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HIGH IMPEDANCE FAULTS IN A DISTRIBUTION FEEDER DETECTION BY ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

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ABSTRACT

A fault on a distribution feeder affects the reliability of supply and also reflects the status on power quality of the system. Improvement in quality, however, can be made by locating the fault as soon as possible This paper addresses the challenge posed to power system protection engineers , where in the high impedance faults are difficult to detect by any conventionally current operated over current relays, by the suggestion of wavelet based ANFIS approach.

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 Adaptive Neuro Fuzzy Inference System (ANFIS). The current wave form, when measured at the relaying point, yields coefficients which are applied as the inputs to the Adaptive Neuro Fuzzy Inference System (ANFIS). A realistically developed HIF model using a typical IEEE 13 Radial Distribution System was used to determine the enactment of the technique for various types of HIF like Capacitor switching , Linear faults , transients etc. The method was adequately robust, fast and accurate.

Keywords-High-Impedance fault Detection, Wavelet transforms, Adaptive Neuro Fuzzy Inference System (ANFIS), Electrical distribution system, No fault.

I. INTRODUCTION

The Detection and identification of High Impedance Faults (HIF) in electrical distribution networks are a challenge for protection engineers. Since the very nature of these types of faults and different levels of low fault current levels with respect to feeder load current. High Impedance Faults in Power networks represent safety hazards, utility liability problems and possibility of equipment damage due to arcing and resistance fires. Various methods have been enunciated by different researchers to cope with the problems associated with HIF.

The last two decades saw a variety of methods proposed by researchers to enhance the detection of HIFs in the power distribution network [1]. The detection techniques are classified as that of Electrical and Mechanical in nature. In detection by mechanical means, the snapped conductors are supported through low impedance paths, whereas the mathematical methods related to electrical parameters are time domain and frequency domain algorithms An algorithm for ground relay / proportional relay [3, 4], a smart relay dependent time domain feature extraction [5], were reported for time domain type and arc detection based frequency domain type was proposed [6]. Research related to harmonics [7,8] and inter harmonic components [9] and high frequency spectra [10] were also published Kalman filters [11] , fractals[12] , neural networks [13] were some of the other methods used to mitigate the limitations of Fourier analysis. Wavelet method [14] and fuzzy decision making IF-THEN rules in [15] were the recent advancements in HIF detection

Also, a methodology for HIF in radial distribution feeders by means of logic of fuzzy reasoning was proposed. This analyzing feeder responses to impulse waves, injected periodically in to the feeder [16].

In this work a new HIF detection technique supported by the wavelet feature extraction and FIS for decision making is presented. The live data on a 33 kV radial distribution feeder for HIF was collected in this research paper. Data for other transient events was simulated of this 33Kv distribution feeder using MATLAB/SIMULINK. The mainly objective of this work is to propose a scheme which can detect normal switching operation and HIF by adapting a combination of WT and ANFIS methods. The interface of wavelet and ANFIS was evaluated for effective combination. Simulation results show that this technique is most efficient in detecting high-impedance faults of distribution systems.

II. HIGH IMPEDANCE FAULT DETECTING METHODOLOGY

The proposed methodology to detect HIFs and discriminate them from normal transient switching operations comprises two step processes [20].

In a first stage, the current signals of the feeders, using WT, are analyses to obtain the relevant data signals In the second stage, a classifier called ANFIS is used as a classifier which is properly trained, to classify the state of each feeder. Fig.1. gives the structure showing the application of WT and Adaptive Neuro Fuzzy Inference System (ANFIS). these different stages of the working of the methodologies are given in the schematic block diagram . 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.

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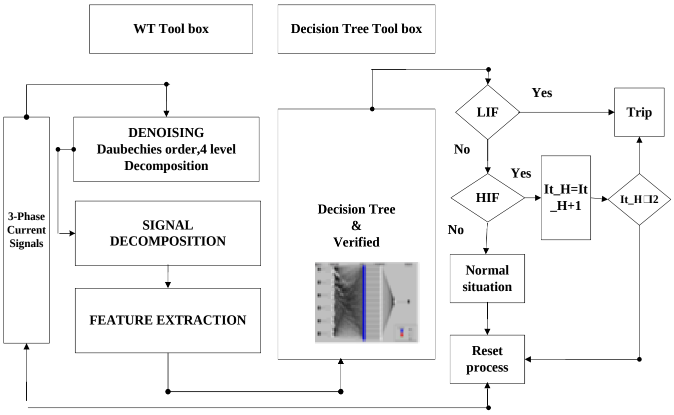

Fig. 1.Schematic diagram of the methodology

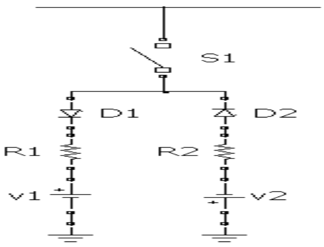

Fig.2.HIF model

HIF currents are generated by using simplified two-diode model. The model having 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 diodes 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. The power quality with better power factor is provided through capacitor banks installed across the 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.

