 3MNBS and also not described previously regarding simultaneous fault in different zones as well as locations. In this paper author mainly focused regarding fault classification in 3MNBS and simultaneous fault as well as effect of fault inception angle, fault resistance, fault location and distance of fault has been considered. In the coming section author discussed proposed method, simulation in Matlab Release 2014 environment and algorithms, result, discussion, conclusion and scope of further improvement in this work.In the coming section author has discussed various soft computing techniques like fuzzy logic, ANN and Machine Learning based fault classification approach.

II. The fault classification methodologies

2.1. Simulation/Mathematical method using MATLAB

As MATLAB and Simulink are integrated, so models can be simulated, analyzed, and revised in either environment at any point.

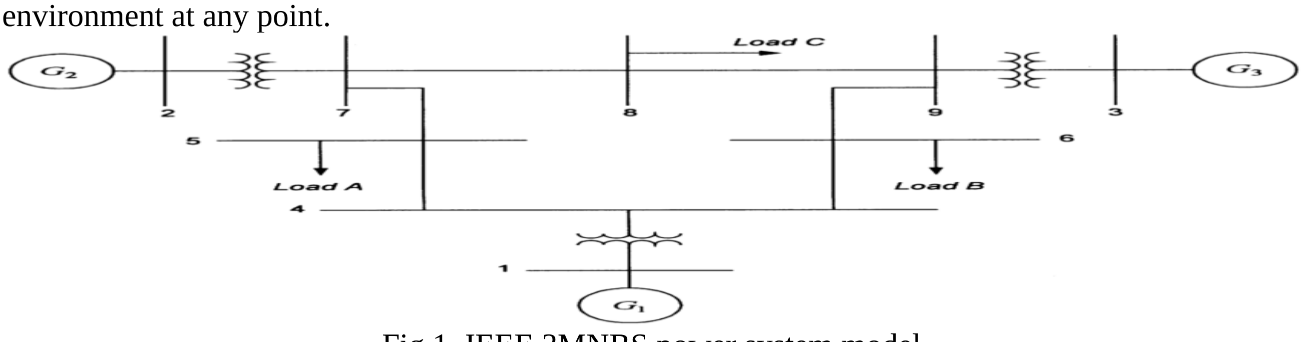

Fig.1. IEEE 3MNBS power system model

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Table-1
Observation of a-g fault under various operating regions

Va	Vb	Vc	Ia	Ib	Ic	Types of fault	Fault location	Rf	D	FIA	Bus
-5183.42	- 115504.34	120565.70	- 1557.67	644.34	913.14	a-g	L7-8	5000	82.46	0	7
-5530.94	-68613.56	69681.32	826.94	-297.83	-533.72	a-g	L9-6 &L8-9	6	196.41 & 115.56	22.5	6
-23134.38	-84778.60	52108.31	- 1520.90	649.11	853.29	a-g	L9-6 &L8-9	6	196.41 & 115.56	22.5	8
13.50	-1272.96	1134.64	- 2352.84	957.09	1395.72	a-g	L9-6 &L8-9	6	196.41 & 115.56	22.5	9
-13639.73	-70748.33	67546.55	828.99	-295.53	-531.43	a-g	L9-6 &L8-9	32	196.41 & 115.56	0	6
-46.99	-1263.90	1143.71	- 2376.82	946.91	1385.54	a-g	L9-6 &L8-9	32	196.41 & 115.56	0	9
-34105.43	-86698.12	50188.80	- 1513.05	657.21	861.39	a-g	L9-6 &L8-9	32	196.41 & 115.56	0	8
132461.66	-	49153.59	88.14	-1.31	-69.64	a-g &	L7-5 &	0.05	176.11	0	5

2.1.2 Mathematical Analysis of power system

In the above table around 60-70 values only matched as per LG fault condition in around 90 total measured sample faults hence it gave around 67% accuracy and remaining errors. This calculation and mismatch in actual and measured fault data shows that simulation results is not accurate as per actual theoretical calculation by the formula that short point has large current and almost zero voltage, so to overcome these accuracy issues in MATLAB result is further validated with the help of some other technique so that error could be minimized. In the next section author will discuss some rule base fuzzy logic system in which rule will be made and then checked for accuracy and error reduction.

