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Power Spectral Density based Identification of Low frequency Oscillations in Multimachine Power system

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Abstract- *The paper presents a Fast Fourier Transform (FFT) based Power Spectral Density (PSD) filter for denoising the PMU signal received from the smart power system network to identify the low frequency Oscillation modes (LFO). Small disturbances are introduced during normal operation of power system causes low frequency oscillations and may hinder the power system transfer capabilities of a system. The traditional signal processing method cannot extract the information from ambient signals effectively during noisy measurement. In this paper, the performance of the Prony analysis with reduced sampling rate is analysed for the PMU data with noiseless and noise environment. It is observed that, the performance of the Prony approach is not satisfactory under noisy measurement data. In the present work FFT-PSD is used to denoise the noisy measurement signal and identify the nature of the decrement factor of the low frequency oscillatory modes. The accuracy of the estimated decrement factors of modes are verified with eigenvalues to validate the proposed method. The performance of proposed method is compared with signal processing method for IEEE New England power system and found effective and suitable during noisy PMU measurements.*

Keyword: Fast Fourier Transform, Power Spectral Density, Wide area Monitoring system.

1. INTRODUCTION

Modern power systems are facilitated by wide-area monitoring (WAM) systems which has an access to the real-time synchronised data obtained from Phasor measurement unit (PMU). The Power transfer in modern smart power systems are challenged by the integration of renewable energy resources by low inertia converters and it weakens the stability of the systems due to rapid change in electrical dynamics. Small disturbance such as switching or line operation events hamper the reliability of the power system due to inception of LFOs. Timely identification and damping of such oscillations are crucial to avoid collapsing of entire power system. The low frequency oscillations are characterized as "inter area mode" for frequency ranges between 0.1 to 0.8 Hz and "local area modes" with frequency between 0.8 and 2 Hz [1][2]. It must be said that there is no strong definition of well-damped low-frequency oscillations, but a generally accepted rule of thumb defines an oscillation as sufficiently damped if the damping ratio is above the range 3–5% [3].

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Research Paper

The signal analysis approaches are extensively used in these years to detect the LFOs from the PMU data. To analysis the presence of LFOs from the data, the various methods are used such as Prony algorithm [4][5], matrix pencil [6], estimation of signal parameters by rotational invariance techniques (ESPRIT)[7], empirical mode decompositions (EMD)[8],dynamic mode decomposition (DMD)[8], eigenvalue realization methods(ERA) [9], wavelet based method[10], and Discrete Fourier transform based methods[11]. Effectiveness of identification process is increased by the combination of two signal analysis method. Phili.et.al in [12] proposed combined method of ESPRIT with exact model order to identify LFOs and Jin t et.al [13] proposed a novel approach to identify the low frequency components in ECG signal by combination of basis pursuit signal denoising with wavelet transform. Fang Liu et.al [14] proposed a combination of Variable mode decomposition (VMD) with Prony analysis to identify mode shapes from ambient signals.

Prony algorithm decomposes the oscillatory signals into linear combination of complex exponentials [15], thereby helps in identifying the oscillatory characteristics of signals by computing the eigenvalues. However, the Prony algorithms is found not effective in a noisy environment. Hence to increase identification accuracy during noisy environment the Prony is combined with modal decomposition methods such as wavelet transforms, EMD, ERA, Kalman filter, system identification methods. In [16], the adaptive matrix pencil algorithm is used to analyse the low frequency oscillation in power system. This method ensures the accuracy of mode identification with lower sensitivity to noise interference. However, it is a challenging task to select the proper mother wavelet and decomposition level. Dominant electromechanical Oscillation mode identification using Modified VMD makes use of the synthetic data of IEEE 16 machine, 68 bus system for the analysis which is proposed in [17]. Due to random selection of initialization parameter for VMD the leads to computational complexity, therefore it demands Optimization techniques for the eliminating unwanted decomposition modes. However selection of appropriate optimization techniques is the limitation of the approach.

In this paper, synthetic data is generated to mimic the real-time Phasor measurement unit (PMU) incorporated at all the generator buses by neglecting the transfer delay to obtain the better results during stability analysis[27]. In this work, the signal measured with the influence of measurement noise is considered for the analysis. The denoising of the signal is performed using Power spectral density of the signal using FFT analysis. The window of fixed sample size is used to check the nature of decrement factor using PSD of the signal under consideration. The noisy measurement signals received from the wide area monitoring unit (WAM) of New England power system during small disturbance is chosen as a case study. The existing methods can only identify the oscillation frequency, damping ratio and mode shapes but not the participation factor. The proposed method uses energy-based computation of participation factor with improved accuracy compared to traditional signal processing methods.

The contributions of this work is as follows

- The Prony analysis with reduced sampling rate is performed on noiseless measurement signals and energy based participation factor is evaluated for the data collected from PMU. This work also addresses the complexity relying in Prony based approaches for the complex data with measurement noise.
- The Power spectral density based signal denoising approach is developed to identify the underlying low frequency oscillation modes in the signal data collected from WAM

The performance of the PSD based method is analysed for IEEE New England Bench mark system by artificially generating random Gaussian noise for the measurement signal.