2.1 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

(c) Feature extraction

The use of the Wavelet Tool box from MATLAB/SIMULINK, which is provides useful functions and an extraordinary computing environment for the implementation of the WT in an efficient way in a computer [26]. 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.

2.1.1. Process of De-noising

The de-noising process is used to eliminate the existing distortion in the current signals, which may have been produced by several events: switching operations and other feeder events etc. The main idea of this process is a DWT pre-processing, in order to convert the three-phase current signals into one dimension hard threshold de-noising stage. For this purpose, a Daubechies order 4(db2), level 4 wavelet decomposition is applied to the registered currents. The heuristic variant of the Steins unbiased estimate principle gives the threshold rule.

2.1.2. decomposition of signal

The information obtained 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. That is, by showing large coefficients in different frequency bands when the disturbance appears. This process is known as Decomposition process, in which the Daubechies basis of order four (db4), in seven decomposition levels, has been applied to produce different frequency bands 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) has been adopted in the developed analysis. 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

2.1.3. 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 multilayer Adaptive Neuro Fuzzy Inference System (ANFIS) 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.

2.2 ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

During the last two decades adaptive neuro-fuzzy approach has been became a popular method in control area. In this part, a brief description of the adaptive neuro-fuzzy inference system (ANFIS) principles is given which are referred to [17]. The fundamental structure of the type of fuzzy inference system (FIS) could be seen as a

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model that maps input characteristics to input membership functions. After that, it maps all membership function as input to rules and rules to a

set of characteristics of FIS output. On the last step, FIS maps characteristics of output to membership functions as output, and the membership function as output to a decision associated with the output. As can be seen that FIS have been stated only non-arbitrary membership functions that were chosen arbitrarily, Fuzzy inference system (FIS) is only used to modeling systems whose the structure of fuzzy rule is essentially predetermined by the operator interpretation of the

variable characteristics in the model. The variations in the magnitude of the data cannot be arbitrarily associated with a membership function. Hence the FIS parameters are to be tailor made for the relevant input – outputs .Therefore, the necessity of adaptive properties in fuzzy inference system becomes obvious.

The adaptive neuro learning concept works similarly to the artificial neural networks. Neuro adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. The network type arrangement for ANN can be used to map inputs and outputs through membership functions and related parameters.

It is observed from the study of (FIS) and (ANN) that the modeling of differential protection system by using any one of them. It will be very complex. The power system operation in transient period cannot be easily described by artificial explicit knowledge, because it is affected by many unknown parameters. These drawback of (FIS) and (ANN) are overcome by the integration between the (ANN) technology and the fuzzy logic system, to originate another artificial intelligence technique called .Adaptive Neuro Fuzzy Inference

System (ANFIS). This research is integrating the learning capabilities of (ANN) to the robustness of fuzzy logic systems in the sense that fuzzy logic concepts are embedded also provides a natural frame work for combining both numerical information in the form of input / output pairs and linguistic information in the form of IF – THEN rules in a uniform fashion as presented in [18].

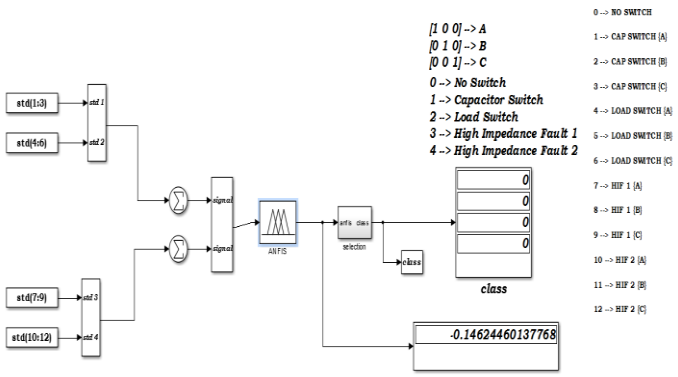

Fig. 3 Simulation diagram of ANFIS

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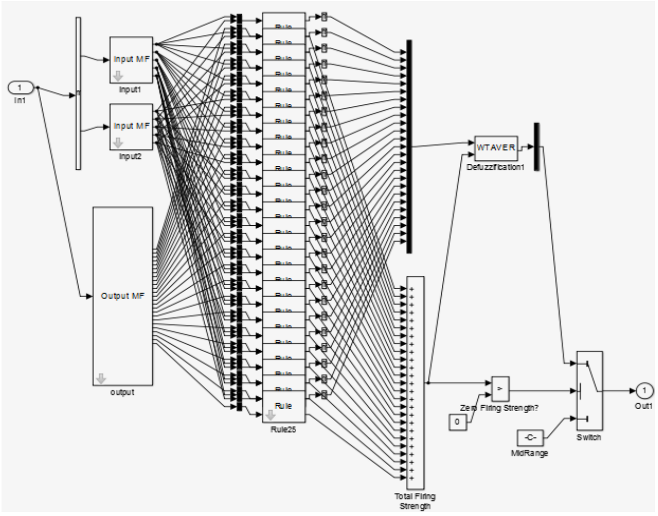

Fig.4 The architecture of the ANFIS

The ANFIS architecture is shown in Figure 4.

