HIGH IMPEDANCE FAULTS DETECTION IN POWER DISTRIBUTION SYSTEM BY COMBINATION OF ARTIFICIAL NEURAL NETWORK AND WAVELET TRANSFORM

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ABSTRACT

In this paper, Discrete Wavelet Transform (DWT) and Artificial Neural Network (ANN) are used to detect High Impedance Faults (HIFs) in Distribution Power System (DPS). In this method, the difference between HIF, Low Impedance Fault and Normal events is established.

The DWT techniques are used as pre-processor to de-noise and extract features from three phase current signals at each DPS's feeder; such features can provide enough information to distinguish by ANN between different fault types.

Faulty and normal operations have been simulated by Matlab 6.5. Details of the design procedure and the performance results of proposed method are presented in this paper. The result shows that the proposed method gives good results in detecting HIFs.

INTRODUCTION

Power system protection has usually based on the power frequency components (50 or 60 Hz) for their fault detection methods. The signal components of high frequency introduced by a fault are removed. However, these high frequency transient components can contain massive information about the fault type and location.

Against to usual techniques, the DWT takes advantage of information contained in the transient components of the signal as in voltage and current fault signals, in electrical power system.

When a HIF takes place, the detection will be hard by over current devices, because of the small current produced in the fault and the high similarity between this type of fault and normal events in power systems. It is related to security problem because it can result in fires.

In particular, the HIF fault detection is focused by several researchers. In [1] fault current flicker is used to detect HIFs. The probability of detection HIFs by DWT was described in[2] and the difficulty in HIF detection leads to using ANN [3] to recognize distortion of the voltage and current waveforms caused by arcing in HIFs.

There are two modes of joining wavelet analysis and ANN. One mode is to use wavelet analysis to provide input to ANN; the other is to collect wavelet and ANN directly, i.e. wavelet and scale functions used as a transfer function of ANN. These combinations are beneficial in signal processing, medical application and protections in power system [4-6].

In this paper, a set of faults have been simulated for the different feeders of the DPS shown in figure 1.these faults have been simulated in a DPS with different condition (Fault inception angle, fault resistance and fault location). According to statistical information, most faults in power systems are single-phase to ground faults; this type of fault was examined for all three phase lines.

In order to determine patterns, the three events data signal is passed through the DWT analysis filter bank which used daubechies of order five (db5) up to seventh level decomposition. Information from the transient fault signals is extracted in time-frequency domain. It is evident that each filter output contains the information of different frequency components of the faulted signal at different levels and can accurately localize the disturbance point.

Finally it is necessary to design an appropriate architecture of ANN with suitable training algorithm to get low error.

The organization of this paper is as follows. In the Second section the examined power system is described, in Section Three and Four, the introduction of using of wavelet analysis for feature extraction and de-noising fault signal is shown. Section Five presents and explains the configuration of the ANN that provides good generalization ability. Finally the conclusion appears in section Six.

POWER SYSTEM DETAILS

To prove the acceptable algorithm performance under every possible operating condition, as explained before, a wide simulation operation was executed on the DPS, which is modeled by Matlab 6.5. In all cases, it has been considered the fundamental frequency of 50 Hz, the convenient sampling frequency of 30 KHz and three cycles of simulation time that corresponds to 600 samples per cycle.

The DPS analyzed is a medium voltage network of 13.8 kV, and 12 MVA of rated power, consisting of five distribution feeders, and grounded solidly in neutral of transformer winding. These feeders are made up of 35.7 km of overhead line and 8.6 km of underground cable. The system supplies a set of 29 simplified loads distributed to the five feeders, as shown in Figure 1

