

Research Article

Closed-Loop Identification of Power System Based on Ambient Data

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Received 28 November 2011; Accepted 14 February 2012

Academic Editor: Alexander P. Seyranian

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Small fluctuations caused by random changes of loads exist continuously in power grids, which are called ambient signals. Using time-synchronized phasor measurements, the closed-loop identification of power system based on ambient data is discussed, which can reflect accurate operating conditions currently and provide critical information for system analyzing and controller designing. The closed-loop identification of a power system with multiple disturbances is theoretically studied, including the closed-loop identifiability, the consistency properties, and the convergence properties. The requirements for realizing the closed-loop identification are summarized, and the theoretical research results are validated by simulation examples.

1. Introduction

Generally, the performance of large interconnected power grids is assessed using simulation methods. In this approach, accurate simulation models and parameters are critical parts to analyzing, controlling, and operating a power system. The identification of models and parameters can be accomplished using two types of data: signals collected from special tests or ringdown signals [1–4]. However, special tests are usually costly, since a lot of preparatory work has to be done in order to avoid negative impact on the system. On the other hand, relatively small quantity of ringdown signals in actual power system and relatively high requirement to calculation speed both limit this approach's application. Moreover, the identification results may not reflect the accurate operating characteristics of power system currently, which would cause serious adaptability problems in system analysis and regulator design.

The development and application of wide area measurement system (WAMS) provides favorable conditions for solving these problems. In actual power system, ambient signals caused by random changes of loads are much easier to be collected. Recently, many publications have offered algorithms for estimating the electromechanical modal properties from ambient data [5–12], which fully demonstrate that this type of signal includes rich information about power grids.

In this paper, the closed-loop identification of power system based on wide area measured ambient data is proposed. The identification is carried out during normal operation and provides critical information for the improved operational reliability of interconnected power grids.

Nowadays, scholars in automation field have done a lot about the system identification, including the identifiability, the identification algorithm, the identification accuracy evaluation, and so forth [13–20]. However, in power system field, researchers mainly focus on the identification algorithm [1–4, 21–23] whereas ignore some basic problems. In actual power systems, multiple stochastic disturbances always exist, and the wide area damping regulators are gradually put into operation for improving the system's oscillation characteristic. All these indicate that the closed-loop system is less sensitive to changes, and ambient signals have less information about the system, thus the system identification is much more difficult.

In this paper, the closed-loop identification of power system based on ambient signals is theoretically studied. Using "true" system and identification model structure shown in Section 2 as the subjects, the closed-loop identifiability is discussed in Section 3, in order to specify the conditions for estimating a unique system model in this situation. Section 4 and Section 5 evaluate the identification accuracy, including the consistency properties and the convergence properties. Then, the necessary conditions for ambient-data-based closed-loop identification of power system are summarized in Section 6, and the simulation examples done in Section 7 are used to validate the theoretical research results.

2. True System and Identification Model Structure

"True" system and identification model structure shown in Figure 1 are used to discuss the power system's closed-loop identification problems. To simulate random changes of loads in actual power grids, multiple small amplitude stochastic disturbances are added to the "true" system. Taken two disturbances existed as an example, in the "true" system, $u(t)$ and $y(t)$ denote the input variable and output variable of the controlled system at time t ($t = 1, 2, \dots$), $e_{10}(t)$ and $e_{20}(t)$ are the "true" independent random disturbance variables with zero mean values and variances λ_{10} and λ_{20} , r is an independent external reference signal, $G_{10}(q)$ and $G_{20}(q)$ denote the "true" controlled system, $H_{10}(q)$ and $H_{20}(q)$ are two inversely stable, monic filters, and $C_0(q)$ is the "true" feedback regulator. In the identification model structure, $e(t)$ is a stochastic disturbance variable with zero mean value and variance λ , $G(q, \theta)$ represents the transfer function of controlled system model corresponding to the parameter value θ , $H(q, \theta)$ and $C(q, \theta)$ denote the transfer functions of noise model and feedback regulator model and q is a forward operator satisfying $qu(t) = u(t + 1)$.

