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DETECTION OF HIGH IMPEDANCE FAULTS IN DISTRIBUTION FEEDERS - K-NEAREST NEIGHBOR METHOD

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ABSTRACT

High-impedance faults (HIFs) caused by downed conductors in electric power systems are in general difficult to be detected using traditional protection relays due to small fault currents. The energized downed conductor can pose a safety risk to the public and cause a fire hazard. This paper presents a new method of HIF in distribution feeders, using Wavelet and k-Nearest Neighbor Method approaches. Wavelet approach has proved to be successful in understanding and evolving solutions to many problems in Power Quality, Power System Protection, and Transient Analysis. The technique adopted, uses Wavelet Transform (WT) in the pre-processing stage for feature extraction, which is used to prepare the necessary data, to be used in the k-Nearest Neighbor Method. The current wave form, when measured at the relaying point, yields coefficients which are used as the inputs to the k-Nearest Neighbor Method. A realistically developed HIF model using a typical IEEE 13 Radial Distribution System was used to determine the performance of the technique for different types of HIF and Capacitor switching, linear faults and non linear load switching etc. The method was found to be robust, fast and accurate.

Keywords-High-Impedance fault Detection, Wavelet transforms, k-Nearest Neighbor Method, Electrical distribution system, No fault.

I. INTRODUCTION

Safety is one of the important issues in distribution electricity networks. Lack of security in the power network may lead to damage to humans and equipment. The prevention is the best Solution to avoid the harmful events. The HIF is one of the issues that results in death and financial damages. The snapped conductor coming into contact with the ground or with any object of high impedance results in High Impedance Faults causing fault current of very low magnitude in the ranges .As the impedance of the current path is high, the current value in this type of fault is low and usually ranges from 0A to 100A [1]. Hence, by the conventional over current relay, it is not possible to detect this kind of fault; it is treated as a normal load current raise. The HIF can occur in two forms. In the first form, a conductor breaks and falls to the ground. In the second form, an electrical conductor is not disconnected but only is to be connected to a high impedance object (such as tree branches and leaves). The HIFs are usually associated with an electric arc, which may cause a fire. Due to the nonlinearity nature of the fault, the HIF current contains various frequency harmonic components including low and high frequency components. It should be noted that other network components have also broad frequency harmonics. Therefore, the HIF should be studied precisely. The researchers have performed several HIF experiments and have studied the associated voltage and current to obtain models that are to be used in the simulations. As the HIF has a random nature and the fault current is influenced by many parameters, developing a model that covers all conditions is difficult. However, since the developed model is based on practical experiments, the researchers considered some aspects of the HIF characteristics [1].

Researchers have proposed various methods for the detection of the HIF. These methods usually start by measuring available signal at the feeder and preparing them for analysis. Then, the signal processing tools are for feature extraction and obtaining discriminative. The latter has been used to discriminate between normal and HIF situations. Finally, the fault classification is performed using simple or intelligent algorithms. References [2] and [3] used discrete Fourier transform to find the voltage signal harmonics and Feeder current. The help of signal processing tools, such as Fourier Transform and Kalman Filtering has been taken in order to extract the features of frequencies of the HIF signals . Also, the magnitude of the harmonics was founded through using Kaman filter [4]. In the power system, time-frequency based methods are used. This leads to more use of the wavelet transform. This fact is due to the time varying behavior of the power system phenomena especially HIF. The wavelet transform based methods were for analysis the measured signal in [5, 6].

After extracting features, the HIF should be distinguished from normal operating conditions. Sequential algorithms such as described in [7] to check the appropriate features. The training data classification is done by the intelligent method of KNN (k- Nearest Neighbour Method) In [4, 8, and 9] different methods of training, the k-Nearest Neighbor Method was used in HIF detection. A combination of the k-Nearest Neighbor Method and WT was used in [10] and the method employed in [11] is based on the Classical pattern recognition method.

In this paper, firstly the signal is decomposed using DWT. In the next stage, the wavelet output is used to find appropriate features for classification. In order to consider the more realistic case, a combined model of the HIF is used. The k-Nearest Neighbor Method (KNN) trained show excellent performance in 100 test cases. This technique is verified with the aid of MAT LAB/SIMULINK. The mainly objective of this work, by combing WT and k-Nearest Neighbor Method (KNN), is to propose a scheme which can detect normal switching operation and HIF. The interface of WT and k-Nearest Neighbor Method (KNN) was evaluated for effective combination.

II. K-NEAREST NEIGHBOR METHOD

Different types of classifiers are used for fault detection in distribution system protection now a day. From these k-NNs are used by many researchers for different purposes for protection of power system. As an instance based learning, where in the function is approximated on a local basis, the fault detection is done using k-NN method

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at the distribution feeder. In this method, for k taking the integer values, the nearest neighbor method has the trained samples, in the feature space with the class of the samples known. k-NN method first store the feature vector and classifying according to classes of k nearest neighbours. The class label is assigned and the training samples are represented as a matrix. Which in the training phase has the feature vector and the class lables.

In testing phase, samples are classified by according to most frequent class among the k samples nearest to that query point. Euclidean method of distance measurement is used in the proposed k-NN method and it is observed that the method is sensitive to the nature of the structure of the data.

Using k-NN classify as the function and training input, argument for the k-NN are given as training input , training target and test inputs [7]. Re-substitution error of training samples are then percentage accuracy of the training set. The confusion matrix, when computed results in the proportional classified and misclassified data, and the diagonal elements represent the correctly classified samples

III. PROPOSED METHOD

The proposed methodology to detect HIFs and discriminate them from normal transient switching operations comprises two step process Wavelet Transform on the first stage of the feeder current signal, lead to the data signals. In the second stage, the properly trained k-Nearest Neighbor Method (KNN) are used as a classifier processing, to classify the state of each feeder. Fig. 1. Gives the structure of the application of WT and k-Nearest Neighbor Method (KNN) this different stages of the working of the methodology are given in the block diagram schematic. Although some methods that use similar approaches may be affected by topology changes in the distribution network, this methodology is specially designed to be applied in the rural distribution systems whose topology is almost invariable. These kinds of distribution systems are very typical in several countries [10].

