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THE ARTIFICIAL NEURAL NETWORKS BASED RELAY ALGORITHM FOR DISTRIBUTION SYSTEM HIGH IMPEDANCE FAULT DETECTION

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Abstract

The paper presents a practical artificial neural network (ANN) based relay algorithm for electric distribution high impedance fault detection. The scheme utilizes the characteristics of high impedance faults (HIFs) in the resulting waveforms of the three phase residual current, voltage, admittance and power. By using Fourier analysis, their low order harmonic vectors were worked out which were then fed to a neural network. The network was based on either perceptron or feed forward algorithm. The trained network was verified using other distribution systems.

1. Introduction

High impedance faults (HIFs) are notorious for being difficult to detect. Unlike other faults that result in a high fault current, HIFs give a very low fault current with a typical magnitude of about 40 A to 100 A.Consequently, conventional non-unit detection will either give unacceptable errors in measurement in terms of overreach or totally fail to detect the presence of the faults. The failure of HIF detection leads to potential hazard to human beings and potential fire. HIFs are usually caused by falling conductors coming into contact with a surface having poor conductivity. However, HIFs usually involve arcing and are often characterized by cyclical patterns and distortions caused by arcing and/or nonlinearity of the fault impedance [1]. The objective of most detection schemes is to evaluate the patterns of the voltages and currents measured at the station.

Some detection schemes have been proposed [2–6] which are based on fractal techniques, digital signal processing, neural networks, high frequency noise pattern and dominant harmonic vector. They offer potential solutions to the problems currently associated with conventional schemes. While direct calculation of fractal dimensions is not effective due to relatively short data sets available for estimation and the use of high frequency harmonics are not feasible in practical relay because of the filtering by substation current transformers. ANN based detection schemes offer a robust relaying because of its ability to match pattern and tolerate against noise. Moreover, these schemes also provide the potential for on-line training and customization using actual field HIF data. In this paper, an ANN detection scheme is proposed which evaluates a low order harmonics of voltage, current, admittance and power.

2. Artificial Neural Networks

A neural network is a dynamic system with one-way interconnections. Its invention was first inspired by the actual learning process taking place in human brains. An ANN simulates this complex learning process. Perceptrons belong to nonbiological class of NN and is one of the biggest branches in NNs. The simplest perceptron is a single layer network whose weights and biases can be trained to produce a correct target vector when presented with the corresponding input vector. The advantages of using perceptron lie in their use as calculation tools and not in the insight they give to neural operation. Back propagation, branches from perceptron [7], was created by generalizing the Widrow-Hoff learning rule to multiple layer networks and nonlinear differentiable transfer functions. Indeed, both perceptron and back propagation are excellent tools for pattern classification.

The Matlab ANN Toolbox was selected for the implementation of perceptron and back propagation because of its simplicity and flexibility. The paper is aimed to show the feasibility of HIF detection using low order harmonics so the complexity of the neural networks is not of top priority. In fact, it was found that the performance of the networks was more than satisfactory when it comes to verification.

2.1 Perceptron

The perceptron network is trained to respond to each input vector with a corresponding target output vector whose elements are either 0 or 1. The perceptron learning rule is applied to each neuron in order to calculate the new weight and bias. Convergence on a solution in finite time can be obtained if a solution exists. The perceptron neuron, which has a hard limit transfer function, is shown below in detail and in abbreviated notation as in Figure 1.

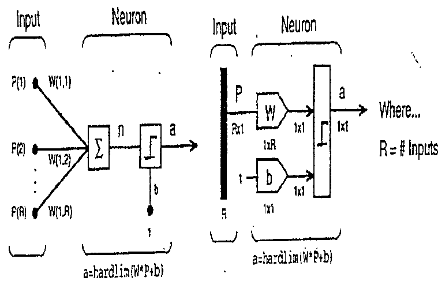

Figure 1 Matlab abbreviated notation for perceptron [8]

Each external input is weighted with an appropriate W, and the sum of the weighted inputs is sent to the hard limit transfer function, which also has an input of 1 transmitted to it through the bias. The transfer function returns a logic 0 or 1. The hard limit transfer function is shown below.