We will assume that the data $Z^N = \{y(1), u(1), y(2), u(2) \dots\}$ of the "true" system Θ are generated as depicted in (2.1):

$$\begin{aligned} y(t) &= G_{10}(q)G_{20}(q)u(t) + H_{10}(q)e_{10}(t) + H_{20}(q)G_{10}(q)e_{20}(t), \\ u(t) &= -C_0(q)y(t) + r(t). \end{aligned} \quad (2.1)$$

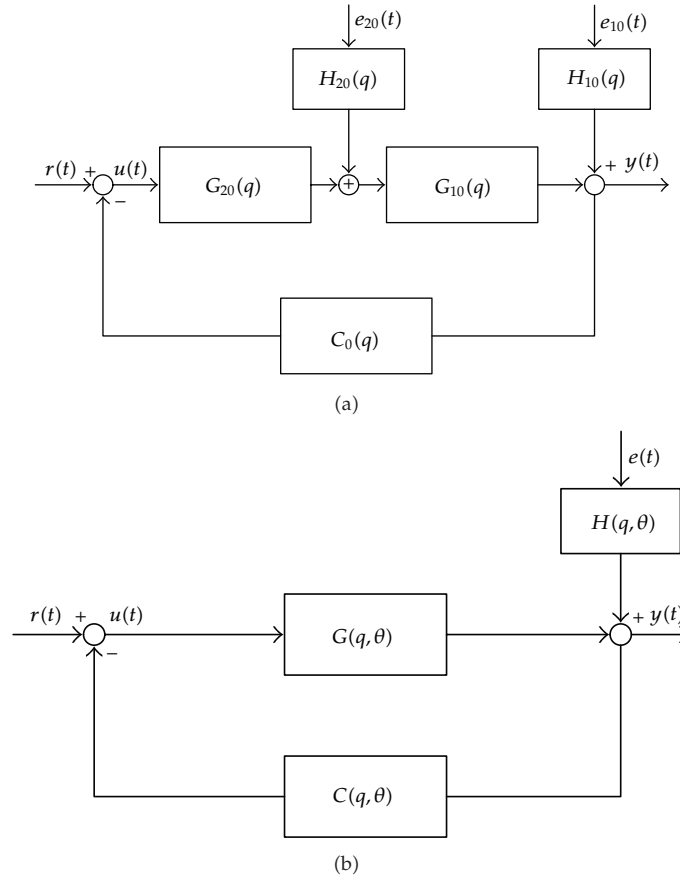


Figure 1: "True system" (a) and identification model structure (b).

Defining

$$\begin{aligned} G_0(q) &= G_{10}(q)G_{20}(q), \\ H'_{20}(q) &= H_{20}(q)G_{10}(q), \\ H_0(q)e_0(t) &= H_{10}(q)e_{10}(t) + H'_{20}(q)e_{20}(t), \end{aligned} \tag{2.2}$$

then, the "true" system Θ can be described as

$$\begin{aligned} y(t) &= G_0(q)u(t) + H_0(q)e_0(t), \\ u(t) &= -C_0(q)y(t) + r(t). \end{aligned} \tag{2.3}$$

The closed-loop system is stated as

$$\begin{aligned} y(t) &= S_0(q)G_0(q)r(t) + S_0(q)H_0(q)e_0(t), \\ u(t) &= S_0(q)r(t) - S_0(q)C_0(q)H_0(q)e_0(t), \end{aligned} \tag{2.4}$$

where $S_0(q) = 1/(1 + G_0(q)C_0(q))$.

The identification model structure Ω is also given:

$$\begin{aligned} y(t) &= G(q, \theta)u(t) + H(q, \theta)e(t), \\ u(t) &= -C(q, \theta)y(t) + r(t). \end{aligned} \quad (2.5)$$

Similar to (2.4), (2.5) can be rewritten as

$$\begin{aligned} y(t) &= S(q, \theta)G(q, \theta)r(t) + S(q, \theta)H(q, \theta)e(t), \\ u(t) &= S(q, \theta)r(t) - S(q, \theta)C(q, \theta)H(q, \theta)e(t), \end{aligned} \quad (2.6)$$

where $S(q, \theta) = 1/(1 + G(q, \theta)C(q, \theta))$.

3. Closed-Loop Identifiability Analysis

For the system identification problem, it is nature to check whether the “true” system described by (2.1) belongs to the model set defined by (2.5). We, thus, introduce the concept of identifiability.

The dataset Z^N is the source of information about the “true” system. This be fit to a model structure Ω of our choice. The structure Ω describes a set of models Ω^* within which the best one is sought for. Identifiability concerns the question whether different parameter vectors of model structure can describe the same model in the set Ω^* , that is to say, whether the dataset Z^N allows us to distinguish between different models in the set [13]. The dataset Z^N is called to be informative if it is capable of distinguishing between different models [13, 24]. Now, we will discuss whether ambient data is informative enough to closed-loop estimate one unique solution of power system model.

