Time-Frequency and Artificial Neural Network Applications and Analysis for Electrical System Power Quality Disturbances in MATLAB

Aslam P. Memon, M. Aslam Uqaili, Zubair A. Memon, Naresh K. Tanwani

Abstract—In recent years due to increasing utilization of nonlinear loads and power electronic equipment, the issue of EPQD (Electrical power quality disturbances) has become the most important apprehension for suppliers and the users of electric power. It is imperative to detect the sources and causes of electrical power quality disturbances in order to improve EPQ problems.

Traditional signal processing techniques permit mapping signals from time to frequency domains by decomposing the signals into several frequency components. Due to this transformation time information is lost. EPQ disturbances vary in the wide range of time and frequency, which means these traditional techniques are not suitable for EPQ problems. This problem can be solved with the application of WT (Wavelet transform) and feedforward neural networks as classifier.

Statistical features extraction data is obtained using DWT (discrete wavelet transformation) and MRDA (multiresolution decomposition analysis) utilizing MATLAB/Simulink and Wavelet toolbox. This minimum feature vector data is used for training FFNN as input. Proposed FFNN classifier reduces training. The results obtained show the promising applicability and suitability of WT analysis with neural network for improved and an efficient methodology for automatic diagnosis of EPQ problems.

Index Terms— Detection and classification, discrete wavelet transform, Electrical power quality disturbances, feedforward neural network, wavelet transform.

I. INTRODUCTION

Power Quality is a very interesting cross-disciplinary topic, including power engineering, power electronics with digital signal processing, software engineering, networking and VLSI. Electrical power quality is defined as" any power problem manifested in voltage, current, or frequency deviations that result in failure or misoperation of customer equipment and system itself [1-2]. In an electrical power system, IEEE and IEC have mentioned all the types of electrical power quality disturbances [3]. The electrical power quality of power supplies is growing to be a major concern of electricity users. Poor power quality may result in malfunctions, instabilities, short life time, and so on.

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The causes of poor power quality are the growing popularity of power electronics and other sensitive non-linear loads. The power supplies for information technology equipment along with high efficiency lighting, rectifiers, inverters, choppers and adjustable frequency devices are considered the main sources of power quality disturbances. These PQ disturbances are produced from the suppliers or by the users load and they may cause malfunctioning of the equipment [4-6]. To improve the quality of the power supply, detection of the disturbance must be done accurately. The power quality disturbances should be detected and classified precisely so that correct mitigation measures could be applied [2]. Recent advances in technologies of digital signal processing have made it feasible to develop more sophisticated automated detection approaches [4]. In this paper DWT with MRA technique with FFNN as classifier is employed. Feature extraction is done with WT to capture the time of occurrence and extract frequency features of power signal disturbances, which are used as input for classifier.

II. ADVANCED SIGNAL PROCESSING TECHNIQUES USED IN EPQD

A. Fourier Transform

Fourier analysis mathematical techniques, based on decomposing signals into sinusoids, can be applied to both continuous and discrete signals, may be either periodic or aperiodic. Both features can produce these categories: *Continuous- Aperiodic:* which includes decaying exponentials and the Gaussian curve and signals can be extended to positive and negative infinity without repeating in a periodic pattern, and this type is called the Fourier Transform (FT).

Continuous- Periodic: which includes sine waves, square waves, and any waveform that repeats itself in a regular pattern from negative to positive infinity such transform is known as the Fourier series (FS).

Discrete- Aperiodic: such signals are at discrete points between positive and negative infinity, and do not repeat themselves in a periodic fashion and this transform is known as Discrete Time Fourier Transform (DTFT).

Discrete- Periodic: which are discrete signals that repeat themselves in a periodic fashion from negative to positive infinity such transform is known as Discrete Fourier Series (DFS) and commonly known as Discrete Fourier Transform (DFT) [7-10].

B. Digital signal processing (DSP) algorithms

Discrete Fourier Transform (DFT): The widely used DSP algorithm having N-point DFT of x (k) of a

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sequence x (n) of length N given as:

$$X(k)=\sum_{n=-\infty}^{n=\infty} X(k)e^{2\pi kn/N} k=0,1,\ldots N-1 \qquad (1.1)$$

In the approach for computing DFT is the Goertzel's Algorithm. Goertzel algorithm is used to implement the non-uniform discrete, to evaluate filter responses [8].

