Confidence Intervals Estimation in the Identification of Electromechanical Modes from Ambient Noise

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***Abstract*— This paper discusses the estimation of uncertainty intervals associated with the electromechanical modes identified from ambient data resulting from random load switching throughout the day in power systems. A connection between the second order statistical properties, including confidence intervals, of the identified electromechanical modes and the variance of the parameters of a selected linear model is demonstrated. The results of the presented method are compared with respect to the ones obtained from a Monte-Carlo technique, showing its effectiveness in reducing the number of trials, which would be beneficial for on-line power system monitoring, as it can decrease the number of samples, thus ensuring that the system dynamics would not change significantly over the monitoring time window, and yielding more dependable results. Two test cases, namely, the 2-area benchmark system and the IEEE 14-bus system, with different orders of the system identification model used, are utilized to demonstrate the effectiveness of the proposed methodology.**

***Index Terms*— Power system oscillations, modal analysis, power system monitoring, system identification, prediction error methods.**

I. Introduction

ON-LINE power system monitoring based on system identification techniques is of great help for providing insightful information regarding the stability condition of the system under study, as well as for validating system models and data used in off-line studies. These techniques have been proposed and are being used to quickly identify poorly damped electromechanical modes of a power system based on field measurements, since the use of linearizations of the system's differential-algebraic equation (DAE) models, and the manipulation of the corresponding matrices in order to calculate the relevant system modes on line is problematic for two main reasons: determining the appropriate model and required data for a large system is an issue, given the changes the system is continuously undergoing; and computing the desired modes using large matrices is a computationally intensive process, which is not particularly well suited for on-line applications. These measurement-based techniques are particularly relevant nowadays that phasor-measurement units (PMUs) are being widely deployed and utilized.

Identification techniques and models are either based on the deterministic transient response of the system to a large disturbance or random ambient noise. The required transient response is normally obtained from ringdown tests and major disturbances, such as adding/removing loads, severe faults and tripping generators; the well-known Prony method, which employs a deterministic model, has been widely used to analyze this kind of response in power systems [1]–[4]. On the other hand, ambient noise, which is a low quality signal, is the natural response of a power system due to small-magnitude, random load switching; thus, stochastic models such as auto-regressive (AR) models [5], auto-regressive moving-average (ARMA) models [6], and stochastic state-space models [7], [8] have been used in this case. Adaptive identification techniques have been employed as well to track both moving and stationary modes on-line [9]–[11].

Identified electromechanical modes from stochastic models are usually represented by a mean value and the corresponding confidence interval, which are estimated by means of Monte-Carlo-based studies applied to either simulated or actual measured data [6], [7]. However, the drawback in this approach is that it requires repeated simulations or measurements, which in turn can violate the stationarity assumption of the measured signal over a long-time window, since system dynamics may undergo significant changes due to, for example, significant changes in the generator units' dispatch conditions. Therefore, experiments should be carried out in a time window as short as possible, which is what motivates the work presented in the current paper. The authors in [12], [13] introduce a bootstrap method to give confidence interval estimates for electromechanical modes, and its performance is studied by comparing the results with respect to the ones obtained by means of a Monte-Carlo approach. This technique requires resampling the measured data to estimate the parameters of the system model (e.g. ARMA) for the new data set, and is hence computationally expensive, since the resampling process is repeated for a large number of trials in order to obtain proper estimates of the confidence intervals.

The electromechanical modes are the roots of the characteristic equation corresponding to the selected model (e.g. AR or ARMA); hence, there is a nonlinear relationship between the model parameters and modes, and between their corresponding variances. Therefore, the theory of the variance of parameters, which is well-understood and developed [14], may be used in this case to determine the variance of these modes. Reference [15] describes a technique that has been used in civil engineering for identification of structures to establish a connection between the variance of parameters and the variance of modal parameters. Preliminary results of applying this particular technique to estimate confidence intervals of electromechanical modes identified from ambient

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data were reported in [16]; however, important issues such as performance and bias were not addressed in this paper. Hence, in the current paper, various aspects of this technique are more thoroughly examined, with the help of two test systems. It is shown here that a relatively small set of data may be used to estimate the mode uncertainties, thus reducing the required number of samples to facilitate the use of ambient noise in on-line modal analysis applications, such as system control or real-time security monitoring.

The rest of the paper is structured as follows: Section II presents the background on estimating the covariance of parameters of a linear parametric model within the context of prediction error methods (PEM) [17]; how to employ this information to estimate the confidence interval of the identified electromechanical modes is also explained in this section. The results of applying the proposed technique to the 2-area benchmark system and the IEEE 14-bus system, along with a discussion of various associated computational issues, are presented and discussed in Section III. Finally, Section IV summarizes the main contributions of this paper.

