Fault Detection, Classification and Location on 132kv Transmission Line based on DWT and ANFIS

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***Abstract*— In this paper, a robust fault detection, classification and location scheme for 132 kV, 100 km transmission line is developed. This scheme combines the feature extraction capability of the discrete wavelet transform and the intelligent classification capability of adaptive neuro-fuzzy inference system (ANFIS). RMS values gotten from the five detail levels (Daubechies dB5 wavelet) of the DWT decomposition of the current signals were used for the training of the ANFIS models. Simulation investigations were done for different fault scenarios with faults at different phases, locations, fault resistance and fault inception angles. From the analysis of the results obtained, it was obvious that the scheme was able to discriminate between actual fault cases from normal condition in a maximum time of 8 milliseconds after fault inception. The classification of fault types was exact and the locations of the faults were identified with a maximum RMSE of 0.109 km and a maximum absolute error of 0.22 km which translate to 99.78 % accuracy.**

Keywords—Discrete wavelet transform, adaptive neuro-fuzzy inference system, fault type, fault detector, fault classifier, fault locator, feature extraction

I. INTRODUCTION

Transmission line is one of the most important components in a power system. It constitutes the major part of power system. Transmission and distribution lines are vital links between the generating unit and consumers to achieve the continuity of electric supply. To economically transfer large blocks of power between systems and from remote generating sites, high voltage (HV) and extra high voltage (EHV) overhead transmission systems are being used. Transmission lines also form a link in interconnected system operation for bi-directional flow of power. Transmission lines run over hundreds of kilometers to supply electrical power to the consumers [1].

A fault occurs when two or more conductors come in contact with each other or ground in three phase systems. Power system components are always subjected to the greatest stresses from excessive currents as a result of fault [2].

Faults on transmission line require fast restoration because it generates damage in the power system. So an accurate, fast and reliable method to detect, classify and locate the fault is needed to be established on the transmission lines to insure healthy power system [3]. Over the years, several fault detection and classification methods on transmission lines have been used. They are classified into conventional and intelligent methods [4]. Conventional method of fault detection and classification is based on the variation of voltage and current lines. In conventional methods phase current or voltage or instantaneous values of current or voltage are directly used as relay inputs [5]. The intelligent method is based on fuzzy logic, artificial intelligence, support vector machine (SVM) algorithm and neural network. Conventional method of fault detection and classification are unreliable due to large power system while wavelet transform in conjunction with AI/Fuzzy/expert system based techniques have the advantage of fast response and increased accuracy as compared to conventional techniques [6, 7].

Previous work by other researchers presents several methods. He, Fu, Lin and Boproposed wavelet singular entropy (WSE) technique which combines the advantages of wavelet transform (WT), singular value decomposition (SVD) and Shannon entropy for fault detection and classification in transmission lines [8]. He, Wu and Qian presented wavelet transform feature extraction method for automatic fault detection and classification in electrical power systems, and the wavelet singular entropy was shown to be sensitive to noise and abrupt variation of signal [9]. Gomes, André, Costa, deFaria, and Caminhas used functional analysis and intelligent computing to detect and classify the fault in transmission line of power system [10]. Al-Kababjie, Al-Durzi and Al-Nuaimidescribed a new distance relay for fault detection and classification in transmission line that is used in wavelet transform [11]. Fault detection based on rate of change of frequency relay (ROCOF) and vector surge (VS) relay was presented by Freitas, Xu, Affonso and Huang [12]. Chanda, Kishore and Sinha presented a method based on wavelet multi-resolution analysis (MRA) for fault classification [13]. Samantaray used S transform to calculate the statistical properties of the current signal and then the tree decision was used as the input index of fuzzy logic to classify the fault [14]. IJayabharata and Mohantadeveloped a wavelet multi-resolution analysis algorithm to classify fault in transmission lines [15]. The developed algorithm had a high accuracy irrespective of the fault location, fault resistance and the fault inception angle. An intelligence technique or automatic fault detection was presented in Srinivasan, Cheu, Poh, and Chwee[16]. The method combined fuzzy logic and genetic algorithms (GA).

This paper presents yet another technique for the classification and detection of faults on a transmission line. It aims at improving power efficiency by providing alternative and improved solutions to the challenges in the conventional fault detection and classification method for high tension transmission lines using discrete wavelet transform and adaptive neuro-fuzzy inference system. The model will be developed and tested using a 132 kV transmission line.

II. METHODOLOGY

In this paper, empirical and simulation approaches is deployed in the development of the models as summarized in Fig. 1. The data (current signals of the three phases) obtained from the simulation of the different fault conditions on the developed Simulink model of 132 kV, Aba - Itu transmission lines (Fig. 2), are first analyzed with DWT for features extraction. The extracted fault current features are then used to train and develop an ANFIS models for the detection, classification of fault types and determining the actual fault location.

