



Input-Output Metrics for the Power-Grid's Swing Dynamics

Final Project Report

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Power Systems Engineering Research Center
*Empowering Minds to Engineer
the Future Electric Energy System*



Input-Output Metrics for the Power-Grid's Swing Dynamics

Final Project Report

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Executive Summary

Power systems around the world are undergoing major changes as we transition from fossil-fuel dominated generation to intermittent renewable generation sources. Moreover, power grids are having to deal with extreme weather events and unforeseen operating conditions. In these circumstances, controller designs which are based on offline studies and detailed physical models may not be able to adjust to sudden changes in system operating conditions. This report proposes an adaptive control design framework for damping inter-area oscillations in power systems. The design is entirely based on ambient synchrophasor measurements and does not require detailed physical system models. The proposed framework consists of three components, namely, input-output transfer function estimation, channel selection, and feedback control implementation. For the first part, we propose a simple yet effective novel estimation algorithm in the frequency domain to identify low-order transfer functions in pre-specified frequency ranges between the measured input and output data using ambient synchrophasor measurements. In the second part, based on the identified transfer functions, the joint controllability-observability (JCO) of all identified channels is estimated and suitable control candidates for damping the target inter-area mode are selected. Finally, an appropriate lead-lag controller is designed using a classical frequency-domain method to improve the damping of a dominant oscillatory inter-area mode. Since ambient data is used in the analysis, the selected channel as well as the designed controller parameters can be updated online whenever the system operating point changes resulting in an efficient adaptive controller. The effectiveness of the proposed framework is illustrated by implementing it on the two-area Kundur test system.

The research developed in this project is partially described in the following paper which is under review.

Project Publications:

- [1] M. Hatami, K. Koorehdavoudi, H. Wajid, V. Venkatasubramanian, P. Panciatici, F. Xavier, and G. Torresan, "Online Transfer Function Estimation and Control Design Using Ambient Synchrophasor Measurements", in review.

Part I

Online Transfer Function Estimation and Control Design Using Ambient Synchrophasor Measurements

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1. Introduction

1.1 Background

Power system electromechanical oscillations have been a major concern for system reliability coordinators for decades. Negatively damped wide-area oscillations can lead to widespread blackouts such as was experienced on August 10, 1996 [1]-[2] in the western American interconnection. Poorly damped inter-area oscillations can be a concern for operational reliability of the system, and recent instances include the European interconnection oscillation event on December 3, 2018 [3]. Poorly damped and sustained oscillations can potentially endanger safety and longevity of expensive system components owing to fatigue and vibrations on physical quantities [4]. In general, oscillation concerns limit inter-area power transfers along tie-lines and can result in a less-economical operating system.

1.2 Overview of the Problem

A significant amount of research has been conducted in the past three decades on both monitoring [5]-[7] and control [8]-[11] of power system low-frequency oscillations. Feedback control is known to be effective in damping out system oscillations through controllers such as power system stabilizers (PSSs) [8], power electronic controllers [10], and High Voltage DC (HVDC) lines [12]. The two key elements in a feedback control scheme are the control location and the choice of feedback signal, together making a control channel. Joint controllability-observability (JCO) has been widely utilized as a measure for ranking the control channels and for choosing the best signals [10], [13]. Early research indicated that wide-area or remote measurements can be much more effective than local ones because of having higher JCO [14].

In [10], in addition to JCO, three other indices are used to determine the best control channel: right-half plane zeros for single-input single-output design and relative gain array and minimum singular value for multi-input multi-output design. An accurate and well-detailed model of the system can result in an effectively designed controller for the real system. However, relying solely on offline system dynamic models for controller design may be problematic in practice for the following reasons:

- Validating the small-signal modal properties of large interconnections in terms of the mode shape properties and their damping levels remains a challenging task even today [4].
- Dynamic models of real power systems are of very high order. For instance, the WECC dynamic model has over 40,000 states. Some of the proposed model-based controller design techniques require handling and operation of such large matrices in computationally expensive optimization problems which makes their application challenging.
- Analysis and control designs based on offline system models tend to be conservative and cannot easily adapt to real-time changes in system operating conditions.

- Detailed models of each system component are required to build the overall system model, and this is becoming challenging with growing integration of renewables with complex power electronic controls.

Phasor measurement units (PMUs) provide time-synchronized measurements throughout the system yielding a *wide-area view* of the system. This report proposes an alternate approach for online control design using available ambient PMU measurements.

Analysis of the PMU data for extracting some of the system dynamic features requires some form of a system identification procedure. Initial attempts for power system identification using system measurements can be traced back to Hauer's work [15] in the late 1970s where a software package for structural transfer function fitting to the given system frequency response was developed. Applications, limitations, and further developments of the aforementioned software package are discussed in [16]. Later, the initial output-only Prony technique was applied for input-output transfer function identification in [17]. Reference [18] extends the time-domain ARMAX model for the multiple-input multiple-output transfer function identification in power systems.

1.3 Proposed Solution

Ambient system measurements are the system responses to inherent random fluctuations of power system loads and renewable generations. In this report, such random load variations are used as independent system inputs and measurements such as tie-line flows, and bus frequencies are formulated as system outputs for estimating the small-signal input-output properties. In this context, there is no need for probing signal injections or system events. Since the ambient signals are always available under normal system conditions, the estimated model and the subsequent controller design can be updated online automatically on a regular basis and after major changes in system topology. Moreover, we show that the proposed frequency domain identification technique can estimate right plane zeros in the transfer function in a specified frequency range and this is helpful in avoiding the pitfalls of non-minimum phase control designs [10].

1.4 Report Organization

The rest of the report is structured as follows. Section II presents the proposed framework. Section III is devoted to simulations and discussions. Finally, conclusions are presented in section IV.

2. The Proposed Framework

In this section, we elaborate on the proposed framework which consists of three parts: (A) the proposed identification technique to estimate low-order transfer functions in pre-specified frequency ranges between the measured inputs and outputs signals, (B) determination of the best control channel for damping a specific inter-area mode based on the identified transfer functions, and (C) designing a simple lead-lag controller using frequency-domain method based on the identified transfer function.

