International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6s
DOI: https://doi.org/10.17762/ijritcc.v11i6s.6943
Article Received: 24 March 2023 Revised: 15 May 2023 Accepted: 30 May 2023

Radial Power Distribution System Fault Classification Model Based on ANFIS

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Abstract—The classification of problems in power systems plays an extremely important part and has evolved into a necessity that is of the utmost importance to the operation of energy grids. For the purpose of fault classification in IEEE 13 node radial distribution systems, this paper makes use of both an Artificial Neural Network (ANN) and a Neural Fuzzy adaptive Inference System (ANFIS). Simulations of the suggested models are carried out in MATLAB/SIMULINK, and fault currents from all three phases are analyzed in order to extract statistical characteristics. Input data vectors include the standard deviation and correlation factors between the currents of any two phases, while output data vectors include the different sorts of faults. The findings demonstrate that the devised method is appropriate for the classification of all symmetrical and unsymmetrical faults.

Keywords-Fault Classification, ANN (Artificial Neural Network), ANFIS (Adaptive Neuro Fuzzy Inference System).

I. INTRODUCTION

The distribution network, being a crucial component of the power system, is inextricably linked to the consumers. These networks are exposed to a number of faults due to several reasons, e.g., lightning stroke, insulation/equipment failure due to ageing, short circuit caused by wind, birds/animals or trees etc.[1]. Fast fault detection in distribution grids makes relays to operate & isolate faulty portion from the remaining network. As a result, the faulty portion's asset is protected while supplying electricity, continuously to rest of the network. Further, accurate fault categorization presents critical information about the defect and speeds up the repair process. Reliable and quick fault classification has become an important requirement of distribution grids [2].

In a distribution system, mainly four faults occur, i.e., single/double line-ground faults, line to line and 3 Ø-ground types of faults. Fault may also be categorized on the basis of severity. Single Line to Ground fault is least severe followed by Line-Line Fault and highly severe is Double line-Ground unsymmetrical fault [3]. Symmetrical Fault is highly dangerous and does not frequently occur. For an efficient Protection system, arises the need for classifying the nature of fault and the fault location within minimum time to prevent major destruction. On account of inherent complexities of the distribution grid (e.g. non-homogeneity, presence of laterals, etc.), the techniques used for fault diagnosis of transmission grids are not immediately applicable to distribution grids [2]. A number of researchers have presented different techniques for fault diagnosis of distribution grids which include the use of positive, negative and zero sequence impedances[4], Kalman filter estimation [5], wavelet transform [6-8], s-transform [10], support vector machine [11] etc. Along with conventional techniques, machine learning tools [12-16] and their combination with signal processing tools [17-19] have also been utilized for this purpose.

The performance of artificial intelligent techniques is unaffected by changes in System parameters. A number of researchers have used these techniques for optimization, control, and forecasting problems due to their better learning and generalizing capabilities [20, 21]. ANN (Artificial Neural Network) is a structure that replicates human' brain and keeps learning from its surroundings and responding appropriately. A number of researchers have used artificial neural networks (ANNs) to construct comprehensive algorithms for fault detection, classification, and localization [22, 23]. However, for the classification of faults, the ANN alone can't provide very precise results and many such networks are needed for faults of different categories. ANFIS is a neuro fuzzy inference system and is adaptive in nature. It was evolved by combining the basic fundamentals of ANN with fuzzy logic, thus capturing their benefits within a single structure. Its inference system is having

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a set of fuzzy rules (IF–THEN) and has ability of learning non-linear relations [24]. In this work, ANFIS is used to detect different types of faults using the energy component of discrete wavelet-transformed three-phase fault current signals [25].

Although current and voltage signals have contained a lot of information within themselves, it is very difficult to transform these raw signals into rules and criteria, which are able to intelligently interpret the basic messages carried within the signals. So, the use of feature-extracting techniques becomes handy to dig out most of the useful information and also to minimize the effect of variance in the system. After using them for feature extraction, researchers gain a better understanding of the nature of fault classification and/or fault location estimation problems. Further, reduced data dimensionality can further boost the execution of some algorithms used for classifying or locating faults and provides better and accurate analysis of transients in power system [28, 22]. Recently, wavelet transform techniques have been used effectually for representing transients in several components. and can be used for the purpose of localizing the information[23].