II. Covariances

A linear parametric model such as AR or ARMA used for representing a power system presents the following typical form:

$$y(k) = H(q)\, e(k) \tag{1}$$

where $y(k)$ is the measured output, such as power through a line; $e(k)$ models the disturbances, i.e. the underlying load switching in a power system; $H(q) = B(q)/A(q)$ is a rational transfer function with unknown parameters θ; and q is the shifting operator defined by $q^{-1}y(k) = y(k-1)$. One-step-ahead prediction $\hat{y}(k|\theta)$ uses the observations available up to time $k-1$ to predict $y(k)$, thus:

$$\hat{y}(k|\theta) = [1 - H^{-1}(q)]\, y(k) \tag{2}$$

This notation is adopted from [14], and is used here to emphasize the dependence on the parameter vector θ. For instance, for the following ARMA(p,d) model:

$$y(k) = -\sum_{i=1}^{p} a_i\, y(k-i) \;+\; \sum_{i=0}^{d} b_i\, e(k-i) \tag{3}$$

with p and d representing the order of the AR and the MA parts, respectively, $\theta = [a_1 \; ... \; a_p \; b_0 \; b_1 \; ... \; b_d]^T$. This vector can be computed, within the context of PEMs, by minimizing an objective function such as:

$$\begin{aligned} \hat{\theta} &= \text{arg min} \quad V_N(\theta) \\ V_N(\theta) &= \frac{1}{N}\sum_{k=1}^{N}\frac{1}{2}\epsilon^2(k,\theta) \\ \epsilon(k,\theta) &= y(k) - \hat{y}(k|\theta) \end{aligned} \tag{4}$$

where the function $V_N(\theta)$ denotes the loss which results from the model in the fitting process; "arg min" stands for the minimization argument of the function $V_N(\theta)$; N is the number of samples; and $\epsilon(k,\theta)$ represents the residuals. This requires an iterative search for θ that yields the minimum of the loss function $V_N(\theta)$. Equation (4) represents a nonlinear optimization problem, and thus may lead to local minima.

In this work, only the coefficients of the polynomial $A(q)$ in (1) are of interest, since the main objective here is to extract the modal content of the signal, which are the roots of $A(q)$. Hence, one may consider applying techniques such as the Yule-Walker method that only estimates the parameters of $A(q)$, thus employing more simplified and robust numerical techniques. It is also possible to model $y(k)$ in (3) with a high-order AR model, rather than using an ARMA model, as a result of Kolmogorov's theorem. This leads to an objective function that can be solved by means of well-known least square methods [18]. A high-order AR model, however, leads to extraneous modes close to the system modes, which could be difficult to distinguish from the true modes. Furthermore, an AR model may result in biased estimates if residuals are not white. It is also important to mention that when the signal-to-noise ratio (SNR) is low, the model structure is an ARMA rather than a pure AR. The least square modified Yule-Walker method, which has been employed in [6] to extract the modal content of the ambient noise, presents superior performance compared to the original Yule-Walker method as reported in [19].

The theory of variance of identified model parameters is well-understood and developed in the context of PEMs. Hence, this theory, as explained below, is used here to estimate the variance of identified modes, based on [17]. Thus, at the solution point $\hat{\theta}$, the differentiation of $V_N(\theta)$ with respect to θ has to be zero, i.e.

$$V_N^{'}(\hat{\theta}) = 0 \tag{5}$$

An iterative algorithm, such as Newton-Raphson's, may be used to obtain an appropriate solution for $\hat{\theta}$. Therefore, the Taylor series expansion of (5) around a given point θ^* close to $\hat{\theta}$, as discussed in [17], yields:

$$0 \approx V_N^{'}(\theta^*) + V_N^{''}(\theta^*)(\hat{\theta} - \theta^*) \tag{6}$$

or

$$(\hat{\theta} - \theta^*) = -\left[V_N^{''}(\theta^*)\right]^{-1} V_N^{'}(\theta^*) \tag{7}$$

Here, the first derivative (gradient) and second derivative (Hessian) are defined as follows:

$$V_N^{'}(\theta^*) = -\frac{1}{N}\sum_{k=1}^{N}\psi(k,\theta^*)\,\epsilon(k,\theta^*) \tag{8}$$

$$V_N^{''}(\theta^*) = \frac{1}{N}\sum_{k=1}^{N}\psi(k,\theta^*)\,\psi^T(k,\theta^*) + \frac{1}{N}\sum_{k=1}^{N}\psi^{'}(k,\theta^*)\;\epsilon(k,\theta^*) \tag{9}$$

where

$$\psi(k,\theta^*) = -\frac{d}{d\theta}\,\epsilon(k,\theta)\bigg|_{\theta^*} = \frac{d}{d\theta}\,\hat{y}(k|\theta)\bigg|_{\theta^*} \tag{10}$$

Observe that $\hat{y}(k|\theta)$ is an explicit function of θ, as per (2) and (3); hence, its derivative is well defined and readily computable. Close to the solution $\hat{\theta}$, the predicted errors $\epsilon(k,\theta)$ are independent; thus:

$$V_N''(\theta^*) \approx \frac{1}{N}\sum_{k=1}^{N}\psi(k,\theta^*)\ \psi^T(k,\theta^*) \tag{11}$$

A. Covariance of Parameters

It is known that $\sqrt{N}(\hat{\theta}-\theta^*)$ is asymptotically Gaussian distributed with zero mean and a covariance matrix P ($\mathcal{N}(0,P)$) [17]. Therefore, an estimate of P from available data can be obtained as follows:

$$\begin{aligned}\hat{P} &= \hat{\lambda}_0\ \left(V_N''(\theta^*)\right)^{-1} \\ \hat{\lambda}_0 &= \frac{1}{N}\sum_{k=1}^{N}\epsilon^2(k,\theta^*)\end{aligned} \tag{12}$$

where $\hat{\lambda}_0$ is an estimate of the variance of the errors. Then, the covariance of parameter estimates $P_{\hat{\theta}} = E[(\hat{\theta}-\theta^*)(\hat{\theta}-\theta^*)^T]$ can be approximated as:

$$P_{\hat{\theta}} \ \approx\ \frac{1}{N}\ \hat{P} \tag{13}$$

The modes of a system are the roots of the characteristic equation, and hence are only dependent on the AR part of an ARMA(p,d). Thus, the covariance matrix $P_{\hat{\theta}}$ is partitioned so that the rows and columns corresponding to the AR and the MA parts are separated as follows:

$$P_{\hat{\theta}} = \begin{bmatrix} P_{\hat{\theta}_{AR}} & P_{\hat{\theta}_{ARMA}} \\ P_{\hat{\theta}_{ARMA}} & P_{\hat{\theta}_{MA}} \end{bmatrix} \tag{14}$$

A relationship between $P_{\hat{\theta}_{AR}}$ and the covariance of modes is established below.

