DETECTION AND CLASSIFICATION OF VOLTAGE SWELLS USING ADAPTIVE DECOMPOSITION & WAVELET TRANSFORMS

M.Sushama, G. Tulasi Ram Das

Associate Professor, Department of Electrical and Electronics Engineering, JNTU college of Engineering, Hyderabad, INDIA.
Professor, Department of Electrical and Electronics Engineering, JNTU college of Engineering, Hyderabad, INDIA.
E-mail: m73sushama@yahoo.com, das_tulasiram@yahoo.co.in

ABSTRACT

Through this paper, 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 paper, voltage swell 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

Transmission-Line relaying involves three major tasks: detection, classification, and location of the fault. It must be done as fast and accurate as possible to de-energize the faulted line, protecting the system from the harmful effects of the fault. With the wide application of high-power electronics switchgear, problems of Power Quality (PQ) are becoming more serious as each passing day. At the same time, the user's demand on power quality gets more critical. Thus it is essential to establish a power quality monitoring system to detect power quality disturbance [1], [2]. From the viewpoint of practicality, a power quality monitoring system should have the following functions: detecting power quality disturbance, identifying the type and duration time of disturbance signals, calculating disturbance amplitude and other relevant parameters, etc. Thus the power quality monitoring system should be as precise and of real time as possible. In recent years, a lot of methods for detection and identification of power quality disturbance based on wavelet technique have been proposed by researchers from home and abroad.

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 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 [5]-[9]. A specific wavelet may be designed to detect, for example, arcing faults in a sinusoidal pre--fault waveform [10]. 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.[1] 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 [1].

ADAPTIVE FILTER BANKS

The concepts of adaptive filtering and sub-band decomposition have been previously used together by a number of researchers [10]-[13]. Most of the proposed adaptation algorithms for sub-band decomposition filter banks consider the problem of system identification and noise removal. In these works, the adaptive filtering problem is considered in the sub-band domain. The issues of efficient complex or real valued filter design methods to increase sub-band domain adaptive filtering performance is also investigated in [10] in which the design of the filter bank satisfying the pre-specified requirements for adaptive filtering in sub-bands is studied. The choice of sub-band filter banks according to the input signal is also considered by some researchers [3]-[5]. The main goal of these works is to find the best wavelet basis for decomposing the entire data, and fixed filter banks chosen according to an optimality criterion are used throughout the entire duration or extent of the signal whereas in this paper the filters vary as the nature of the input changes. 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 [2] 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 [3]. These filters are time varying **F**inite duration **I**mpulse **R**esponse (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. 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. The theoretical background of the statistical properties of this structure is explained in detail in [4].

WAVELET TRANSFORMS

Wavelet Transform provides the time-scale analysis of the non-stationary signal [1][2]. 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 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 paper in order to characterize a type of short duration faults (voltage swells).

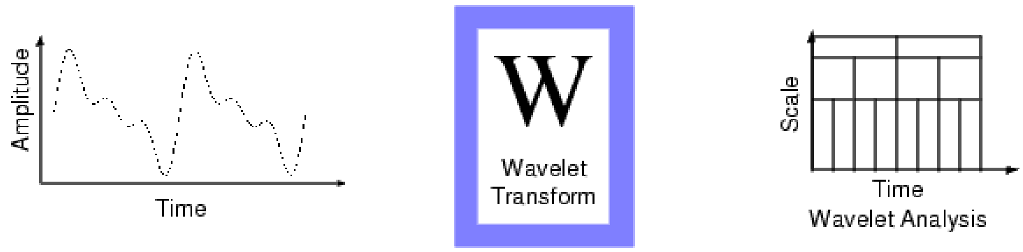


Figure.1(a) *Wavelet Transform*

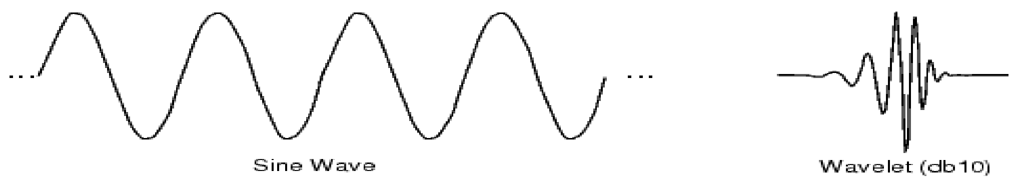


Fig1(b) . *Comparison between Sinusoidal wave and a Wavelet*

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 [3].

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.

