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Analysis of Power Quality Disturbances using DWT and Artificial Neural Networks

T.Jayasree[**] *M.S.Ragavi*[*] *R.Sarojini*[*] *Snekha.R* [*] *M.Tamilselvi*[*]
*BE final year, ECE Department, Govt. College of Engineering, Tirunelveli
**Assistant professor, ECE Department, Govt. College of Engineering, Tirunelveli

ABSTRACT

The effectiveness of wavelet transform (WT) methods for analyzing different power quality (PQ) events has been demonstrated in this paper. Multi-resolution signal decomposition based on discrete WT is used to localize and to classify different power quality disturbances. The energy distribution at different levels using MRA is unique for a disturbance and can be used as a feature for automatic classification of the power quality events. The PQ event duration and energy distribution of pure sine voltage wave, voltage sag, swell, transients, harmonics, impulse, notching, fluctuation and flicker are obtained using wavelet transform. The presence of noise degrades the detection capability of wavelet based method and therefore effect of noise on different signal is analyzed. Hence a Wavelet based denoising technique is proposed in this work before feature extraction process. Two very distinct features common to all PQ disturbances like and Total Harmonic Distortion (THD) are extracted using discrete wavelet transform and are fed as inputs to the fuzzy expert system for accurate detection and classification of various PQ disturbances. The fuzzy expert system not only classifies the PQ disturbances but also indicates whether the disturbance is pure or contains harmonics. A neural network based Power Quality Disturbance (PQD) detection system is also modeled implementing Multilayer Feed forward Neural Network (MFNN).

I. INTRODUCTION

The quality of power supply has become a major issue for electrical utilities and electricity consumers. The poor quality of the power supply may cause malfunctions of power service equipment's, instabilities, short life time of equipment's, and so on. The power signal disturbances are classified as impulse, notches, glitches, momentary interruption, voltage sag, voltage swell, harmonic distortion and flicker. To improve the quality of the power supply, it is required to detect source of the disturbances accurately. The power quality events should be detected, localized and classified accurately so that proper mitigation measures could be applied. Wavelet analysis techniques have been implemented as a new tool for fault detection, localization and classification of different power system transients. According to the literature, different wavelets can be used to decompose the signal. Commonly Daubechies (Db), biorthogonal (bior) and coiflet has used for identifying the imbalance in active power in power system. Wavelets are mathematical functions that divide data into different frequency components. These frequency components are simple and easy to study. The basic idea in wavelets is to analyze signal according to scale rather than frequency. Wavelet has been used for the analysis of signal with discontinuities and sharp spikes.

II. POWERQUALITY DISTURBANCES

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Detection of power quality disturbances has become a major issue. According to International Electro technical Commission (IEC) impulsive and oscillatory transients, brief interruption, harmonic distortion, voltage swell or sag are considered as disturbances. The power quality disturbance is a temporary deviation in value from the steady state value due to sudden change of load and faults. Definition and causes of different disturbance are describe below according to IEEE Std-1159, 1250.

Voltage Sag

Voltage sag is a short-duration decrease of the Root Mean Square (RMS) voltage (between 10% to 90%) that lasts from 0.5 seconds to several seconds. If it lasts for less than half a cycle then it is considered as transient. Voltage sag results due to switching operations of large motors, lightning strokes and transmission faults (disconnection of supply). These momentary events can cause a complete shutdown of power plants, which may take hours to return to normal operation.

Voltage Swell

An increase in RMS value of voltage from 1.1p.u.to 1.8p.u., and the lasting time is 0.5 period to1min. is known as voltage swell. A voltage swell occur temporary, on the phase without fault of a three phase circuit due to single line to ground fault. They can also occur on adding a large capacitor bank, removing a large load and due to transfer of loads from one power source to another.

Harmonics

A harmonic is a sinusoidal component of a periodic wave or signal having a frequency that is an integer multiple of fundamental frequency. The term harmonic refers to the decomposition of a non-sinusoidal but periodic signal into a sum of sinusoidal components.Either time-domain or frequency domain approach can be used for harmonic analysis. Harmonics are mainlycaused by non-linear loads. Harmonic distortion has become progressively more important in recent years, due to the increase in nonlinear loads.

Transients

Voltage disturbances which persist shorter than sags or swells are classified as transients. These are caused by the sudden changes in the power system. The transient over voltage of duration in the range of milliseconds are called switching surge and in the range of microseconds are called impulse spike.