2.1.3 Waveform without fault

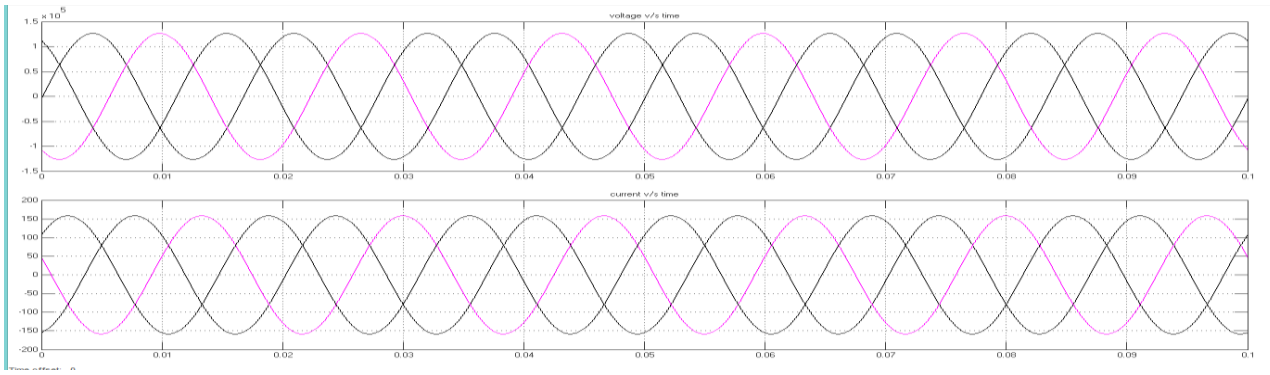


Fig.3. Voltage and current waveform at bus 5without fault incorporation

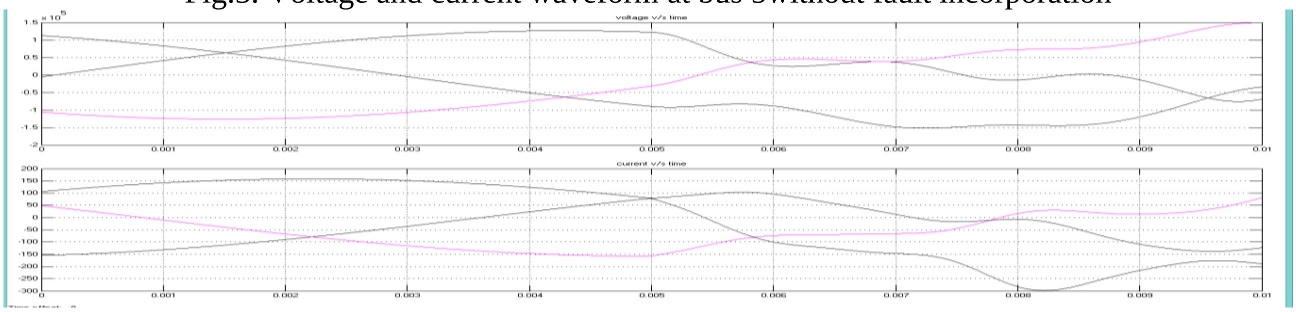


Fig.4. ag fault at buses 7-9 and location L7-8 with fault resistance 0.001 ohm

2.2. Artificial Neural Network Based Technique

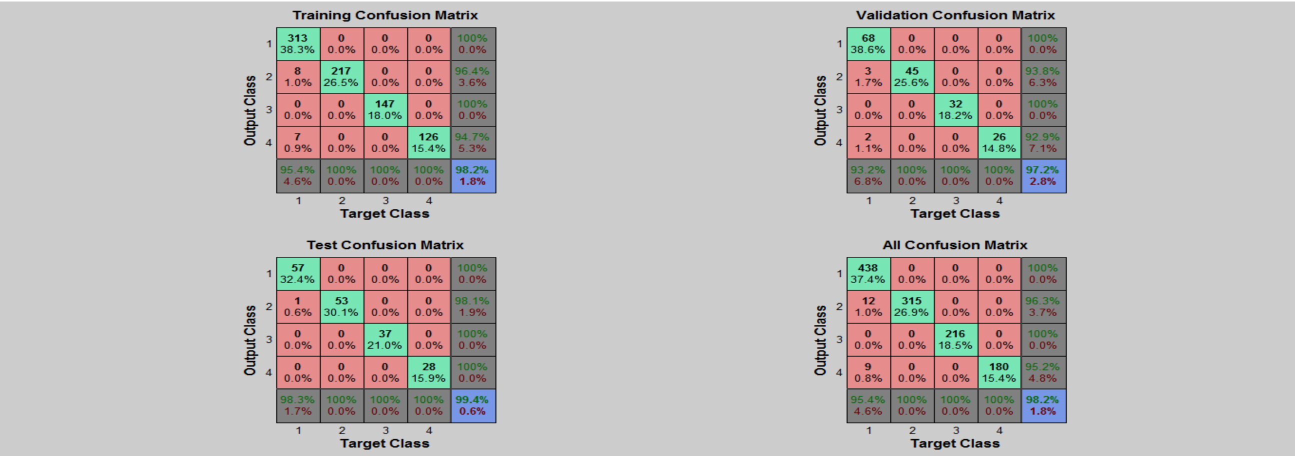
2.2.1. Artificial neural network

U Table-1 Normalized Input variable and target output

Input variables Target

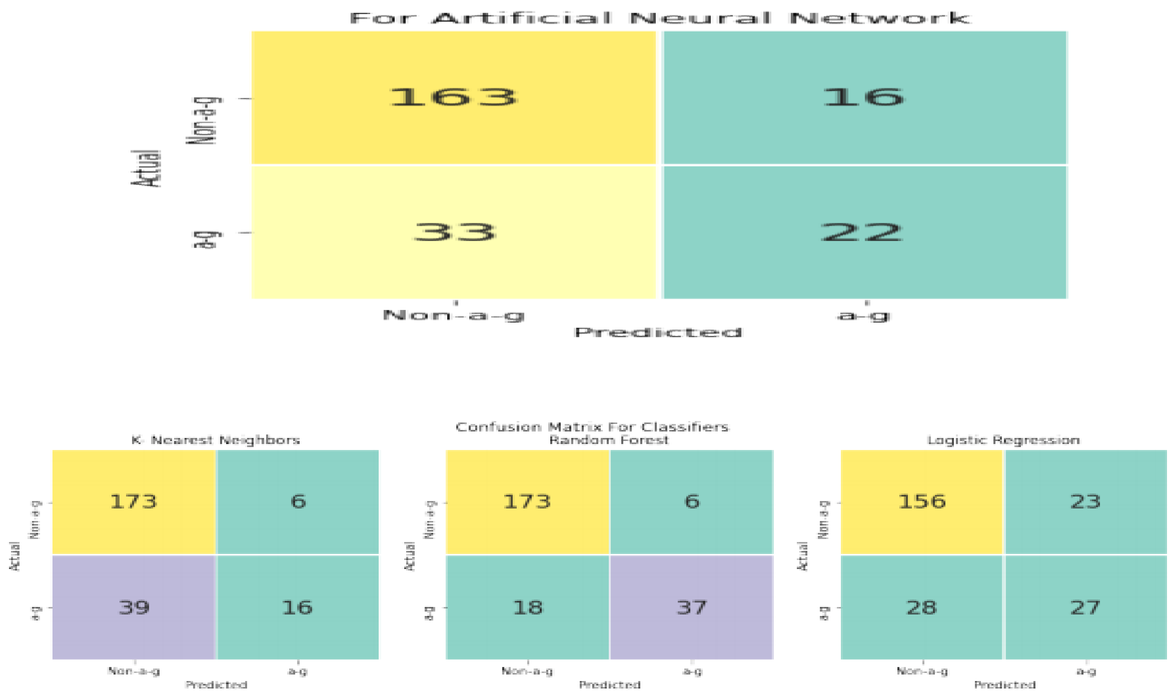
Va(norm)	Vb(norm)	Vc(norm)	Ia(norm)	Ib(norm)	Ic(norm)	LG	LL	LLG	LLLG
0.5465	0.5722	0.3076	0.3138	0.7420	0.2774	0	0	0	1
0.5607	0.5398	0.3198	0.3256	0.7416	0.2685	0	0	0	1
0.5460	0.5752	0.3054	0.3253	0.7336	0.2767	0	0	0	1
0.5563	0.3495	0.5105	0.3598	0.7313	0.2521	0	0	0	1

0.5682	0.2872	0.5548	0.3455	0.7348	0.2597	0	0	0	1
0.5650	0.2350	0.6097	0.3584	0.7313	0.2531	0	0	0	1
0.5492	0.5424	0.3328	0.3457	0.7341	0.2603	0	0	0	1
0.5502	0.5324	0.3412	0.0605	0.7343	0.4836	0	0	0	1
0.5498	0.5360	0.3382	0.4938	0.7030	0.1753	0	0	0	1