An obvious approach is to estimate the model parameters θ by the prediction error method. Assuming two models called $W(q, \theta_1)$ and $W(q, \theta_2)$ are identified based on the quasistationary dataset Z^N , obviously

$$\begin{aligned} 0 &= \overline{E}[(W(q, \theta_1) - W(q, \theta_2))Z(t)]^2 \\ &= \overline{E} \left| \begin{bmatrix} \Delta W_u & \Delta W_y \end{bmatrix} \begin{bmatrix} u(t) \\ y(t) \end{bmatrix} \right|^2, \end{aligned} \quad (3.1)$$

where $\overline{E}x = \lim_{N \rightarrow \infty} (1/N) \sum_{t=1}^N Ex(t), i = 1, 2, \dots$

$$\begin{aligned} W(q, \theta_i) &= [W_u(q, \theta_i) \quad W_y(q, \theta_i)], \\ W_u(q, \theta_i) &= H^{-1}(q, \theta_i)G(q, \theta_i), \\ W_y(q, \theta_i) &= [1 - H^{-1}(q, \theta_i)], \\ \Delta W_u &= W_u(q, \theta_1) - W_u(q, \theta_2), \\ \Delta W_y &= W_y(q, \theta_1) - W_y(q, \theta_2). \end{aligned} \quad (3.2)$$

We will discuss the closed-loop identifiability problem in two cases: without reference signal and with reference signal.

3.1. Without Reference Signal

When no reference signal is added to the system, $W(q, \theta_1)$ and $W(q, \theta_2)$ are identified based on the quasistationary data set Z^N , (3.1) establishes.

The input and output of the “true” system are stated as

$$\begin{bmatrix} u(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} -S_0(q)C_0(q) \\ S_0(q) \end{bmatrix} H_0(q)e_0(t). \quad (3.3)$$

Then, substituting (3.3) into (3.1),

$$\bar{E} |(-\Delta W_u C_0 + \Delta W_y) S_0 H_0 e_0(t)|^2 = 0. \quad (3.4)$$

As defined above, e_0 is a combination of two filtered uncorrelated white-noise disturbances e_{10} and e_{20} , and the two corresponding filters are both stable and nonsingular. Clearly, $\Phi_{e_{10}u}(\omega) > 0$ establishes.

When the feedback regulator in the “true” system satisfies $C_0 \neq \Delta W_y / \Delta W_u$, then

$$\Delta W_y = \Delta W_u = 0. \quad (3.5)$$

It means that

$$W(q, \theta_1) = W(q, \theta_2). \quad (3.6)$$

In actual power system, this condition shows up as the feedback regulator should be not too simple. High-order complex or nonlinear or time-varying regulator can ensure the identification data informative enough, and then the model structure is closed-loop identifiability.

3.2. With Reference Signal

Once the feedback regulator could not assure the identification data set informative enough, an external reference signal should be added. Likewise, $W(q, \theta_1)$ and $W(q, \theta_2)$ are identified based on the quasistationary data set Z^N , (3.1) establishes.

The input and output of the “true” system are stated as

$$\begin{bmatrix} u(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} 1 & -S_0(q)C_0(q) \\ G_0(q) & S_0(q) \end{bmatrix} \cdot \begin{bmatrix} S_0(q)r(t) \\ H_0(q)e_0(t) \end{bmatrix}. \quad (3.7)$$

Substituting (3.7) into (3.1), then

$$\begin{aligned} 0 &= \bar{E} \left| \begin{bmatrix} \widetilde{W}_u & \widetilde{W}_y \end{bmatrix} \begin{bmatrix} S_0 r(t) \\ H_0 e_0(t) \end{bmatrix} \right|^2 \\ &= \bar{E} \left| \widetilde{W}_y H_0 e_0(t) \right|^2 + \bar{E} \left| \widetilde{W}_u S_0 r(t) \right|^2, \end{aligned} \quad (3.8)$$

where

$$\begin{bmatrix} \widetilde{W}_u & \widetilde{W}_y \end{bmatrix} = [\Delta W_u \quad \Delta W_y] \begin{bmatrix} 1 & -S_0 C_0 \\ G_0 & S_0 \end{bmatrix}. \quad (3.9)$$

Recalling that the signals r and e_0 are uncorrelated by the assumption, apparently the two components in (3.8) both equal zero.