2. MAIN BODY

2.1. Eigenvalue estimation using Modal Analysis

Stability analysis in a power system is performed using a set of differential-algebraic equations (DAE) described as

$$\left.\begin{aligned}\dot{\boldsymbol{x}} &= \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{i}) \\ \boldsymbol{y} &= \boldsymbol{h}(\boldsymbol{x}, \boldsymbol{i})\end{aligned}\right\} \tag{1}$$

Where x is a state vector $x \in R^m$, input vector $i \in R^k$ and the output vector $y \in R^n$. Linearization of equation (1) at an equilibrium point x_0, i_0 results in the state space representation of system expressed as

$$\left.\begin{aligned}\boldsymbol{\Delta\dot{x}} &= \boldsymbol{A\Delta x} + \boldsymbol{B\Delta i} \\ \boldsymbol{\Delta y} &= \boldsymbol{C\Delta x} + \boldsymbol{D\Delta i}\end{aligned}\right\} \tag{2}$$

Where A is the state matrix and the dimension is $m \times m$, B is control matrix with dimension $m \times k$,output matrix C has $n \times m$ dimension and the dimension of feedforward matrix D is $n \times k$.

To implement eigenvalue analysis (EA) method on state matrix A, the eigenvectors and eigenvalues must satisfy following equation

$$\left.\begin{aligned}\boldsymbol{AU_j} &= \boldsymbol{\lambda_j U_j} \\ \boldsymbol{V_j A} &= \boldsymbol{\lambda_j V_j^T}\end{aligned}\right\} \tag{3}$$

where λ_j is the j^{th} eigenvalue of A, U_j is right eigenvector of A associated with λ_j and dimension is $m \times 1$, left eigenvector of A is represented as V_j associated with λ_j.The $U_j$and V_j satisfy $V_j^T U_j = 1$

To represent the relationship between the system states and the modes, the participation factor is computed by

$$\boldsymbol{P_{jr}} = \frac{\boldsymbol{V_{rj} M_{jr}^{EA}}}{\boldsymbol{V_j^T M_J^{EA}}} \tag{4}$$

where $P_{r,j}$ is the participation factor which measure the participation of j^{th} state variable over r^{th} mode ; v_{rj} is the r^{th} entry of V_j and M_{jr}^{EA} is the r^{th} entry of U_j. The small-signal oscillation in the power system causes system oscillation to increase due to the presence of low-frequency oscillation modes. Based on the frequency, the low frequency oscillatory modes are categorized as, inter-area oscillatory modes and swing modes. The mode shape matrix is used to estimate the coherency between the generators associated with low-frequency oscillatory modes [18][19][20][21] i.e represented as

$$M^{EA} = [M_1 \quad M_2 \quad M_3 \quad \dots\dots \quad M_k]$$

$$\boldsymbol{M^{EA}} = \begin{bmatrix} \boldsymbol{M_{11}} & \boldsymbol{M_{21}} & .. & .. & \boldsymbol{M_{k1}} \\ \boldsymbol{M_{12}} & \boldsymbol{M_{22}} & .. & .. & \boldsymbol{M_{k2}} \\ . & . & .. & .. & . \\ . & . & .. & .. & . \\ \boldsymbol{M_{1m}} & \boldsymbol{M_{2m}} & .. & .. & \boldsymbol{M_{km}} \end{bmatrix}$$
(5)

where M^{EA} is mode shapes matrix associated with multiple low frequency oscillatory modes.

2.2. Prony analysis

Consider the signals extracted from the PMU data of multimachine power system which is represented as x(0),x(1),………x(N-1) are approximated by the exponential components [20]

$$\hat{x}(n) = \sum_{k=1}^{q} a_k z_k^n \text{for}(n = 0,1, \dots\dots N-1) \quad (6)$$

Where $a_k = A_k\, e^{j\theta_k}$ and $z_k = e^{[(\sigma_k + 2\pi f_k)\Delta t]}$

Where q is the order, Δt is sampling interval A_k , θ_k , σ_k and f_k are amplitude, phase, attenuation factor and frequency. The objective of the Prony algorithm is to calculated the parameter a_k and z_k.Here, $\hat{x}(n)$ is approximated value of $x(n)$ and error can be calculated as

$$er(n) = x(n) - \hat{x}(n) \quad \text{for } n = 0,1, \dots\dots N-1 \quad (7)$$

The constant coefficient linear differential equations can be obtained as

$$\hat{x}(n) = -\sum_{k=1}^{q} b_k \hat{x}(n-k) \quad \text{for } n = q, \dots N-1 \quad (8)$$

