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Detection and Classification of Voltage Sags Using Adaptive Decomposition and Wavelet Transforms

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Abstract: In this study, two prominent methods for detection and classification of power quality disturbance are proposed. The first one, based on the statistical analysis of adaptive decomposition signals is proposed, the second one is a new technique for detecting and characterizing disturbances in power systems based on wavelet transforms. The voltage signal under investigation is often corrupted by noises, therefore the signal is first de-noised and then wavelet transform is applied. Using the first detail wavelet coefficients, voltage disturbance is detected and its duration is determined. The combination of an adaptive prediction filter based sub-band decomposition structure with a rule based histogram analysis block produce successful detection and classification results on our real life power system transient data. In this study, voltage sag is considered for comparing both approaches. Proposed scheme is implemented using MATLAB (7.0.1), Simulink, DSP and Wavelet toolboxes.

Key words: Power Quality (PQ), Multi Resolution Analysis (MRA), Daubechies (Db), Discrete Wavelet Transform (DWT), statistical methods, adaptive decomposition

INTRODUCTION

Nowadays, the electricity dependence of industries commerce and services has provoked the regulation of power quality. The objective is to reduce damages or misbehaviors to consumer devices and/or processes. Basically, four parameters are used to measure and characterize the supplied voltage waveform (sine wave of 50/60 Hz): frequency, amplitude, shape and symmetry. However, from generators to customers, these parameters can suffer alterations that affect quality. The origin of such alterations can be the electrical facility operation, external agents or due to the operation of specific loads. This alteration of the sinusoidal wave is usually transmitted to the electrical system (Bollen, 2000) and the responsibility of possible damages caused to customers is usually assigned to distribution companies. Consequently, these are interested in monitoring their power systems. Once, the voltage and/or current waveforms are captured and stored, an automated post event analysis is needed. Recent contributions in the area of PQ analysis use various wavelets such as daubechies wavelets, Morlet wavelets, etc., to analyze the disturbances, while pre-event voltage or current waveforms are assumed to be sinusoid by Gaouda *et al.* (1999). A specific wavelet may be designed to detect, for example, arcing faults in a sinusoidal prefault waveform .

The sources and causes of disturbances must be known before appropriate mitigating action can be taken and continuous recording of disturbance waveforms is necessary. Unfortunately, most of these recorders rely on visual inspection of data record creating an unprecedented volume of data to be inspected by engineers. Wavelet Transform (WT) is a mathematical tool, which provides an automatic detection of Power Quality Disturbance (PQD) waveforms, especially using Daubechies family. Several types of wavelets network algorithms have been considered for detection of power quality problems. But both time and frequency information are available by Multi Resolution Analysis (MRA) alone (Sushama *et al.*, 2007).

In this research, a new event detection scheme for power quality analysis based on the statistical analysis of adaptive decomposition signals is proposed. The adaptive method is developed to detect and classify power quality disturbances regardless of the type of the pre-event voltage or current waveforms. The significance

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of the proposed method is that it provides a way of detecting variety of events without changing the structure.

If we do not have any prior information on whether, the waveform is pure sinusoid, or not, the steady state properties of a waveform can be well approximated using adaptive systems. The only assumption is that the pre-event steady state waveform has variations of relatively lower frequency as compared to the noise imposed waveform due to a transient event. This idea is utilized to construct a decomposition filter bank structure which operates on the current or voltage waveforms and at the same time, adapts its filter bank according to the waveform behavior.

Least Mean Squared (LMS) type adaptive filters are used in our filter bank structure. These filters are time varying Finite duration Impulse Response (FIR) filters whose coefficients are continuously updated according to, the minimization of an error sequence, which corresponds to one of the sub-bands in our case. When the adaptation converges to a steady state, the disturbance contribution of any transient event on the waveform will take some time for the adaptive filter bank to adapt. Meanwhile, the decomposition structure will exhibit large adaptation error signals in the high-pass sub-band (Haykin, 1986). Time length of this large adaptation error signal is expected to be short for transient-type events, such as arcing line-to-ground faults, sags and swells and the adaptation time is expected to be longer for dynamic changes in load (Bollen, 2000). The theoretical background of the statistical properties of this structure is explained in detail in (Rioul *et al*., 1991).

