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FAST COMPUTING NEURAL NETWORK MODELING FOR FAULT DIAGNOSIS IN POWER SYSTEMS

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ABSTRACT

In this paper an approach for fault location based on online neural network is designed. The approach of learning the neural network based on the running fault values are trained for the suggested neural network. This approach result in running fault diagnosis based on the fault observation parameter based on the diagnosis tool. The approach is designed to run on running values of the distributed system so as to overcome the level of fault happening in a run time environment, which is not observed in case of the conventional neural controlling method.

Keywords: adaptive learning, neural network, fault diagnosis, distributed power system

1. INTRODUCTION

An overhead transmission line is one of the main components in every electric power system. The transmission line is exposed to the environment and the possibility of experiencing faults on the transmission line is generally higher than that on other main components. Line faults are the most common faults. They may be triggered by lightning strokes, trees falling across lines. Fog and salt spray on dirty insulators may cause the insulator strings to flash over, and ice and snow loadings may cause insulator strings to fail mechanically. When a fault occurs on an electrical transmission line, it is very important to detect it and to find it's location in order to make necessary repairs and to restore power as soon as possible. The time needed to determine the fault point along the line will affect the quality of the power delivery. Therefore, an accurate fault location on the line is an important requirement for a permanent fault. Pointing to a weak spot, it is also helpful for a transient fault, which may result from a marginally contaminated insulator, or a swaying or growing tree under the line. Fault location in transmission lines has been a subject of interest for many years.

During the last decade a number of fault location algorithms have been developed, including the steady state phasor approach, the differential equation approach and the traveling wave approach [4], as well as two-end [13] and one-end [14] algorithms. In the last category, synchronized [5] and non-synchronized [9] sampling techniques are used. However, two-terminal data are not widely available. From a practical viewpoint, it is desirable for equipment to use only one-terminal data. The one-end algorithms, in turn, utilize different assumptions to replace the remote end measurements. Most of fault locators are only based on local measurements. Currently, the most widely used method of overhead line fault location is to determine the apparent reactance of the line during the time the fault current is flowing and to convert the ohmic result into a distance based on the parameters of the line. It is widely recognized that this method is subject to errors when the fault resistance is high and the line is fed from both ends, and when parallel circuits exist over only parts of the length of the faulty line. Many successful applications of artificial neural networks (ANNs) to power systems have been demonstrated, including security assessment, load forecasting, control, etc. Recent applications in protection have covered fault diagnosis for electric power systems [8], transformer protection [2] and generator protection [7]. However, almost all of these applications in protection merely use the ANN ability of classification, that is, ANNs only output 1 or 0. Various approaches have been published describing applications of ANNs to fault detection and location in transmission lines [10],[11],[12]. In this paper, a single-end fault detector and three fault locators are proposed for on-line applications using ANN. A feed forward neural network based on the supervised back propagation learning algorithm was used to implement the fault detector and locators. The neural fault detector and locators were trained and tested with a number of simulation cases by considering various fault conditions (fault types, fault locations, fault resistances and fault inception angles) and various power system data (source capacities, source voltages, source angles, time constants of the sources) in a selected network model.

2. NEURAL NETWORK

In this paper, the fully connected multilayer Feed Forward Neural Network (FFNN) was used and trained with a supervised learning algorithm called Back Propagation Algorithm (BPA). The FFNN consists of an input layer representing the input data to the network, some hidden layers and an output layer representing the response of the network. Each layer consists of a certain number of neurons; each neuron is connected to other neurons of the previous layer through adaptable synaptic weights w and biases b as shown in Figure-1.

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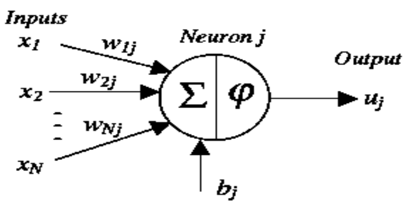

Figure-1. Information processing in a neural network unit.