- (1) $\bar{E} |\widetilde{W}_y H_0 e_0(t)|^2 = 0$. The signal e_0 is defined as a combination of two filtered uncorrelated white-noise disturbances e_{10} and e_{20} , and the two corresponding filters are both stable and nonsingular, $\Phi_{e_0}(\omega) > 0$ establishes, therefore, $\widetilde{W}_y = 0$.
- (2) $\bar{E} |\widetilde{W}_u S_0 r(t)|^2 = 0$. Obviously, when $\bar{E} |S_0 r(t)|^2 > 0$, $\widetilde{W}_u = 0$ establishes. According to the definition, the analytical function S_0 depends on the "true" system G_0 and H_0 , then $|S_0|^2$ may be zero at most finitely many points. Only when $\Phi_r(\omega) > 0$, $\bar{E} |S_0 r(t)|^2 > 0$. Only when the reference signal is persistently exciting, $\widetilde{W}_u = 0$ establishes.

On the other hand, the determinant of matrix $\begin{vmatrix} 1 & -S_0 C_0 \\ G_0 & S_0 \end{vmatrix}$ equals 1, the matrix is always invertible. It indicates that

$$\begin{bmatrix} \widetilde{W}_u & \widetilde{W}_y \end{bmatrix} = 0. \quad (3.10)$$

Clearly, (3.5) and (3.6) are established.

Besides, it has found that if there is just a simple feedback regulator like $u(t) = ay(t)$, the data set is not informative enough to realize the closed-loop identification even with a persistently exciting reference signal [13].

Therefore, not only a persistently exciting reference signal will assure the informative data set, but also certain complexity feedback regulator should, in general, yield data set informative enough.

3.3. Closed-Loop Identifiability Conditions

When multiple random changes exist in the power system, in order to ensure the ambient signals informative enough to realize the closed-loop identification, at least one of the following conditions must be met.

- (1) The feedback regulator is high-order complex or time-varying or nonlinear.
- (2) A persistently exciting reference signal is added, and the feedback regulator should have a certain complexity.

We will now characterize in what sense the identified model approximates to the “true” system, including the consistency properties and the convergence properties. The following discussions are based on the frequency domain expression for the limiting criterion function.

4. Consistency Analysis of Closed-loop Identification

For the “true” system and the identification model shown in Figure 1, let us focus on the case with a fixed noise model $H_\theta = H_*$, the spectrum of the prediction error is

$$\begin{aligned}
\Phi_\varepsilon(\omega, \theta) &= \frac{|G_0 + B_\theta - G_\theta|^2 \Phi_u(\omega)}{|H_*|^2} \\
&+ \frac{|D_\theta|^2}{|H_*|^2} \left(\lambda_{20} - \frac{\Phi_{ue_{20}}(\omega) \Phi_{e_{20}u}(\omega)}{\Phi_u(\omega)} \right) \\
&+ \frac{|H_{10} - H_*|^2}{|H_*|^2} \lambda_{10} + \lambda_{20} \\
&- \frac{|H_{10} - H_*|^2 \Phi_{ue_{10}}(\omega) \Phi_{e_{10}u}(\omega) \lambda_{20}}{|H_*|^2 (\lambda_{20} \Phi_u(\omega) - \Phi_{ue_{20}}(\omega) \Phi_{e_{20}u}(\omega))}, \\
B_\theta &= \frac{\Phi_{e_{20}u}(\omega) (H'_{20} - H_\theta)}{\Phi_u(\omega)} + \frac{\Phi_{e_{10}u}(\omega) (H_{10} - H_\theta)}{\Phi_u(\omega)}, \\
D_\theta &= (H'_{20} - H_\theta) - \frac{\Phi_{e_{10}u}(\omega) \Phi_{ue_{20}}(\omega) (H_{10} - H_\theta)}{\lambda_{20} \Phi_u(\omega) - \Phi_{ue_{20}}(\omega) \Phi_{e_{20}u}(\omega)},
\end{aligned} \tag{4.1}$$

where $\Phi_u(\omega)$ denotes the spectrum of input u , λ_{10} and λ_{20} denote the spectra of disturbances e_{10} and e_{20} , $\Phi_{ue_{i0}}(\omega)$ and $\Phi_{e_{i0}u}(\omega)$ denote the cross-spectra between signal u and e_{i0} , $i = 1, 2$, and the operator $e^{i\omega}$ is omitted in the formula.

