Power Quality Analysis using Complex Wavelet Transform

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***Abstract*-- This paper deals with analysis of power signals using complex wavelet transform. In the first step power signals containing sag, swell, harmonic, sag-harmonic, swell harmonic, transient and spike were generated using Matlab. Various features like energy, kurtosis, entropy, skewness etc. were extracted using 'db4' and complex wavelet decomposition up to 11 levels. Next, an extensive database of these features was created. A neural network based on these parameters was trained and tested. It has been shown that the classification accuracy achieved by using complex wavelet is higher than obtained by the use of 'db4' wavelet.**

***Index Terms*-- Complex wavelet, Feature extraction, Neural network, Power quality**

I. INTRODUCTION

Power quality analysis has been of utmost importance to experts which helps in determining any disturbances in the network and proposes if any fault is present in the system. Through effective power monitoring, system errors can be classified at an earlier stage and thus the safety and reliability can be improved.

It is important to note that the disturbances like harmonics give a non-stationary characteristic to the power signal. Various techniques [1-7] have been used for analysis of signals. FT gives the frequency-amplitude plot of a signal. Consider a stationary voltage signal and choose another signal having varying frequency components. FT analysis of both signals will give the same plot. Hence FT cannot be applied to non-stationary signals. STFT considers some part of the non-stationary signal as stationary and then analyses it. This involves the use of a window function of a constant width and thus is a mono-resolution technique. To beat the problem of resolution WT was developed. The history of wavelets can be traced in [8]. WT is similar to STFT as it also involves a signal which is multiplied with a window function but differs because width of the window changes with every spectral component. This is also called Multi Resolution Analysis. It is a powerful time-frequency analysis tool which also gives information about the time instant at which a particular frequency component is present unlike FT or STFT. Wavelet based analysis finds application in image processing, video compression, numerical methods and power signal analysis. It is shown that power quality analysis using complex wavelet transformation is superior to that obtained by discrete wavelet transform.

II. WAVELET TRANSFORM

Wavelets are localised waves having their energy concerted in space and time. The wavelet transformation yields poor frequency resolution and better time resolution at high frequency but better frequency resolution at lower frequencies. WT can be classified into continuous WT and DWT. In continuous WT, each wavelet is created by scaling and translating operations in a mother wavelet. The mother wavelet is an oscillate function with finite energy and zero average [9]. The continuous WT of a continuous time signal *x(t)* is defined as

$$\psi_{a,b} = \int_{-\infty}^{\infty} x(t)\psi_{a,b}^{*}(t)dt \qquad (1)$$

where

$\psi(t)$ is the mother wavelet, a is scaling parameter, b is translating parameter

$$\text{and } \psi_{a,b}^{*}(t) = \frac{1}{\sqrt{a}}\psi^{*}\left(\frac{t-b}{a}\right) \qquad (2)$$

The discrete WT of the sampled signal *x(i)* is given by

$$\psi_{c,d} = \sum_{i} x(i)\psi_{c,d}^{*}(i) \qquad (3)$$

where

$$\psi_{c,d}^{*}(i) = \frac{1}{\sqrt{a_o^c}}\psi^{*}\left(\frac{i-db_o a_o^c}{a_o^c}\right) \qquad (4)$$

'c' and 'd' are scaling and sampling numbers respectively.

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There are many wavelet functions named as mother wavelets. A mother wavelet which closely resembles the signal to be analysed is chosen for transformation. Wavelet families include *Haar, Coiflet, Daubechies, Morlet and Symlet* wavelets.

A. db4

The db4 wavelet is compactly supported, orthogonal and has highest number of vanishing moment for a given width but is shift variant in nature. The scaling filters are minimum-phase filters. These wavelets best match to signals with sag, swell or harmonic disturbances and so are considered for feature extraction. DWT is performed by the use of low pass and high pass decomposition filters and down sampling by two at each level.

B. Complex Wavelet

Family of complex wavelets is built using complex Gaussian function. The complex wavelet transform has a real filter and an imaginary filter for both low pass and high pass and so a total of four filters per level. The real and imaginary coefficients are used to compute amplitude and phase information of the signal, which are needed to describe the energy localizations of the functions on the wavelet basis. Fig.1 gives the structure of complex wavelet decomposition of a signal x(t).

