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# Signal Analysis using Wavelet-based Disturbance analysis for Power System Wide-Area Monitoring

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***Abstract*—This paper proposes a Wavelet-based method for signal analysis. By generating the frequency and voltage responses of the different generators at a particular fix point of bus are studied. Wavelet transform (WT) based multiresolution analysis and its properties are studied for frequency and voltage responses of power system signals in smart grid. Considering wavelet energy of wavelet coefficients (WCs) as a criterion, order 2 Daubechies wavelet and scale 5 as the excellent wavelet function and optimal decomposition scale. The voltage and frequency responses are obtained in IEEE New England 39- bus system.**

***Keywords—Wavelet transform–based multiresolution analysis, disturbances, wide-area monitoring systems.***

## I. INTRODUCTION

The blackout experiences in previous critical events are putting more pressure on industries to develop a more automatic, adaptive control system to prevent such incidents. The system deterioration starts with alarming of steady-state violations and gradually evolves to faster dynamic phenomena. Some of the challenges the industry is facing are ,proper representing of existing protective devices and schemes ,proper processing of the information and simulation decision making for each network structure ie RTO,ISO ,etc, accurate and acceptable defence plans against disturbances .To tackle these challenge, there is a need of proper simulation ,modelling of the dynamics of the system .In recent past there has been fast development of wide-area monitoring systems(WAMS)[1]-[3].The synchronised measurement for disturbances over wide-area power systems is discussed in application of GPS-synchronized devices such as phasor measurement units (PMUs) and frequency disturbances recorder(FDRs) [4]-[7] .So far ,the data collected in phasor data concentrator (PDC) or server database is processed in time-domain [8]-[10] and frequency -domain analysis[11]-[13].It is well known from Fourier theory that a signal can be expressed as the sum of a infinite series of sines and cosines. This sum is also referred to as a Fourier expansion. The major drawback of a Fourier expansion however is that it has only frequency resolution and no time resolution. It states that if one is able to find all the frequencies, he is unable to find the exact location of them. To resolve this problem in the past decades many solutions have been developed which are somewhat able to represent a signal in the time and frequency domain at the same time [14]. The time information contained in synchrophasor data can be acquired directly, so for accurately detecting the timing information of disturbances time-domain analysis is preferred.

The idea behind these time-frequency joint representations is to cut the signal of interest into several parts and then study the parts separately. It is clear that analysing a signal this way will give more information about the positions of several frequency components. In [15], Mei uses the Wavelet transform (WT) to locate dynamic events in power systems. The location of frequency features of the analysed signal in time domain can be done by WT. The abrupt changing behaviour of the signal in time domain can be done by WT. The abrupt changing behaviour of the signal can be extracted by WT [16]-[20]. So WT is important tool to analyse WAMS-based disturbance.

The disturbances dynamics are identified using frequency variation ($\Delta f$) voltage variation ($\Delta v$) and frequency derivative ($df/dt$) .Frequency and voltage closely resemble to power variation. So frequency and voltage are taken as disturbance indicators in WAMS-based disturbances analysis [8]-[10]. The approximate linear relationship has been proposed between ($\Delta f$) and ($\Delta P$) [8] [9]. $\Delta f$ and $df/dt$ was combined to study disturbance pattern for classification [8], but we can consider $df/dt$ as dynamic indicator ,as the magnitude of $df/dt$ gives the severity degree of the disturbance. The biggest $df/dt$ usually occur at initial moment will not only provide system protection but also control in terms of computational efficiency.

WT is very sensitive to abrupt-changing signals. Hence WT can be used instead of time domain analysis to accurately analyse signal dynamics. Wavelet coefficients (WCs) obtained by WT-based multiresolution analysis (MRA) are used as disturbance indicators. Fig 1 shows the IEEE New England bus system.

The paper is organised as follows: in section II, WT-based multiresolution analysis is briefly introduced; in section III, the selection of wavelet function and decomposition scale for different frequency and voltage signals is discussed; in section IV conclusion is given.