2.1 Estimation Formulation

In this report, the aim is to estimate and utilize the input-output characteristics between available ambient inputs and the outputs of interest. For instance, active and reactive power load fluctuations can be natural system inputs in the context of ambient measurements. PMU measurements such as bus voltage magnitudes and phase angles, active and reactive power-flows and bus frequencies can be formulated as typical system outputs that are excited by the ambient inputs.

Small-signal formulation justifies the assumption of an underlying linear system so that superposition holds for input-output combinations. Therefore, the model estimation problem can be well-formulated simultaneously for subsets of input and output measurements. For instance, for a SVC design, the required input signal would be the reactive power injection at the bus which is equivalent to the reactive power load variation which is an available input to the system ambient response. Similarly, if a controllable storage device is available at the bus, the transfer function related to the active power input at that bus may be of interest as well. In other words, *any device that can control active or reactive power injection at a bus can be formulated as a candidate choice for the ambient transfer function estimation method proposed in this report.*

2.2 Transfer Function (Matrix) Identification

In this part, we present the proposed technique for identifying transfer functions between the measured input and output signals. When deriving the system properties from the system time-domain measurements, ARMAX [18] and Subspace State-Space Identification (SSI) [19] have been used in the past [20] for obtaining a reduced-order model for the system from measurements. In most identification techniques, a full state-space model, or a full transfer function (over the entire frequency band) is estimated. From there, one can examine the system characteristics near the frequency of a mode of interest. However, there are major challenges for implementing ARMAX and SSI such as the choice of the model order which has a significant impact on estimation accuracy and the presence of spurious modes [18],[19].

If the system frequency response is given, there are so many techniques to fit a transfer function to the frequency response data (e.g., [15], [16], [21]). However, in real power systems, the frequency response of a specific channel cannot be determined at present unless some probing tests are conducted.

The identification technique we propose here is based on the input and output data and does not

require the knowledge of frequency responses. Here, the idea is to estimate second-order transfer functions between the available input and output data in a limited pre-specified range of frequency where there exists a known system dominant mode of interest. The significance of the mode can be confirmed, and its approximate frequency can be obtained from the output signals spectrum. The reason we can employ only a small range of frequency over the entire frequency range is that the modal information (i.e., the frequency and the damping of a mode) as well as the controllability-observability characteristic of the channels can be extracted from a neighborhood range of the mode frequency where most of the mode energy is concentrated.

Let us assume that M ambient input signals and N ambient output signals are measured by PMUs. As mentioned before, by inputs, we mean active and reactive load variations and by outputs, we mean all dependent quantities such as bus voltage magnitudes or angle differences, active or reactive line currents and line power-flows.

Let us assume a second-order continuous-time transfer function $H_{i,m}(s)$ between the m^{th} input and the i^{th} output as follows.

$$H_{i,m}(s) = \frac{d_{i,m}s^2 + \alpha_{i,m}s + \beta_{i,m}}{s^2 + \sigma s + \Omega} \quad (1)$$

where σ and Ω parameters describe the target inter-area mode and are common between different input-output pairs, whereas the $d_{i,m}$, $\alpha_{i,m}$ and $\beta_{i,m}$ parameters are specific to each channel, and therefore signify input and output relationships. We note that the d parameter is included in the numerator since the feedforward matrix D entries are non-zero for most of the channels. In general, the overall transfer function is not of order two and what we have considered here approximates the overall transfer function in the vicinity of a dominant mode frequency, where it is assumed that no other mode has a significant effect on the mode of interest. The formulation can be readily extended to handle higher-order transfer function formulations, though it is not shown here due to space limitations. Then, the system outputs can be represented as follows.

$$Y_i(s) = \sum_{m=1}^M \frac{d_{i,m}s^2 + \alpha_{i,m}s + \beta_{i,m}}{s^2 + \sigma s + \Omega} U_m(s) \quad (2)$$

with $i = 1, 2, \dots, N$

In the above equations, $Y_i(s)$ and $U_m(s)$ are the Laplace transform of the i^{th} output and the m^{th} input signals, respectively. Let us rewrite the above equations in the Fourier domain for the specific frequency range $\omega_1 < \omega < \omega_2$ around the mode of interest as follows.

$$Y_i(j\omega) = \sum_{m=1}^M \frac{j\alpha_{i,m}\omega + (\beta_{i,m} - d_{i,m}\omega^2)}{j\sigma\omega + (\Omega - \omega^2)} U_m(j\omega) \quad (3)$$

with $i = 1, 2, \dots, N$ & $\omega_1 < \omega < \omega_2$

For notational convenience, we will drop $j\omega$ in $Y_i(j\omega)$ and $U_m(j\omega)$ for the rest of derivations.

Solving the above set of equations as in (3) requires solving a nonlinear least-squares problem which by itself requires the initial values for all the parameters and may lead to multiple (local) solutions. We propose to do a cross-multiplication and restate the equation as follows.

$$j\sigma\omega Y_i + (\Omega - \omega^2)Y_i = \sum_{m=1}^M j\alpha_{i,m}\omega U_m + \sum_{m=1}^M (\beta_{i,m} - d_{i,m}\omega^2)U_m \quad (4)$$

with $i = 1, 2, \dots, N$ & $\omega_1 < \omega < \omega_2$

By rearranging the equations and putting all the unknown terms on the left and the known term on the right, we get:

$$(j\omega Y_i)\sigma + (Y_i)\Omega - \sum_{m=1}^M (j\omega U_m)\alpha_{i,m} - \sum_{m=1}^M (U_m)\beta_{i,m} + \sum_{m=1}^M (\omega^2 U_m) d_{i,m} = Y_i \omega^2 \quad (5)$$

with $i = 1, 2, \dots, N$ & $\omega_1 < \omega < \omega_2$

Now, we have a set of linear equations that can be solved as a simple linear least-squares problem. Remark 1: By doing the cross-multiplication, we are introducing a frequency-dependent weighting function to the original problem as follows:

$$\min_{\text{after cross-multiplication}} \|Y \cdot Den - Num \cdot U\|^2 = \min_{\text{original formulation}} \left\| Y - \frac{Num}{Den} U \right\|^2 \cdot \underbrace{|Den|^2}_{\text{weighting}} \quad (6)$$

where, $Den = j\sigma\omega + (\Omega - \omega^2)$ is the common denominator of all channels and Num is the numerator of the transfer function. By its nature, Den gets very small values as ω approaches the mode angular frequency and gets higher values as ω approaches ω_1 and ω_2 . This means that less importance will be given to equations around the mode frequency and more will be given to equations at the two sides of the frequency range. Since the mode damping is dominantly correlated by the changes of transfer function magnitude around the mode frequency, this weighting function will bias the mode damping estimates. To overcome this problem, we propose the following steps:

