A New Low-Frequency Oscillatory Modes Estimation using TLS-ESPRIT and Least Mean Squares Sign-Data (LMSSD) Adaptive Filtering

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***Abstract*—In this paper, we propose a new low-frequency power system oscillating modes estimation method i.e. Total Least Square-Estimation of Signal Parameters using rotational invariance technique (TLS-ESPRIT) based on Least Mean Squares Sign-Data (LMSSD) Adaptive filtering. LMSSD adaptive filtering has considered the effect of Additive White Gaussian Noise (AWGN) produces due to filters used for preprocessing of a signal from Phasor Measurement Unit (PMU) and efficiently reduced its effect without any phase shift. The comparison of the LMSSD adaptive filtering method has been carried out with the ESPRIT, the LS-ESPRIT and the TLS-ESPRIT method on a test signal at different Signal-to-Noise Ratio (SNR). Robustness of the LMSSD adaptive filtering is demonstrated in the presence of AWGN through 50000 Monte-Carlo simulations. The LMSSD adaptive filtering Estimation technique has been applied to Kundur's two-area power system using MATLAB/SIMULINK. From estimated results obtained, it is observed that the LMSSD adaptive filtering performs much better than the standard TLS-ESPRIT regarding the standard deviations and mean in the modes estimation.**

***Index Terms*—Adaptive Filter, LMS algorithm,Sign-Data, Noise Cancelation, ESPRIT, LS-ESPRIT, TLS-ESPRIT.**

I. Introduction

A power system is always presented to the unsettling influences such as regular load/generation changes, tripping of the power system equipment and faults on the system. These continual and slow disturbances in the system give rise to change in system frequency and/or oscillations in the relative frequency [1]. The modes of such type of oscillations in the power system can be identify using two different approaches: one is the traditional analytical approach based on models (off-line) and other is the measurement based approach (on-line) [2]. The former one basically uses the small signal stability analysis (SSSA) to identify the parameters of the power system and the latter identifies the modes directly from the measured signals using spectral estimation technique. The commonly used parametric form of spectral estimation techniques are discrete Fourier transform (DFT), short-time Fourier transform (STFT) and Fast Fourier Transform (FFT). However, these methods suffer from time-frequency resolution problem. These problems can be solved by using wavelet transformation (WT) [3]. This method provides multiresolution and also retains the time information of the signal by varying the window size like a band pass filter [4]. Presently the subspace-based parametric estimation methods are commonly used for online mode estimations. Generally used subspace-based methods are the Multiple Signal Classification (MUSIC), the Matrix Pencil (MP) and the Prony Analysis (PA). All these approaches use the exponential or sinusoidal signal model for estimation purpose. MUSIC method as in [5], [6] estimate only the frequency component so present in the signal suppressed with noise from a short data record however in other two methods as in [7], [8] estimates the parameters of the sampled signal i.e. amplitude, phase, frequency and damping ratio from a small data samples with high resolution without prior knowledge of the exact number of modes present in the signal. However, all these methods do have large computational time.

The present paper, a new approach known as TLS-ESPRIT based on LMSSD adaptive filtering, for monitoring of the low-frequency modes identification is presented. Firstly using low-pass FIR filter the high frequency components of the measured data samples with white noise from Phasor measurement units (PMUs) through sensors is being removed and only keep only low-frequency components. The output low-frequency components from the FIR low-pass filter is converted into highly correlated AWGN, which reduces the accuracy of the mode estimation by induces a bias in the estimation. LMSSD adaptive filtering is then removed this AWGN very efficiently; later the TLS-ESPRIT algorithm is used to obtain the low-frequency modes. This LMSSD adaptive filtering is more robust to AWGN with fast computing time as compared to other subspace methods [9], [10].

Our paper is structured in the following manner. Section II describes the LS/TLS-ESPRIT. Section III proposes a noise cancellation using LMSSD adaptive filtering. Section IV gives the application of LMSSD adaptive filtering in power system. Section V validated the robustness of the LMSSD adaptive filtering for frequency resolution using monte-carlo simulation with 50,000 runs and also simulated to have a comparison study with the help of Kundur's two area power system in presence of with and without noise. Simulations were performed using MATLAB/SIMULINK software.