Fast Fourier Transform Algorithm: DFT is computed by An FFT and the same result is evaluated. The only difference is the fastest calculation by an FFT as compared to DFT. The radix is the size of FFT decomposition. The types of radix are radix-2, radix-4, radix-8, which are the size of FFT decomposition. The FFT algorithms are found to be more accurate than DFT direct computation when we evaluate the round-off error of signal. Having set of complex date

$$X(k)\sum_{n=0}^{N-1} x_n e^{-i\pi k\frac{n}{N}} k=0,1,\ldots N-1 \qquad (1.2)$$

Short Time Fourier Transform (STFT): It is used as transform to determine the sinusoidal frequency and phase content of local sections of a signal with changing time. If the time window is sufficiently narrow, each frame extracted can be viewed as stationary so that Fourier transform can be used. STFT transform may be divided into discrete-time STFT, and continuous-time.

Mathematically we can express discrete time STFT and continuous time STFT as

$$STFT\{x[n]\}=X(m,\omega)=\sum_{n=-\infty}^{\infty} x[n]\varpi[n-m]e^{-j\omega n} \qquad (1.3)$$

$$STFT\{x[t]\}=X(\tau,\omega)=\int_{-\infty}^{\infty} x(t)\omega(t-\tau)e^{-j\omega t}dt \qquad (1.4)$$

Where m is discrete, ω is continuous, $\omega(t)$ is window function, $x(t)$ signal to be transformed, $X(\tau-\omega)$ is Fourier of $x(t)\omega(t-\tau)$ [8-10]. (1.5)

C. Wavelet Transform (WT)

In wavelet theory known as the mathematics tool, defining a model for non-stationary signals $x(t)$ are decomposed by a set of small wave components called wavelet. Every wavelet is created by scaling and translation operations in the functions called mother wavelet. Firstly this transformation is expressed by continues wavelet transform (CWT) as:

$$W_\psi(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \qquad (1.6)$$

Where a and b are scale and translation real numbers, $a\neq 0$ and ψ^* is complex conjugate of ψ and $W_\psi(a,b)$ are the wavelet coefficients. Secondly for computer implementations discrete wavelet transform (DWT) will be utilized as:

$$W_\psi(m,n)=\frac{1}{\sqrt{a_0{}^m}}\sum_{k=-\infty}^{+\infty} x(k)\left(\frac{k-a_0{}^m nb_0}{a_0{}^m}\right) \qquad (1.7)$$

Where $a=a_0{}^m$, $b=a_0{}^m nb_0$, m and n are the integer numbers provided $a_0\rangle 1$ and $b_0\neq 0$[ ]. Due to this process redundancy of continuous form must be eliminated hence a_0 and b_0 be selected as to from orthogonal basis by satisfying the condition as $a_0=2$ and $b_0=1$. This requirement invites us to use multiresolution analysis (MRA), which is also known as multiresolution wavelet method (MWM). In this method original signal $x(t)$ is decomposed into different scales resolutions and the mother wavelet function

$\psi(t)=2\sum_{n=-\infty}^{+\infty} d_n(2t-n)$ is chosen with function $\phi(t)=2\sum_{n=-\infty}^{+\infty} c_n\phi(2t-n)$ known as scaling function, where d_n and c_n are squared summable sequences [11-13].

Choosing an appropriate mother wavelet for EPQD is an art, instead of developing algorithms of wavelets for different problems. At the lowest scale like scale 1, the mother wavelet is most localized in time and oscillates most rapidly within a very short period of time. As the wavelet goes to higher scales, the analyzing wavelets become less localized in time and oscillate less due to the dilation nature of the wavelet transform analysis. As a result of higher scale signal decomposition, fast and short transient disturbances will be detected at lower scales, whereas slow and long transient disturbances will be detected at higher scales [14-15].