- 1) Estimate the transfer function parameters by solving (5).
- 2) Build the frequency-dependent weighting function $\widehat{Den} = j\sigma\omega + (\Omega - \omega^2)$ using the estimated σ and Ω parameters.
- 3) Estimate the transfer function parameters again by solving (5) with including a frequency weighting function $\frac{1}{\widehat{Den}^2}$ where $\widehat{Den}$ is built in Step 2. This will counter the effect of the natural weighting Den^2 to a great extent.

As an alternative, one can use the σ and Ω from the previous window estimation (please note that we are performing a moving window analysis) to create $\widehat{Den}$ and solve (5) by considering the weighting function $\widehat{Den}$ from the beginning.

2.3 Input-Output Channel Selection

When employing a feedback controller to damp out the system oscillations, three factors are of importance, that is, the control location, the feedback signal, and the designed controller by itself. The first two factors are associated with the controllability and observability, respectively. The best input-output channel for control implementation has the highest joint controllability-observability [10], [13], and [14].

In the power system literature, three different approaches can be found addressing the joint controllability-observability problem.

The first approach evaluates the joint controllability-observability based on the Hankel Singular Values (HSVs) which are defined as $\sigma_i = \sqrt{\lambda_i(PQ)}$ where $i = 1, \dots, n$ and P and Q are the controllability and observability grammian matrices, respectively, and n is the order of the system. The channel with higher HSV has higher JCO [10].

The second approach, known as the “geometric” measure [13], defines the controllability index as $|q_i^T b_j| / (\|q_i\| \|b_j\|)$, where q_i is the left eigenvector associated with the i^{th} mode and b_j is the column vector of the input matrix B associated with the j^{th} input. Similarly, the observability index is defined as $|c_k^T p_i| / (\|c_k\| \|p_i\|)$, where p_i is the right eigenvector associated with the i^{th} mode and c_k is the k^{th} row of the output matrix C associated with the k^{th} output. One advantage of this method is that the indices from different physical quantities (with different units) can be compared together, due to the normalization placed in the denominator [11].

The third approach is based on the partial fraction expansion of different channels transfer functions, where the channel with higher residue at the mode of interest has higher joint controllability-observability [13], [14]. In fact, it is shown in [13] that the residue $R_{k,j}$ associated with the j^{th} input and the k^{th} output is related to the A , B , and C matrices as $R_{k,j} = c_k p_i q_i b_j$. As mentioned in [13], when the inputs are of the same type, the normalization by $\|b_j\|$ in the denominator of $|q_i^T b_j| / (\|q_i\| \|b_j\|)$ should be removed as it shows the power injected by the input to the system. A similar discussion can be made for the observability measure. Moreover, it is mentioned that when examining the joint controllability-observability, the normalizations by $\|q_i\|$ and $\|p_i\|$ can be removed as the different choice of state similarity transformations will be canceled out in their multiplications. In other words, if the inputs are of the same type (outputs as well), the residues from transfer function expansion and the “geometry” measure defined in [13] will be equivalent. To obtain the JCO of each channel, we will do partial fraction expansion on each channel’s identified transfer function and obtain the residues. The channel with highest residue has highest JCO and therefore most suitable for feedback control implementation.

2.4 Feedback Controller Design

After selecting the best input-output channel in the previous part, a feedback controller should be designed to effectively damp out the inter-area oscillations. Since the system identification is

performed in the frequency domain, it is a natural choice to design the controller in frequency domain as well. Numerous techniques have been used in power system literature (e.g., [22], Chapter 17). In this work, we will use the bode plot-based lead-lag compensator where the controller is updated as the system operating point changes with time. This will make the control adaptive in nature, thus capable of tracking changes in system conditions and providing proper stabilization as needed.

For the sake of space, we will not present the complete classical feedback lead-lag controller design in detail and we refer readers to [23], Pages 751 to 757 for details. A small overview will be presented here though. In this report, for the system open loop identified transfer function and the feedback controller we will use the notations, $G(s)$ and $H(s)$, respectively. First, the phase margin of open loop system is assessed from the identified frequency response at the mode of interest. Then, an appropriate amount of phase is added to this using a series compensator, centered around the mode of interest, to bring the phase margin of the closed loop system to a desired value. An additional amount of phase is also added to accommodate for the change in phase margin of closed loop system, due to the gain of controller, this is referred to as safety margin in the literature. Moreover, the center frequency of compensator is set slightly higher than the frequency of the mode of interest. This accommodates for the change of gain crossover frequency due to the feedback controller and results in much less controller phase and gain to be created. Depending on the total amount of phase contribution to be achieved, the number of compensator stages is determined such that maximum phase of each stage is limited to 60° . The magnitude of controller is chosen so that its gain contribution is minimal at the mode of interest. Finally, the response of the closed loop system is observed for the updated phase margin. Frequency response-based controller design is an iterative procedure widely used in the industry, and maybe repeated until the desired stability margins are achieved.

3. Simulation and Results

In this section, the effectiveness of the proposed framework is demonstrated using the simulations in a test power system. Modelling and simulation of independent random load fluctuations in many loads is numerically challenging and can introduce numerical instability for simulations ranging several minutes. Accordingly, *none of the available commercial transient stability simulation programs can simulate the ambient response of large-scale power system models*. Therefore, we use Kundur test system [22] in this report and the simulations are carried out using Matlab.