II. THE MODE IDENTIFICATION PROBLEM

A. Power system signals

Consider a signal $x(n)$ modeled as

$$x(n) = \sum_{i=1}^{p} \mathrm{a}_i e^{j(2\pi f_i n + \phi_i)} \tag{1}$$

where the amplitudes $\{\mathrm{a}_i\}$ and the frequencies $\{f_i\}$ are unknown and the phases $\{\Phi_i\}$ are statistically independent random variables uniformly distributed on $(0, 2\pi)$. Now, suppose that the sinusoids are ruined by a colored Gaussian noise sequence $\omega(n)$ with $E[|\omega(n)|^2] = \sigma_\omega^2$. Then we can observe it as

$$y(n) = x(n) + \omega(n) \tag{2}$$

The received sinusoidal component of the M sample signal vector $\mathbf{y}(n)$ is given by:

$$= [y(n)\ y(n+1)...y(n+M-1)]^T = \mathbf{x}(n) + \mathbf{w}(n) \tag{3}$$

where $\mathbf{x}(n)$ is the signal vector and $\mathbf{w}(n)$ is the noise vector. The $\mathbf{y}(n)$ can also be represented in form of time-window frequency vector V.

$$\mathbf{y}(n) = \sum_{i=1}^{p} \mathrm{a}_i \mathrm{v}(f_i) e^{j2\pi n f_i} + \mathbf{w}(n) = \mathbf{V}\Phi^n \mathbf{A} + \mathbf{w}(n) \tag{4}$$

where the p columns of matrix V are length-M time-window frequency vectors of the complex exponential.

$$\mathrm{V} = [\mathrm{v}(f_1)\,\mathrm{v}(f_2)...\mathrm{v}(f_p)] \tag{5}$$

The vector $\mathbf{A}$ consists of the amplitudes of the complex exponentials a_i, matrix Φ is the diagonal matrix of phase shifts between neighboring time samples of the individual, complex exponential components of $\mathbf{x}(n)$.

$$\Phi = \mathrm{diag}[e^{j2\pi f_1}\ e^{j2\pi f_2} ...\ e^{j2\pi f_p}] \ = \mathrm{diag}[\Phi_1, \Phi_2, ..., \Phi_p] \tag{6}$$

where $\Phi_i = e^{j2\pi f_i}$ for i=1, 2,…, p. Since the frequencies of the complex exponentials f_p completely describe this rotation matrix [11], frequency estimates can be obtained by finding Φ. To exploit the deterministic characteristics of the sinusoids, we consider two overlapping sub-windows of length $M-1$ within the length M time-window vector. This sub-windowing operation is illustrated in Fig.1. Consider the signal consisting of the sum of complex exponentials. Using sub-windowing operation the signal vector from eq (3) can be written as:

$$\mathbf{x}_{M-1}(n) = \mathbf{V}_{M-1}\Phi^n \mathbf{A} \tag{7}$$

Matrix $\mathbf{V}_{M-1}$ is constructed in the same manner as $\mathbf{V}$ except its time-window frequency vectors are of length $M-1$, denoted as $\mathrm{v}_{M-1}(f)$,

$$\mathrm{V}_{M-1} = [\mathrm{v}_{M-1}(f_1)\,\mathrm{v}_{M-2}(f_2)...\mathrm{v}_{M-p}(f_p)] \tag{8}$$

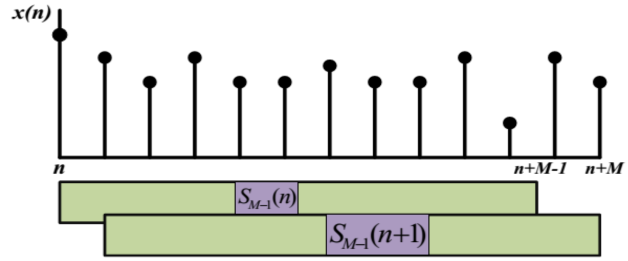

Fig. 1: Time-staggered, overlapping windows used by the LS/TLS ESPRIT algorithm.