III. DISCRETE WAVELET TRANSFORM (DWT)

Traditionally, the Fourier transforms permits mapping signals from time domain to frequency domain by decomposing the signals into several frequency components. This technique is criticized in that the time information of transients is totally lost, although the accuracy of frequency components is high. Fourier transform does not fit the analysis of transients owing to the non-stationary property of its signals in both time and frequency domains. Wavelet transform generally offers this facility. Latest advances in electrical power quality mitigation techniques are based on extraction of disturbances data instead of traditional methods. Hence time-frequency analysis is more suitable to detect disturbances from data. PQ disturbances also vary in a wide range of time and frequency, and (WT) Wavelet transformation has unique ability to examine the signal in time and frequency ranges at the same time which makes WT a best suited tool for power quality disturbances [4 & 10].

The continuous wavelet transform was developed as an alternative approach to the short time Fourier transforms to overcome the resolution problem. The important point to note here is the fact that the computation is not a true continuous wavelet. From the computation at finite number of location, it is only a discretized version of the continuous wavelet. Note, however, that this is not discrete wavelet transform (DWT). These days, computers are used to do almost all computations. It is evident that neither the FT, nor STFT, nor the CWT can be practically computed by using analytical equations, integrals, etc. It is therefore necessary to discretize the transforms. As the discretize CWT enables the computation of the continuous wavelet transform by computers, it is not a true discrete transform. As a matter of fact, the wavelet series is simply a sampled version of the CWT, and the information it provides is highly redundant as for as the reconstruction of the signal is concerned. This redundancy, on the other hand, requires a significant amount of computation time and resources. The discrete wavelet transform DWT provides sufficient information both for analysis and the synthesis of the original signal, with a significant reduction in the computation time. The DWT is considerably easier to implement when compared to the CWT [4, 6 & 10].

IV.METHODOLOGY SIMULATION AND RESULTS

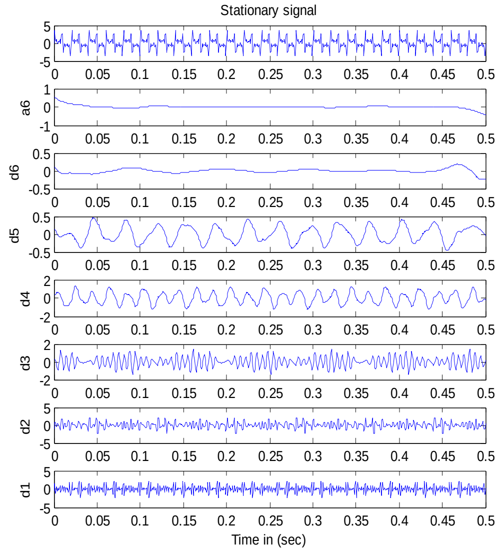
Distorted signals of EPQ (like stationary, non stationary, transient, impulse, periodic notch with noisy data) generated by the power system block set in Matlab Simulink.

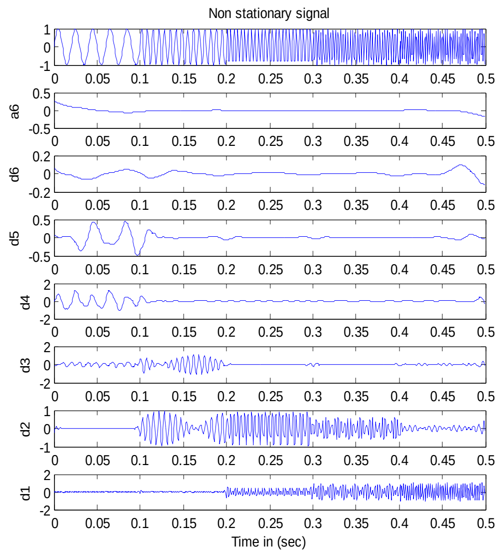
Considering the best computational efficient analysis, we select six level decomposition with (db4) Daubechies mother wavelet, which will be sufficient for the required data. DWT with MRD analysis algorithm is proposed, applying on original distorted signals generated at 25 cycles or 0.5 seconds, and 10 KHz sampling rate in MATLAB 7.13, Simulink 7.8, DSP System Toolbox 8.1, and Wavelet Toolbox 4.8 versions respectively.

