

# Identification and classification of high impedance fault on a medium voltage distribution line using radial base function neural network (RBFNN)

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## Abstract:

High impedance fault (HIF) can be described as a fault which does not produce enough fault current to be detectable by conventional protection schemes which present high risks to lives and electrical equipment's. Several methods have been employed to identification and classification of HIF but come with their limitations. In this research, RBFNN has been used in which it has been trained from the data extracted from HIF current signal, using wavelet decomposition at level 8 and Daubechies4 wavelet transform (db4) so as to have a unique feature or finger print of this fault, Radial base function neural network was used and the training performance of this model is 0.0176164 and accuracy of 94.45% has been obtained

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## 1. Introduction

High Impedance Faults (HIF) on medium voltage distribution system can be unidentifiable abnormal fault conditions which cannot be identified, classified or cleared using conventional relay protection method, due to low level of fault current[1], HIF present a great challenge to Power Protection Engineers [2] It's generally required that a good protection scheme should archive some specific objective that includes: proper diagnosis of fault condition, examining all possible type of fault and consider that protection equipment can fail to operate[3] HIF does not make contact with ground which makes it difficult for protection equipment to identify and protect making it undetectable and pose a huge risk to safety of live and equipment [4]. Fault resistance of a fault define HIF state, for a system with voltage level of 35KV below are considered point of interest because they are more prone to effect of HIF[5]. HIF does not only pose danger to live and equipment but can also degrade customer's service which will cost utilities company money [6]. This fault condition or event at takes place on either transmission line or distribution line introduce nonlinear characteristics or stochastic nonlinear current which affect both transient and steady state of the system [7]. Identification of high impedance fault is very so challenging using conventional protection system and Power System Relaying Committee (PSRC) working group indicates that the success rate is estimated to be about 20% using conventional protection schemes [8] high impedance fault is classified into two categories: active and passive [9]. Active high impedance fault occurs when underground conductor insulation failed over a period of time but it's not a critical issue because almost 90% of underground cable has mechanical protection which helps in making a good

contact to earth when this fault is in existence [10]. On the other hand, Passive high impedance fault occurs on an overhead conductor which is the most common with high risk [10], High impedance fault has been a recurring issue to electrical power system protection engineers and this present the need for a comprehensive understanding of this fault condition, in order to develop a practical solution [11]. A verity of protection and identification methods has been employed such as artificial neural network, multi resolution techniques, wave transform, advanced distortion detection techniques, deep reinforcement learning and lots more are used in addressing complex problems in a variety of domains [12] for identification of high impedance fault a learning algorithm can be necessary and will play a key role. However, some parameters have to determine in advance in the existing learning algorithm which is difficult or not feasible in many applications [13]. Artificial neural networks have been engineered as generalizations of mathematical models of human neural biology which can be recognized as tool for understanding brain complex activities [14].

## 2. Methodology

### 2.1 Radial basis function neural network (RBFNN)

RBFNs can be identify as a special condition of ANN involving neurons that utilize RBFNN as their activation function where by the senses of each neuron consists of a radial basis function neural network that there is only one hidden layer of neurons, there is only one output node, and that two-stage training procedure can be used [15]. Radial basis function neural networks present a powerful technique for generating multivariate, nonlinear mappings[16] Radial Basis Functions (RBFs) were first introduced by M.J.D.

Powell in 1985 he used it for multivariable interpolations and function approximations but Broom head and were the first to introduced them into a neural network [15].

$$\phi_c(\bar{x}) = \phi(||\bar{x} - \bar{U}_c||) \quad (1)$$

Where  $|| \cdot ||$  denotes the vector norm.

One symmetric function that is often used as an RBF is the Gaussian function

$$\phi(r) = e^{-r^2/\sigma^2} \quad (2)$$

With the Euclidean norm. Gaussian functions can be characterized by its width or scale parameters. Radial based function neural network can also, in many cases be dependent on a scale parameter which is called the width of the function.

