Detection and Classification of Voltage Swells Using Wavelet Transforms

Anoop Mathew, *Member, IACSIT*, N.O. Gunasekar, D. Bensiker Raja Singh and S.Uma Mahaswaran

Abstract—**Through this paper a novel technique for detecting and characterizing disturbances in power systems based on wavelet transforms is proposed. 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, Simulink, DSP and Wavelet toolboxes.**

Index Terms— **Adaptive decomposition, Daubechies (Db), Discrete Wavelet Transform (DWT), Multi Resolution Analysis (MRA), Power Quality (PQ), Statistical methods.**

I. 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 and protecting the system from the harmful effects of the fault. With the wide application of high-power electronics switchgears, problems of Power Quality (PQ) are becoming more serious day by day. At the same time, the 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]. Practically, a power quality monitoring system should have the following functions: detect power quality disturbance, identify the type and duration of disturbance signals, calculate 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 supply voltage waveform (sine wave of 50/60 Hz): frequency, amplitude, shape and symmetry. However, from generators to customers, these parameters may suffer alterations due to 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 they 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 sinusoidal [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 in Multi Resolution Analysis (MRA) [1].

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Anoop Mathew is Head of the Electronics and Communication Engineering Department, VedaVyasa Institute of Technology, Karadparamba, Malappuram Dt; Kerala, India 673632 (Phone : +91-9567398001, 0483 2832157; fax: 0483 2832156; e-mail: anoopmathew@ieee.org)

N. O. Gunasekar is Professor and Head of the Electrical and Electronics Engineering Department, Bharath University, Chennai-73

D. Bensiker Raja Singh is working with Bharath University, Chennai-73 as a lecturer in Electrical and Electronics Engineering Department. (Phone: +91-9486089841; e-mail: benzees003@gmail.com)

S. Uma Mageswaran is working with Bharath University, Chennai-73 as a lecturer in Electrical and Electronics Engineering Department. (Phone: +91-9840749738; e-mail: u.mag125@gmail.com)

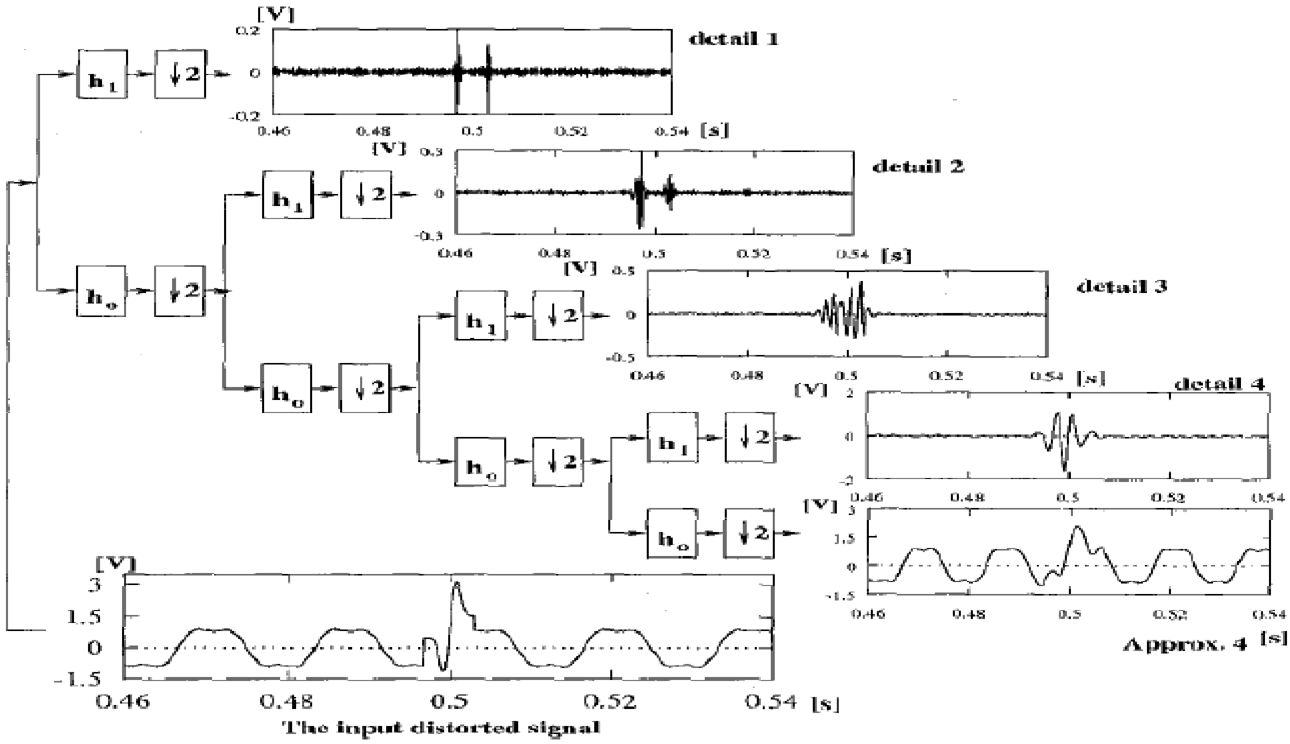

Fig. 1 Four level multi resolution signal decomposition

II. Adaptive Filter Banks

The main goal of studies in adaptive filtering is to find the best wavelet for decomposing the entire data, and fixed filter banks chosen according to an optimality criterion for the entire duration or extent of the signal.

