Power System Oscillation Modes Identifications: Guidelines for applying TLS-ESPRIT Method

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Abstract—Fast measurements of power system quantities available through wide area measurement systems enables direct observations of power system electromechanical oscillations. But the raw observations data need to be processed to obtain the quantitative measures required to make any inference regarding the power system state. Detailed discussion is presented for the theory behind the general problem of oscillatory mode identification. This paper presents some results on oscillation mode identification applied to a wide area frequency measurements system. Guidelines for selection of parameters for obtaining most reliable results from the applied method is provided. Finally some results on real measurements are presented with our inference on them.

Index Terms—Power System Oscillations, Ambient Measurements, TLS-ESPRIT

I. INTRODUCTION

POWER systems continuously undergo changes due to stochastic nature of the loads. Each change in load also leads to an oscillatory response from the power system. This is due to the dynamic nature of the power generation system. The power system oscillations are observed in most of the measured variables like bus voltage, transmission line currents, branch powers and in the frequency as well.

With development of Wide Area Measurement Systems (WAMS) the availability of data sample at rate suitable for power system oscillations measurement has improved. Moreover the synchronized data from places separated by a distance in terms of hundreds of kilometers is available a single place. This data can be used to monitor the state of power system by measuring observed oscillation modes.

There are several previous studies that propose methods of extracting the system oscillation mode information from the ambient power system measurements. The research in this area goes as far back as thirty years [1], [2]. They used a simple Discrete Fourier Transform (DFT) techniques to perform the spectral analysis and Prony and Auto correlation techniques for mode identifications. Recent studies [3]–[7] have developed several advances signal processing methods for performing the task of mode identification. Ref. [8] suggested a subspace separation based technique called Total Least Square - Estimation of Signal Parameters through Rotational Invariant Technique TLS-ESPRIT. This method was originally proposed for direction of arrival measurement for antenna systems [9], and it has been also applied for analysis of power quality events [10]. The major conclusion of [3], [7] is that most of the methods give comparable results under similar conditions. In this paper we are going to use the TLS-ESPRIT method for mode identification from ambient frequency measurements and discuss some of the interesting findings.

In the following sections we discuss salient features of power system oscillations and the wide area frequency measurement system which measured the input data used in the study. Finally some details about methodology followed in mode identifications and discuss the results obtained on the real life data.

II. POWER SYSTEM OSCILLATIONS

In order to study the dynamic response of the power systems a detailed multi machine analysis has to be performed as described in [11], [12]. Reviewing the details of multi machine analysis is beyond scope of this paper. But major results of the analysis is that any large power system will have a few dominant electromechanical modes of oscillations that observable in most of the system measured values. The bus voltage frequency is one of such output variable. The modes of oscillations can be broadly classified as inter area, local and intra plant modes. The inter area modes have frequency in range of 0.2 to 0.5 Hz. and are observable in several measurement outputs spread over a wide area. The local modes have frequency range of 0.8 to 1.8 Hz. and are associated with a small group of generators oscillating against a larger system. It is observable in fewer measured values of smaller area. The intra plant modes have higher frequency in range of 1.5 to 3 Hz and are observable only within and near by a generating plant. Over and above these there are some modes of oscillations associated with controls like HVDC, FACTS and turbine governors. Their frequency of oscillation is not fixed and depends on the controller parameters and their observability in measured values depend on the power handling capacity of the controlled equipment and the parameter that is controlled. The controller mode of large HVDC line may be observable in wide area in active power and frequency of the system, while a small SVC controller mode may observable in bus voltage magnitude in its neighbourhood.

We show the method of measuring these modes of oscillation through a simple wide area frequency measurement system.
III. Wide Area Frequency Measurement System

Frequency is one parameter that is measurable at every point in a power system. Frequency measured at a low voltage level will also provide the measurements of the electromechanical modes that are observable in the high voltage bus of that area [13], [14]. Unlike phase angle measurement that require highly accurate clock synchronization, the frequency measurement is tolerant to an error of few milli seconds in clock synchronization.

