# Arcing Fault Detection in Feeder Networks Using Discrete Wavelet Transform and Artificial Neural Networks

**Gayathri Vijayachandran, Bobin.K.Mthew**

***Abstract***— ***Arcing faults in transmission networks are caused when a current carrying conductor makes an unwanted electrical contact with ground or is temporarily short circuited with another current carrying conductor through a high impedance medium. High impedance arcing faults restricts the flow of current below the detection level of the protective devices and hence cannot be detected by conventional relays. In this paper a new method is proposed for the detection of arcing faults due to leaning trees in medium voltage (MV) networks. Firstly, an arc model is developed in order to reproduce the fault circumstances. Then based on a fault detection algorithm the fault features are extracted using a signal processing technique called Discrete Wavelet Transform (DWT).The proposed algorithm is implemented in a simple MV network to identify the faulty phase and in a feeder network to identify both the faulty phase and feeder. Further the results obtained using DWT is validated with the help of Artificial Neural Networks (ANN).The results obtained above validate the effectiveness of the proposed methodology.***

***Index Terms***— ***Absolute sum, Arc model, Artificial Neural Networks, Back propagation algorithm, Discrete Wavelet Transform ,High impedance fault, Universal Arc representation.***

## I. INTRODUCTION

Over the years, conventional protection schemes have been successfully used to detect and to protect against the low impedance faults in power system networks where a small resistance only limits the fault current. However, when the resistance of the fault path is very high and therefore the fault current cannot be easily recognized, it is called a high impedance fault.

A high impedance arcing fault result either from high impedance fault object or when a primary circuit conductor makes an unwanted electrical contact, which restricts the flow of current below the detection level of the protective devices. High impedance faults often occur when an energized conductor breaks and falls to the ground.

Due to the existence of air between ground and conductor, the high potential difference in such a short distance excites the appearance of the arc.eg. fault caused due to contact of leaning trees on conductors in EHV and MV networks. Such a fault case cannot be reliably detected, in particular in distribution systems, using the conventional relays because its current is very small. It may also create a public hazard, and any unsafe condition is of concern to utilities. For this reason, the detection of high impedance arcing faults in electric distribution systems has been the subject of intense interest over the history of utility systems. Arcing often accompanies these faults, which further poses fire hazard and therefore the detection of such faults is critically important.

The faults which especially occur in medium voltage networks in rural areas with overhead lines are often due to leaning trees. They are categorized as high impedance arcing faults due to the tree resistance (several hundred ohms) and the associated arcs. Such faults often draw small currents which cannot be detected by conventional relays. Detection of arcing faults due to leaning tress is hence important as they pose a threat to the safety of general public and animals. In this paper arcing fault due to leaning trees in MV networks is studied.

### A. Methodology

Towards modeling and detecting of the high impedance arcing faults, the arc representation has to be studied and the fault characteristics have to be measured using experiments or to be captured from field tests. For this different arc models and its characteristics has to be studied. The most suitable arc model is then simulated to obtain fault characteristics .The simulated arc model is inserted in the test systems to reproduce the fault circumstances. Then the fault features are extracted using DWT.

Based on the proposed detection algorithm a suitable MATLAB program is written and the extracted fault features are utilized in this program. Using this program the faulty section of the test system can be identified and is displayed in the command window.

In the second stage, the features extracted using DWT are fed as inputs to neural networks. Thus a combination of DWT and ANN is used which validates the effectiveness of the proposed fault detection algorithm.

### B. Literature Survey on Arc Models

In [1],[2],[3],[4] arc was firstly studied concerning interruption capabilities of circuit breakers, in which arc models were initially introduced to enhance circuit breaker testing. The arc models have been recently modified to study the performance of arcing faults in different voltage levels and to test their detections and their discriminations**.** Arc models can be classified into physical models, black box/thermal models and thermal models as discussed in [3].Physical

**Manuscript received August 14, 2013.**

**Gayathri Vijayachandran**, Department of Electrical and Electronics, Sree Buddha College of Engineering, Pattoor, India.

**Bobin.K.Mathew**, Department of Electrical and Electronics, Amal Jyothi College of Engineering,, Kanjirapally, India.

models are based on the actual physical process of the arc. These models use the principle of fluid dynamics, thermodynamics and Maxwell's equations. These physical models are normally used in the development of circuit breakers. Thermal models are described by simple mathematical differential equations. These equations give the relation between the arc conductance and measurable parameters such as arc voltage and arc current. Typical well known black box models are the Cassie model and the Mayr model.. The Cassie equation is used during the high current conditions and the Mayr equation for the zero current periods. Based on these two models a number of arc models were developed likeHadebank model, Schwarz model, Modified mayr model, Improved Mayr model, KEMA model. The differential equations of these models are given in [14]. These models are also known as thermal models. Arcing fault models are also based on these models. Parameter models are more accurate black box models. Parameters are obtained from complex functions and tables.

For transmission line arcing faults in [6] there are two arcing fault models that have been recently introduced using the dynamic equations. The first one is the Kizilcay model. The second one is the Johns model. In this paper for developing an arc fault model due to leaning trees in MV networks a combination of Johns and Kizilcay model is appropriate and the empirical equation is mentioned in [5], [6],[7] and the parameters were obtained from the experimental setup described in[5]. The Johns-Kizilcay model is known as the universal arc representation .The universality of this approach is verified in papers like [5], [6], [7] etc. Hence this model representation is implemented in MV networks. The arcing fault model is represented in two parts: an arc model and a high resistance (tree resistance) [7].

### C. Discrete Wavelet Transform

Discrete Wavelet Transform is found to be useful in analyzing transient phenomenon such as that associated with faults on the transmission lines. Multi-Resolution Analysis (MRA) is one of the tools of Discrete Wavelet Transform (DWT), which decomposes original, typically non-stationary signal into low frequency signals called approximations and high frequency signals called details, with different levels or scales of resolution. It uses a prototype function called mother wavelet for this. At each level, approximation signal is obtained by convolving signal with low pass filter followed by dyadic decimation, whereas detail signal is obtained by convolving signal with high pass filter followed by dyadic decimation. The three level decomposition of a signal as given in [9] is shown in Fig. 1.