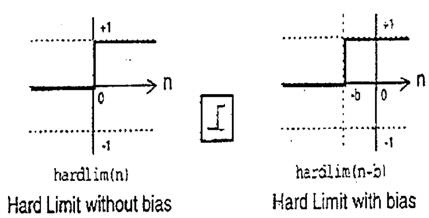

Figure 2 hard limit function in Matlab [8]

2.2 Backpropagation

In Matlab, the back propagation learning rules are to adjust the weights and biases of networks so as to minimize the sum squared error (SSE) of the network. This is done by continually changing the value of the network weights and biases in the direction of steepest descent with respect to error. This is called a gradient descent procedure. Changes in each weight and bias are proportional to that element's effect on the sum-squared error of the network. Figure 3 shows an elementary back propagation neuron with R inputs.

In the actual implementation of perceptron and back propagation, the basic structure of the network consists of at least one input layer, one output and one hidden layer. More complicated classification usually requires more than one hidden layer with more neurons to match the inputs to the appropriate outputs.

3. Detection Schemes

Neural networks are renowned for pattern recognition. The aim here is to demonstrate that with proper training, neural networks can acquire

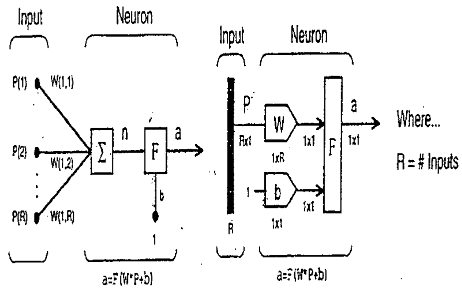

Figure 3 An elementary back propagation diagram[8]

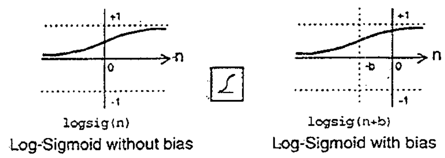

Figure 4 Log-Sigmoid function [8]

HIF detection. Networks were trained by feeding them with input vectors and the corresponding target vectors. An input vector is one consisting of magnitudes or phase angles of low order harmonics which are considered to be able to reveal the presence of HIFs.

The data in the training set were obtained from simulation results based on a typical distribution system as shown in Figure 5. It depicts the sample study system of a radial distribution feeder with linear, nonlinear, solid state loads, voltage correction capacitor banks and an equivalent HIF arc model. Since disturbances resulting from HIFs may resemble those from capacitor switching and transformer tap changing, it is therefore necessary to include cases with these contingencies to ensure that the ANNs will not be confounded even under the high level of ambient harmonics so generated.

Digital simulations were performed using EMTP (Electromagnetic Transient Program) for different types of faults, fault location and other contingencies such as capacitor switching, single phase load switching, etc. The HIF arc model is based on the one developed by Emanual's1 et al [9]. This high impedance fault model is based on arcing on sandy soil. It includes two dc sources, V_p and V_n, connected in anti-parallel by means of two diodes D_p and D_n. The series impedance (R_p and R_n) represent the fault and arcing resistance. The circuit for the model and the waveform of the fault current are shown in Figure 2. The model was enhanced by varying the fault conductance, ignition and extinction voltage to obtain asymmetrical fault current.

4. Test cases

Data for training were obtained by simulation based on the distribution system in figure 1. A total of 46 test cases were built and there were another 30 cases in the verification data set. The test cases and the verification cases studied are shown in Table 1 and Table 2 respectively. In both tables, different kind of contingencies and HIFs are listed. Contingencies which may confound an HIF relay include capacitor switching, single phase line switching and nonlinear load switching. In addition to the distribution system which was used for training (Figure 1), two additional networks were used for verification and they are shown in Figure 7 and Figure 8. The digital data were sampled at a frequency of 20 kHz and were transformed from time domain to frequency domain by Fourier series.