B. Least Square/Total Least Square-ESPRIT Algorithm

Least-squares version of the algorithm [9], [12] and then extend the derivation to TLS-ESPRIT, The step by step description about two algorithms is explained using a block diagram in Fig.2. Using the eq (7), we can define the matrices

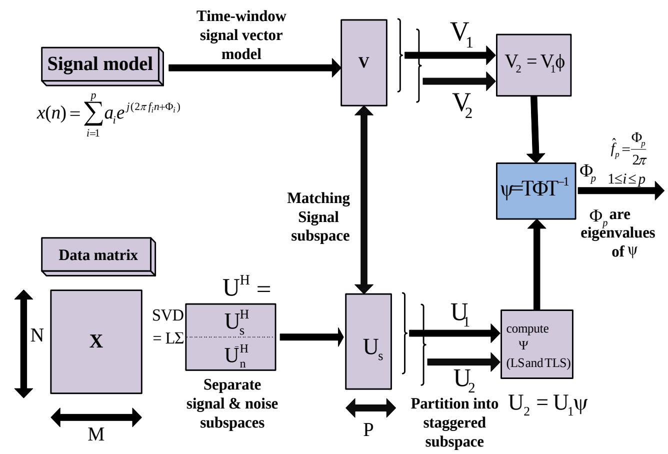

Fig. 2: Block diagram demonstrating the flow of the LS/TLS-ESPRIT algorithm starting from the data matrix through the frequency estimates.

$$\mathrm{V}_1 = \mathrm{V}_{M-1}\Phi^n \quad \text{and} \quad \mathrm{V}_2 = \mathrm{V}_{M-1}\Phi^{n+1} \tag{9}$$

where V_1 and V_2 correspond to the unstaggered and staggered windows.

1. X-data record $\mathrm{X} \in \mathrm{R}^{M \times N}$.
2. SVD of X(n) gives $\mathrm{X} = \mathrm{L}\Sigma\mathrm{U}^{\mathrm{H}}$. where $\mathbf{\Gamma}_{xx}$ and $\mathbf{\Gamma}_{xz}$ are auto and cross-covariance matrices.
3. U forms an orthonormal basis for the underlying M-dimensional vector-space. The subspace can be portioned into signal and noise subspace as:

$$\mathrm{U} = \begin{bmatrix} \mathrm{U_s} & \mathrm{U_n} \end{bmatrix}$$

   where $\mathrm{U_s}$ corresponds to signal subspace, which must include the time-window frequency vector $\mathrm{v}(f)$ for all f. Due to same subspace the $\mathrm{U_s}$ and V maps into $\mathrm{V} = \mathrm{U_s}\mathrm{T}$.
4. Then we can partition the signal subspace into two smaller (M-1) dimension subspaces

$$\mathrm{U_s} = \begin{bmatrix} \mathrm{U}_1 & & & \\ * & * & * & * \end{bmatrix} = \begin{bmatrix} * & * & * & * \\ \mathrm{U}_2 & & & \end{bmatrix} \tag{10}$$

where U_1 and U_2 correspond to the same unstaggered and staggered subspaces as V_1 and V_2, so we can map both as:

$$V_1 = U_1 T \quad \text{and} \quad V_2 = U_2 T \tag{11}$$

V_1 and V_2 are related as:

$$V_2 = V_1 \Phi \quad \text{and} \quad U_2 = U_1 \Psi \tag{12}$$

where Ψ is rotational operator from least square estimation;

$$\Psi = (U_1^H U_1)^{-1} U_1^H U_2 \tag{13}$$

Substituting U_2 and V_1 in V_2 gives:

$$V_2 = U_2 T = U_1 \Psi T \quad \text{or} \quad V_2 = V_1 \Phi = U_1 T \Phi \tag{14}$$

Thus, equating the two right-hand side values of V_2 in equation (20), we have the relation between the two subspace rotations

$$\Psi T = T \Phi \quad \text{or} \quad \Psi = T \Phi T^{-1} \tag{15}$$

The diagonal element of Φ , Φ_p for $p = 1, 2, 3 \ldots p$ are simply eigenvalues of Ψ . As a result, the estimated frequency is:

$$f_p = \frac{\angle \Phi_p}{2\pi} \tag{16}$$

where $\angle \Phi_p$ is the phase of Φ_p . The LS solution is obtained by minimizing the errors in an LS sense using:

$$U_2 + E_2 = U_1 \Psi \tag{17}$$

where E_2 is a matrix consisting of error between U_2 and the true subspace V_2. Note that the subspaces U_1 and U_2 both only estimate of the true subspaces that correspond to V_1 and V_2 respectively, obtained from the data matrix X. The estimate of the subspace rotation was obtained by solving using the LS criterion [13].