The Architecture comprising by input, fuzzification layers, inference unit and defuzzification layers. The ANFIS architecture can be desripted as consisting of N neurons in the input layer and F membership functions for each input, and F*N neurons in the fuzzification layer. The inference unit and defuzzification have FN rules with FN neurons, while the output layer has one neuron. For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs x and y and one output z as shown in Figure 4. For a zero-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following:

Rule 1: If x is A1 and y is B1, Then f1 = r1 (2)

Rule 2: If x is A2 and y is B2, Then f2 = r2 (3)

Here the output of the i-th node in layer n is denoted as $O_{n,i}$

Layer 1: Every node i in this layer is a square node with a node function:

$$O_i^1 = \mu A_i(X), \quad for\ i = 1, 2. \qquad (4)$$

or

$$O_i^1 = \mu B_{i-2}(y), \quad for\ i = 3, 4. \qquad (5)$$

where x is the node-i input, and A_i is the label of linguistic terms (big, low, etc.) associated with this node function. O_i^1 is the Ai membership function. O_i^1 Specifies the degree to which the given x satisfies the Ai. Usually mAi (x) is chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function:

$$\mu_A(x) = \frac{1}{1 + [\frac{x - c_i}{a_i}]^{2b_i}} \qquad (6)$$

Parameters in this layer are referred to as premise parameters.

Layer 2. Each node in layer 2 is labeled by Π which multiplies the incoming data and sends the product out. For instance,

$$O_i^2 = w_i = \mu A_i(X) X \mu B(y), \quad for\ i = 1, 2. \qquad (6)$$

Each node output represents the firing strength of a rule. Other T-norm operators which shows generalized AND can be used in layer 2.

Layer 3 Every node in this layer is a circle node labeled N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules firing strengths:

$$O_i^3 = \bar{w} = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \qquad (8)$$

The outputs of layer 3 will be mentioned as normalized firing strengths.

Layer 4. Every node i in this layer is a square node with a node function:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \qquad (9)$$

$\bar{w}_i$ is the layer 3 output, while $\{p_i, q_i, r_i\}$ is the set of parameter. All parameter in this layer will be mentioned as consequent parameters.

Layer 5. The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals, i.e.,

$$O_i^5 = \sum \bar{w}_i f \qquad (10)$$

2.2.1 Adaptive Neuro-Fuzzy Inference System (ANFIS) 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)

$$\%Error = \frac{target\ output - calculated\ output}{target\ output} X100 \qquad (2)$$

Taking as an example the dataset of feeder number one (Section3), the solutions matrix obtained from (2) shows the percentage comparison between the outputs and targets of testing cases, using the previously mentioned Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture.

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.

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

2.2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS) stage

Adaptive Neuro-Fuzzy Inference System (ANFIS) stage once the training and testing processes have been concluded, the resulting networks are ready to operate. The Adaptive Neuro-Fuzzy Inference System (ANFIS) 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 nearest integer value. 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

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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 Adaptive Neuro-Fuzzy Inference system (ANFIS) in MATLAB/ SIMULINK is shown in Fig. 5and a typical Structure of ANFIS controller model is designed as in Fig. 6.