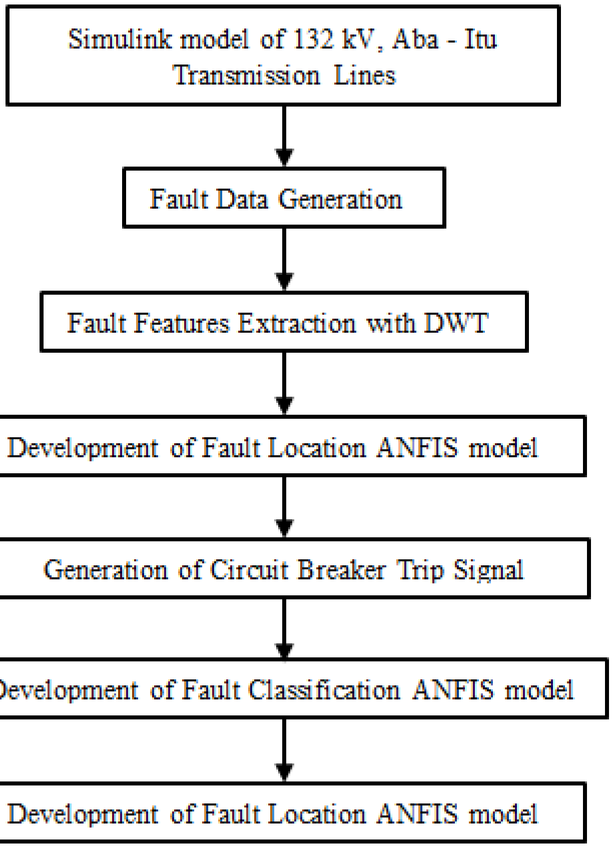

Fig. 1: Overview of the fault detection, classification and location models development

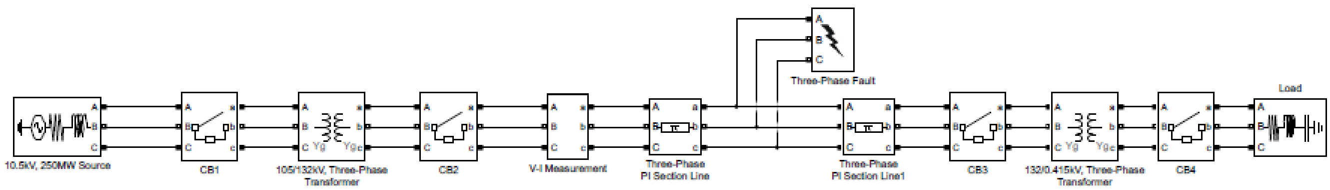

Fig. 2: 132 kV, Aba – Itu transmission lines Simulink model for the fault data generation

The line parameters for the case study transmission lines are presented in Table 1, while the parameter settings for generating fault values of currents for 132 kV, Aba – Itu transmission lines are in Table 2.

Table 1: Line parameters for 132 kV, Aba – Itu transmission lines

Line Parameter	Resistance per unit length (Ω/km)	Inductance per unit length (mH/km)	Capacitance per unit length (nF/km)
Positive Sequence	0.01273	0.9337	12.74
Zero Sequence	0.3864	4.1264	7.751

Table 2: Parameter settings for generation of fault data

Parameter	Set values
Fault Type	L-G, L-L-G, L-L,L-L-L, No fault
Fault Location (km)	0.1 – 99.9
Fault Resistance (Ω)	0.1 – 2.5
Firing angle	0^o – 180^o
Fault Time (s)	0.1
Load (MVA)	100
Base Power (MVA)	100

A. *Generation of Fault Data*

A total of 1211 simulations of different fault conditions at different locations were done at a sampling rate of 20 kHz with a simulation time of 0.1 second. The fault was initiated at 0.05 second in each simulation. Fault current of the three phases were used for the fault features extraction and analysis.

B. *Fault Features Extraction with DWT*

The descriptions of the wavelet and associated parameters employed are given in Table 3. The three current signals for the different fault conditions were taken into consideration. In order to distinguish between L-L fault and L-L-G types of fault, zero sequence current was also taken into consideration. The root mean square (RMS) values of the details component of the data window of each signal represent the quantity of extracted features.