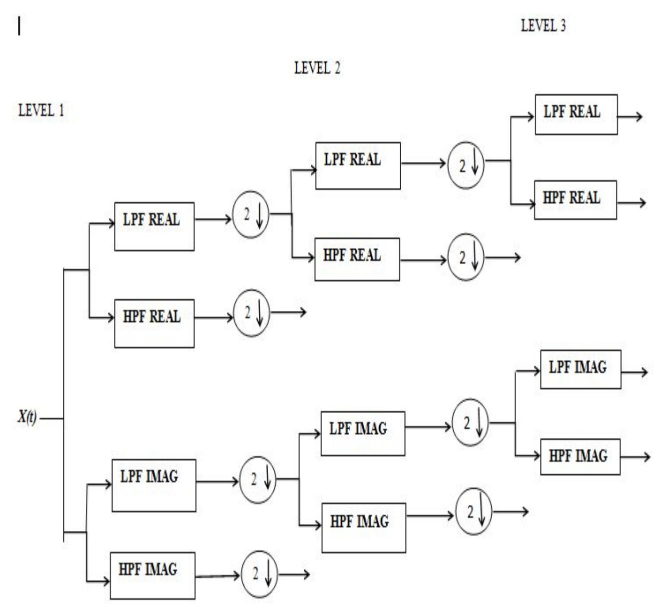

Fig. 1 Decomposition of signal using Complex wavelet Transformation

CWT is shift invariant [10], unlike DWT. To show this, a sine signal was generated using the parametric equations. Complex wavelet filters were used to extract energy feature. This was performed on the original signal and also on the signals obtained by phase-shift. Fig2 confirms the shift invariant nature of CWT.

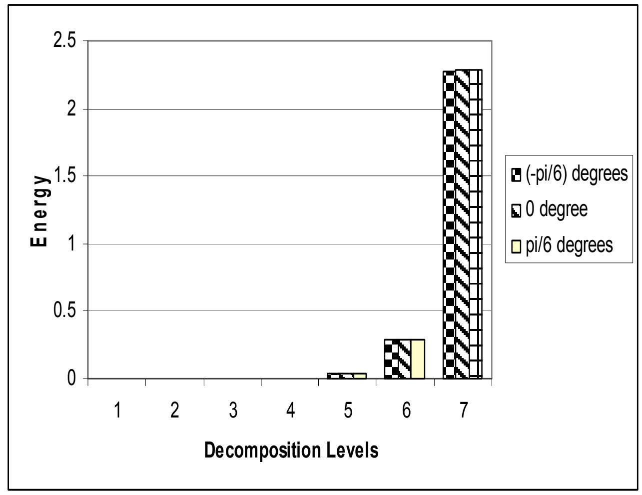

Fig. 2 Wave Energies of Coefficients at each level using CWT

III. POWER QULAITY ANALYSIS

A. Feature Extraction

The detail and approximation coefficients are not directly used as classifier inputs. To reduce the feature dimension, the feature extraction methods have been applied to the coefficients at every decomposition level. In this study, all the methods of mean, standard deviation, skewness, kurtosis, energy and shannon-entropy given in Table I were used as the features extractors. All methods were individually applied to the detail coefficients of each level up to 11 levels and features were extracted.

TABLE I.

FORMULATION OF FEATURES EXTRACTION TECHNIQUES

Features	**Formulation of Detailed Coefficients (i=1,2…..,11)**
Mean	$\mu_d = \frac{1}{N}\sum_{j=1}^{N} d_{ij}$
Standard Deviation	$\sigma_d^{\ 2} = \frac{1}{N}\sum_{j=1}^{N}(d_{ij}-\mu_d)^2$
Skewness	$S = \sqrt{\frac{1}{6N}}\sum_{j=1}^{N}\frac{(d_{ij}-\mu_d)^3}{\sigma_d^{\ 3}}$
Kurtosis	$K = \sqrt{\frac{N}{24}}\frac{1}{N}\sum_{j=1}^{N}\{\frac{(d_{ij}-\mu_d)^4}{\sigma_d^{\ 4}}-3\}$
Energy	$E = \sum_{j=1}^{N}\left\lvert d_{ij}\right\rvert^2$
Shanon Entropy	$\overline{E} = -\sum_{j=1}^{N} d_{ij}^{\ 2}\log(d_{ij}^{\ 2})$