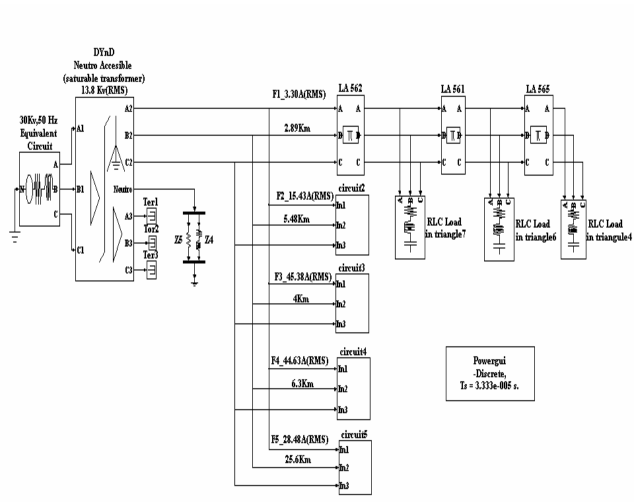

Figure: 1: Distribution Power System

During the power system normal operation condition, voltages and currents are practically sinusoidal with low levels of harmonic. But when power system affected by many normal operations like switching nonlinear elements (semiconductor devices) and capacitor switching, the variation of current and voltage signals can produce. In both cases, the relay input voltage and current are not greater than its rated values. Another situation that can modify the voltage and current magnitudes, without trip the relay, is the appearance of HIFs. However, these situations must be clearly differentiated.

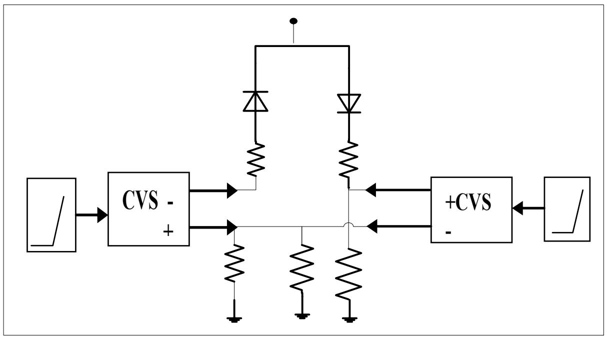

Figure: 2 A

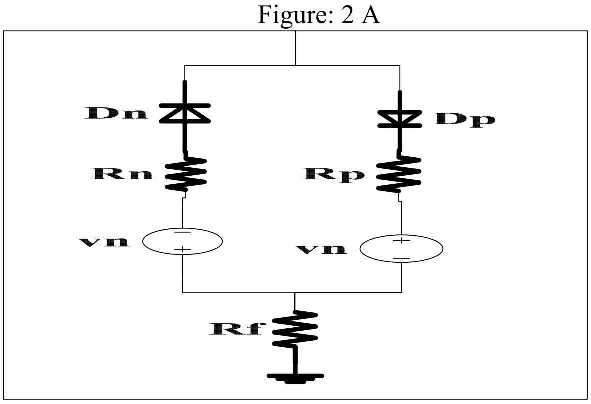

Figure:2B

Figure: 2(A&B): are Tow high impedance fault model

The models used for the simulation of HIF in this paper are shown in Figure 2, which correspond to the sandy soil with different percents of humidity level of soil [7]. These faulted models reveal the most important performances of the original physical fault. There are other models of HIFs simulated with EMTP with the same result of signal wave forms [8].

WAVELET TRANSFORM

Sines and cosines in Fourier transform are non local and extend to infinity; therefore, they do a very poor work in analyzing non-stationary signals.

In addition the Short Time Fourier Transform (STFT) is not ideal for signal analysis as the size of the window remains constant over time and frequency. However, WT provides an enormous range of analyzing functions ψ (τ) that change their size over time and scale. It uses short windows at high frequencies and long windows at low frequencies. Thus the windowing is adjusted automatically for low or high frequencies.

The DWT of discrete data signal is consist in a series of filtering and down-sampling operations, which repeatedly split a signal into low frequency and high frequency components.