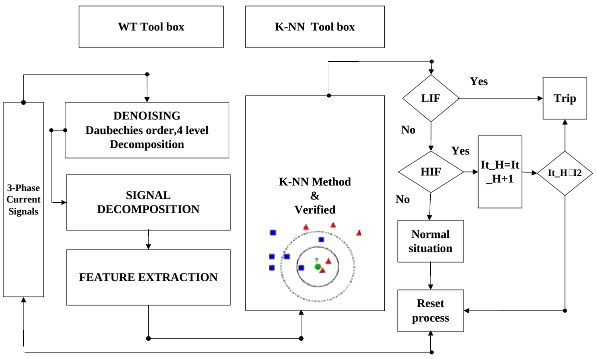

Fig. 1.Schematic diagram of the methodology

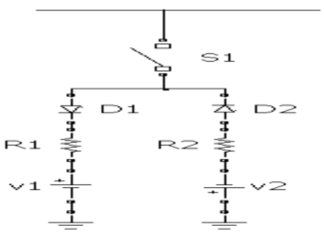

Fig.2.HIF model

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HIF currents are generated by using simplified two-diode model. The model consists of two DC sources V1 and V2. It also consists of two variable resistances R1 and R2 represents the fault resistance. In this model if phase voltage is more than V1 the fault current flows towards the ground. If the phase voltage is less than V2 then the fault current flows in reverse direction. Two diode HIF model implemented here is shown in fig 2. Varying the resistances R1 and R2 generate the waveforms. Capacitive switching transients shows high frequency current in its waveform and its magnitude depends on size and distance from the monitoring point. Capacitor banks for power factor improvement are generally installed in distribution system. These capacitors are switched into the system in accordance to load. Generally these capacitors are permanently connected in the substation and some of them are connected back to back so that they can operate whenever it is required.

3.1 Wavelet Transform

In the process of HIF detection, the signal data is to be analyzed to find adequate information that can be useful for the fault detection, as it may not clearly appear in the original time signal. The application of WT can be segregated as :

(a) De-noising process of the current signals.

(b) Signal decomposition and (c) Feature extraction

The use of the Wavelet Toolbox from MATLAB which provides useful functions and an extraordinary computing environment for the implementation of the WT in an efficient way in a computer. This implementation can be done either by command line functions or by graphical interactive tools. The DWT instead of the continuous wavelet transform (CWT) is considered for application in order to reduce the vast amount of computational work and data the latter would require.

3.1.1. De-Noising Process

De-noising process the de-noising process is applied to eliminate the existing distortion in the current signals, which may have been produced by several events: switching operations and other feeder events. The idea of DWT preprocessing is to convert the three-phase current signals into one dimension hard threshold de-noising stage. For this purpose, a Daubechie's order 4(db2), level 4 wavelet decomposition is applied to the registered currents. The heuristic Steins unbiased estimate principle gives the threshold rule. The decomposition level and basis function have been selected after a thorough analysis of different levels and many types of basic functions. The objective is to find the optimum de-noising for the signals in every simulated case of each feeder of the distribution power system described in Section 3.

3.1.2. Signal Decomposition

Signal decomposition: The information from the time-domain signals registered under normal or fault situations is usually not enough to detect the HIFs. Therefore, the DWT is applied to transform the de-noised time signals to time-frequency domain signals, where the different characteristics of each current signal may appear more clearly, by the large coefficients in different frequencies.

This process is known as Decomposition process, in which the Daubechie's basis of order four (db4), in seven decomposition levels, has been applied.. The features from all these frequencies are used to give discrimination. When analyzing the characteristics of current signals by the use of DWT, the following parameters must be specified:

(i) Sampling frequency

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(ii) Window length

(iii) Levels of decomposition

(iv)Wavelet basis type

Usually, a low sampling rate leads to the reduction of the computation process. However, in some cases, such as in fault situation and switching operations, the sampling rate needs to be high so as to capture the characteristic information of the signal. After testing many possibilities, among 128, 256 and 512 samples per cycle, a sampling frequency of 512 samples per cycle (sampling rate of 2.56 kHz) is adopted in the analysis. The sampling frequency, along with the selected Wavelet basis function also influences the window length and on the decomposition level number. In this methodology, the implementation of the DWT is based on the Multi Resolution Analysis (MRA) theory, which requires filtering and down sampling. This decomposition level (number of stages) is inversely related to the frequency components of any level.

Consequently, the higher decomposition level, the lower frequency components are considered. The characteristics of the Wavelet basis functions play an important role in their implementation too. Therefore, selecting an appropriate mother Wavelet to extract the useful information quickly and efficiently is crucial to increase the performance of any particular application. The Wavelet basis selection usually depends on the type of application or the similarity between the basis function and the signal to be analyzed.

For example, Wavelets with small number of filter coefficients or vanishing points are less localized in frequency and more localized in time. Therefore, in applications where the information needed is located at a specific instant of time, lower Wavelet basis with less number of coefficients are a better choice than Wavelets with higher number of coefficients. In the course of this present work, different vanishing moments of the Daubechie wavelet, are tested such as db4, db6 etc. These mother functions are orthogonal to any function obtained by stretching them by a 2j factor or shifting them right or left by the product of a constant to 2j. The orthogonal functions are selected for their speed in calculation. Besides, Daubechies waveforms have some other useful properties to be considered, such as accurate detection of low amplitude of signals, short duration and fast decay [10].

3.1.3. Feature extraction

The feature extraction is to reduce the amount of information, either from original waveform or from its transformation format in the distinct waveform parameter, having the significant information which represents the fundamental characteristics of the problem in the feature extraction process of this work. The k-Nearest Neighbor Method (KNN) has the input data vector, for each frequency band extracted using the coefficients standard deviation.

This feature has been selected after tests and comparisons between the performance of neural networks (generalization, simplicity, efficiency and convergence speed) and other features like energy and RMS of each frequency bands (signals and coefficients).The STD of the output signal is the square root of the data vector variance, as it is shown in (1). This feature provides information about the level of variation of the signal frequency distribution.

$$STD = \sqrt{\left(\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \frac{1}{n}\sum_{i=1}^{n}x_i)^2\right)} \qquad (1)$$

where “x” is the data vector and “n” the number of elements in that data vector.