Wide Area Frequency Measurement System (WAFMS) [15] developed and deployed by Power Systems Laboratory of IIT Bombay, India uses Network Time Protocol (NTP) for time tagging the measured frequency. The frequency measurement devices are placed at power outlets of several laboratories in academic institutes spread over a synchronously connected network in India. The measurements are performed locally by each device at period of every 20 ms., and the measured data is streamed to a central server. The project is operational since mid 2009, and at least two years of measurement archive is available for this study.

There are several incidents of power system oscillations measured through this system, some of them are reported in [13]. The swings arising out of the large disturbances are of great interest and provide important information regarding the system behaviour. However, the focus of this paper is more on the power system oscillation modes that are measured during ambient conditions when there is no large event like fault, generator tripping or load shedding etc.

IV. Response of Stochastic Linear Time Invariant System

The previous sections discussed the typical oscillatory modes of a power system networks and their measurements. These forms a part of a vast field of the study of linear time invariant (LTI) systems. The properties of LTI systems are well studied. The response of LTI system consists of two components. One is dependent on the forcing function and it forms steady state component. The other component is independent of the forcing function, but depends on the properties of the system it self. This paper is repeating all the well known facts of LTI system but suffice to say that the system response is a linear combination of damped exponential in time. The exponential can be over-damped, without any oscillations, or under-damped with few cycles of oscillations. These responses can be elicited from they system by giving it known forcing function like a impulse function or a unit step function.

Consider a simple continuous time single input single output (SISO) system given by

\[ \dot{x} = Ax + Bu \]
\[ y = Cx + Du \]  \hspace{1cm} (1)  \hspace{1cm} (2)

where,
\[ A = \begin{bmatrix} -0.1 & 2\pi \cdot 0.4 \\ -2\pi \cdot 0.4 & -0.1 \end{bmatrix} \quad B = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \]
\[ C = \begin{bmatrix} 1 & 0 \end{bmatrix} \quad D = \begin{bmatrix} 0 \end{bmatrix} \]  \hspace{1cm} (3)

The system has a single oscillatory mode with natural frequency \( \omega_n \) equal to 0.40032 Hz and the damping factor \( \zeta \) equal to 3.97 %. The natural frequency and damping factor is calculated from the complex eigen value pairs of the state matrix \( A \) as

\[ \lambda = \alpha + j\omega \]  \hspace{1cm} (4)
\[ \omega_n = \sqrt{\alpha^2 + \omega^2} \]  \hspace{1cm} (5)
\[ \zeta = -\frac{\alpha}{\omega_n} \]  \hspace{1cm} (6)

The step and impulse response of the above system is shown in Fig. 1. If we already don’t know the model then measuring the step or impulse response can be used to estimate the model.

However, it is not always possible to get the step or impulse response of the dynamical system. In case the system is excited by a white noise stochastic input the output is as shown in Fig. 2.

If our aim is to obtain the properties of the power system through measurement of its parameters, we have to do it through the measurements that can be best approximated as the response of system excited by white noise. The power system is inherently a nonlinear system and time variant. But for a short time period (few minutes) and for small disturbances the system can be linearized around a given operating point and the system can be approximated as a LTI system.

In this paper our aim to obtain the system properties through measurements of power system variables that can be considered as response of the LTI system excited by white noise. But before we do it we have to study some of properties of LTI system and also investigate the assumption about white noise excitation.
A. Validity of white noise assumption

White noise is defined as a signal that has uniform power distribution along frequency axis in a given band. It statistics the white noise signal is mapped to a random variable with zero mean and constant variance [16, 17]. Any independent and identically distributed (iid) random variable satisfies the properties of white noise. Particularly the so called normally distributed random variable i.e. with zero mean and constant variance Gaussian distribution is very common example of a white noise. In this paper the white noise is always meant as a Gaussian white noise. Here is should be noted that if a random variable is having non zero mean then the white noise signal is obtained from a Gaussian distributed random variable by subtracting its mean value from the variable.