Figure 1 shows the single-line diagram of the well-known two-area Kundur system [22] where it is modified to include an SVC at Bus 7. The two-axis representation is used for modeling system generators. Each generator is equipped with a first order AVR and a two-stage PSS to adjust the system damping to the desirable level. SVC operates in voltage regulation mode and is modelled with single order dynamic model, as recommended in manuals available in [24]. The system has a dominant inter-area mode which causes an oscillation of generators 1 and 2 (in Area 1) against generators 3 and 4 (in Area 2) with a frequency around $f = 0.6$ Hz. As an initial setting, the system damping ratio is set to be low at 2% and the ambient data is generated by modulating the system loads (active and reactive load powers at Buses 7 and 9) with white Gaussian noise (1%) around their nominal values and solving the system non-linear equations. We will use five minutes of ambient data to perform the analysis (same as in [18]).

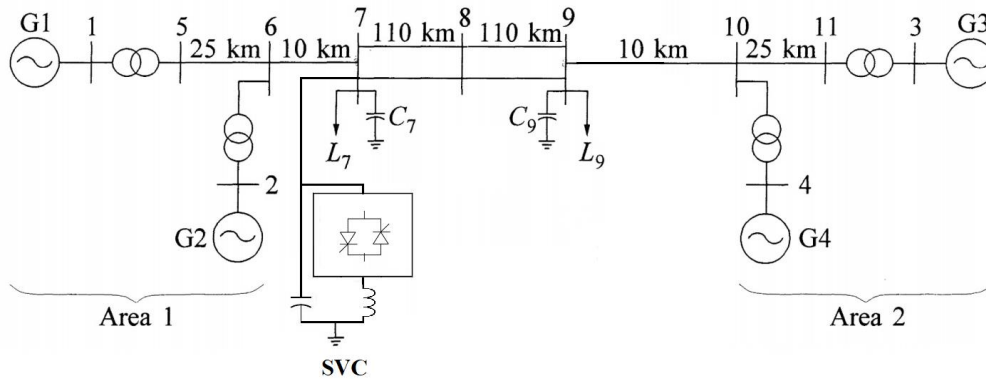


Figure 1. The modified Kundur test system with an SVC at bus 7 [22].

For the feedback we will consider the bus voltage angle differences as feedback signal candidates. As mentioned before, the system inputs are load active and reactive power fluctuations. Accordingly, if the best input is determined as the reactive power injection at a bus, we will need a dynamic VAR-compensator to modulate the reactive power, whereas if the best input is determined as the active power injection at a bus, an energy storage device [25] is needed as the actuator to modulate the active power at the very bus. It may be noted here that a dedicated element is not required for this purpose.

A small portion of the capacity from already installed devices can be reserved for oscillation damping control. This is illustrated later in our control implementation.

3.1 System Identification and Control

In this part, three bus voltage angle differences $y_1 = \delta_5 - \delta_6$ (from Area 1), $y_2 = \delta_{11} - \delta_{10}$ (from Area 2), and $y_3 = \delta_6 - \delta_{10}$ (between Area 1 and Area 2) are considered as feedback signal candidates among which we will choose the best one to use as feedback signal to the feedback controller. These signals will serve as output signals in the identification process. The modulation signals of P_{L7} , P_{L9} , Q_{L7} , and Q_{L9} are system inputs. The three output and four input signals together create twelve channels to be identified. To model the measurement noise, independent white Gaussian noise signals are added to both input signals and output signals (as 1% of amplitude of each signal). Figure 2 shows the estimated transfer functions (magnitude and phase plots) of the twelve channels versus the true ones.

Based on the mentioned channel selection criteria, it can be observed that P-channels have larger residues compared to corresponding Q-channels. This is natural because P-actuation travels longer compared to Q-actuation generally in power systems [22]. However, since active power-based energy storage devices for P-based actuation are not readily available in present-day power systems, we look for a feasible Q-channel with the highest residue. We observe that while the channel (3,4), associated with output $y_3 = \delta_6 - \delta_{10}$ and input Q_{L9} , seems to be the best control channel with reference to our previous discussion, the identified transfer functions indicate the presence of a right half-plane (RHP) zero. That makes it a non-minimum phase channel. All the 100 Monte-Carlo transfer function estimates of this channel show one and only one RHP zero. This is consistent with the presence of a RHP zero at +3.53 in the linearized model-based transfer function. Figure 3 shows the zero estimates from the transfer function estimates from the ambient data for the 100 Monte-Carlo tests of this channel. The mean and standard deviation (STD) of these estimates are 2.875 and 0.432, respectively. These results show the potential use of the proposed approach for identifying the non-minimum phase input-output channels. These channels have the potential to drag the closed-loop system into instability and are thus not preferred from the control theory perspective [10]. In this regard, the channel (3,3) associated with (output $y_3 = \delta_6 - \delta_{10}$ and input Q_{L7}) is chosen as the next best available channel for implementing the feedback control in our example.

An SVC is connected to bus 7 in our modified system. We will use a fraction of SVC VAR-capacity to control inter-area oscillations, more specifically, to improve the damping characteristics of the mode of interest. JCO based queueing of control channels offers online information on the next-in-line best channel in case of unavailability of a resource at a bus or infeasibility of a control channel.

In the next step, we will design the feedback controller for SVC operation, based on the identified transfer function of Channel (3,3). We performed one hundred independent Monte-Carlo simulations, and one hundred transfer functions are estimated for each channel using a five-minute ambient data length with the sampling frequency of 30 Hz. To test the design methodology, we