B. Covariance of Modes

System modes can be related to θ_{AR}, which are the coefficients of the characteristic equation, as follows [15]:

$$\Phi = \gamma(\theta_{AR}) \tag{15}$$

where $\gamma(\theta_{AR})$ is a nonlinear function, and Φ denotes a vector containing the modal parameters. For instance, the real part α and the frequency f of the modes can be used to define:

$$\Phi = [\alpha_1, f_1, \alpha_2, f_2, \ldots, \alpha_p, f_p]^T \in \Re^{2p} \tag{16}$$

In order to obtain the mean and variance of the modes, the expected value operator may be applied to a Taylor series expansion of the function γ about an operating point ($\hat{\Phi}$, $\hat{\theta}_{AR}$); thus:

$$\Phi \approx \hat{\Phi} + J(\hat{\theta}_{AR})\left(\theta_{AR} - \hat{\theta}_{AR}\right) \tag{17}$$

where

$$J(\hat{\theta}_{AR}) = \left.\frac{\partial\gamma(\theta_{AR})}{\partial\theta_{AR}}\right|_{\hat{\theta}_{AR}} \ \in\ \Re^{2p\times p} \tag{18}$$

Rearranging (17) and applying the second moment operator (covariance) yields:

$$\begin{aligned}\text{Cov }\Phi &= E\left[(\Phi-\hat{\Phi})\ (\Phi-\hat{\Phi})^T\right] \\ &= J(\hat{\theta}_{AR})\ P_{\hat{\theta}_{AR}}\ J^T(\hat{\theta}_{AR})\end{aligned} \tag{19}$$

This clearly shows the connection between the covariance of estimates $P(\hat{\theta}_{AR})$ and the covariance of modes Cov Φ. Therefore, in (19), $P_{\hat{\theta}_{AR}}$ can be estimated using (13), and a numeric Jacobian $J(\hat{\theta}_{AR})$ can be obtained as follows:

$$\begin{aligned}J_{ij}(\hat{\theta}_{AR}) &\approx \frac{\gamma_i(\hat{\theta}_{AR}+\Delta\theta_j) - \gamma_i(\hat{\theta}_{AR}-\Delta\theta_j)}{2h} \\ &\approx \frac{\Phi_{i_{+\Delta\theta_j}} - \Phi_{i_{-\Delta\theta j}}}{2h}\end{aligned} \tag{20}$$

where $\Delta\theta_j = [0\ \cdots\ 0\ \underbrace{h}_{j}\ 0\ \cdots\ 0]$, with h being a small number. Observe that a numerical Jacobian is needed since (15) cannot be written in explicit form in practice.

C. Implementation Issues

Regardless of the approach used to estimate an electromechanical mode, i.e. a Monte-Carlo technique or the aforementioned method, and the corresponding uncertainty, selecting proper orders is essential for obtaining accurate results. For power system monitoring applications, as a common practice, model order selection has been mostly carried out by means of trial and error; however, analytical approaches have been employed as well [20], [21]. For PEM-based techniques, different criteria such as the Akaike information criterion (AIC) or the final prediction error (FPE) have been proposed to select the best order of the model [14]; these techniques are defined based on prediction error variance. For instance, to choose the orders of an ARMA (p,d) model, a range for p and d is selected first, and then, for each pair, the parameters of the model are estimated; the pair obtaining the lowest value of the AIC or FPE criterion is selected as the best estimate of the model order.

For a given ARMA(p,d) model, the following steps, along with some built in functions of MATLAB's System Identification Toolbox [22], were used to obtain the estimates:

1) Compute $\hat{\theta}$ and $P_{\hat{\theta}}$, which also yields $P_{\hat{\theta}_{AR}}$ when partitioned as in (14), by means of the PEM (4); the MATLAB function `armax()` was used here for this purpose.
2) Define Φ for the mode(s) of interest and compute the corresponding numeric Jacobian $J(\hat{\theta}_{AR})$ as per (16) and (20), respectively.
3) Calculate the covariance of modes using (19).

III. Test cases

The proposed method for estimating the standard deviation of the identified modes is tested with the 2-area benchmark system and the IEEE 14-bus system. First, a Monte-Carlo analysis with 150 independent simulations is performed. For these trials, 1% of the loads are represented as Gaussian noise; 4 min data blocks of a generator output power are recorded in each simulation, and white Gaussian noise is added to the output signals as measurement noise, so that the SNR is 20 db. The signals are then passed through a Chebyshev low-pass filter with a cut-off frequency of 2 Hz, and resampled at a 10 Hz rate. The preprocessed data blocks along with a PEM are employed to estimate the parameters of an ARMA(p,d) model representing the power system transfer function.

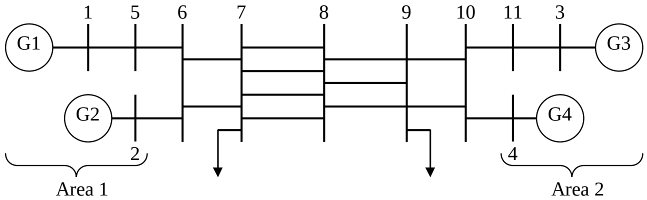

Fig. 1. Two-area benchmark system.