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 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) & 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 [5]. 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 paper, we have presented 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)* can be mapped into the wavelet domain and represented at different resolution levels in terms of the following expansion coefficients :

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

Where, d_i, represent the detail coefficients at different resolution levels, and 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 [5-6].

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.

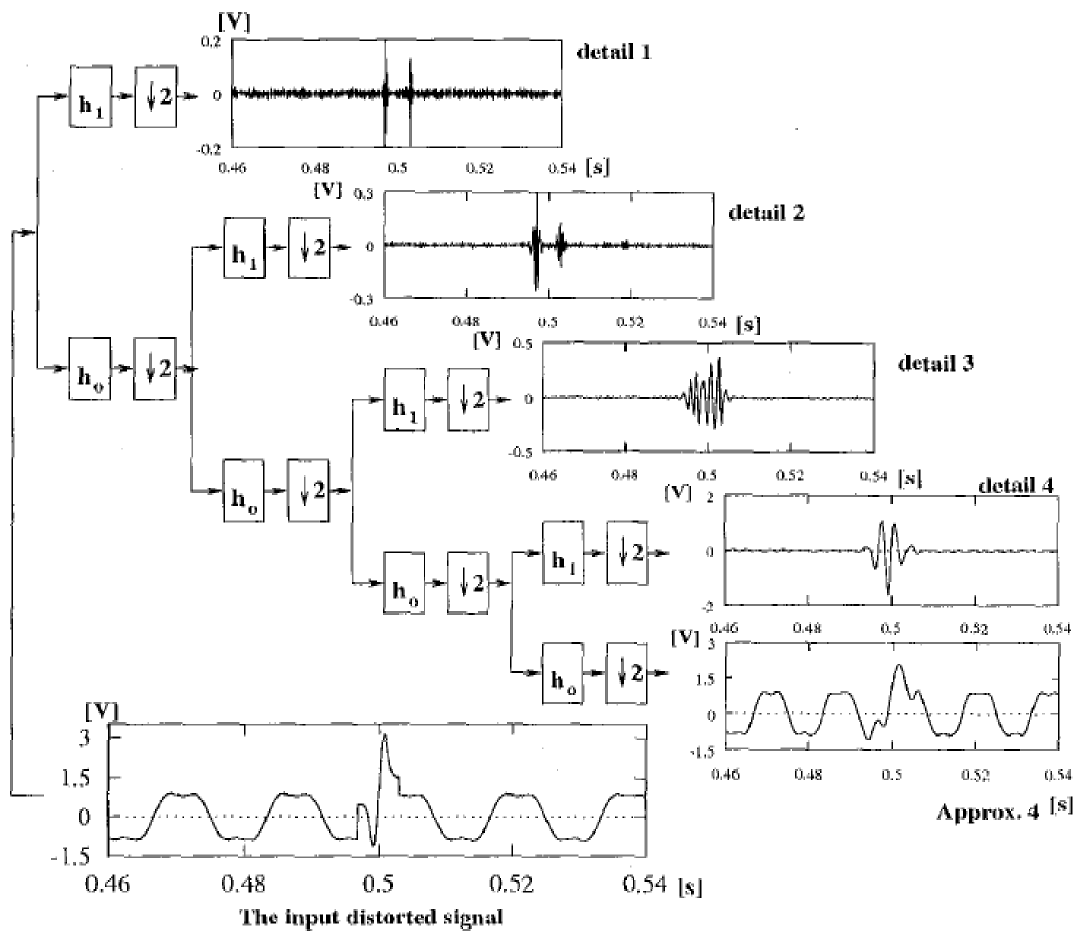


Fig. 2: *Four level multi resolution signal decomposition*

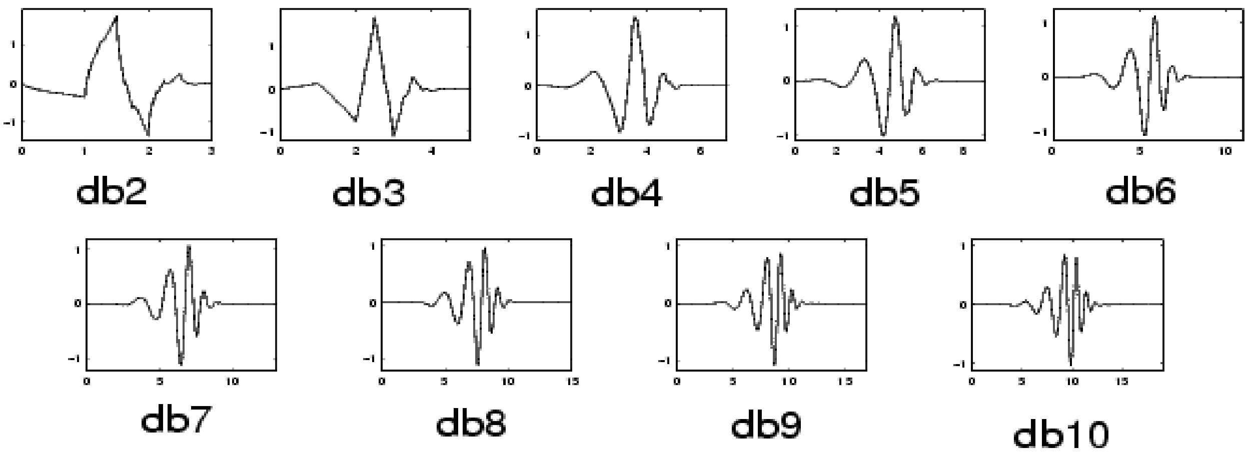


Fig 3 *Daubechies family wavelets*

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 [10]. In this aspect, the overall scheme resembles the lifting-style wavelet decomposition due to its filter bank implementation [13]. 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 [4]. 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[4].