Power systems loads can be can be approximated by very large numbers of uniform loads connected by binary switches. When a switch is ON, one unit load gets connected while when the switch is OFF that load gets disconnected. In statistics Binomial distribution is probability distribution of number of success X in n trials [18]. When number of trials n is large and probability p of success of individual trial is not too near 0 or 1, then the discrete Binomial distribution can be approximated as a continuous Gaussian distribution, due to Central Limit Theorem. In fact [18] states that the normal (Gaussian) approximation of Binomial distributed random variable will be quite good for values of n satisfying np(1−p) ≥ 10. This condition is comfortably met in any practical power systems. The results reported by [7] also supports this assumption.

From above discussion it can be safely assumed that indeed the LTI system representing a linearized model of power system at a given operating point is excited by constantly changing load that can be approximated as a white noise for a short time. The mean value of load it self and hence the operating point of the power system changes over period of time. It is expected that variance of the white noise representing the stochastic change in load will also change over a period of time. However that time period could be in terms of tens of minutes. For a short period of few minutes the white noise assumption can still be valid.

B. Output of LTI system when excited by white noise

We have seen the plot of the time response of the system (1) when excited by a white noise in Fig. 2. The proper analysis of LTI system excited by white noise is presented here.

The analysis becomes easy if the continuous time LTI system in (1) is discretized as (7).

\[
\begin{align*}
A_d &= e^{AT} \
B_d &= \left( \int_0^T e^{A\tau}d\tau \right) B \
C_d &= C \
D_d &= D
\end{align*}
\]

With sampling time T of 0.1 sec, the discrete representation of example in (1) becomes,

\[
\begin{align*}
A_d &= \begin{bmatrix} 0.9589 & 0.2462 \\
-0.2462 & 0.9589 \end{bmatrix} \
B_d &= \begin{bmatrix} 0.09846 \\
-0.01242 \end{bmatrix} \
C_d &= \begin{bmatrix} 1 & 0 \end{bmatrix} \
D_d &= \begin{bmatrix} 0 \end{bmatrix}
\end{align*}
\]

And with sampling time T of 0.01 sec, the discrete representation of example in (1) becomes,

\[
\begin{align*}
A_d &= \begin{bmatrix} 0.9987 & 0.0251 \\
-0.0251 & 0.9987 \end{bmatrix} \
B_d &= \begin{bmatrix} 9.994e-3 \\
-1.256e-4 \end{bmatrix} \
C_d &= \begin{bmatrix} 1 & 0 \end{bmatrix} \
D_d &= \begin{bmatrix} 0 \end{bmatrix}
\end{align*}
\]

It can be seen from (9) that the values in the discretized matrix depends on the sampling time period used.

Using the form of (7), we now show relationship between the white noise input u and the corresponding output y. It can be shown that if A is stable and input u is zero mean and a constant variance signal than the output signal y will also have zero mean and its variance is derives as [20],

\[
X_{cov} = \sum_{k=0}^{\infty} A_d^k B_d U_{cov} B_d^T (A_d^T)^k
\]

Where, \( U_{cov} \), \( X_{cov} \) and \( Y_{cov} \) are the covariance matrices defined as expected values,

\[
U_{cov} := E \{ [u[n] - \mu_u] [u[n] - \mu_u]^T \}
\]

Here \( \mu_u \) is mean value of \( u \), it is equal to zero and can be ignored. Similar equations apply for \( X_{cov} \) and \( Y_{cov} \). The auto covariance matrix is also defined for different integer lags l.

\[
U_{cov}[l] := E \{ [u[n]u[n+l]]^T \}
\]

This shows that mean of \( x \) and \( y \) are zero and their covariance matrix are constant hence both \( x \) and \( y \) are stationary processes. This is of course subject to stability of \( A \), which implies that all eigen values of \( A \) have a non positive real part. For \( A_d \) this translate into the requirement that absolute values of all its eigen values are less than or equal to 1.