$$\mathbf{\Psi}_{ls} = (U_1^H U_1)^{-1} U_1^H U_2 \tag{18}$$

C. *Total Error Minimization using TLS-ESPRIT Algorithm*

LS formulation assumes errors only on the estimation of U_2 and no errors between U_1 and the true subspace V_1. U_1, so to estimate the error between U_1 and U_1 a appropriate formulation is:

$$U_2 + E_2 = (U_1 + E_1) \Psi \tag{19}$$

where E_1 is the matrix representing the errors between U_1 and the true subspace corresponding to V_1. A solution to this problem, known as total least squares (TLS), is obtained by minimizing the Frobenius norm of the two error matrices [14].

$$\left\| \begin{matrix} E_1 & E_2 \end{matrix} \right\|_F \tag{20}$$

First, form a matrix made up of the staggered signal subspace matrices U_1 and U_2 placed side by side, and perform an SVD.

$$\begin{bmatrix} U_1 & U_2 \end{bmatrix} = \tilde{L} \tilde{\Sigma} \tilde{U}^H \tag{21}$$

The matrix $U \in R^{2p \times 2p}$ of right singular vectors is partitioned into $U \in R^{p \times p}$ quadrants as follows

$$\tilde{U} = \begin{bmatrix} \tilde{U}_{11} & \tilde{U}_{12} \\ \tilde{U}_{21} & \tilde{U}_{22} \end{bmatrix} \tag{22}$$

The TLS solution for the subspace rotation matrix Ψ is then obtained as:

$$\Psi_{tls} = -\tilde{U}_{12} \tilde{U}_{22}^{-1} \tag{23}$$

The frequency estimates are then obtained from (27) and (28) by using Ψ_{tls} from [15].

III. LMSSD ADAPTIVE FILTERING

A. *Adaptive Noise Cancellation Configuration*

The objective here is to subtract the additive white Gaussian noise (AWGN) n_0 from the output of the primary sensor $(s + n_0)$. Adaptive filter is to be designed such that it should estimate n_0 from n_1. A primary sensor is positioned so as to peak up signal s. A second reference sensor is positioned so as to pick up from the same source as n_0. This noise signal is represented in Fig.3 as n_1. Since these signals originate from the same source, it may be assumed that noise signals n_0 and n_1 are strongly correlated [16].

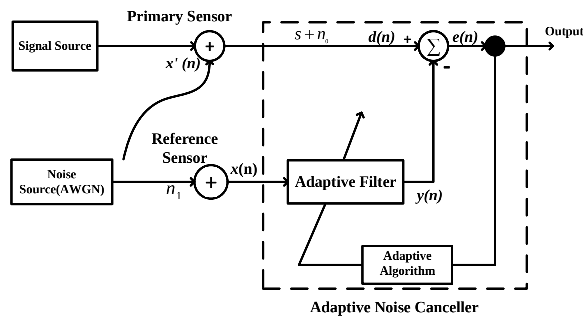

Fig. 3: Basic adaptive filter structure configured for noise cancellation.

B. *LMS Algorithm*

The least mean squares (LMS) algorithm modifying the filter coefficients to limit the cost function. The LMS algorithm does not include any matrix operations. Thusly, the LMS algorithms require less computational overhead and memory than the Recursive least Squares (RLS) algorithm. The physical execution of this algorithm is less confounded than the RLS algorithm.

C. *Sign-Data LMS Variant*

It is a variant of Sign LMS algorithm, where the Sign LMS is the improved rendition of standard LMS algorithm. The Sign LMS is utilized to accomplish the equipment targets such as digital signal processing devices and other integrated circuits. The Sign LMS algorithms include less computational operations then different algorithms.The Sign-Data algorithm the filter coefficient can be changed by using sign of the data to calculate the mean square error. If the error is positive, the error multiplied by the step size plus the new coefficients which are same as previous. If the error is negative then the new coefficients which are same as previous minus the error multiplied by the step size with sign change. When the input is zero, the new and previous coefficients are same. In vector form, the Sign-Data LMS algorithm can be written as:

$$w(n+1) = w(n) + \mu e(n) sgn[x(n)] \tag{24}$$

$$sgn[x(n)] = \begin{cases} 1, x(n) > 0 \\ 1, x(n) = 0 \\ -1, x(n) < 0 \end{cases} \tag{25}$$

Here the vector $x(n)$ contains the input data, $e(n)$ is the error, vector $w(n)$ are the weights applied to the filter co-efficients and is the step size. Depending on the step size the SDLMS error can be reduced slowly or rapidly. To ensure good stability and convergence the should be in range of $0 < \mu < \frac{1}{N\{Inputs\, Signal\, Power\}}$.