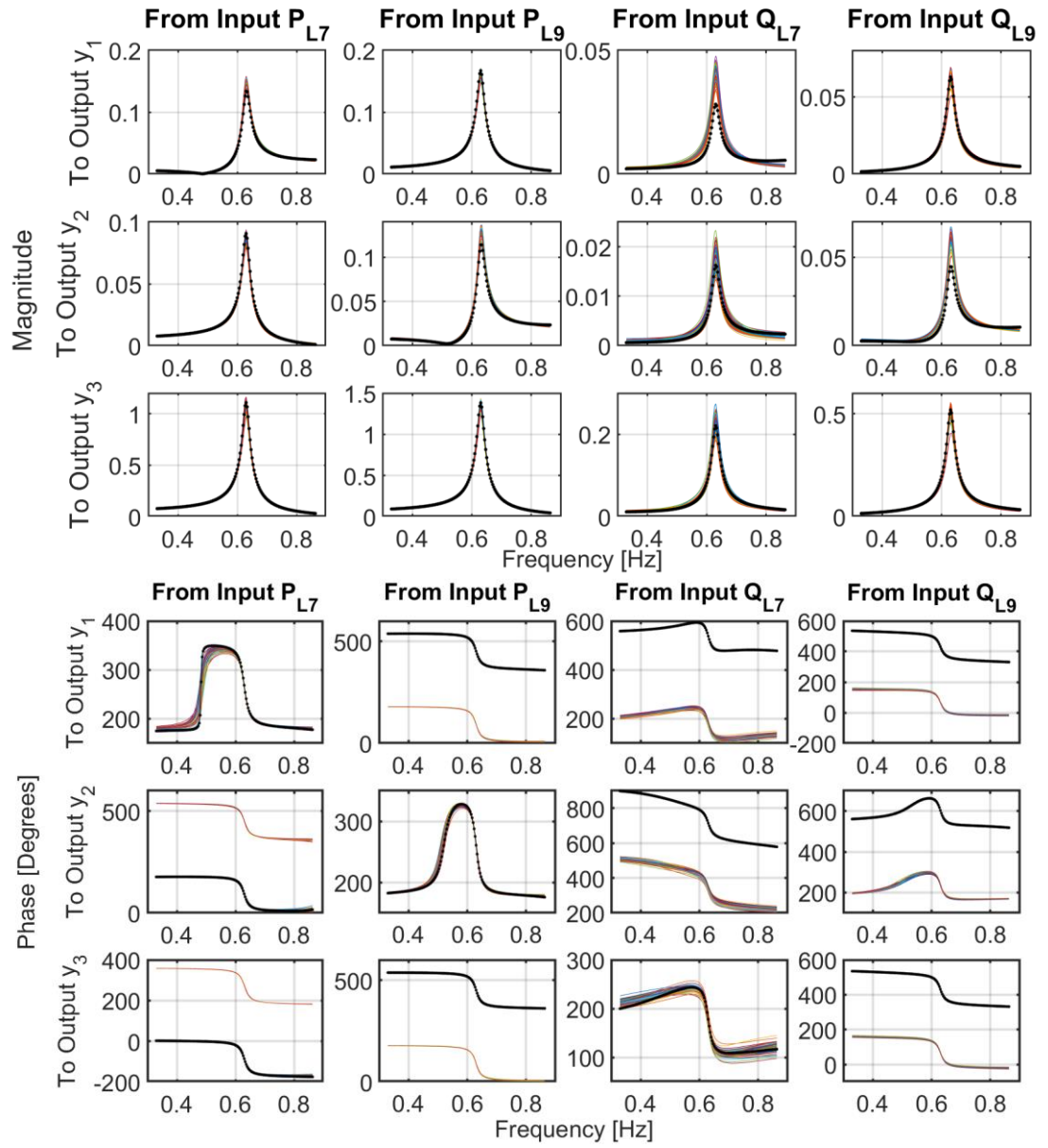


Figure 1. Frequency domain transfer function magnitudes (top) and phase plots (bottom): estimated (colored) versus the true ones (black graphs).

will design the controller based on the worst transfer function estimate (the one with the largest deviation from the true transfer function in the frequency domain). The identified transfer function with the highest deviation from the true transfer function is as follows.

$$G_1 = \frac{-0.01093s^2 - 0.04177s - 0.1829}{s^2 + 0.1594s + 15.71} \quad (7)$$

From the denominator of this identified transfer function, the (open-loop) inter-area mode is at $-0.0797 \pm 3.96i$ and the frequency and the damping ratio of this mode is $f = 0.63\text{Hz}$ and $\zeta = 2.01\%$, respectively. Say we want to increase the mode damping ratio to be above 8%. The designed controller is obtained as follows (A bandpass filter from [26] is added to controller to prevent other modes from getting affected).

$$H_1 = \frac{2s}{s^2 + 2s + 15} \frac{-0.1550s - 0.5522}{0.2547s + 1} \quad (8)$$

By applying the designed feedback controller to the identified model, the closed-loop system pole is obtained as $-0.366 \pm 4.04i$ which is desirable. As can be seen, the damping ratio of the mode is increased to be above 8%. However, one needs to evaluate the performance of the designed feedback controller on the full system model, rather than the identified model. Table I provides the system modal characteristics from four cases: 1) the actual (linearized) system model without the controller, 2) the identified system model without the controller, 3) the actual (linearized) system model with the controller, and 4) the identified system model with controller. As can be observed, there is a close match between the open- (closed-) loop actual and identified system model quantities indicating that the controller from proposed measurement-based approach has provided enough level of damping for the system. Figure 4 presents the time response, both with and without the designed controller, for the insertion of a 50 MVAR shunt capacitor bank at bus 9 at time $t=0$ in the modified Kundur system.

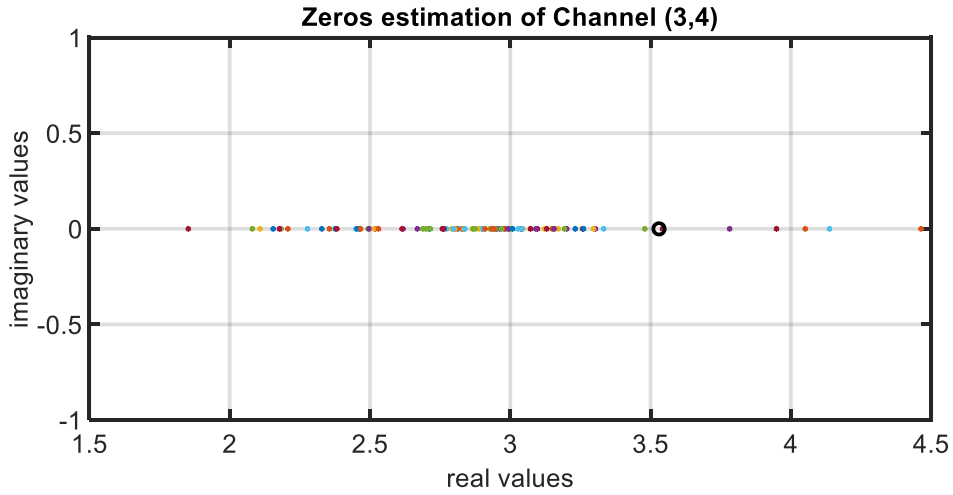


Figure 3. Zeros of channel (3,4): Estimated (colored dots) versus true (large black circle).