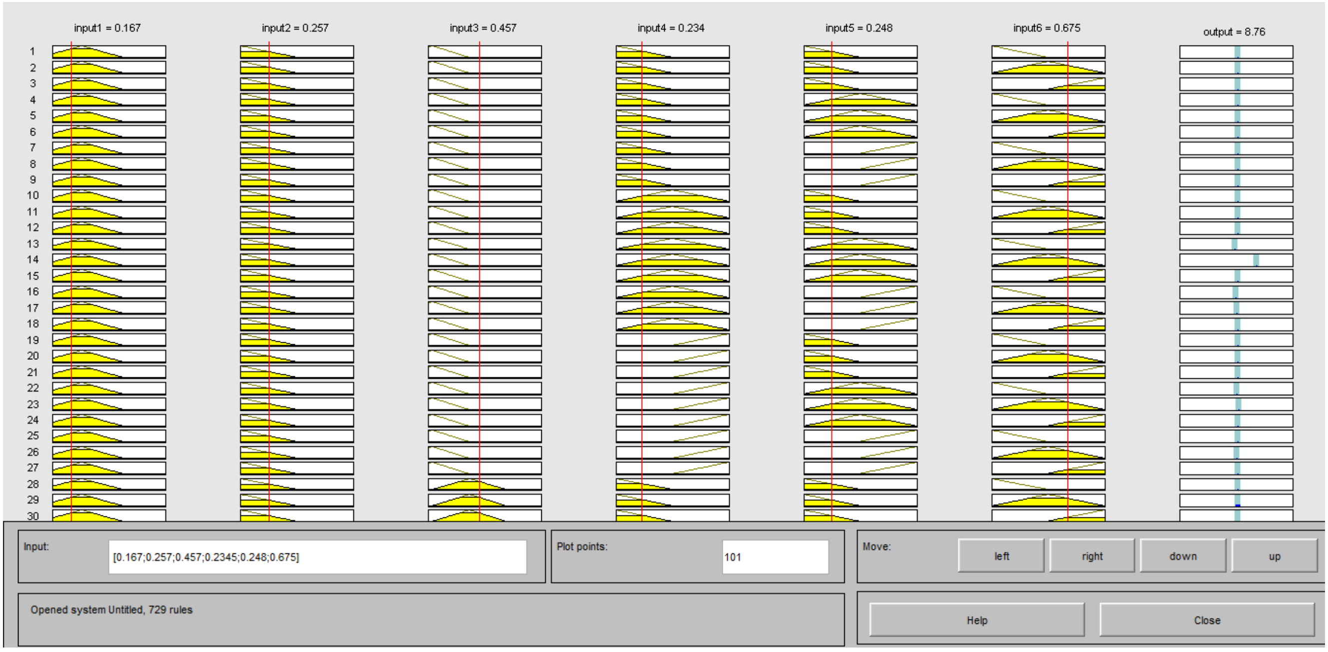
Confusion matrix plot for LG, LL, LLG and LLLG fault classification target of training testing and validation of output