The model parameters are estimated using the prediction error method whose principle is to make the prediction error as small as possible [13]. Therefore, the model G_θ would approximate to the biased transfer function $G_0 + B_\theta$ as well as possible, according to the weighted frequency domain function above. It means that the function B_θ denotes the identification bias.

We can split up the input spectrum $\Phi_u(\omega)$ into one part that originates from r and two parts that come from e_{i0} :

$$\Phi_u(\omega) = \Phi_u^r(\omega) + \Phi_u^{e_{10}}(\omega) + \Phi_u^{e_{20}}(\omega). \tag{4.2}$$

The cross-spectrum between the signal u and e_{i0} satisfies

$$|\Phi_{e_{i0}u}(\omega)|^2 = \Phi_u^{e_{i0}}(\omega) \lambda_{i0}. \tag{4.3}$$

Let us comment on the bias function B_θ .

$$\begin{aligned} |B_\theta|^2 &= \left| \frac{\Phi_{e_{20}u}(\omega)}{\Phi_u(\omega)} (H'_{20} - H_*) + \frac{\Phi_{e_{10}u}(\omega)}{\Phi_u(\omega)} (H_{10} - H_*) \right|^2 \\ &\geq \frac{\lambda_{20} \Phi_u^{e_{20}}(\omega)}{|\Phi_u(\omega)|^2} |H'_{20} - H_*|^2 + \frac{\lambda_{10} \Phi_u^{e_{10}}(\omega)}{|\Phi_u(\omega)|^2} |H_{10} - H_*|^2. \end{aligned} \quad (4.4)$$

From (4.4), we see that the bias inclination will be small in the frequency range where either (or all) of the followings holds.

- (1) The noise model is good ($(H_\theta - H_*)$ is small).
- (2) The input signal-to-noise ratio is good.
- (3) The feedback contribution to the input spectrum is small.

The conditions (2.3) and (2.4) are both associated with the disturbances. In this paper, small amplitude stochastic changes of loads in actual power system are considered to be disturbances, which are hard to be manipulated. Thus, in order to reduce the identification bias, we should focus on improving the noise model's accuracy.

Moreover, in the "true" system, the filters of disturbances are generally different from each other, namely, $H_{10} \neq H'_{20}$, which implies that the noise model H_* is impossible equal to the true filters H_{10} and H'_{20} at the same time. Then, it can be deduced from (4.1) that $B_\theta \neq 0$, the identification bias inevitably exists in this situation.

Then, extending to the situation that L disturbances exist in the "true" system, the bias B_θ is described as

$$\begin{aligned} |B_\theta|^2 &= \left| \sum_{i=1}^L \left[\frac{\Phi_{e_{i0}u}(\omega)}{\Phi_u(\omega)} (H'_{i0} - H_*) \right] \right|^2 \\ &\geq \sum_{i=1}^L \left[\frac{\lambda_{i0} \Phi_u^{e_{i0}}(\omega)}{|\Phi_u(\omega)|^2} |H'_{i0} - H_*|^2 \right]. \end{aligned} \quad (4.5)$$

Obviously, with the increase in the disturbance number, the identification bias also rises. When we magnify the reference signal's energy, its contribution to input also increases and the input's total power amplifies correspondingly, then the identification bias reduces.

Therefore, when multiple small amplitude stochastic disturbances exist in a power system, the closed-loop identification bias inevitably exists. It will rise with the increase in disturbance number. In order to improve the consistency prosperities of identification, it is necessary to add a persistently exciting reference signal with certain power.

5. Convergence Analysis of Closed-Loop Identification

Let us now consider the convergence prosperities of closed-loop identification in two cases: with unfixed noise model, and with fixed noise model.

5.1. Identification with Unfixed Noise Model

It can be deduced that the asymptotic variance of the estimated transfer function is

$$\text{cov } \hat{G}_N \approx \frac{n}{N} \frac{\Phi_{v_0}(\omega)}{\Phi_u^r(\omega)}, \quad (5.1)$$

where N denotes the length of identification data, the signal v_0 is defined as

$$v_0(t) = H_{10}(q)e_{10}(t) + H'_{20}(q)e_{20}(t). \quad (5.2)$$

Substituting the spectra of associated signals into (5.1), the variance of the estimated transfer function is rewritten as

$$\text{cov } \hat{G}_N \approx \frac{n}{N} \frac{|H'_{20}|^2 \lambda_{20} + |H_{10}|^2 \lambda_{10}}{|S_0|^2 \Phi_r(\omega)}. \quad (5.3)$$

When the noise model is unfixed during the closed-loop identification the following hold.