Both the lower resolution and non-predictable parts are produced using the two polyphase components of the original signal:

$$x_1[n]=x[2n] \quad \text{………(2)}$$

$$x_2[n]=x[2n+1] \quad \text{……..(3)}$$

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

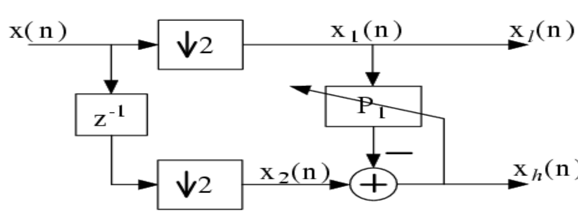
Fig. 4 Analysis stage of the 2-channel adaptive filter bank

Comparing the above difference with Fig. 4, it can be seen that the difference sequence corresponds to the lower branch output: $x_h[n]$

$$\varepsilon= x_2[n]-P_1(x_1[n-m],\ldots,x_1[n-m]) \quad \text{……….(4)}$$

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 figure 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.7. LMS block, and compared to the LMS output using a subtraction module [14]. 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 $x_h[n]$.

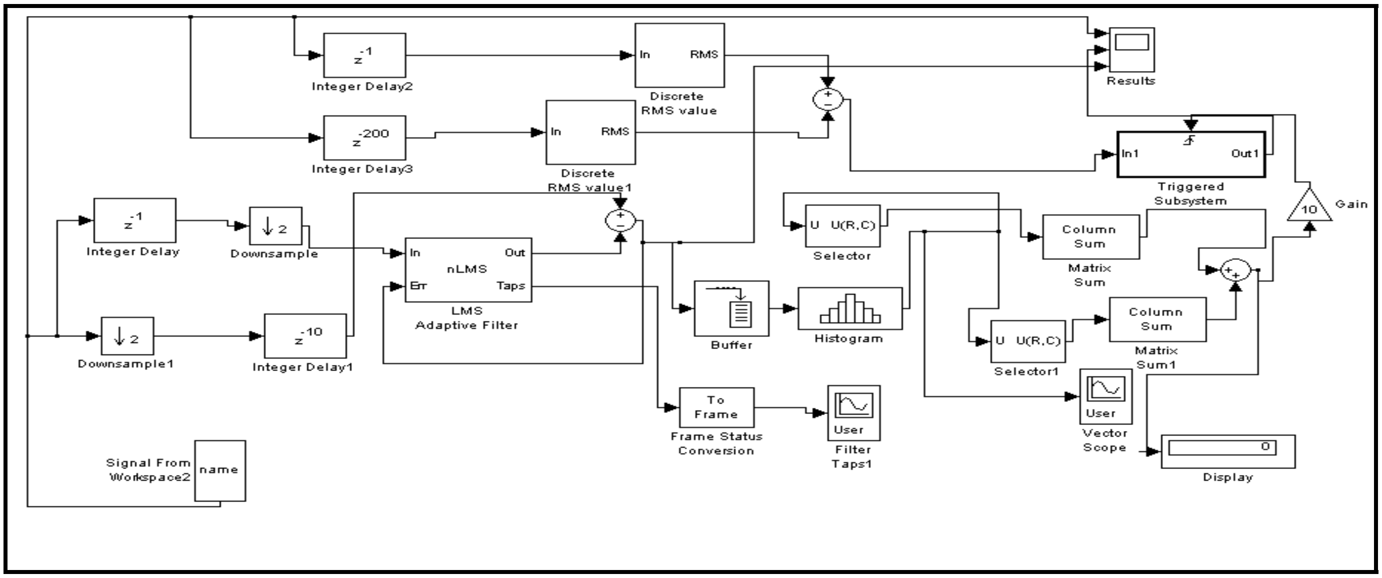


Fig .5 *Simulink Layout Of The System For Analysation*

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 work, we 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[10].