A. Two-area Benchmark System

A single line diagram of the system is shown in Fig. 1 [23]. The generators are modeled using subtransient models and simple exciters equipped with PSSs. The corresponding static and dynamic data is given in [19]. The total base loading level is 2734 MW and 200 MVar, and loads are modeled as constant PQ loads.

Areas 1 and 2 are connected through tie-lines, and an inter-area mode with a frequency of about 0.75 Hz is observed. The individual machines in each area also contribute to a local mode in the same area with frequencies of about 1.2 Hz and 1.4 Hz in Areas 1 and 2, respectively. Thus, an inter-area rotor angle mode and two local modes are observed for this test case. Figure 2 shows typical ambient noise on the generator G_3's output power P_{G_3}. The power spectrum density of P_{G_3}, obtained via an averaged modified periodogram Welch method [24], is depicted in Fig. 3, showing that both the inter-area and the local modes in Area 2 are being excited due to underlying, random load switching in the system.

An ARMA(p,d) model with different p's and d's is employed to model the measured signal in every simulation. The mean of the estimated electromechanical mode corresponding to each model for 150 trials is depicted in Fig. 4, together with the "true" mode, $-0.1228 \pm j4.7824$, obtained from a linearized model (LM) of the power system. Observe that when a pure AR(15) model, i.e. ARMA(15,0), is selected, the results are not as close to the LM mode as ARMA(p,d) with $d \neq 0$; this was also noticed in [6], [15]. From the system identification point of view, an ARMA model set is more likely to adequately represent the true system than an AR model; in this case, the estimated parameters would be asymptotically unbiased [14], as it can be seen comparing Figs. 5 and 6. In these plots, as in other similar plots discussed further ahead in this section, the Monte-Carlo results are shown as a cumulative mean, i.e. the sum of the corresponding values divided by the number of trials.

The estimated standard deviation of both the real part and frequency of the inter-area mode obtained using (19) is depicted in Figs. 7 and 8. Observe that the estimates track the results corresponding to the Monte-Carlo simulation, and the mean of the estimates can provide reasonably good accuracy with a significantly reduced number of trials. For instance, in Fig. 8, the convergence speed of the standard deviation of estimates is about 5 times faster than the Monte-Carlo method, thus yielding significant reduction in the monitoring time.

Notice that the uncertainty associated with the real part of the mode is relatively large when compared with the one for the frequency (e.g. the standard deviation of the real part of the mode depicted in Fig. 8 is about 25% of the actual real part, whereas it is only about 0.6% for the frequency). This is due to the fact that obtaining accurate estimates of mode damping in power systems using system identification is more difficult [5]–[7].

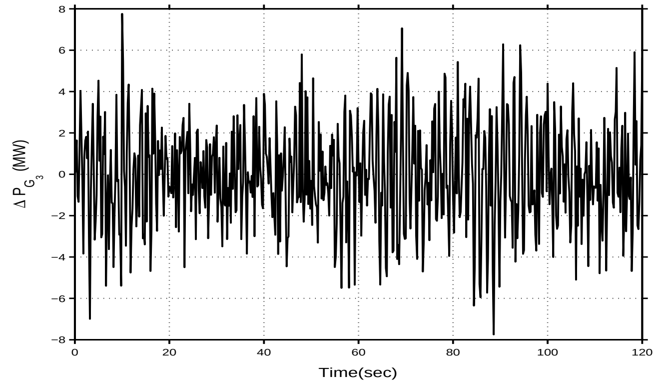

Fig. 2. Two-minute block measurement of the change in G_3's power at 2734 MW loading level for the 2-area benchmark system.

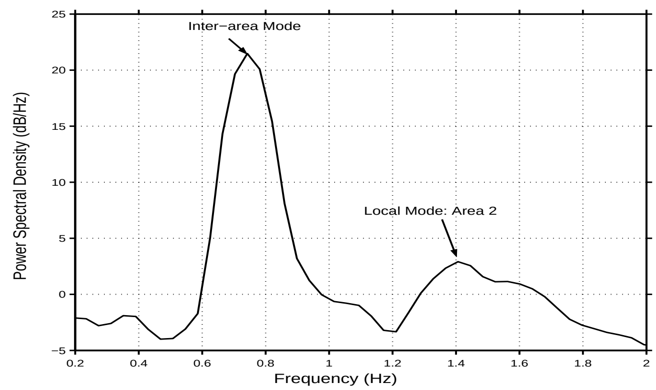

Fig. 3. Power spectral density of ΔP_{G_3} in the 2-area benchmark system.

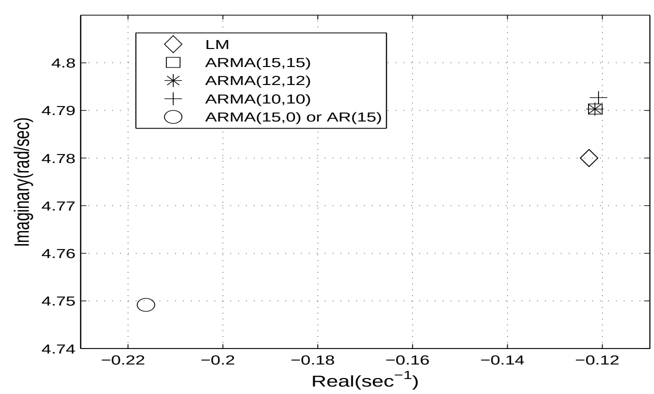

Fig. 4. Mean of the identified inter-area mode $-0.1228 \pm j4.7824$ for the 2-area benchmark system using a Monte-Carlo method with 150 independent simulations.