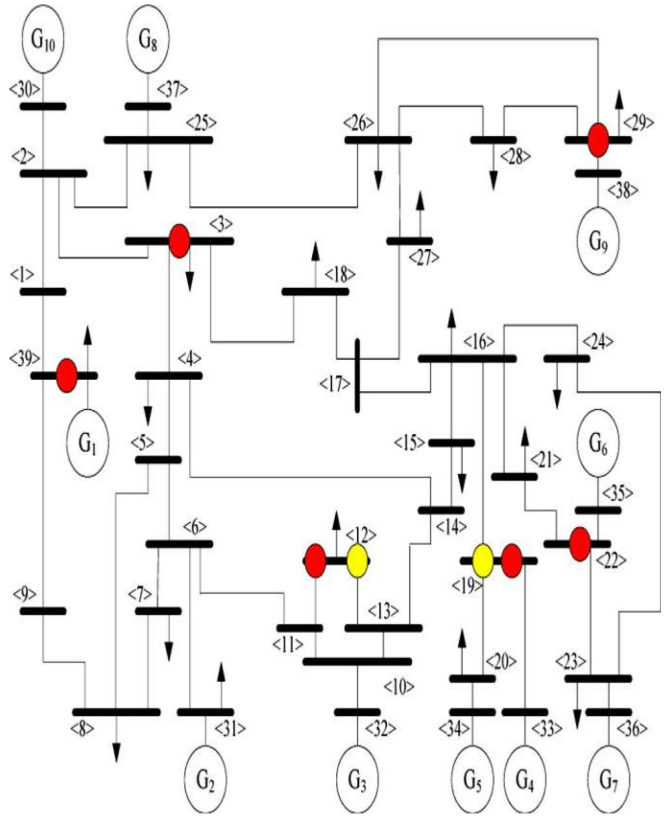



Fig. 1. IEEE New England 39-bus power system

## II. WT-BASED MULTIRESOLUTION ANALYSIS

In signal analysis, one can perform number of different functions on that analysed signal. The signal gets translated into several forms that are more suitable for several applications. Fourier transform converts a signal from time versus amplitude to frequency versus amplitude. Fourier transform has a limitation of not giving time information. Hence Short Term Fourier transform which is able to convert a signal to frequency versus time came up to be used. This transform also has its drawbacks. It cannot get decent resolution for both high and low frequency at the same time. WT can convert and manipulate a signal while keeping resolution across the entire signal and still be based in time .Wavelets are finite windows. The window can be moved along the length of the signal. In order to do that the wavelet can be translated about time in addition to being compressed and widened.

The procedure of WT-based MRA for decomposition and reconstruction of any signal is illustrated in Fig 2(a)(b). The scaling coefficients or approximation is given by A= $\{a_j\}$.Wavelet coefficient or details are given by D=$\{d_j\}$

The low pass filter and high pass filter are denoted by G=$\{g_j\}$ and H= $\{h_j\}$ respectively. By shifting and dilating a specific Mother Wavelet G and H can be obtained. Down- sampling rate is 2 times for decomposition .WCs contains information in high frequency bandwidth of signal and noise. The trend of change the analyzed signal is represented by SCs. The MRA performs the decomposition of a signal x[n] by using low pass filter $g_i$ and high pass filter $h_i$.. The use of scaling function Φi and a wavelet function Ψi satisfies $\Phi_i \perp \Psi_i$. SCs or "Approximation " $a_i$ and WCs or "detail" $d_i$ are generated by MRA .The WCs represent high frequency components and SCs represents the low frequency components. WCs represents the dynamic feature in high frequency band SCs represent the trend of the signal .WCs are more important as they reflect more features of disturbances at incipient moment in terms of its intensity (amplitude) and time location.