Table 3: Description of Wavelet and associated parameters

Parameters	Properties
Mother wavelet	Doubechies, dB5
Sampling frequency	20 kHz
Information analyzed	Details: d1 - d5
Number of samples per cycle	400
Occurrence of fault	Third cycle
Data window length analyzed	One cycle (20 ms)

C. *ANFIS-based Fault Detection Model*

The fault detection model was developed using ANFIS as shown in Fig. 3. The inputs are the RMS values of the entire detail components of phases A, B and C of the transmission lines under consideration, while the output is a binary value which signifies the state of the line (i.e. 0 – no fault, 1 – fault). Whenever fault is confirmed to occur, a trip signal is sent to open the line circuit breakers. The 1211 sets of data simulated are divided into three groups of 80 % (training data), 10 % (testing data) and10 % (validation data).

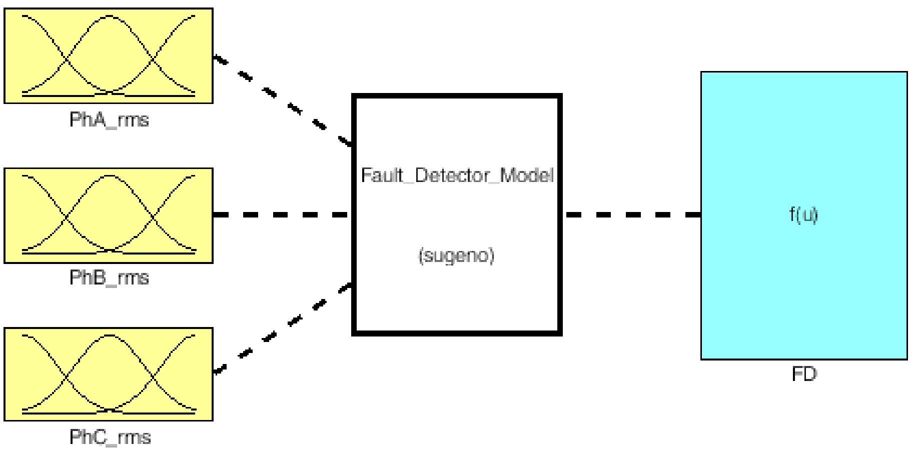

Fig. 3: Block diagram of ANFIS-based fault detection model

D. ANFIS-based Fault Classification Model

The fault classification model was developed using ANFIS as shown in Fig. 4. The inputs are the RMS values of the entire detail components of phases A, B, C and zero sequence current of the transmission lines under consideration, while the output is an integer which signifies the fault type.

E. ANFIS-based Fault Location Model

The fault location model was developed using ANFIS as shown in Fig. 5. The first three inputs are the RMS values of the entire detail components of phases A, B and C of the transmission lines under consideration, while the last input is the type of fault. The output is the location of fault occurrence.

F. DWT and ANFIS-Based Fault Classification and Location System

Fig. 6 shows the block diagram of the developed DWT and ANFIS-based system for fault detection, classification and location on a 132 kV transmission lines. The analogue-to-digital (ADC) discretized the current signals obtained by the current transformer (CT) at a sampling frequency of 20 kHz. Whenever the value of any of the phase currents exceeds the preset threshold (five times the rated current), discrete wavelet transform is applied on a data window frame of 400 samples by the feature extractor unit to obtain the details components at level 1 to 5. The output of the extractor is the RMS values of the detail components of the current signals which are fed into the fault detector for the detection of the shunt fault. If any of the shunt faults is detected, a trip signal is sent to trip the circuit breaker (CB) at busbar A.

The fault classifier, on receiving notification of fault from the detector, uses the RMS values of the current of the three phases detail components as well as that of the zero sequence current to determine the type of fault. While the fault locator uses the RMS values of the detail components of the current signals together with the fault type to determine the fault location. Fig. 7 present a flowchart that summarizes the working of the developed system.

