A Novel Approach for the Classification of Power Quality Disturbance Using Combined Adaptive Decomposition Structure and Neural Network

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Abstract:- Power quality disturbance (PQD) are normally subjected to transients and non periodic components which present a problem to the overall performance of the system. The use of traditional wavelet transform to extract the fundamental frequency components from the disturbed signal is inappropriate to different faults with single mother wavelet. A novel adaptive decomposition structure based technique for PQD has been presented in this paper, which has the ability to perform the statistical analysis using histogram analysis block of adaptive decomposition signals and neural network for classification of fault. The proposed method is described in detail and implemented using MATLAB and SIMULINK. Finally, the effect of different parameters on the algorithm is examined in order to highlight its performance. It is found that the adaptive decomposition is an excellent tool for disturbance detection and classification.

Key – Word :- Adaptive filter, LMS algorithm, power quality disturbance, statistical analysis and neural networks

1. INTRODUCTION

Power quality is the concept of powering and grounding sensitive equipment in a matter that is suitable to the operation of that equipment. One of the main problems experienced by manufacturing industries is the distortion in electrical supply. This power quality problem interrupts the sensitive manufacturing devices and results in very expensive consequences. Most steady state power line signals consist of a fundamental frequency e.g., 50Hz or 60Hz, several harmonics with relatively small amplitudes and noise. To this steady state, transient disturbances are sporadically added. Power quality is the combination of voltage quality & current quality concerned with the deviations of voltage from its ideal waveform [1]. Such a deviation is called a “Power quality phenomenon” or a “power quality disturbance”. The small deviations from the nominal or desired value are called “voltage variations” or “current variations”. A property of any variation is that it has a value at any moment in time, e.g., the frequency is never exactly equal to 50 Hz or 60 Hz. Monitoring the variations thus has to take place continuously.

Recent contributions in the area of power quality analysis use various techniques. The primary tool in signal estimation, the Fourier transform does not have the ability to accurately represent functions that have non-periodic components that are localized in time or space, such as transient impulses [2]. STFT, commonly known as sliding window version of the FFT, maps a signal into a two dimensional function of time and frequency. STFT shows better results in terms of resolution and frequency selectivity, but has a fixed frequency resolution for all frequencies and has been shown suitable for harmonic analysis of voltage disturbances. Another approach to time-frequency analysis is by wavelet transform, which allows exceptional localization in both time domain via translations of the mother wavelet and in the scale (frequency) domain via dilations. It allows use of long time intervals for precise low frequency information and shorter regions for high frequency information. Though Wavelet transform is an efficient tool for non-stationary signal analysis, it has some drawbacks [3]. A specific wavelet may be designed to detect, for example, arcing faults in a sinusoidal pre-fault waveform. However, the selected wavelet may not correspond to the optimal discriminating system for another type of transient event.

In this work, a new event detection and classification scheme for power quality analysis based on the statistical analysis of adaptive decomposition signals is proposed. Even if there is no prior information on whether the waveform is pure sinusoid or not the steady state properties of a waveform can be well approximated. The adaptive method is developed to detect and classify power quality disturbances regardless of the type of the pre-event voltage or current waveforms. 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 [4]. The ability to classify and distinguish transients from changes in load makes the proposed method more flexible as compared to the commonly used transform domain thresholding techniques for the analysis of power quality events. The significance of the proposed method is that it provides a way of detecting and classifying variety of events without changing the structure. This method is tested for different disturbed power signals which give better results than conventional methods.

2. OVERVIEW OF ADAPTIVE FILTERS

An adaptive filter is one whose characteristics can be modified to achieve some objective and is usually assumed to accomplish this modification (adaptation) automatically without the need for substantial intervention by the user. It is self designing and relies for its operation on a recursive algorithm which makes it possible for the filter to perform satisfactorily in an environment where complete knowledge of the relevant signal characteristics is not available. In a non-stationary environment, the algorithm offers a tracking capability in which it can track time variations in the statistics of the input data.