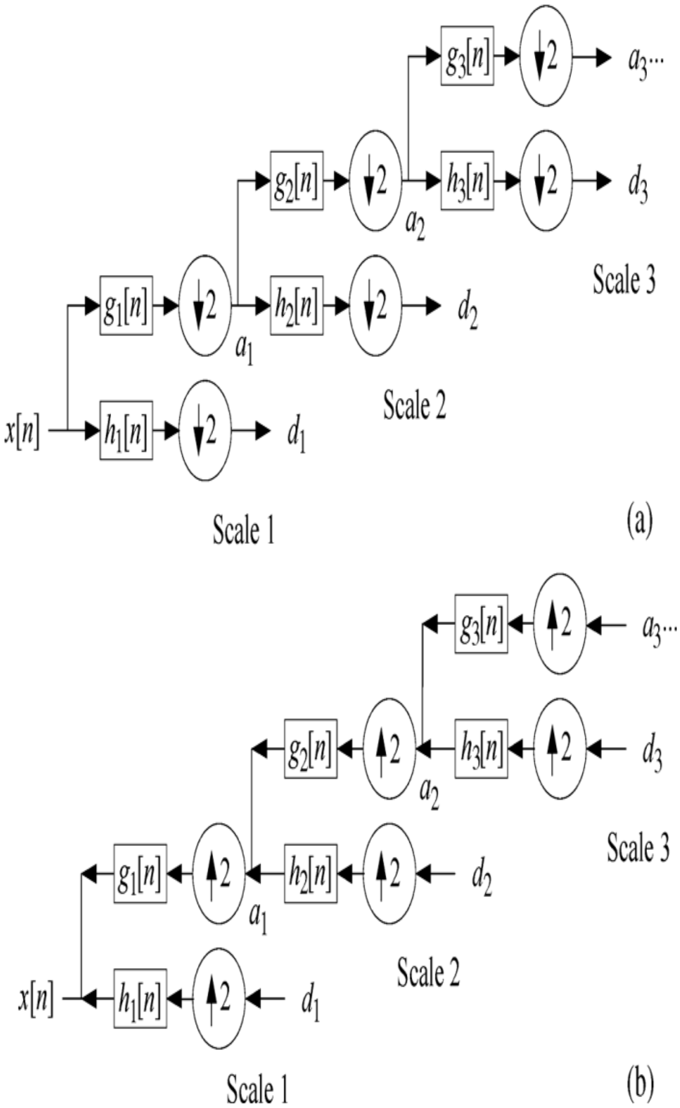



Fig. 2. Procedure of WT-based MRA (a) Decomposition (b) Reconstruction

In Fig. 3. The abrupt change in frequency signal can be observed by WCs at all scales. The disturbances and intensity is shown by the highest amplitude at each scales. The amplitude at each scale is different from each other. So there is need for the proper selection of wavelet function and optimal decomposition scale.

Freq (Hz)