5. Choice of Input Signals

HIFs are generally non-symmetrical in nature. Residual quantities, defined as:

$$I_R = I_a + I_b + I_c$$
$$V_R = V_a + V_b + V_c$$
$$P_R = I_R \cdot V_R$$
$$Y_R = \frac{I_R}{V_R}$$

were considered likely candidates because they effectively filter out the symmetrical components of the voltages, currents, etc. In order to find the best candidates, other quantities such as phase currents, phase voltages were also utilized at first. But they did not seem to contain substantial information for HIF detection and the chosen neural networks could not be trained successfully. To enhance the practicality of the detection scheme, low order harmonics were given priority over high order ones and the number of inputs required were kept as small as possible. After trying different combinations of the likely candidates, it was observed that the magnitude of the first and the third harmonics of residual current(I_R), the second harmonics of residual admittance(Y_R), the first and third harmonics of residual voltage(V_R) and the second harmonics of residual power(P_R) led to the fastest convergent neural network training and showed the greatest contrast in magnitude for cases having or without the fault.

Figures 11 and 12 show typical time-based and frequency based waveforms for the selected signals, corresponding to a high impedance fault and capacitor switching, respectively.

6. Neural Network Training

Two kinds of neural networks were used, namely perceptron and backpropagation [10]. Both were successfully trained and verified. Perceptron involves less complicated network structure, but is limited by the fact that its output can only take on two values: 0 or 1. On the other hand, back propagation employs more complex network architecture and gives analog outputs which may require further analysis.

In Matlab, the implementation of neural networks is performed by means of matrix manipulation of the inputs, outputs, weights and biases vectors. Vectors from a training set are presented to the networks sequentially. If the network's output is correct no change has to be made. Otherwise the weights and biases are updated based on the network's training algorithm. The entire pass of all the input vectors is called an epoch.

Effective training of an ANN requires that all the vectors in different rows span similar numerical ranges. In this particular case, the range of the elements in the input matrix was –1 to +1. The scaling for the selected harmonic vectors was: I_R x 10, Y_R / 100, V_R x 100, P_R x 100.

Apart from scaling, there are some other factors that facilitate the convergence of the solution. It is obvious that in order to obtain a convergent solution, the training vectors must be indicative and able to tell the difference between cases with and without high impedance faults. Another factor to consider is then the choice of networks. For feed forward networks, the number of hidden layers required is dependent on the complexity of the input and output vectors in the training set. Three logsigmoid hidden layers with 10 neurons in each hidden layer was found to be the optimum network structure. However, plane back propagation was too slow to achieve an error goal of 0.001. Sometimes it did not even converge. The convergent case took about 20000 epochs to accomplish the training. The pitfalls of back propagation are mentioned in reference [10]. Nevertheless, the MATLAB toolbox provides some ways to improve the performance of back propagation. The use of momentum can prevent the solution from being trapped in one of the local minima and hence facilitate the reaching of the global minimum. Adaptive learning rate makes use of delta correction algorithm and attempts to keep the learning step size as large as possible while keeping learning stable. The improved network achieved the error goal of 0.001 after 2,000 epochs with an initial learning rate of 0.4.

7. Training Results

The trained network was verified with a verification data set comprising 30 cases. Logic 0 and logic 1 represent the absence and presence of the fault respectively. Cases in the verification set have either different parameters using the same distribution system as in the training set or distribution system with completely different configuration. The success rate of verification was found to be 100% with a maximum error of 0.001. Table 1 and 2 depict the training data and verification data obtained from Fourier series calculation. In both sets of data, a variety of combinations of faults, system components and contingencies are included which facilitate successful training and verification. For comparison of the performance of plane back propagation and one with momentum and adaptive learning rate, the Matlab generated training progress graphs of sum-squared error against number of epoch for both cases are shown in Figure 9 and 10. In Figure 9, the network does not seem to converge while a solution is found after about 5000 epoches for the improved network as shown Figure 10.

8. Tripping Criteria

Though the trained network could verify all those cases in the verification set, the network may still be fooled by contingencies which the network did not encounter before. A simple threshold relay tripping criterion can be based on the number of HIF relay logic 1 classifications in a continuous period of ten cycles. The threshold of five positive identifications in ten consecutive cycles will result in a tripping.