B. IEEE 14-bus System

The test system is shown in Fig. 9. It has 5 generators with two of them providing both active and reactive power at Buses 1 and 2; the generators at Buses 3, 6 and 8 are basically synchronous condensers [25]. The generators are modeled by

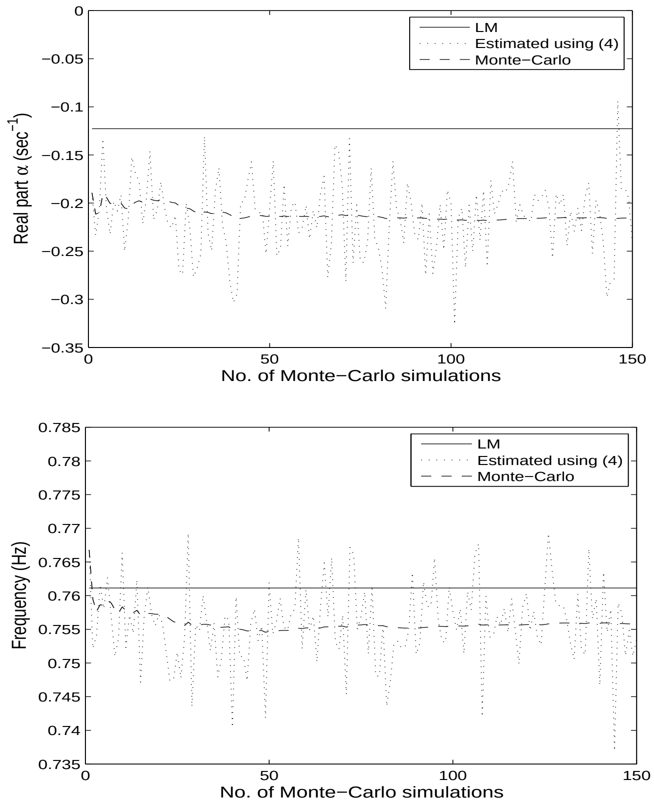

Fig. 5. Real part and frequency of the identified inter-area mode $-0.1228 \pm j4.7824$ for the 2-area benchmark system; AR(15).

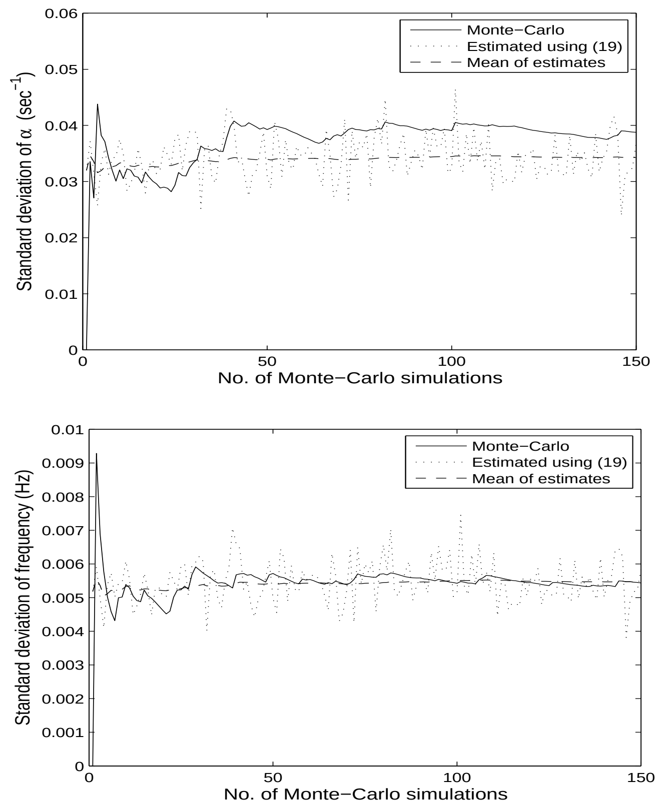

Fig. 7. Standard deviation of the real part and the frequency of the identified inter-area mode $-0.1228 \pm j4.7824$ for the 2-area benchmark system; AR(15).