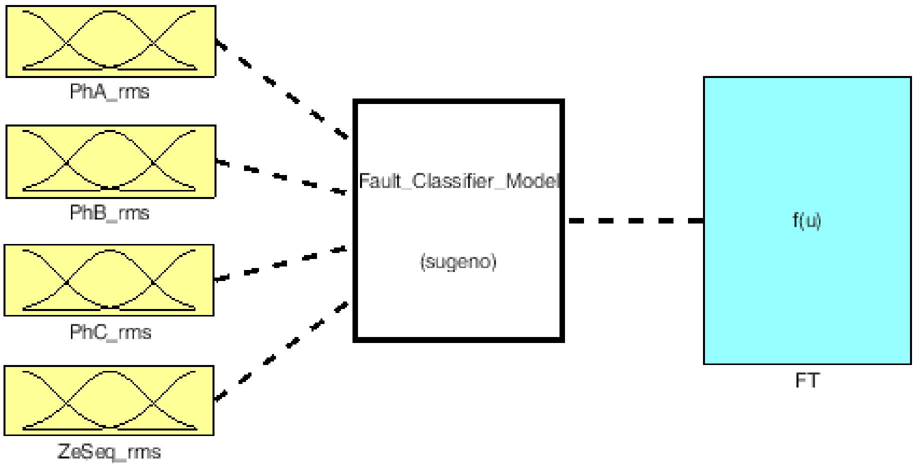

Fig. 4: Block diagram of ANFIS-based fault classification model

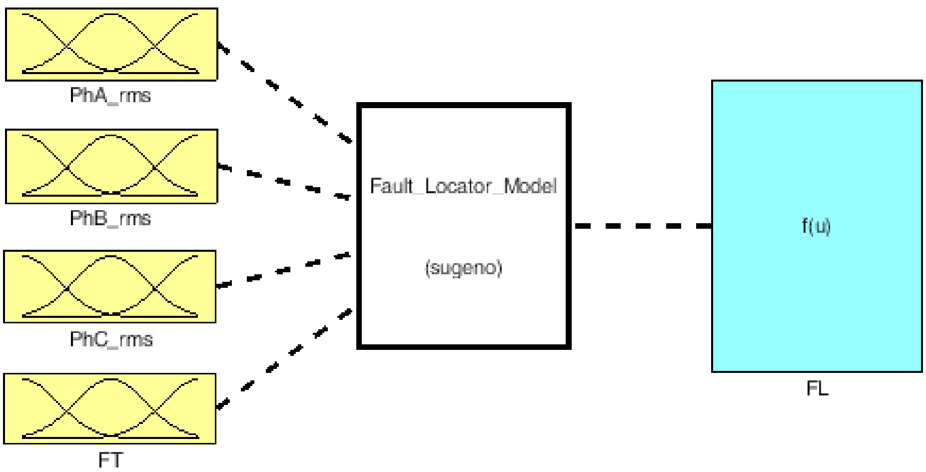

Fig. 5: Block diagram of ANFIS-based fault location model

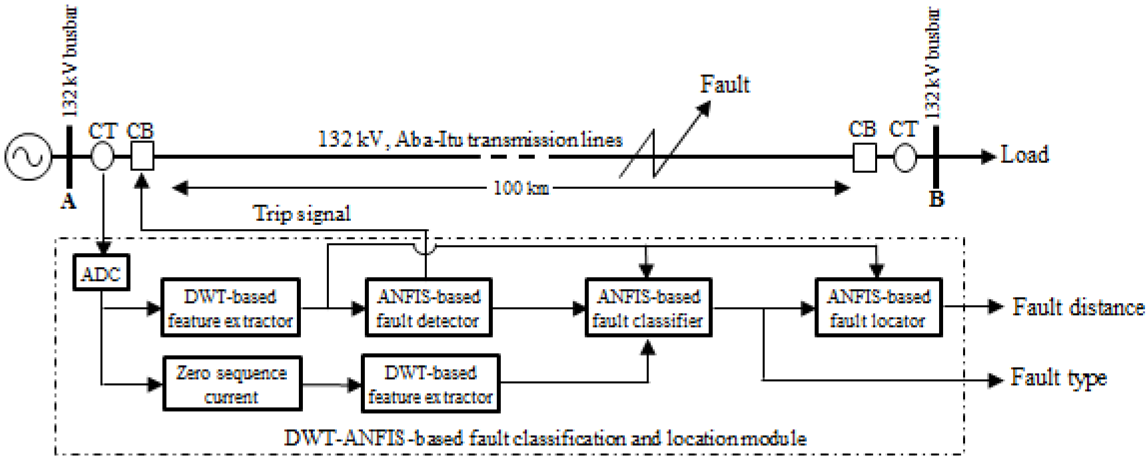

Fig. 6: Single line diagram of the developed system

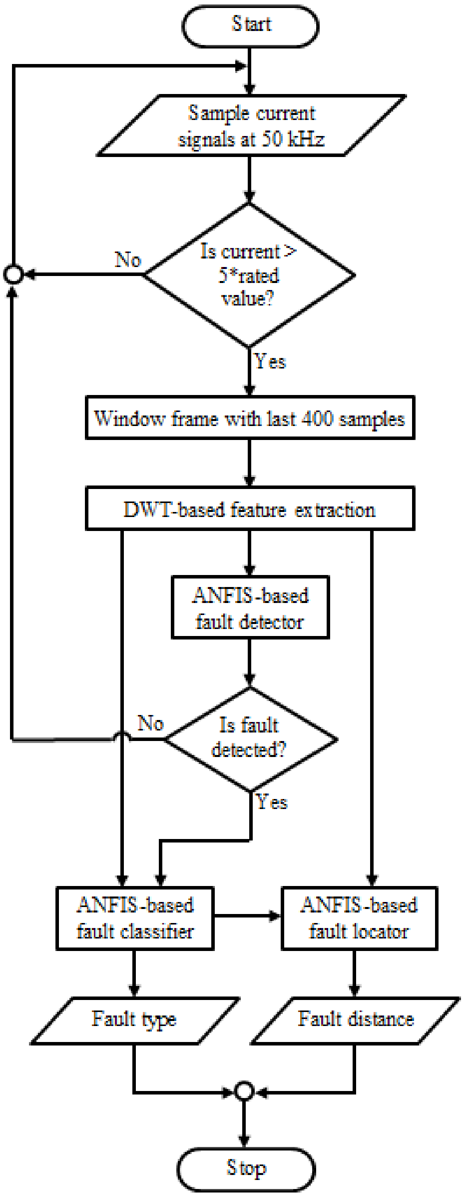

Fig. 7: DWT and ANFIS-based fault classification and location system flowchart

III. RESULTS AND DISCUSSION

The MATLAB/Simulink software was used for the implementation of DWT and ANFIS-based fault classification and location system. The current waveform of a single phase to ground fault on phase A in Fig. 8 shows that the value of the faulted phase current exceeds the threshold value (5 p.u.). Comparing the DWT decomposition of the faulty phase (Fig. 9) to those of the other phases (Figs. 10 and 11) shows that the faulty phase has far higher amplitude for all the detail levels (d1 – d5). This is further confirmed in Table 4.

Three phase fault was initiated at 0.05 second at a distance of 10 km with generator firing angle of 90^o and a fault resistance of 1 Ω. The output is either "0" (no fault) or "1" (fault). As seen in Table 5, the developed fault detector was able to discriminate between actual fault cases from normal condition. It is also observed that the maximum tripping time for all fault occurrence is 8 milliseconds (Fig. 12). This mean that the fault is detected within one cycle of fault occurrence.

The ability for the DWT-ANFIS based classifier to accurately distinguish between the different fault types under different fault conditions is excellent as can be seen in Table 6.Some of simulation results from the DWT-ANFIS based fault locator are also presented in Table 6. It shows near accurate predictions of fault distance in all cases. In Table 7, the R-squared values of the predicted fault distances are approximately equal to 1. The maximum value of RMSE and absolute error for all fault types are 0.109 and 0.22 km respectively.