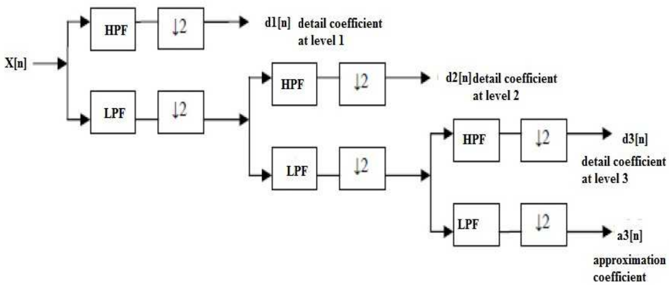



Fig.1 Three level decomposition of a signal

### D. Artificial Neural Networks

An ANN may be considered as a greatly simplified model of the human brain which can be used to perform a particular task or function of interest [16]. It is a powerful tool used for pattern recognition and classification. Hence it can be used to detect faults in transmission line networks. ANNs also possess excellent features such as generalization capability, noise immunity, robustness and fault tolerance. The standard multilayer feed forward network is the neural network architecture selected for the proposed work, and is described below. It consists of three kinds of layers: the input layer, hidden layer and output layer. The function of the input layer is simply to buffer the external inputs to the network. The hidden neurons have no connections to the inputs or outputs. By including hidden layers, the network is empowered to extract higher-order statistics as the network acquires a global perspective despite its local connectivity by virtue of the extra set of synaptic connections and the extra dimension of neural interactions [16]. Figure 2.shows the structure of multi-layer feed forward network.

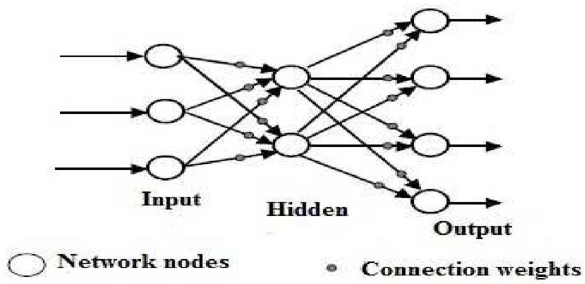



Fig.2 Structure of a multilayer feed forward network

Neural network for a particular application must be trained. There are different training algorithms for feed-forward networks. All of these algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance function. The gradient is determined using a technique called back propagation, which involves performing computations backwards through the network. A variation of back propagation algorithm, called Levenberg-Marquardt (LM) algorithm was used for neural network training, since this algorithm is one of the fastest methods for training moderate-sized feed forward neural networks. It also has a very efficient MATLAB implementation[10].The simple MV network and feeder network used for implementation of proposed work is given in Figs.3 (a) & (b).

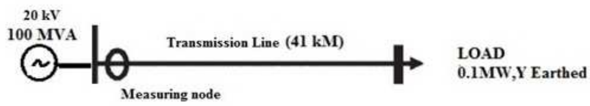



Fig.3 (a) Simple MV network test system

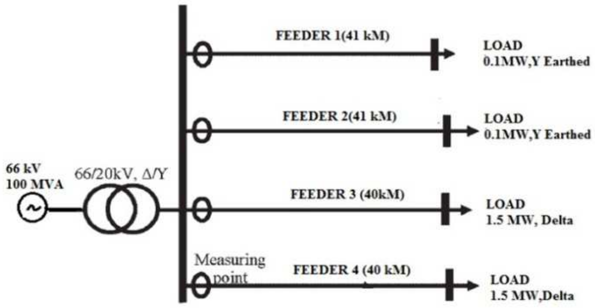



Fig.3 (b) Feeder network test system

## II. MODELING OF ARC USING UNIVERSAL ARC REPRESENTATION

To model arcing fault due to leaning trees in MV networks universal arc representation is used. It is represented by the differential equation as given in Eq. (1).

$$\frac{dg}{dt} = \frac{1}{\tau}(G - g) \qquad (1)$$

where $g$ is the time varying arc conductance, $G=|i|/V_{arc}$ is the stationary arc conductance, $|i|$ is the absolute value of the arc current, $V_{arc}$ is a constant arc voltage parameter, and $\tau$ is the arc time constant and is defined by Eq.(2).

$$\tau = Ae^{Bg} \qquad (2)$$

where A and B are constants or called fitting coefficients. These parameters were obtained from the experimental setup as described in [5] which was conducted by Power Systems and High Voltage Laboratory, Helsinki University of Technology (TKK), Finland by N.I.Elkalashy and M.Lehtonen.

Using Eqns.(1)&2 the universal arc model was modeled in MATLAB/Simulink.It was implemented in the test systems under study as described in [8].The simulated arc characteristics, arc voltage and arc current waveforms obtained were similar to those obtained in[5].This confirms the model accuracy. The suitable parameters selected were: $U_{arc}$=2050 V,A=8.5e-5,B=41977.The simulation time chosen was 0.08s and fault was inserted to the system via a circuit breaker at 0.02s.The MATLAB implementation of MV network with universal arc model inserted is shown in Fig.4.

From Fig.4 it is evident that arc resistance consists of a dynamic arc resistance and a tree resistance. The tree resistance is represented as series resistance as shown in Fig.4.The value of series resistance inserted is about 150kilo ohms.

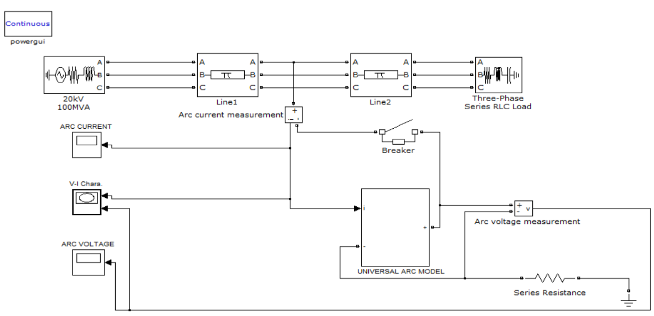



Fig.4 MATLAB implementation of universal arc model in a MV network

The simulated arc voltage, arc current waveforms and arc characteristics obtained is shown in Fig.5(a),(b)&c).Similar results were obtained when the same arc model was implemented in the feeder network.