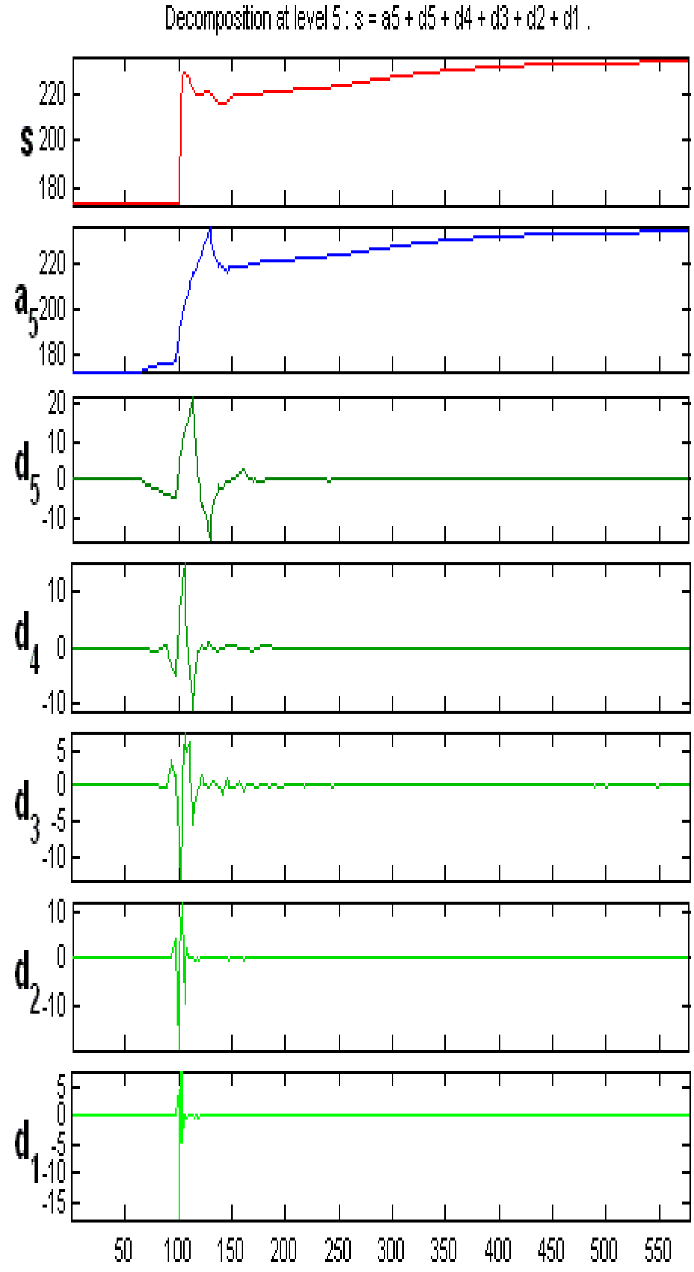
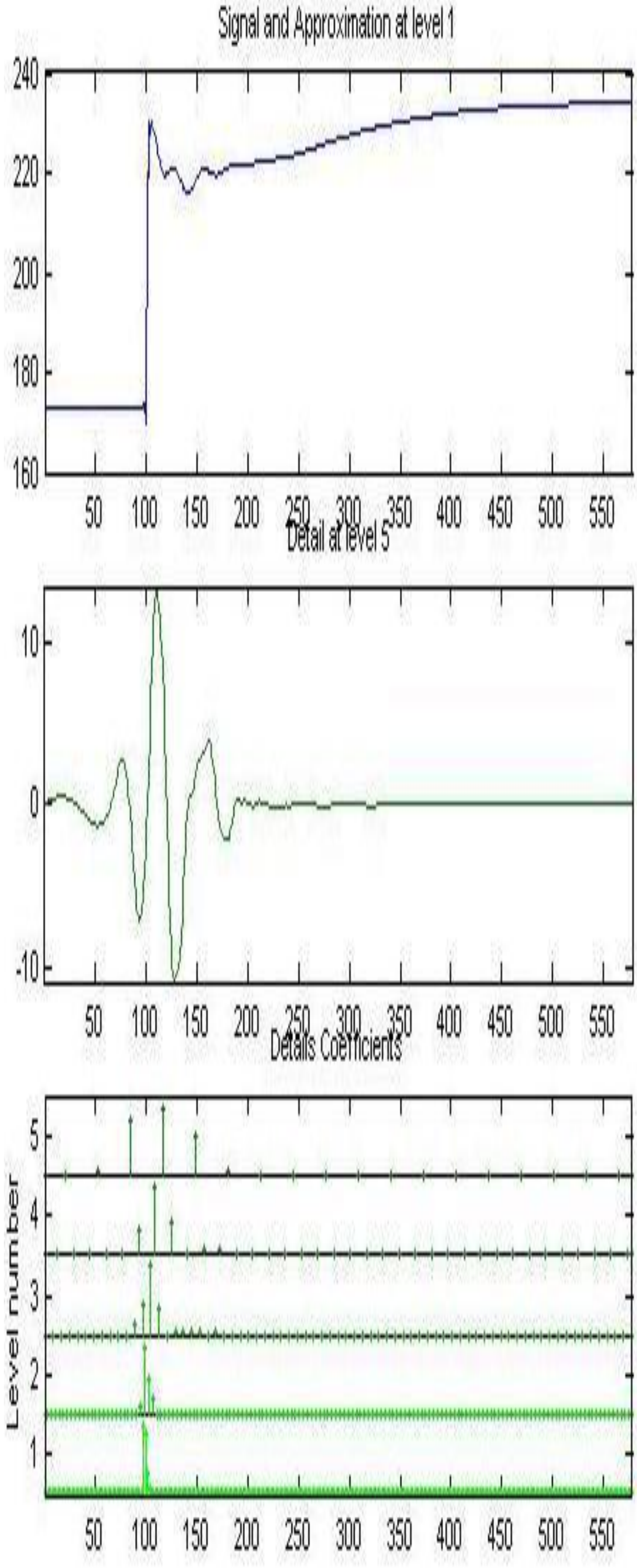
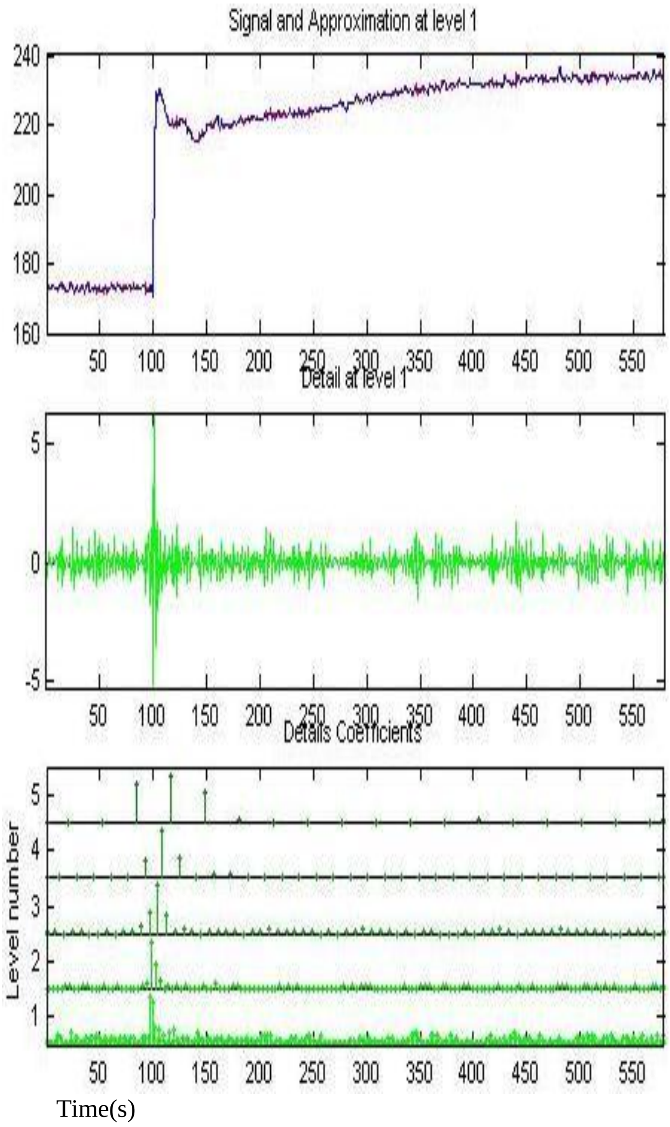