A diagram of the general form of adaptive linear combiner is shown in Fig.(1). This filter has discrete time finite impulse structure based on tapped delay line. There is an input signal vector with elements x0.,x1 …….xL, a corresponding set of adjustable weights w0,w1…..wL, a summing unit , and a single output signal, y. A procedure for adjusting or adapting the weights is called weight adjustment, gain adjustment or adaptation procedure [5]. The filter output y(k) is simply the sum of delayed and scaled inputs which is given by

$$y(k)=\sum_{i=0}^{n} w_i x(k-i) \qquad (1)$$

The filter output is compared directly to a desired waveform *d*(k) and any difference between the two constitutes an error. The error signal with time index k is given by,

$$e_k = d_k - y_k \qquad (2)$$

and the MSE(Mean Square Error) is given by

$$\text{MSE}= E\left(e_k^2\right)=E\left(d_k^2\right)+w^T R w-2p^T w \qquad (3)$$

It is seen that MSE is a quadratic function of the components of weight vector w. This function is called performance function. The point at the bottom of the error performance surface gives the optimum weight vector w^*. The optimum weight vector w^* is given by

$$w^* = R^{-1} p \qquad (4)$$

Hence the minimum MSE

$$\min = E\left[d_k^2\right]=p^T w \qquad (5)$$

where R is the input correlation matrix and p is the cross correlation matrix between input and desired response. LMS algorithm (Least Mean Square) is one of the easiest and simplest algorithms used for descending towards the minimum on the performance surface. This requires an estimation of the gradient at each iteration and uses a special estimate of the gradient.

In this work an adaptation algorithm is considered for a FIR filter of length N. The problem is to adaptively update the tap weights of the FIR filter such that for a given input sequence the output of the filter is close to the desired response.

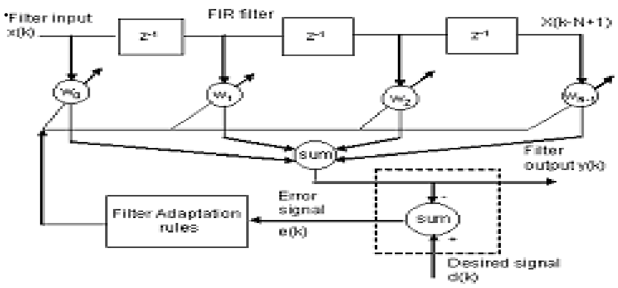


Fig.1 Adaptive Linear combiner

It is appropriate to minimize the error function. The task of LMS algorithm is to find a set of filter coefficients that minimizes the expected value of the quadratic error signal i.e., to achieve least mean squared error [6]. The algorithm is given by

$$w_{k+1} = w_k + 2\mu e_k x_k \qquad (6)$$

$$E_k = d_k - x_k w_k \qquad (7)$$

where μ is the step size or gain parameter that regulates the speed and stability of adaptation i.e., it controls the distance moved along the error surface. If this is small, correction to the filter weights gets smaller and LMS error falls more slowly. If it is large, it changes weights more for each step, so error falls more rapidly but the resulting error does not approach ideal solution.

3. CLASSIFICATION USING NEURAL NETWORK

Since neural network can be fully applied for pattern recognition, it has been widely investigated for transient classification (including faults) [7]. The major problem with Back Propogation(BP) network is its architecture parameters had to be tried experimentally, which is very time consuming and also has problems like limited flexibility, long time training, and unsuitability for on-line automatic learning. The preference of Probabilistic Neural Network (PNN) over other Artificial Neural Network (ANN) algorithms is attributed to the salient features of the PNN. The PNN is basically a Bayesian classifier implemented in parallel. As it is implemented in parallel, the standard PNN is not iteratively trained. The training vectors are transformed into the weight vectors. As a result, the weight matrix can be extremely large if we have a large training set. The PNN has the potential to be a very fast classifier, especially when implemented on hardware systems designed specifically for PNN implementation [8]. Furthermore, the PNN can easily add new pattern neurons to incorporate new typical transients or even new classes of transients. The architecture of the PNN is shown in Fig. 2. The pattern layer contains one neuron for each training case.