9. Conclusions

The paper presents practical harmonic HIF detection schemes using feed forward neural networks. The proposed ANN algorithm is an effective relaying scheme that can be readily implemented using available ANN hardware chips or software. The trained ANN reacts promptly to HIFs and has a high success detection rate. The relay scheme can be trained using realistic data from digital computer simulation or field measurements. It can also be retrained on line using actual field measurements and can be implemented using available DSP and parallel hardware. The proposed detection scheme only utilizes low harmonics of residual quantities which greatly enhances its feasibility and flexibility.

Since HIF detection schemes can still be fooled by fast feeder transients due to line switching, capacitor energization and de-energization as well as noisy substation signals, a simple counter-tripping criteria is used based on the number of positive logic 1 classifications in an assessment time window. For example, five positive identifications in a ten-cycle time window will result in feeder tripping.

10. Reference

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Table 1: Training Cases

Case	Fault ohms/kV/dist/type	Capacitors S.E./R.E 300kVAR	Other* Contingency/type
1	200/7/M/L-G		
2			
3	200/7/N/L-G		
4	150/7/N/L-G	300/300	
5	150/7/F/L-G		
6		300/0	1
7		0/300	2
8			1
9			2
10	25/12/M/L-G		
11	25/12/N/L-G	300/300	
12	25/12/N/L-G		
13	25/12/N/L-G	300/300	
14	25/12/N/L-G	0/300	
15	25/12/N/L-G	300/0	
16			3
17			3
18			3
19			4
20	150/0.7/M/LL-G		
21	150/0.7/M/LL-G	300/300	
22	150/0.7/M/LL-G	0/300	
23	150/0.7/M/LL-G	300/0	
24		300/300	4
25	25/12/N/LL-G	300/300	
26	25/12/N/LL-G		
27	25/12/F/LL-G	300/300	
28	25/12/F/LL-G		
29	25/12/M/LL-G	300/300	
30	100/10/N/L-G		
31	100/10/F/L-G	300/300	
32	100/10/N/L-G	300/300	
33	100/10/M/L-G		
34	100/10/M/L-G	300/300	
35	200/7/F/L-G	300/300	
36	150/7/N/L-G		
37	150/7/M/L-G	300/300	
38	50/12/N/L-G	300/300	
39	50/12/F/L-G		
40	50/12/M/L-G		
41	25/12/F/L-G		
42	25/12/N/L-G	300/300	
43	150/0.7/N/LL-G		
44	150/0.7/F/LL-G	300/300	
45	150,200/0.7/M/L-G		
46	150,200/0.7/N/L-G	300/300	

* Type of contingencies: (1) switch 300 kVAR at R.E (2) switch 300 kVAR at S.E. (3) single phase load switching - 1.4 MW (4) nonlinear load switching - 0.5 MW

Table 2: Verification Cases

Case	Fault ohms/kV/dist/type	Capacitors S.E./R.E. kVAR	Distribution System (figure)	Other Contingency
v1	200/7/M/L-G	300/300	5	
v2	150/7/F/L-G	300/300	5	
v3		300/0	5	300kVAR at R.E
v4	200/7/N/L-G		5	
v5	170/7/M/L-G		5	
v6	50/12/F/L-G	300/300	5	
v7	40/12/M/L-G		5	
v8		300/0	5	150kVAR at R.E.
v9		0/300	5	150kVAR at S.E.
v10			5	150kVAR at R.E.
v11			5	150kVAR at S.E.
v12*	200/7/M/L-G		5	
v13**	200/7/M/L-G		5	
v14			5	1.4MW 1-phase load
v15			5	300kVAR at S.E.
v16	200/3/M/LL-G		7	
v17	200/3/M/L-G		7	
v18	200/3,2/M/L-G		7	
v19	200/2,3/N/L-G		7	
v20			7	
v21	100/15/N/L-G		8	
v22	100/15/M/L-G		8	
v23	100/15/F/L-G		8	
v24			8	
v25	100/15,10/M/L-G		8	
v26	100/15,10/N/L-G		8	
v27	100,70/15/F/L-G		8	
v28	100/15,10/M/LL-G		8	
v29	100/15,10/N/LL-G		8	
v30	100,70/15/F/LL-G		8	

*
In case v12, the distribution system in figure 1 is used except for the following changes:
~ transformer rating becomes 7.5 MVA 33kV/33kV.
~ the transmission is lengthened to a span of 40 km.
~ dc loading becomes 2 MW.
~ linear load at receiving becomes 5.5 MVA.