In this work, fault detection and their classification (in 11 (eleven) different classes) in an IEEE 13 node distribution system (radial) has been done by using ANN and ANFIS. Standard deviations of the wavelet extracted fault currents of three phases and correlation factors between wavelet extracted fault currents of any two phases are used as features and constitute input vector of the intelligent networks, i.e., ANN and ANFIS. Remaining paper has a structure as follows: Structure of the distribution system is given in section 2. Overall methodology is given in section 3. Section 4 is devoted to simulation results and error calculation followed by conclusion, and references

II. MODEL OF IEEE 13 NODE DISTRIBUTION SYSTEM (RADIAL)

Single line diagram of an IEEE 13 NODE DISTRIBUTION SYSTEM (RADIAL) (used in this work) and its MATLAB Simulink model are shown in Figs. 1 & 2 respectively. It has a 4.16KV voltage source and 12 load flow Bus blocks are used to compute load flow (unbalanced) on the model (published originally by the IEEE Distribution System Analysis Subcommittee Report).

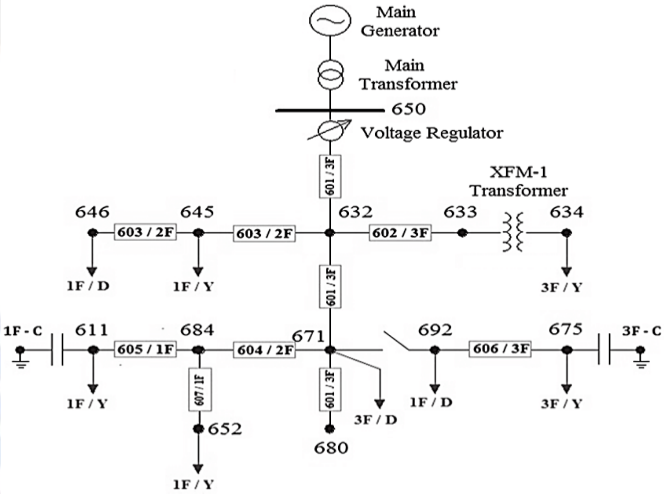

Figure.1 Single Line Diagram of IEEE 13 NODE DISTRIBUTION SYSTEM (RADIAL)