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3.1.4. k-Nearest Neighbor Method (KNN) verification

When the training process is finished, the optimal network configurations obtained are verified with the MAT LAB software tool, in reference to their generalization ability under untrained situations. The comparison between the network outputs and its corresponding targets over the test dataset, by means of (2)

$$\%Error = \frac{t\arg et\, output - calculated\ output}{t\arg et\, output} X100 \quad (2)$$

Taking as an example the dataset of feeder number one (Section 4), the solutions matrix obtained from (2) shows the percentage comparison between the outputs and targets of testing cases, using the previously mentioned The k-Nearest Neighbor Method (KNN) architecture[10].

This matrix (3) is organized such that the first column corresponds to the percentage output error (three outputs) under normal situations, while the second and the third columns correspond to the percentage output error of LIF and HIF cases, respectively.

$$\%Error = \begin{bmatrix} 0.0030 & 0.0003 & 0.0003 \\ 0.0000 & 0.0000 & 0.0001 \\ 0.0015 & 0.0001 & 0.0006 \end{bmatrix} \quad (3)$$

3.1.5. The k-Nearest Neighbor Method (KNN) stage

Decision Tree stage once the training and testing processes have been concluded, the resulting networks are ready to operate. The k-Nearest Neighbor Method (KNN) outputs vary from ‘0’ to ‘1’. Therefore, to reach the desired results of either ‘1’ or ‘0’, the outputs are processed with a ‘round’ function, in order to round the output data vector to the next integer. Finally, the outputs of the proposed method give the state (healthy or faulty) of a distribution feeder, when all stages of the method are followed. If the method gives indication of LIF or HIF in12 consecutive iterations, the outputs of the method may be used to take an appropriate control action. Nevertheless, when a feeder is under a normal situation, the method turns back to take a new data window after 200 samples and then every step of this detection methodology is repeated again. The designed The k-Nearest Neighbor Method (KNN) in MATLAB/ SIMULINK is shown in Fig. 3and a typical two layer ANN model is designed as in Fig. 4.

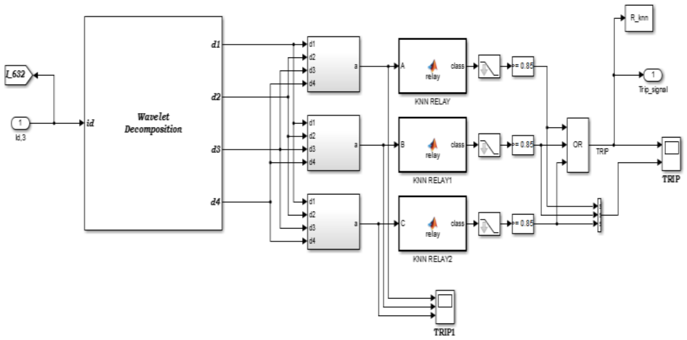

Fig. 3 Wavelet with k-Nearest Neighbor Method (KNN)

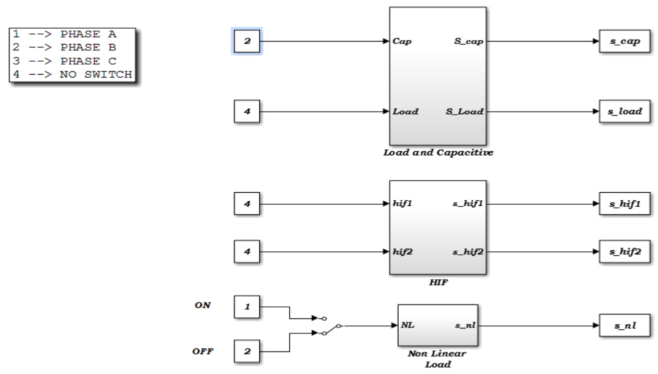

Fig. 4 Structure of k-Nearest Neighbor Method (KNN)

The flowchart of the algorithm for K-NN based Distribution Feeder is shown in Figure 5

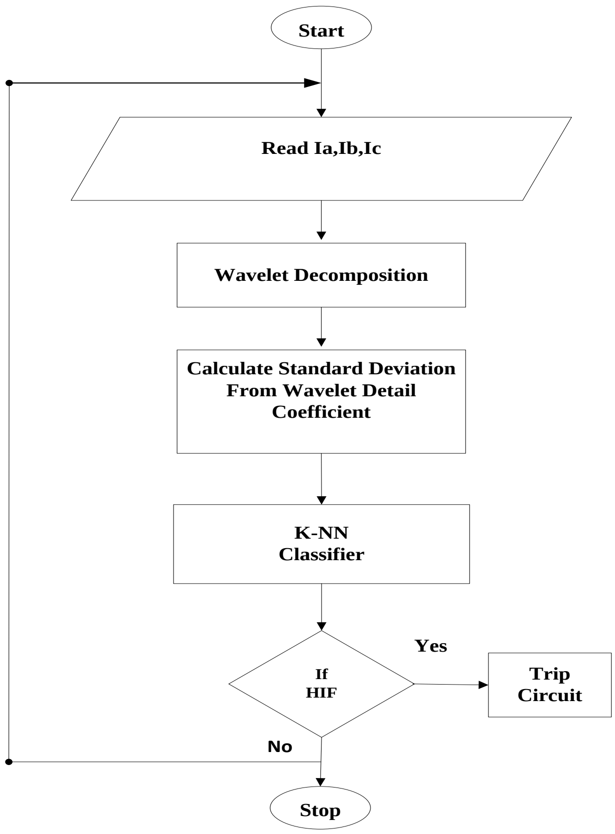

Fig.5 Flowchart of the algorithm for K-NN

IV. THE DISTRIBUTION TEST FEEDER

The data for the feeders being voluminous only the data for the 13 node feeder will be given in this paper. The solution consists of:

(a) Line Configuration Data:

Listing of the per mile phase impedance and admittance matrices for each of the configurations used in the feeder. The impedance and Admittance matrices assume a 100ohm-meter resistivity and 2.3 relative permittivity respectively [12].

***(b) Radial Flow Summary*:**

Details about the system inputs, Total load and losses along with shunt capacitor on phase and three phase basis.