III. DETECTION OF PQ EVENT USING WAVELET TRANSFORM

Now-a-days with the advent of the digital techniques, the PQ disturbances are monitored onsite and online. Recently the wavelet transform (WT) has emerged as a powerful tool for the detection of PQ disturbances. The Wavelet transform uses wavelet function as the basis function which scales itself according to the frequency under analysis. The scheme shows better results because the basis function used in the WT is a wavelet instead of an exponential function used in FT and STFT. Using the WT the signal is decomposed into different frequency levels and presented as wavelet coefficients. Depending on the types of signal, continuous wavelet transform (CWT) and discrete wavelet transform (DWT) are employed. For continuous time signal, CWT based decomposition is adopted and for discrete time signal DWT based decomposition is employed. However in this work all the signals shown are discrete in nature hence DWT based decomposition is employed here in this part of the work different PQ disturbances such as Sag, Swell, Interruption, Sag with harmonics and Swell with harmonics are generated using MATLAB and then decomposed using decomposition algorithm of WT and point of actual disturbance is located and type of disturbance is detected.

WAVELET TRANSFORM

Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. The resulting wavelets, called daughter wavelets, are localized both in time and frequency. Thus, wavelet transform provides a local representation of signal in both time and frequency unlike Fourier transform which gives a global representation of signal in terms of frequency. Continuous wavelet transform (CWT), wavelet series (WS) and discrete wavelet transform (DWT) are three ways by which wavelet transform can be implemented.

Discrete wavelet transform

Discrete Wavelet Transform has two stages. First wavelet coefficients hd(n) and gd(n) have to bedetermined. It represents the signal X(n) in the wavelet domain. After the first stage,approximate and detailed coefficients have to be calculated from the decomposed power signal. These coefficients are cA1 (n) and cD1 (n) as defined below.

After the decomposition of power signal, to get the original signal in time domain, inverse fourier transform has to be applied. So the signal X(t) in wavelet domain is as follows

$$WT_x(a,b) = \int_{-\infty}^{\infty} S(t)\ \Psi_{a,b} dt \text{ - - - -}$$

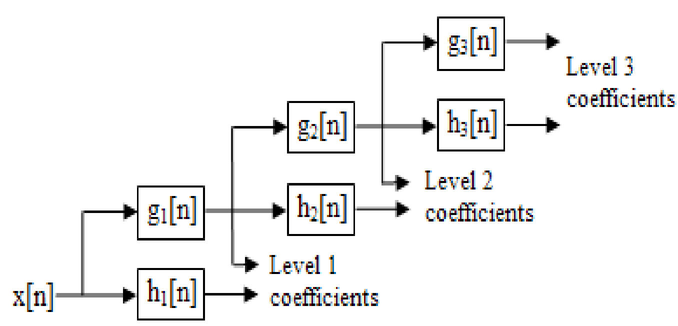
$$\text{Where } \Psi a, b\ (t) = \Psi\ ((t-b)/a)/\sqrt{a} \text{ - - - -}$$

is a scaled and shifted version of the mother wavelet Ψ(t).The parameter a corresponds to scale andfrequency domain property of Ψ(t).The parameter b corresponds to time domain property of Ψ(t) .In addition 1/√ a is the normalization value of Ψa,b(t) for having spectrum power as same as mother wavelet in every scale. The DWT is introduced by considering sub band decomposition using the digital filter equivalent to DWT. The filter bank structure is shown in The Band pass filter is implemented as a low pass and high pass filter pair which has mirrored characteristics. While the low pass filter approximates the signal. The high pass filter provides the details lost in the approximation. The approximations are low frequency high scale component whereas the details are high frequency low scale component.

MULTI-RESOLUTION ANALYSIS

The multi-resolution analysis (MRA) introduced by Mallat (Mallat, 1989) decomposes a signal into scale with different time and frequency resolution. In MRA, a signal f(t) can be completely decomposed into its detailed version (high frequency components) and smoothed/ approximated versions. The wavelet function serving as high pass filter with filter coefficients g(n), generates the detailed version of the distorted signal, while the scaling function associated with low pass filter with filter coefficient h(n), generates the approximated version of the distortedsignal. Thus, by using MRA high frequency transients can be easily analyzed in presence of low frequency components such as non-stationary and non-

Fig 1 Block diagram of voltage resolution



periodic wide-band signals.