The points on the z-plane z_k are the solutions of the equation

$$1 + \sum_{k=1}^{q} b_k\, z^{-k} = 0 \quad (9)$$

The error equation can be obtained from equation (3) and (4) is $x(n) = -\sum_{k=1}^{q} b_k\, \hat{x}(n-k) + \Phi(n)$

$$n = q, \dots\dots N-1 \quad (10)$$

Where $\Phi(n)$ satisfies the following equation

$$\Phi(n) = -\sum_{k=0}^{p} b_k er(n-k) \quad (11)$$

Using Least square algorithm the error can be minimized as

$\sum_{n=q}^{N-1} |\Phi(n)\,|^2$ the coefficients $b1, b2, \dots\dots .b_q$ is obtained with the following equation

$$\begin{bmatrix} M(1,0) & M(1,1) \dots\dots & M(1,q) \\ M(2,0) & M(2,1) \dots\dots & M(2,q) \\ \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} 1 \\ b_1 \\ \vdots \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \end{bmatrix} \quad (12)$$

Where $M(i,j) = \sum_{n=q}^{N-1} x(n-j)x(n-k) \;\; where \;\; k,j = 0,1,2, \dots .q$

The following equation can be obtained from the equation (1)

$$\begin{bmatrix} z_1^0 & \dots & z_q^0 \\ \vdots & \vdots & \vdots \\ z_1^{N-1} & \dots & z_q^{N-1} \end{bmatrix} \begin{bmatrix} a_1 \\ \vdots \\ a_q \end{bmatrix} = \begin{bmatrix} \hat{x}(0) \\ \vdots \\ \hat{x}(N-1) \end{bmatrix} \quad (13)$$

Where $\hat{x}(n) = \begin{cases} x(n) & 0 \le n \le q \\ -\sum_{k=1}^{q} b_k\, \hat{x}(n-k) & q+1 \le n \le N-1 \end{cases}$

Energy of the estimated signal is

$$\text{E} = \sum_{n=0}^{q} |\hat{x}(n)|^2 \quad (14)$$

The computation of coefficients $\boldsymbol{a_k}$ is carried out using procedures of Prony algorithm from equations (10) and (13).

2.3. Fast Fourier Transform based signal denoising using Power spectral density method

The measured signals can be represented as

$$y(t) = x(t) + \; noise \quad (15)$$

Where y(t) is noisy measurement signal, x(t) is the actual signal and noise is the random noise present in the signal. The noise can be zero mean white gaussian noise or any non-gaussian noise present in the practical signal. This paper presents the data driven approaches to denoise the signal to estimate the eigenmodes of oscillations.

The measurement data in WAM are discrete in nature. Therefore the Discrete Fourier Transform (DFT) is employed to approximate on discrete data. For any discrete signal $x(m)\; the$, the DFT is defined as [22]

$$X(k) = \sum_{n=0}^{N-1} x[m]\, e^{-j2\pi km/N} for 0 \le \text{k} \le \quad (16)$$

N is the number of available data points; k is each discrete instants and the synthesis equation to reconstruct the signal after processing is given by

$$x(m) = \frac{1}{N} \sum_{n=0}^{N-1} X[k]\, e^{j2\pi km/N} for 0 \le \text{n} \le \text{N} - 1 \quad (17)$$

Hence DFT acts as a linear operator to map the data points in vector $x(m)$ to frequency domain $X(k)$. DFT is most useful tool for numerical approximation and computation. However, its computational complexity increases for the larger data points as it requires N^2 multiplications for mapping N point data to frequency. To overcome this, the fast Fourier transform (FFT) developed by James W cooley and John W Turkey is employed which scales the multiplication operation to $(N\, \log N)$. The basic idea behind the FFT is that the DFT may be implemented much more efficiently if the number of data points N is a power of 2. In this case, the DFT may be written as

$$X(k) = {W_N}^{km} x(m) \quad (18)$$

Where $W_N = e^{-j2\pi/N}$ is the twiddle factor matrix also termed as DFT matrix.

For any data point $N = 2^p$, the equation (3) can be represented as

$$X(k) = W_{2^P}\, x(m) = \begin{bmatrix} I_{2^{P-1}} & -D_{2^{P-1}} \\ I_{2^{P-1}} & D_{2^{P-1}} \end{bmatrix} \begin{bmatrix} W_{2^{P-1}} & 0 \\ 0 & W_{2^{P-1}} \end{bmatrix} \begin{bmatrix} x_{even} \\ x_{odd} \end{bmatrix} \quad (19)$$

Where x_{even} and x_{odd} are the even and odd index elements of $x(m)$.

$I_{2^{P-1}}$ is 2^{P-1} x 2^{P-1} identity matrix.

$D_{2^{P-1}}$ is given by

$$D_{2^{P-1}} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & W & 0 & \cdots & 0 \\ 0 & 0 & W^2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & W^{2^{P-1}} \end{bmatrix} \quad (20)$$

The process is repeated for until 2 X 2 DFT computations. If the number of data points in a signal is $N \neq 2^P$, then to perform FFT the number of zeros are padded to convert the data vector into the power of 2.