If the inputs of neuron j are the variables $x_1, x_2, \ldots, x_i, \ldots, x_N$, the output u_j of neuron j is obtained as follows:

$$u_j = \varphi\left(\sum_{i=1}^{N} w_{ij} x_i + b_j\right)$$

Where w_{ij} represents the weight of the connection between neuron j and the i^{th} input, b_j represents the bias of neuron j and φ is the transfer function (activation function) of neuron j. A feed forward neural network of three layers (one hidden layer) is considered with N, M and Q neurons for the input, hidden and output layers, respectively. The input patterns of the ANN represented by a vector of variables $x = (x_1, x_2, \ldots, x_i, \ldots, x_N)$ submitted to the ANN by the input layer are transferred to the hidden layer. Using the weight of the connection between the input and the hidden layer, and the bias of the hidden layer, the output vector $u = (u_1, u_2, \ldots, u_j, \ldots, u_M)$ of the hidden layer is then determined. The output u_j of neuron j is obtained as follows:

$$u_j = \varphi_{hid}\left(\sum_{i=1}^{N} w_{ij}^{hid} x_i + b_j^{hid}\right)$$

Where w_{ij}^{hid} represents the weight of connection between neuron j in the hidden layer and the i^{th} neuron of the input layer, b_j^{hid} represents the bias of neuron j and hid is the activation function of the hidden layer. The values of the vector u of the hidden layer are transferred to the output layer. Using the weight of the connection between the hidden and output layers and the bias of the output layer, the output vector $y = (y_1, y_2, \ldots, y_k, \ldots, y_Q)$ of the output layer is determined.

The output y_k of neuron k (of the output layer) is obtained as follows:

$$y_k = \varphi_{out}\left(\sum_{j=1}^{M} w_{jk}^{out} u_j + b_k^{out}\right)$$

Where w_{jk}^{out} represents the weight of the connection between neuron k in the output layer and the j^{th} neuron of the hidden layer, b_k^{out} represents the bias of neuron k and φ_{out} is the activation function of the output layer. The output y_k (corresponding to the given input vector x) is compared with the desired output (target value) y_k^d. The error in the output layer between y_k and y_k^d ($y_k^d - y_k$) is minimized using the mean square error at the output layer (which is composed of Q output neurons), defined by

$$E = \frac{1}{2}\sum_{k=1}^{Q}\left(y_k^d - y_k\right)^2$$

Training is the process of adjusting connection weights w and biases b. In the first step, the network outputs and the difference between the actual (obtained) output and the desired (target) output (i.e., the error) is calculated for the initialized weights and biases (arbitrary values). During the second stage, the initialized weights in all links and biases in all neurons are adjusted to minimize the error by propagating the error backwards (the back-propagation algorithm). The network outputs and the error are calculated again with the adapted weights and biases, and the process (the training of the ANN) is repeated at each epoch until a satisfied output y_k (corresponding to the values of the input variables x) is obtained and the error is acceptably small.

3. ADAPTIVE LEARNING

The design process of the ANN fault detector and the fault locator goes through the following steps:

1. Preparation of a suitable training data set that represents cases the ANN needs to learn.
2. Selection of a suitable ANN structure for a given application.
3. Training the ANN.
4. Evaluation of the trained ANN using test patterns until it's performance is satisfactory.

In order to build up an ANN, the inputs and outputs of the neural network have to be defined for pattern recognition. The inputs to the network should provide a true representation of the situation under consideration. For the developed system the current (I) and voltage (V) signals are calculated as a string of samples corresponding to a 100 kHz sampling frequency. These signals are processed so as to simulate a 2 kHz sampling process (40 samples per 50 Hz cycle) using an anti-aliasing filter to remove the unwanted frequencies from a sampled waveform. This sampling rate is compatible with sampling rates presently used in digital relays.

The phase current (I_a, I_b, I_c) and voltage (V_a, V_b, V_c) signals, and the zero sequence current (I_0) and voltage (V_0) signals sampled at 2 kHz are used as the inputs to the ANN. It should be mentioned that the input current and voltage samples have to be normalized in order to reach the ANN input level (±1). The ANN output is indexed with either a value of 1 (the presence of a fault) or 0 (the non-faulty situation).

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4. PROPOSED FAULT DIAGNOSIS SYSTEM

The fault detection task can be formulated as a pattern classification problem. The fully connected three-layer feed forward neural network was used to classify faulty/non-faulty data sets and the error back-propagation algorithm was used for training. The number of neurons in the input and hidden layers were selected empirically through extensive simulations. Various network configurations were trained and tested in order to establish an appropriate network with satisfactory performances, which were the fault tolerance, time response and generalization capabilities. Data strings of 7 consecutive samples of each signal sampled at 2 kHz are found to be appropriate inputs to the neural network. This represents a moving window with a length of 3 ms. In order to construct a good neural network system, it is vitally important to train and test it correctly.

