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RESEARCH ARTICLE

CLASSIFICATION OF POWER SYSTEM FAULTS USING WT AND PNN

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ABSTRACT

Automation of power system fault identification using information conveyed by the wavelet analysis of power system transients is proposed. Probabilistic Neural Network (PNN) for detecting the type of fault is used. The work presented in this paper is focused on identification of simple power system faults. Wavelet Transform (WT) of the transient disturbance caused as a result of occurrence of fault is performed. The detail coefficient for each type of simple fault is characteristic in nature. PNN is used for distinguishing the detail coefficients and hence the faults.

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INTRODUCTION

In recent years, researchers have developed powerful wavelet techniques for the multiscale representation and analysis of signals. Wavelets localize the information in the time-frequency plane. One of the areas where these properties have been applied is power engineering. Due to the wide variety of signals and problems encountered in power engineering, there are various applications of wavelet transform. Another important aspect of power disturbance signals is the fact that the information of interest is often a combination of features that are well localized temporally or spatially such as power system transients. This requires the use of analysis methods sufficiently, which are versatile to handle signals in terms of their time-frequency localization (Kezunovic and Galijasevic, 2001). The power system transients caused by disturbances have vital information embedded. The main advantage of WT over STFT (Short Time-Fourier Transform) is that the size of analysis window varies in proportion to the frequency. Fourier techniques cannot simultaneously achieve good localization in both time and frequency for a signal. Most power signals of interest include a combination of impulse-like events such as spikes and transients for which STFT and other conventional time-frequency methods are much less suited for analysis. WT can hence offer a better compromise in terms of localization (Chien-Hsing lee *et al.,* 2000).

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The wavelet transform decomposes transients into a series of wavelet components, each of which corresponds to a time domain signal that covers a specific octave frequency band containing more detailed information. Such wavelet components appear to be useful for detecting, localizing, and classifying the sources of transients. Hence, the wavelet transform is feasible and practical for analyzing power system transients (Chen, 1999).

Power system transients

Transients are signals, which decay to zero in finite time. Frequency based analysis has been common since Fourier's time; however frequency analysis is not ideally suited for transient analysis, because Fourier based analysis is based on the sine and cosine functions, which are not transients. This results in a very wide frequency spectrum in the analysis of transients (Fan Mo, 1998). Electromagnetic transients in power systems result from a variety of disturbances on transmission lines, such as switching, lightning strikes, faults, as well as from other intended or unintended events. Such transients are extremely important, for it is at such times that the power system components are subjected to the greatest stresses from excessive currents or over voltages (Kinsner *et al.,* 1983; Mo and Kinsner, 1996).

Analysis of transients by wavelet transform

Wavelet theory is the mathematics, which deals with building a model for non-stationary signals, using a set of components that look like small waves, called wavelets. It has become a wellknown useful tool since its introduction, especially in signal and image processing (Kinsner and Langi, 1993; Kinsner, 1997).

Continuous Wavelet Transform

Considering a time series, Xn, with equal time spacing Δt translation:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\,\psi\left(\frac{t-\tau}{s}\right) \quad (1)$$

In (1) s is the scale factor, τ is the translation factor and the $-1/$

and $n = 0 \ldots N-1$. Considering a *wavelet function*, $\psi_0(\eta)$,

that depends on a nondimensional time parameter η. This function must have zero mean and be localized in both time and frequency domain. The wavelets are generated from a single basic wavelet ψ (t), namely, *mother wavelet*, by scaling and factor s^2 is for energy normalization across the different Scales.

Discrete Wavelet Transform (DWT)

To obtain the DWT, the parameters a and b need to discretized. Discretizing $a = 2^j$ and $b = 2^j$

k will yield orthonormal basis functions for certain choices of ψ.

$$\psi_{(j,k)}(t) = 2^{-j/2}\,\psi\left(2^{-j}t-k\right) \quad (2)$$

Mallat showed that Multi Resolution Analysis (MRA) can be used to obtain the DWT of a discrete signal by applying lowpass and highpass filters, iteratively, and subsequently down sampling them by two. Fig. 1 illustrates this process, where g[n] and h[n] are the highpass and lowpass filters, respectively [4]. At each level, this procedure computes,

$$y_{high}[k] = \sum_{n} x[n]\cdot g[2k-n] \quad (3)$$

$$y_{low}[k] = \sum_{n} x[n]\cdot h[2k-n] \quad (4)$$

where

$$h[N-1-n] = (-1)^n\, g[n] \quad (5)$$

With N being the total number of samples in x[n] and y_{high} and y_{low} are the outputs of highpass and lowpass filters, respectively, at each level. The number of levels this process is r epeated depends on the choice of the user. At the last level, the y_{low} [k] obtained is called as Approximation. The y_{high} [k] computed at each level is called as the detail coefficient at that level. Voltage obtained at the generating station, plotted against time, is the transient source signal, X(n), considered in this paper.