- (1) The variance of estimated transfer function will approximate to infinite if there is no reference signal.
- (2) The variance of estimated transfer function is proportional to the model order, and inversely proportional to the length of identification data.

Then, extending to the situation that L disturbances exist in the “true” system, the variance of the estimated transfer function is

$$\text{cov } \hat{G}_N \approx \frac{n}{N} \frac{\sum_{i=1}^L |H'_{i0}|^2 \lambda_{i0}}{|S_0|^2 \Phi_r(\omega)}. \quad (5.4)$$

The variance of the estimated transfer function rises with the increase in disturbance number. Magnifying the energy of reference signal leads to a reduction of identification variance. It demonstrates again the necessity of the persistently exciting reference signal.

5.2. Identification with Fixed Noise Model

Likewise, in this situation, the variance of the estimated transfer function is

$$\text{cov } \hat{G}_N \approx \frac{n}{N} \frac{\Phi_{v_0}(\omega)}{\Phi_u(\omega)} = \frac{n}{N} \frac{|H'_{20}|^2 \lambda_{20} + |H_{10}|^2 \lambda_{10}}{\Phi_u(\omega)}. \quad (5.5)$$

In this case, since the noise model is fixed in advance, the variance of the estimated transfer function would not trend to infinite even no reference signal existed.

Then, extending to the situation that L disturbances exist in the “true” system, the variance of the estimated transfer function is

$$\text{cov } \hat{G}_N \approx \frac{n}{N} \frac{\sum_{i=1}^L |H'_{i0}|^2 \lambda_{i0}}{\Phi_u(\omega)}. \quad (5.6)$$

Clearly, the variance of estimated transfer function rises with the increase in disturbance number. Similarly, amplifying the power of reference signal will lead to the reduction of identification variance. The result also demonstrates that, it is necessary to add a persistently exciting reference signal.

Then, comparing the identification variances in the two cases, obviously

$$\frac{n}{N} \frac{\Phi_{v_0}(\omega)}{\Phi_u(\omega)} < \frac{n}{N} \frac{\Phi_{v_0}(\omega)}{\Phi_u^r(\omega)}. \quad (5.7)$$

A fixed noise model is effective to reduce the identification variance.

Therefore, when multiple small amplitude stochastic disturbances exist in a power system, the closed-loop identification variance rises with the increase in disturbance number. A persistently exciting reference signal with certain energy and a fixed noise model are both helpful to improve the convergence prosperities of closed-loop identification.

6. Conditions for Realizing Ambient Signals Based Closed-Loop Identification of Power System

We summarize the conditions for ambient signals based closed-loop identification of system as follows.

- (1) In the aspect of closed-loop identifiability, the feedback regulator should be high-order complex or nonlinear or time varying, otherwise, a persistently exciting reference signal is added and the feedback regulator has a certain complexity.
- (2) In the aspect of identification accuracy, the identification bias always exists, and the identification bias and variance both rise with the increase in disturbance number. For improving the identification accuracy, it is necessary to add a persistently exciting reference signal with certain energy and fix the noise model during the identification process.

Taking actual power systems into account, in order to realize the closed-loop identification, a high-order complex feedback regulator, a persistently exciting reference signal with certain power and a fixed noise model are necessary.

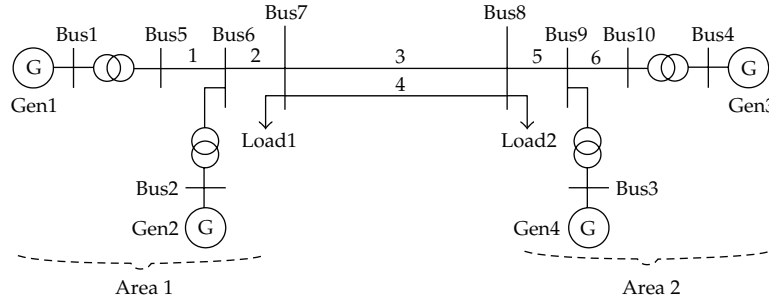
7. Simulation Examples

A two-area four-machine power system [25] shown in Figure 2 is selected to validate the closed-loop identification theoretical results. Area 1 consists of generators at bus 1 and 2, and load at bus 7; Area 2 consists of generators at bus 3 and 4, and load at bus 8. The two areas are connected through long transmission lines between bus 7 and 8.