With supervised learning, the ANN is trained with various input patterns corresponding to different types of fault (a–g, b–g, c–g, a–b–g, a–c–g, b–c–g, a–b, a–c, b–c, a–b–c and a–b–c–g, where a, b, and c are related to the phases and g refers to the ground) at various locations for different fault conditions (fault inception angles, fault resistances) and different power system data (source capacities, source voltages, source angles, time constants of the sources). The ANN fault detector consists of 56 input neurons (seven samples of each signal: I_a, I_b, I_c, V_a, V_b, V_c, I_0, V_0), 18 neurons in the hidden layer (chosen after a series of trials) and one output neuron to indicate the transmission line state. Then the ANN structure of the fault detector is (56–18–1).

The sigmoid transfer function

$$\varphi(S) = \frac{1}{1 + e^{-s}}$$

was used for the hidden and output layers.

To evaluate the performance of the proposed neural network based fault detector and locator, a 400 kV, 120 km transmission line extending between two sources as shown in figure-2 is considered in this study. The transmission line is represented by distributed parameters and the frequency dependence of the line parameters is taken into account.

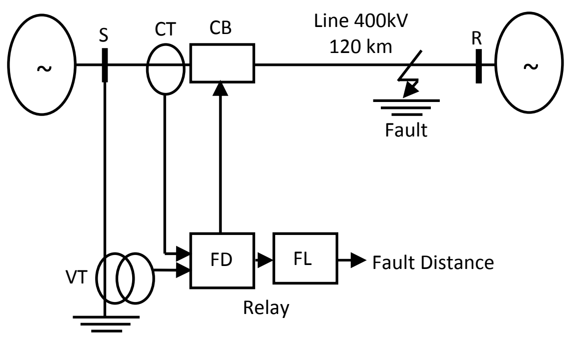

Figure-2. System studied

VT: Voltage Transformer, CT: Current Transformer,
CB: Circuit-Breaker, FD: Fault Detector,
FL: Fault Locator.

A highly accurate transmission line simulation technique was utilized to generate voltage and current waveforms at the relay location (end S) for different fault types, fault conditions and different power system data. Voltage and current signals at the transmission line end S (relay location) will be acquired by the relay through CTs and VTs. After preprocessing, they will be fed to the fault detector (FD) to detect a fault, and if the fault is detected, the fault locator (FL) estimates the distance to the fault in the transmission line.

The proposed fault detector (FD) is designed to indicate the presence or absence of a fault. The occurrence of the fault is determined by identifying the power system state directly from instantaneous current (I) and voltage (V) data. The fault locator (FL) is designed to estimate the distance of the fault in the transmission line using the fundamental phasor magnitude of the voltage and current signals. The fault detector (FD) and the fault locator(FL) use only one-terminal line datum extracted at the relay location (S).

5. SIMULATION RESULTS

In order to test the three-phase system a simulation was performed on the system using the pi circuit model representation of the transmission line.

For the test purposes, a three- phase fault has been triggered following 2 cycles of system operation. The obtained output current and phase voltage in one line-ground fault is as shown below:

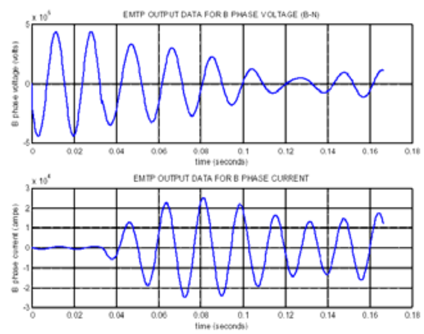

Figure-3. Current and voltage waveforms from the B phase

The data points, which make up these curves, are then converted to the frequency domain by use of the Fourier transform. Then, a high order curve fit is used to determine the amount of corruption present in the fundamental frequency component due to the presence of the sub-synchronous component. This procedure is completed for the real and imaginary parts of the initial Fourier transform separately. One real and one imaginary transform solution curve fit for voltage, and one real and one imaginary transform solution curve fit for the current.

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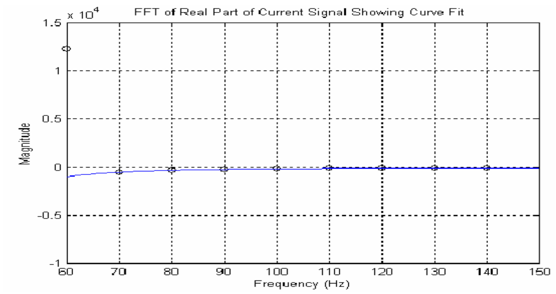

Figure- 4. Curve fitting of the obtained current magnitude using transformation features

