Power Disturbance Recognition Using Back-Propagation Neural Networks

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***Abstract*—This paper presents power disturbance recognition using back-propagation neural networks (BPNN). First, the discrete wavelet transform is used to extract the features of the power disturbance waveforms in the form of series coefficients of several levels. The Parseval theory is then utilized to calculate the energy of each level so that the number of coefficients can be reduced; then, the extracted results are used for recognition by the BPNN. Multi-event power disturbances are also fed to the recognition system for testing. From experiment results, the recognition rate is at least 83.67%. It proves the feasibility of the proposed method.**

***Index Terms*—Discrete wavelet transforms (DWT), power quality, back-propagation neural networks, parseval theory.**

I. Introduction

Due to the rapid increasing usage of precision instruments in recent years, high power source quality is necessary to avoid the malfunction or breakdown of equipment. Scientists need some electronic detection, classification, and recording devices to monitor the power system behavior, so that we can find out the causes and the kinds of power quality events and then try to improve the quality.

According to the periodicity of power disturbances, the power disturbance waveforms can be classified as stationary or non-stationary signals [1-2]. For stationary signals or periodic waveforms, Fast Fourier transform (FT) is good for signal analysis. Practical measurements using FFT assume infinite periodicity of the signal to be transformed. Furthermore, the time-domain information in the signal would be spread out on the whole frequency axis and become unobservable. Therefore, FFT is not suitable for analyzing non-stationary signals.

To improve this deficiency of FFT, the Short-Time Fourier Transform (STFT) is proposed, which maps a signal into a two-dimensional function of time and frequency. The STFT extracts time-frequency information. However, the disadvantage is that the size for the time-window is fixed for all frequencies. The wavelet transform represents a windowing technique with variable-sized regions to improve the deficiency of STFT [3-4].

Therefore, this paper uses discrete wavelet transform (DWT) to extract the features of power disturbance waveforms and associates with back-propagation neural networks (BPNN) to recognize single power quality events and multi-events.

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II. Wavelet Analysis

The wavelet transform has been applied in variety of research areas such as signal analysis, data processing and compression. The main feature of wavelets is the oscillating and has average value of zero as well as the major advantage afforded by wavelets is the ability to perform local. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects such as trends, breakdown points etc.

Generally, smooth wavelets indicate higher frequency resolution than wavelets with sharp steps; the opposite applies to time resolution. One of the most widely used mother wavelets suitable for power quality analysis is the Daubechies (db) wavelet. The mother wavelets function is define as:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

where

$$\begin{cases} a: scale \quad parameter \\ b: shift \quad parameter \end{cases} \tag{1}$$

This wavelet analysis is particularly suitable for detecting low amplitude, short duration, fast decaying and oscillating type of signals, encountered frequently in power systems, which is a popular signal analysis method, offers continuous and discrete wavelet transforms (CWT and DWT). The DWT is defined as:

$$DWT_x^{\psi}(a,b) = \frac{1}{\sqrt{a}}\int x(t)\psi^*(t)$$

where

$$\left.\begin{aligned} a &= 2^m \\ b &= na \end{aligned}\right\} \; m,n \in Z \tag{2}$$

The DWT can realize a time domain signal into time-frequency domain using a multi-stage filter to implement, low frequency filter $g(t)$ and high frequency filter $h(t)$. The filters $g(t)$ and $h(t)$ can be calculated using Matlab, defined as:

$$h(K-1+k) = (-1)^k g(k) \tag{3}$$

With the mother wavelet function $\psi(t)$ as the low pass filter and the scaling function $\phi(t)$ as the high pass filter. The mother wavelet and scaling function are defined as:

$$\psi(t) = \sum_k h(k)\phi(2t-k)$$
$$\phi(t) = \sum_k g(k)\phi(2t-k) \quad (4)$$

The multi-stage filter technique, called Multi-resolution analysis (MRA)[5-6], is described by Fig. 1:

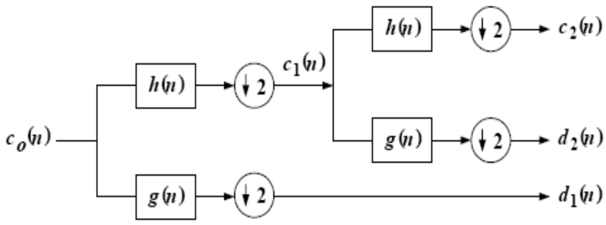


Fig. 1. Multiresolution signal decomposition (MSD) diagram

From the Multi-Resolution Analysis (MRA), we can obtain decomposed signal at scale one, where the approximate parameter $c_1(n)$ is the smooth version of the original signal and detail parameter $d_1(n)$ is the detailed version. They are defined as:

$$c_1(n) = \sum_k h(k-2n)c_0(k)$$
$$d_1(n) = \sum_k g(k-2n)c_0(k) \quad (5)$$

And then the high pass filter is based on approximate parameter $c_1(n)$, the decomposed $c_2(n)$ and $d_2(n)$ at scale two are given as:

$$c_2(n) = \sum_k h(k-2n)c_1(k)$$
$$d_2(n) = \sum_k g(k-2n)c_1(k) \quad (6)$$

Therefore, the output of the high pass filter gives the detailed version of the high-frequency component of the signal. In contrast, the low pass filter provides the approximate version of the low-frequency component, which is then further split to go through other high pass and low pass filters to obtain the next level of the detail and approximation versions. By conducting this process, the DWT can be implemented to extract the feature of detected signal.

The DWT results are initially a series of coefficients in each level. The Parseval theory, defined in (7), is utilized to calculate the energy of each level so that the number of coefficients can be reduced. Then, the Probabilistic Neural Network (PNN) is adopted to recognize the power disturbances.

$$\int |f|^2 dt = \sum_{k=-\infty}^{+\infty} |c(t)|^2 + \sum_{j=0}^{+\infty}\sum_{k=-\infty}^{+\infty} |d_j(t)|^2 \quad (7)$$

III. Back-Propagation Neural Networks

Artificial neural network is made of many neurons connected with each other. In this paper, the proposed recognition system is carried out in a Back-propagation neural network (BPNN).The BPNN has been the most widely used and representative neural network, presented by Rumelhart, Hinton and Williams in 1985. The BPNN uses the gradient decent theory to adjust each weight in neurons based on the form of back propagation style. The output error of the BPNN is back-propagated and spread into each neuron.

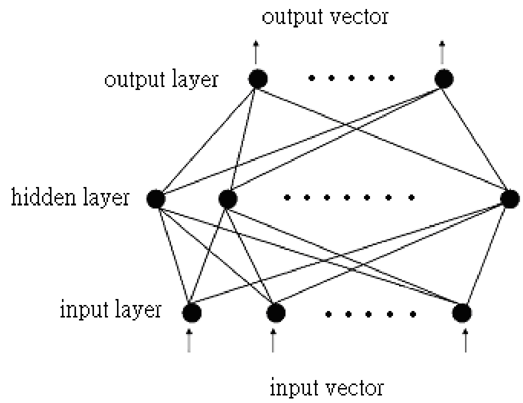


Fig. 2. Architecture of a three-layers BPNN.