The $h(n)$ and $g(n)$ are the low pass and high pass filters. If $f(n)$ is the discrete time signal, from MRA, the decomposed signal at scale-1 are $c1(n)$ and $d1(n)$, where $c1(n)$ is the smoothed version of the original signal, and $d1(n)$ is the detailed version of the original signal down-sampled by a factor 2. Since both the high pass filter and low pass filters are half band, these decomposition halves the time resolution since now only half the number of sample characterize the entire signal. However, this operation doubles the frequency resolution since the frequency band of signal now spans only half the previous frequency band, effectively reducing the uncertainty in the frequency by half. The next higher scale decomposition is now based on the signal $c1(n)$, which decomposes it further into $c2(n)$ and $d2(n)$. At each scale, the filtering and sub sampling result in half the number of samples and thus half the time resolution and double the frequency resolution.

IV. MULTILAYER FEED FORWARD NEURAL NETWORK

An artificial neural network (ANN) (or, neural network) provides a practical general method for, discrete-valued, learning real-valued and vector-valued functions from examples. The type of neural network is supervised learning,regression problem, the main task is learning of real-valued target function. How we will structure our Artificial Network Network mainly depend on the problem (classification problem or regression problem) we are trying to solve and that has become largely interested subject for the convenience of handling complex and non-linear problems and they are applicable for wide range. Artificial Network Network consists of simple element which is parallel interconnected and is intended to interact with real world as the biological nervous system interacts.

BACK PROPAGATION ALGORITHM

BPA is a method of supervised learning which can be visualized as a generalized form of the delta rule. BPA demands a teacher that can predict desired output for any input in training set. For feed forward networks, BPA is much effective technique. The term "backward propagation of errors" is another definition back propagation algorithm. In case of Back propagation the activation function which is used by the artificial neurons has to be differentiable.

V. SIMULATION AND ANALYSIS

DATA GENERATION

The simulation data is generated in MATLAB based on the model in paper (Rodney et al., 2010). One pure sine-wave signal(frequency = 50 Hz, amplitude 1p.u) and nine PQ disturbance signals are generated. The disturbance signal includes voltage sag,voltage swell, harmonics, low frequency transient, high frequency transient, impulse, voltage fluctuation, notching and flicker.

Signal models and their parameters

PQ DISTURBANCES	MODEL	PARAMETERS
Sine-wave	x(t)=Asinwt	A-1.0
Sag	$x(t) = A(1-\alpha (u(t-t1) - u(t-t2)))$; $t1 < t2$, $u(t) = 1, t \geq 0$	$0.1 \leq \alpha \leq 0.9$, $T \leq t2 - t1 \leq 8T$
Swell	$x(t) = A(1+\alpha (u(t-t1) - u(t-t2)))$; $t1 < t2$, $u(t)$	$0.1 \leq \alpha \leq 0.8$, $T \leq t2 - t1 \leq 8T$

	$=1, t \geq 0$	
Harmonics	$x(t) = A[\sin\omega t+\alpha 3 \sin(3\omega t) +\alpha 5 \sin(5\omega t)]$	$0.1 \leq \alpha 3 \leq 0.2$, $0.05 \leq \alpha 5 \leq 0.1$
Flicker	$x(t) = A[1+ \beta \sin(\gamma\omega t)]\sin(\omega t)$	$0.1 \leq \beta \leq 0.2$, $0.1 \leq \gamma \leq 0.2$