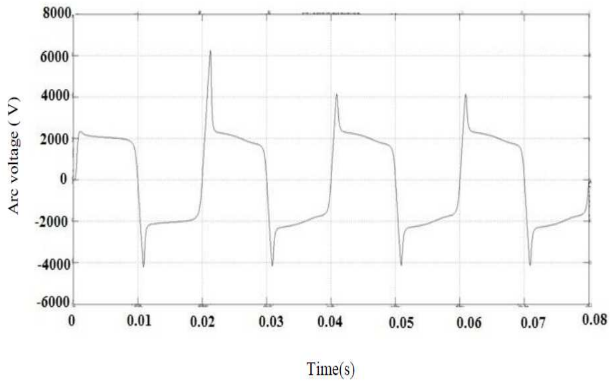



Fig.5 (a) Arc voltage waveform

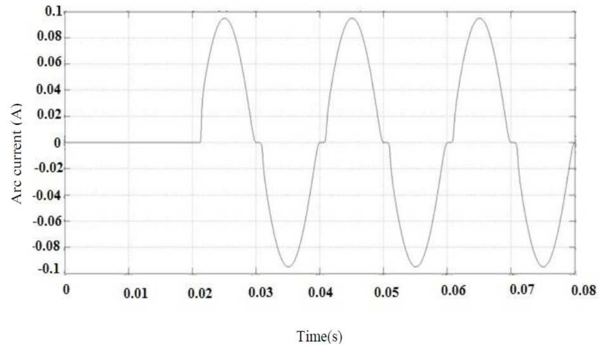



Fig.5 (b) Arc current waveform

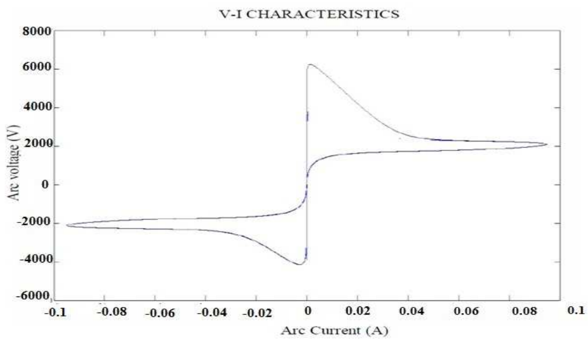



Fig 5(c) Arc characteristics

## III. PROPOSED FAULT DETECTION METHOD USING DISCRETE WAVELET TRANSFORM

During the process of HIF detection, the signal data need to be analyzed to find adequate information that can be useful for the fault detection, because it may not clearly appear in the original signal. That is why we apply a signal processing technique such as DWT. The implementation of DWT can be done either by command line functions or by using Wavelet Toolbox in MATLAB. For this work, the detection algorithm was executed using command line functions.

After inserting the arc model in the test system as described in section II, the required signals has to be analyzed in order to extract the fault features. To analyze the signal they have to undergo the process of signal decomposition. Signal decomposition is done with the help of an appropriate wavelet family. Several wavelet families were tested to extract the fault features using the Wavelet commands which are inbuilt in MATLAB.Daubechies wavelet 14 (db14) is found appropriate for localizing this fault with a sampling frequency of 3 kHz. The details d1 including the frequency band1.5–0.75 kHz have been investigated for the proposed work. The time of occurrence of fault chosen was 0.02s and simulation time 0.08s.

After setting the above parameters suitable MATLAB programs can be written according to the algorithms given in the next two subsections.

### *A. High Impedance Arcing Fault Detection algorithm for MV Network*

**Step 1**: Measure the phase currents or voltages of the test system in Fig.3 (a) after the insertion of arc fault model. For the proposed work phase voltages has been selected.
**Step 2:** The phase voltages are subjected to level 1 decomposition using DWT. Thus we obtain the d1 detail coefficients.
**Step 3**: The absolute sum of d1 detail coefficients for one cycle of power frequency is computed. Let it be Sa, Sb, Sc for respective phase voltages.
**Step 4**: Compare the absolute sums. The faulty phase will have the highest absolute sum and corresponding phase will be printed in the command window. If it is a no fault condition the absolute sum of all three phases will be the same.
**Step 5**: Stop.

This algorithm can be illustrated more clearly using the flowchart shown in Fig.6.

Figure.7 (a) & (b) shows the plot of detail coefficients of each phase during faulty and no fault condition respectively. At 0.02s the voltage signals undergoes disturbance as seen in Fig.7(a).Whereas in no fault condition no disturbance is visible in the signals as shown in Fig.7(b).

Figure.8(a),(b),(c),(d) shows the plot of absolute sums of each phase when phase 'a' is faulty, phase 'b' is faulty, phase 'c' is faulty, no fault condition respectively. From these plots the faulty phase can be easily identified as they have the highest absolute sum.

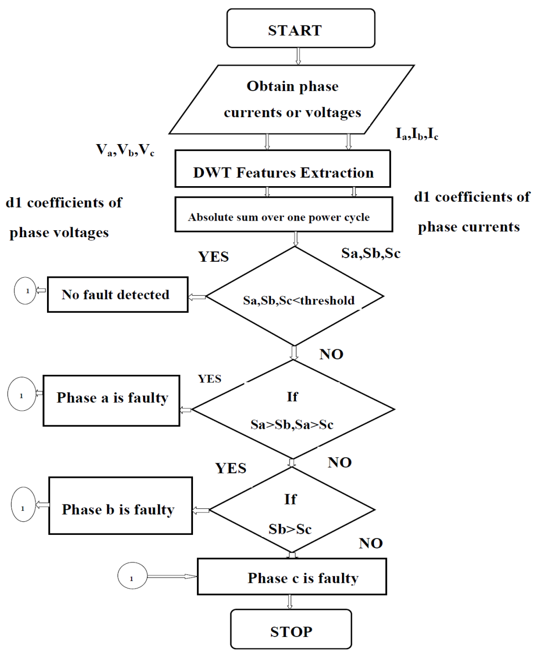



Fig.6. Flowchart for fault detection in MV network using DWT

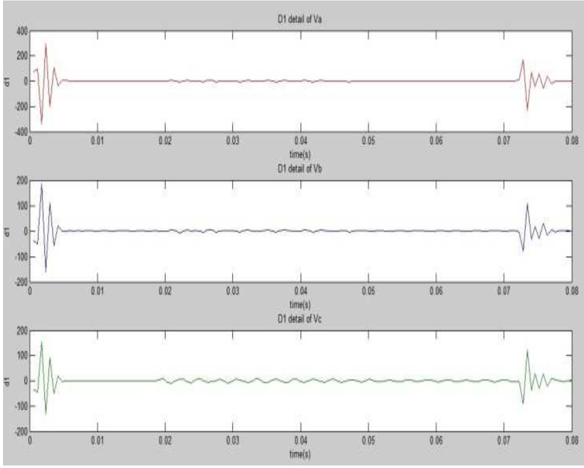



Fig.7 (a) Plot of d1 coefficients during faulty condition (say phase 'c' is faulty)