Energy of the signal x is computed using

$$E(n) = \sum_{k=0}^{N-1} |x(k)|^2 \quad (21)$$

Processing a Noisy signal and identifying decrement factor $\boldsymbol{\sigma}$:

Powe spectral density (PSD) is computed from FFT of a signal which is defined by

$$PSD\ of\ signal\ x(m) = \frac{|(fft(x(m)))|^2}{N} \quad (22)$$

PSD computes the power at each signal frequency and power at actual signals are higher than the noise content present in the signal. Hence, by setting the threshold PSD values and by zeroing out the components with power lesser than threshold to remove the noise from the signal. The reconstruction of the signal is obtained using inverse fast Fourier transform using equation (2). In this work, the statistical features of denoised signal is compared with noise free signal to check the accuracy of the method. The sliding window of size 'h' seconds is used over the denoised signal $x(m)$ to compute the decrement factor for the LFO modes.

Consider an sinusoidal exponential signal

$$x(t) = e^{\sigma t} \sin(\omega t + \varphi) \quad (23)$$

which can be decomposed into

$$x(t) = x(t_1) + x(t_2) + \ldots\ldots.. + x(t_m), \quad (24)$$

where window size $t_1 = t_2 = \ldots\ldots = t_m$ = 'm' seconds. Equation (23),can be re-written as

$$x(t) = e^{\sigma t_1} \sin(\omega t_1 + \varphi) + e^{\sigma t_2} \sin(\omega t_2 + \varphi) + \ldots. \; e^{\sigma t_m} \sin(\omega t_m + \varphi) \quad (25)$$

The decrement factor is computed by observing the PSD computed for $x(t_1)$, $x(t_2), \ldots\ldots.., x(t_m)$ using (10)

$$\sigma = \frac{1}{(t_2 - t_1)} \ln\left(\frac{PSD(x(t_2))}{PSD(x(t_1))}\right) = \frac{1}{(t_3 - t_2)} \ln\left(\frac{PSD(x(t_3))}{PSD(x(t_2))}\right) =$$

$$\ldots. = \frac{1}{(t_m - t_{m-1})} \ln\left(\frac{PSD(x(t_m))}{PSD(x(t_{m-1}))}\right) \quad (26)$$

The effectiveness of denoising is analysed using statistical metric:

Mean Square error (MSE):

$$\mathrm{MSE} = \frac{1}{\mathrm{N}} \sum_{\mathrm{k}=1}^{\mathrm{N}-1} (\mathrm{x_k} - \hat{\mathrm{x}})^2 \quad (27)$$

Root Mean Squared Error (RMSE)

$$\mathrm{RMSE} = \frac{1}{\mathrm{N}} \sum_{\mathrm{k}=1}^{\mathrm{N}-1} (\mathrm{x_k} - \hat{\mathrm{x}})^2 \quad (28)$$

The Mean Absolute Error(MAE):

$$\mathrm{MAE} = \frac{1}{\mathrm{N}} \sum_{\mathrm{k}=1}^{\mathrm{N}-1} (\mathrm{x_k} - \hat{\mathrm{x}}) \quad (29)$$

Signal to Noise ratio (SNR)

$$\mathrm{SNR} = 20 \log \frac{\text{rms value of signal}}{\text{rms value of noise}} \ \mathrm{dB} \quad (30)$$

$$\mathrm{SNR} = 10 \log \frac{\text{signal power}}{\text{noise power}}$$

Fit co-efficient

$$\mathrm{fit} = \left(1 - \frac{\sum_{\mathrm{k}=1}^{\mathrm{n}} [\hat{\mathrm{x}}_{\mathrm{k}} - \mathrm{X_k}]^2}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \left[\mathrm{x_k} - \left(\frac{1}{\mathrm{n}}\right) \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{x_k}\right]^2}\right) * 100 \quad (31)$$

Error in the Signal Energy is computed to verify the energy preservation after the reconstruction using (26).

$$EE(t) = \sum_{k=0}^{N-1} |x(k)|^2 - \sum_{k=0}^{N-1} |\hat{\mathrm{x}}_{\mathrm{k}}(k)|^2 \quad (32)$$

Where $x(k)$ is amplitude of actual signal and $\hat{\mathrm{x}}_{\mathrm{k}}(k)$-is amplitude of denoised signal.