Wavelet Transform provides the time-scale analysis of the non-stationary signal Sidney *et al*. (2007) and Ecel and Nezih (2003). It decomposes the signal to time scale representation rather than time- frequency representation. Wavelet Transform (WT) expands a signal into several scales belonging to different frequency regions by using translation (shift in time) and dilation (compression in time) of a fixed wavelet function known as Mother Wavelet. Wavelet based, signal processing technique is one of the new tools for power system transient analysis and power quality disturbance classification and also transmission line protection. The Discrete Wavelet Transform (DWT) and Multi Resolution Analysis (MRA) provides a short window for high frequency components and long window for low frequency components and hence provides an excellent time frequency resolution. This allows wavelet transform for analysis of signals with localized transient components.

During the detection process, the event data is applied to the system, which is a combination of an adaptive prediction filter based sub-band decomposition structure and a rule based histogram analysis block.

Two methodologies have been integrated in this study in order to characterize one specific type of short duration faults (voltage sags).

WAVELET TRANSFORMS

Fourier Transforms gives information about the frequency contents of the signal. But it does not give information about the time of occurrence of the frequency. Hence, suitable for stationary signal analysis where frequency component doesn't vary with time.

A wavelet is a transient signal that can be defined as an oscillatory function, or a non-stationary signal which has a zero mean and decays quickly to zero. The wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. The fundamental idea behind wavelets is to analyze according to scale as discussed by Sidney (1998) in introduction to wavelets and wavelet transforms).

The wavelet transform procedure is to adopt a wavelet prototype function, called an analyzing wavelet or mother wavelet. Frequency analysis is performed with contracted, high frequency version of the prototype wavelet and a dilated, low frequency version of the prototype wavelet (Fig. 1a).

Other applied fields that are making use of wavelets are astronomy , acoustics , nuclear engineering, sub-band coding, signal and image processing neurophysiology, music magnetic resonance imaging, speech discriminations, optics earthquake predictions, radar, human vision and in pure mathematics applications such as solving partial differential equations.

The wavelet transform, as frequencies increases, the time resolution increases; like wise, as frequency decrease, the frequency resolution increases. A low frequency component can be located more accurately in

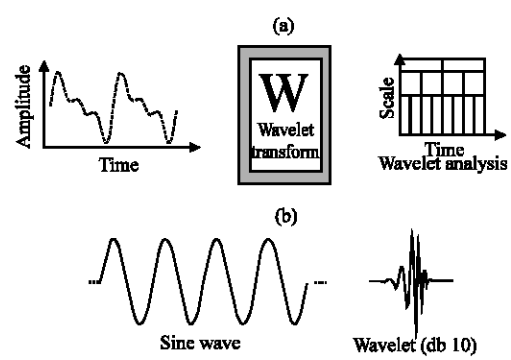

Fig. 1: a) Wavelet transform, b): Comparison between sinusoidal wave and a wavelet

the time and a low frequency component can be located more accurately in frequency compared to high frequency component (Fig. 1b).

The extensive use of the wavelet transform in various fields is due to its variety of properties.

Scaling and shifting: Scaling a wavelet simply means stretching (or Compressing) it. The parameter scale in the wavelet analysis is similar to the scale used in maps.

As the case of maps, high scales corresponding to a non detailed global view and low scales correspond to a detail view. Similarly, in terms of frequency, low frequencies correspond to global information of the signal, where as high frequencies correspond to detailed information of hidden pattern in the signal.

To go beyond colloquial descriptions such as stretching, we introduce the scale, often denote by the letter α.

Shifting: Shifting a wavelet means delaying its onset. Mathematically, delaying a function f(t) by k represented by f (t-k).

DISCRETE WAVELET TRANSFORM (DWT) AND MULTI-RESOLUTION ANALYSIS (MRA)

Wavelets have been applied successfully in a wide variety of research areas such as signal analysis, image processing, data compression, de-noising and numerical solution of differential equations. In recent years, wavelet analysis techniques have been proposed extensively in the literature as a new tool for fault detection, localization and classification of different power system transients.

In this study, we present the wavelet-multi-resolution analysis as a new tool for extracting the distortion features. The MRA is a tool that utilizes the DWT to represent the time domain signal f(t) that can be mapped into the wavelet domain and represented at different resolution levels in terms of the following expansion coefficients:

$$C_{signal} = [C_0|d_0|d_1| \text{ and --- } d_{f-n}|] \quad (1)$$

Where:

$d_{i,}$ = Represent the detail coefficients at different resolution levels.