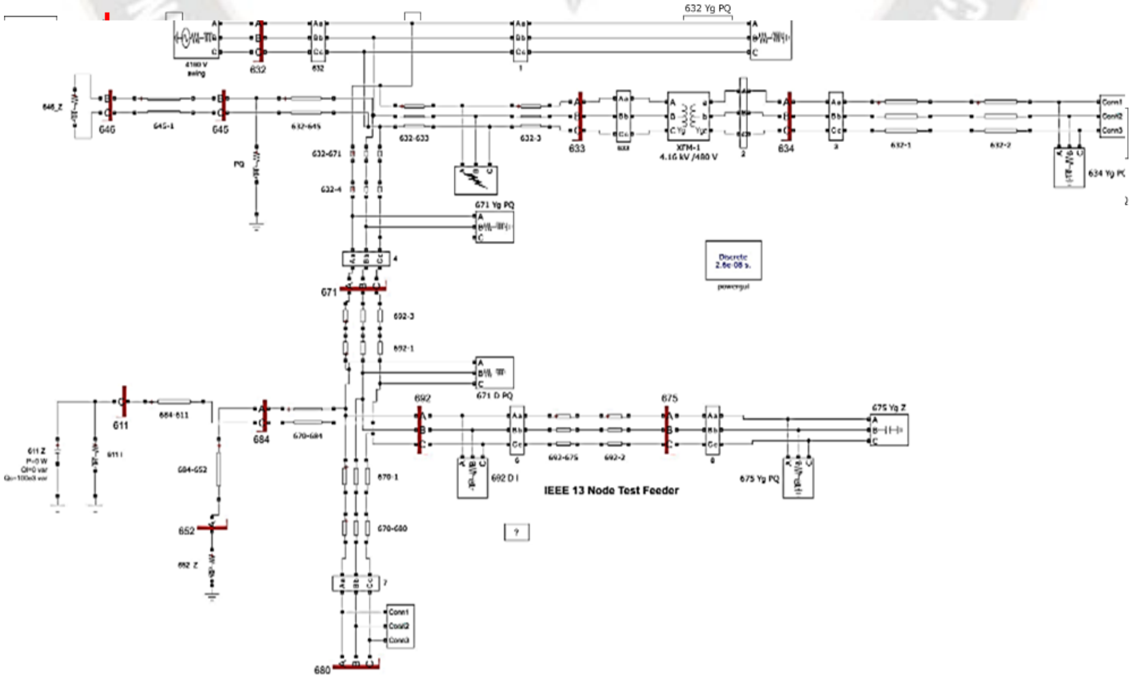

Figure.2 MATLAB/SIMULINK MODEL of IEEE 13 NODE DISTRIBUTION SYSTEM (RADIAL)

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III. METHODOLOGY

As presented in the flowchart of Figure 3, the procedure used has mainly two steps, i.e. to determine statistics quantities of three phases current and then train them by using ANN & ANFIS. Details are given in the following subsections:

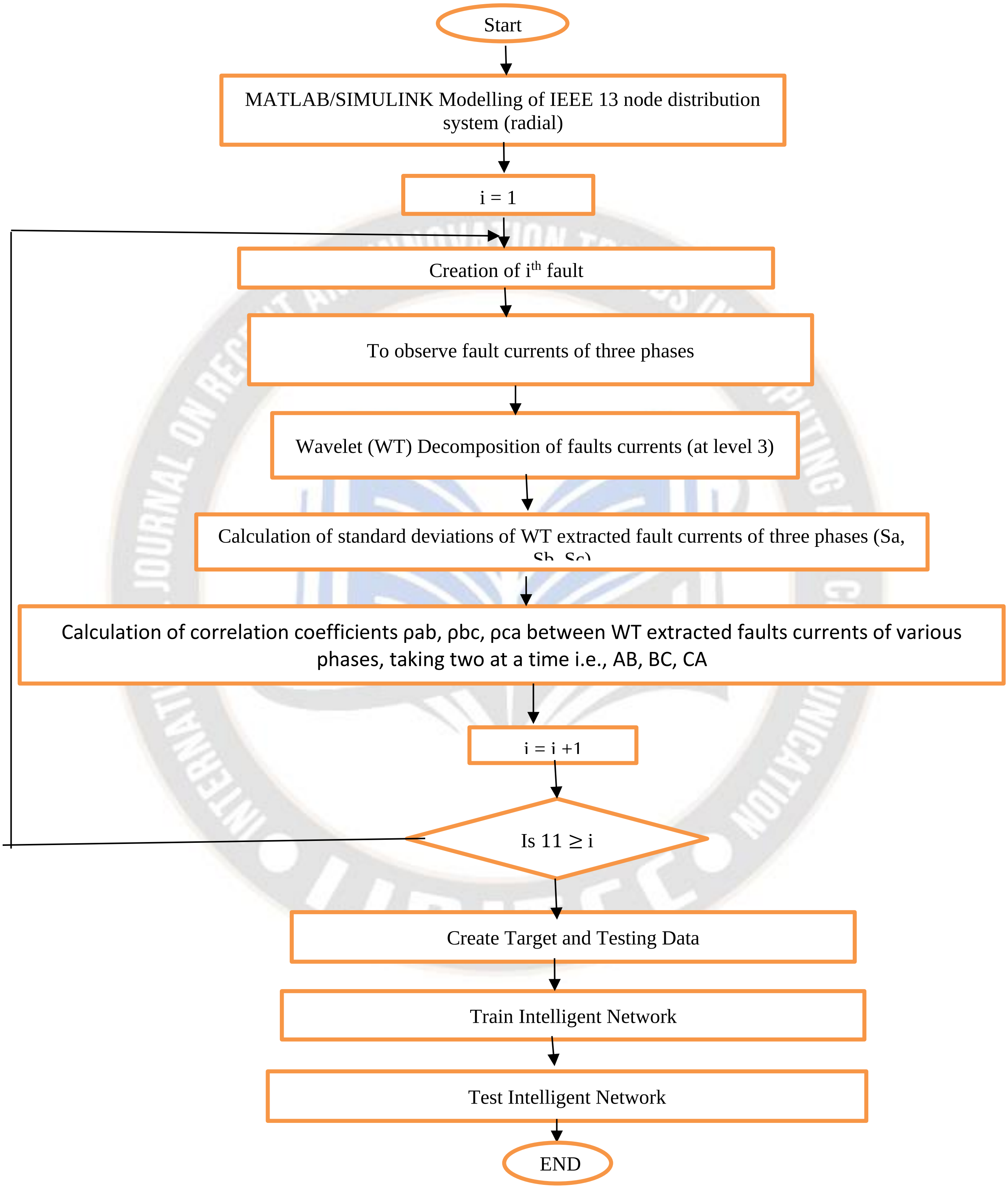

Figure 3. Flow Chart of Methodology

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A. Calculation of features of fault currents