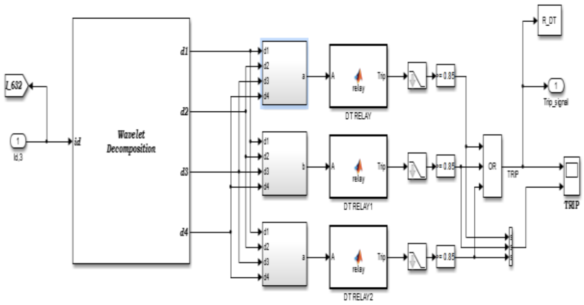

Fig. 5 Wavelet with ANFIS

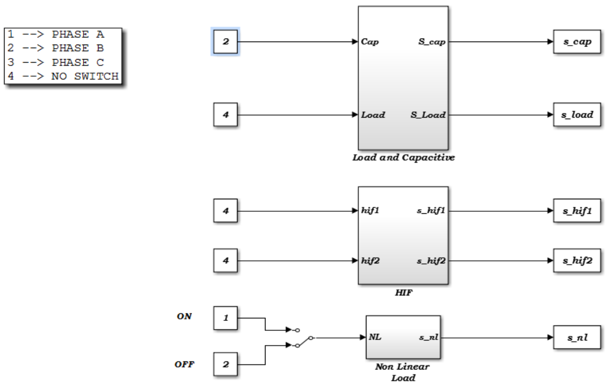

Fig. 6 Structure of ANFIS controller

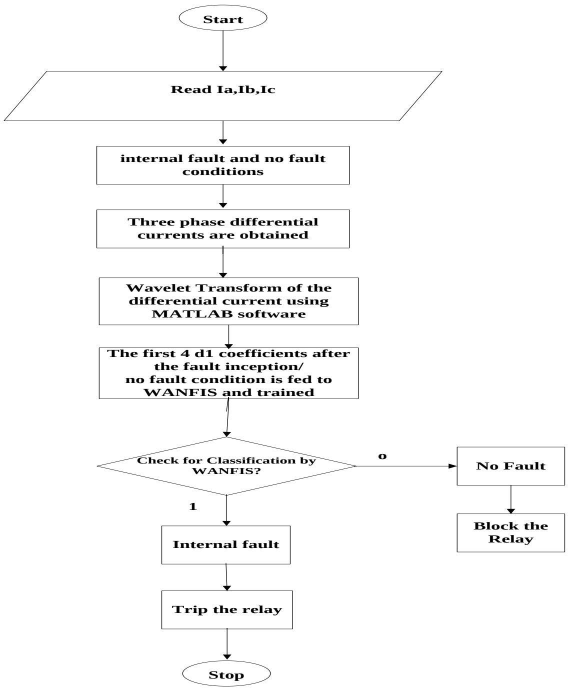

Fig. 7 Flow Chat for adaptive neuro-fuzzy inference system (ANFIS)

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III. 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 matrix assumes a resistivity of 100 Ohm-meters and the admittance matrix assumes a relative permittivity of 2.3.

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

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

***(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.

***(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 [20]. The test feeder is IEEE 13 Which Inspite of Being a small Feeder displays the following characteristics.

1. Short and relatively highly loaded for a 4.16 kV feeder
2. Overhead and underground lines
4. Shunt capacitor banks, shunt connected
5. In-line transformer
6. Unbalanced loads- concentrated and distributed

The complete data for this system is given below to illustrate the form of the data for all of the test feeders [14].

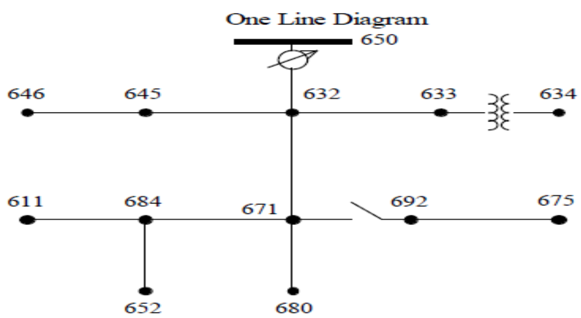

Fig.8 13 Node IEEE Test Feeders

IV 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 modelled and simulated with MATLAB/SIMULINK as given in Fig.9

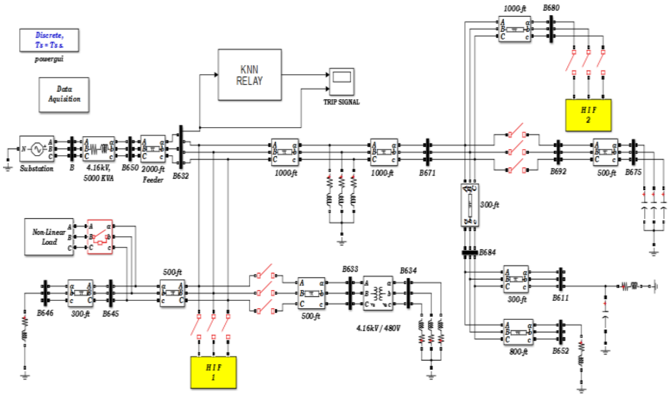

Fig. 9 Configuration of Distribution feeder

Finally, the DT 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. 7 shows the current signal produced by High Impedance Fault 1applied in feeder 632.

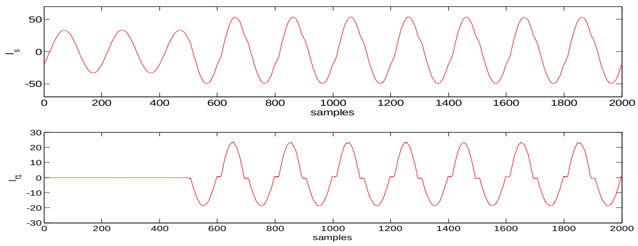

Fig. 10 High Impedance Fault 1distorted current on phase- A

After the de-noising process, Fig. 10,11 and 12shows the behavior 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.