A set of RBFs can be used to construct a basis of functions. Linear combinations of RBFs, as

$$y(\bar{x}) = \sum_{j=1}^m W_j \phi(||\bar{x} - \bar{U}_j||) \quad (3)$$

Where  $W_j$  is the weights, which can be used for representing a wide class of functions. RBFN is a feed forward network with about three layers: these layers are inputs, hidden layer or kernel, and output node(s). The RBFN, each hidden node is represented by an RBF, where each RBF, where each  $\phi_j$ ,  $f$ , has a center position,  $U_j$ , and a width,  $\sigma_j$ , associated with it [15]. Generalization in RBF Neural Networks

The principle of radial based neural network varies from another neural network. Gaussian nonlinearity is taken:

$$\phi(x) = \exp\{-\frac{x^2}{\sigma^2}\} \quad (4)$$

The network outputs which are from the weighted sum of the output

$$Z_i = \sum_j W_{ij} \phi_j + \theta_i \quad (5)$$

Where  $W_{ij}$  = synaptic weights and  $\theta_i$  = the biases

These biases are adaptive variables which are set in the stage of learning. The bias terms can be coupled into the weight matrix by introducing, extra hidden unit whose output  $\phi_k = 1$ . The training data which is in form of pairs and is supplied to the network, where  $p = 1, \dots, P$  labels the individual training pairs. This learning process aims in minimizing the sum-of squares error given by

$$E^s = \frac{1}{2} \sum_p \sum_i (Z_{ip} - t_{ip})^2 \quad (6)$$

Where  $Z_{ip} = Z_i(x_p)$  denotes the output of unit when the network is presented with input vector  $x_p$  [16]. To determine Parameter for the designing of an RBFN involves selecting a number of parameters, namely: ( $\phi$ ) base functions, ( $M$ )

number of basic functions, ( $\mu_j$ ) centers for basis functions, ( $\sigma_j$ ) widths of the basis functions and ( $W_j$ ) weights of the basic functions [15].

## 2.2 Exponential growth and decay algorithm

Among the most important application of derivatives of calculus is the description of dynamically changing quantities by differential equation, this contains an unknown functions and derivatives [17]

If  $U = K(t)$ , then  $K^I(t) = \frac{du}{dt}$  represent the rate of change of  $U$  with respect to  $t$ .

Another important measure of rate of change is called relative rate of change, which can be represented as:

$$\frac{K^I(t)}{K(t)} = \frac{U^I}{U} \quad (7)$$

If the quantity is a constant, say  $p$ , then this formula for  $y$  as a function of  $t$  can be developed:

$$U = U_0 e^{k(t-t_0)} \quad (8)$$

$U_0$  is the value of  $U$  when  $t = t_0$

$$\text{If } t_0 = 0 \text{ } U(t) = U_0 e^{k^I t} \quad [18] \quad (9)$$

A variable  $y$  is proportional to a variable  $x$  if  $U = px$ , where  $P$  is constant

Given a function  $h(t)$ , where  $x$  is a function of time  $t$ , the rate of change of  $h$  with respect to the time  $t$  which is given by  $\frac{dx}{dt} = h^I(t)$ .

Function  $h(t)$  increases over an interval if

$$\frac{dx}{dt} = h^I(t) > 0$$

Function  $h(t)$  decreases over an interval if

$$\frac{dx}{dt} = h^I(t) < 0$$

Function  $h(t)$  neither increases nor decreases over an interval if

$$\frac{dx}{dt} = h^I(t) = 0 \quad [19]$$

Where  $U_0$  = initial population at time  $t = 0$ ,

$p$  = constant relative growth rate

$t$  = time for the population growth.

$U(t)$  = is the population growth at time  $t$ .

## 2.3 Process flow diagram

Figure 1 below present the process flow for high impedance fault identification and classification, which consist of four blocks.