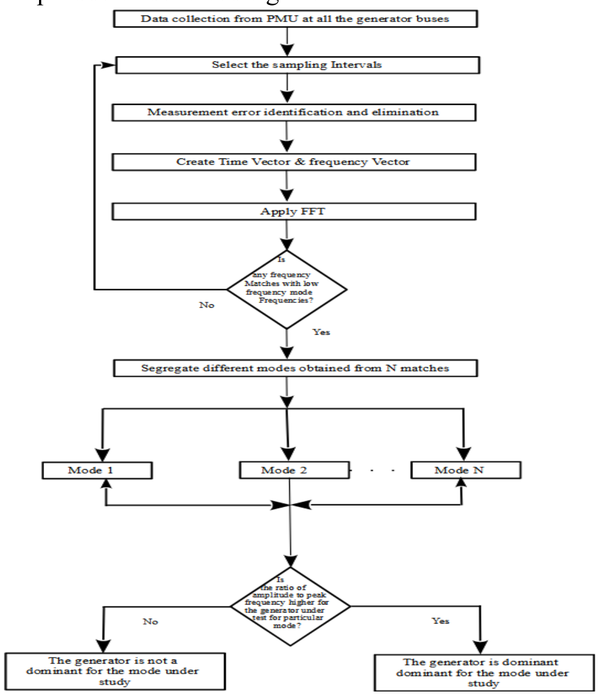

Fig. 1. Flow chart of algorithm to detect the dominant generators

The process of identification of oscillation modes are as shown in flowchart in Fig. 1. Data collected from PMU are pre-processed. Bad data are removed from the data vector and missing data are added using data interpolation in MATLAB environment. Low frequency of the range for crucial low frequency oscillation in power system is 0.1 Hz to 3 Hz which is fixed as threshold value. The Fast Fourier transform is applied to pre-processed data and frequency spectrum is evaluated. The modes of the generators appearing under the low frequency range are separated. The dominancy of the generator for the critical mode is verified by computing the ratio of amplitude to the critical frequency. The generator with highest ratio for the particular critical mode is chosen as dominant generator.

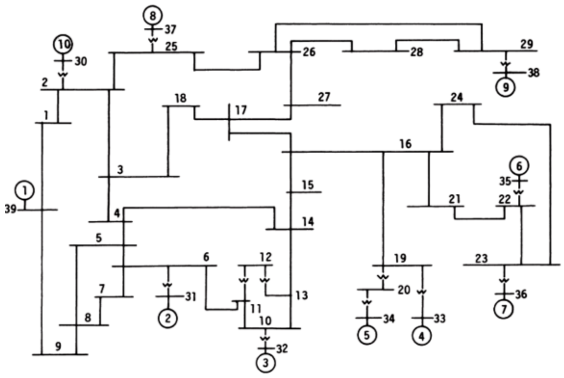

Fig. 2. IEEE 39 bus, 10 Machine New England system [1]

3. RESULTS AND DISCUSSIONS

The performance of the propose FFT-PSD method is verified for Synthetic data generated using MATLAB Simulink 2021 a for IEEE-39 bus New England system shown in Fig. 2. Small signal stability analysis is carried out by perturbing mechanical input at machine 7 at 0.5 secs. The bus power at the all generator buses is used as signal for the analysis. The data collected at every step size of 0.001 sec for 10 seconds and data vector is modified to replicate the PMU data of 60 samples / seconds [17] [23][24][25][26]. The PMU block available in MATLAB 2021 b is used to meet the requirement.

4.1 Eigenvalue analysis and Computation of Participation factor

The mathematical model for IEEE-39 bus New England System is developed using MATLAB Simulink 2021 a . The machines are represented by 1.0 model and the loads by constant power model. The model is linearised to extract continuous-time linear state-space model around operating point & eigenvalues of the linearized model is computed using (3) [27][28][29]. It is observed from the results that, there are nine swing modes as shown in Table 1, out of which the swing mode 1(SM1) and swing mode 6 (SM6)considered as critical and dominant modes since their decrement factor is positive and swing mode 5(SM5) for decrement factor less than 0.1. Therefore the study system has three dominant swing modes (SM1,SM5 and SM6) identified which decided upon the stability of the system which is considered as a base case for further study. The participation factor is computed for generators against the critical swing modes using (4). It is seen from the Fig. 4 and Fig. 5 that, Generator 2 dominantly contributes to SM-1, Generator 3 for SM-5 and Generator 9 for SM-6.

Table 1. Computation of eigenmodes

Sl.No	Eigenvalues	Comments	f(Hz)	ω in rad/sec	Damping ratio
1	0.0619 ± j3.9157	Swing Mode #1	0.623	3.9157	-0.015802
2	-0.2740 ± j8.6877	Swing Mode #2	1.383	8.6877	0.031526
3	-0.1580 ± j7.1570	Swing Mode #3	1.139	7.1570	0.022073
4	-0.1627 ± j6.9796	Swing Mode #4	1.11	6.9796	0.023307
5	-0.0845 ± j6.2698	Swing Mode #5	0.998	6.2698	0.013482
6	0.2041 ± j5.8835	Swing Mode #6	0.936	5.8835	-0.034676
7	-0.2039 ± j8.2621	Swing Mode #7	1.315	8.2621	0.024667
8	-0.1879 ± j6.1803	Swing Mode #8	0.9836	6.1803	0.030396
9	-0.2055 ± j8.3453	Swing Mode #9	1.328	8.3453	0.024622

Table 2. Comparison of error in computation of swing modes using Prony Algorithm

Swing mode	F in Hz	Noiseless signal		Signal with noise	
		Decrement factor(σ)	Error in(σ)	Decrement factor(σ)	Error in(σ)
SM1	0.62	0.071	14.2%	0.16	142.2%
SM5	0.998	-0.098	15.1%	-0.017	79.2%
SM6	0.93	0.22	6.8%	0.0066	97%