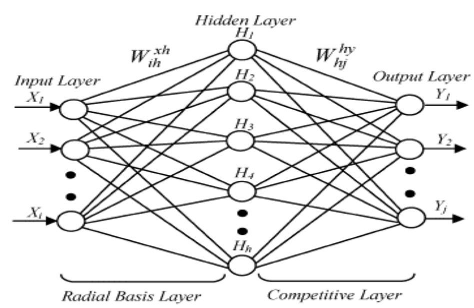


Fig.2. Architecture of the PNN

4. **SIMULINK MODEL**

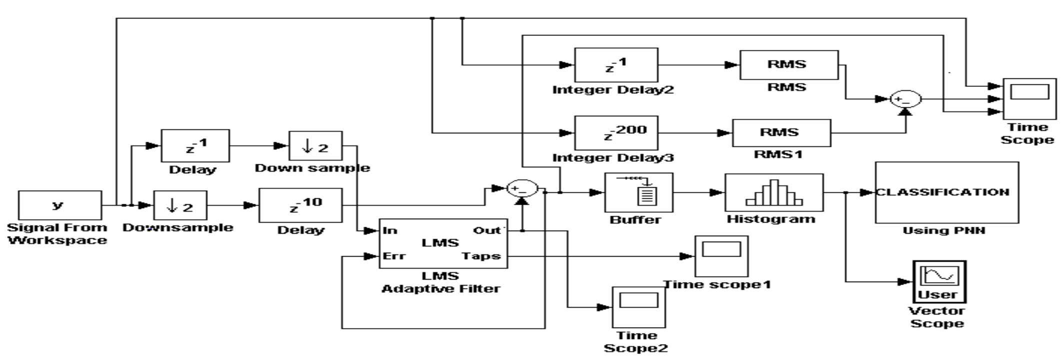


Fig.3. Block Diagram of the System

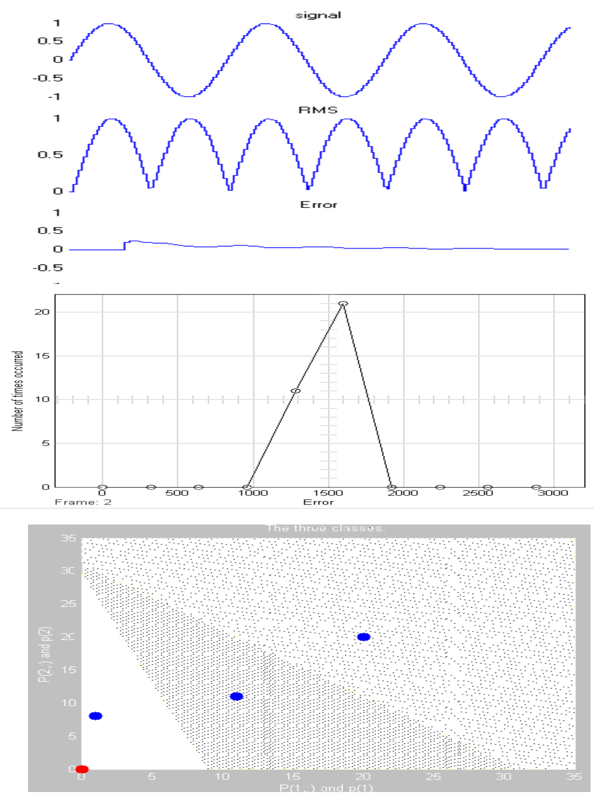
The proposed techniques are used to analyze the power quality disturbance transients in a power distribution system simulated using a power system block set. A sample distribution system is shown in Fig.3. The sampling rate for the collection of power quality transient data is taken as 10 kHz. The residual output generated by the adaptive decomposition block carries clearly visible information about the detection of various types of events. An experimental histogram-based analysis stage is developed which provides automated detection. The residual signal is first buffered to produce a time windowed portion. Then this vector is fed into a component which calculates the histogram. In the adaptive decomposition structure the residual error becomes large in magnitude when an event happens. This is clearly the point that must be detected. If this error signal is monitored in a time-windowed manner, the histogram is well centered. This is the case when the waveform exhibits no event. As soon as an event happens, its histogram becomes no longer centered; instead, the tails of the histogram becomes heavy. Using the above observation, a simple comparison rule is developed in which the weights of the center and tail portions of the histogram are compared. If the tails are weak as compared to the center portion, it means there is no event. If the tails are heavy, then an event is detected. There are other blocks in the integrated systems which are activated by the event. These blocks are designed to discriminate arcing faults from sags and swells. RMS voltage profiles are used for event analysis. By using the output of the histogram, classification is done using PNN. The tails of the histogram indicate the presence of any disturbance and classification can be done based on the amplitude of the tails of the histogram. By taking the two end points of the tails of histogram as 2x1 vector elements, classification can be done easily. Here a three two-element input vectors corresponding to the amplitude of the tails of the histogram output are taken and their associated classes are specified. From this output, the disturbance can be classified according to the region in which it lies. The system is implemented using SIMULINK and MATLAB.

5. RESULTS AND DISCUSSIONS

Different distorted data are generated by varying different parameters in the power distribution system. The following case studies are presented in this paper:

5.1 Detection of Power Quality Disturbances

Case 1: Fig. 4(a) shows pure sine wave and Fig. 4(b) shows RMS value of normal wave. The error output of the adaptive filter for a filter length of 32 and step size of 0.65 is also shown in 4(c). Since there is no disturbance, the error output is small in magnitude. The histogram plot is shown in 4(d) which indicates that there is no disturbance, and has a single peak corresponding to single frequency (50Hz) component. Since there is no disturbance and the amplitude of tails are zero, this is indicated by a point at origin in the PNN classification plot in Fig 4(e).