A General framework

The transient disturbance generated due to fault is decomposed by wavelet transform into several detail coefficients and Approximations. The decomposition of the signal into these detail coefficients and approximations are carried out until the fundamental frequency signal (50Hz) is obtained as the approximation at that level. The detail coefficient obtained at the final level is characteristic for each type of simple power system fault. The Probabilistic Neural Network recognizes this Final level detail coefficient corresponding to the fault Fig. 2. Depicts illustrated the framework.

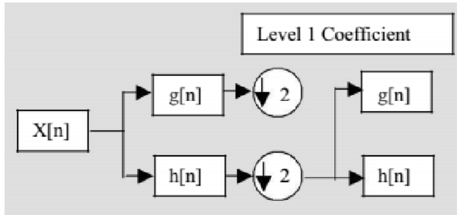


Figure 1. Computation of DWT by MRA

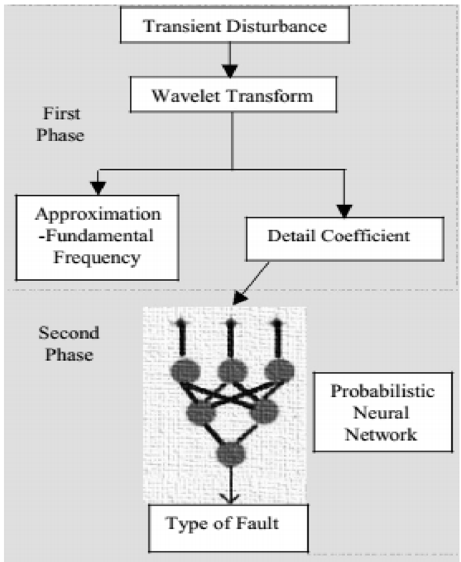


Figure 2. Block diagram shows the fault detection system. In the first phase, the detail coefficient is obtained by wavelet transform. The second phase involves fault type detection

Application of pnn to wavelet detail coefficient

PNN has an input layer, a exemplar layer, a summation layer and an output layer as shown in Fig.3. The activation function of a neuron in the case of the PNN is statistically derived from estimates of probability density functions (PDFs) based on training patterns (Bose, 1998). The wavelet detail coefficient (vector **X**) of the level 4 is fed to the input layer consisting of 119 neurons (samples of the detail coefficient) of the Probabilistic Neural Network. The exemplar layer, having 9 neurons (3 faults x 3 sets of data for each fault), consists of the activation functions corresponding to each of the training sets. Estimator for the PDF is,

$$p(x \mid s_i) = \frac{1}{(2\pi)^{m/2}\sigma_i^m |s_i|} \sum_{j=1}^{n_i} \exp\left[\frac{-(x-x_j^{(i)})^T (x-x_j^{(i)})}{2\sigma_i^2}\right] \quad (6)$$

Where p(x|Si) is the probability of vector x occurring in Set $_{Si}$, corresponding to the type of fault.

$x_j^{(i)}$ = j[th]Exemplar pattern or training pattern belonging to class Si, type of fault.

ni = is the cardinality of the set of patterns in class Si. □□*i* = Smoothing parameter.

The summation layer consisting of one summation unit corresponding to each class has a total of 3 neurons. Each unit is used to compute the sum in (7) from the outputs of the previous layer. The output layer is the decision layer governed by Winner-take-all mechanism selects the maximum posterior probability *pr* (*Si* | *x*), from the outputs of the previous summation layer for each i. Graphical model is shown in Fig. 3. Posterior probability *pr* (*Si* | *x*), that the test input data, the wavelet detail coefficient, is from Class Si, is given by Bayes' rule,

$$p_r(s_i \mid x) = \frac{p(x \mid s_i)\, p_r(s_i)}{p(x)} \qquad (7)$$

Where *pr* (*x* | *Si*) , I=1,2,…,k is the priori PDF of the pattern in classes to be separated. *pr* (*si*) , priori probabilities of the classes are equal (assumed equally l ikely). P(X) is assumed to be constant. The decision rule is to select class *Si* of the fault type, for which *pr* (*Si* | *x*) is maximum.

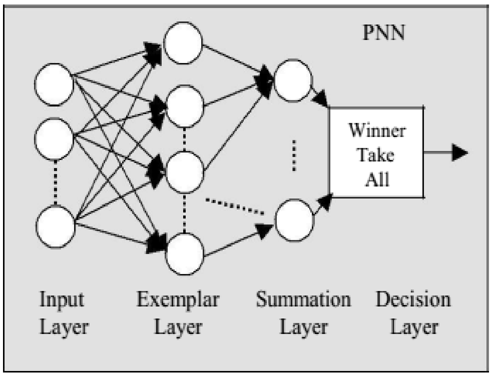


Figure 3. Model of a Probabilistic Neural Network. Detail Coefficient is fed to the input layer and the type of fault is obtained at the output

SYSTEM STUDY AND RESULTS

A simple power system network, shown in Fig.4 consisting of a generator, a load, two buses and a transmission line was used for the simulation purpose.