Table.3 Statistical Metric for PSD based denoising approach

Signal	SNR	MSE	MAE	FIT	RMSE	correlation	% energy error
M2	49.488	0.0012	0.01731	97.17	0.0302	0.9969	0.017%
M3	51.05	0.0003241	0.01255	93.529	0.01814	0.96112	0.00171%
M9	52.054	0.0004269	0.0165	97.41	0.02055	0.9839	-0.042%

Table 4. Computation of swing modes for noise signal using FFT-PSD

	Decrement factor and frequency		%error	
Modes	σ	f	σ	f
SM1	0.068	0.62	9.6%	1.3%
SM5	-0.092	0.967	8.19%	1.32%
SM6	0.21	0.932	2.81	0.85%

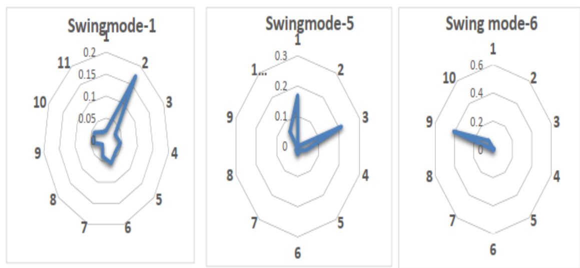

Fig. 4. Participation factors of the Generators for the critical swing mode

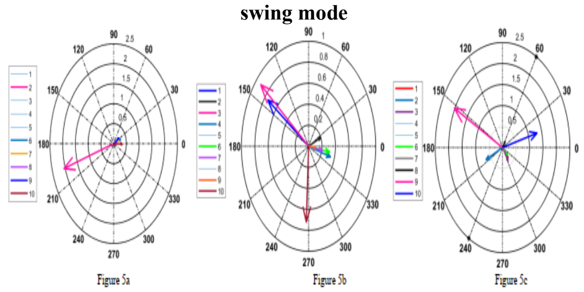

Fig. 5a. Mode shapes for swing mode 1, 5b. Mode shapes for swing

mode 5, 5c. Mode shapes for swing mod

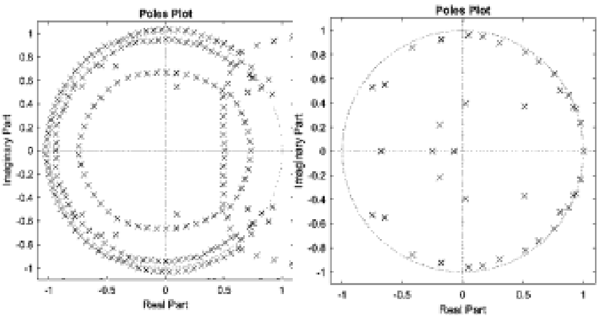

Fig. 6 a: 60samples/second, b: 10samples/second

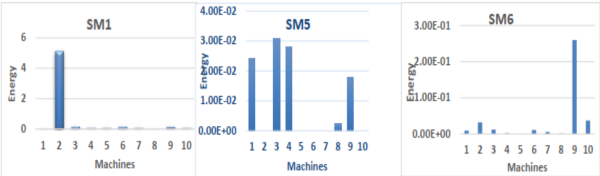

Fig. 6. Energy based participation factors for dominant modes

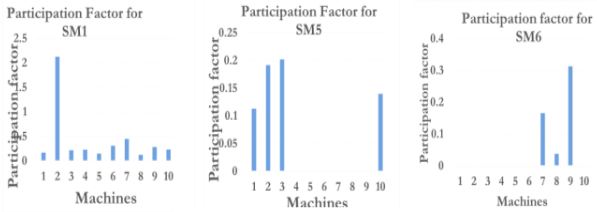

Fig. 7.Participation factors for dominant modes using FFT

4.2. Prony analysis

The Prony analysis is carried out for the PMU data of machine using (13). The measurement of bus power at the all generator buses is used as signal for the analysis collected step size of 0.001 sec for 10 seconds and data vector is modified to replicate the PMU data of 60 samples / seconds. The reduced sampling rate Prony analysis is applied for the detrended data collected from PMU allocated at different locations. The estimated system order is approximately 200. This is termed as overfitting in machine learning with increased number of features. Therefore, in this manuscript the reducing sampling rate approach of Prony analysis is performed to reduce the order of estimation. The sampling rate is reduced to 10 sample /second and estimated order for the fitness is approximately 35. Reducing sampling rate resembles the average filter. It can be observed from Fig. 6a that real part of roots are very denser near to unit circle and Fig. 6 b shows the more dispersed roots around unit circle and hence identification of dominant roots are more accurate in low sampling rates. The energy based participation factor of the machine for the critical modes are analysis using signal energy obtained by Prony analysis for all the machines using equation (14). It can observed from the chart in Fig. 6 that, Machine 2 contribute to critical mode SM1, Machine 3 for SM5 and Machine 9 for SM6 which is in consistent with Model based EA method.