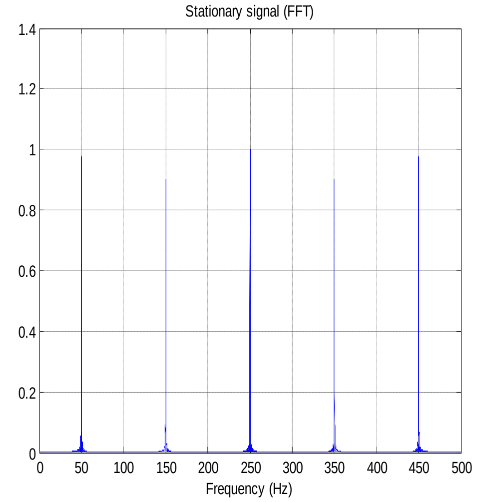
According to multiresolution wavelet decomposition, the frequency division of approximate coefficients (a_1-a_6) and their frequency bands are 0-2500 to 0-78.125. Detail coefficients (d_1-d_6) and their frequency bands are 2500-5000 to 78.125-156.25 respectively.

It has been proved that DWT coefficient at the detail interval $\left(d_1 - d_6\right)$ of disturbance are much higher than other times, because (d_1) the first scale detail of the signal shows the highest component detection of the disturbance very quickly [4, 16-19]. Six scale approximations (a6) of the signal show the low frequency components detection of the signal disturbances. As the scale increases, the accuracy of disturbance time localization decreases [20]. This method of decomposition creates time-frequency data information of the original signal with good resolution.

When the signal is stationary, frequency contents do not change with respect to time and we do not need time domain analysis of such stationary signals. Fig. 01 shows stationary (Fig. 01 a) and non stationary signal (Fig. 01 b) and their FFT responses (Fig. 01 c and & d). Both FFT responses shown in figures c and d indicate the same frequency contents for stationary and non stationary signals.







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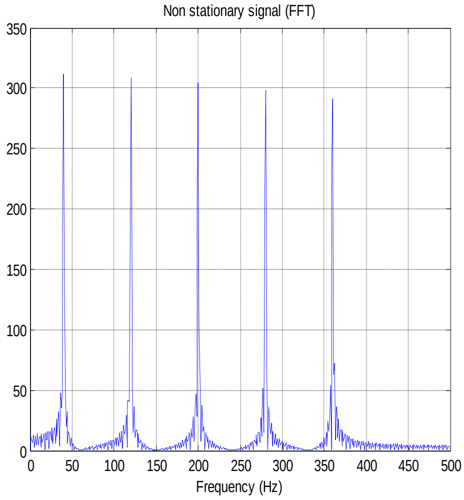
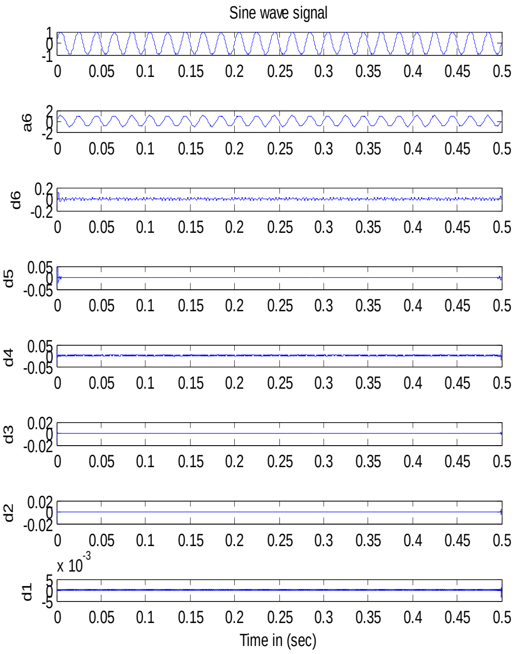


Figure 01: Stationary and non stationary signals with wavelet and FFT analysis.

Although non stationary signal changes with time and stationary remain same at all times. Therefore, there is no information of time in the FFT responses is shown. This clearly gives the ideas that FFT technique is not suitable for non stationary signals. On the other hand WT responses of signals shown in Fig. 01 (a & b), lower level detail coefficients d_2 and d_3 of stationary signal gives frequency-time domain responses at the same time. In case of non stationary signal (Fig. 01 b) d_1 and d_2 coefficients indicate the frequency-time responses instantaneously. These both coefficients suggest that WT can easily detect and distinguish the disturbances of power signals easily and efficiently.