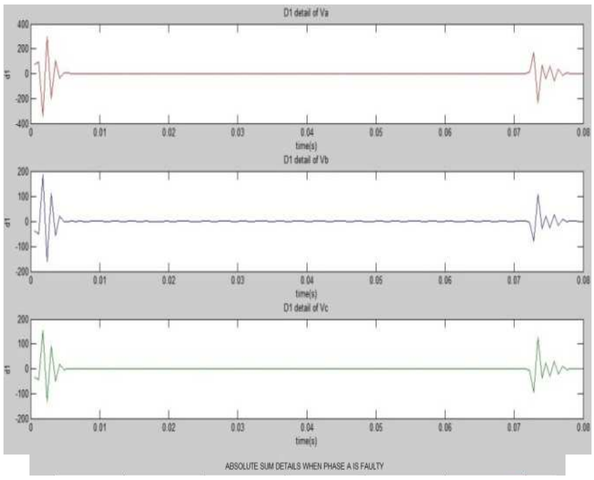



Fig.7 (b) Plot of d1 coefficients during no fault condition

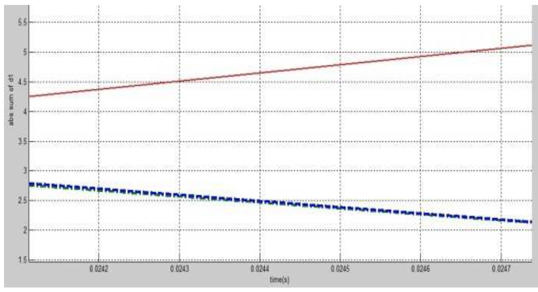


Fig.8 (a) Plot of absolute sums of phase voltages when phase 'a' is faulty

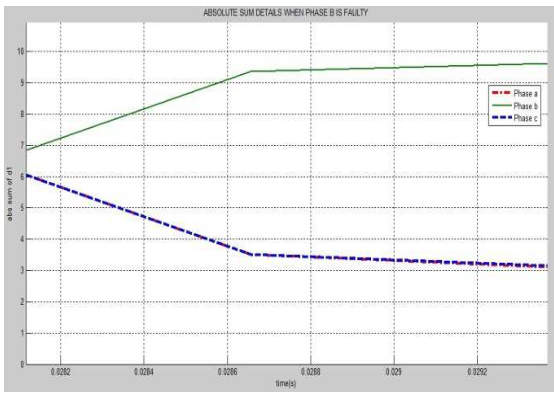



Fig.8 (b) Plot of absolute sums of phase voltages when phase 'b' is faulty

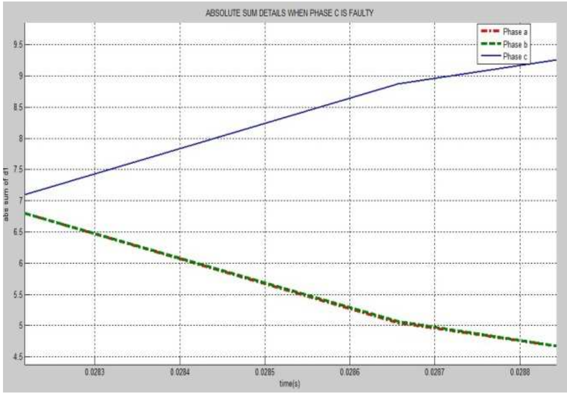



Fig.8 (c) Plot of absolute sums of phase voltages when phase 'c' is faulty

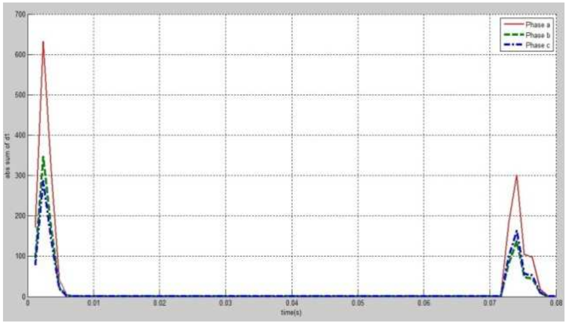



Fig.8 (d) Plot of absolute sums of phase voltages at no fault condition

### *B. High Impedance Arcing Fault Detection Algorithm for Feeder Network*

Using the algorithm given below the faulty phase and feeder can be identified.

**Step 1;** Measure phase currents or phase voltages in all the feeders of Fig.3 (b) after the insertion of arc fault model .For the proposed work phase currents have been selected.

**Step 2:** The phase currents are subjected to level 1 decomposition using DWT. Thus we obtain the d1 detail coefficients.

**Step 3**: The absolute sum of d1 detail coefficients for one cycle of power frequency is computed. Let it be Sa1,Sb1,Sc1 for feeder 1,Sa2,Sb2,Sc2 for feeder 2,Sa3,Sb3,Sc3 for feeder3,Sa4,Sb4,Sc4 for feeder 4.

**Step 4**: Compare the absolute sums.

If Sa1>Sb1&Sa1>Sb1&Sa1>Sc1 and
Sa2>Sb2&Sa2>Sb2&Sa2>Sc2 and
Sa3>Sb3&Sa3>Sb3&Sa3>Sc3and
Sa4>Sb4&Sa4>Sb4&Sa4>Sc4, then print phase 'a' is faulty else go to step 5.

**Step 5**: Sb1>Sc1and Sb2>Sc2 and Sb3>Sc3 and Sb4> Sc4.Then print phase 'b' is faulty else print phase 'c' is faulty. Go to step 6.

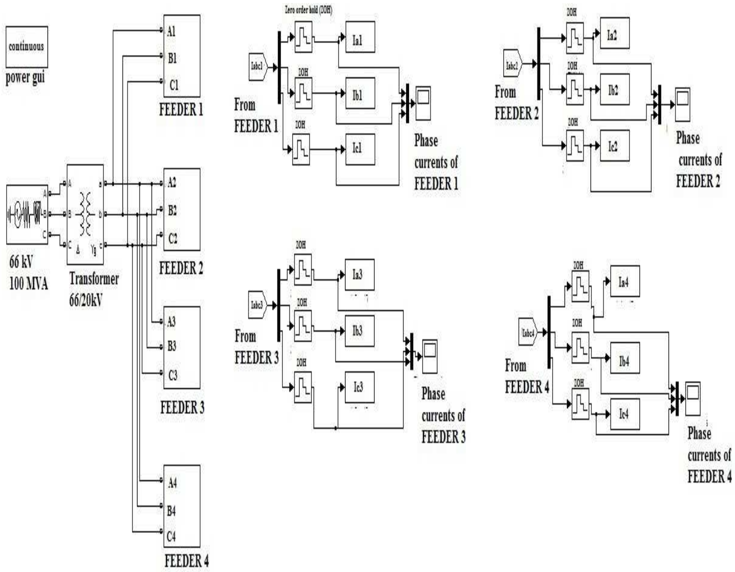
**Step 6**: If Sa1>Sa2&Sa3&Sa4 or
Sb1>Sb2&Sb3&Sb4or
Sc1>Sc2&Sc3&Sc4, then feeder 1 is faulty else go to next step.