Table 1. Estimated versus the true open- and closed-loop system modes.

	Frequency (Hz)	Damping ratio - mean (%)	Damping ratio – STD (%)
Open-loop mode from system linearized model without controller	0.6302	2.02	-
Open-loop mode estimates from ambient data without controller	0.6302	1.98	0.42
Closed-loop mode from system linearized model with controller	0.6350	8.27	-
Closed-loop mode estimates from ambient data with controller	0.6429	8.24	0.45

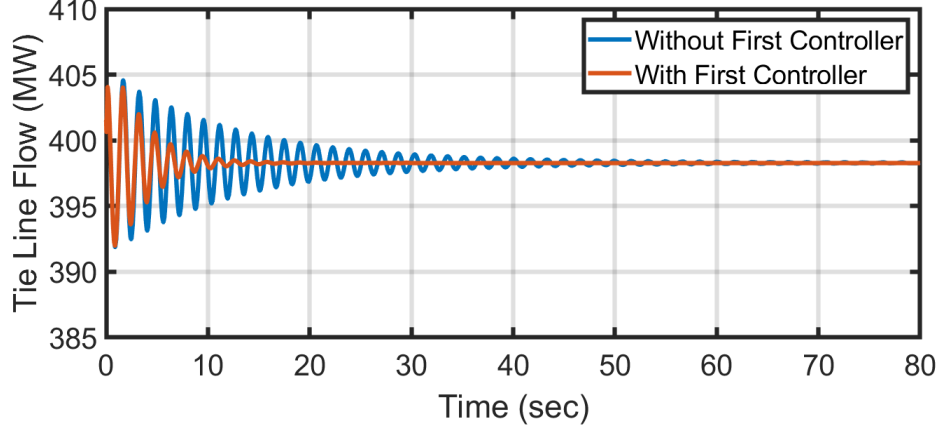


Figure 4. Time response of modified Kundur two-area system for a 50 MVAR shunt capacitor insertion at bus 9 at $t=0$, demonstrating tie-line oscillation with and without identification-based closed loop control.

To illustrate the adaptive nature of our online ambient data-based control, we simulate a PSS malfunction on generator 1 in area 1, in our closed loop system, specifically we assume that the stabilizer gain changes by accident. If the controller were to remain the same as in (8) (like in offline designs), the damping of the interarea mode would have dropped to 2.30% after the PSS malfunction. However, the controller as proposed identifies the new system transfer function based on ambient data for the closed-loop system that uses the first controller (8) and computes a new set of control parameters which can be implemented as the second outer loop. The identified closed loop transfer function (worst) with PSS malfunction at Bus 1 and the second controller are shown below:

$$G_2 = \frac{-0.0000856s^2 - 0.04497s - 0.06148}{s^2 + 0.1385s + 16.19} \quad (9)$$

$$H_2 = \frac{2s}{s^2 + 2s + 15} \frac{-0.1357s - 0.3972}{0.2032s + 1} \quad (10)$$

Table II lists the closed loop characteristics of system with the first controller versus the system with adaptive controller design with the second feedback loop. The adaptive controller keeps up with the changing system conditions leading to a closed loop damping ratio of 8.27%. Figure 5 presents the time response, both with the first controller only and with the adaptive controller in case of PSS malfunction, for the switching of a 50 MVAR shunt capacitor bank at bus 9 in detailed nonlinear dynamic model of the Kundur system.

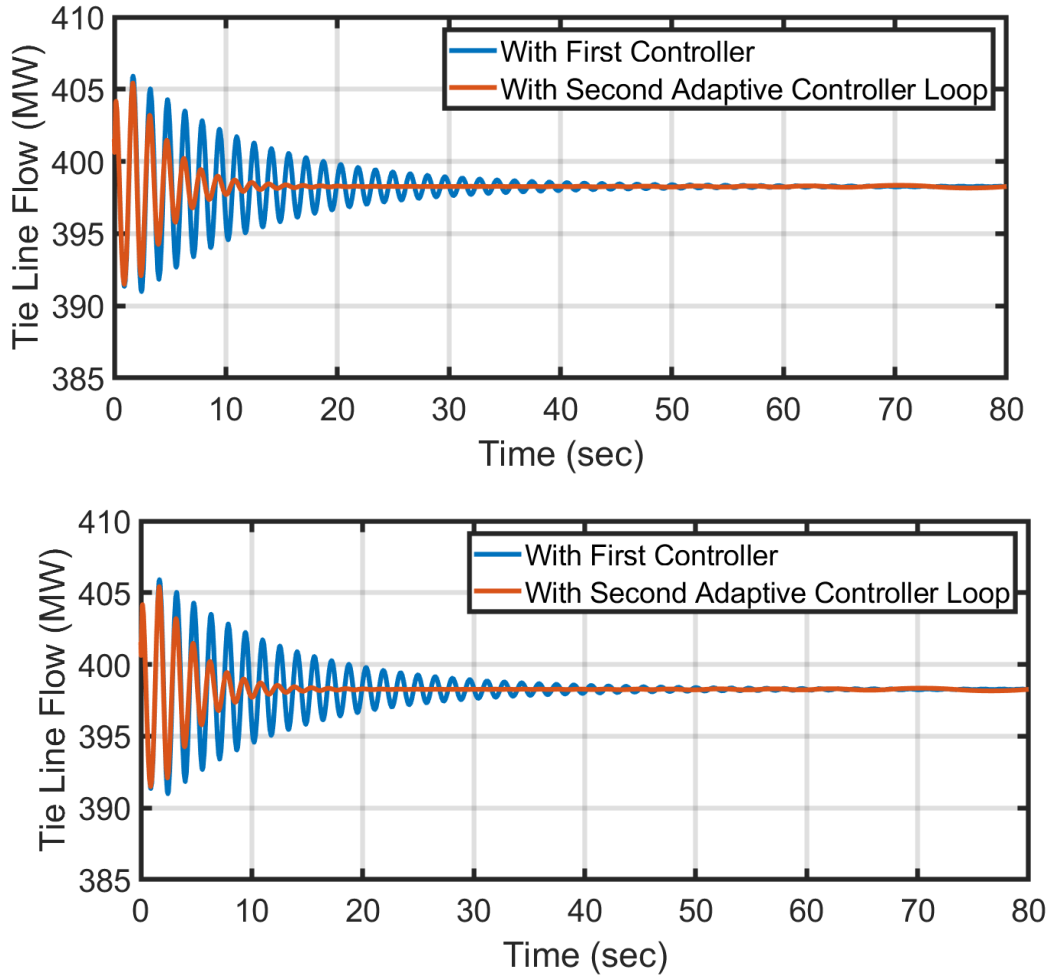


Figure 5. Closed-loop performance comparison of the first vs second adaptive controller loop in case of PSS malfunction on generator 1.