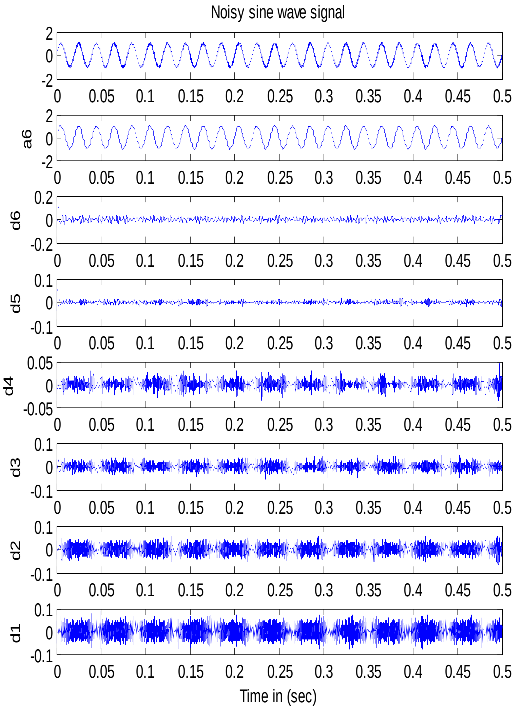
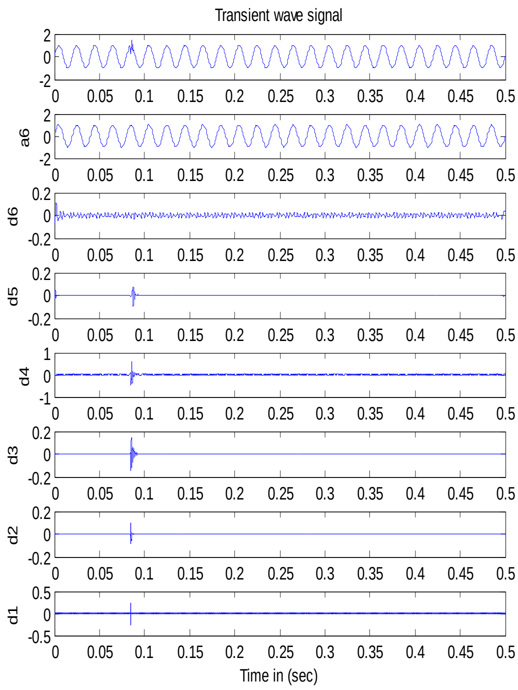


Figure 02: Sine wave and noisy sine wave with WT analysis

It is considered that almost all power signals are contaminated with noise. WT shows another property of de noising and identifying the signal as shown in Fig. 02, where sine wave and noisy sine wave are analyzed with proposed technique of wavelet.



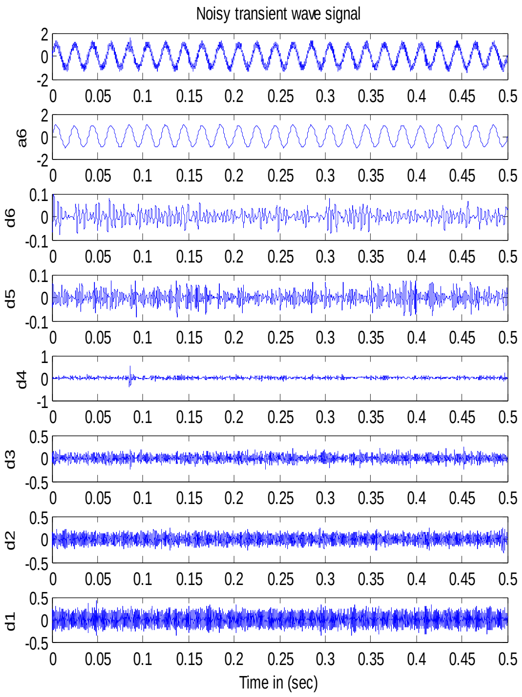


Figure 03: Transient and noisy transient signal of power system analyzed with wavelet

Fig 03 shows the decomposition of transient signal at d_1 and up to d_5, and de noising transient signal at d_4 level, showing both properties of frequency time analysis and filtering process.