**Step 7**: If Sa2>Sa3&Sa4 or Sb2>Sb3&Sb4or Sc2>Sc3&Sc4 then feeder 2 is faulty else go to next step.

**Step 8:** If Sa3> Sa4 or Sb3 > Sb4 or Sc3> Sc4 then feeder 3 is faulty else feeder 4 is faulty.

**Step 9**: Stop.

The MATLAB implementation of feeder network is shown in Fig.9(a) and subsystem for feeder 1 is shown in Fig.9(b).Assume that fault inserted in phase 'a' of feeder 1 as shown in Fig.9(b).The other three feeders can be also modeled similarly.



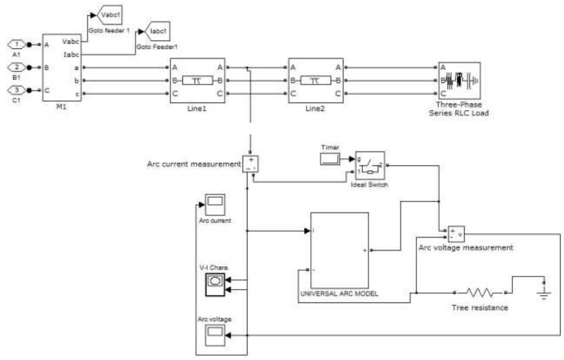




Fig .9 (b) Subsystem of Feeder 1

Figure.10 (a) & (b) shows the plot of detail 1 coefficients when feeder 1, phase 'a' is faulty and no fault condition respectively.

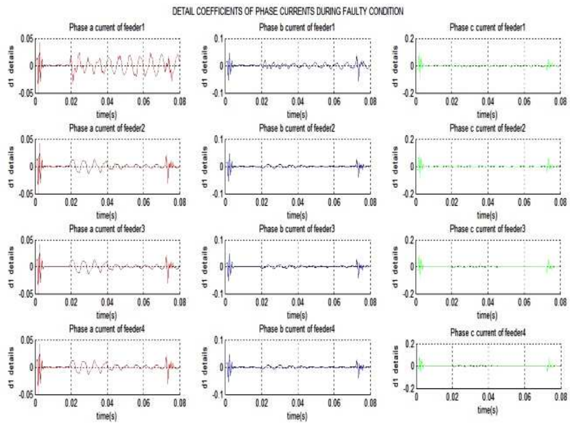



Fig.10 (a) Plot of d1 coefficients when feeder 1, phase 'a' is faulty

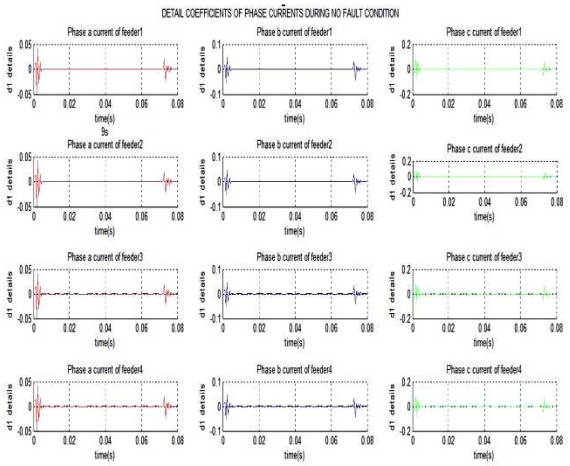



Fig.10 (b) Plot of d1 coefficients at no fault condition

Figures 11(a), (b), (c) & (d) shows the plots of absolute sum of detail coefficients of phase currents in all feeders. Figure.11(a) shows the case when feeder1, phase 'a' is faulty. Similarly Fig.11 (b), (c) & (d) shows the case when phase 'b', phase 'c' is faulty and no fault condition respectively.

From the figures it is evident the absolute sum of faulty phase and faulty feeder is the highest.

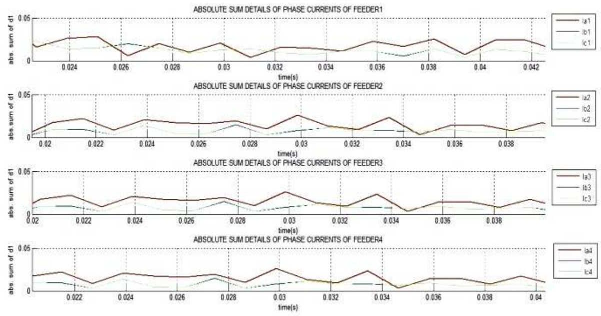


Fig.11 (a) Plot of absolute sums of phase currents when Feeder 1, phase 'a' is faulty

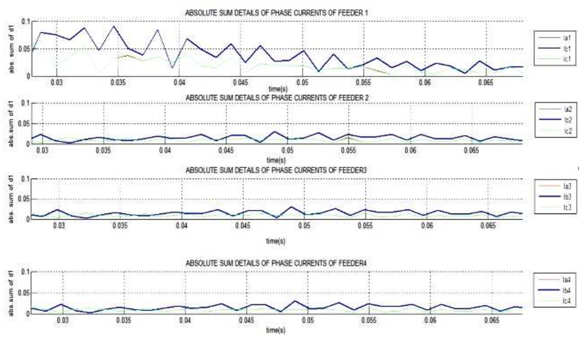


Fig.11 (b) Plot of absolute sums of phase currents when Feeder 1, phase 'b' is faulty

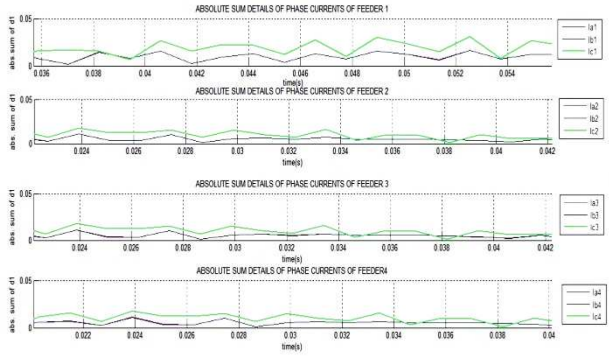


Fig.11(c) Plot of absolute sums of phase currents when Feeder 1, phase 'c' is faulty