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***(c) Voltage Profile*:**

The voltage magnitude on per unit basis at each node detailing their magnitudes and phase angles

***(d) Voltage Regulator Data*:**

for each regulator in the system a summary of the settings and the final tap settings [12]

***(f) Radial Power Flow*:**

The node data is expressed as complete information giving ampere line and phase angle in degrees, line and total three phase losses [15]. The test feeder is IEEE 13 Which In spite of Being a small Feeder displays the following characteristics.

1. 4.16 kV feeders is a short and relatively high loaded feeder.
2. Over head lines and underground cables
3. Parallel connected capacitor banks
4. In-line transformer
5. Concentrated and distributed , unbalanced loads

The data in detail is as given below

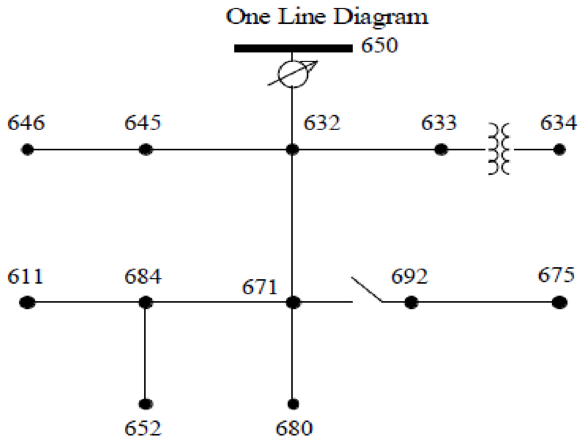

Fig.6 13 Node IEEE Test Feeder

Underground Line Configuration Data:

Config.	Phasing	Cable	Neutral	Space ID
606	A B C N	250,000 AA, CN	None	515
607	AN	1/0 AA, TS	1/0 Cu	520

Overhead Line Configuration Data:

Config.	Phasing	Phase ACSR	Neutral ACSR	Spacing ID
601	B A C N	556,500 26/7	4/0 6/1	500
602	C A	4/0 6/1	4/0 6/1	500
603	C B N	1/0	1/0	505

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604	A C N	1/0	1/0	505
605	C N	1/0	1/0	510

Line Segment Data:

Node A	Node B.	Length(ft.)	Config.
632	645	500	603
632	633	500	602
633	634	0	XFM-1
645	646	300	603
650	632	2000	601
684	652	800	607
632	671	2000	601
671	684	300	604
671	680	1000	601
671	692	0	Switch
684	611	300	605
692	675	500	606

Capacitor Data:

Node	Ph-A	Ph-B	Ph-C
	kVAr	kVAr	kVAr
675	200	200	200
611			100
Total	200	200	300

Regulator Data:

Regulator ID:		1	
Line Segment:	650 - 632		
Location:	650		
Phases:	A - B -C		
Connection:	3-Ph,LG		
Monitoring Phase:	A-B-C		
Bandwidth:	2.0 volts		
PT Ratio:	20		
Primary CT Rating:	700		
Compensator Settings:	Ph-A	Ph-B	Ph-C
R - Setting:	3	3	3
X - Setting:	9	9	9
Voltage Level:	122	122	122

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Transformer Data:

	kVA	kV-high	kV-low	R - %	X - %
Substation:	5,000	115 - D	4.16 Gr.Y	1	8
XFM -1	500	4.16 – Gr.	W 0.48 – Gr.W	1.1	2

Spot Load Data:

Node	Load	Ph-1	Ph-1	Ph-2	Ph-2	Ph-3	Ph-3
	Model	kW	kVAr	kW	kVAr	kw	kVAr
634	Y-PQ	160	110	120	90	120	90
645	Y-PQ	0	0	170	125	0	0
646	D-Z	0	0	230	232	0	0
652	Y-Z	128	86	0	0	0	0
671	D-PQ	385	220	385	220	385	220
675	Y-PQ	485	190	68	60	290	212
692	D-I	0	0	0	0	170	151
611	Y-I	0	0	0	0	170	80
	TOTAL	1158	606	973	627	1135	753

Distributed Load Data:

NodeA	NodeB	Load	Ph-1	Ph-1	Ph-2	Ph-2	Ph-3	Ph-3
	Model	kW	kVAr	kW	kVAr	kw	kVAr	Model
632	671	Y-PQ	17	10	66	38	117	68

V.SIMULATION AND RESULTS

The verification of the methodology developed is done on all the test cases. As an example, the following circuit Situations developed in this section:

It is well known that fault testing on real Distribution systems is difficult because of technical and economical reasons; also the test data usually suffer from certain limitations. That is why a real IEE 13 bus Test Feeder, under different conditions, has been accurately modeled and simulated with MATLAB/SIMULINK as given in fig.6 / Fig.

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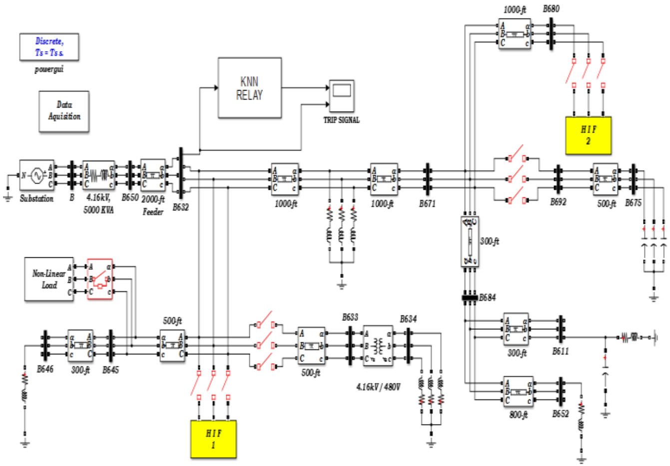

Fig. 7 Configuration of Distribution feeder

Finally, the choosing k-Nearest Neighbor Method (KNN) is tested using following cases.

High impedance fault1: High Impedance Fault 1 created at feeder bus 632 in phase A, phase B and phase C with a fault resistance of 100 Ω. Fig. 8 shows the current signal produced by High Impedance Fault 1applied in feeder 632.