Prony analysis is a traditional method employed to calculate the low frequency oscillations in power system. But it is not an efficient method if the number of measurements are increased or due to measurement noise. Due to complexity in data handling capacity, it requires proper data pre-processing techniques. Percentage error in the identification of decrement factor using the Prony method during noise for particular machine is more compared to noiseless as shown in table

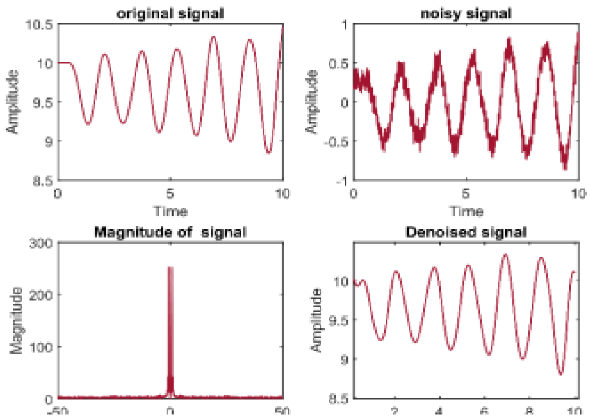

Fig. 8 a. Denoised signal using PSD for Machine 2

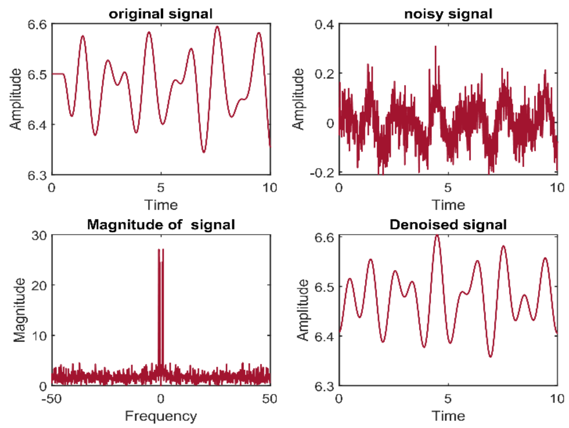

Fig. 8 b. Denoised signal using PSD for Machine 3

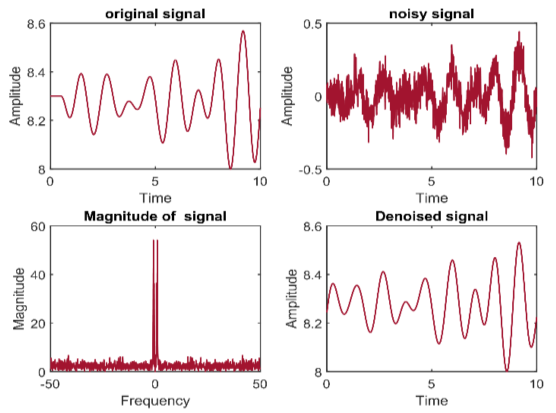

Fig. 8 c: Denoised signal using PSD for Machine 9

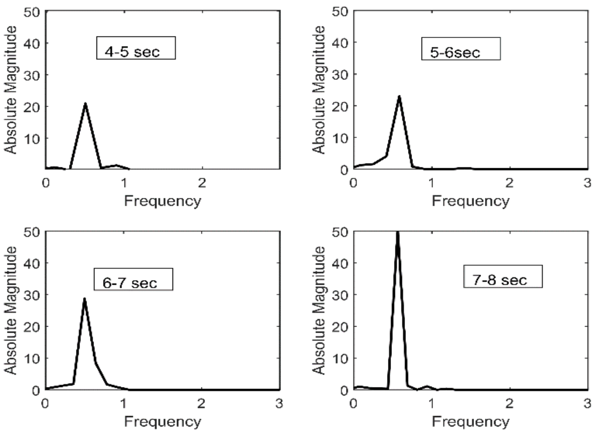

Fig. 9 a. FFT 1 sec window for M2

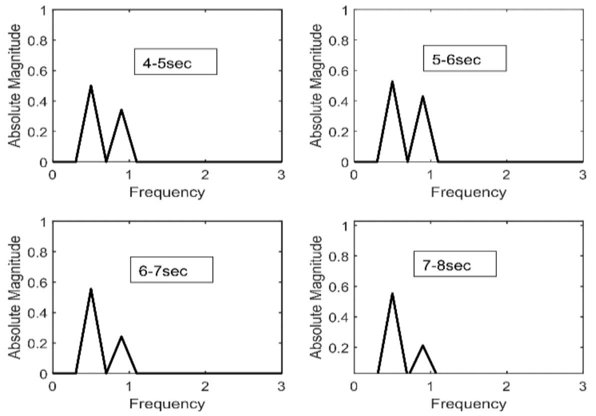

Fig. 9 b. FFT 1 sec window for M3

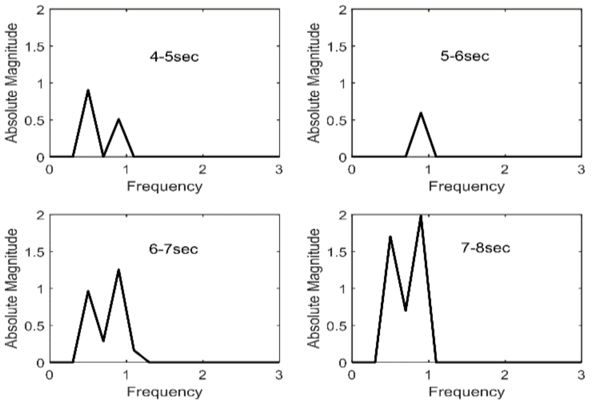

Fig. 9 c. FFT 1 sec window for M9

Prony Analysis can be good choice only for ringdown data. Therefore, we proposed, the FFT-PSD based approach which used PSD for denoising the signal and used sliding window with FFT technique on denoised signals to extract the frequency and decrement factor as mentioned in page 10. Based on the results the proposed FFT PSD approach is concluded as better than Prony approach. To justify the proper denoising, the statistical metrics are used and mentioned in table 3.

4.3. FFT Denoising using power spectral density

The participation factor is computed to identify the dominant generators for critical mode under noiseless condition for the measured data shown in Fig. 7 by computing the ratio of amplitude to peak frequency. The results is in consistent with the EA approach. However, the effectiveness of the approach is verified for the measurement signal contaminated by white noise of 30dB and denoised using Power Spectral Density (PSD) shown in Fig. 8 a,8b &8c. Spectrum analysis is carried out for the measured signal and Noise spectrum is identified and the required cut-off PSD is chosen to filter out the noise and performance of the denoising approach is analysed using statistical metric as shown in table 3. The result shows increased SNR, very low MSE, adequate MAE and %fit , reduced RMSE and improved correlation which indicates the higher degree of reconstructed signal after denoising. Energy error computed for denoised signal against noiseless signal is approximated almost zero indicates exact matching with original. FFT is computed for denoised signal for sliding window of the width 1 sec to capture the low frequency Oscillation information. Fig. 9a represents FFT applied over denoised signal of machine 2 for window length of 1 sec from 4 sec to 8 secs .It is observed that, the amplitude of FFT increases as the slider moves which indicates the positive decrement factor. The computed frequency and respective decrement factor are in line with the SM1 of the system.