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[13]. 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.9.

DIFFERENT CONDITIONS OF VOLTAGE SWELL EVENTS

A voltage swell occurs when a single line-to-ground fault on the system results in a temporary voltage rise on the unfaulted phases (fig.7(a)). Removing a large load or adding a large capacitor bank can also cause voltage swells. Several typical voltage swell disturbances are taken into consideration in this paper. Using MATLAB 7.0, the most commonly occurring disturbances are initially simulated. The categories that are simulated are normal sinusoid, swell, categorized as Momentary, Temporary and long term swell.

GENERATION OF VOLTAGE SIGNALS

These 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 (table 1).

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 (fig.6).

Voltage Swells

Voltage swell 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 swell are :

1. Voltage swell are caused by system faults
2. It can also be caused by energisation of heavy loads.

This signal generated in fig.7 (a), (b) are from the model equation

$$\mathbf{x(t) = A(1+\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)} \quad ....(5)$$

where, $t_1<t_2$, $u(t) = 1,\ t \geq 0$

$0.1\leq\alpha\leq0.9; T\leq t_2-t_1\leq 9T$

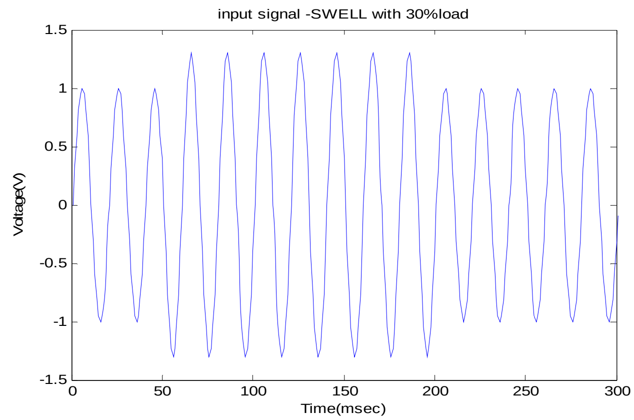
Table .1

PQ disturbances	Class Symbol	Model	Parameters
Pure Sinusoidal	C1	$x(t) = \sin(\omega t)$	
Momentary Swell	C2	$x(t) = A(1+\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1\leq\alpha\leq0.4$
Temporary Swell	C3	$x(t) = A(1+\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1\leq\alpha\leq0.4$
Long-term Swell (Over voltage)	C4	$x(t) = A(1+\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1\leq\alpha\leq0.2$

$= 0,\ t < 0.$

VOLTAGE SWELL

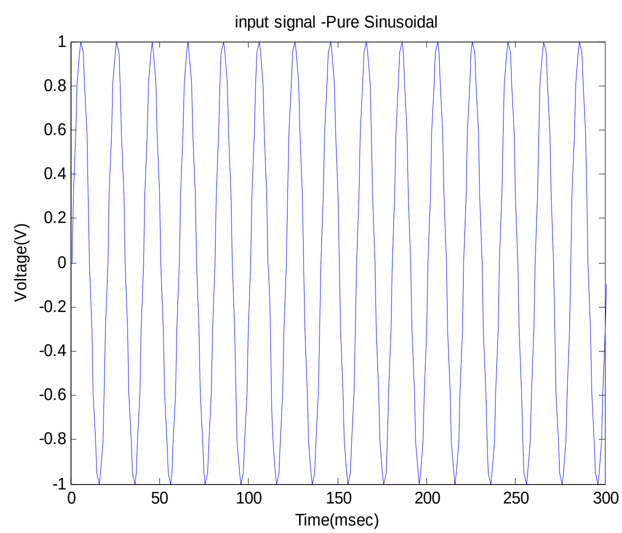
Fig.6 *Pure Sinusoidal Wave*



form and the decomposition up to four levels (a_4, d_4) using Db4.

The 10%, 20%, 30% swell disturbances lasting for 15 cycles canbe generated for analysis. One of such is shown in the figure 7(a) below are generated with the simulation diagram as shown in Fig.10.