B. *Training Stage*

An experimental study was carried out to test the robustness and effectiveness of the proposed classification using complex WT. The recognition problem of the power system disturbances was considered as the classification problem with seven classes consisting of the disturbance signals called as sag, swell, harmonics, sag with harmonics, swell with harmonics, oscillatory transients and spike. The simulation data was generated using MATLAB and the parametric equations.

Two hundred disturbance signals of each class were randomly generated for training, validating and testing. The signals were sampled at 512 points/cycle and generated for a total of 5120 points (10 cycles) which contain the disturbances.

Features obtained from single feature extraction technique are not sufficient to address all possible power system disturbances. This paper focuses using selection of features obtained from different feature extraction techniques. The feature selection process is fulfilled in the training stage of the FNN.

To address the classification problem, firstly the decomposition coefficients related to the disturbance signals were obtained using the DWT with db4 wavelet. Sixty-six features for each signal were extracted by applying six different feature extraction methods to the detail coefficients belonging to each level. Amplitude, phase angle and harmonic properties were varied to create an extensive database of features of various types of each signal class. A neural network was trained with 80 percent of the database and remaining features were employed for testing.

The above was also followed by taking the complex wavelet. While calculating the features in complex WT, the detail coefficients for both the real as well as the imaginary tree was considered and its value is taken as the magnitude of the complex coefficients. A separate database was created and the neural network was separately trained for complex as well.

While training the neural network, each feature was considered separately and classification accuracy of the neural network on previously determined validation set was examined. The errors in each case were recorded and the results were tabulated in Table II. This is represented graphically in Fig 3.

C. *Testing Stage*

The disturbances in a power signal must be controlled which first requires them to be localized and classified. Wavelet transform is a powerful way of analysing the power signal in both time and frequency domain. The accuracy of the two wavelets is tested during the testing period.

A new set of data, different from training data, is generated by changing the variables like amplitude and phase in the parametric equations for all classes. 200 samples of each type of signal are collected and a separate database is made using this data. The new database is now used for testing the FNN.

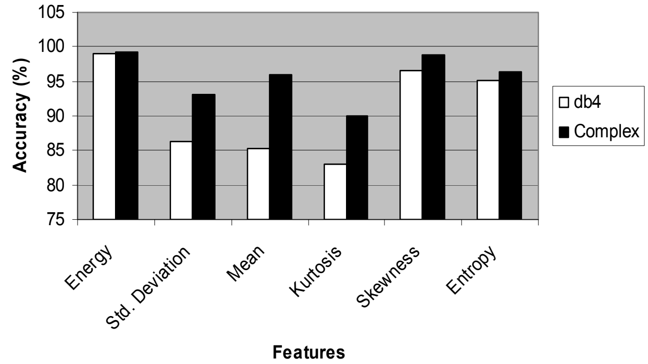

Fig. 3 Error comparison of features using db4 and Complex Wavelet

TABLE II
COMPARISON OF FEATURES EXTRACTED USING DB4AND COMPLEX WAVELETS DURING TRAINING PERIOD

No.	Features Trained	db4		Complex	
		Errors	Percentage Error (%)	Errors	Percentage Error (%)
1	Energy	17	1.03	13	0.8
2	Standard Deviation	226	13.74	115	6.99
3	Mean	243	14.78	65	3.95
4	Kurtosis	278	16.91	164	9.97
5	Skew ness	57	3.46	19	1.15
6	Entropy	80	4.87	61	3.71

IV. RESULTS AND DISCUSSION

The shift invariant nature of complex wavelet, as seen from Fig2, makes it preferable when compared to other wavelets. Six features were collected at each level, totalling to 66 features.

It can be seen in Fig3 that 'Energy' as a feature has the least errors while 'Kurtosis' incurred the maximum number of errors.