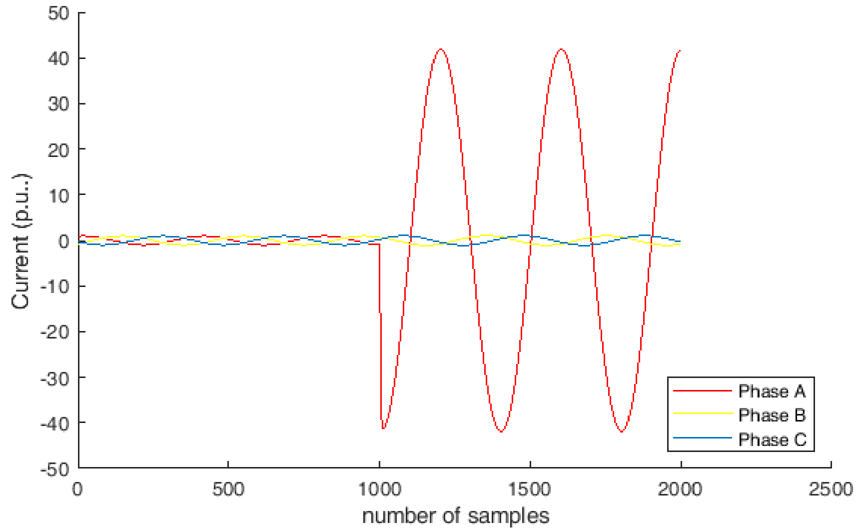

Fig. 8: Current waveform of single phase to ground fault on line A

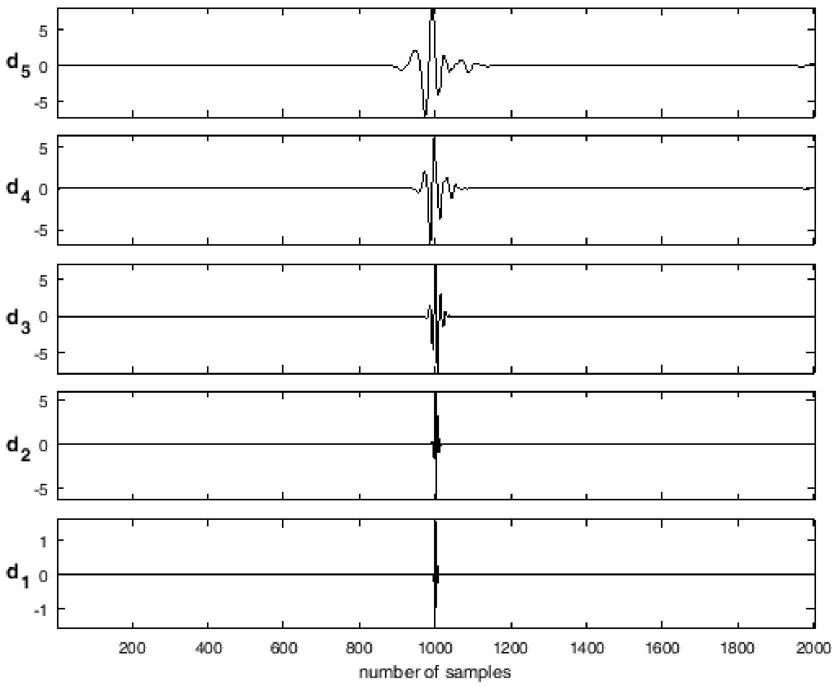

Fig. 9: DWT decomposition of phase A

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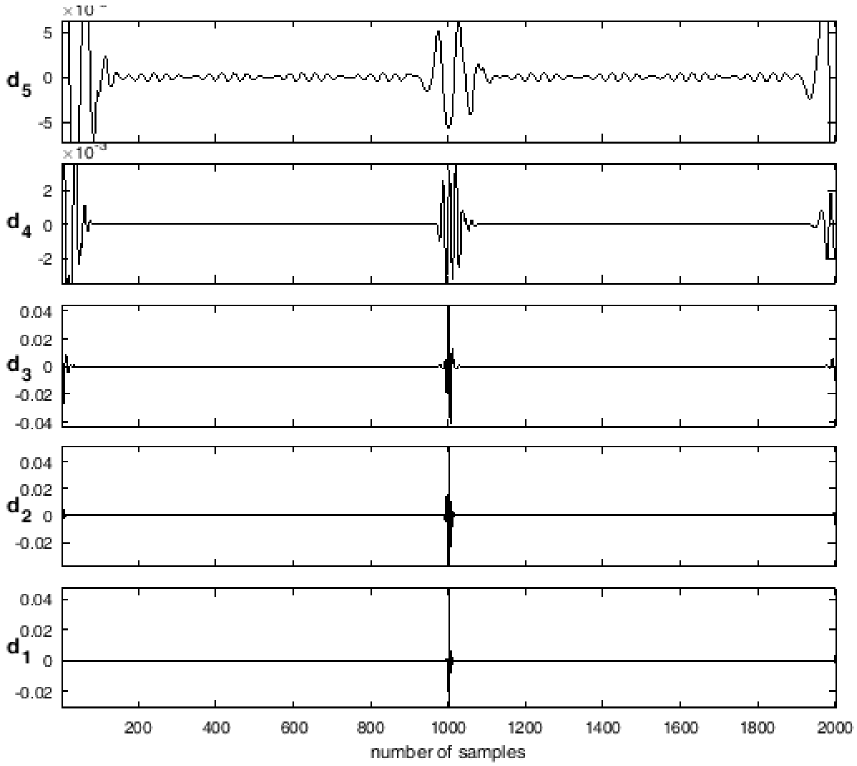