The coefficients calculated by applying a high-pass wavelet filter to the time domain signal (convolution) are detail coefficients ``cDj´´. At the same level, a low-pass scale filter is also applied to produce the approximation coefficient ``cAj´´ for the next level. Both the wavelet and scale filters can be obtained from a Single Quadrature Mirror Filter (QMF) function. The filter outputs are defined by the following equations.

$$y_{high}[k] = \sum_{n} x(n)\, g_{(-2k+n)} \qquad (1)$$

$$y_{low}[k] = \sum_{n} x(n) h_{(-2k+n)} \qquad (2)$$

Where) and $y_{low}(k)$ are the outputs of the high-pass $\boldsymbol{g}$ (wavelet filter associated with wavelet) and low-pass $\boldsymbol{h}$ (scaling filter associated with wavelet) filters, respectively after down-sampling by 2.

In this system, hard threshold are used to remove the useless coefficients whose absolute values are lower than the threshold and then the DWT of a signal is calculated.

FEATURE EXTRACTION

The process of detection works by extracting a set of particular features, which should vary sufficiently with any variation in power system operation.

After DWT, the extracted wavelet coefficients provide a compact representation that show the energy distribution of the signal in time and frequency. In order to further reduce the dimensionality of the coefficient vectors, statistics over the set of the wavelet coefficients are used. For example, the standard deviation of the coefficients in each subbands (cD1-cD7 and cA7). These features provide information about the amount of change of the frequency distribution.

$$std = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \qquad (3)$$

Where $\bar{x}$ is mean value of x_i

The feature extraction it is necessary because it is unreasonable to use generated samples of current waveforms on three phases directly as input to ANN, because these samples are taken at high frequency. Then, certain characteristics of the waveforms must be identified and reduced, so that a small size and fast ANN can distinguish between normal and abnormal feeder operation.

ARTIFICIAL NEURAL NETWORK

An ANN can be defined as greatly connected neurons, organized in layers. Figure 3 shows the model for a neuron.

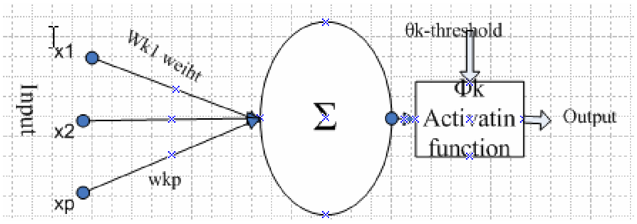

Figure 3: neuron model

The input layer receives the input vector. Each element of this vector is weighted by the input to the hidden interconnection (w), to form a weighted sum.

This sum is reduced and changed by threshold θ and activation functions φ respectively, to create the state of each neuron.

Each neuron in the hidden layer and output layer receives output vectors of their previous layer to calculate the weighted sum of vectors and then, to limit the amplitude of output vectors by the activation functions of the neurons.

The process of adjusting weights and biases carry out by means of training rules. There are several types of training algorithms; the back- propagation learning algorithm is one of the most popularly used algorithms. An abstract of the back propagation algorithm is as follows.

The feature vectors are applied to input and output of the network repeatedly and the network changes its variable parameters (weights and biases), started from small values until it formulate the relationship between the input patterns and outputs (learned). That means the error was calculated continually and propagated backward through the network until error between the actual and knowable output values was reached to a probable minimum value.

According to the mathematical formulation:

If *(x1, x2... xp)* are the input signal, the ANN input to the kth unit in the hth hidden layer is

$$net^h_{pk} = \sum_{j=1}^{p} w^h_{kj} x_{pj} - \theta^h_k . \qquad (4)$$

Where $w_{k1}....w_{kp}$ are the weights of neuron k, θ_k is the threshold (bias); φ_k is the activation function; and net^h_{pk} is the input to the neuron k.

The output from the hidden layer is

$$o^h_{pk} = f^h_k(net^h_{pk}) \qquad (5)$$

Where f^h_k is the activation function at node k of the hidden layer h.

ANN input at the gth unit in the output layer is

$$net^o_{pg} = \sum_{k=1}^{L} w^o_{gk} O_{pk} - \theta^o_g \qquad (6)$$

Where O_{pk} is the output of the previous layer neuron, and the output from the gth unit in the output layer is

$$O^o_{pg} = f^o_g(net^o_{pg}) \qquad (7)$$

In order to find a convergent solution to HIF detection, the training patterns must be able to inform the difference between cases with and without HIFs on the one hand and rightly separate between faulty and sound conditions on the other hand.