Table 2. Closed-loop system modes with the first and second adaptive controllers after the PSS malfunction.

	Frequency (Hz)	Damping ratio - mean (%)	Damping ratio – STD (%)
Closed-loop mode from system linearized model with the first controller	0.6398	2.02	-
Closed-loop mode estimates from ambient data with the first controller	0.6414	2.00	0.38
Closed-loop mode from system linearized model with the second adaptive controller loop	0.6525	8.08	-
Closed-loop mode estimates from ambient data with the second adaptive controller loop	0.6589	8.26	0.40

This example demonstrates the strength of the model-free damping controller over its offline model-based counterpart. When the system conditions improve, the additional control loop can be removed, and the design can revert back to a single loop design.

3.2 Sensitivity analysis of the proposed identification technique

In this part, first, the sensitivity of the proposed identification method to measurement noise will be examined. To do so, the input-output data obtained in Part A is contaminated with two different levels of white Gaussian multiplicative noise signals (noise with 10% and 50% energy of original noise-free signal) and the identification of the twelve channels is repeated using the same setting. demonstrates the frequency domain transfer function magnitude estimates of the channel (3,3) at the presence of measurement noise. Moreover, the estimate without any measurement noise is also presented for comparison. As can be seen, adding measurement noise has no discernible effect on the accuracy of the identification technique. This is mostly because of simultaneously engaging multiple channels in the identification which have the system poles as a common characteristic. Efficient handling of white measurement noise is also an inherent strength of frequency domain approaches such as the one proposed here.

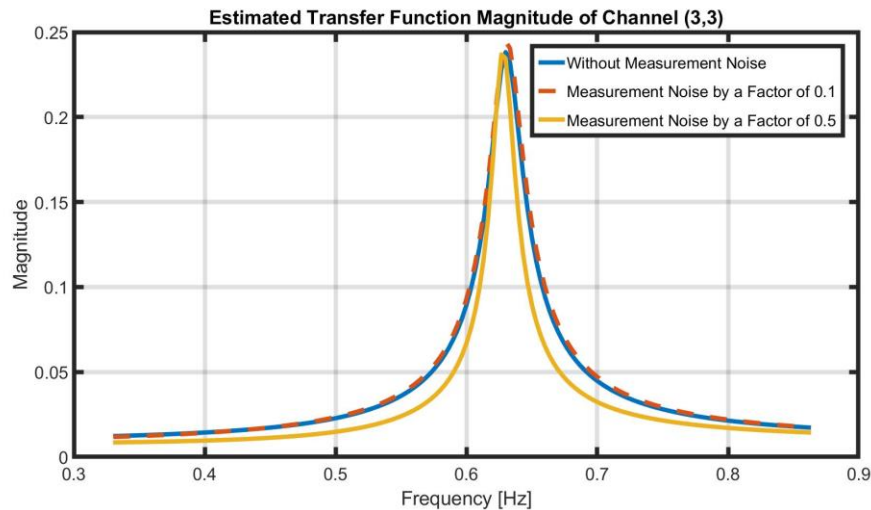


Figure 6. Frequency domain transfer function magnitude estimation with the presence of measurement noise.

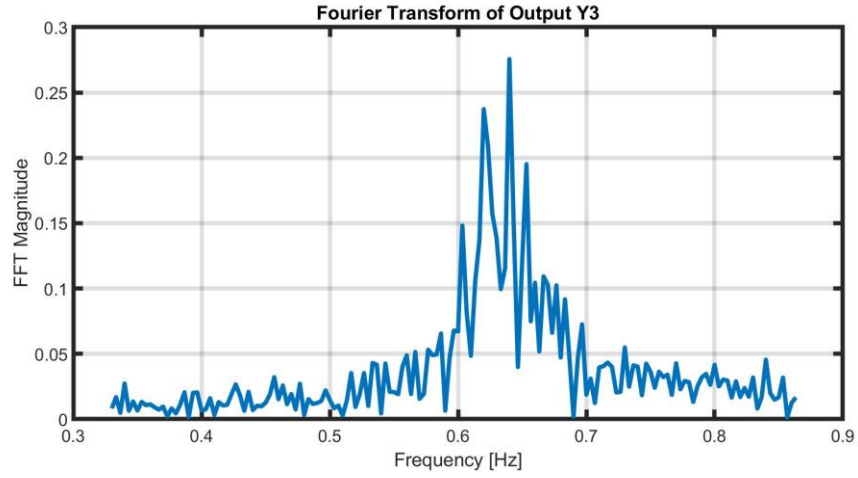


Figure 7. Fourier transform of output y_3 for a sample input signal.