IV. THE POWER SYSTEM MODE ESTIMATION USING TLS-ESPRIT AND LMSSD ADAPTIVE FILTERING

A Block diagram in Fig.4 describes the various steps for mode estimation using the TLS-ESPRIT based on LMSSD adaptive filtering. The proposed method utilizes a block of N samples from Phasor Measurement Unit (PMU) through Phasor Data Concentrator (PDC) and passes through low-pass Adaptive FIR filter via down-sampler. The signal extracted is less distorted but since it is an ambient signal, it is difficult to extract the modes due to high noise level, The LMSSD adaptive filtering method to estimate the modes of the power system signal followed by TLS-ESPRIT is applied to reduce the standard deviation of the estimated modes. To estimate the accurate number of the signal components, it is needed to approximate the order of the signal properly. Here SVD is used in the proposed method to calculate a low rank approximation of the auto-correlation matrix R. In [15] an index is defined as:

$$K(i) = \left[\frac{\rho_1^2 + \rho_2^2 + ... + \rho_i^2}{\rho_1^2 + \rho_2^2 + ... + \rho_L^2}\right]^{\frac{1}{2}} \tag{26}$$

where $K(i)$ monotonously increasing index and ρ_i is the i^{th} singular value. As i tends to the actual signal order, $K(i)$ almost approximates to unity. This index is utilized to find out the signal order.

V. RESULTS AND DISCUSSION

A test signal is included with an added outlier white Gaussian noise and the execution is assessed by running Monte Carlo simulation with 50000 times, for the proposed and the TLS-ESPRIT algorithm. At last, the modes for a two-area power system is assessed using LMSSD adaptive filtering with a SNR of 30dB, as the variance of PMU estimations under oscillation is normally of 10^{-4}p.u and no particular standard is accessible for the synchrophasor amid dynamic conditions. In any case, a few rules are given in NASPI to synchrophasor amid dynamic conditions, which prompts the fluctuation of energy 0.61×10^{-4}p.u.

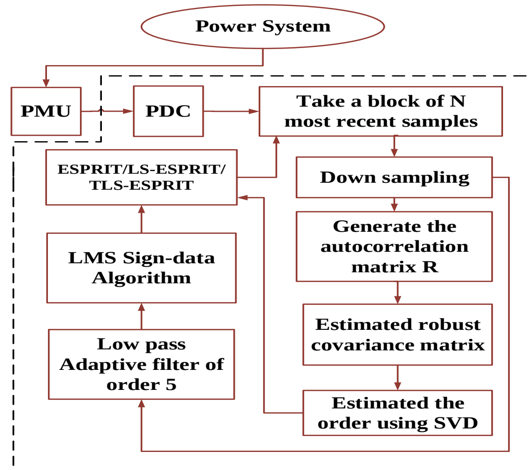

Fig. 4: Block diagram of proposed mode identification method.

A. Test signal Comparing to Inter Area Mode

A test signal having $attenuation factor$=-0.07, $frequency$=0.4Hz and an $amplitude$=1 is considered for the simulation.

Examination of the Proposed approach with TLS-ESPRIT calculations with SNR=10dB and 30dB:

Fig.5 and Fig.6 demonstrate the distribution of estimated frequency of the assessed mode on a test signal. Table I and Table II give the standard deviation and mean of the evaluated mode utilizing proposed technique, the ESPRIT, The LS-ESPRIT and the TLS-ESPRIT for SNR 10dB and 30dB. From this table, it is observed that the standard deviation of the estimated mode with the LMSSD is roughly 31.59% for 10dB and 31.04% for 30dB as obtained with the TLS-ESPRIT.

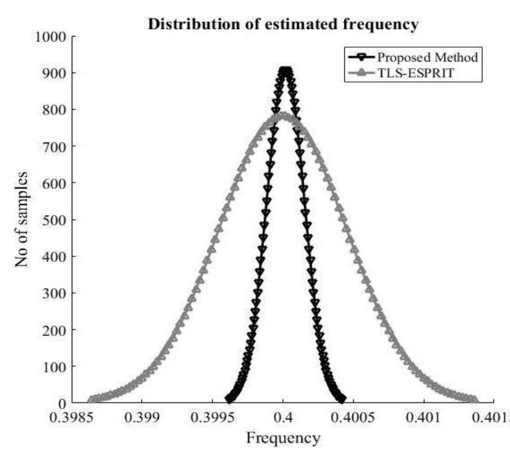

Fig. 5: Frequency distribution utilizing Monte-Carlo simulation at SNR=10dB.