Figure 4. A simple power system network considered for analysis

Faults were created at a distance of 10kms from both the buses. Different types of faults were simulated using Electromagnetic Transient Analysis in Mipower package. Different types of faults were created and the transients were recorded for analysis. Simulation is carried out for Phase-A, Double Phase AB-Ground and 3 phase symmetric faults. Data sets for each type of fault were obtained by varying the fault inception angles. Fig.5. shows a sample voltage transient of a fault. The voltage at the generator is measured.

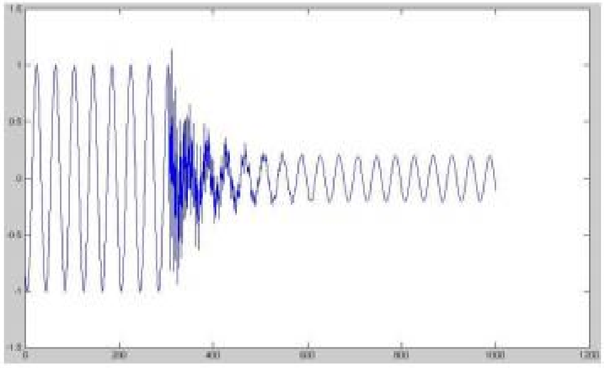


Figure 5. Example of Transient Disturbance

Application of Wavelets

Meyer wavelet shown in Fig.6 is used as the mother wavelet. The transient wave obtained is decomposed to the 4[th] level.

Observing the 4[th] level of decomposition in Fig.7, the approximation obtained, *a*4 is the fundamental frequency component of 50Hz uncorrupted by noise. The 4[Th] level detail coefficient obtained is thus fed to the PNN.

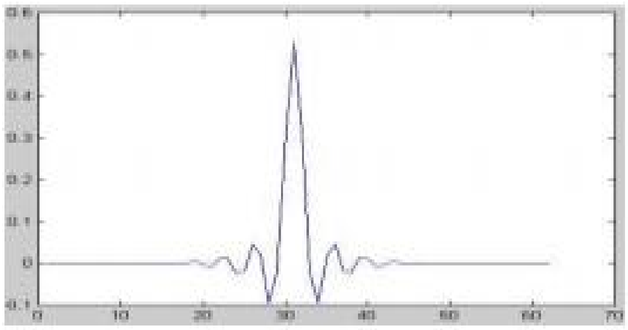


Figure 6. Meyer Wavelet used for the analysis

Multiple Level Decomposition

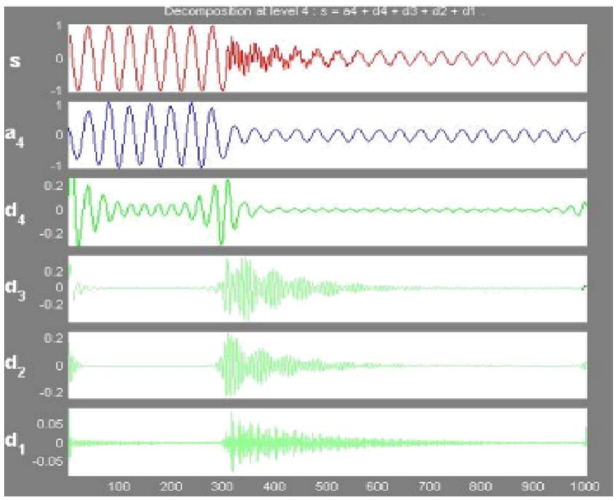


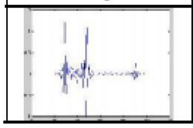
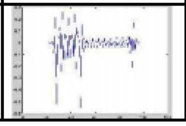
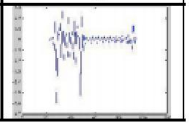
Figure 7. Source Signal decomposed into approximation and detail coefficients. S is the source signal or the transient disturbance

Fig.7 shows the decomposition of the transient wave by wavelet transform. S is the source voltage transient wave obtained from MIPOWER package. d1, d2, d3 and d4 are the detail coefficients and a4 is the approximation at level 4.

Classification Results of PNN

3 different sets of each type of fault, obtained by varying fault inception angles, are stored as interconnection weights of the PNN. A sample set is shown in Table I.

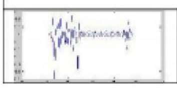
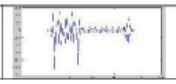
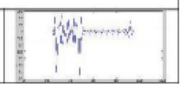
Table 1

Detail coefficients of 3 phase symmetric fault, Phase A-Ground & Phase BC-Ground Faults.		
1	2	3
		

Testing Data sets identified accurately by the PNN are shown in Table 2 for 3 phase symmetric fault, Phase A-Ground & Phase BC-Ground Faults.

Table 2

Detail coefficients of 3phase symmetric Fault		
1	2	3
		
Detail coefficients of Phase A-Ground Fault		
		

Detail coefficients of Phase BC-Ground fault.		
		

Conclusion and Future scope

The application of wavelet transform to determine the type of fault and its automation incorporating PNN could achieve an accuracy of 100% for all type of faults. Back propagation algorithm could not distinguish all of phase-ground and double-line to ground faults.

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