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In case v13, the distribution system in figure 1 is used except for the following change:
~ the dc nonlinear load and the linear load are replaced by 7.5 MVA linear load.

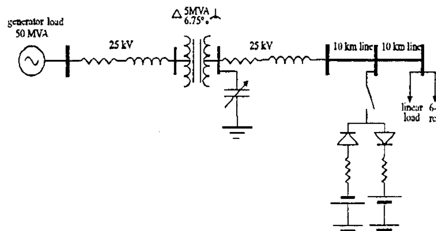

Figure 5 distribution system for training

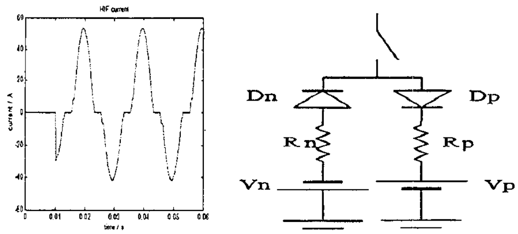

Figure 6 asymmetrical arc fault model and fault current

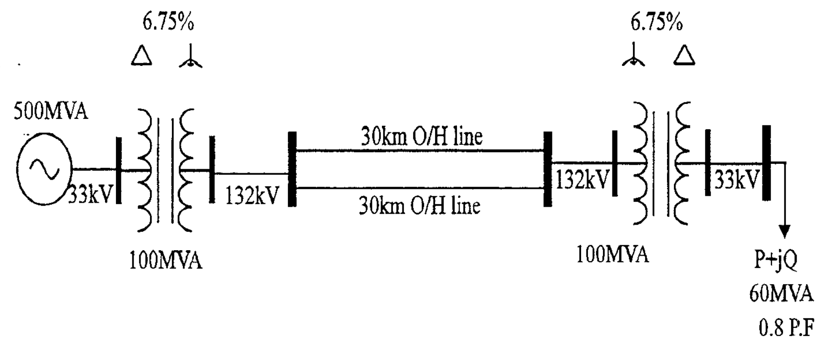

Figure 7 distribution system for verification