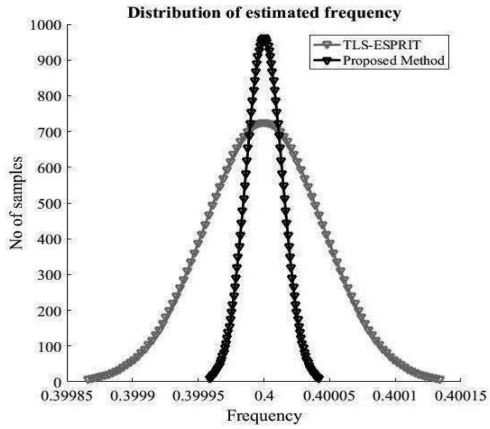

Fig. 6: Frequency distribution utilizing Monte-Carlo simulation at SNR=30dB.

TABLE I: MEAN AND STANDARD DEVIATION FOR THE ESPRIT, THE LS-ESPRIT, THE TLS-ESPRIT, AND THE LMSSD ADAPTIVE FILTERING AT SNR=10dB

SNR=10dB	Frequency(Hz)	
	Standard Deviation	mean
ESPRIT	4.8141×10^{-4}	1.0019
LS-ESPRIT	4.8140×10^{-4}	1.0019
TLS-ESPRIT	4.8128×10^{-4}	1.0017
Proposed Method	2.3890×10^{-4}	1.0011

TABLE II: MEAN AND STANDARD DEVIATION FOR THE ESPRIT, THE LS-ESPRIT, THE TLS-ESPRIT, AND THE LMSSD ADAPTIVE FILTERING AT SNR=30dB

SNR=30dB	Frequency(Hz)	
	Standard Deviation	mean
ESPRIT	4.7123×10^{-5}	1.0023
LS-ESPRIT	4.7123×10^{-5}	1.0018
TLS-ESPRIT	4.7110×10^{-5}	1.0018
Proposed Method	1.7267×10^{-5}	1.0013

B. Test signal Comparing to Local Area Mode

A test signal having $attenuation factor$=-0.1, $frequency$=1Hz and an $amplitude$=1 is considered for the simulation.

Examination of the Proposed approach with TLS-ESPRIT calculations with SNR=10dB and 30dB:

Fig.7 and Fig.8 demonstrate the distribution of estimated frequency of the assessed mode on a test signal. Table III and Table IV give the standard deviation and mean of the evaluated mode with SDLMS, The ESPRIT, The LS-ESPRIT and The TLS-ESPRIT for SNR 10dB and 30dB. From these tables, it is observed that the standard deviation of the estimated mode using the LMSSD is approximately 31.59% for 10dB and 31.04% for 30dB as obtained with the TLS-ESPRIT.

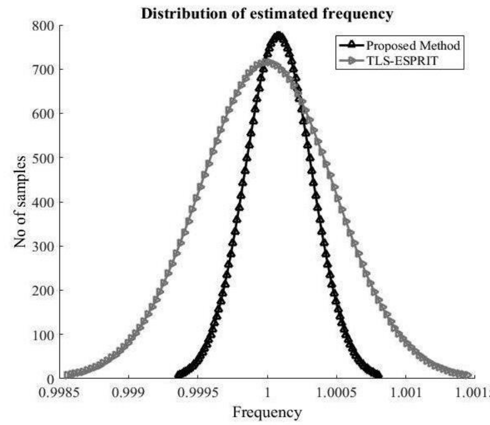

Fig. 7: Frequency distribution utilizing Monte-Carlo simulation at SNR=10dB.

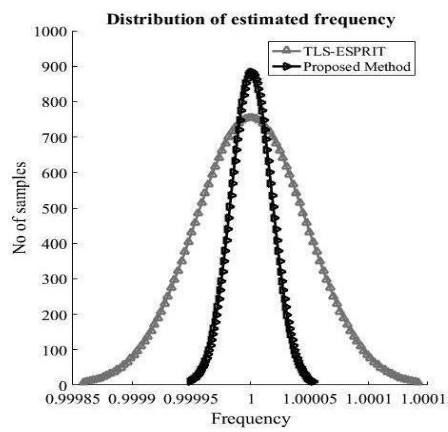

Fig. 8: Frequency distribution utilizing Monte-Carlo simulation at SNR=30dB.