Finally, it can be shown that the impulse response of the LTI system is directly related to \( Y_{cov}[l] \). \( h[lT] \) is discrete valued impulse response of LTI system and \( Y_{cov}[0] \) is covariance of \( y \) with zero lag as in (13).

\[
h[lT] = \frac{Y_{cov}[l]}{Y_{cov}[0]}
\]
C. Some important aspects of response of stochastic LTI systems

Our aim is to identify the systems or the components of the signal from the measured signals that are response of stochastic LTI system. In general power systems signal the excitation applied to the system is not in our control. However, there are some methods that apply artificial excitation called probing signal [21], [22]. The main aim of that signal is to excite the system modes with enough energy that their measurement becomes easier. In terms of our analysis the probing signals corresponds the white noise input, and through extra probing signal effort is made to increase the variance $U_{cov}$, in order to get higher variance in $y$. Important choice for probing signal is its bandwidth. Higher bandwidth probing signal requires fast varying devices and possibly higher energy. Here we compare the response of the LTI system of (1) for excitation by unit variance $u$, and through extra probing effort is made to increase the variance $U_{cov}$, in order to get higher variance in $y$. Important choice for probing signal is its bandwidth. Higher bandwidth probing signal requires fast varying devices and possibly higher energy. Here we compare the response of the LTI system of (1) for excitation by unit variance $u$ with bandwidth of $10\pi$ and $100\pi$ radians. The output $y$ is shown in Fig. 3, and plot of covariance of $y$ obtained from output of length 150 Sec is shown in Fig. 4. It can be seen that it resembles quite nearly to the impulse response of the system shown in Fig. 1, except for the scaling factor. It can also be seen that the frequency of oscillation is captured quite accurately, while the damping of oscillation shows some error compared to actual impulse response. This is because of finite time period used for estimating the covariance matrix as against the infinite time required by for calculating expected value as (15). Next, we see the effect of damping on understanding of damping stresses more on the damping ratio. But, here it is seen that even very low frequency oscillation with higher damping ratio will have equal SNR ratio to a signal with higher frequency lower damping ratio. As observed in Table I where the covariance of case 1 and case 2 are almost same even though their damping ratio is very different. This shows that we can hope to observe very low frequency oscillations even if its damping ratio is very high. Fig. 5 and Fig. 6 shows the output and covariance plot corresponding to response of case 2 and case 4. However, still care must be taken in using covariance data with limited lag. As can be seen in Fig. 5 the covariance plot beyond 20 sec is very erroneous. This is covariance plot is derived from simulation time duration of 600 sec (10 minutes). The accuracy beyond 20 sec lag can be improved but it require very long duration data, which is unreasonable. Our experiments have shown that reasonable accuracy of covariance estimate for up to 30 sec lag is achievable with data of 3600 sec (1 hour). This discussion applies to all cases with the real part of $\lambda$ i.e. $\alpha$ is equal to $-0.1$. If the damping is lower, i.e. if $0 > \alpha > -0.1$ then covariance even beyond lag of 20 sec is accurate as seen in Fig. 6.

![Fig. 3. LTI excited by white noise of different bandwidths](image)

![Fig. 4. Covariance for response with different bandwidths](image)

![Fig. 5. Output $y$ and $Y_{cov}$ for LTI system with $\lambda = -0.1 + j2\pi0.04$, $\zeta = 36.97$](image)

![Fig. 6. Output $y$ and $Y_{cov}$ for LTI system with $\lambda = -0.01 + j2\pi0.04$, $\zeta = 3.97$](image)