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 sinusoidal 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 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. 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.

III. Wavelet Transforms

Wavelets are mathematical functions defined over a finite interval and having an average value of zero that transform data into different frequency components, representing each component with a resolution matched to its scale. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts). The Discrete Wavelet Transform and Multi Resolution Analysis (MRA) provide a short window for high frequency components and long window for low frequency components and hence provide 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.

IV. Multi-Resolution Analysis (MRA)

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 :

$$C_{Signal} = \lfloor C_0 \mid d_0 \mid \quad d_1 \mid ---d_{f-n} \mid \rfloor \qquad (1)$$

Where, di, represent the detail coefficients at different resolution levels, and C_0, presents the least approximate coefficients. Wavelet transform can be achieved by convolution and decimation. The detail coefficients dj, and the approximated coefficients Cj can be used to reconstruct a detailed version D1 and an approximated version A1, 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 $H_0(\acute{\omega})$ and $H_1(\acute{\omega})$ of the mother wavelet Daubechies (Db4) and its scaling function are shown in Fig.1. 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. 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.

V. DAUBECHIES FAMILY WAVELETS

Daubechies wavelet transform is a very accurate wavelet transform for analyzing Power Quality Disturbances 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.

VI. FILTER BANK STRUCTURE

The wavelet filter banks decompose the signal according to the frequency content of the filters with fixed coefficients. Here, the frequency content or spectral decomposition 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 poly-phase components of the original signal:

$$X1[n] = X[2n] \qquad (2)$$

$$X2[n] = X[2n+1] \qquad (3)$$

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 poly-phase components, let's say $X_2[n]$, can be successfully approximated using the other component samples $X_1[n]$ and a prediction filter. In that case, one can expect the difference between the prediction output and $X_2[n]$ to be relatively small:

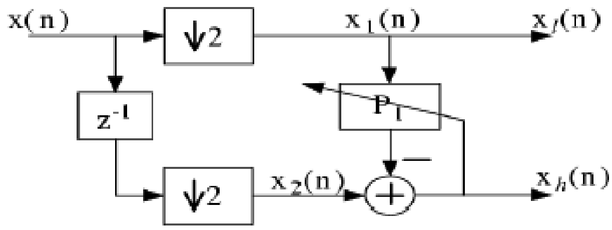

Fig. 2 Analysis of the 2-channel adaptive filter bank

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

$$\varepsilon = X_2[n]-P_1 \,.\, X_1[n-m],\ldots,X_1[n-m] \qquad (4)$$

VII. SIMULATION OF THE ADAPTIVE FILTER BANK

Simulink layout of the system is given in Fig. 3. The signal is first decomposed into poly-phase components by down sampler and integer delay modules. The above poly-phase 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.

$x_h[n]$ and the LMS output are compared using a subtraction module. 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.