Fig 3. WT-based MRA to frequency response. Original frequency signal and WCs of original frequency signal.

A 50 Hz periodical noise of 0.2 in amplitude and the white noise of 0.05 in amplitude are mixed with frequency signal .The procedure is done to demonstrate the denoising of WT –based MRA .Two signals first original frequency signal and other the noisy signals are decomposed by db2 wavelet into 5 scales. The thresholding of universal and soft thresholding are applied to WCs. Comparing the two signals after denoising it is seen the thresholding does not affect the property of WCs.




(a)




(b)

Fig 4.Denoising of frequency signal mixed with white noise.(a)original signal and WCs of original signal. (b) Signal mixed with white noise and WCs of noisy signal.

## III. SELECTION OF WAVELET FUNCTION AND DECOMPOSITION SCALE

The energy of WCs can be used as a criterion to select the optimal wavelet function and decomposition scale .The total wavelet energy is given by

$$E=\sum_{i=1}^{p}\sum_{j=1}^{q_i} | d_{ij} |^2 \quad (1)$$

and wavelet energy contained in WCs is given by

$$E_i=\sum_{j=1}^{n_i} | d_{ij} |^2 \quad (2)$$

Where subscript i stand for scale, p stands for maximum number of scale .Points in WCs are denoted by subscript j. $q_i$ is length of WCs at scale i. i=1,..........I; j=1,.............n; stands for number of points contained in each detail.