2.3. Algorithm for Confusion matrix - ANN, KNN, RF and LR

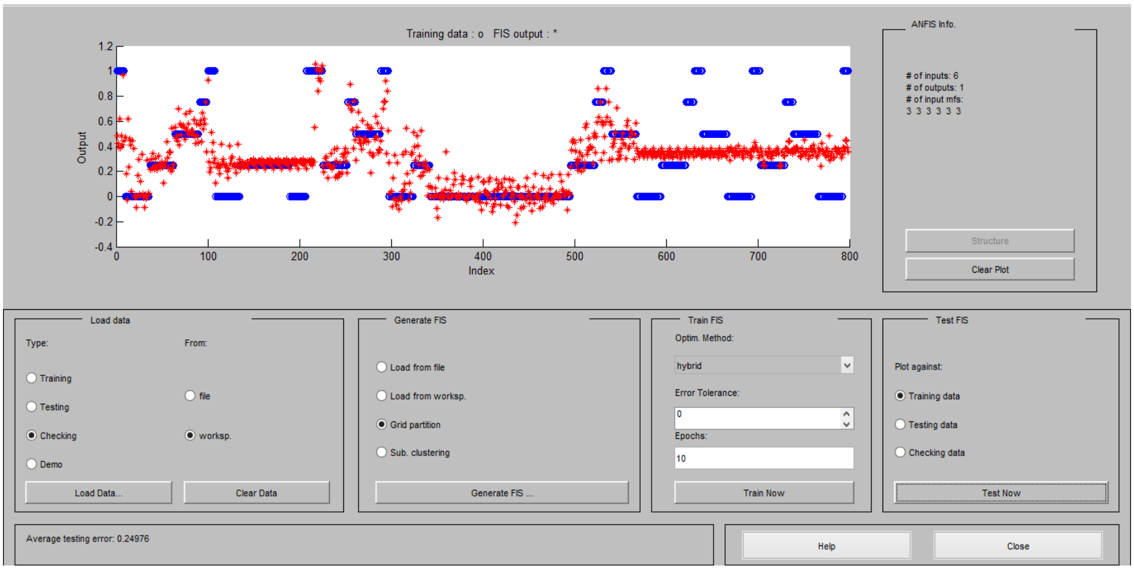


Confusion matrix plot obtained using binary classifier
Table-6
Accuracy of training and testing of fault data

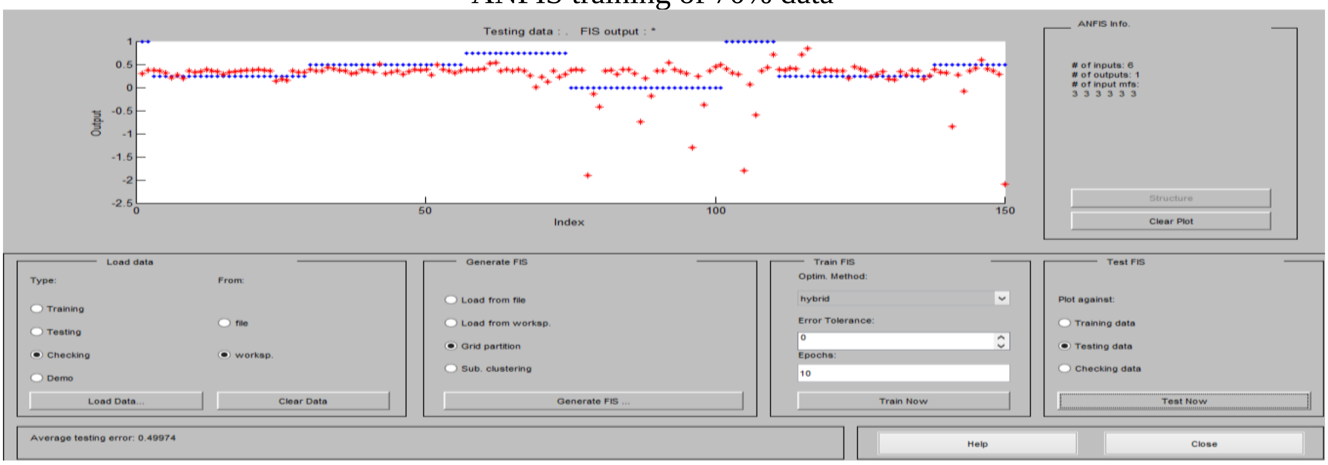
2.4. ANFIS Analysis and result



ANFIS rules viewer



ANFIS training of 70% data



ANFIS testing of 15% data

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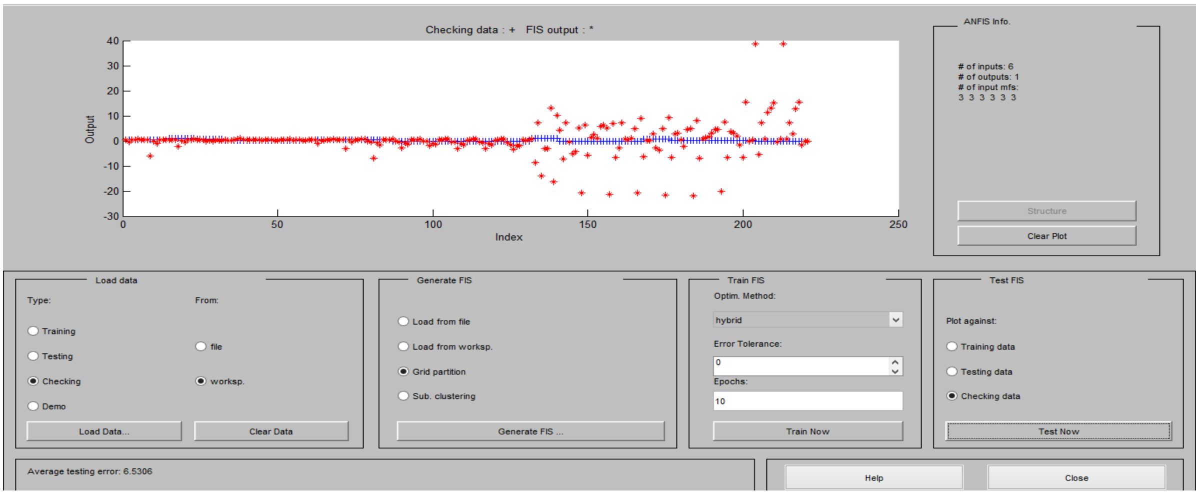

ANFIS checking of 15% data.