TABLE III: MEAN AND STANDARD DEVIATION FOR THE ESPRIT, THE LS-ESPRIT, THE TLS-ESPRIT, AND THE LMSSD ADAPTIVE FILTERING AT SNR=10dB

SNR=10dB	Frequency(Hz)	
	Standard Deviation	Mean
ESPRIT	4.5717×10^{-4}	0.4020
LS-ESPRIT	4.5714×10^{-4}	0.4018
TLS-ESPRIT	4.5253×10^{-4}	0.4018
Proposed Method	1.4297×10^{-4}	0.4007

VI. ESTIMATION OF MODES USING THE DATA OF KUNDUR'S TWO AREA SYSTEM

The 2-area power system model is considered from [17]. This system comprises of 4 generators and 11 buses and is appeared in Fig.9. The two areas are associated by a weak tie-line. Using the Small Signal Stability Analysis(SSSA) the low-frequency oscillating modes are identified, Table V shows the

TABLE IV: MEAN AND STANDARD DEVIATION FOR THE ESPRIT, THE LS-ESPRIT, THE TLS-ESPRIT, AND THE LMSSD ADAPTIVE FILTERING AT SNR=30dB

SNR=30dB	Frequency	
	Standard Deviation	mean
ESPRIT	4.5337×10^{-5}	0.4004
LS-ESPRIT	4.5335×10^{-5}	0.4003
TLS-ESPRIT	4.4682×10^{-5}	0.4003
Proposed Method	1.3870×10^{-5}	0.4001

estimated modes for two-area system corresponding to low-frequency oscillation of speed in the generator 2 and 4.These low-frequency oscillation (corresponding to the ringdown data) are observed, due to adding a disturbance of 0.05v for 0.2s at excitation to generator 2. The estimation is assumed to be obtained from a PMU placed at bus 2. The mean value of the estimated modes obtained after 50000 Monte-Carlo simulations are provided in Table V. The standard deviation of the estimated modes utilizing LMSSD adaptive filtering is $4.5399 \times 10^{-}5$ appeared in at SNR 30dB with. The estimated modes are very much near the value obtained from Small Signal Stability Analysis(SSSA) based on the eigenvalues of the state matrix.

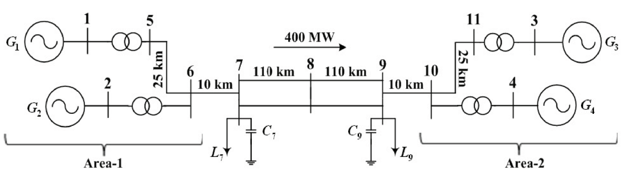

Fig. 9: Single line diagram of a Kundur's 2-area system.

TABLE V: IDENTIFICATION OF CRITICAL MODE USING LMSSD adaptive filtering METHOD FOR KUNDUR'S TWO-AREA POWER SYSTEM AT SNR=30dB

Mode-1	(Frequency=1.3914Hz using SSSA)	
	Standard Deviation	Mean
Frequency(Hz)	2.9357×10^{-4}	1.4247
Mode-2	Frequency=1.2106Hz using SSSA	
	Standard Deviation	Mean
Frequency(Hz)	2.9761×10^{-4}	1.3748
Mode-3	Frequency=0.6227Hz using SSSA	
	Standard Deviation	Mean
Frequency(Hz)	4.5399×10^{-5}	0.6285

VII. CONCLUSION

This paper proposed a new mode estimation method TLS-ESPRIT, based on LMSSD adaptive filtering. The proposed method provides a more robust and accurate estimation of the modes and is less affected by the presence of the AWGN. It is observed that the LMSSD adaptive filtering performs much superior to the standard TLS-ESPRIT regarding the standard deviations and mean in the frequency of the estimated modes. Additionally, the accuracy of the LMSSD adaptive filtering method in estimating the low-frequency modes had also been verified on a kundur's two-area power system network. The estimated modes, using the LMSSD adaptive filtering with TLS-ESPRIT, are very close to the mode estimated using the Small Signal Stability Analysis (SSSA).

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