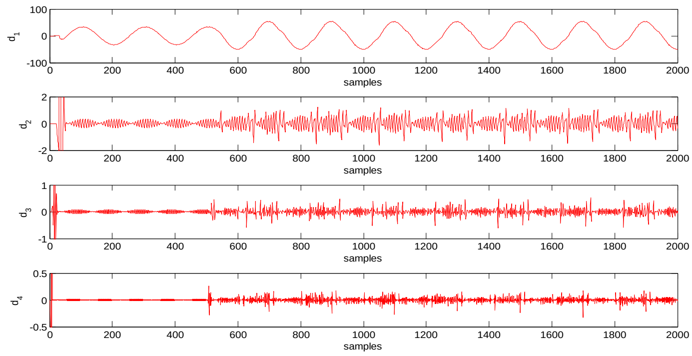

Fig. 11 Wavelet Transform of phase-A current signal of Distribution feeder during HIF1 Transients

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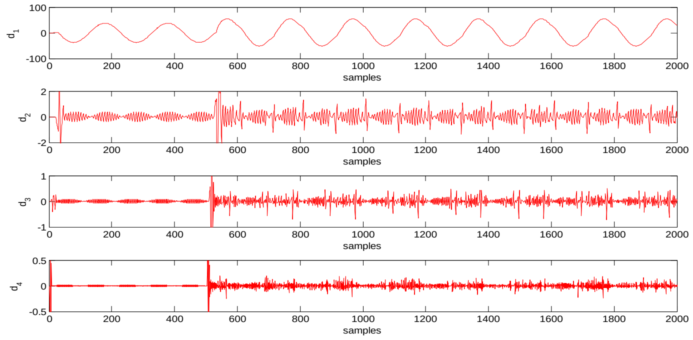

Fig.12 Wavelet Transform of phase-B current signal of Distribution feeder during HIF1 Transients

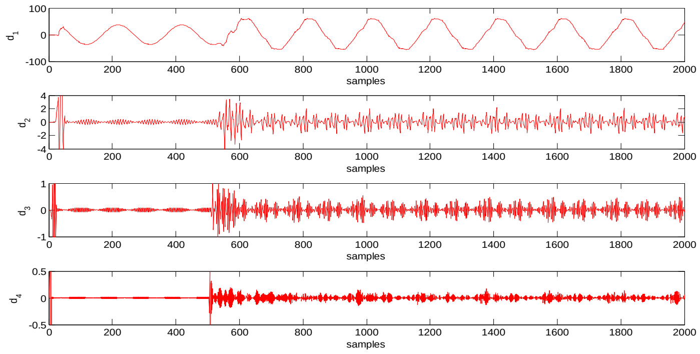

Fig.13Wavelet Transform of phase-C current signal of Distribution feeder during HIF1 Transients

Applying the STD of each decomposition level, the numerical values of patterns can be realized from the analyzed signal. Applying these data matrix as the input to the selected adaptive neuro-fuzzy inference system (ANFIS), 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. 14 shows the current signal produced by High Impedance Fault 2applied in feeder 680.

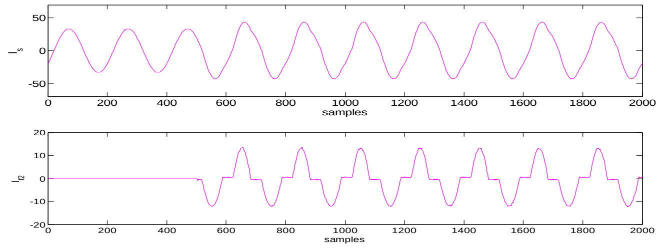

Fig.14 High Impedance Fault 2distorted current on phase A.

After the de-noising process, Fig. 15, 16 and 17 shows the behavior 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.

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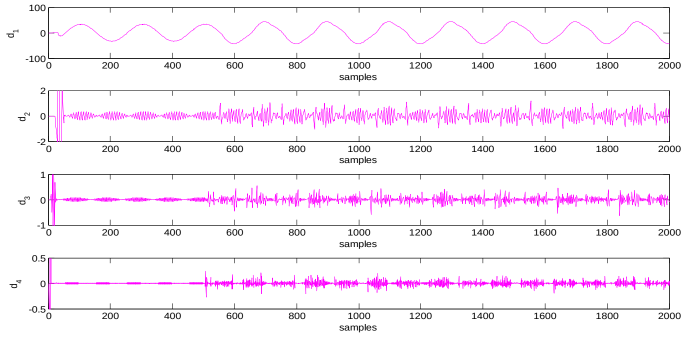

Fig.15 Wavelet Transform of phase-A current signal of Distribution feeder during HIF2 transients

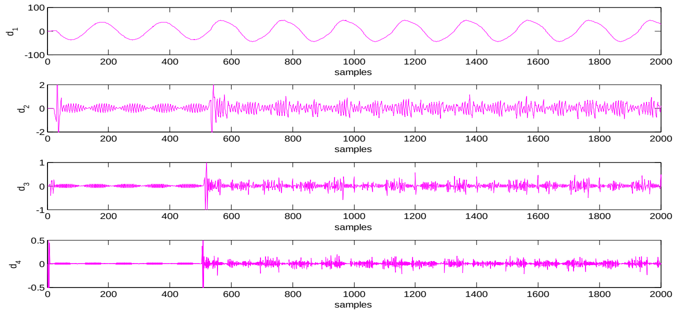

Fig.16Wavelet Transform of phase-B current signal of Distribution feeder during HIF2 Transients