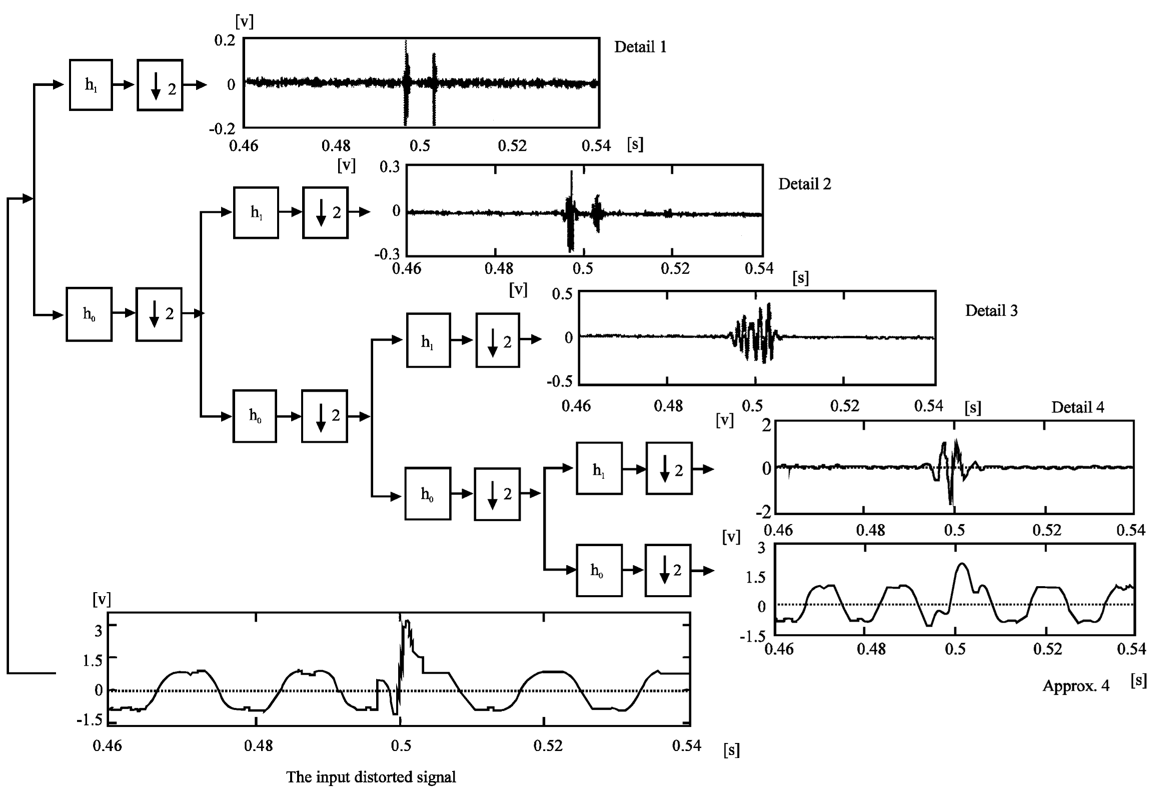

Fig. 2: Four level multi resolution signal decomposition

C_0 = Presents the last approximate coefficients. Wavelet transform can be achieved by convolution and decimation.

The detail coefficients d_j and the approximated coefficients c_j can be used to reconstruct a detailed version D_1 and an approximated version A_1, of signal f(t) at that scale. Effectively, the wavelet coefficients h(n) and the scaling function coefficients $h_0(n)$ will act as high pass and low pass digital filters, respectively. The frequency responses $h_0(\omega)$ and $h_1(\omega)$ of the mother wavelet Daubechies (db4) and its scaling function are shown in Fig. 2. These two functions divide the spectrum of the input signal f(t) equally (Gaouda *et al*., 1999; Jaideva and Chan, 1983).

Decimation (or down sampling) is an efficient multi-rate digital processing technique for changing the sampling frequency of a signal in the digital domain and efficiently compressing the data. As indicated in Fig. 2, the sampling rate compression and data reduction in detail coefficients are achieved by discarding every second sample resulting from convolution process. Since, half of the data is discarded (decimation by 2), there is a possibility of losing information (aliasing); however, the wavelet and the scaling function coefficients ($h_1(n)$ and $h_0(n)$) will act as digital filters that limit the band of the input c_{j+1} and prevent aliasing.