Fig. 10: DWT decomposition of phase B

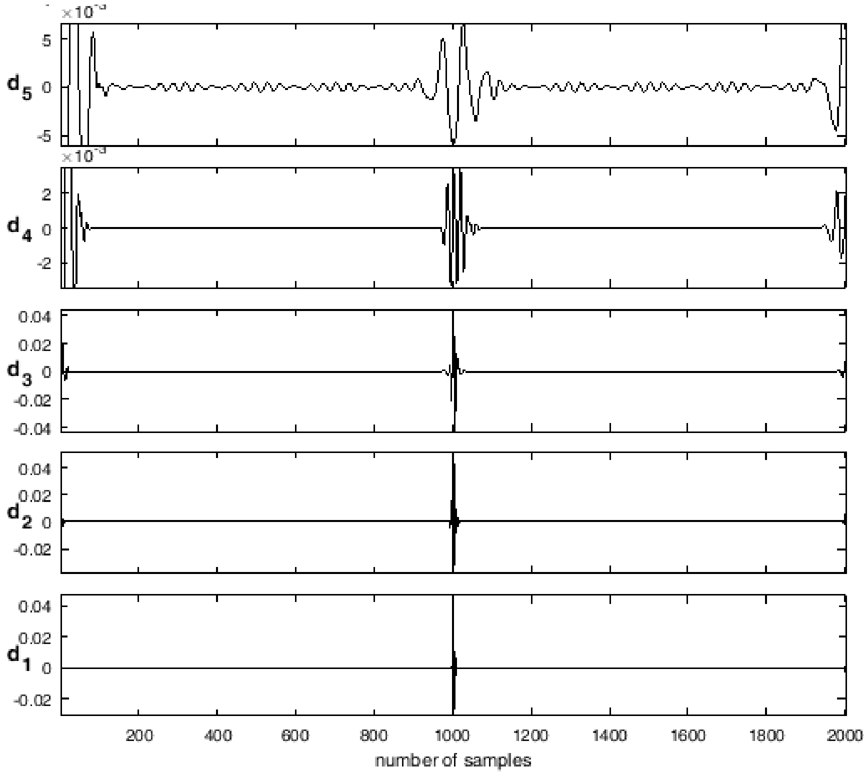

Fig. 11: DWT decomposition of phase C

Table 4: RMS values of the detail components of the three phases for L-G fault

	d1	d2	d3	d4	d5	Entire details (Ph_rms)
Phase A	0.0819	0.5228	1.3376	2.1774	4.4604	1.1587
Phase B	0.0019	0.0041	0.0103	0.0153	0.0354	0.0090
Phase C	0.0019	0.0040	0.0090	0.0125	0.0286	0.0075

Table 5: Fault detection output for different fault scenarios

Fault Type	Fault Time (sec)	RMS Values Phase A	Phase B	Phase C	Fault Detector (output)	Tripping Time (sec)
Normal	-	0.0024	0.0082	0.0067	0	-
A-G	0.05	1.1587	0.0090	0.0075	1	0.0576
B-G	0.05	0.0032	0.6875	0.0070	1	0.0576
C-G	0.05	0.0029	0.0085	0.5696	1	0.0576
AB	0.05	1.3729	1.3732	0.0067	1	0.0576
BC	0.05	0.0024	0.3808	0.3800	1	0.058
AC	0.05	1.2698	0.0082	1.2701	1	0.0576
AB-G	0.05	1.5527	1.2047	0.0069	1	0.0576
BC-G	0.05	0.0037	0.6400	0.5061	1	0.0576
AC-G	0.05	1.5035	0.085	1.0472	1	0.0576
ABC	0.05	1.7450	1.0429	0.8511	1	0.0576

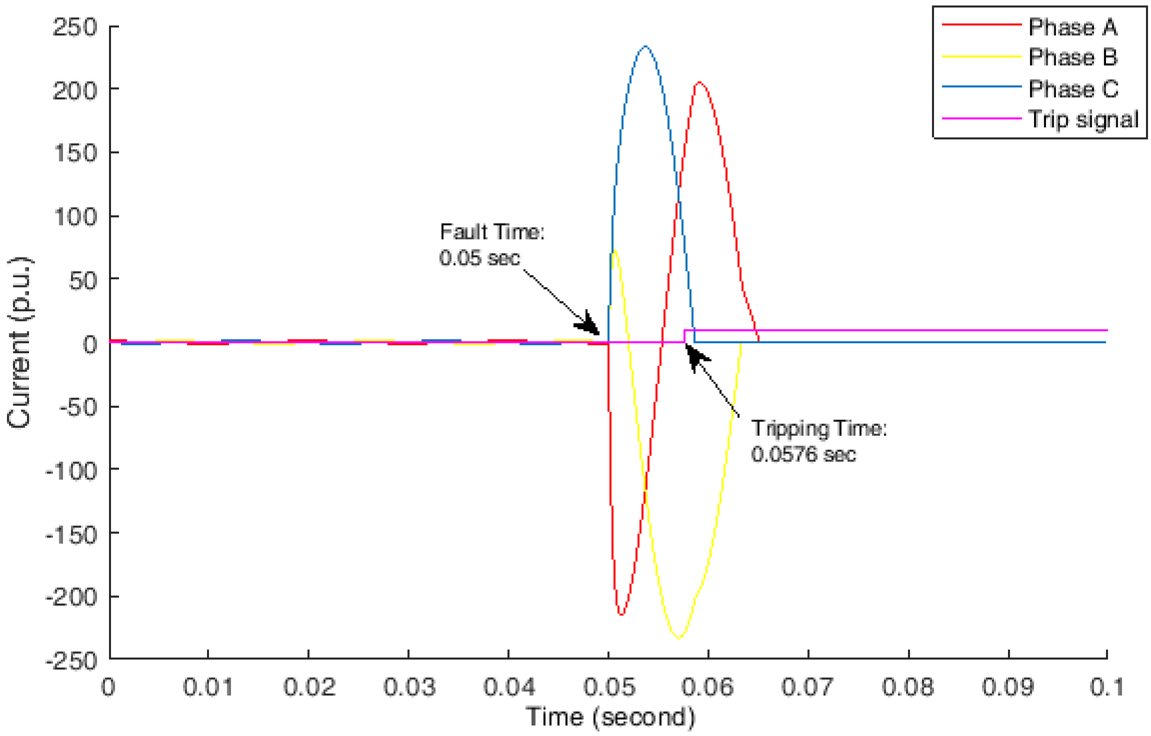

Fig. 12: Current waveform of three phase shunt fault with the trip signal sent to the circuit breaker