The Transient oscillations are dominant during fault event in a power system. In this work, Daubechies wavelet is used for feature extraction of fault currents of three phases. Shapes and energy of the signals can be easily characterized by statistic quantities, so, three selected features are standard deviations (Sa, Sb, Sc) for each phase WT-extracted current signal (as the standard deviation of faulty phase is much higher as compared to healthy phases).

For data set A (i), i=1, 2…N, standard deviations is calculated by using eqn. 1.

$$S=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|A(i)-\mu|^2} \quad (1)$$

Where μ is Mean of A & is calculated by using eqn. 2

$$\mu=\frac{1}{N}\sum_{i=1}^{N}Ai \quad (2)$$

Besides this, three more selected features are correlation coefficients (ρab, ρbc, ρca) between WT-extracted current signals of any two phases. For data sets a(i), i=1,2,…N and b(i), i=1,2,…N, correlation coefficient is calculated by using eqn. 3.

$$\rho ab=\frac{1}{N-1}\sum_{i=1}^{N}\frac{(Ai-\mu A)}{\sigma A}\frac{(Bi-\mu B)}{\sigma B} \quad (3)$$

Where (μA & σA) and (μB & σB) represent the mean and standard deviation of data set 'a' and data set 'b' respectively.

B. Input and Target Vectors for fault classification

For problem of fault classification, an artificial neural network (ANN) has been used in this work. The combination of ANN with fuzzy logic creates ANFIS (Adaptive Neuro-fuzzy inference System),which can easily adjust the membership functions parameters (of FIS) adaptively by using historical data and very well takes the uncertainties in the distribution system (caused by varying fault resistances, fault location etc). So, the fault type classification results are further improved by replacing ANN with ANFIS. The input vector for ANN/ANFIS is I1, as defined by eqn. 4.

$$I_1 = [Sa \;\; Sb \;\; Sc \;\; \rho ab \;\; \rho bc \;\; \rho ca] \quad (4)$$

The Target vector for ANN/ANFIS is defined by second column of Table-I.

Table- I: Target Vector for fault classifications

PARAMETERS	VALUES
Fault AG	1
Fault BG	2
Fault CG	3
Fault ABG	4
Fault BCG	5
Fault CAG	6
Fault AB	7
Fault BC	8
Fault CA	9
Fault ABC	10
Fault ABCG	11

IV. SIMULATION RESULTS

After An IEEE 13 NODE distribution system (radial) is simulated in MATLAB/SIMULINK. It has provisions to put in fault at nodes (e.g., 632, 633 634, 675 & 692 etc.) and measure fault current. Simulation run time is 0.1 seconds and fault switching on time is from 0.04 seconds to 0.08 seconds. For AG fault, original and WT-extracted 3 Ø fault currents are shown in Figures. 4 & 5 respectively. Three levels of wavelet decomposition is implemented using Daubechies wavelet as WT-extracted current signals of faulty phases have more intensive variation than that of healthy phases. Input training data to ANN/ANFIS are standard deviation

and correlation coefficients Sa, Sb, Sc, ρab, ρbc, ρca of WT-extracted fault current signals. Training/testing data is collected for combination of six different fault resistances, (i.e., 1 Ω, 5 Ω, 10 Ω, 15 Ω, 20 Ω, and 25 Ω) and five different fault locations (i.e., at nodes 632, 633, 634, 675 & 692) as shown in Table II. Eleven different types of short circuit faults are considered.