Fig. 9 b represents the FFT applied over denoised signal of Machine 3. The first peak of the FFT is related to the SM1, however the amplitude variation is not surpassing the machine 2 signal. Therefore Machine 3 cannot be a dominant for SM1. Dominancy of Machine 3 is observed for the frequency of SM5 at which the amplitude of the FFT decreases as slider moves indicating the negative decrement factor. The computed frequency and decrement factors are in line with SM5. In Fig. 9 a, the dominancy of the Machine 9 is observed for the SM6 and computed decrement factor is in line with SM6.

Table 4 shows the computed values of decrement factor and frequency for modes of interest using FFT - PSD. It is observed that, the % error for estimation of decrement factor is negligible & are inconsistent with the eigenvalues computed using EA approach. It can observed from Table 4 that , the proposed approach is very effective under noisy measurement environment compared to the Prony analysis performed with reduced sampling rate shown in Table 2.

5. CONCLUSION

In this paper, FFT- PSD algorithm is developed to estimate low frequency oscillation from Noisy PMU data in IEEE 39 bus, New England system. The following are the deliberations from the proposed work.

- The dynamic characteristics eigenmodes, mode shapes and generator participation factor for various modes are computed for system under consideration using eigenvalue approach using mathematical model of the system and it is considered as a base case.
- The Synthetic data is generated for the system is pre-processed to imitate the behaviour of PMU using heuristic approach. PMU reporting rate is 60 samples / second is considered in this work. The Prony analysis is performed for original data and compared it with Prony with reduced sampling rate at 10 samples / second. It is observed that, the accuracy of the identification of LFO is better in case of reduced sampling rate. Energy based participation factor for identification of dominant generators for LFO's is computed using Prony algorithm for the PMU data collected at various locations at same time. The signal energy based participation factor is computed for noiseless measurement is in consistent with EA approach.
- The effectiveness of the Prony algorithm with reducing sampling rate is verified to identify the decrement factor and low frequency oscillations for the system under noiseless and noisy measurement. It is observed that, the complexity of the Prony algorithm increases with noisy measurement and necessitates the denoising prior to the identification.
- The performance of proposed FFT-PSD is validated against Prony approach for detrended data in MATLAB/Simulink environment.
- The FFT-PSD based denoising techniques for the noisy measurement signal identifies the nature of the decrement factor of the low frequency oscillatory modes. The The effectiveness of the denoised signal is validated using MSE, RMSE, MAE, SNR and FIT statistical metrics. The estimated decrement factors computed for the swing mode frequencies using FFT-PSD approach has high degree of accuracy in comparison with Prony approach but in consistent with the eigenmodes computed using eigenvalue analysis. The FFT-PSD can be used as a suitable feature extraction method for online detection of LFO using machine learning algorithm and initiating power oscillation damping.

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