DAUBECHIES FAMILY WAVELETS

As per IEEE standards, Daubechies wavelet transform is very accurate for analyzing Power Quality Disturbances among all the wavelet families, for transient faults. The names of the Daubechies family wavelets are written as dbN, where N is the order and db the surname of the wavelet (Fig. 3).

FILTER BANK STRUCTURE

The signal decomposition consists of an adaptive prediction filter in a poly phase structure . In this aspect, the overall scheme resembles the lifting-style wavelet decomposition due to its filter bank implementation (Greek and Cieten, 2002). Adaptive Polyphase Sub-band Decomposition Structure in Image Compression). However, the basic idea is to produce decomposition signals, which converge to a minimal residual signal that can be considered as the non-predictable content of the steady state signal. This idea is also, very new in the signal processing field and quite recently it has been applied to signal compression (Haykins, 1986). Normally, the wavelet filter banks decompose the signal according to the frequency content of the filters with fixed coefficients. Here, the frequency content or spectral decompositions are irrelevant due to the fact that the adaptive prediction filter constantly changes the filter coefficients.

The analysis structure is illustrated in Fig. 4. Both the lower resolution and non-predictable parts are produced using the two poly phase components of the original signal:

$$x_1[n] = x[2n] \tag{2}$$

$$x_2[n] = x[2n + 1] \tag{3}$$

These components can be thought of as even and odd indexed terms of the discrete-time signal. For a signal with slow variations, the two poly phase components have strong correlation. Therefore one of the polyphase components, let's say $x_2[n]$, can be successfully approximated using the other component samples $x_1[n]$ and a prediction filter, say, $P_1(.)$. In that case, one can

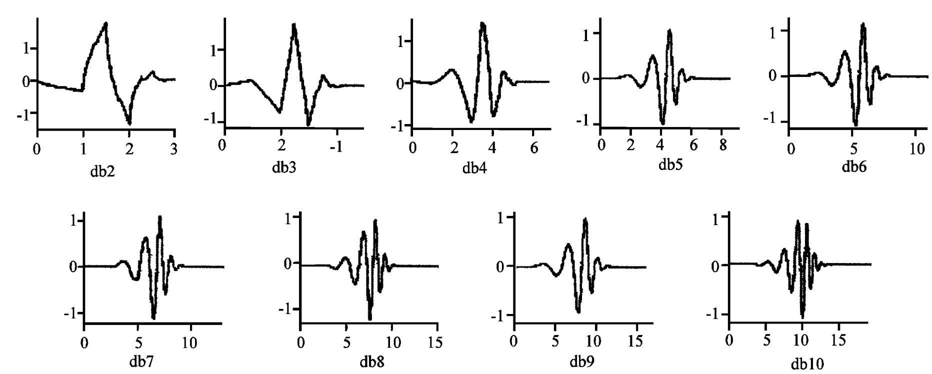

Fig. 3: Daubechies family wavelets

expect the difference between the prediction output and $x_2[n]$ to be relatively small:

$$\epsilon = x_2[n]-P_1\ (x_1[n-m], \ldots, x_1[n-m]) \tag{4}$$

Comparing the above difference with Fig. 2, it can be seen that the difference sequence corresponds to the lower branch output: $x_h[n]$.

SIMULINK IMPLEMENTATION OF THE ADAPTIVE FILTER BANK

We developed an integrated detection tool using DSP block sets. This portion can be easily matched to the structure shown in Fig. 4. Notice that the signal is first decomposed into poly phase components by down sampler and integer delay modules. The above polyphase component, $x_1[n]$, is directly fed into the LMS block as the input signal. The other component, $x_2[n]$, is delayed by a factor of 10, which is half of the filter tap size of the LMS block and compared to the LMS output. The result of this difference corresponds to $x_h[n]$ and it is fed back to the error input part of the LMS block, by which the adaptation occurs. The rest of the simulink layout deals with the analysis of the produced $x_h[n]$ is shown in Fig. 5.