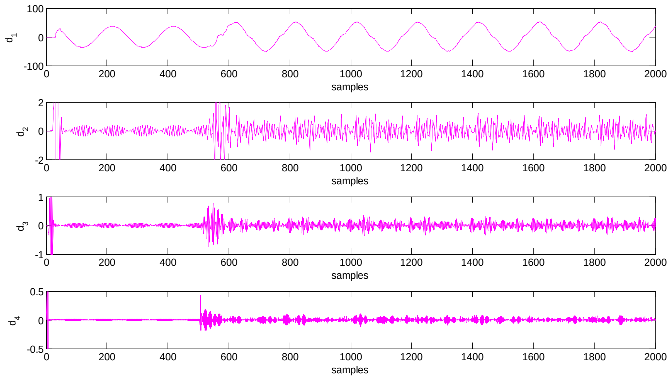

Fig.17 Wavelet Transform of phase-C current signal of Distribution feeder during HIF2 Transients

Applying the STD of each decomposition level, the numerical values of patterns can be obtained from the analyzed signal. Applying these data matrix as the input to the selected adaptive neuro-fuzzy inference system (ANFIS), 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 HIF2.

Capacitor switching: capacitor switching created at feeder bus 675inphase A, phase B and phase C with 100 kVAr and 0.05Sec. to 0.5 Sec. of inception time. Fig. 18 shows the current signal produced by capacitor switching applied in feeder 675.

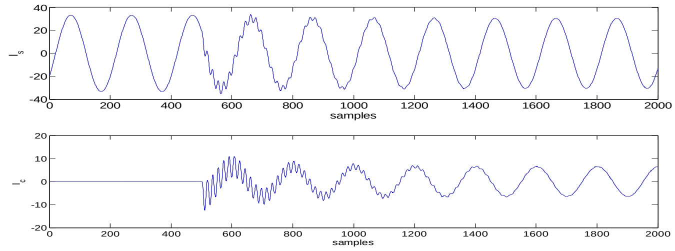

Fig.18 capacitor switching distorted current on phase- A

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 adaptive neuro-fuzzy inference system (ANFIS). Finally, the state of a feeder is calculated according to the outputs of the neural network.

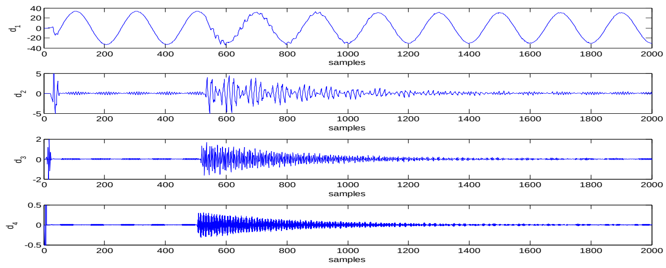

Fig.19Wavelet Transform of phase-A current signal of Distribution feeder during capacitor switching

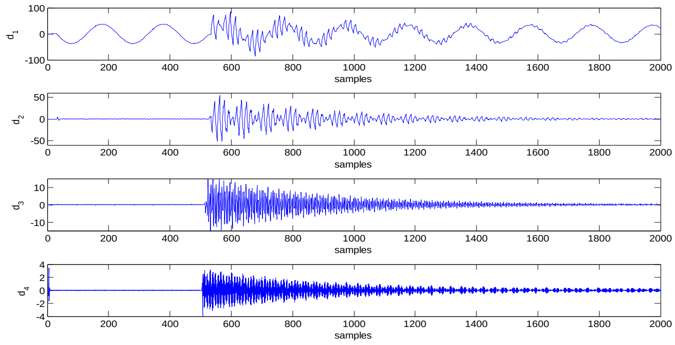

Fig.20 Wavelet Transform of phase-B current signal of Distribution feeder during capacitor switching

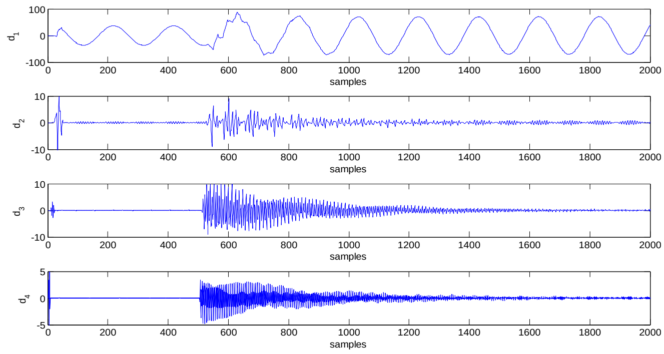

Fig.21Wavelet Transform of phase-C current signal of Distribution feeder during capacitor switching

The complete performance of the proposed technique has been

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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 spike in d1 to d4 coefficient in signal waveform as shown in fig.19, 20 and 21. It is clearly observed for capacitor switching.