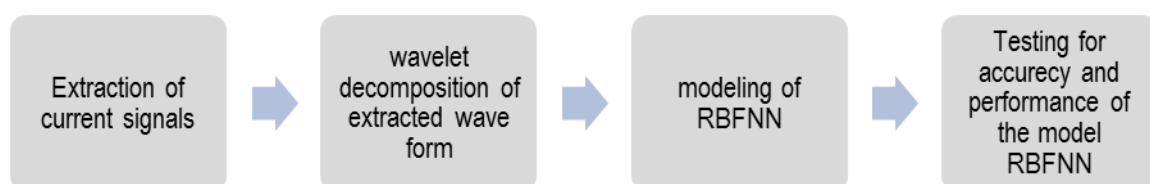


Figure 1: Process flow for HIF identification and classification

The extraction of current signal has been repeated as done and has been used as the input, where by wavelet decomposition of this signal is done using Daubechies-4 wavelet transforms for generating coefficient of this signals of 140 states has been generate, 85% of the data is used for training while 15% is used for the testing of the RBFNN, after which the performance testing has been carried out.

## 2.4 HIF identification and classification

### 2.4.1 Simulation model

Figure 2 below shows a Power distribution system from Nseobong I. Okpura which was adopted and modified to a system that consist of three phase source star-delta connected (three phase and neutral), three phase measurement with two section of parameters line of three phase RLC load has been used for this research.

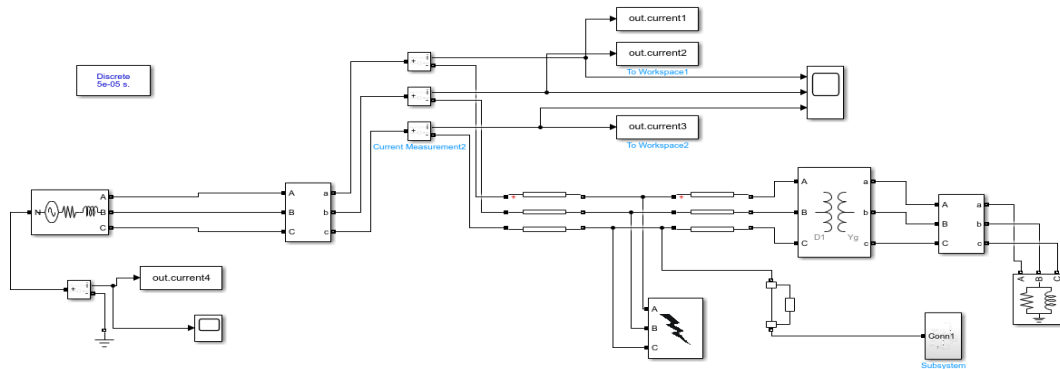


Figure 2: Model medium voltage distribution system

This simulated model of distribution system lengths of 20km who's corresponding to a three-phase source, star-delta connected, made of 11KV phase to phase voltage (Vrms), Frequency of 50Hz with three phase RLC load star configured, three phase measurement with two section of parameters line of three phase RLC load has been used for this research.

Figure 2 shows Veerasamy model which is improved Emanuel arc model adopted for this research because of it features that gives a non-linear characteristic and the diodes. This developed model has improvement in dynamics of arc current features which replicates the non-linearity of ground resistance. Fault signal, under normal operating condition, earth fault and over current conditions has been extracted from the developed distribution power system model generated.

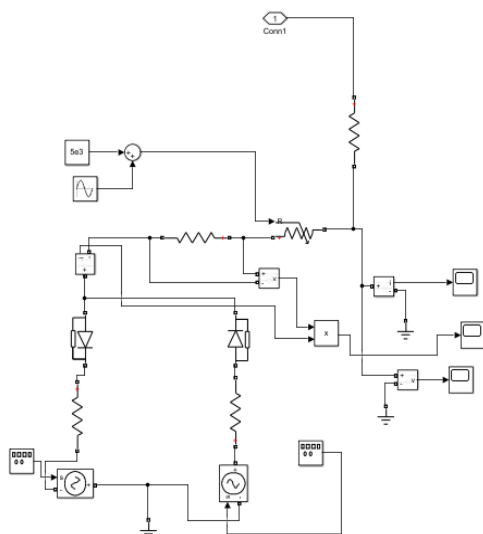


Figure 3: Improved Emanuel arc model

### 2.4.2 Data collection

After implementing the distribution system and high impedance fault on Matlab Simulink, the current signal for normal working condition and for possible earth faults conditions has been extract and the result has been sent to work space. After extraction of the current signal, plots have been developed using time series plot by defining sampling frequency (fs) and time, wavelet decomposition of the fault signal has been carried out using Daubechies 4 at level 8 after which detailed coefficient identification at different point of the distribution network. This coefficient will be used as the training data of the RBNN and the Matlab code below has been implemented for that.