Fig 7 (a) *Swell with 30%load*,



In the swell waveform obtained above it can be observed that there is an increase in value of R.M.S voltage during swell. The error signal will show smooth variation during swell period and finally the adoption error will be reduced to zero.

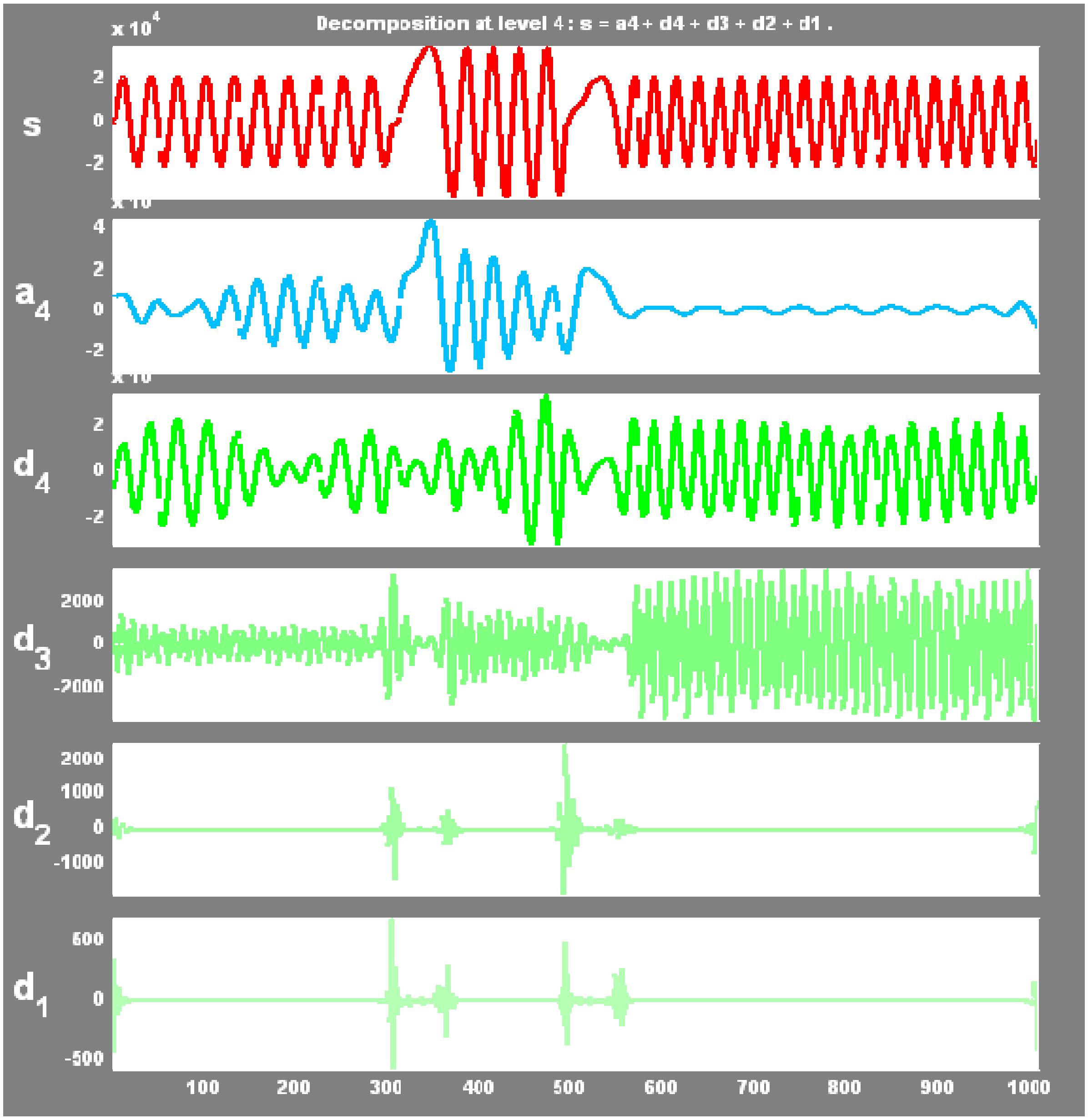


Fig.7(b) *Wavelet Decomposition of Voltage Sag(Db4)*

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 Figure 8, voltage variation during the swell 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.8. This sharp drop of RMS magnitude of the voltage should be compared with the reduction with noisy steps as observed in arcing fault.