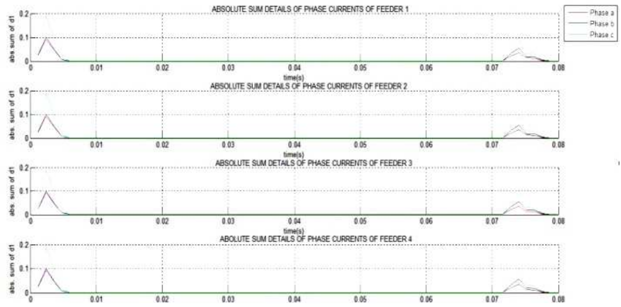


Fig.11 (d) Plot of absolute sums of phase currents at no fault condition

## IV. APPLICATION OF ARTIFICIAL NEURAL NETWORKS

In order to validate the above results obtained using DWT artificial neural networks are employed. The procedure is depicted as shown in Fig.12.This includes a combination of DWT and ANN.

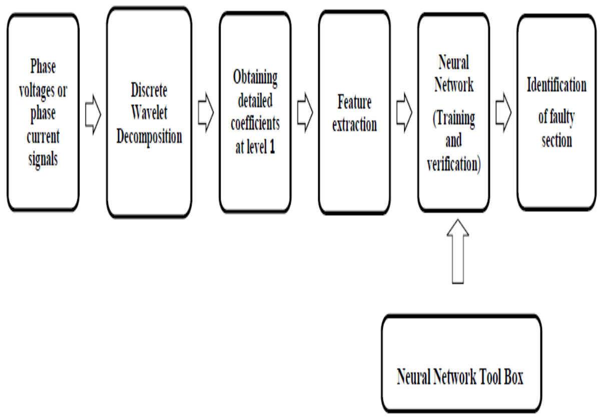



Fig.12 Procedure to detect high impedance arcing fault using combination of DWT and ANN

The ANN operation is based in three important stages that are described below in the subsections. For this purpose Neural Network Toolbox from MATLAB provides different functions to design, initialize, simulate, train and show results of a neural network[15]. Among the various networks available feed forward network is selected for the proposed work and the training algorithm chosen is Levenberg-Marquardt (LM) algorithm. The stages of ANN operation are:

### *A. Artificial Neural Network Training*

This process is based on providing the input data training set and the desired output data training set. Using these training sets the Neural Network is trained. The network stops learning when Mean Squared Error performance function (MSE) or the number of iterations reach a predetermined value[15]. During training, the input and desired target are repeatedly presented to the network. As the network learns, the error decreases towards zero.

After testing different configurations the number of layers selected for MV network and feeder network was four. The number of neurons selected for both cases were 15, 15, 15 and 15, 30, 30 respectively. The design of hidden layer is basically based on a heuristic approach.

For the MV network the input training set consists of the absolute sums of phase voltages for different faulty conditions. For example the absolute sums Sa,Sb,Sc constitute one input when phase 'a' is faulty. Similarly three more sets of inputs when phase 'b' is faulty, phase 'c' is faulty and no fault condition is chosen .Thus for MV network the total number of inputs to ANN is four. Similarly the output training set consists of four numbers of outputs. Each output corresponds to each of the faulty condition. Based on which phase is faulty the network outputs are either 0 or 1.The input and output training sets used for training neural network(for MV network) shown in Table I & Table II respectively.

TABLE I. INPUT TRAINING SET OF MV NETWORK

TABLE II. OUTPUT TRAINING SET OF MV NETWORK

From Table II it is evident that output will be high when corresponding phase is faulty while it will be zero in other cases. This training set is entered as the desired/target output to the Neural Network Toolbox in order to train the network.

To train the neural network for feeder network given in Fig.3 (b) the input and output training sets are chosen based on the concept described above.

The input training set consists of thirteen sets of inputs. The thirteen sets corresponds to different faulty feeder and faulty phase feeder configurations. Each training set constitutes the absolute sums of detail coefficients of phase currents of all the four feeders. The output training set also consists of thirteen sets of outputs. Based on which feeder and phase is faulty the network outputs are either 0 or 1.

The input and output training sets for the feeder network are shown in Table III and Table IV.

The neural networks for MV network and feeder network were trained with the given input and output training data sets. The training stopped when MSE reached a performance of 1e-6.The numbers of iterations required in both cases were 6.

The next step is to ensure whether the performance of the trained networks is valid or not. This procedure is explained in the next subsection.

| OUTPUT 1 PHASE A FAULTY | OUTPUT 2 PHASE B FAULTY | OUTPUT 3 PHASE C FAULTY | OUTPUT 4 NO FAULT CONDITION |
|---|---|---|---|
| 1 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 |
| 0 | 0. | 1 | 0 |

| ABSOLUTE SUM DETAILS OF PHASE CURRENTS | INPUT 1 PHASE A FAULTY | INPUT 2 PHASE B FAULTY | INPUT 3 PHASE C FAULTY | INPUT 4 NO FAULT CONDITION |
|---|---|---|---|---|
| *ABSOLUTE SUM OF PHASE 'A' CURRENT* | 0.0436 | 0.0285 | 0.0262 | 0.0007 |
| *ABSOLUTE SUM OF PHASE 'B' CURRENT* | 0.0135 | 0.0982 | 0.0259 | 0.0007 |
| *ABSOLUTE SUM OF PHASE 'C' CURRENT* | 0.0135 | 0.0290 | 0.1135 | 0.0008 |