Statistical analysis: The residual output, $x_h[n\ ]$, generated by the adaptive decomposition block carries clearly visible information about the detection of various types of events. Therefore, it may be sufficient to present the above decomposition which produces necessary features for detection and leave the detection part to the practicing engineer. Nevertheless, we give a sample detection method to post-process the adaptive decomposition output with satisfactory results. In this research, we have developed an experimental histogram-based analysis stage which provides automated detection. The analysis stage consists of a windowed-histogram generation block and the statistical analysis of the histogram. Statistically, the windowed-histogram provides a short time approximation of the density function, Probability Density Function (PDF). The PDF naturally carries all the statistical information of a process, therefore its approximation, the histogram, is also observed to be useful for generating the detection rule.

In the adaptive decomposition structure explanations, we have seen that the residual error $x_h[n]$ becomes large in magnitude when an event happens. This is clearly the point that must be detected. If we monitor $x_h[n]$ signal in a time-windowed manner, we can see that the histogram is well centered when the magnitudes of $x_h[n]$ samples are small. This is the case, when the waveform exhibits no event. As soon as, an event happens, due to large-in magnitude samples of $x_h[n]$, its histogram becomes no longer centered. Instead, the tails of the histogram becomes heavy as shown in Fig. 6.

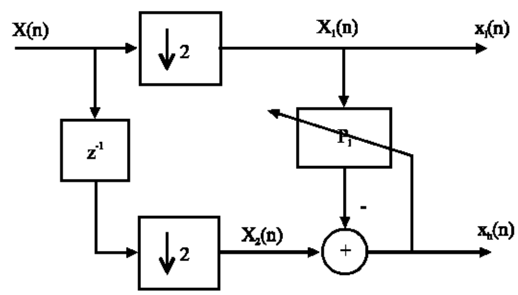

Fig. 4: Analysis stage of the 2-channel adaptive filter bank

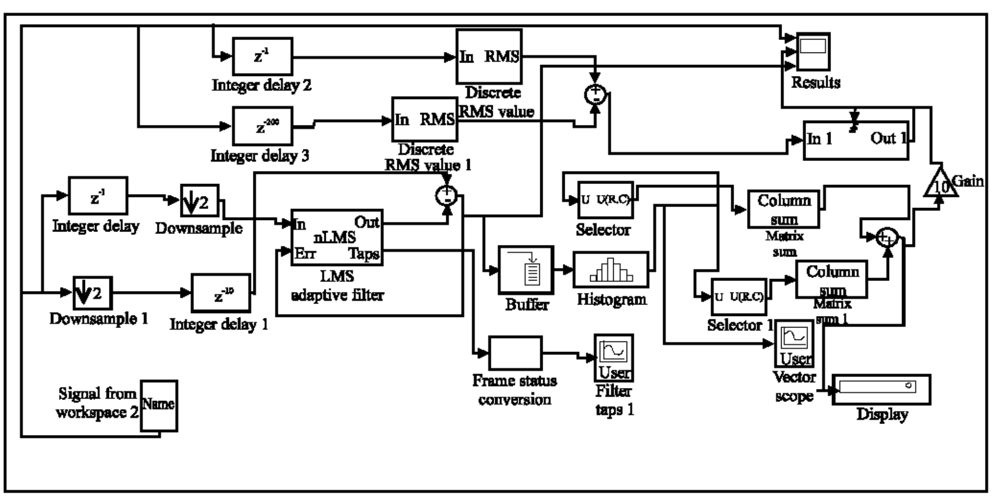

Fig. 5: Simulink layout of the system for analysation

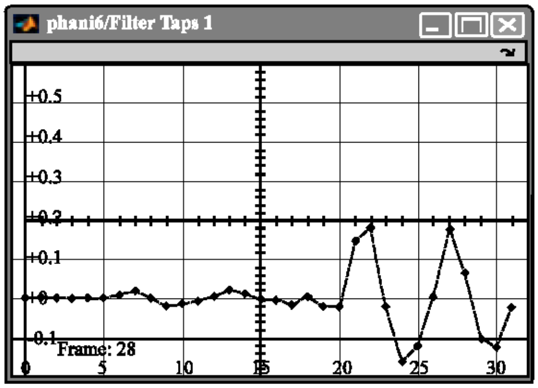

Fig. 6: Histogram for the voltage sag

Table 1: Voltage sag

PQ disturbances	Class symbol	Model	Parameters
Pure sinusoidal	C1	$x(t) = \sin(\omega t)$	
Momentaneous sag	C2	$x(t) = A(1-a(u(t-t_1)$ $-u(t-t_2)))\sin(\omega t)$ $t1<t_2,, u(t) = 1,$ $t\geq 0 =0, t < 0$	$0.1\leq\alpha\leq 0.9;$ $T\leq t_2-t_1\leq 9T$
Temporary sag	C3	$x(t) = A(1-\alpha(u(t-t_1)$ $-u(t-t_2)\sin(\omega t)$	$0.1\leq\alpha\leq 0.9$
Long-term sag (Under voltage)	C4	$x(t) = A(1-\alpha(u(t-t_1)$ $-u(t-t_2)\sin(\omega t)$	$0.1\leq a\leq 0.2$