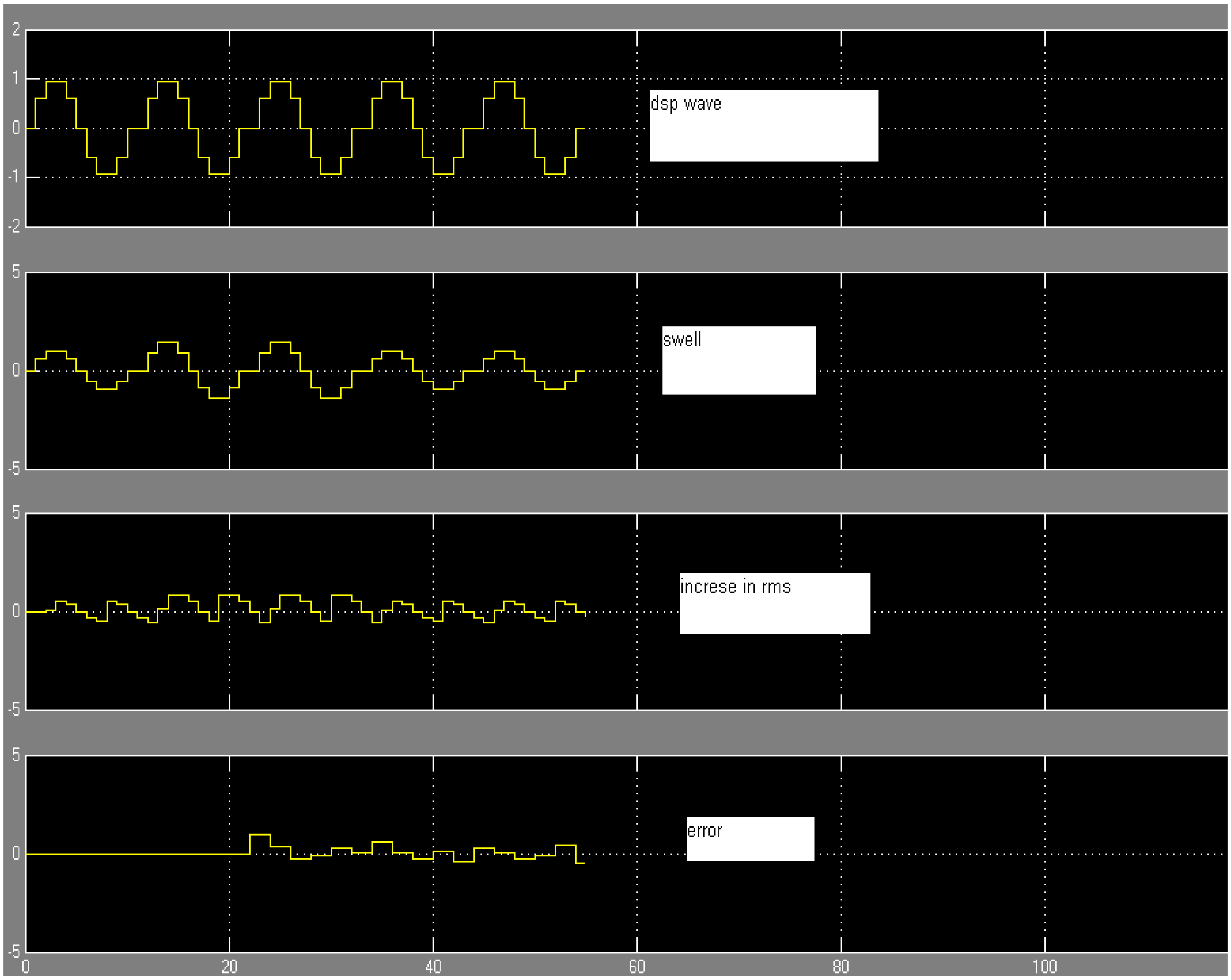


Fig.8 *Wave Forms During Swell*

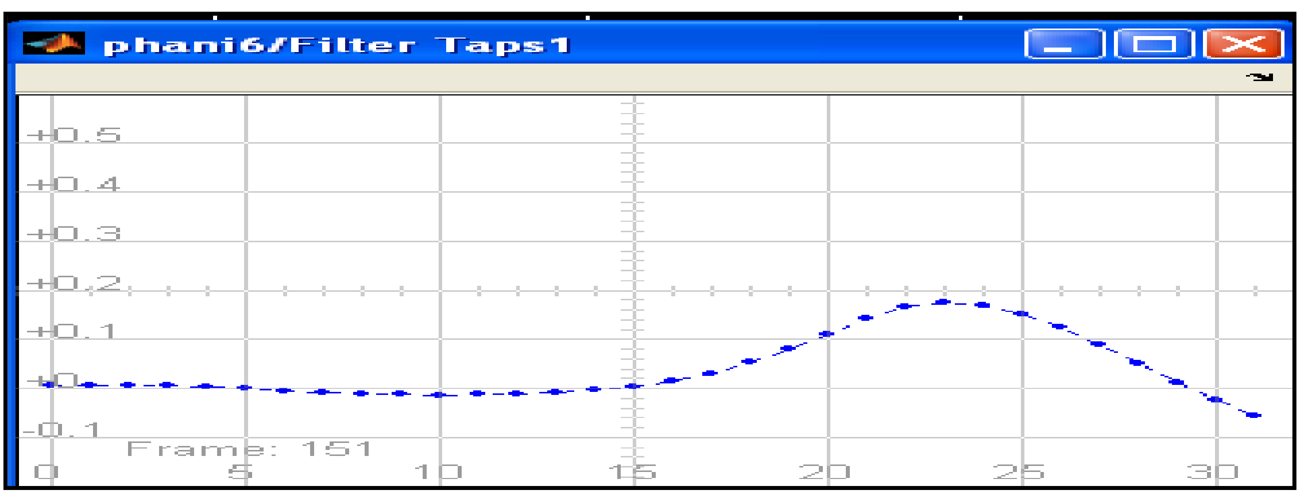


Fig 9. *Histogram for the voltage Swell Signals Using Simulink*

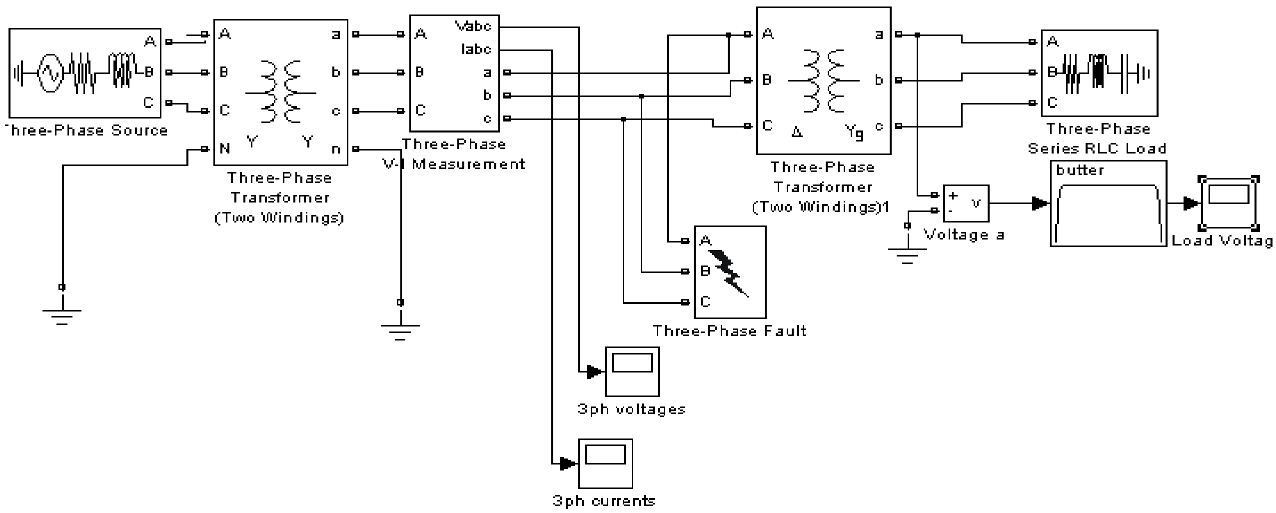


Fig10 *Circuit For Creating Power Quality Disturbance*

PROPAGATION

A single-layer network of S **logsig** neurons having R number of inputs is shown below in figure 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 wants 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**).

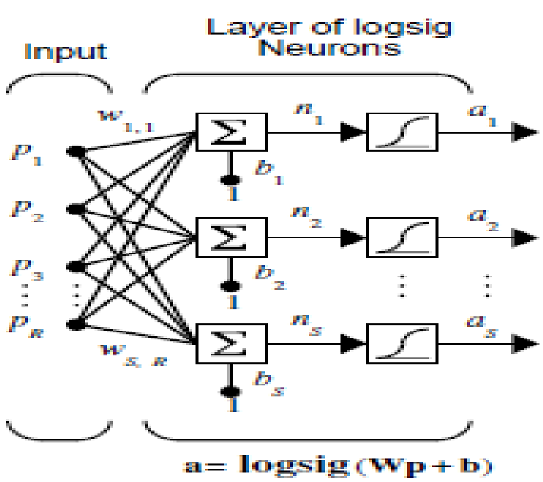


Fig. 11 *Single layer network*

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 swell events or disturbances, namely undisturbed sinusoid (normal), swell and its different categories. Table 2 gives the signal generation models and their control parameters.