Load switching: load switching created in between feeder bus 632 and 671in phase A, phase B and phase C with 160 kw and 0.05Sec.to 0.5Sec. of inception time. Fig. 22 shows the current signal produced by load switching applied in between feeder bus 632 and 671.

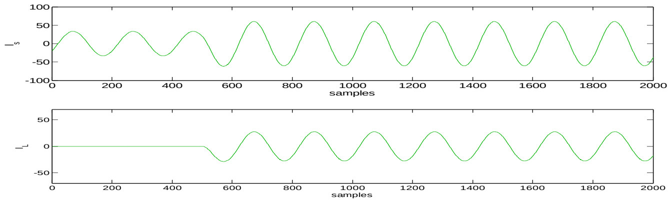

Fig.22 Load switching distorted current on phase A

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 adaptive neuro-fuzzy inference system (ANFIS). Finally, the state of a feeder is calculated according to the outputs of the neural network.

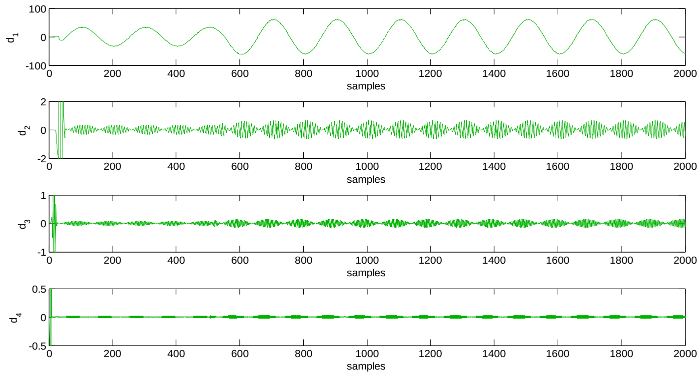

Fig.23Wavelet Transform of phase-A current signal of Distribution feeder during load switching

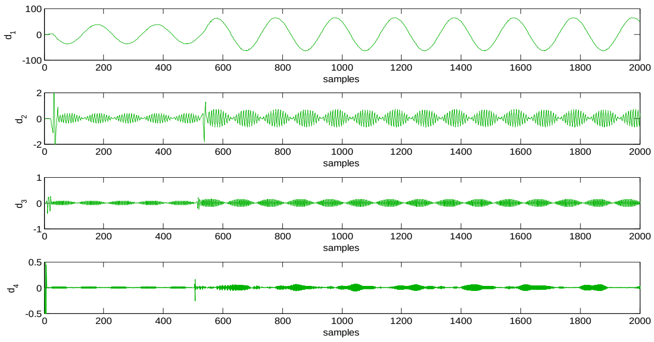

Fig.24 Wavelet Transform of phase-B current signal of Distribution feeder during load switching

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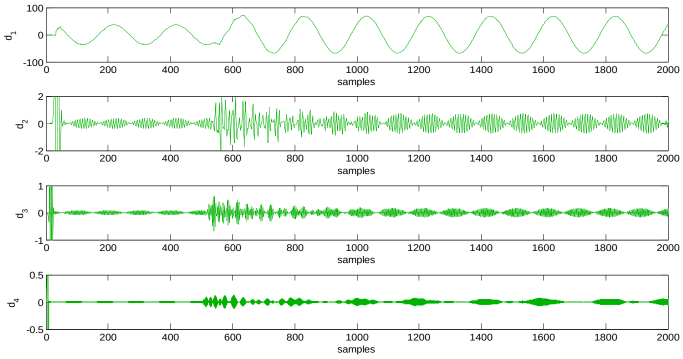

Fig.25 Wavelet Transform of phase-C current signal of Distribution feeder during load switching

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.23, 24 and 25. It is clearly observed for load switching.

Non Linear Load Switching:

Non-linear load switching created at feeder bus 645in phase A, phase B and phase C with 0.5kVAr and 0.05Sec.to 0.5 Sec. of inception time Fig. 26 shows the current signal produced by the nonlinear load applied in feeder 645.

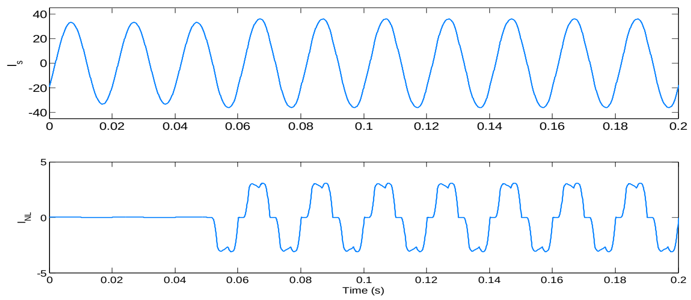

Fig.26 Nonlinear load distorted current on phase A.

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 adaptive neuro-fuzzy inference system (ANFIS). Finally, the state of a feeder is calculated according to the outputs of the neural network.