TABLE III. INPUT TRAINING SET OF FEEDER NETWORK

| ABSOLUTE SUM DETAILS OF PHASE CURRENTS IN ALL FEEDERS | | INPUT 1 Feeder 1 Phase a faulty | INPUT 2 Feeder 1 Phase b faulty | INPUT 3 Feeder 1 Phase c faulty | INPUT 4 Feeder 2 Phase a faulty | INPUT 5 Feeder 2 Phase b faulty | INPUT 6 Feeder 2 Phase c faulty | INPUT 7 Feeder 3 Phase a faulty | INPUT 8 Feeder 3 Phase b faulty | INPUT 9 Feeder 3 Phase c faulty | INPUT 10 Feeder 4 Phase a faulty | INPUT 11 Feeder 4 Phase b faulty | INPUT 12 Feeder 4 Phase c faulty | INPUT 13 No Fault condition |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Absolute sum of Phase 'a' currents of Feeders 1,2,3,4* | Ia1 | 0.0280 | 0.0050 | 0.0057 | 0.0065 | 0.0064 | 0.0023 | 0.0069 | 0.0065 | 0.0023 | 0.0071 | 0.0065 | 0.0023 | 2.6e-05 |
| | Ia2 | 0.0068 | 0.0065 | 0.0159 | 0.0268 | 0.0050 | 0.0096 | 0.0069 | 0.0065 | 0.0023 | 0.0071 | 0.0065 | 0.0023 | 2.6e-05 |
| | Ia3 | 0.0068 | 0.0065 | 0.0159 | 0.0065 | 0.0064 | 0.0023 | 0.0281 | 0.0050 | 0.0097 | 0.0071 | 0.0015 | 0.0023 | 2.6e-05 |
| | Ia4 | 0.0068 | 0.0065 | 0.0159 | 0.0065 | 0.0064 | 0.0023 | 0.0069 | 0.0065 | 0.0023 | 0.0286 | 0.0050 | 0.0096 | 2.6e-05 |
| *Absolute sum of Phase 'b' currents of Feeders 1,2,3,4* | Ib1 | 0.0168 | 0.0159 | 0.0196 | 0.0033 | 0.0123 | 0.0023 | 0.0036 | 0.0125 | 0.0023 | 0.0036 | 0.0125 | 0.0023 | 2.7e-05 |
| | Ib2 | 0.0035 | 0.0125 | 0.0036 | 0.0162 | 0.0152 | 0.0096 | 0.0036 | 0.0125 | 0.0023 | 0.0036 | 0.0125 | 0.0023 | 2.7e-05 |
| | Ib3 | 0.0035 | 0.0125 | 0.0036 | 0.0033 | 0.0123 | 0.0023 | 0.0169 | 0.0159 | 0.0097 | 0.0036 | 0.0125 | 0.0023 | 2.7e-05 |
| | Ib4 | 0.0035 | 0.0125 | 0.0036 | 0.0033 | 0.0123 | 0.0023 | 0.0036 | 0.0125 | 0.0023 | 0.0171 | 0.0160 | 0.0096 | 2.7e-05 |
| *Absolute sum of Phase c' currents of Feeders 1,2,3,4* | Ic1 | 0.0169 | 0.0050 | 0.0196 | 0.0033 | 0.0064 | 0.0058 | 0.0035 | 0.0065 | 0.0058 | 0.0036 | 0.0065 | 0.0057 | 2.9e-05 |
| | Ic2 | 0.0035 | 0.0065 | 0.0036 | 0.0162 | 0.0050 | 0.0205 | 0.0035 | 0.0065 | 0.0058 | 0.0036 | 0.0065 | 0.0057 | 2.9e-05 |
| | Ic3 | 0.0035 | 0.0065 | 0.0036 | 0.0033 | 0.0064 | 0.0058 | 0.0169 | 0.0050 | 0.0202 | 0.0036 | 0.0065 | 0.0057 | 2.9e-05 |
| | Ic4 | 0.0035 | 0.0065 | 0.0036 | 0.0033 | 0.0064 | 0.0058 | 0.0035 | 0.0065 | 0.0058 | 0.0172 | 0.0050 | 0.0201 | 2.9e-05 |

TABLE IV. OUTPUT TRAINING SET OF FEEDER NETWORK

| Output 1 Feeder 1 Phase a faulty | Output 2 Feeder 1 Phase b faulty | Output 3 Feeder 1 Phase c faulty | Output 4 Feeder 2 Phase a faulty | Output 5 Feeder 2 Phase b faulty | Output 6 Feeder 2 Phase c faulty | Output 7 Feeder 3 Phase a faulty | Output 8 Feeder 3 Phase b faulty | Output 9 Feeder 3 Phase c faulty | Output 10 Feeder 4 Phase a faulty | Output 11 Feeder 4 Phase b faulty | Output 12 Feeder 4 Phase c faulty | Output 13 No Fault condition |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |

### *B. Artificial Neural Network Validation*

The performance of a trained network can be measured to some some extent by the errors on the training, validation and test sets, but it is often useful to investigate the network response in more detail. One option is to perform a regression analysis between the network response and the corresponding targets. Figures.13&14 shows the regression plots obtained for the trained networks of MV network and feeder network respectively.

The network outputs are plotted versus the targets as open circles. The best linear fit is indicated by a dashed line. The perfect fit is indicated by the solid line. From the figures, it is difficult to distinguish the best linear fit line from the perfect fit line, because the fit is good. This means that the desired output and the output obtained by training (network output) are almost the same. Hence the trained networks obtained are valid. These are saved as say, ‘network1’ and ‘network2’ and imported to MATLAB workspace.

If the obtained plots are not satisfactory the training process should be continued until a satisfactory performance level is reached.

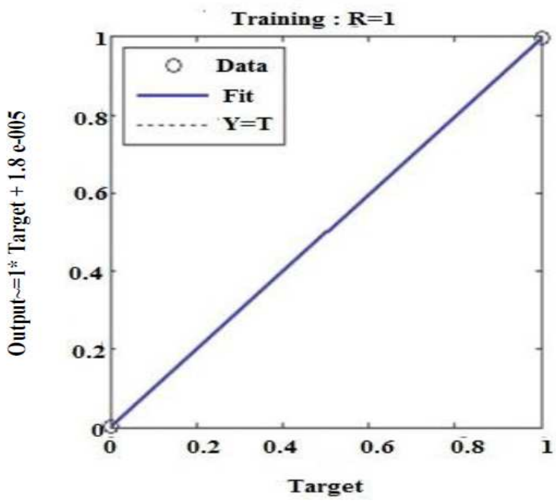



Fig.13 Regression plot of MV network

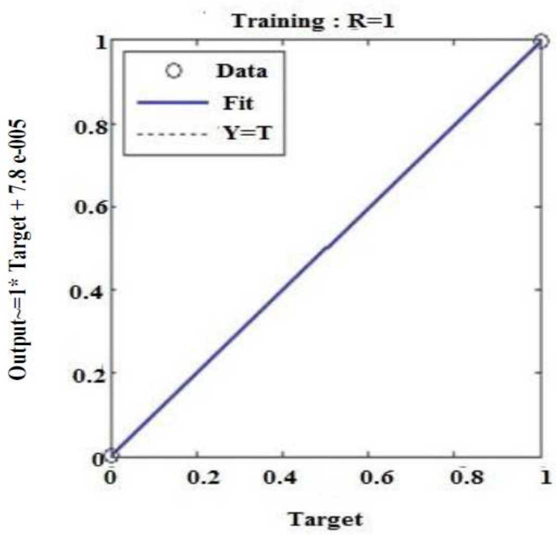



Fig.14 Regression plot of feeder network

### *C. Artificial Neural Network Operation*

The trained networks are saved and imported to MATLAB workspace. These networks are further incorporated into the suitable MATALAB program. Suppose ‘network1’ is incorporated into the MATLAB program using the command sim(network1,INPUT1).If the trained network is genuine then after running the program the output obtained should be ‘OUTPUT1’ as shown in Table II. Likewise corresponding to each input the corresponding outputs are obtained.