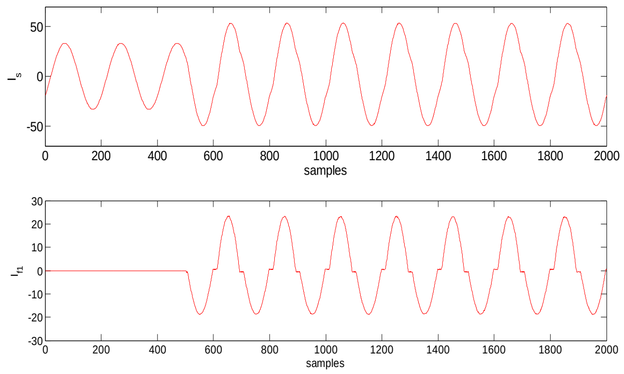

Fig. 8 High Impedance Fault 1distorted current on phase- A.

After the denoising process, Fig. 9, 10 and 11shows the behaviour of the decomposed signals of the faulty phase currents under a HIF1 situation. The dominant Wavelet levels (high amplitude) are D1 and D4, which represent the sub-harmonic frequency component. The high transient frequencies appear during the arc period which is seen in the Wavelet levels D2 to D4.

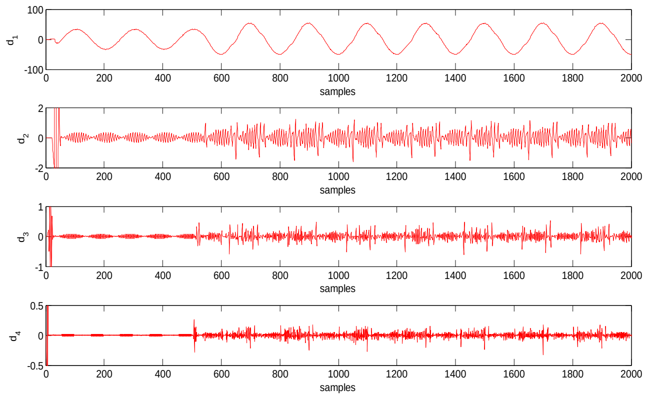

Fig. 9 Wavelet Transform of phase-A current signal of Distribution feeder during HIF1 Transients

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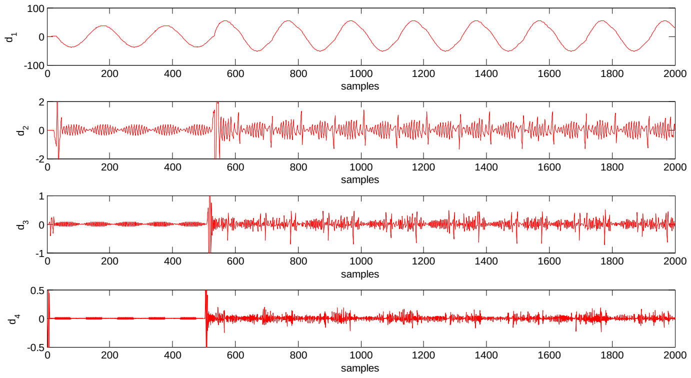

Fig.10 Wavelet Transform of phase-B current signal of Distribution feeder during HIF1 transients

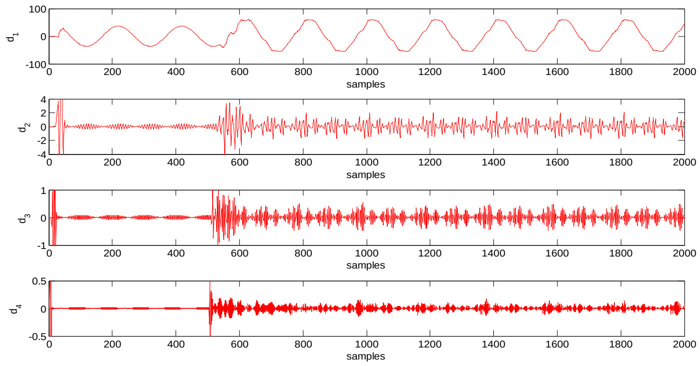

Fig.11 Wavelet Transform of phase-C current signal of Distribution feeder during HIF1 Transients

Applying the STD of each decomposition level, the numerical values of patterns are realizable from the analysis of the signal. Applying these data matrix as the input to the selected choosing k-Nearest Neighbor Method (KNN), this methodology gives the exact output corresponding to each HIF situation, and it is not confused by the transients caused by LIFs and normal switching events. It can be concluded that feeder 632 is under HIF1.

High Impedance Fault 2 created at feeder bus 680 in phase A, phase B and phase C respectively with a fault resistance of 100 Ω. Fig. 12 shows the current signal produced by High Impedance Fault 2 applied in feeder 680.

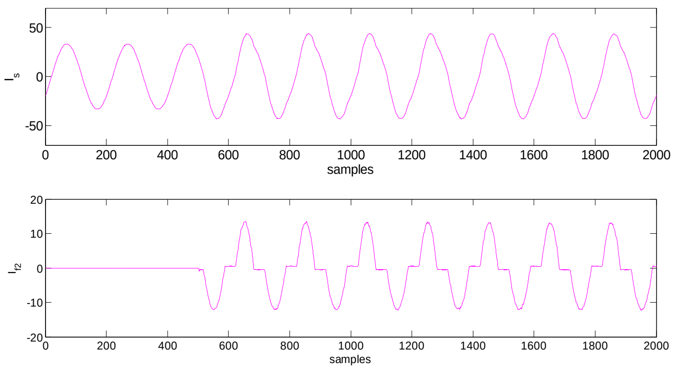

Fig.12High Impedance Fault 2distorted current on phase A.

After the denoising process, Fig. 13, 14 and 15shows the behaviour of the decomposed signals of the faulty phase currents under a HIF2 situation. The dominant Wavelet levels (high amplitude) are D1 and D4, which

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represent the sub-harmonic frequency component. The high transient frequencies appear during the arc period which is seen in the Wavelet levels D2 to D4.