DIFFERENT CONDITIONS OF VOLTAGE SAG EVENTS

Several typical PQ disturbances are taken into consideration in this study. Using MATLAB 7.0, the most commonly occurring disturbances are initially simulated. The categories that are simulated are normal sinusoid, sag, categorized as Momentary, Temporary and long term sag as listed in Table 1.

GENERATION OF VOLTAGE SIGNALS

The voltage signals generated are sampled at a frequency of 4 kHz. The unique attributes for each disturbance type are used and allowed to change randomly, within specified limits, in order to create different disturbances. The frequently occurring power quality events like sags, swells, interruption, harmonics and combination of these events are chosen.

PURE SINUSOIDAL

It is the ideal voltage waveform generated by pure sinusoidal signal. The signal is generated at 50 Hz having 1 p.u magnitude as shown in Fig. 7.

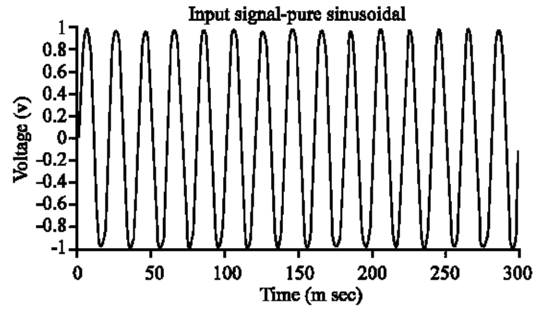

Fig. 7: Pure sinusoidal wave form

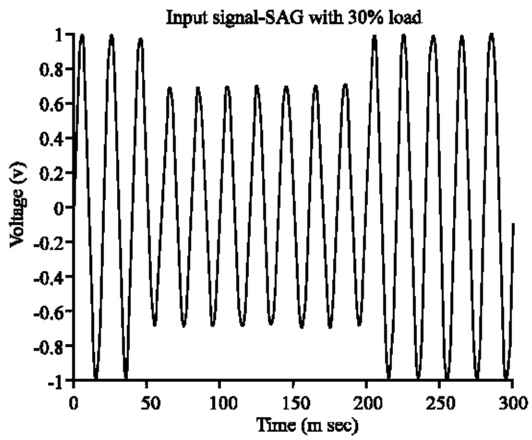

Fig. 8 a: Sag with 30% load

VOLTAGE SAG

Voltage sag is described as a drop of 10-90% of the rated system voltage lasting for half a cycle to one minute. The causes of voltage sag are:

- Voltage sags are caused by system faults.
- It can also be caused by energisation of heavy loads.

The 10, 20 and 30% sag disturbances lasting for 15 cycles are shown in the Fig. 8, are generated with the simulation diagram as shown in Fig. 9.

In the sag wave form obtained by adaptive decomposition, can be observed that there is a decrease in value of R.M.S voltage during sag. The error signal will show spikes during sag period and finally the adoption error will be reduced to zero.

Detection of any type of event using an adaptive decomposition scheme, wavelet transformation and other frequency domain techniques would become easier if there is some high frequency noise at the start of an event. However, as shown in Fig. 10, voltage variation during the sag event is very smooth and free of noise.

Even in this case, there is a large adaptation error which triggers the RMS voltage measurement block and a sharp drop of RMS voltage magnitude is seen as given in the middle waveform of Fig. 10. This sharp drop of RMS magnitude of the voltage should be compared with the reduction with noisy steps as observed in arcing fault.