<table>
<thead>
<tr>
<th>Case</th>
<th>$\lambda$</th>
<th>$\omega_N$ (rad)</th>
<th>$\zeta$ (%)</th>
<th>$Y_{cov}$ Calc.</th>
<th>$Y_{cov}$ Meas.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.1$+\pi$2 0.4</td>
<td>2.5153</td>
<td>3.97</td>
<td>0.246</td>
<td>0.243</td>
</tr>
<tr>
<td>2</td>
<td>-0.1$+\pi$2 0.04</td>
<td>0.2705</td>
<td>36.97</td>
<td>0.247</td>
<td>0.282</td>
</tr>
<tr>
<td>3</td>
<td>-0.01$+\pi$2 0.4</td>
<td>2.5133</td>
<td>0.40</td>
<td>2.484</td>
<td>2.097</td>
</tr>
<tr>
<td>4</td>
<td>-0.01$+\pi$2 0.04</td>
<td>0.2515</td>
<td>3.97</td>
<td>2.497</td>
<td>2.049</td>
</tr>
<tr>
<td>5</td>
<td>-0.5$+\pi$2 0.4</td>
<td>2.5625</td>
<td>19.51</td>
<td>0.047</td>
<td>0.052</td>
</tr>
</tbody>
</table>
V. Methodology

It is reasonable to assume that in ambient conditions the power system behaves as a linear time invariant system. The system response can be expressed as a sum of finite numbers of damped sinusoidal signals. Expressed as function of time

\[
y(t) = \sum_{l=1}^{d} a_l e^{\alpha_l t} \cos(\omega_l t + \phi_l)
\]  

(17)

The main aim is to identify or estimate all \(a, \alpha, \omega\) and \(\phi\) from discrete measurement samples of the signal \(y(t)\). The usual methods take the cue from the results shown in previous section that covariance of the measured signal with sufficient lags is proportional to the impulse response of the system. The effect of additive measurement noise and the inherent noise due to finite period of measurements can be mitigated from increasing the measurement period.

Once the auto-covariance matrix is obtained with enough accuracy then one of the numerous methods for parametric curve fitting can be applied to estimate the parameters of the system [16]. There are several methods used till now with almost similar results, here we will use the TLS-ESPRIT method which is shown to be one of the most accurate methods for spectrum estimation in [16].

Estimation of Signal Parameters Through Rotational Invariant Techniques (TLS-ESPRIT) [9] algorithm is used to estimate all \(a, \alpha, \omega\) and \(\phi\), from discrete measurement samples of the signal \(y(t)\).

The mathematical details of TLS-ESPRIT method is provided in [9], [16]. Here we discuss the application of the method to real power system frequency signal. There are several parameters in the method that require proper tuning to get the reliable results. The major parameters include, ensuring the adherence to basic assumption regarding stationarity and zero mean nature of the input signal. Next, is selection of number of dominant modes, the duration of input data and the sampling time.

A. Preprocessing

As discussed in the [13], we have a simple frequency meter working of a zero crossing detector principle. Moreover the frequency meter is connected to academic laboratories measuring frequencies at 230 V power outlets.

The input data sometimes have some missing sample and also some samples that are outliers. In the preprocessing stage we eliminate such data points and concatenate the remaining data. Ref. [3], as well as our own studies have confirmed that discarding some small percentage of bad data does not effect the final result.

The frequency in India varies by a large margin due to absence of automatic secondary frequency system. This variation in frequency is not due to any power system oscillations but a very slow (compared to usual oscillation frequencies) random drift. To ensure the stationarity and zero mean nature of the input signal this drift have to be filtered out. Moreover the measurement itself contains a high frequency measurement noise, which is also filtered out so that it does not mask the real oscillation frequencies.

Initially a fourth order Butterworth filter was considered for preprocessing. The fourth order IIR Butterworth filter is very efficient filter, but its phase response is non linear and hence different frequencies in the pass bands are phase shifted by different angles. Also its transition band from pass band to stop band is not very sharp. Hence another FIR filter is also implemented as a substitute for Butterworth filter. This FIR filter has linear phase response and sharper transition band. As the actual signal is measured at 50 Hz while the pass band required is from 0.1 Hz to 1.5 Hz the default FIR filter is of more than 2000 order. Here we applied multistage filtering and resampling techniques [16] to overcome this high order filtering. The actual high pass filter to remove frequency below 0.1 Hz was implemented as four stages of 5 Hz, 1 Hz, 0.2 Hz and 0.1 Hz, with first three stages of order 40 and the last stage with order 80.