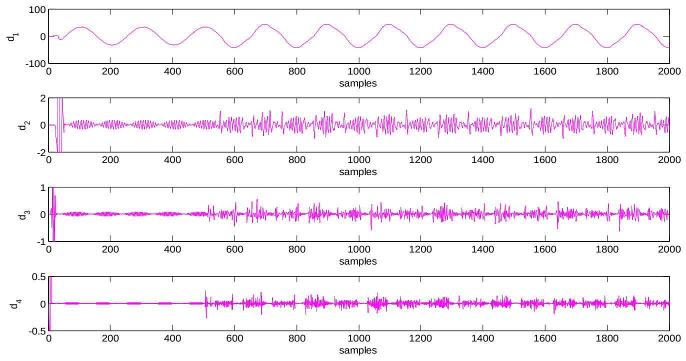

Fig.13Wavelet Transform of phase-A current signal of Distribution feeder during HIF2 transients

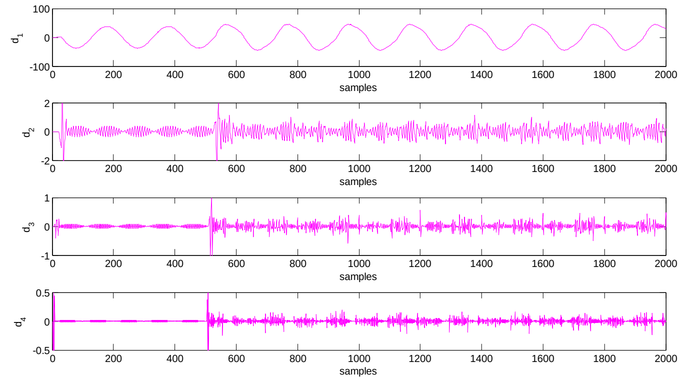

Fig.14Wavelet Transform of phase-B current signal of Distribution feeder during HIF2 Transients

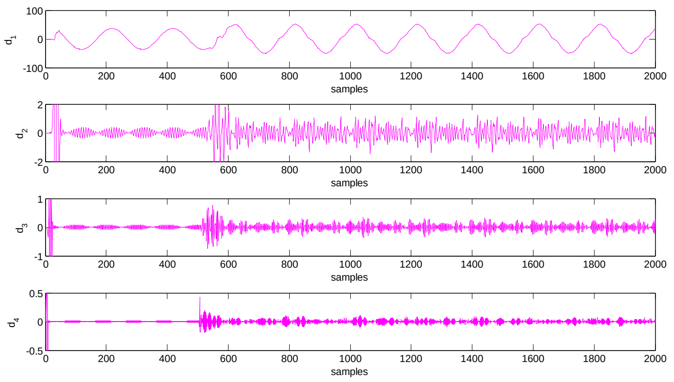

Fig.15 Wavelet Transform of phase-C current signal of Distribution feeder during HIF2 Transients

Applying the STD of each decomposition level, the numerical values of patterns are realizable from the analysis of the signal Applying these data matrix as the input to the selected k-Nearest Neighbor Method (KNN), this methodology gives the exact output corresponding to each HIF situation, and it is not confused by the transients caused by LIFs and normal switching events. It can be concluded that feeder 680 is under HIF2.

Capacitor switching: capacitor switching created at feeder bus 675 in phase A, phase B and phase C with 100 kVAr and 0.05Sec. to 0.5 Sec. of inception time. Fig. 16 shows the current signal produced by capacitor switching applied in feeder 675.

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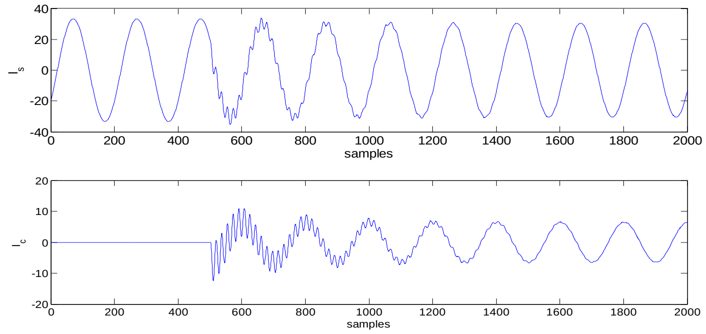

Fig.16 capacitor switching distorted current on phase- A

The process starts by a de-noising process and the application of WT to the current signals. Then, the STD from all frequency levels are calculated and used as the inputs to the trained k-Nearest Neighbor Method (KNN). Finally, the state of a feeder is calculated according to the outputs of the k-Nearest Neighbor Method (KNN).

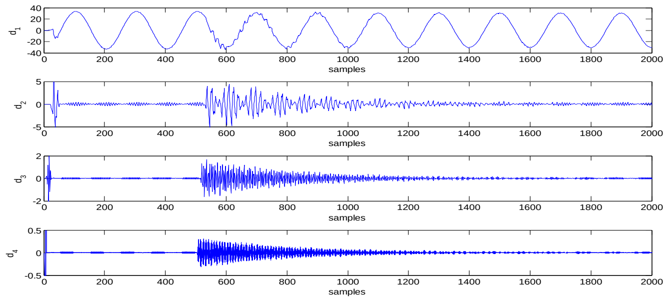

Fig.17 Wavelet Transform of phase-A current signal of Distribution feeder during capacitor switching

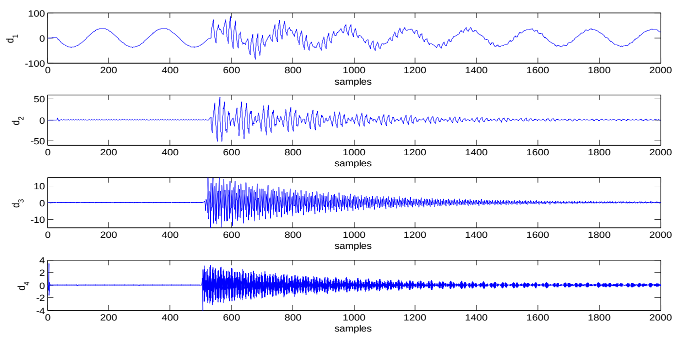

Fig.18 Wavelet Transform of phase-B current signal of Distribution feeder during capacitor switching

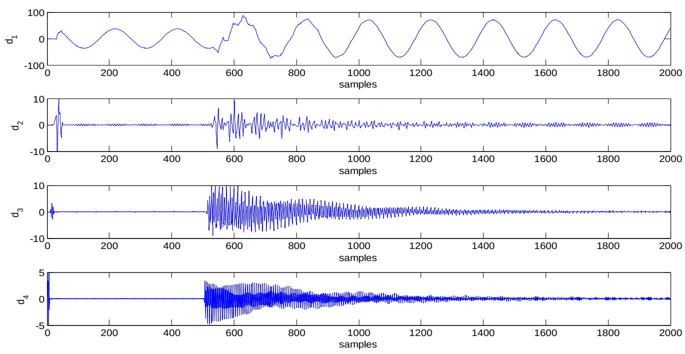

Fig.19 Wavelet Transform of phase-C current signal of Distribution feeder during capacitor switching

The complete performance of the proposed technique has been tested by its application to data under different conditions. The test set was formed by patterns from different situations compared to the training patterns.