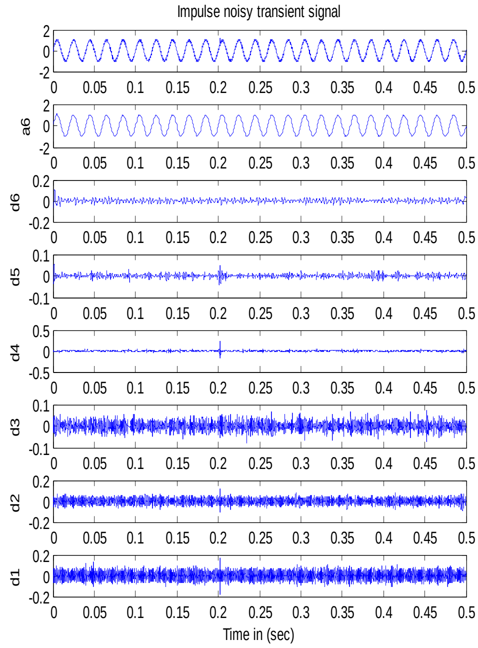
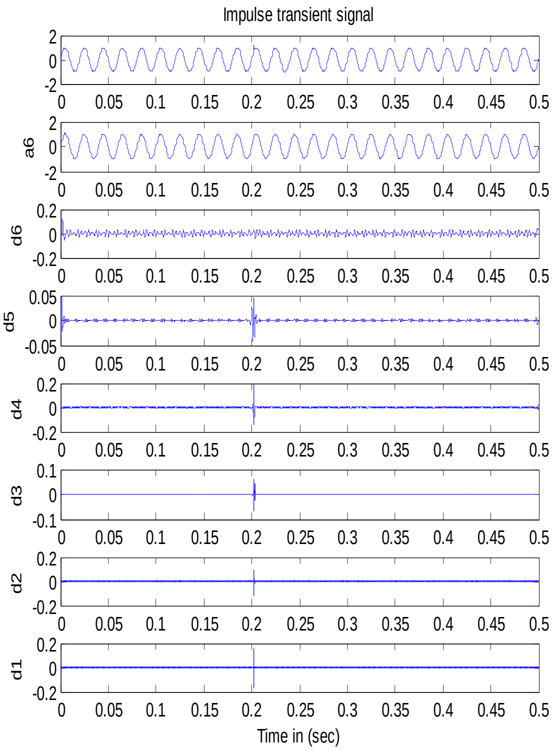
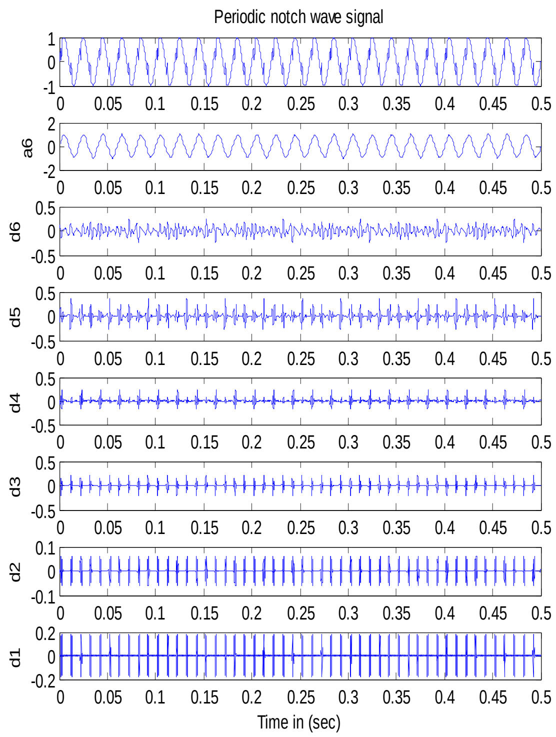


Figure 04: Impulse transient and its noisy signal with WT decomposition

Fig 04 and 05 shows periodic and impulse responses with their noisy signals. Their decompositions and filtering properties due to the application of wavelet transformation are also shown. The characteristics of periodic notch and impulse transient signals are accurately detected and identified with proposed method time-frequency analysis.