Table2

Type of Swell	Time duration	Typical amplitude
Momentary swell	30 cycles to 3 sec	1.1 p.u to 1.4 p.u
Temporary swell	3 sec to 1 min	1.1 p.u to 1.4 p.u
Long-term Over Voltage	> 1min	1.1 p.u to 1.2 p.u

Types of Swell (as per IEEE Standards)

Simulation results

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(Table 3).

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 100x4, 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 for training(Fig.12) and testing. The results are tabulated for all the 4 events in Table 3. According to the simulation results shown in table 3 the accuracy of classification can be approximately 97%.

Conclusions

Digital Signal Processor 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. With wavelet Multi Resolution Analysis and Feed

Table 3

CLASS	C1	C2	C3	C4
C1	100	0	0	0
C2	0	80	7	0
C3	0	5	93	1
C4	0	5	2	93

Forward Back Propagation Neural Networks, the detection and classification has been done more accurately. This paper has presented two effective methods to detect the disturbed voltage waveforms of arbitrary sampling rate and number of cycles .Hence it can be concluded that the wavelet MRA and adaptive decomposition techniques can effectively detect any type of Power Quality Disturbances at a faster rate.

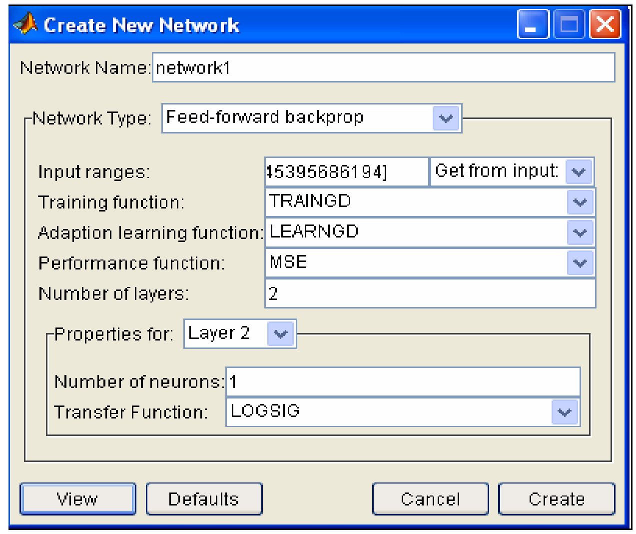


Fig. 12 *Training the BPNN*

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ABOUT THE AUTHORS

G.Tulasi Ram Das born in the year 1960, in Hyderabad Andhra Pradesh, India and received his B.Tech degree is in Electrical & Electronics Engineering from J.N.T.U College of Engineering, Hyderabad, India in 1983 and M.E with Industrial Drives & Control from O.U College of Engineering, Hyderabad, India in 1986. He received the PhD, degree from the Indian Institute of Technology, Madras, India in 1996. He is having 22 years of teaching and research experience. He is currently Professor at J.N.T.U College of Engineering, Hyderabad- 500 072, India. He held positions of Head, Department of Electrical and Electronics Engg., Vice-Principal and Principal of JNTU College of Engineering, Hyderabad. His Research interests are Power Electronics, Industrial Drives & FACTS Devices. He has supervised 7 Ph.D. theses and 7 Ph.D. theses are under progress. He has published/presented 71 technical research papers in national and international conferences and journals. He has visited countries namely, Singapore, Malaysia and Eastern States of US.

M.Sushama, born on 8th Feb 1973, in Nalgonda , a small town near Nagarjuna Sagar, A.P., India .Obtained her B.Tech degree in 1993 and M.Tech degree in 2003 with a specialization in **Electrical Power Systems** from JAWAHARLAL NEHRU TECHNOLOGICAL UNIVERSITY , INDIA. Joined as **Lecturer** in the Department of EEE, JNTU College of Engg., Anantapur, in the year 1995. In the year 1996, redesignated as Assistant Professor. Presently working as **Associate Professor**, Electrical & Electronics Engineering in the Department of EEE, JNTU College of Engineering, Kukatpally, Hyderabad. She had 13 years of teaching experience. During her teaching career she taught various subjects like C language & Data Strucures, Microprocessors and Micro controllers etc., Doing research in Power Quality using Wavelets, she published 5 international papers in various IEEE sponsored conferences.