After several simulations with different arrangements of ANN, activation functions, and training algorithms with SARENEUR software[9], It was concluded that a MLP, through the architecture of '24-14-7-3' neurons per layer and 'logsig-tansig-purelin' as transfer functions for the second, third and output layer respectively, is the best structure for this application, Figure 4. And through the different training algorithms tested, BP was found to be the best algorithm, taking 78 second for gathering the error convergence goal of 10e-5 after 148 epochs, for 340 training patterns for feeder number One, Figure 5.

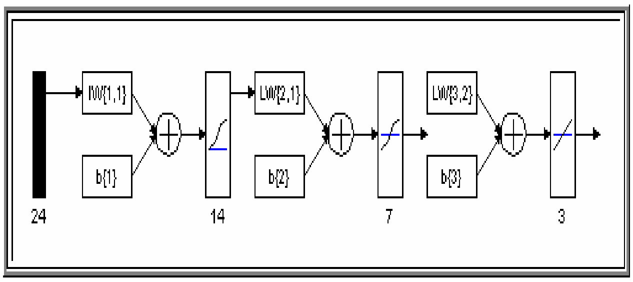

Figure: 4 NN achieved for feeder one.

Once the network is trained with the algorithm it was tested by a set of testing patterns (1100 cases in feeder 1). Then it can be used to identify the output pattern given an appropriate input pattern.

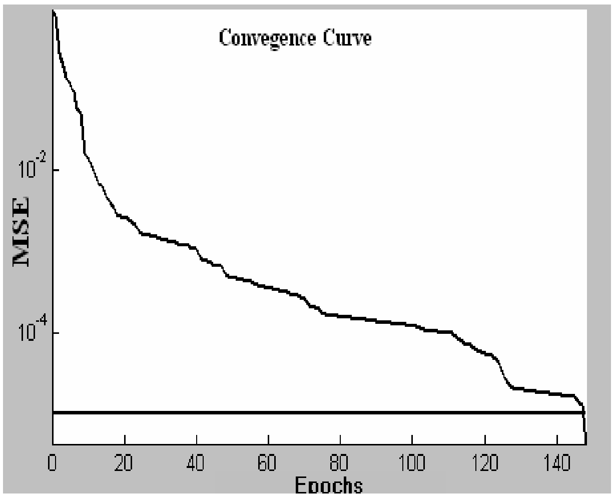

Figure: 5 MSE of (24-14-7-3) MLP

The same procedure to trained ANN has been used by a large number of typical system measurement patterns for all remaining feeders (900, 820, 800, and 1300 cases respectively). After having been trained, the ANNs are tested using 2950, 2350, 2500, and 2800 fault cases. This process is called generalization. In this process of generalization, the error in HIF detection was less than 1% of the tested cases

CONCLUSION

A high frequency transient disturbance waveform are found during switching operation, such as capacitor bank switching and energizing large motor load , also in fault situations, etc.

The transient signal is nonstationary, whose properties change quite a lot with time. Therefore, it is difficult for FFT to achieve both high resolution in frequency domain and accurate location in the time domain. The properties of both time and frequency domain localizations in DWT demonstrate that the wavelet transform is an excellent tool for processing the transient signal of power system faults.

Signals give significant information about the state of the Power system. This paper shows how these signals were decomposed into time-frequency representations using wavelet transform and the method shows how statistics may be used for choice of optimal input signals to the ANN. An ANN-based system was implemented for the identification of faults.

This fault identification information can be used for protective relaying purposes to make the decision and give the correct trip signal.

It has been shown that using hybrid approach provides better performance in term of accuracy and speed of ANN, because reduction the number of inputs to the ANN helps it to learn more easily. And when signals are decomposed into multiple sub-signals using wavelet transform, change corresponding to faults in each subsignal may manifest notable difference, and some of the sub-signals may have high sensitivity to small change in the signal.

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