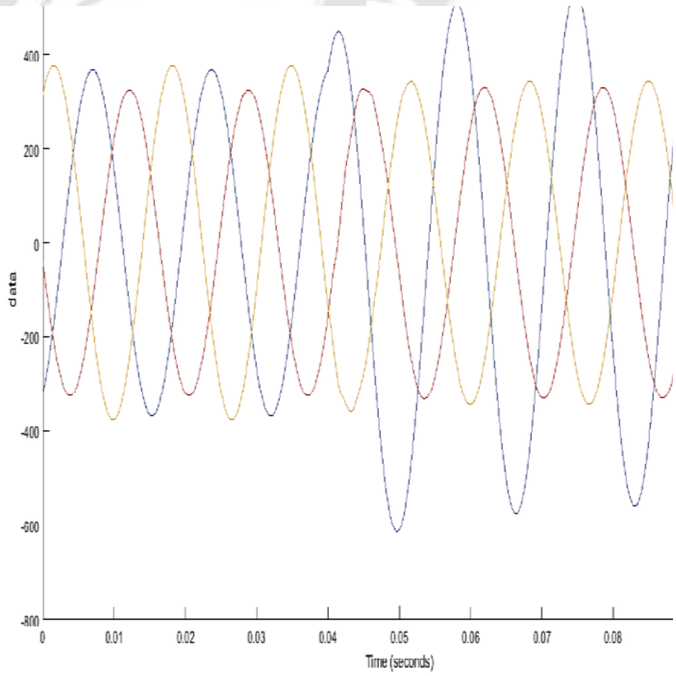

Figure.4 3 Ø currents for AG fault (Blue; Red; Yellow: Phases A;B; C)

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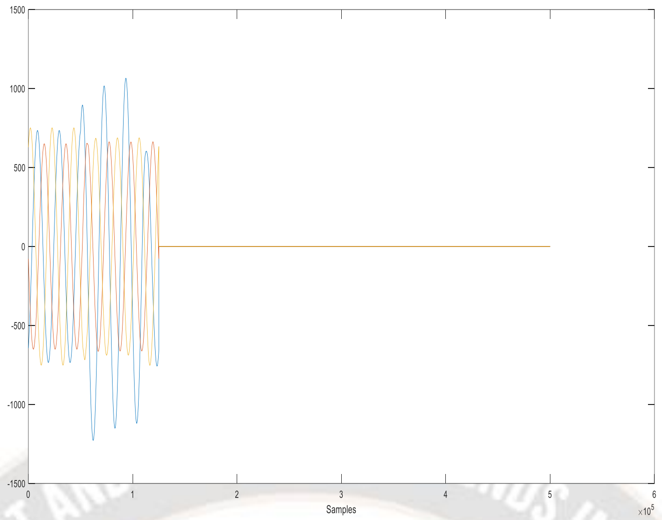

Figure.5 WT-extracted 3 Ø currents for AG fault (Blue; Red; Yellow: Phases A; B;C)

Table II: Statistical features of Data

ABC fault for different resistance at different node NODE No. - Fault resistance	**Sa**	**Sb**	**Sc**	**ρab**	**ρbc**	**ρca**
632-001	324.9552	322.5805	327.674	-0.46223	-0.56506	-0.46481
632-5	291.4176	272.2882	292.8992	-0.41627	-0.61144	-0.46313
632-10	278.8126	255.7925	282.1704	-0.39894	-0.62642	-0.46403
632-15	273.7818	248.3259	279.1382	-0.38557	-0.63311	-0.46963
632-20	270.5687	244.1562	276.0829	-0.38266	-0.63573	-0.4696
632-25	268.5353	241.5046	274.1384	-0.38091	-0.63725	-0.63725
633-001	252.0867	272.1107	254.542	-0.52076	-0.54796	-0.42824
633-5	118.8315	129.009	111.8004	-0.54098	-0.54341	-0.41003
633-10	83.06824	89.55219	75.81423	-0.52303	-0.55061	-0.42022
633-15	70.70791	71.83516	63.00558	-0.48275	-0.5263	-0.48718
633-20	62.2972	62.65973	54.1024	-0.47495	-0.5289	-0.49207
633-25	57.16654	56.99497	48.5841	-0.46962	-0.53108	-0.49515
634-001	1735.4	1904.296	1749.125	-0.52366	-0.55954	-0.41227

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A. ANN/ANFIS Results

ANN used here has 5 layers; one layer of input nodes, 2 hidden layers of neurons and an output layer of neurons as shown in Figure. 6. In ANN's training, hidden layers' neurons play a vital role, there are 15 neurons used for each hidden layer (as decided with help of ample trial simulations). Figure. 6 exhibits all other parameters of ANN.