Based on the reduced-order model calculated by the MATLAB linearization tool, the electromechanical modal properties of system are estimated, shown in Table 1.

Table 1: Estimated electromechanical modal properties based on the closed-loop identification model.

	Closed-loop identification	Theoretical calculation	error/%
Mode 1 frequency/Hz	1.174618	1.163930	0.918268
Mode 1 damping ratio/%	10.9619	10.0376	9.208263
Mode 2 frequency/Hz	0.648041	0.653445	0.827002
Mode 2 damping ratio/%	4.8910	5.3702	8.924001

**Figure 2:** Two-area four-machine system.

For the examples that follows, using MATLAB as the tool, a typical time-domain simulation that consists of driving the system with random load variations is done. Each load in this system is split into a portion consisting of constant power and random power. The random portions of real and reactive loads are obtained by passing independent Gaussian white noises through lowpass filters with very low cutoff frequency. The system's responses consist of small random variations in the system states.

In order to improve the oscillation characteristic of power system, a wide area damping regulator is designed and put into operation. Using the comprehensive dominant mode ratio and the improving residue method [26, 27], the active power of tieline between the two areas and the excitation side of Gen4 are selected to be the feedback signal and the control position. Thus, the input signal on the excitation side of Gen4 and the active power of tieline are collected to closed-loop identify the controlled system.

In this paper, the moving data window approach is adopted. The length of each data window is 1 minute, and the time interval between adjacent windows is 30 seconds. With the model order selected automatically by the method proposed in [8], the autoregressive exogenous (ARX) model is used to process ambient signals.

Defining the amplitude frequency response fitting degree index ($\Delta_M\%$) and the phase frequency response variance index (Δ_P) to evaluate the closed-loop identification performance, obviously the larger the $\Delta_M\%$ value and the smaller the Δ_P value will indicate a more precise closed-loop identification:

$$\Delta_M\% = \left[1 - \frac{\sum_{i=1}^{N_\omega} |M_{\text{idn}}(\omega_i) - M_0(\omega_i)|^2}{\sum_{i=1}^{N_\omega} |M_0(\omega_i)|^2} \right] \times 100\%, \quad (7.1)$$

$$\Delta_P = \frac{1}{N_\omega} \sum_{i=1}^{N_\omega} \left\{ \Delta P_{\text{idn}}(\omega_i) - \frac{\sum_{i=1}^{N_\omega} \Delta P_{\text{idn}}(\omega_i)}{N_\omega} \right\}^2, \quad \Delta P_{\text{idn}}(\omega_i) = P_{\text{idn}}(\omega_i) - P_0(\omega_i),$$

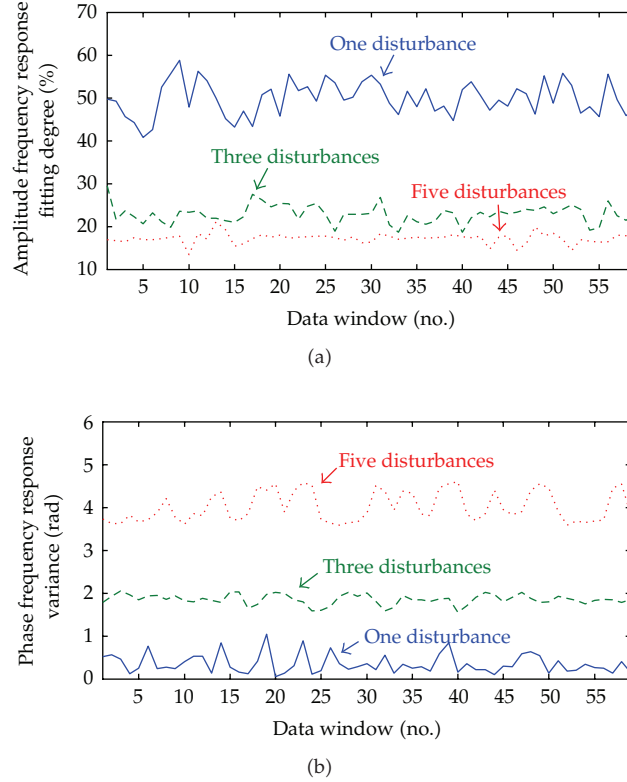


Figure 3: Closed-loop identification results with different number of disturbances.

where M_{iden} and M_0 denote the amplitude frequency response of the identification model and the “true” system, P_{iden} and P_0 represent the phase frequency response of the identification model and the “true” system, ΔP_{iden} is the error of phase frequency response, and N_ω is the number of frequency points.