## 3. Results and discussion

The figures 4 to 7 are representation of wave forms of normal working condition and that of HIF conditions.

### 3.1 Modeling of radial based neural network

Figure 8 show performance of the RBFNN during the training process which started from epoch 0 with performance of about  $10^{-0.08}$  and steal around epoch 82 with performance of  $10^{-18}$ .

### 3.2 Testing and validation of model RBFNN

Table 1, present Comparison of radial based function neural network simulation result with the expected output. It has been observed that the model radial base function neural network has successfully identified and classified HIF. This makes it 94.45% accurate.

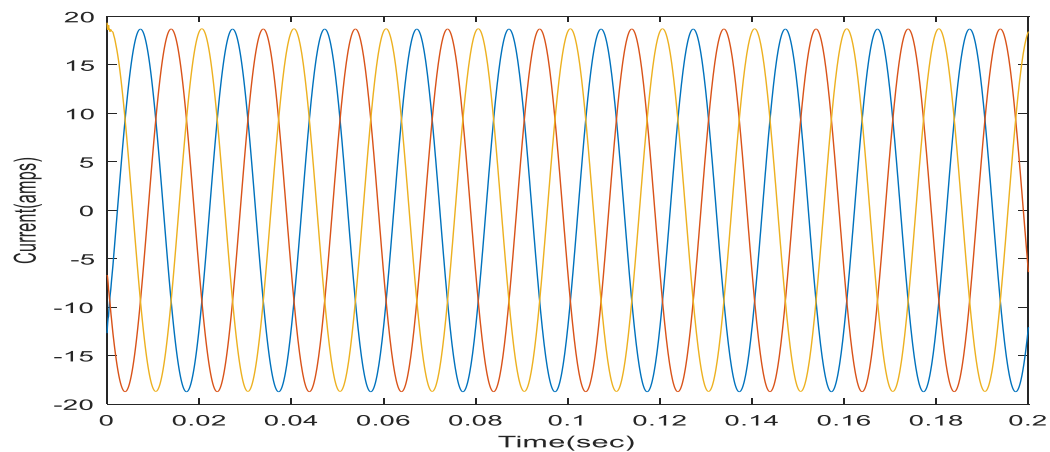


Figure 4: Plot of current against time for normal condition

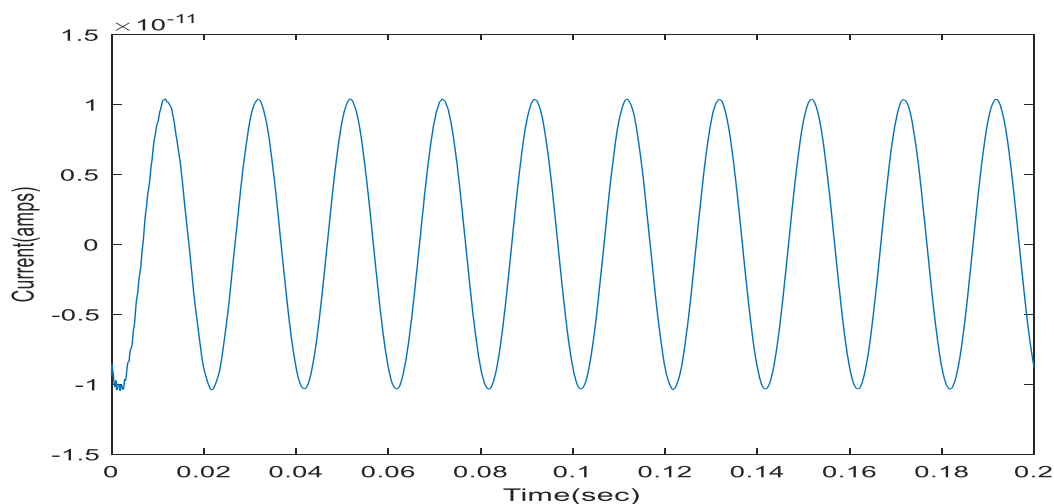


Figure 5: Neutral current wave form for normal condition

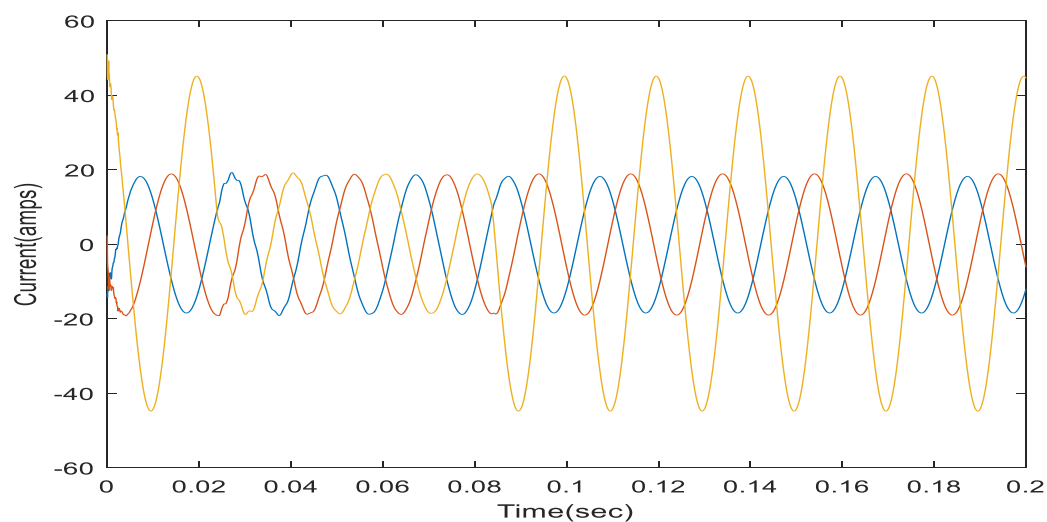


Figure 6: Waveform of High impedance fault condition wave form

#### 4. Proposed frame work

From the result in Table 1 was obtained from comparison of radial based function neural network simulation result with the expected output shows that there is need for improvement so as to make the method more efficient, this proposed method, will make use of exponential

growth algorithm as initiation state of the protection scheme so that it will be more effective. Considering distribution system to always have a reasonable amount of load current and whenever there is high impedance load there will be reasonable amount of load loss on that phase or it can be called load decay which we can take the transformer with

lowest load current on that feeder. Whenever there is an instant load loss equivalent to that load current this protection scheme will be initiated and our RBFNN will come

in place. Figure 9 below is a flow chart that gives details of the developed protection scheme proposed.