(a)
(b)
(c)
(d)
(e)

Fig.4(a) –(e) Pure sinusoidal waveform

Case 2: As a second example, we use a variable frequency signal (Transient event) as shown in Fig. 5(a), where, at 1000s, time frequency changes. Fig.5(b) shows the corresponding change in RMS signal of the waveform which indicates the point at which the transients occur. The error output of the adaptive filter for a filter length of 4 and step size of 0.65 is also shown 5(c). Since there is a transient, the error output is large in magnitude at the corresponding time instant. The histogram plot in 5(d) indicates that there is an event and the tails are heavy corresponding to different frequency components due to the transients. The PNN classifier uses the amplitude of the tails of histogram as input and classifies it to be a transient and this is indicated by a point in the first region as shown in Fig 5(e).

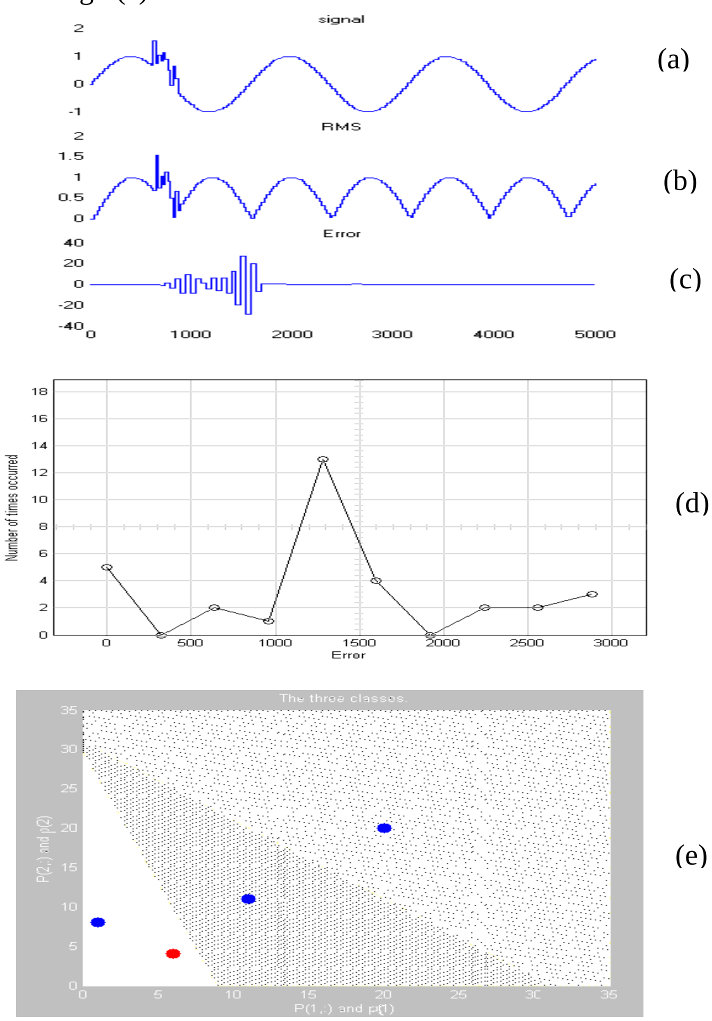


Fig.5 (a)-(e) Transient event signal

Case 3: Voltage sag shown in Fig.6(a) can be seen as a loss of voltage on a power system. These disturbances describe a drop of 90 to 100% of the rated system voltage lasting for 0.5 cycle to 1 min. Fig.6(b) shows the corresponding change in RMS signal of the waveform which indicates the point at which the variations occur. The error output of the adaptive filter for a filter length of 4 and step size of 0.65 is also shown in Fig. 6(c). Fig. 6(d) also shows the histogram plot which indicates that there is a disturbance and the tails are heavier corresponding to different frequency components due to the variations. Since the tails of the histogram are heavier, the PNN classifies the disturbance to be a voltage sag event , indicating this by a point in the second region in Fig 6(e).