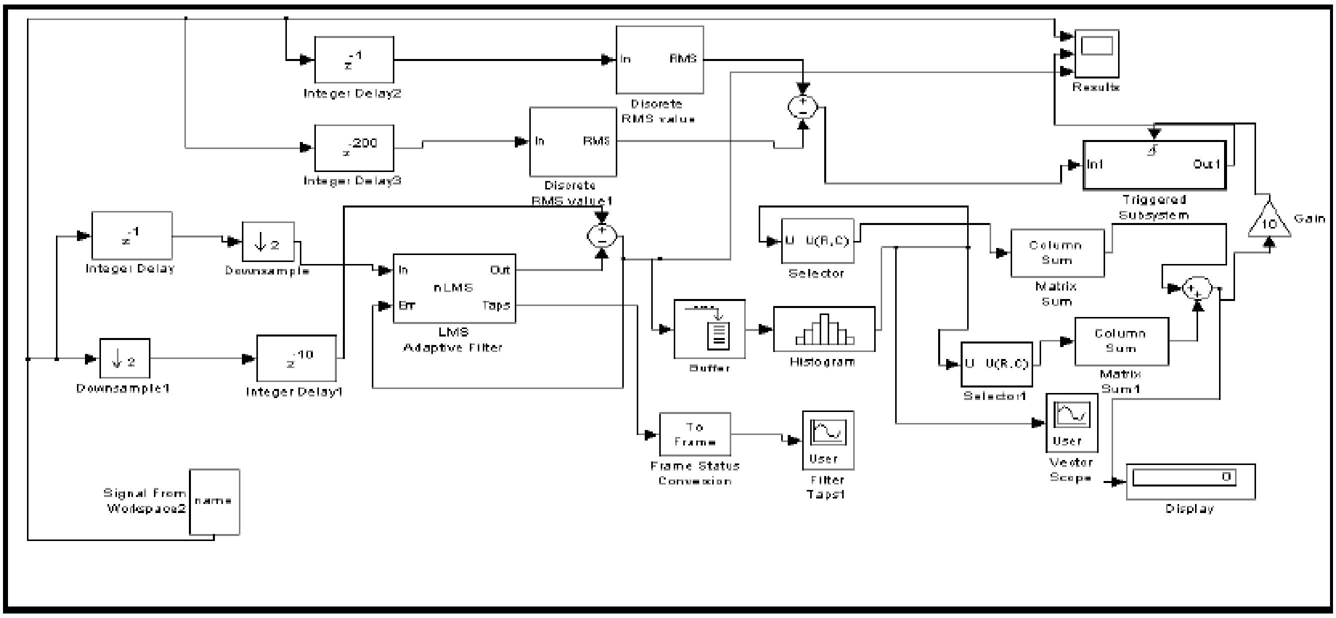

Fig.3 Simulink layout of the system

VIII. 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. Using MATLAB, the most commonly occurring disturbances are simulated. The categories that simulated are normal sinusoid, swell, temporary and long term swell.

IX. 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 swells, interruption, harmonics, and combination of these events are chosen. Different disturbance types and its models are given in Table 1.

TABLE1.DISTURBANCE MODELS

Disturbance Type	Class	Model	Parameters
Pure Sinusoidal	C1	X(t)=Sin ώt	—
Momentary swell	C2	X(t)= A{1+α [u(t-t_1)]- [u(t-t_1)]}Sin ώt	$0.1 \leq α \leq 0.4$
Long-term swell	C4	X(t)= A{1+α [u(t-t_1)]- [u(t-t_1)]} Sin ώt	$0.1 \leq α \leq 0.2$

X. DETECTION OF VOLTAFE SWELLS

Detection of any type of event using an adaptive decomposition scheme, wavelet transformation or any 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 4, 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 Fig.4. This sharp drop of RMS magnitude of the voltage should be compared with the reduction with noisy steps as observed in arcing fault.

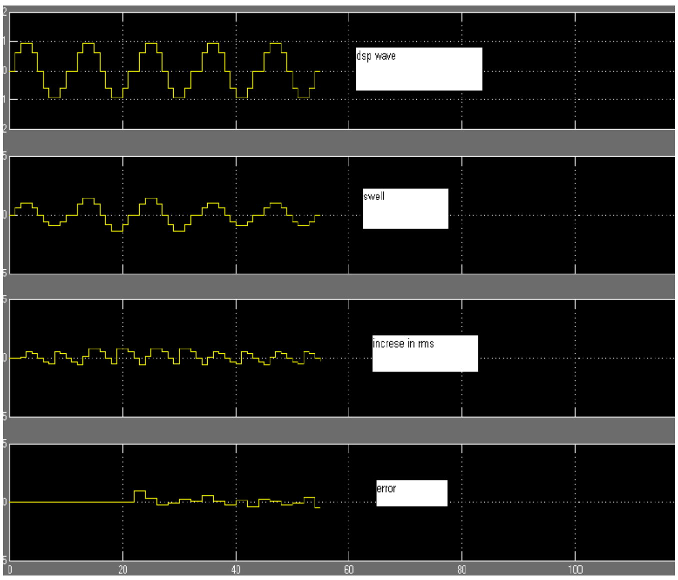

Fig. 4 Waveforms during swell

XI. PROPAGATION

A single-layer network of S logsig neurons having R number of inputs is shown in figure 5. 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).

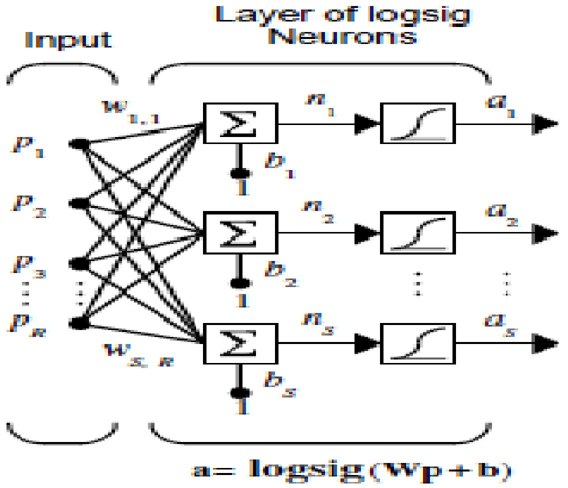

Fig. 5 Single layer network

XII. Simulation Results for Different Types of Swells

The simulation data was generated in MATLAB, based on the model in Table 2. .All the four classes (C1–C4) of different voltage swell events or disturbances, namely undisturbed sinusoid (normal), swell and its different categories are simulated. Table 2 gives the signal generation models and their control parameters.

TABLE2 TYPES OF SWELL - SIMULATION RESULTS

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

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, 4-dimensional feature sets for training and testing data were constructed and it is shown in Table 3.

TABLE 3. TRAINING AND TESTING DATA

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

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 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 is approximately 97%.

XIII. 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 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 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.

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