2.5 Results and Discussion

If three phase fault is introduced then current rises and voltage false in particular phase of transmission line. If L-G fault is introduced in phase A and from graph of voltage and current, it can be seen that voltage is almost low and current is high during the switching time. After that system is stable and voltage settled and current distorted in each phase as per output waveform. The various classification of fault is categorised in 4 class namely class1, class2, class3 and class4, they are represented as LG, LL, LLG, and LLLG faults. From this table it has been observed that accuracy on training and testing fault data is almost closed to 96%. The proposed binary classifier technique is better as compared to previous fault classification as it does not require any computation. As in case of practical results obtained by MATLAB/SIMULINK has not given accurate result, so to check accuracy the proposed binary classifier technique has given excellent results and almost testing accuracy is around 98.29%. From Table -9 AG fault data has been observed in different cases and found that theoretically it has given only 67% of accuracy. As per theoretical concept at fault point current rises while voltage falls but in around 70 cases of fault it is matched but remaining fault sample has missed in particular AG fault. By comparing this practical simulation result with proposed technique, it can be observed that the accuracy shown in Table-8 is best as compared to accuracy obtained in mathematical/simulation results in Table-9. Hence this proposed method is best in fault classification of 3MNBS under various attributes.

2.6. Comparative Table of percentage accuracy in fault classification

FLS	Traditional	ANFIS
70%	67%	99.45%
Classifier Techniques	Train Accuracy	Test Accuracy
Using KNN Classifier	88.46 %	80.77 %
Using Random Forest Classifier	96.47 %	88.89 %
Using Logistic Regression Classifier	81.94 %	78.21 %
Using Deep learning (Neural Network)	84.51%	79.06%

2.7. Comparative analysis of fault classification methods,

Fault classification Technique	Fault type	Accuracy Training	Accuracy Testing	Accuracy Validation	Overall Accuracy

Simulation/Mathematical	Ag	-	-	-	67%
Fuzzy Logic System	Ag	-	-	-	70%
ANN	Ag	77.9%	76.1%	80.1%	77.9%
KNN	Ag	88.46%	80.77%	-	85%
RF	Ag	96.47%	88.89%	-	93%
LR	Ag	81.94%	78.21%	-	80%
Deep Learning	Ag	84.57%	79.06%	-	82%

2.8 Conclusions

This paper concludes that with the MATLAB Simulation of multi-terminal transmission system various fault has been incorporated in different location and taking different attributes like fault point resistance, fault inception angle, fault distance in particular location, as per mathematical formula the theoretical result and practical results observed with the help Matlab/Simulink are differ much. Around 100 AG fault data has been observed for fuzzy rule base fired and around 70 data matched with the actual rule base and 30 data is not matched and it moved in AB, CG and ABC fault so accuracy of fault classification in terms of type of fault is around 70 %. With respects to previous simulation results fuzzy logic based fault technique improved little bit but not 100% accurate. With the analysis of several time of training, testing and validation MSE is only 2-5% and that shows overall average fault accuracy of 98.2% fault classification result is obtained with the help pattern recognition tools. The error in fuzzy rule in fault classification is almost removed and that shows that large no of training testing ultimately gives better classification of fault in transmission line of 3MNBS. From above discussion and result analysis author concludes that proposed ANN method for fault classification in 3MNBS is best in terms of accuracy and fast classification using pattern recognition tool of ANN. Previously none as discussed about fault classification in 3MNBS and also simultaneous fault in different location as well as different effects/attributes like fault inception angle, fault resistance, distance, zones are also discussed in this paper. Accurate classification of fault provides better information to design suitable protective devices and hence reliability of supply. This paper presented a novel fault classification technique. The mathematical/simulation result obtained by MATLAB/SIMULINK has not given good accuracy in identification of fault types and its location. Hence the proposed method of fault classification is excellent in terms of accuracy for training and testing of fault data. It has given good accuracy in training and testing the fault data and closely observed that in near future it would be best in classification of fault in multi-terminal lines with input as voltage and current.

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