CLASSIFICATION USING BACK PROPAGATION

A single-layer network of S logsig neurons having R number of inputs is shown in Fig. 11. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range –1 to +1. On the other hand, if one want to constrain the outputs of a network (such as between 0 and 1), then the output layer should use a sigmoid transfer function (such as logsig).

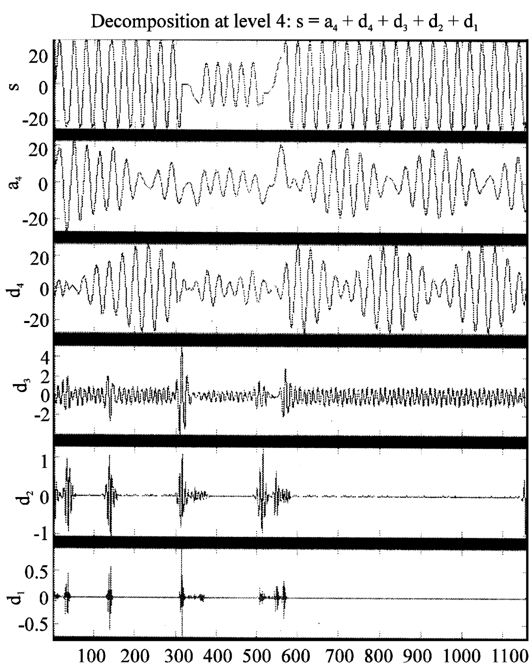

Fig. 8 b: Wavelet decomposition of voltage sag (Db4)

Simulation and analysis: The simulation data was generated in MATLAB based on the model in Table 2 as per IEEE standards. All the four classes (C1-C4) of different voltage sag events or disturbances, namely undisturbed sinusoid (normal), sag and its different categories. Table 2 gives the signal generation models and their control parameters.

Seventy five cases of each class with different parameters were generated for training and another 25 cases were generated for testing. Both the training and testing signals are sampled at 200 points/cycle and the normal frequency is 50 Hz. Fifteen power frequency cycles which contain the disturbance are used for a total of 300 points. Daubechies4 (Db4) wavelets with four levels of decomposition were used for analysis (l = 4). Based on the feature extraction shown above, 4-dimensional feature sets for training and testing data were constructed (Wilkinson and Cox, 1996; Collins and Hurley, 1994;

Table 2: Types of sag (As per IEEE standards)

Type of SAG	Time duration	Typical amplitude
Momentaneous sag	30 cycles to 3 sec	0.1-0.9 p.u
Temporary sag	3 sec to 1 min	0.1-0.9 p.u
Long-term Under	>1 min	0.8-0.9 p.u

C1→Pure sinusoidal, C3→Temporary sag, C2→Momentary sag, C4→Long-term sag or (Under voltage)