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There is a large spike in d1 to d4 coefficient in signal waveform as shown in fig.17, 18 and 19. It is clearly observed for capacitor switching.

Load switching: load switching created in between feeder bus 632 and 671inphase A, phase B and phase C with 160 kw and 0.05Sec.to 0.5Sec. Of inception time .Fig. 20 shows the current signal produced by load switching applied in between feeder bus 632 and 671.

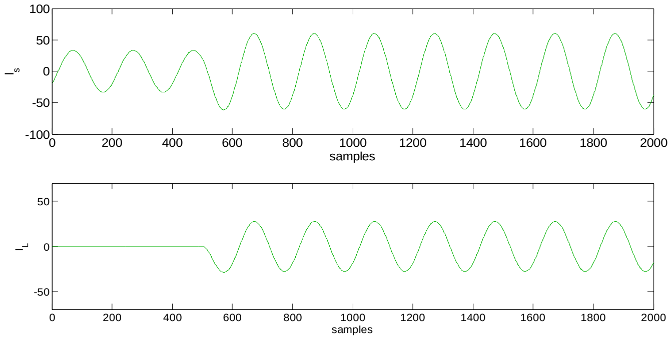

Fig.20 Load switching distorted current on phase A

The process starts by a de-noising process and the application of DWT to the current signals. Then, the STD from all frequency levels are calculated and used as the inputs to the trained k-Nearest Neighbor Method (KNN). Finally, the state of a feeder is calculated according to the outputs of the decision tree.

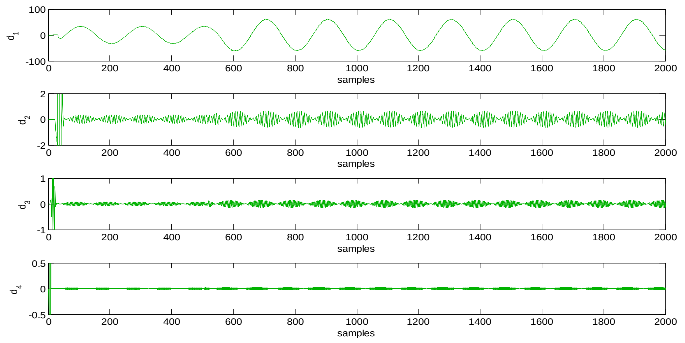

Fig.21 Wavelet Transform of phase-A current signal of Distribution feeder during load switching

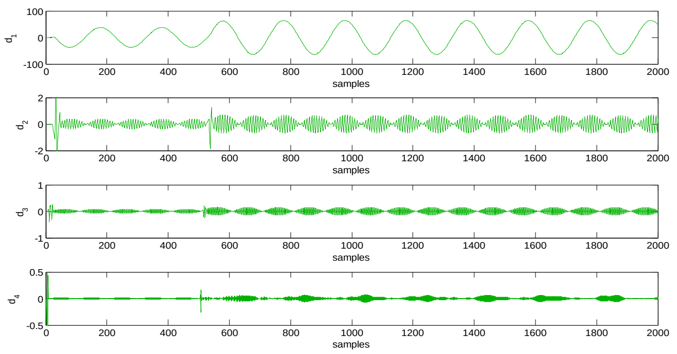

Fig.22 Wavelet Transform of phase-B current signal of Distribution feeder during load switching

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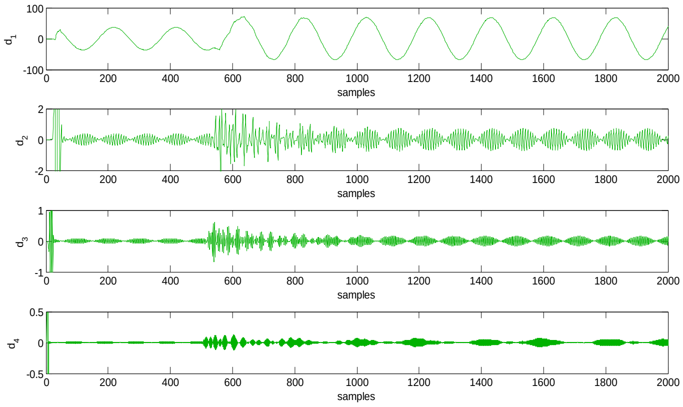

Fig.23 Wavelet Transform of phase-C current signal of Distribution feeder during load switching

The complete performance of the proposed technique has been tested by its application to data under different conditions. The test set was formed by patterns from different situations compared to the training patterns. There is a large spikes in d1 to d4 coefficient in signal waveform as shown in fig.21, 22 and 23. It is clearly observed for load switching.

Non Linear Load Switching:

Non-linear load switching created at feeder bus 645inphase A, phase B and phase C with 0.5kVAr and 0.05 Sec.to 0.5 Sec. of inception time Fig. 24 shows the current signal produced by the nonlinear load applied in feeder 645.

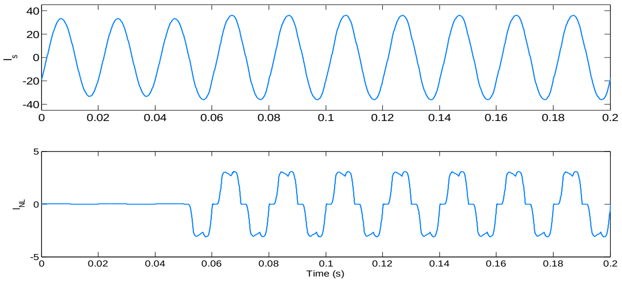

Fig.24 Nonlinear load distorted current on phase A.