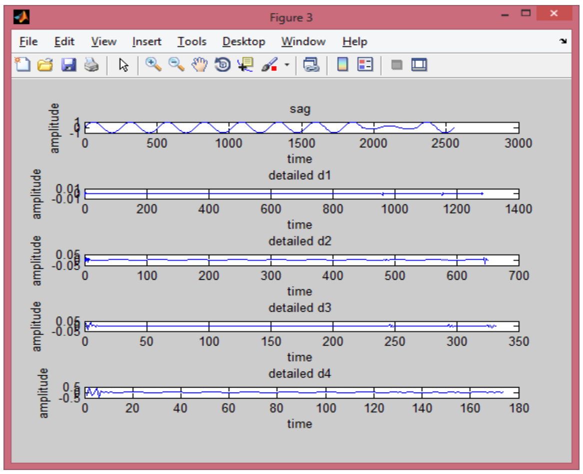


Fig 2 detailed version of sag

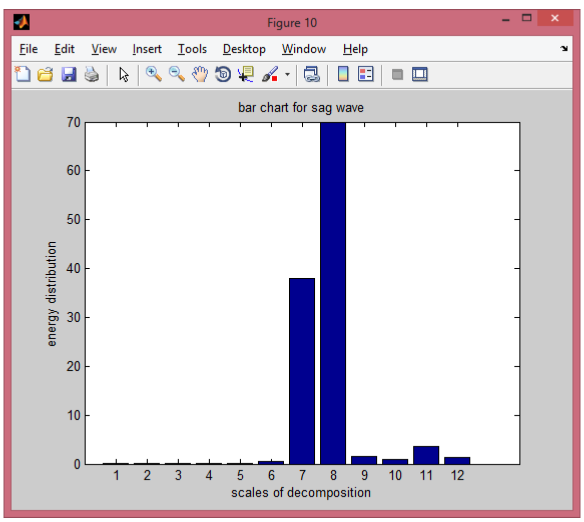


Fig 3 energy distribution of voltage sag

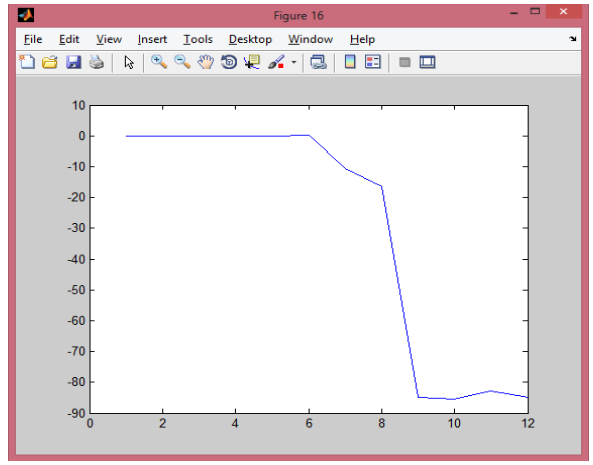


Fig 4 energy deviation of sag

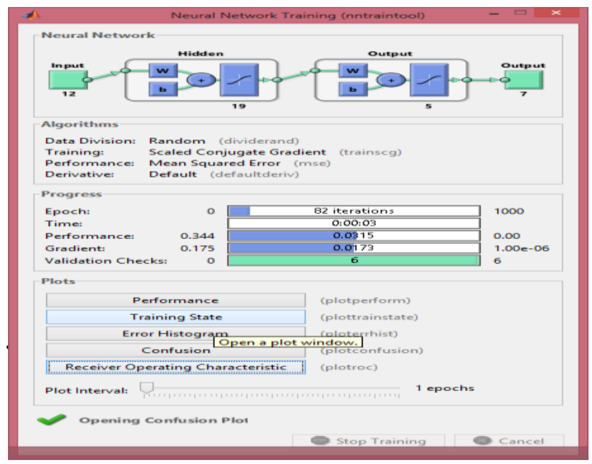


Fig 5 neural network

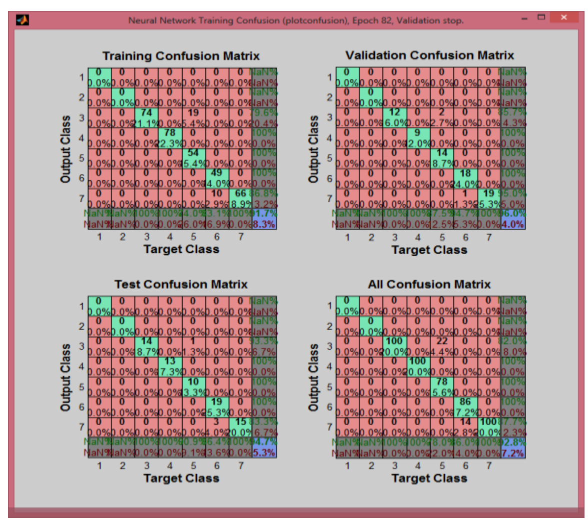


Fig 6 confusion matrix

RESULT

SNO	FEATURES	CLASSIFICATIO N PERCENTAGE
1	E1,E2,E3,E4,E5,E6,E7,E8,E9,E10,E11,E12	97.333333
2	E1,E2,E3,E4,E5,E6,E7,E8,E9,E10,E11	98.666667
3	E1,E2,E3,E4,E5,E6,E7,E8,E9,E10	96.000000
4	E1,E2,E3,E4,E5,E6,E7,E8,E9	100.000000

CONCLUSION

In this paper,it is tried to classify pure sine and PQ disturbances such as voltage sag, swell,harmonics,transients and flicker at power system frequency.Data is normalized by using 12 levels DB8 wavelet filter and energy distributions of detail coefficients of PQ disturbances and pure sine are obtained.After obtaining feature vector, powerful classifier MFNN is used in classification stage 97.905 % average performance is obtained. The use of wavelet multi-resolution analysis standard deviation curves along with fourier domain parameters with the help of a 4 layer feed forward neural network proved to achieve almost a zero error rate for the considered datasets.

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