The testing disturbances signal is generated in IEEE New England 39 bus system. Energy concentration of WCs on certain scale is denoted by wavelet energy. More information preserved after decomposition is resultant of the more wavelet energy.

In this paper db2-db 10 and sym 2-sym 10 are chosen as wavelet candidates for analysis .These wavelet show excellent performance in analysing dynamic signals. Their performance in also excellent in analysing signals with discontinuity and abrupt change. The wavelet with highest total wavelet energy (1) is chosen as the best wavelet function and corresponding scale of wavelet with highest wavelet energy (2) is chosen as optimal decomposition scale.

TABLE I. RESULT OF SELECTION OF WAVELET FUNCTION

| DB | GL12G2 | GL12G3 | GL12G4 | GL12G5 |
|---|---|---|---|---|
| 2 | 0.0278 | 0.0606 | 0.006 | 0.0533 |
| 3 | 0.045 | 0.036 | 0.0038 | 0.0286 |
| 4 | 0.024 | 0.037 | 0.005 | 0.0433 |
| 5 | 0.022 | 0.0355 | 0.004 | 0.0385 |
| 6 | 0.033 | 0.024 | 0.003 | 0.0226 |
| 7 | 0.026 | 0.0238 | 0.003 | 0.0282 |
| 8 | 0.018 | 0.0261 | 0.004 | 0.0328 |
| 9 | 0.024 | 0.0209 | 0.003 | 0.0224 |
| 10 | 0.0258 | 0.0177 | 0.0027 | 0.0205 |

TABLE II .RESULT OF SELECTION OF WAVELET FUNCTION

| SYM | GL12G2 | GL12G3 | GL12G4 | GL12G5 |
|---|---|---|---|---|
| 2 | 0.0378 | 0.0606 | 0.0053 | 0.0278 |
| 3 | 0.00352 | 0.0362 | 0.0038 | 0.0286 |
| 4 | 0.037 | 0.0367 | 0.0036 | 0.0262 |
| 5 | 0.0243 | 0.0404 | 0.0041 | 0.0299 |
| 6 | 0.0303 | 0.0305 | 0.0032 | 0.0229 |
| 7 | 0.0175 | 0.0337 | 0.004 | 0.033 |
| 8 | 0.0255 | 0.0266 | 0.0029 | 0.0212 |
| 9 | 0.0228 | 0.0264 | 0.0029 | 0.0191 |
| 10 | 0.0217 | 0.0243 | 0.0027 | 0.0202 |

TABLE III. RESULT OF SCALE FUNCTION

| DB | d1 | d2 | d3 | d4 | d5 |
|---|---|---|---|---|---|
| GL12G2 | 0.0016 | 0.0029 | 0.002 | 0.0042 | 0.0169 |
| GL12G3 | 0.0023 | 0.0003 | 0.006 | 0.0192 | 0.0324 |
| GL12G5 | 0.0000 | 0.0001 | 0.0002 | 0.0007 | 0.0050 |
| GL12G4 | 0.0003 | 0.0045 | 0.0005 | 0.0089 | 0.03346 |

Order 2-10 Daubechies wavelet and Symlet 2-10 wavelet families are chosen to create database .WT based MRA is applied to frequency signal to obtain WCs with each wavelet functions. WCs energy of each scale is added to obtain WCs energy of the signal. The biggest WCs energy is regarded as a best for particular wavelet function .Table I and Table II lists the total WCs percentage energy corresponding to each wavelet function .In table III the percentage of energy given for WCs. GL12G2 stands for generation loss at bus 12 of generator 2.The first column in Table I corresponds to “db2” ”and first column in Table II corresponds to “sym2.The maximum energy lies in first column .So “db2” and “sym2” are chosen as best wavelet function s. Table III shows most WCs energies concentrate at scale5 .So scale 5 is chosen as optimal.

## IV. CONCLUSIONS

This paper proposes a wavelet-based method for signal analysis. This proposed approach is capable of effectively generating WCs of frequency response. The Order 2 of Daubechies wavelet and Symlet wavelet is chosen as best wavelet function. Scale 5 is chosen as optimal decomposition scale depending upon the maximum wavelet energy as the criterion. This approach can be implemented in smart grid to improve data transmission and quality.

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