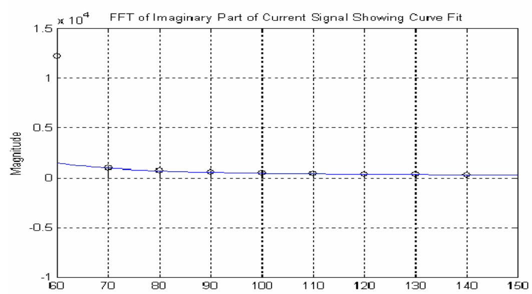

Figure-5. Curve fitting for the imaginary component of the fault current

Figures-5, 6 shows the transform results and the curve fit used to predict the corruption in the 60Hz (fundamental) component in the transmission lines for real and imaginary part.
Once the corruption has been identified, the proper 60Hz magnitude is computed, and the fundamental component of the spectrum shown in Figures 5,6 is replaced with the curve fit estimate of the corruption. A spectrum of the subsynchronous component only with quite a bit of "leakage" is computed.

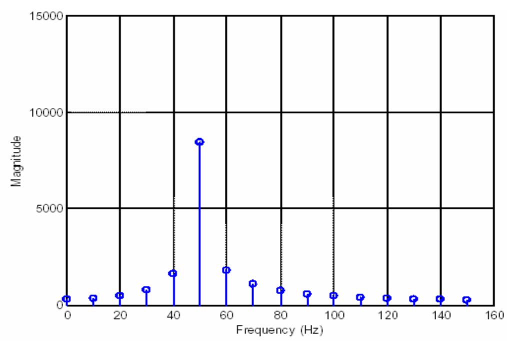

Figure-6. Magnitude correction component of the developed fault current

With the variation of the weight factor of the training neural network a proper current spectrum is obtained which when applied to the current simulation obtains the fault current corrections as shown below:

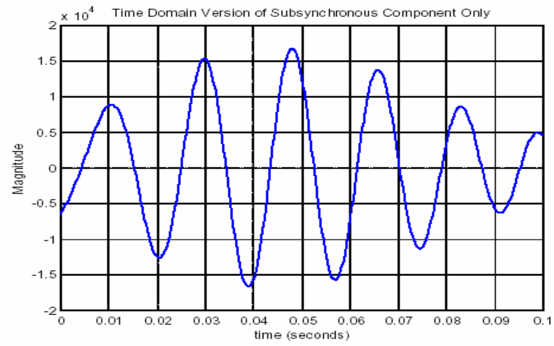

Figure-7. Compensated fault current for the given logic

The discrete fault components for the given current samples for 4 processing windows are shown below:

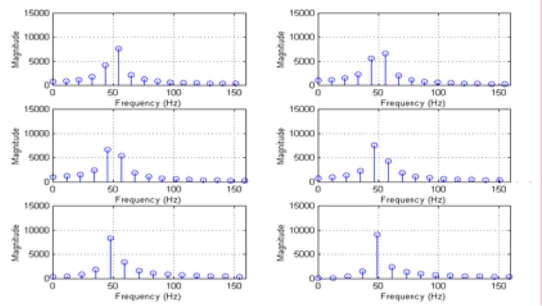

Figure-8. Obtained current block samples of the continuous fault current

The magnitude of the next adjacent frequency component for each observation is carried out. When the ratio is maximum there is little or no remaining "leakage" and the fundamental frequency component of the signal will be equal to, or an even multiple / submultiples of one harmonics of the corresponding transform. Therefore, the frequency and magnitude calculated with the transform for that window length should be correct. The computed frequency of the subsynchronous component is found to be 49.873Hz. When this value is used and the impedance (V/I ratio) is computed at that frequency, the resulting values for L and C to the fault location are j61.4788 Ω of inductive reactance, and –j64 Ω of capacitive reactance. This represents a determination of fault location, for either relaying or fault location purposes, with an accuracy of 97.6%. The EMTP analysis was performed using a time dependent switch between the A phase and ground. The following graphs depict the A phase voltage and current through the test.

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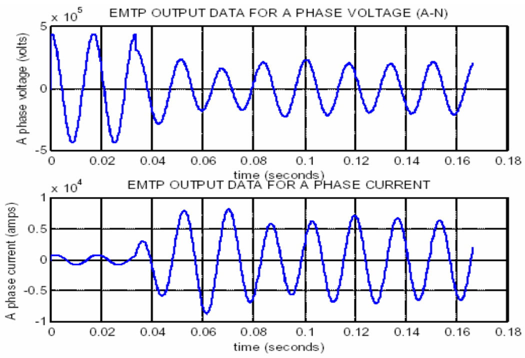

Figure- 9. Fault observed at line phase A.