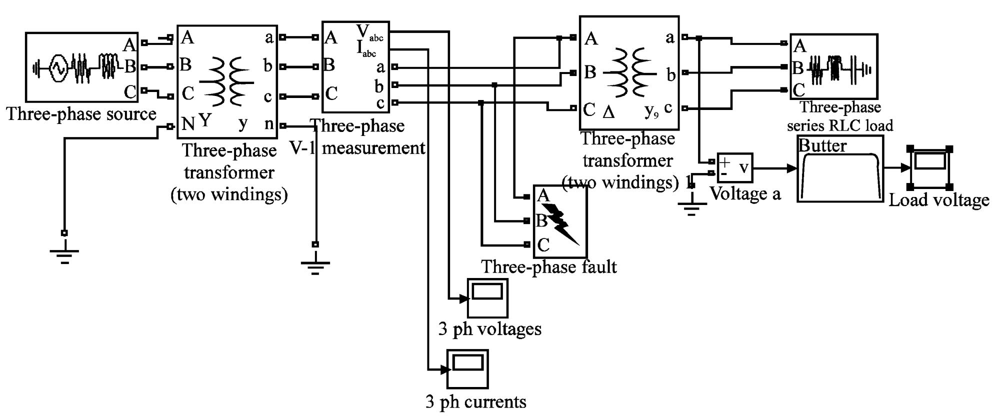

Fig. 9: Circuit for creating power quality disturbance signals using simulink

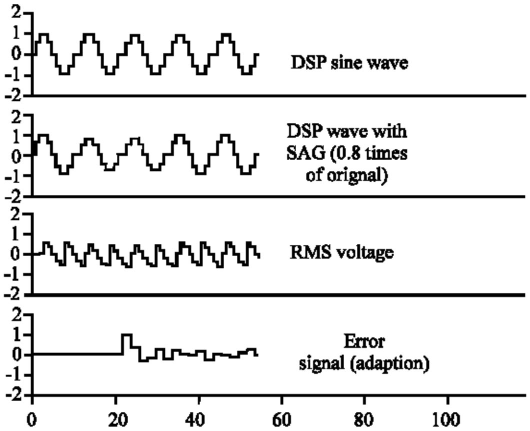

Fig. 10: Wave forms during sag

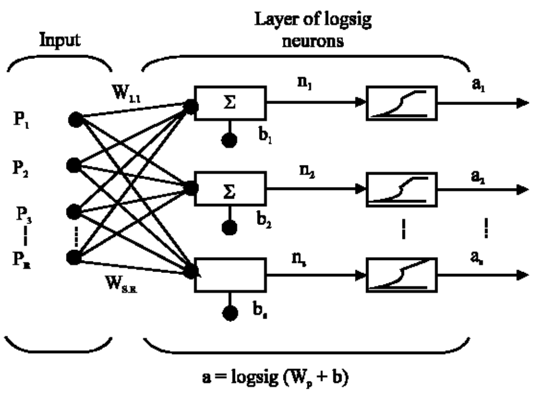

Fig. 11: Single layer network

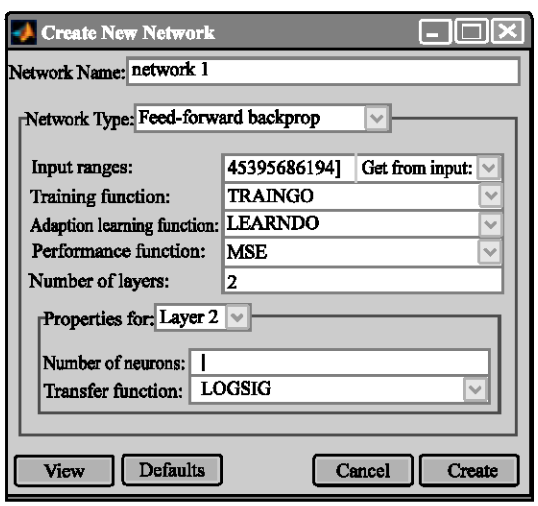

Fig. 12: Training the BPNN

Ghosh and Lubkeman, 1995; Lovisolo *et al*., 2002; Ibrahim and Morcos, 2002).

The dimensions here describe different features resulting from the wavelet transform, that is to say, the total size of the training data or testing data set is 100×4, where 400 comes from 100 cases per class multiplied by 4 classes and 4 is the dimension of the feature size of each case. All data sets were scaled to the range of (1-200) before being applied to Feed-Forward Back Propagation Network (FFBPNN) for training as in Fig. 12 and testing. The results are tabulated for all the 4 events in Table 3.

Table 3: Simulation results

	C1	C2	C3	C4
C1	100	0	0	0
C2	0	93	0	0
C3	0	4	92	1
C4	0	0	20	80

According to, the simulation results shown in Table 3 the accuracy of classification can be approximately 97%.

CONCLUSION

Digital Signal Processing based analysis of the adaptive decomposition outputs can clearly distinguish events such as faults and abrupt changes from the steady state waveforms. The central and tail histogram portions are then fed into comparators for an event detection. By applying proper thresholds for the final comparator output, power quality events can be classified and dynamic changes in load can be distinguished. For different types of voltage sag conditions like momentary sag, temporary sag and long term under voltage sag, the classification has also been done with the help feature extraction using Multi Resolution Analysis (MRA) and Feed Forward Back Propagation Neural Network (FFBPNN) training Algorithm. In both methodologies detection and classification can be done with higher accuracy levels. This study has presented, 2 effective methods to detect the disturbed voltage waveforms of arbitrary sampling rate and number of cycles. Hence, it can be conclude that the wavelet MRA and adaptive decomposition techniques can be efficiently used to detect and classify any type of power quality disturbances at a faster rate.

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