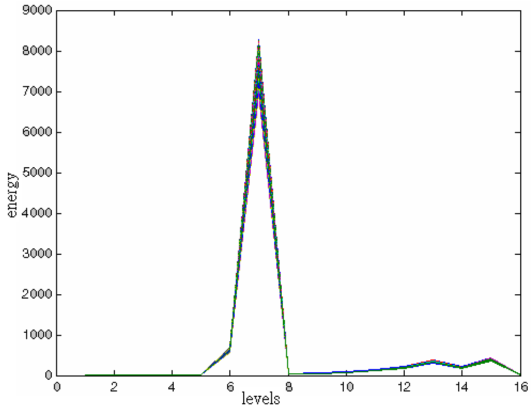
IV. Discrete Wavelet Transform Results

The mother wavelet used in this study is Daubechies (D8). We applied LabVIEW to generate the desired power disturbance waveforms, such as 60Hz pure sinusoidal signal, voltage swell, sag, harmonic, interruption, surge, and voltage flicker. The generated power disturbance waveform is captured and sampled by the A/D device. The sampling rate is set at 20000Hz. The captured power signal is sent to PC for the 16-level discrete wavelet transform. Table 1 represents the corresponding frequency of each level of DWT results. As known, higher level is the lower frequency is. The main frequency (60Hz) is located in scale 7. The transformed results are shown in the following figures. Fig. 2a contains 100 pure sinusoidal voltage waveforms, Fig. 2b contains 100 voltage swell waveforms, and so on. As seen in Fig. 2(f) the voltage flicker presents certain energy in the higher levels and no values in the lower level, that tells the voltage flicker is a low-frequency vibration.

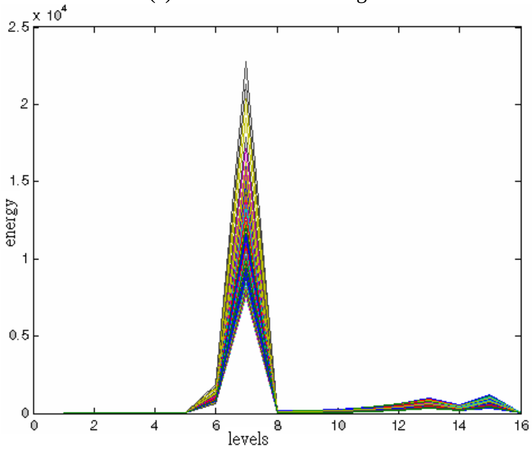
TABLE I: The Corresponding Frequency of Each Level of DWT Results

Scale	Scale 1	Scale 2	Scale 3	Scale 4	Scale 5	Scale 6	Scale 7
Freq	444.66Hz	222.33Hz	148.22 Hz	111.17Hz	88.93Hz	74.11 Hz	63.52 Hz

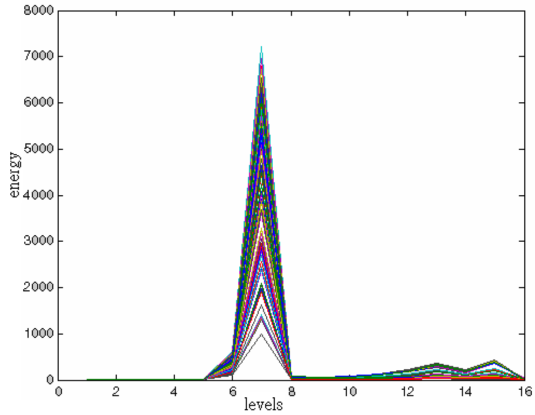
Scale	Scale 8	Scale 9	Scale 10	Scale 11	Scale 12	Scale 13	Scale 14
Freq	55.58 Hz	49.41 Hz	44.46 Hz	40.42 Hz	37.05 Hz	34.21 Hz	31.76 Hz