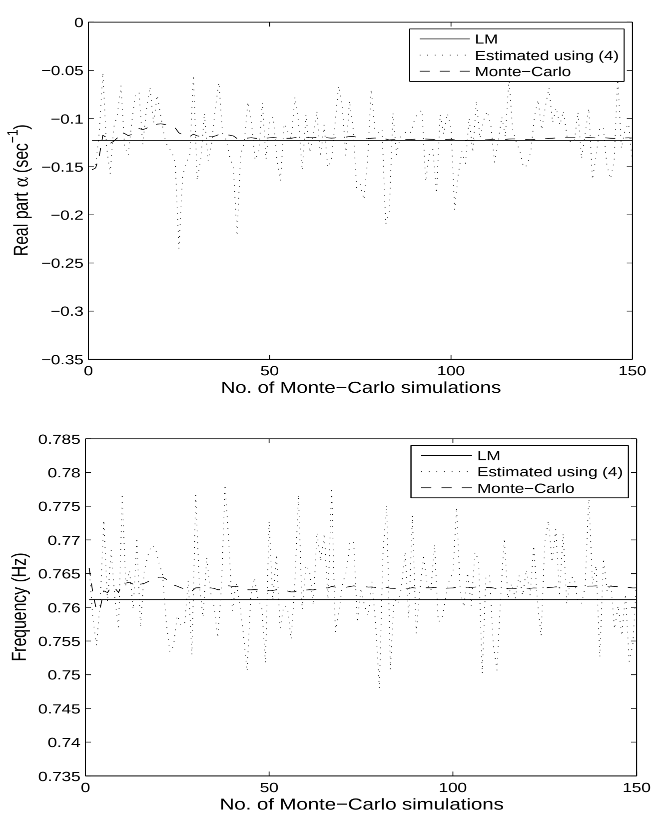

Fig. 6. Real part and frequency of the identified inter-area mode $-0.1228 \pm j4.7824$ for the 2-area benchmark system; ARMA(10,10).

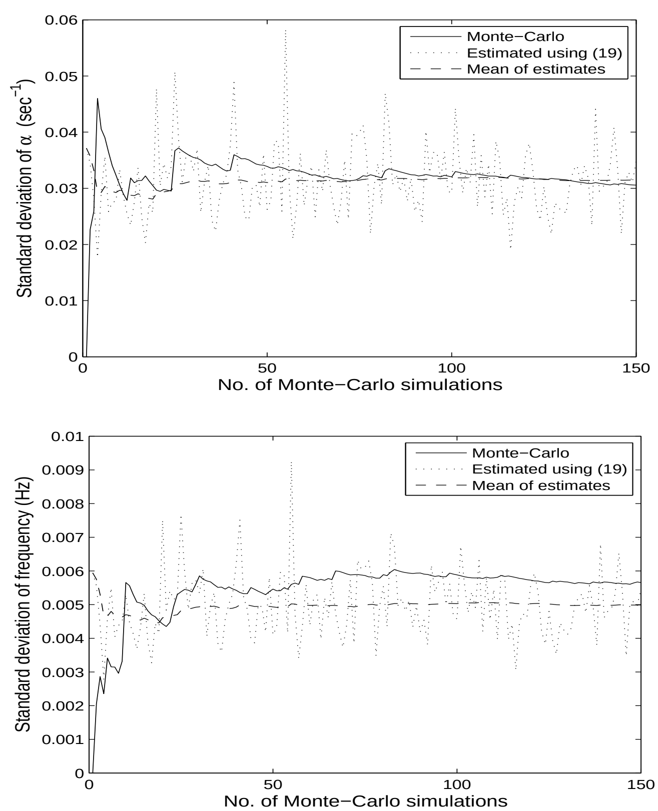

Fig. 8. Standard deviation of the real part and the frequency of the identified inter-area mode $-0.1228 \pm j4.7824$ for the 2-area benchmark system; ARMA(10,10).

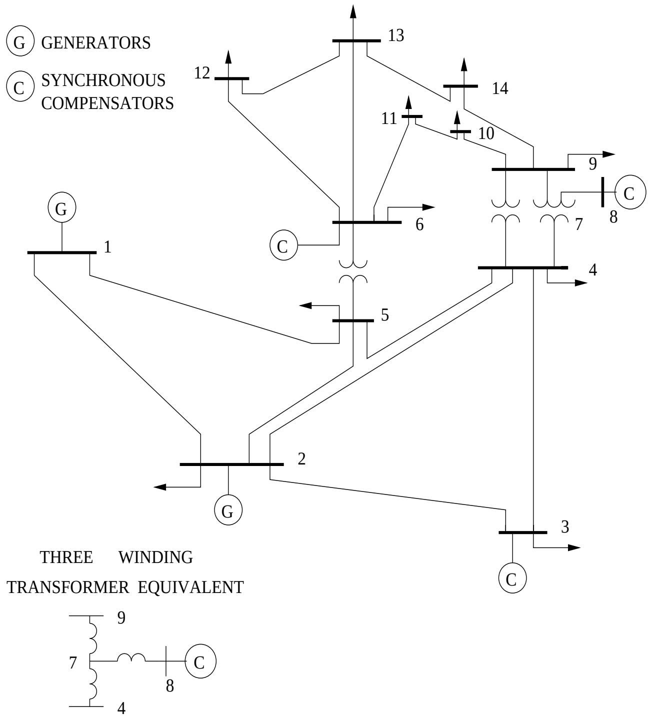

Fig. 9. IEEE 14-bus test system.

means of subtransient models and equipped with DC exciters (type 1), and the loads are represented as constant impedances. The base total loading level of the system is 259 MW and 81.3 Mvar. The corresponding static and dynamic data is presented in [19].

As with the 2-area benchmark system, an ARMA model is also used here to model the system from measured signals. The parameters of the model, which are used to calculate the modes, are estimated by PEM. The cumulative means of the real part and frequency of the identified electromechanical mode for an ARMA model with different orders are depicted in Figs. 10 and 11, compared with respect to the true mode, $-0.22 \pm j8.83$, obtained from an LM of the power system. These plots show that the ARMA models used capture the mode effectively, as the calculated results are relatively accurate. Observe that the differences in the results obtained with the ARMA(12,12) and ARMA(14,14) models is minimal; this indicates that the ARMA(12,12) model is a better choice for representing the system, as per the parsimony principle [14], which suggests selecting the simplest model that can accurately represent a system. It is important to highlight the fact that these models are not able to remove the bias as effectively as in the previous example. This is mainly due to the use of short 4 min data blocks; as shown in [6], [7], this bias can be eliminated by using longer data blocks (in [6], the authors show that for a test system's mode with 3% damping, the bias can be eliminated by using data blocks that are at least 20 min long). The use of short data blocks here is because of the need to test the feasibility of the method for on-line applications, which requires the use of short time windows to avoid violating the stationarity assumptions.