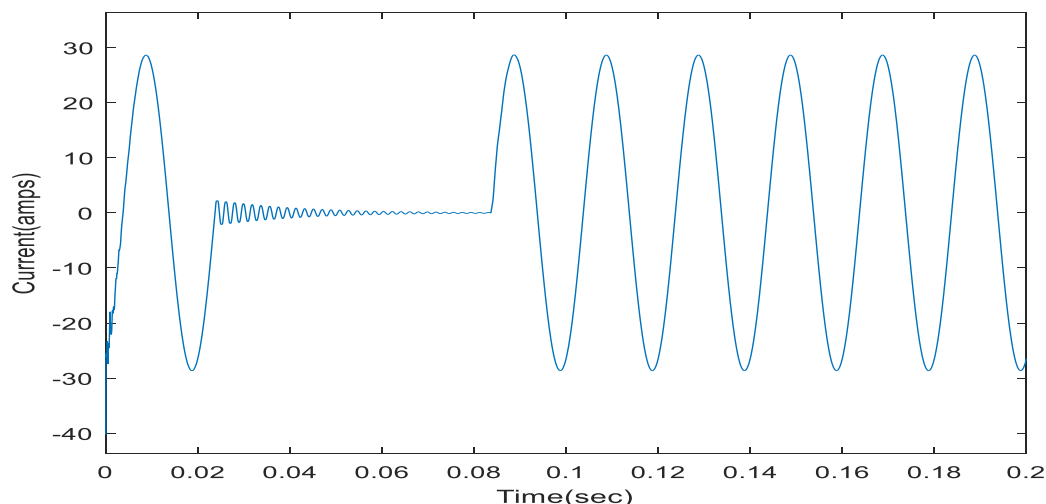


Figure 7: Neutral current wave form for high impedance condition

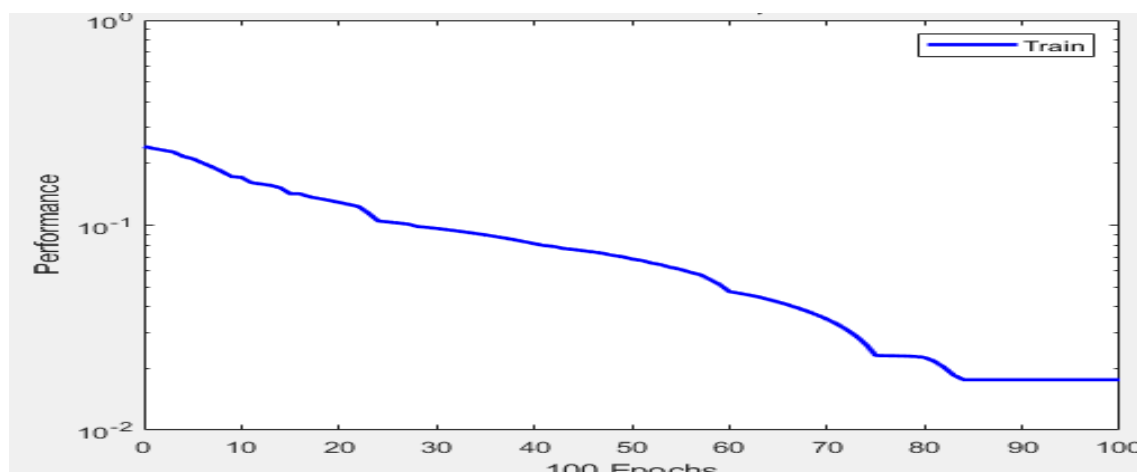


Figure 8: Performance graph for the trained RBFNN

Table 1. Comparison of radial based function neural network simulation result with the Expected output.

S/No	simulation result				expected output			
1	0.0000	-0.0000	-0.0000	0.0000	0	0	0	0
2	1.0000	1.0000	1.0000	1.0000	1	1	1	1
3	1.0000	1.0000	0.5000	0.5000	1	1	1	0
4	1.0000	1.0000	0.5000	0.5000	1	1	0	1
5	1.0000	-0.0000	1.0000	1.0000	1	0	1	1
6	0.0000	1.0000	1.0000	1.0000	0	1	1	1
7	1.0000	1.0000	0.0000	0.0000	1	1	0	0
8	0.0000	1.0000	1.0000	0.0000	0	1	1	0
9	1.0000	-0.0000	1.0000	0.0000	1	0	1	0
10	1.0000	-0.0000	-0.0000	1.0000	1	0	0	1
11	0.0000	1.0000	0.0000	1.0000	0	1	0	1
12	0.0000	-0.0000	1.0000	1.0000	0	0	1	1
13	1.0000	1.0000	1.0000	1.0000	1	1	1	1
14	1.0000	1.0000	0.0000	1.0000	1	1	0	1
15	1.0000	-0.0000	1.0000	1.0000	1	0	1	1
16	0.0000	1.0000	1.0000	1.0000	0	1	1	1
17	0.6767	0.3333	-0.0000	1.0000	1	0	0	1
18	1.0000	1.0000	0.0000	1.0000	0	1	0	1