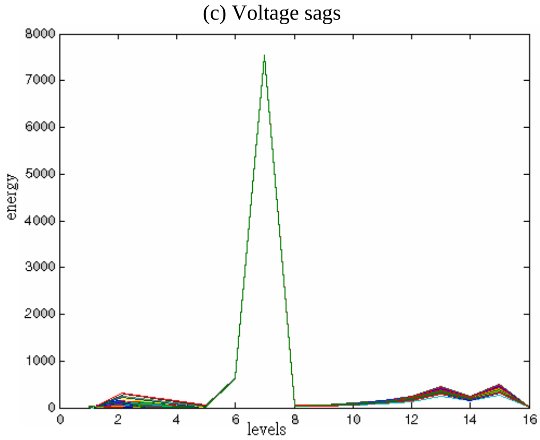
(a) Pure sinusoidal voltages



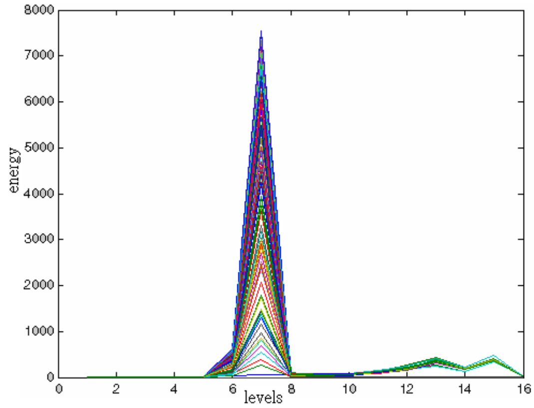
(b) Voltage swells



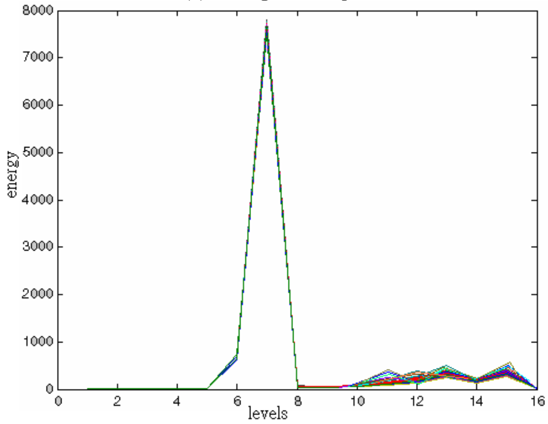
(c) Voltage sags



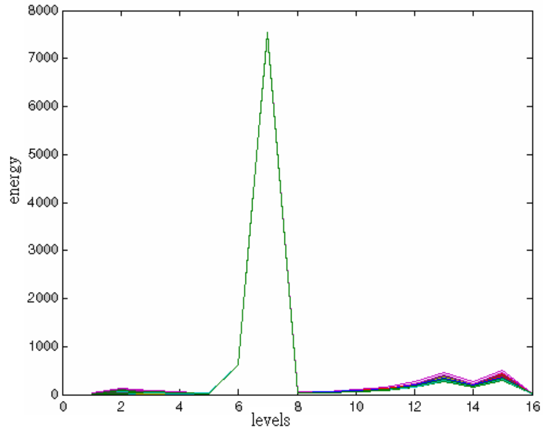
(d) Harmonics



(e) Voltage interrupts



(f) Voltage flickers



(g) Voltage surges

Fig. 3. Analysis results of DWT for power disturbance events.

V. Experimental Results

A. Figures and Tables

The structure of BPNN in this study includes one input layer with 16 neurons, one hidden layer with 25 neurons and output layer with 12 neurons. The learning rate is 0.1. Hidden layer contains Gauss transfer functions; output layer contains constant functions. Each event has 70 waveforms for training and 30 for testing. The recognition result is shown in table2. The experimental result tells that the BPNN combined with the discrete wavelet transforms has ability to recognize power disturbances accurately. The training recognition rates are all above 90%, and the testing recognition rates are above 83.67% for both single and multiple power disturbance events.

TABLE II: BPNN RECOGNITION RATE OF SINGLE AND MULTIPLE EVENTS.

	BPNN Recognition Rate			
	Training samples	Testing samples	Training recognition rate (%)	Testing recognition rate (%)
Flicker+Harmonic	70	30	98.33	85.96
Flicker	70	30	99.31	94.8
Harmonic	70	30	92.88	86.63
Interruption	70	30	92.88	87.88
Interrupt+ Harmonic	70	30	100	83.67
Pure sinusoidal	70	30	98.19	92.71
Sag	70	30	100	93.75
Sag + Harmonic	70	30	98.19	88.96
Surge+ Harmonic	70	30	98.19	88.96
Surge	70	30	94.87	91.45
Swell	70	30	100	93.95
Swell+ Harmonic	70	30	100	89.75

VI. CONCLUSION

The purpose of this paper is to use DWT based BPNN to recognize power disturbance events, including multiple events. To test the recognition rate of the proposed method, we successfully used LabVIEW to generate the power disturbance waveforms and utilized Matlab on PC to conduct DWT and BPNN for power disturbance recognition. From the experiment results, the recognition rates are above 83.67 %. It proves the feasibility of the proposed method.

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