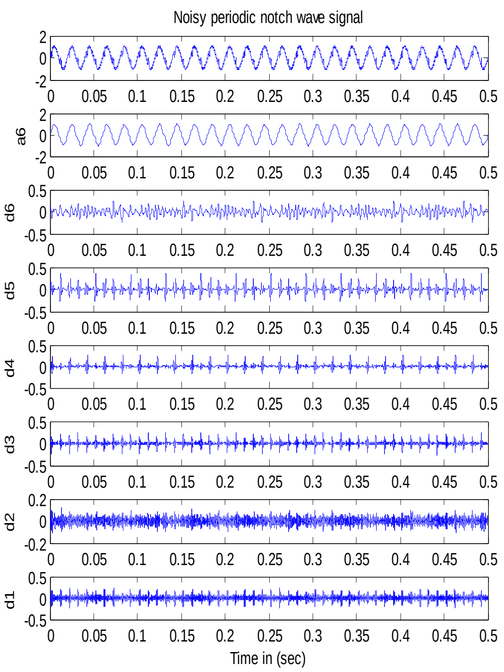


Figure 05: Periodic notch and noisy periodic notch WT decomposition of power signal

A. Implementation of artificial neural network (ANN) for the classification of PQ disturbances

ANN has been recommended in the literature of power system for automatic classification of waveform distortion [21]. Artificial neural network (ANN) is a great potential because they are based on a solid mathematical approaches, which have versatile and well-understood mathematical tools. ANNs are universal function approximators. Hence, they are capable of approximating any continuous nonlinear functions to arbitrary accuracy and the inherent in NNs show their robustness, parallel architecture and fault tolerant capability [22-23]. The aptitude of ANNs to model complex relationships makes them superior to conventional pattern reconditioned. Because the traditional classifiers demand a good knowledge of mathematical model of the signal system, which may not be obtainable in most cases. Most ANN classifiers do not need such requirements because they can handle complex systems easily and efficiently. They become skilled at to map input-output relations by training process. The ANNs are trained to identify a process or signaling either off-line or on-line during the real time operation of the system [24-26]. Due to these diverse properties, the learning speed of the RBF NN model is very fast and makes it the most suitable in real time applications of the fault diagnosis and classification of power signals analysis.

Popular type of ANN is feedforward NN, which is further sub divided into radial basis function (RBF) and multilayer perceptron (MLP) [21]. RBF NN is proposed in this work due to distinctive properties of best approximation, simple network structure and efficient learning procedure, RBF networks possess best characteristics as classifier, when compared with MLP networks. RBF networks suggested in this work are trained with the help of orthogonal least squares OLS algorithm, which selects an appropriate number of the radial basis function centres from input data. This solves the problem of selecting an optimal number of hidden layer neurons automatically [27].

At best-required specified mean square error (mse) goal, RBF due to good function approximate adds neurons to the hidden layer up to best level. For achieving required level of mse goal, first the network is simulated, then input vector with the greatest error is found and radial basis transfer function neuron is added with weights equal to the input vector of greatest error and finally linear transfer function layer weights are redesigned to minimize error [28].

It is proposed that such disturbed signals can be analysed with the help of discrete wavelet transformation (time-frequency) technique with MRA algorithm. With this technique, the features of the input data are extracted, by applying standard statistical techniques using Wavelet toolbox of Matlab. These feature vectors will be introduced as input to RBF NN for training, which can have the ability to identify and classify the various types of EPQDs waveforms.

Ten types of different EPQ disturbances are proposed as:

S_1 Stationary
S_2 Non stationary
S_3 Sine wave
S_4 Noisy sine wave
S_5 Transient
S_6 Noisy transient
S_7 Impulse
S_8 Noisy impulse
S_9 Periodic notch
S_{10} Noisy periodic notch

The feature extractions achieved from the WT technique provide the five-dimensional feature sets (standard deviation, minimum, maximum, absolute value, and mean values) of transformed signal for training and testing RBF classifier. These vectors provide distinctive knowledge of EPQ signals within minimum data amount required as input for training of RBF as automatically classifier of EPQDs signal.