Hence the outputs obtained confirm the successful operation of trained neural networks.

## V.CONCLUSION

A model for high impedance arcing faults due to leaning trees in MV networks have been studied and simulated. The arc model has been realized using the universal arc representation. Based on the proposed fault detection algorithm using DWT the faulty sections of a simple MV network and feeder network could be identified. A new methodology using combination of DWT and ANN were used to validate the results obtained using DWT alone.

Future works include distance location of high impedance arcing faults using DWT. The proposed method can also be implemented by techniques like Support Vector Machine (SVM), ANFIS etc.

## ACKNOWLEDGMENT

The authors wish to thank Mr .GeevargheseTitus ,Assistant Professor ,Department of Electronics and Communication and MrAnish Benny ,Assistant Professor ,Department of Electrical and Electronics of Amal Jyothi College of Engineering, Kottayam ,India for their valuable suggestions for the completion of this paper.

## REFERENCES

[1] M.Sedighizadeh,A.Rezazadeh, Nagy I.Ekalashy,‘Approaches in High Impedance fault detection–A chronological Review’, *Advances in Electrical and ComputerEngineering*,**10**(3),114-128,2010.

[2] Pieter H.Schavemaker and LouVanderSluis,‘An improved Mayr-type model based on current–zero measurements’, *IEEE Transactions on Power Delivery*, **15**(2), 580-584, April 2000.

[3] J.L.Guardado, S.G.Maximov, E.Melgoza, J.L.Naredo and P.Moreno, ‘An improved arc model before current zero based on the combined Mayr and Cassie arc models’, *IEEE Transactions on Power Delivery*,**20**(1),138-142,January2005.

[4] Karel Jansen van Rensburg, ‘*Analysis of Arcing Faults on Distribution lines for Protection and Monitoring*’, Ph.D Thesis, School of Electrical and Electronic Systems Engineering, Queensland University of Technology, 2003.

[5] Nagy Ibrahim Elkalashy, ‘*Modeling and Detection of High Impedance Arcing Fault in Medium Voltage Networks*’, Ph.D Thesis, Department of Electrical and Communications Engineering, Helsinki University of Technology, Finland,2007.

[6] H. A. Darwish and N. I. Elkalashy, “Universal Arc Representation Using EMTP”, *IEEE Transactions on Power Delivery*, **20**(2), 772-779, April 2005.

[7] Nagy. I. Elkalashy, M. Lehtonen, H. A. Darwish, A.M.I. Taalab and M. A.Izzularab,‘A Novel Selectivity Technique for High Impedance Arcing Fault Detection in Compensated MV networks’, *European Transactions on Electrical Power*, ETEP, in press, published online on 23 April 2007.

[8] Kamal M. Shebl, Ebrahim A. Badran, and Elsaeed Abdalla,‘A Combined MODELS-TACS ATPdraw General Model of the High Impedance Faults in Distribution Networks’,*Proceedings of the 14th International Middle East Power System Conference* , Cairo University, Egypt, 527-531, 2010.

[9] Wavelet Toolbox User’s Guide for MATLAB,Version 1, Mathworks 2009.

[10] Neural Network Toolbox User’s Guide for MATLAB,Version 1, Mathworks 2009.

[11] NagyI.Elkalashy,Matti.Lehtonen,Hatem.A.Darwish, Mohammed A.Izzularab and Abdel-MaksoudI.Taalab, ‘DWT

Based Investigation of Phase currents for detecting High Impedance Faults due to leaning trees in Unearthed MV Networks', *IEEE Power Engineering Society General Meeting*,Florida,103- 108,2007.

[12] Chul-Hwan Kim, Hyun Kim, Young-Hun Ko, Sung-Hyun Byun, Raj K. Aggarwal and Allan T. Johns, 'A Novel Fault-Detection Technique of High Impedance Arcing Faults in Transmission Lines Using the Wavelet Transform',*IEEE Transactions On Power Delivery*,**17**(4), 921-929,October,2002.

[13] David C. Robertson, Octavia I. Camps, Jeffrey S. Mayer, WiUiam B. Gish, 'Wavelets and Electromagnetic Power System Transients', *IEEE Transactions on Power Delivery*, **11**(2),1050-1056,April 1996.

[14] ArcModele Blockset, User Guide Version 2, Delft University of Technology,2001.

[15] Ibrahim Baqui,Inmaculada Zamora,Javier Mazon, 'High Impedance fault detection methodolgy using wavelet transform and artificial neural networks',*Electric Power Systems Research*,1325-1333,2011.

[16] Wong, K. C. P.; Ryan, H. M. and Tindle.J, 'Power system fault prediction using artificial neural networks', *International Conference on Neural Information Processing,* 24-27 September 1996,Hong Kong.

**Gayathri Vijayachandran** is Assistant Professor in Department of Electrical and Electronics at Sree Buddha College of Engineering, Pattoor, Kerala. She did her M. Tech in Power Electronics and Power Systems at Amal Jyothi College of Engineering, Kanjirappally. Earlier she has completed her undergraduate in the field of Electrical and Electronics Engineering at Sree Buddha College of Engineering,, Pattoor. Her email id is vijayachandrangayathri3@gmail.com .

**Bobin.K.Mathew** is Assistant Professor of Electrical & Electronics Engineering Department, Amal Jyothi College of Engineering, Kanjirappally. He received his M.Tech degree (Integrated Power Systems) from Vishwesharaiya National Institute of Technology, (2009), Nagpur. His area of research includes multilevel inverters, PFC converters and Power Quality. His email id is bobinkmathew@amaljyothi.ac.in