Table 6: Fault classification and location output for different fault scenarios

S/N	Fault Type @ Fault Resistance	Actual Distance	Predicted Distance	|error| (%)	Fault Type Classifier
1	AG @ 2.25 Ω	0.1	0.133	0.033	AG √
2	AG @ 1 Ω	50.0	50.008	0.008	AG √
3	AG @ 2.5 Ω	90.0	89.967	0.033	AG √
4	BG @ 1.5 Ω	20.0	19.988	0.012	BG √
5	BG @ 0.1 Ω	80.0	80.004	0.004	BG √
6	BG @ 2 Ω	99.9	99.874	0.026	BG √
7	CG @ 1 Ω	30.0	30.045	0.045	CG √
8	CG @ 0.25 Ω	60.0	59.987	0.013	CG √
9	CG @ 2 Ω	90.0	89.944	0.056	CG √
10	AB @ 1.25 Ω	10.0	9.993	0.007	AB √
11	AB @ 0.5 Ω	40.0	40.000	0.000	AB √
12	AB @ 2.25 Ω	70.0	70.012	0.012	AB √
13	AC @ 0.75 Ω	20.0	20.030	0.030	AC √
14	AC @ 0.1 Ω	50.0	49.970	0.030	AC √
15	AC @ 2 Ω	70.0	70.002	0.002	AC √
16	BC @ 1 Ω	0.1	0.171	0.071	BC √
17	BC @ 0.75 Ω	10.0	9.948	0.052	BC √
18	BC @ 0.1 Ω	40.0	40.027	0.027	BC √
19	ABG @ 0.25 Ω	20.0	19.866	0.134	ABG √
20	ABG @ 1.75 Ω	60.0	59.976	0.024	ABG √
21	ABG @ 0.75 Ω	99.9	99.836	0.064	ABG √
22	ACG @ 2.25 Ω	30.0	30.134	0.134	ACG √
23	ACG @ 1.25 Ω	70.0	69.929	0.071	ACG √
24	ACG @ 1 Ω	80.0	80.018	0.018	ACG √
25	BCG @ 2.5 Ω	10.0	9.940	0.060	BCG √
26	BCG @ 1.5 Ω	50.0	50.000	0.000	BCG √
27	BCG @ 0.75 Ω	80.0	80.078	0.078	BCG √
28	ABC @ 2.5 Ω	0.1	0.126	0.026	ABC √
29	ABC @ 1.5 Ω	40.0	40.047	0.047	ABC √
30	ABC @ 0.5 Ω	80.0	79.953	0.047	ABC √

Table 7:Performance evaluation of DWT-ANFIS based system for fault location

S/N	R-squared	RMSE	|error|
1	1.00000	0.0232	0 - 0.037
2	1.00000	0.0418	0.002 - 0.087
3	1.00000	0.0378	0 - 0.07
4	1.00000	0.0228	0 - 0.031
5	1.00000	0.0252	0.002 - 0.035
6	1.00000	0.0451	0 - 0.071
7	0.99999	0.1091	0.009 - 0.221
8	0.99999	0.0796	0.007 - 0.163
9	1.00000	0.0411	0 - 0.078
10	1.00000	0.0455	0.01 - 0.077

IV. Conclusion

Transmission lines are highways for the transfer of electric energy from generating stations through a long distance to distribution stations. These lines are sometimes exposed to severe atmospheric conditions and unfavourable terrains, thus the likelihood of fault occurrence is very high. Under fault condition, power system equipment is subjected to the greatest stress which can damage the equipment as well as affect the quality and stability of the power. It is necessary to ensure that the fault is cleared as quickly as possible. In this work, a reliable scheme for the detection, classification and location of fault on transmission lines is developed. This scheme combines the feature extraction capability of the discrete waveform transform and the intelligent classification capability of adaptive neuro-fuzzy inference system. The developed DWT-ANFIS model was tested and the results compared with Impedance-ANFIS model. Faults were detected within 8ms that is less than one complete cycle from fault inception to prevent equipment damage and prolonged power outage. An accuracy level of 99.78% and a RMSE of 0.0228-0.1091 were obtained.

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