The obtained observations for this case are as shown below:

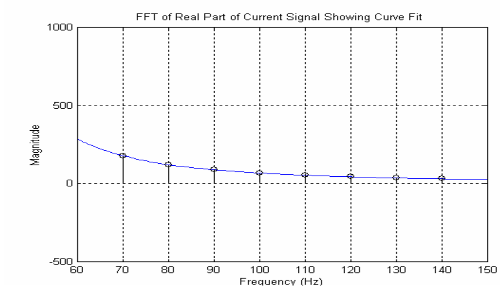

Figure-10. Curve fitting of the obtained current magnitude using transformation features

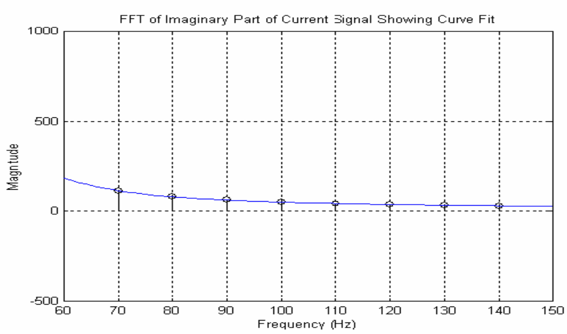

Figure -11. Curve fitting for the imaginary component of the fault current

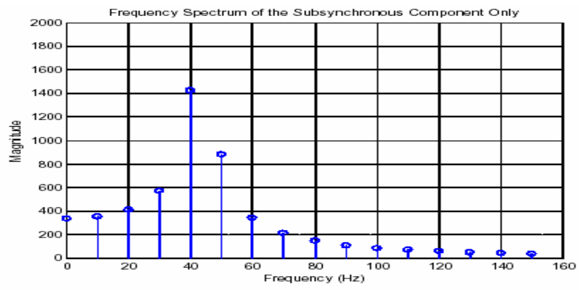

Figure-12: Magnitude correction component of the developed fault current

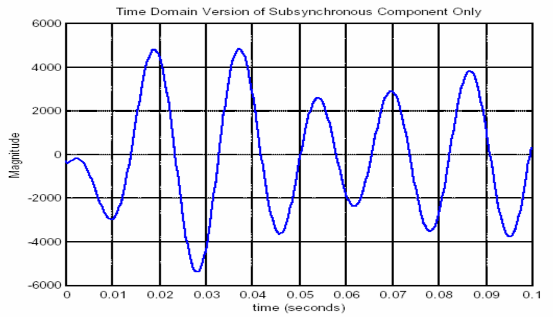

Figure-13. Compensated fault current for the given logic

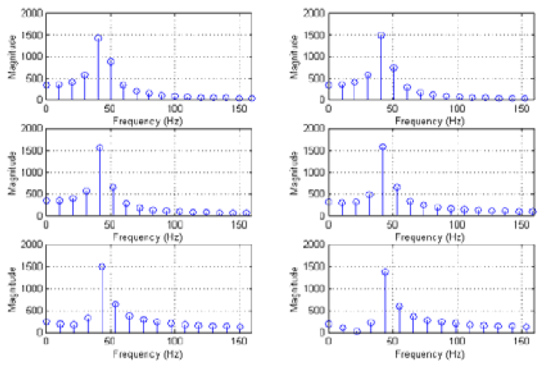

Figure-14. Obtained current block samples of the continuous fault current

Once the proper values for the magnitude and frequency of the subsynchronous component have been found as well as the proper magnitude of the fundamental, it is then necessary, when working with a phase to ground fault, to compute the compensated current in order to arrive at the value of impedance to the fault. In an uncompensated transmission line, the factor "m" is found as follows:

$$m = \frac{Z_0 - Z_1}{Z_1}$$

This works out well since all terms in the equation are based on the line length to the fault, and it is possible to simply use the Z_0 and Z_1 parameters for the

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entire length of the line. Therefore, the quantity "m" for an uncompensated line remains constant for a given line and is not dependent on fault location.

6. CONCLUSIONS

An efficient neural network based fault detector for very fast EHV transmission line protection and three neural network based fault locators have been proposed. The results demonstrated the ability of ANNs to generalize the situation from the provided patterns and to accurately indicate the presence and location of faults using only one terminal line datum. The neural fault detector uses only instantaneous current and voltage values, while the neural fault locator uses the magnitudes at the fundamental frequency of the voltage and/or current phasors. The presented test results demonstrate the effectiveness and the precision of fault detection in a variety of fault situations including fault types, fault locations, fault inception angles and fault resistances, and different power system data including source capacities, source voltages, source angles and source time constants. The ANNs thus have the possibility to be used for on-line fault detection and location in transmission lines

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