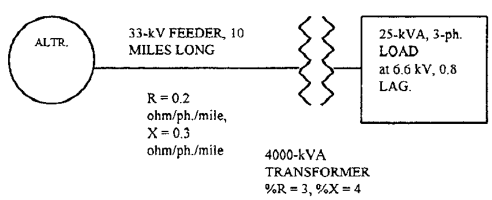

Figure 8 distribution system for verification

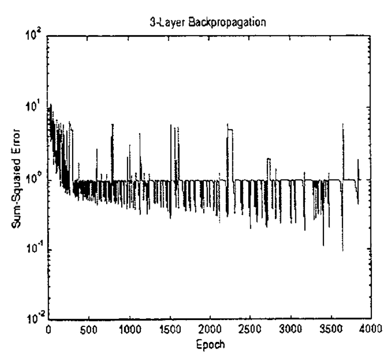

Figure 9 divergent back propagation training

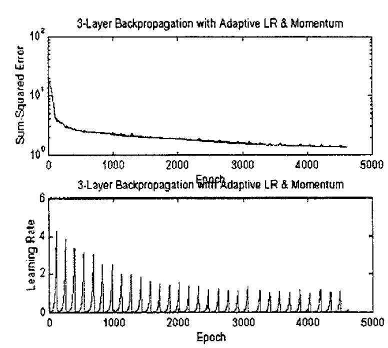

Figure 10 convergent back propagation training

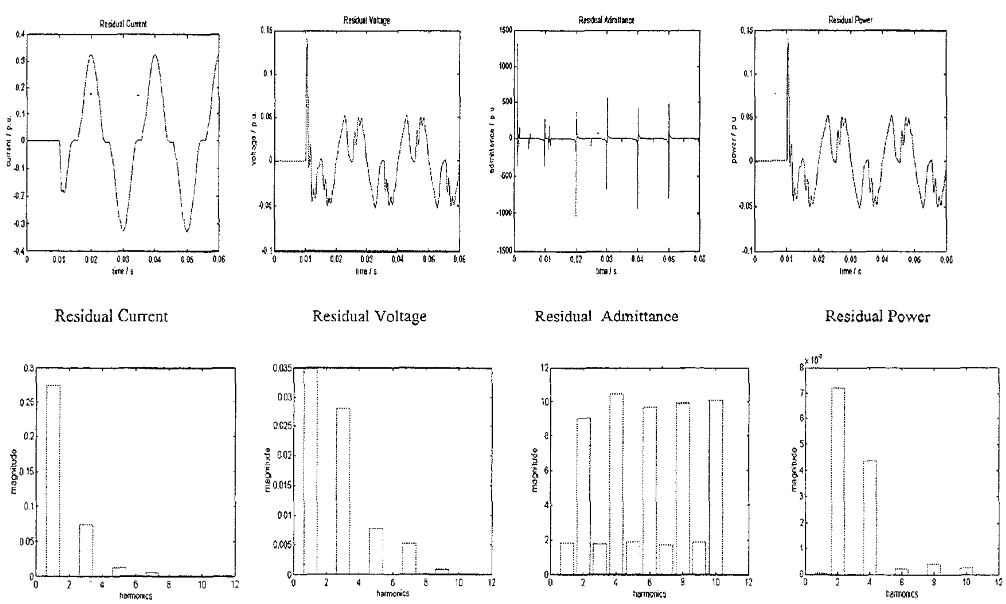

Figure 11 Residual Quantities in Time Domain and Frequency Domain under HIF

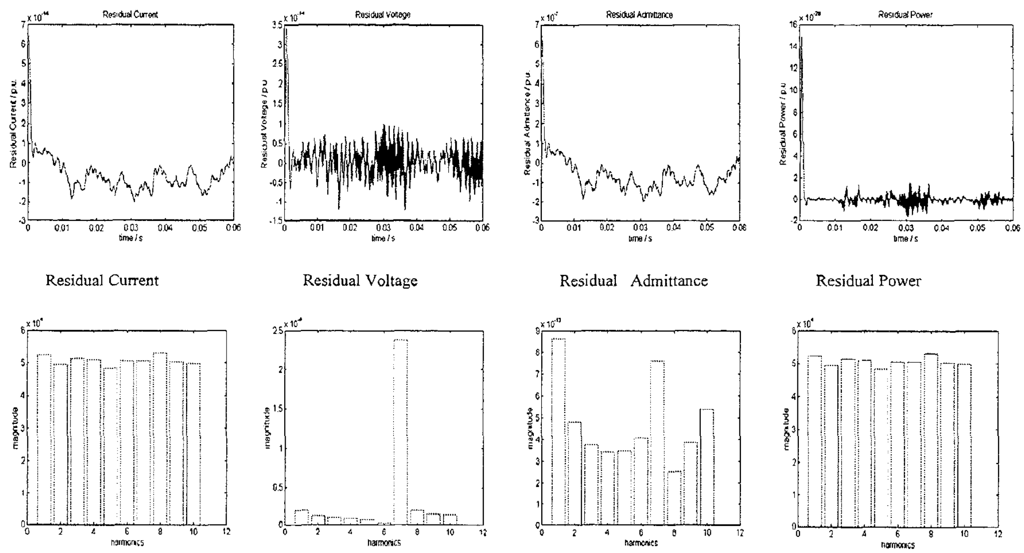

Figure 12 Residual Quantities in Time Domain and Frequency Domain under Capacitor Switching