The estimated standard deviations of both the real part and

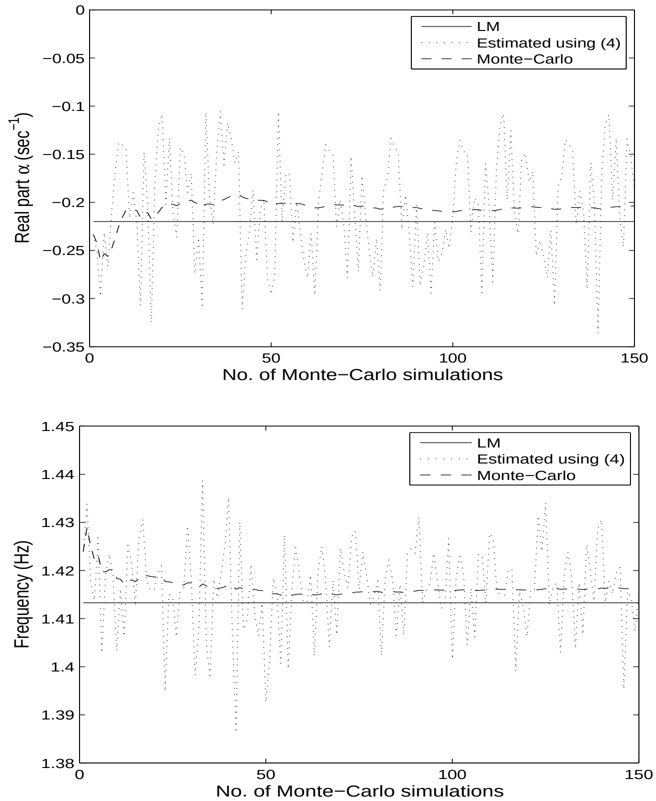

Fig. 10. Real part and frequency of the identified inter-area mode $-0.22 \pm j8.83$ for the IEEE 14-bus system; ARMA(12,12).

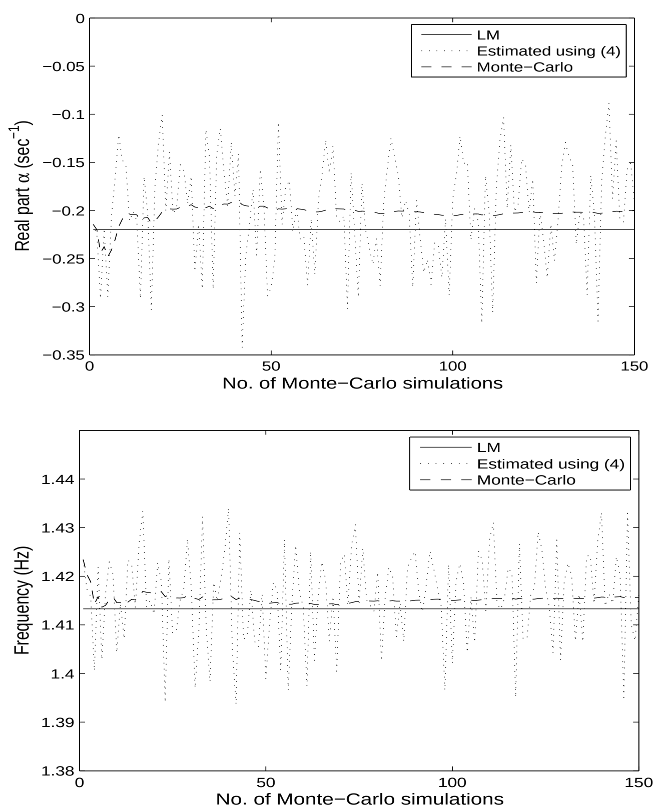

Fig. 11. Real part and frequency of the identified inter-area mode $-0.22 \pm j8.83$ for the IEEE 14-bus system; ARMA(14,14).

the frequency of the electromechanical mode obtained using (19) for the two model orders are depicted in Figs. 12 and 13. Observe that the estimated standard deviations properly track the results corresponding to the Monte-Carlo simulation; hence, the estimated means can be used to significantly reduce the number of Monte-Carlo trials needed to determine the standard deviation values. As expected, the uncertainty associated with the real part is relatively large compared to the uncertainty associated with the frequency.

C. Computational Issues

The previous sections concentrate on discussing the accuracy of the proposed method for estimating the confidence intervals. For on-line applications, CPU times and stationarity assumptions are important; hence, the performance of the proposed method from these perspectives is discussed here.

As explained in Section II-C, in order to estimate the confidence interval of a mode, one needs to first estimate $\hat{\theta}$ and $P_{\hat{\theta}}$ using PEMs; this in turn requires solving the optimization problem (4), which is computationally more demanding compared to previously used conventional parameter estimation techniques [5], [6]. For the analysis of the 2-area benchmark system using an ARMA(10,10) model, the CPU time required to complete all the proposed method steps is 0.7 s. On the other hand, a Monte-Carlo analysis with only 30 trials, which from the previous discussions is about the number of trials required to obtain a somewhat adequate approximation of the confidence interval in this case, and employing the modified least-square Yule-Walker method [6], [18] takes 0.33 s. The CPU time differences are insignificant, and are not dependent on system size, but rather on the size and length of the data blocks and the ARMA model; however, the differences in the amount of data required is quite significant, since 30 trials require 120 min of data (4 min data blocks have been used here), thus clearly violating the stationarity assumptions, whereas the proposed method requires 5-10 data blocks, i.e. 20-40 min of data, to produce a reasonable estimate of the confidence interval.