The target output of the RBF network is a 10 element vector. For each disturbance only one of the elements will be 1. For S_1 it will [1 0 0 0 0 0 0 0 0 0], S_2 = [0 1 0 0 0 0 0 0 0 0], S_{10} = [0 0 1 0 0 0 0 0 0 0] and for S_{10} = [0 0 0 0 0 0 0 0 0 1]. The evaluations performance of developed model of RBF, with its classification results during testing are shown in Table 01.

Figure 05 shows RBF neural networks model for EPQDS classification. RBF architecture produces a two-layer network. First layer has radbas neurons, and computes its weighted inputs with dist and its net input with net product (netprod). Second layer has compet neurons, and computes its weighted input with dot product (dotprod) and its net inputs with net sum (netsum). Only the first layer has biases. The error goal is set at 0.000011 with 1.05 spread constant. Then input layer of PNN contains 50 neurons (10*5=50) neurons/nodes with radbas transfer function and only 11 neuron/node with purelin transfer functions in output layer are required. This process of training takes only 3.5 seconds and the networks are trained by using orthogonal least squares (OLS) algorithm. Fig. 10 shows ten types of EPQDs with five-dimensional feature sets of transformed signal introduced as input for training and out put of RBF classifier for EPQDs.

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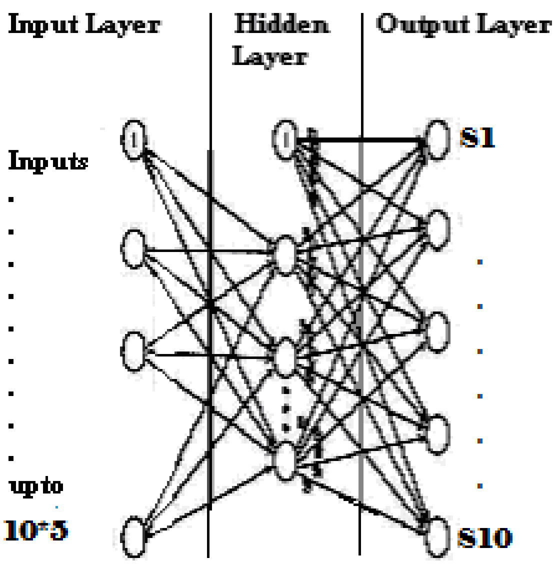

FIG. 05. RBF NEURAL NETWORKS MODEL FOR EPQDS CLASSIFICATION

The overall accuracy of correct classification is the ratio of correctly classified power quality disturbances to that of the total number of EPQDs. The overall classification accuracy of RBF is 97.45% when 200 samples were tested.

The RBF is simple in training because it requires less learning time, number of epochs, and less time to classify a particular input data during testing. This has been also verified that with suggested five extracted features obtained from WT are sufficient for a RBF to classify the different types of EPQ disturbances.

Table 1. Shows Classification Results After Developing RBF Nn With 200 Samples of Epqds Signals.

EPQDs	Samples	Identified	Unidentified
C1	200	200	0
C2	200	192	08
C3	200	197	03
C4	200	195	05
C5	200	189	11
C6	200	193	07
C7	200	199	01
C8	200	199	01
C9	200	196	04
C10	200	189	11
09	2000	1949	**51**
Overall accuracy 97.45%.			

V. CONCLUSIONS

In this work, we have proposed an advanced approach of DSP for detection and classification of EPQ disturbances, in order to extract the signal features with DWT and MRDA technique. This method transforms the signal of time-domain into frequency-time domain by using Matlab/Simulink and wavelet Toolbox. By the help of this methodology, feature vectors with statistical analysis of signals processing are obtained with minimized required important data. This feature data will be presented to RBF as input. After training RBF performs as classifier for EPQDs.
EPQ disturbances vary in the wide range of time-frequency domain, which suggests that the traditional techniques of FFT are not suitable for EPQ problems; here this problem has been solved and proved in this process.

This combined proposed methodology of WT and RBF demonstrates the successful applicability and suitability for the diagnosis of power quality problems in simple and an efficient way.

Proposed technique will provide a clear understanding for utilities, regulators and customers to identify power quality problems in order to propose the solutions to mitigate them..

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