B. Mode Identification

A major decision is the selection of the parameter for length of the covariance lag and number of dominant modes. The TLS-ESPRIT algorithm decomposes the signal as linear combination of \(d\) vectors in \(M\) dimensional subspace, where \(M\) is length of lag of covariance. Hence, it is required that \(M > d\). Moreover in presence of noise, it is observed that the frequency estimation is reliable when there is at least half a cycle of the signal covered by the vector of length \(M\). The lowest frequency component in the input signal is 0.1 Hz, due to the lower cut off frequency of the preprocessing filter. Combined with the knowledge of sampling time of 200 msec. we get the limit of \(M\) equal to 25. Here we selected \(M = 100\) corresponding to frequency limit of 0.025 Hz. Larger value of \(M\) is not desirable as it increases the dimension of the covariance matrix \(Y_{\text{cov}}\), whose dimension is \(2M \times 2M\). The first step of the TLS-ESPRIT algorithm is to calculate \(2d\) dominant eigen values of \(Y_{\text{cov}}\).

Choice of \(d\) depends on the expected number of the independent frequency components in the signal. Usually large \(d\) will better fit of the signal, but also give rise to spurious signals that are mere numerical artifacts. TLS-ESPRIT method provides an easy way to identify the spurious signals and discard them at the very beginning. The idea of subspace separation is that the signal subspace is dominant over the noise subspace. There are only few singular values of \(Y\) corresponding the signal subspace with dimension \(2d\). The rest of the singular values corresponds to the noise subspace. We use the fact that vector norm of set of all eigen values of a matrix is equal to the Frobenious norm of that matrix. The dimension of signal subspace can be identified by a criteria such that.

\[
\begin{align*}
\text{min } p & \quad p = 1, \cdots, N \\
\text{s.t. } & \sqrt{\sum_{k=1}^{p} \sigma_k^2} \geq \kappa ||Y||_F \\
\end{align*}
\]  

(18)

Where \(\sigma_k\) are singular values of \(Y\). \(\kappa\) is parameter for controlling how many signal components are considered. Usually value of \(\kappa\) is kept larger than 0.9. \(p\) separates out the dominant
signal subspace created by the range of the first $p$ vectors of $V$. The subspace spanned by rest of the vectors of $V$ corresponds to the noise subspace. In practice we do not calculate the SVD of $\mathbf{Y}$ as it is numerically very costly. Instead we use limited eigen value calculation of $\mathbf{Y}_{\text{cov}}$. Using the knowledge that eigen values of $\mathbf{Y}_{\text{cov}}$ are equal to square of the singular values of $\mathbf{Y}$, and applying (18) we can find $p$.

Then the usual TLS-ESPRIT algorithm is followed for calculating the selected signals frequency $\omega$ and amplitude $a$ are calculated. The phase angle term $\phi$, do not make much sense for frequency estimation from ambient signals.

C. Calculation Window

We use the time block of 600 sec, at a sample time on 200 msec. for calculating the oscillatory modes through TLS-ESPRIT. The available data sampled at 20 msec, is down sampled for this purpose. Use of down sampled data does not lead to any big loss of accuracy, but provides a very significant saving in the computation time. These choices correspond to parameter $h = 0.2$ and $M \times N \approx 3000$.

A sliding window frequency estimation is performed with the shift of 100 seconds for each window. Hence we obtain new frequency parameters of oscillatory modes every 100 seconds using the preprocessed data of previous 600 seconds. One could select a shift of smaller value like 20 seconds or a larger value like 300 seconds, with corresponding increase or decrease in the computation effort respectively. The choice of shift of 100 seconds is just for convenience. The amplitude of each mode is calculated in a batch five vectors each of length $M$, corresponding the frequency data of 20 seconds. So five such vectors taken at consecutive time cover the sliding window shift of 100 seconds.