It is important to highlight the fact that the proposed method is adequate for monitoring the system in normal operating conditions, which are characterized by relatively small and continuous changes in the system, so that low damped modes can be properly tracked in case these become critical. When relatively large perturbations occur, as in the case of system contingencies, one should switch to a Prony method type of identification approach, which yields adequate estimates of critical modes from large system transients using relatively short data blocks, so that sudden changes in critical modes can be properly monitored.

IV. Conclusions

A novel procedure to calculate the second order statistical properties of identified electromechanical modes from ambient noise in power systems is presented and justified. The proposed method is based on a technique that uses Taylor series expansions to establish a connection between the variance of model parameters and the variance of eigenvalues. The

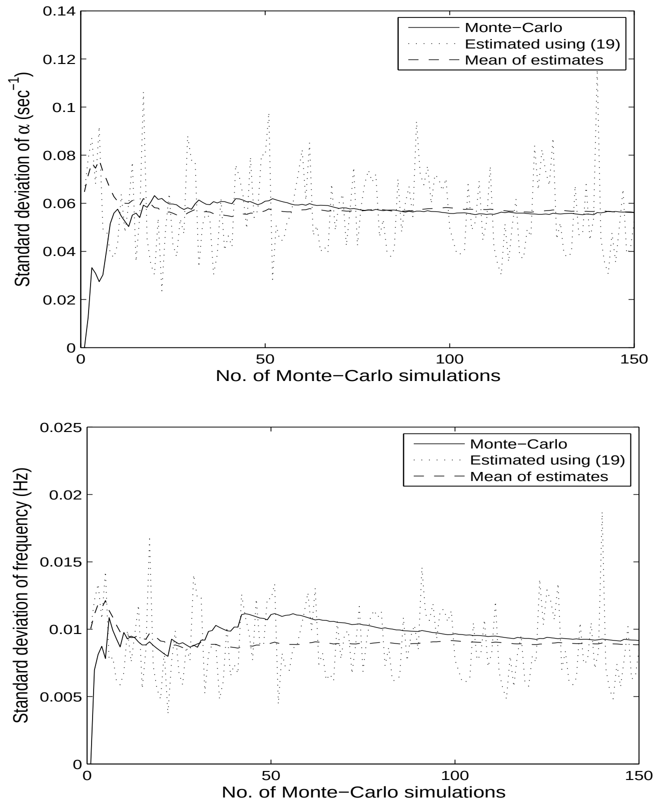

Fig. 12. Standard deviation of the real part and the frequency of the identified electromechanical mode $-0.22 \pm j8.83$ for the IEEE 14-bus system; ARMA(12,12).

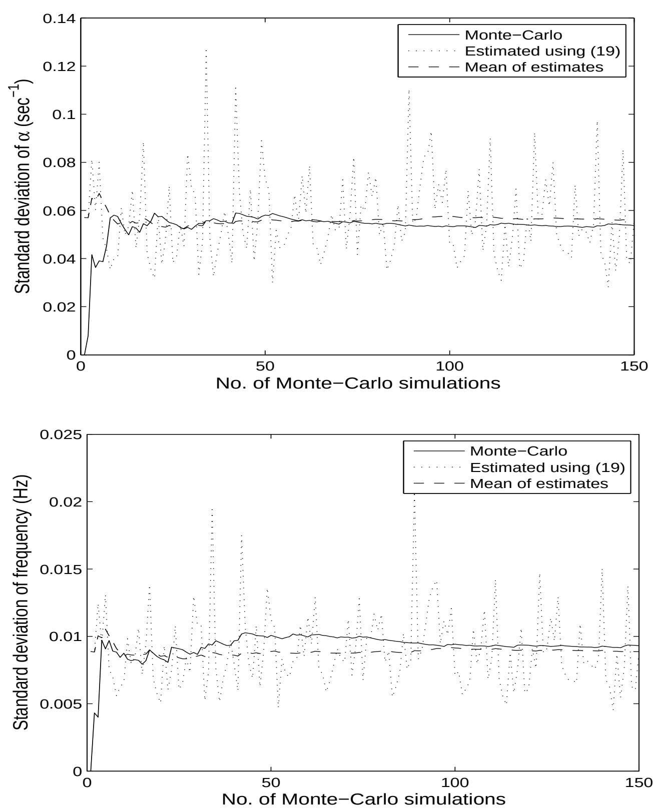

Fig. 13. Standard deviation of the real part and the frequency of the identified electromechanical mode $-0.22 \pm j8.83$ for the IEEE 14-bus system; ARMA(14,14).

variance of parameters are estimated using only one data block, i.e. one set of simulation data, and this information is then employed to estimate the uncertainty associated with the identified electromechanical modes. The proposed methodology was tested using simulated measurements obtained from two benchmark systems; the results obtained demonstrate the accuracy and possible advantages of the proposed method for on-line modal analysis applications.

The proposed technique can be used to avoid Monte-Carlo-based methods, thus resulting in a significant reduction in the monitoring time windows. This method should facilitate the use of ambient noise in on-line modal analysis applications, such as system control or real-time security monitoring, when the system is not undergoing significant disturbances such as tripping of lines or generators.

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