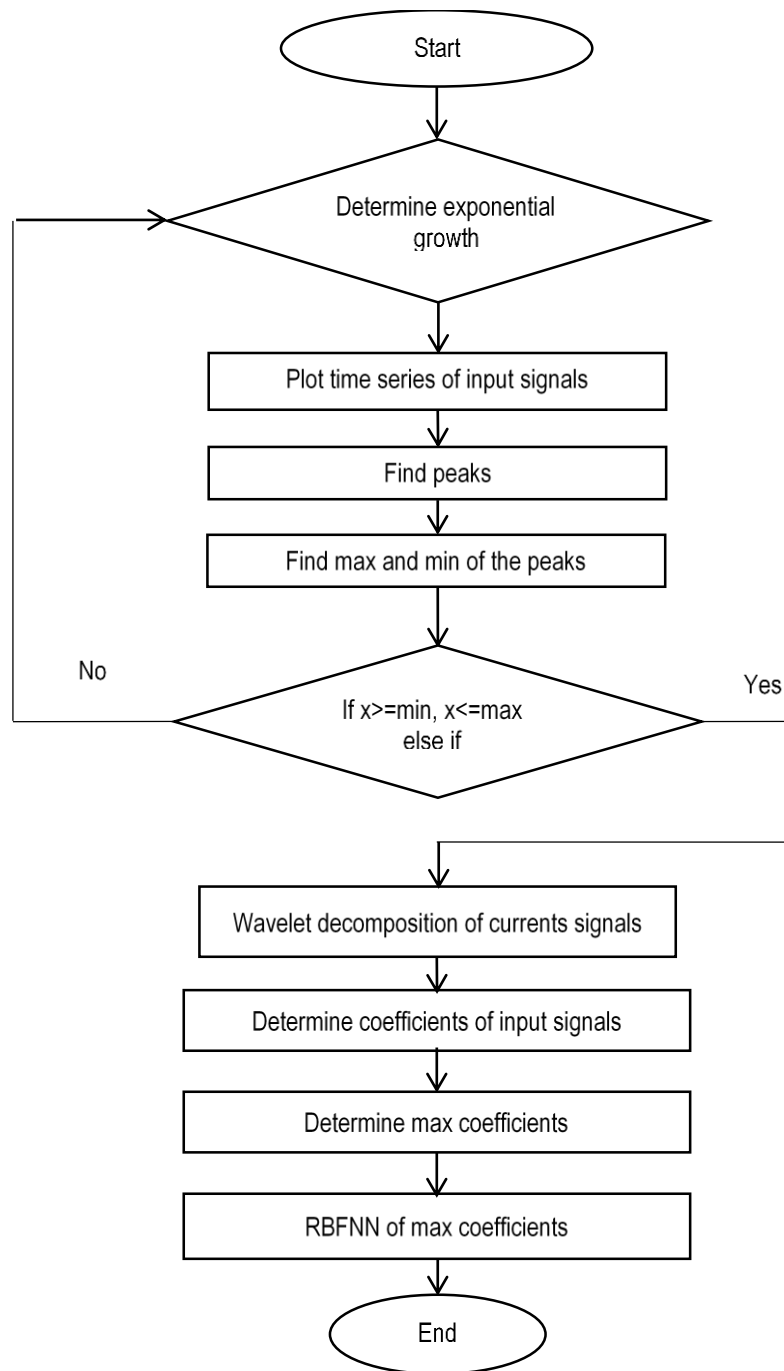


Figure 9: Flow chart for high impedance protection

## 5. Conclusion

HIF is recurring problem in the field of power protection engineering. This challenge present high risks and is costing infrastructures, recent advanced technologies such as ANN, wavelet transform are frequently used for general fault identification. This paper used RBFNN in matlab Simulink to model neural network for the protection and identification of HIF and it has been concluded that RBFNN are suitable method to identify and classify HIF because training performance of 0.0177219 was achieved with accuracy of 94.44444444% and a proposed frame work has been developed for HIF protection scheme has been developed.

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