D. Mode Identification

The analysis is performed on the measured frequency signals using the methodology described in the previous sections. As we are interested in identification of the dominant oscillating modes from ambient frequency measurements, the sequential analysis is performed on a continuous basis. The frequency and the amplitudes of oscillations are compared over different periods and over different locations. Some inferences about the state of the network is drawn through the evolution of modes over a period of time, absence or presence of some modes and their magnitude. The next sections gives preliminary results and discusses their significance.

VI. RESULTS AND DISCUSSIONS

TLS-ESPRIT algorithm was applied to frequency measurements for a period of 12 hours on frequency measured. The results of one such calculation are displayed in Fig. 7 - 9. The first two plots corresponds to measurements for same period at two different locations viz. Mumbai and Kanpur.

Clipping the complete result of 12 hours together the mode frequency amplitude and histogram reveals a clearer picture. The resolved frequencies are clustered around two distinct modes, centered around 0.1 Hz, and between 0.4 Hz to 0.5 Hz. This is true for both the locations. The 12 hours period with sliding window rate shift of 100 seconds gives 432 slots of mode calculations. Histogram shows the measured numbers of occurrence of a given mode in these slots. The dominant peak of histogram is at 0.1 Hz, which is the cut off frequency of the preprocessing filter, and it can be ignored as an artifact of the preprocessing algorithm. The rest of the center frequencies of cluster show the intermittent nature of the 0.4 Hz mode. Further calculation of different periods also shows similar results.

![Fig. 7. Modes Identified at Mumbai Through WAFMS](image)

![Fig. 8. Modes Identified at Kanpur Through WAFMS](image)

![Fig. 9. Modes Identified Through PMU measurements](image)

Apart from the frequency signal obtained from WAFMS system, an actual PMU measurement of frequency was obtained from PowerGrid India. This data was sampled at rate of 1 sample per sec. The result of similar analysis as above is presented in Fig. 9. Here it is observed that modes between 0.4 Hz and 0.5 Hz is intermittently measured, and all other modes are absent. This compares well with the results obtained from WAFMS measurements.
Voltage magnitude data measured from PMU is also available. However it is very noisy and the analysis through TLS-ESPRIT fails to identify any dominant frequencies from that data. This could be the case of errors introduced due to feedback coupling that is locally possible in voltage data.

Out of the identified mode frequencies, the 0.4 Hz frequency seems to be in agreement with the established theory of the inter area oscillations, which states the range of their frequency between 0.2 to 0.5 Hz.

A recent report [23] published by PowerGrid India, have highlighted the observations of 0.4 Hz mode for a long time of about 5 minutes. This was attributed to a faulty control system of two 500 MW thermal generators. Power generation of the units varied from 30 MW to 250 MW and caused this mode to be excited at high amplitude. Indirectly this shows the validity of using probing signal to elicit the modes of system. But, the report overlooks the fact that similar oscillations of 0.4 Hz but of lower magnitude were observed throughout the period of 12 before the said observation. Such incidents also require further investigations.

VII. Conclusion

Identification of oscillations modes in power system through observation of the ambient disturbance in frequency can be achieved with a reasonable accuracy. The analysis through LTI system response to white noise gives valuable insights regarding the methods and expected outcome of the identification techniques. The paper demonstrates the use of TLS-ESPRIT algorithm for power system oscillation mode identifications. With applications to real life data, and through testing with tuning of different parameters of the algorithm the characteristics of the algorithm is judged. The TLS-ESPRIT algorithm, combined with proper preprocessing, was found reliable in identifying the modes of oscillations even under noisy measurement environment. This paper also shows effectiveness of using simple NTP based wide area frequency measurement system in performing quite useful analysis. The modes revealed by the analysis of this paper give motivation for further research in characterization of very low frequency oscillations observed in Indian power network.

Acknowledgment

The authors would like to thank Prof. A M Kulkarni and his students for WAFMS and PowerGrid India for providing an actual PMU data.

References