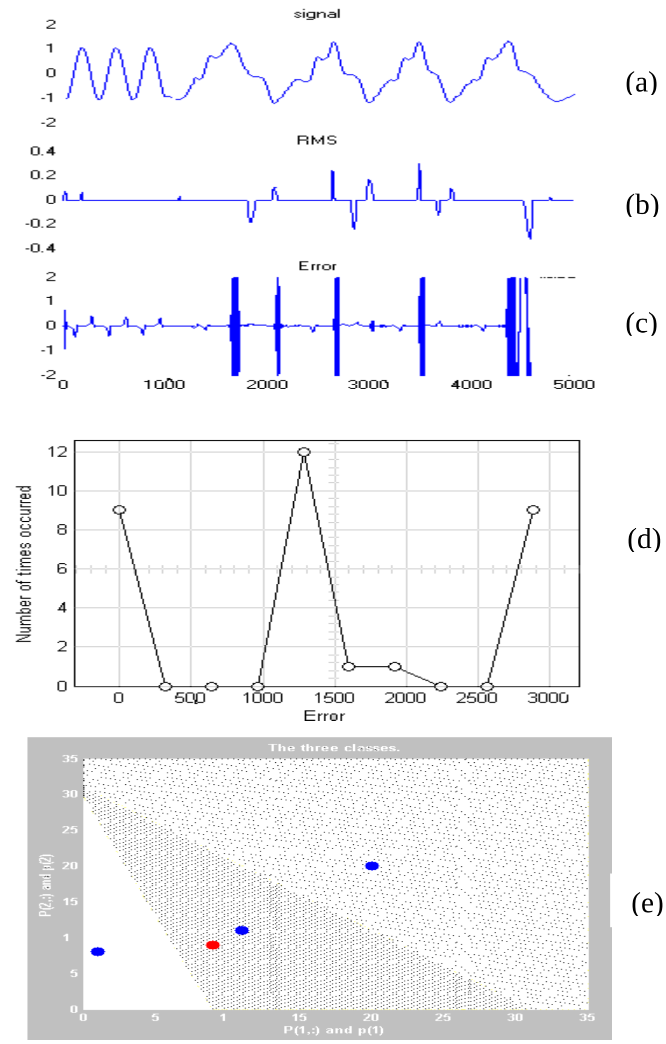


Fig.6 (a)-(e) Voltage sag event

5.2 Classification of power quality disturbances

From the results presented in Figs. 4–6, it can be seen that the histogram plot provides visual classification of the power quality disturbance waveforms. However, a few simple features can be derived from the histogram output to provide an automated power quality recognition system from the adaptive filter data. First, we employed 35 (half of all training examples) and 70 training examples to train the PNN model, respectively. We also randomly created 20 distorted voltage waves to test the proposed approach. The experimental results are shown in Table 1. As can be seen, with 35 training examples, the classified accuracy rate of the distorted signals of the proposed approach was 80% (four distorted signal failures). When the training examples were 70, the classified accuracy rate was 90% (two distorted signal failures). The results show that the more the training examples, the better the accuracy rate. Because the PNN model requires little learning time, the proposed approach is suitable for real-time processing in a modern digital recorder. The learning time and recalling time of the PNN model are also shown in Table 1.

In this experiment, classification is done based on the values of the tails of histogram. Presence of any other event other than considered is indicated by “out of range”. This can be further extended to include many other classes of power quality disturbance signals. The summarized results are given in table.1

Number of training examples	25	50
Number of testing examples	10	10
Learning time (sec)	0.03	0.05
Recall time (sec)	0.2	0.40
Accuracy rate	75%	85%

Table.1. Classification results

6. CONCLUSION AND FUTURE WORK

The proposed method is able to detect any disturbances or events in the power signal for unknown pre-event voltage or current waveforms. The main features of the new technique are its ability to detect the disturbance both sinusoidal and non-sinusoidal inputs. However, for automated classification of power quality disturbances, the histogram output matrix is searched to provide a few simple features which when used in a rule-based system yields the disturbance class. Hence, sources of such disturbances can be identified and controlled to improve electric power quality. Further, this work can also be extended for noise cancellation in on line application. This paper proposed a prototype of wavelet-based neural-network classifiers for power disturbance recognition and classification. The proposed method can reduce the quantity of extracted features of distorted signal without losing its property, thus requiring less memory space and computing time for proper classification of disturbance types. The experimental results showed that the proposed method has the ability of recognizing and classifying different power disturbance types efficiently, and it has the potential to enhance the performance of the power transient recorder with real-time processing capability. Because the distorted signals in this study were generated by simulation software, employing real distorted signals measured by the digital recorder to improve the proposed method is one of our future works.

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