The process starts by a de-noising process and the application of DWT to the current signals. Then, the STD from all frequency levels are calculated and used as the inputs to the trained k-Nearest Neighbor Method (KNN). Finally, the state of a feeder is calculated according to the outputs of the k-Nearest Neighbor Method (KNN).

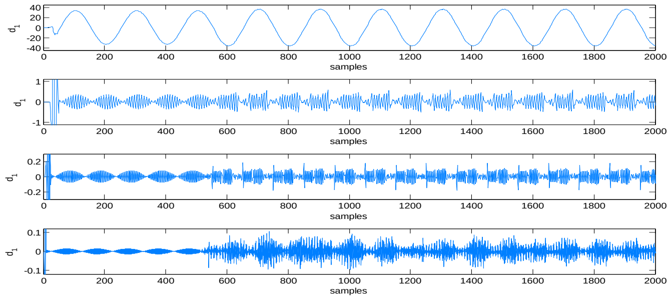

Fig.25 Wavelet Transform of phase-A current signal of Distribution feeder during Non-linear load switching

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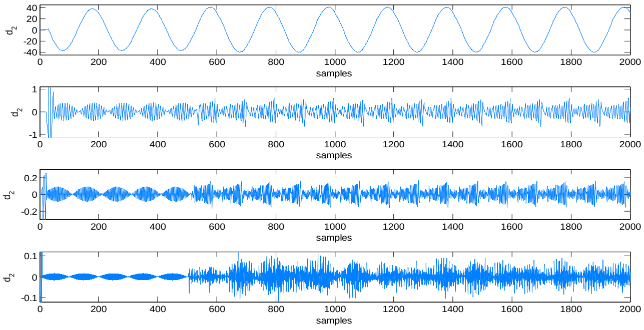

Fig.26 Wavelet Transform of phase-B current signal of Distribution feeder during Non-linear load switching

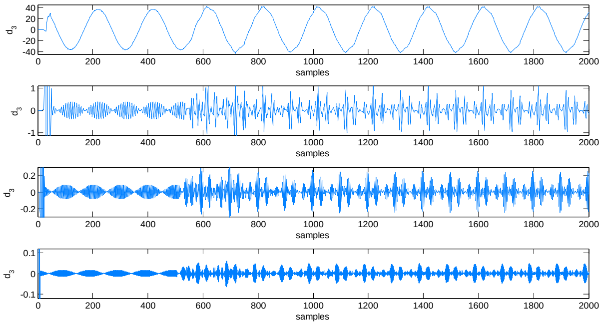

Fig.27 Wavelet Transform of phase-C current signal of Distribution feeder during Non-linear load switching

The complete performance of the proposed technique has been tested by its application to data under different conditions. The test set was formed by patterns from different situations compared to the training patterns. There is a large spikes in d1 to d4 coefficient in signal waveform as shown in fig. 25, 26 and 27. It is clearly observed for Non-linear load switching.

Protection of distribution Feeder:

The relay in distribution feeder is a sensor, which senses abnormal signals in the power system and trips the protective circuit. The inverse definite minimum time characteristics of over current and earth fault relay may be considered for developing k-Nearest Neighbor Method (KNN). There is a stabilized relationship between plug setting currents and operating time of relay.

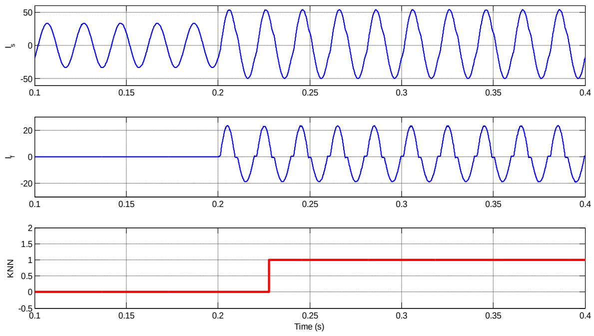

Fig.28 Decision Tree based relay output Response

The training performance curve of k-Nearest Neighbor Method (KNN) is shown in Fig.28.Simulation results show that, with the application of k-Nearest Neighbor Method (KNN) and the unique way of choosing k-Nearest

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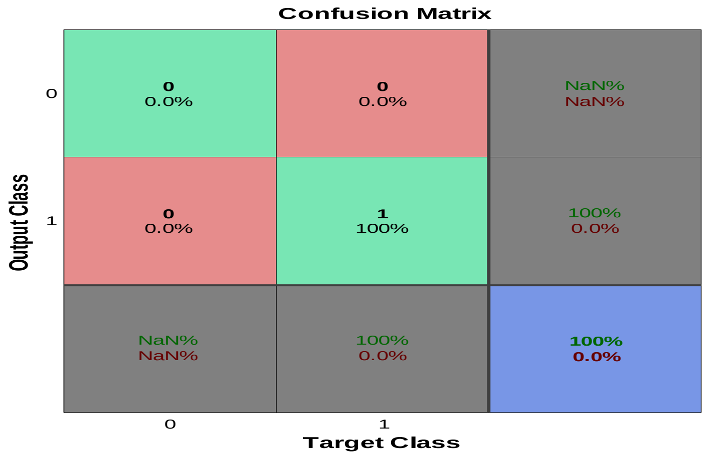
Neighbor Method (KNN) inputs, the proposed differential relay operates properly under different conditions and the diagnosis is both accurate and fast.



VI. CONCLUSIONS

The proposed new technique for HIF detection using Wavelet Transform and Decision Tree .The simulation results of the developed HIF model, incorporated in MATLAB. Wavelet and DT analysis for HIF, faults, load switching and capacitor switching and Non-Linear load are presented. To verify the performance, numerous cases have been analyzed. The results obtained have proved the correct operation (secure and reliable) of the developed method under various transient operation conditions in electrical distribution networks. This methodology gives the exact output corresponding to each HIF situation, and it is not confused by the transients caused by LIFs and normal switching events. After the test data has been fed into the DT and the results obtained, it was noted that the efficiency of the decision trr in terms of its ability to detect the occurrence of a fault is more than 71percent.

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