The errors obtained in classification using 'db4' as mother wavelet have been shown in Table III. Out of the total samples chosen (200 for each level), 29 data have been wrongly classified.

It is seen that of all the disturbances, swell disturbances have been most incorrectly classified as sag disturbances when using db4 wavelet for feature extraction. The overall classification accuracy achieved by using db4 wavelet is 97.92 %.

A new database is also generated by extracting features from untrained signals using complex WT. This is fed to FNN for classification. The results obtained can be seen in Table IV. It is observed that only 3 data are incorrectly classified by FNN when complex wavelet transform is used.

TABLE III.
CONFUSION TABLE FOR DB4 WAVELET TRANSFORM DURING TESTING PERIOD

CLASS	C1	C2	C3	C4	C5	C6	C7
C1	200	0	0	0	0	0	0
C2	17	183	0	0	0	0	0
C3	0	0	200	0	0	0	0
C4	0	0	2	198	0	0	0
C5	0	0	0	0	200	0	0
C6	0	0	0	0	1	199	0
C7	0	0	0	0	1	4	191 + *4**

TABLE IV
CONFUSION TABLE FOR COMPLEX WAVELET TRANSFORM DURING TESTING PERIOD

CLASS	C1	C2	C3	C4	C5	C6	C7
C1	200	0	0	0	0	0	0
C2	0	200	0	0	0	0	0
C3	0	0	200	0	0	0	0
C4	0	0	0	200	0	0	0
C5	0	0	0	0	200	0	0
C6	0	0	0	0	0	200	0
C7	0	0	0	0	0	3	197

* *4* errors do not belong to any of the seven classes

Compared to db4, complex wavelet has correctly classified the swell signals with hundred percent precision. The overall accuracy attained using complex wavelet transform is 99.78%. Current algorithms for power quality monitoring involve the use of db4 wavelets and studies so far have proved it to be the most efficient. But on comparing with the results obtained above, it clearly shows that complex wavelet is better than db4 for efficient classification of disturbances.

V. CONCLUSION

This paper shows complex wavelet transform as a powerful tool which can effectively classify the disturbances like sag, swell, harmonic, sag harmonic, swell harmonic, transients and spike in power signals through feature extraction.

The present method of analyzing power signals involves the use of db4 wavelet. The results obtained in this paper show the superiority of complex wavelet transform in analysis and monitoring of power signals. The proposed signal classification through complex wavelet transform gives reduced error when compared to db4 wavelet which is at the moment the most widely used tool for power quality analysis. This study paves the way for complex wavelets to be employed as a noble technique for power quality monitoring in the near future.

VI. APPENDIX

db4	Daubechies wavelet of order 4
FT	Fourier Transform
STFT	Short Time Fourier Transform
WT	Wavelet Transform
DWT	Discrete Wavelet Transform
CWT	Complex Wavelet Transform
FNN	Fuzzy Neural Network
$x(t)$	Continuous time signal
$x(i)$	Discrete time signal
$\Psi(t)$	Mother wavelet function
a	Scaling Parameter
b	Translation Parameter
c	Scaling number
d	Sampling number
C1	Sag
C2	Swell
C3	Harmonic
C4	Sag Harmonic

C5 Swell Harmonic
C6 Oscillatory transient
C7 Spike signal

Analysis Filters used in CWT

Real Tree	
Low pass	**High pass**
0	0
-0.08838834764832	-0.01122679215254
0.08838834764832	0.01122679215254
0.69587998903400	0.08838834764832
0.69587998903400	0.08838834764832
0.08838834764832	-0.69587998903400
-0.08838834764832	0.69587998903400
0.01122679215254	-0.08838834764832
0.01122679215254	-0.08838834764832
0	00

Imaginary Tree	
Low pass	**High pass**
0.01122679215254	0
0.01122679215254	0
-0.08838834764832	-0.08838834764832
0.08838834764832	-0.08838834764832
0.69587998903400	0.69587998903400
0.69587998903400	-0.69587998903400
0.08838834764832	0.08838834764832
-0.08838834764832	0.08838834764832
0	0.01122679215254
0	-0.01122679215254

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