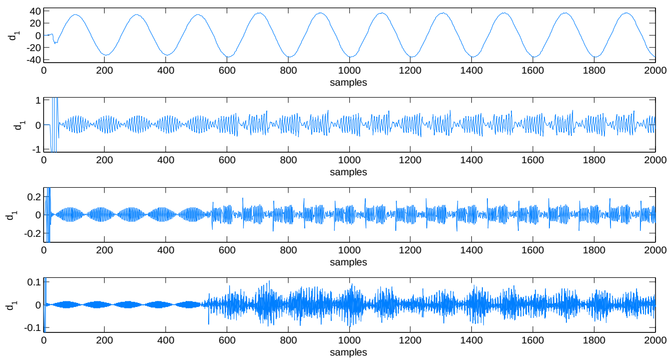

Fig.27 Wavelet Transform of phase-A current signal of

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Distribution feeder during Non-linear load switching

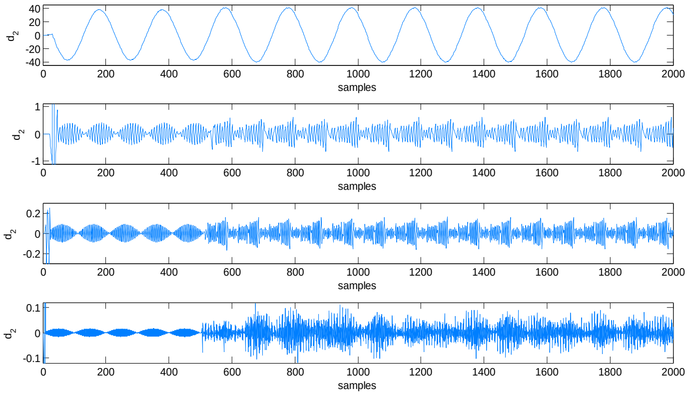

Fig.28 Wavelet Transform of phase-B current signal of Distribution feeder during Non-linear load switching

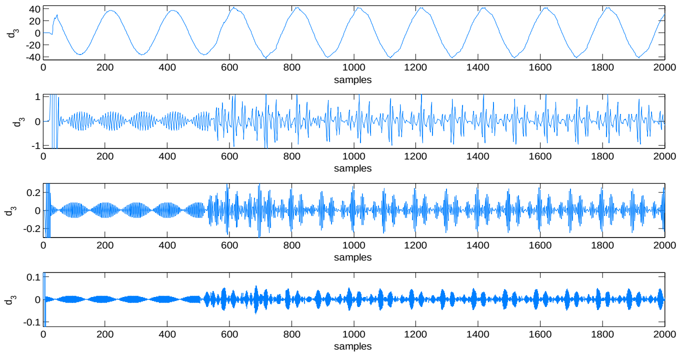

Fig.29 Wavelet Transform of phase-C current signal of Distribution feeder during Non-linear load switching

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. 27, 28 and 29. 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 adaptive neuro-fuzzy inference system (ANFIS). There is a stabilized relationship between plug setting currents and operating time of relay.

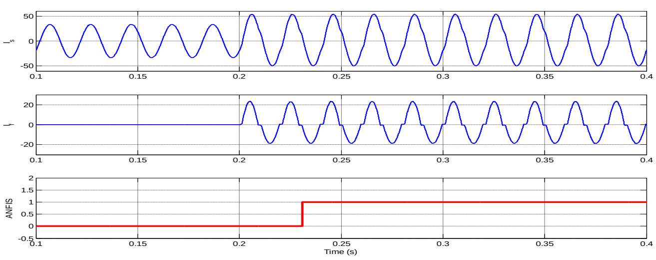

Fig.30 ANFIS based relay output Response

The training performance curve of Decision Tree is shown in Fig.27.Simulation results show that, with the application of adaptive neuro-fuzzy inference system (ANFIS) and the unique way of choosing adaptive neuro-fuzzy inference system (ANFIS) inputs, the proposed differential relay operates properly under different conditions and the diagnosis is both accurate and fast.

V. CONCLUSIONS

In this paper, a new HIF detection method based on the combination of Adaptive Neuro-Fuzzy Inference System (ANFIS) and WT is proposed. This method is an alternative method for diagnosing of HIF from no fault case. In this method, the feature is extracted using wavelet output. By investigating different mother wavelets, feeder signals and detail types, the base case is selected. In the proposed method, the Adaptive Neuro-Fuzzy Inference System (ANFIS) system is used for classification. The Adaptive Neuro-Fuzzy Inference System (ANFIS) system uses training data to perform classification. The 80 training data used in this paper. The Adaptive Neuro-Fuzzy Inference System (ANFIS) system is able to perform classification accuracy. In addition, an accurate combined model used to model the HIF. This combined model has the high ability to model different types of HIF. In order to study the performance of the proposed method for different types of HIF case and different normal Working conditions such as Capacitor Switching, Load Switching and Non Linear Switching were examined. The obtained results have a very good accuracy as high as 94.19%. This indicates that the proposed algorithm has correct performance under different operating conditions in the distribution feeder network.

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