Figure. 6 Training of data using ANN

For classification by use of ANFIS (to improve the classification accuracy), first of all, the training data is loaded in MATLAB/SIMULINK environment and the grid-pattern method is used for generating the FIS (Fuzzy Inference System). ANFIS is further trained by use of a hybrid type method using a combination of least square estimation and the Runge-Kutta algorithm. 'Zero' tolerance of error and '300' epochs are used for training as shown in Figure. 7

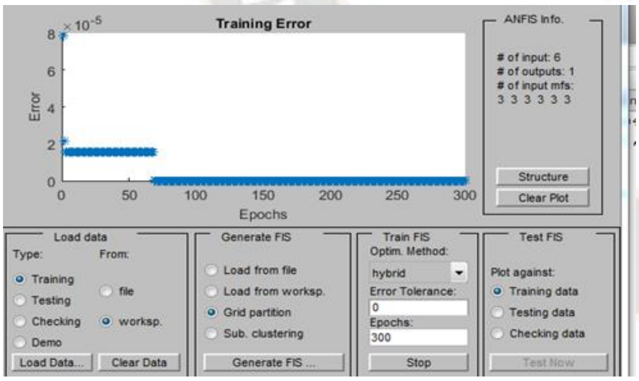

Figure. 7 Training of ANFIS

B. Erroerror Calculations

After training, the classification accuracy of trained ANN and ANFIS is calculated by calculation of percentage errors using equation 5 using testing data.

Percentage Accuracy= [(No. of Right Case in each type of fault)/total Case in each type of fault] *100 (5)

Table- III: Comparative errors of ANN and ANFIS

Types of Faults	ANN Results (in %)	ANFIS Results (in %)
Fault AG	87.5	100
Fault BG	81.25	100
Fault CG	87.5	100
Fault ABG	76.25	96.75
Fault BCG	87.5	100
Fault CAG	81.25	100
Fault AB	78.75	96.75
Fault BC	87.5	100
Fault CA	87.5	100
Fault ABC	62.5	94.25
Fault ABCG	50	87.25

From Table III and the bar graph of Figure 8, a considerable improvement in fault classification accuracy is observed by the replacement of ANN with ANFIS.

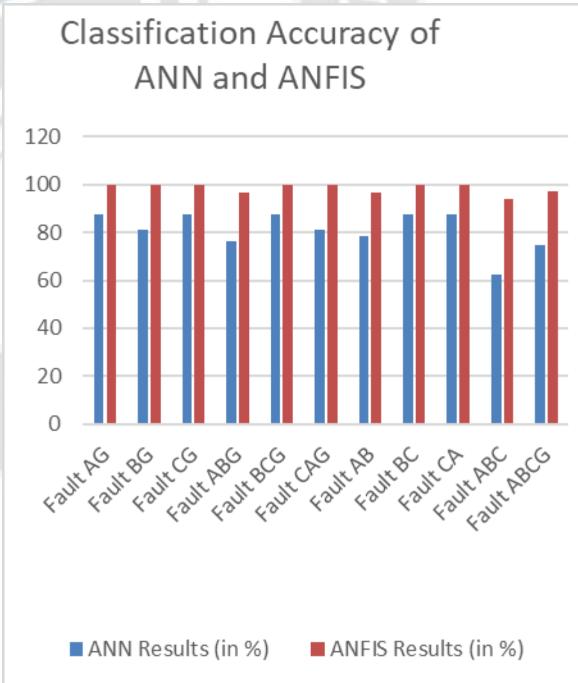

Figure. 8 Comparison of classification accuracy of ANN & ANFIS

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V. CONCLUSION

An ANFIS-based model is used for the efficient classification of faults in an IEEE 13 NODE distribution System (Radial). The proposed model uses WT-extracted three-phase fault currents only and classifies eleven different types of faults with high accuracy as verified via simulations in MATLAB. The model has been found to give good results for combination of six values of fault resistances with fault occurring at different nodes. Highest fault resistance used in this paper is 25 Ω. In future, for modelling of faults, other platforms like PSCAD may be used to actualize high-resistance fault-classification. Learning of ANN/ANFIS can be further made more efficient by using optimization techniques, e.g. genetic algorithms etc.

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