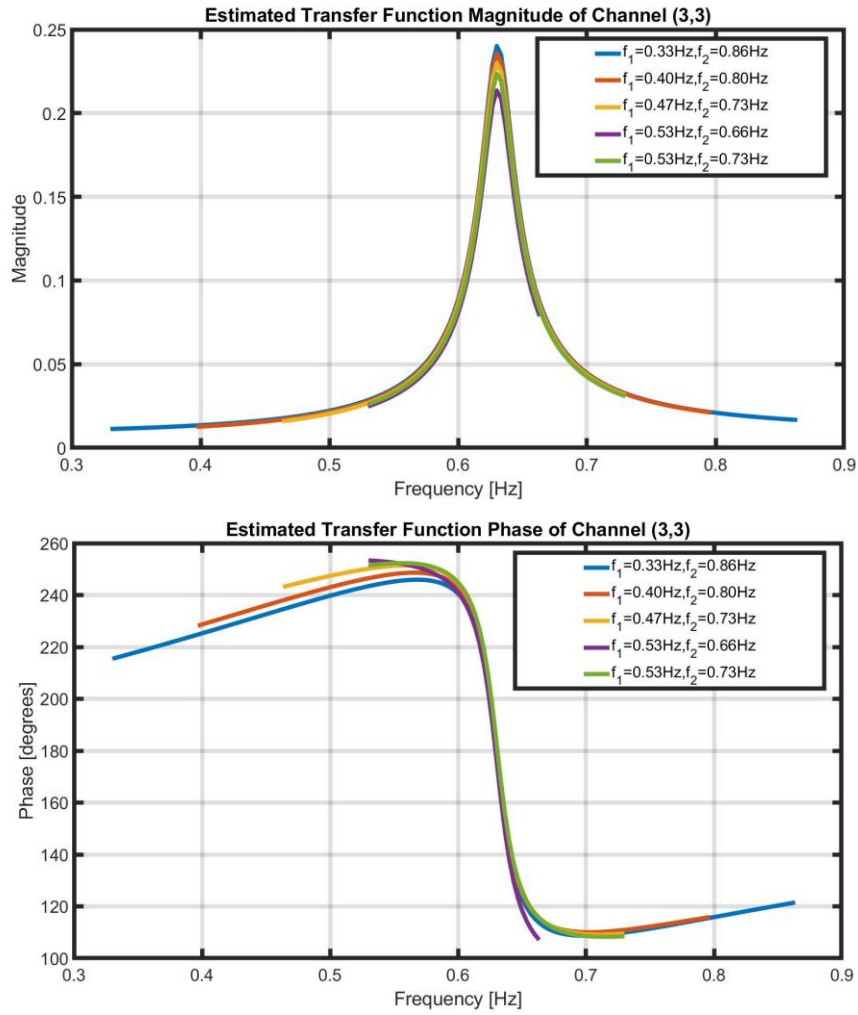


Figure 8. Estimated frequency domain transfer function of channel (3,3): a) magnitude (top), b) phase (bottom).

Next, the sensitivity of the proposed identification method to the selected range of frequency around the mode of interest will be examined. To do so, we will use the same input-output data, but we will choose different ω_1 and ω_2 and perform the identification on the previously mentioned twelve channels. Figure 7 shows the FFT magnitude of Output 3 signal for a sample data. Let us denote the frequency window used in the identification by its corner frequencies, f_1 and f_2 .

Figure 8 depicts the estimates of Channel (3,3) frequency domain transfer function for the following f_1 and f_2 choices: 1) $f_1 = 0.33\text{Hz}$, and $f_2 = 0.86\text{Hz}$, 2) $f_1 = 0.40\text{Hz}$, and $f_2 = 0.80\text{Hz}$, 3) $f_1 = 0.47\text{Hz}$, and $f_2 = 0.73\text{Hz}$, 4) $f_1 = 0.53\text{Hz}$, and $f_2 = 0.66\text{Hz}$, and 5) $f_1 = 0.53\text{Hz}$, and $f_2 = 0.73\text{Hz}$. Note that the other eleven identified channels are not shown here for the sake of space. Figure 8 shows that different choices of f_1 and f_2 only have subtle effects on the accuracy of the identification process which in turn indicates the robustness of the proposed identification technique.

3.3 Discussion

The performance features of the proposed framework and the simulations results are discussed below.

- 1) In the proposed method, the joint controllability-observability of a pair of the input-output channel cannot be determined unless both the input and output signals are measured. For example, if a bus does not have any load to measure or if the load measurements are not available, the JCO of this bus location to system outputs cannot be estimated by the proposed method. Considering the test case above, we will be only able to determine whether the controller should be installed at buses 7 or 9, whereas from the system model-based analysis, bus 8 might be a better control location as shown by some researchers (page 1143, [22]).
- 2) Those input signals which are exciting the system but are not measured will act as process noise and will impact the estimation of the transfer function of available (measurable) input-output pairs. In other words, the more measurements we have, the better the model estimates we can obtain.
- 3) In equation (5), the total number of unknowns is $2 + 3NM$ where 2 corresponds to the denominator parameters σ and Ω and $3NM$ is from 3 parameters in numerator corresponding to N outputs and M inputs. Now, let us assume that there are n frequency points in the range of $\omega_1 < \omega < \omega_2$. Then, the total number of equations will be $2Nn$ (Nn from real equations and Nn from imaginary equations). Therefore, as far as the number of frequency points is roughly 1.5 times larger than the number of (dominant) inputs, we will be able to determine the parameters uniquely, in a least-squares sense.
- 4) As can be seen from the simulation results, the identification method is robust against the measurement noise as it establishes the common properties of all available channels in the identification.
- 5) The proposed method can point to presence of RHP zeros of channels in the ambient data-estimated transfer functions which can help us avoid the problems associated with non-

minimum phase control designs.

4. Conclusion

In this work, a framework for both identification and adaptive control design of power system low-frequency electromechanical oscillations is proposed. The methodology is entirely based upon PMU ambient measurements and it does not require any knowledge of the system model. As the first step, second-order transfer functions in the Fourier domain are fitted to the measured input-output data in a pre-specified frequency range. Next, the best input-output pair (the controller location and the feedback signal, respectively) for feedback control implementation is determined by choosing the channel with the highest joint controllability-observability. Finally, an appropriate controller is designed by utilizing the identified transfer function and using the Bode plot-based technique. Simulations on a test power system demonstrate the applicability of the proposed framework in identifying and control of a dominant inter-area mode. It is also shown that the proposed identification technique is very robust against the measurement noise. There is only one user specified parameter, namely, the analysis frequency range, and it is shown that it has little effect on the accuracy of estimates. Future work includes examining the applicability of the proposed framework in larger power system models and for wide-area measurements based multiple-input multiple-output (MIMO) control of PSS and modern power electronic controllers for enhanced system stability. Another area of interest could be consideration of communication system issues such as network delays and packet dropouts in the transfer function identification procedure.

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Part II

Not Submitted

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