First, the effect of disturbances on closed-loop identification is analyzed. One, three and five disturbance signals are added to the controlled system, respectively. Ambient data are collected for identifying the system model. The results are shown in Figure 3.

When one disturbance exists in the simulation system, the $\Delta_M\%$ value fluctuates between 40% and 60%, and the Δ_P value is less than 1; when three disturbances are added to the system, the $\Delta_M\%$ value changes between 20% and 30%, and the Δ_P value are about 2; when five disturbances exist, the $\Delta_M\%$ value is less than 20%, and the Δ_P value is up to 4. Obviously, when the disturbance number increases, the $\Delta_M\%$ value decreases, whereas the Δ_P value rises. The accuracy of closed-loop identification reduces with the increase of disturbance number.

As mentioned in Section 4, a persistently exciting reference signal is helpful to improve the identification performance. Therefore, when three disturbances exist in the controlled system, a reference signal is added. This signal is obtained by passing Gaussian white noise through a one-order filter with cutoff frequency 2 Hz, and we guarantee that it would not affect the fluctuation amplitude of system’s responses. The identification data are collected and the corresponding results are shown in Figure 4.

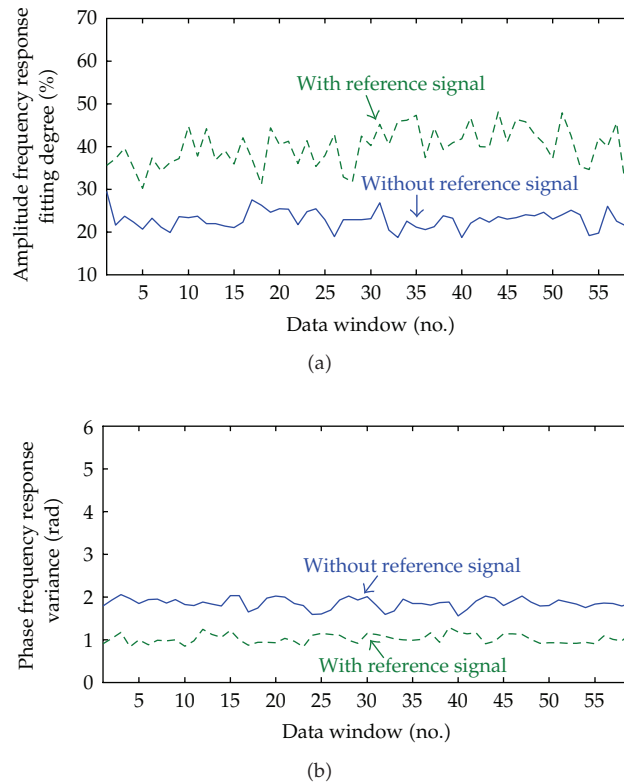


Figure 4: Closed-loop identification results with\without reference signal.

When the reference signal is added to the simulation system, the $\Delta_M\%$ value fluctuates between 30% and 45%, and the Δ_P value is about 1. Comparing with the results of system without reference signal, it is clear that due to the existence of reference signal, the $\Delta_M\%$ value rises and the Δ_P value falls. A persistently exciting reference signal is helpful to improve the identification accuracy.

Then, the effect of reference signal's energy is further analyzed. When three disturbances exist in the controlled system, we magnify the power of reference signal gradually, and collect ambient signals to identify the system. The results are shown in Figure 5. These reference signals are ensured no obvious affect on the system's response.

When we gradually increase the energy of reference signal, the fluctuation ranges of $\Delta_M\%$ value are 30–45%, 60–75%, 85–95%, respectively. On the other hand, the change ranges of Δ_P value are 0.8–1.2, 0.6–0.7, 0.1–0.3. Clearly, with the increase of reference signal's energy, the $\Delta_M\%$ value rises, and the Δ_P value decreases. It demonstrates that appropriately boosting the reference signal's power is effective to improve the closed-loop identification accuracy.

Then, basing on the result corresponding to the reference signal with medium energy, the electromechanical modal properties are estimated, listed in Table 1, and the corresponding Bode diagram is shown in Figure 6.

Obviously, the closed-loop identification results are basically consistent with the theoretical calculation results, that is to say, the system is identified accurately based on ambient signals.

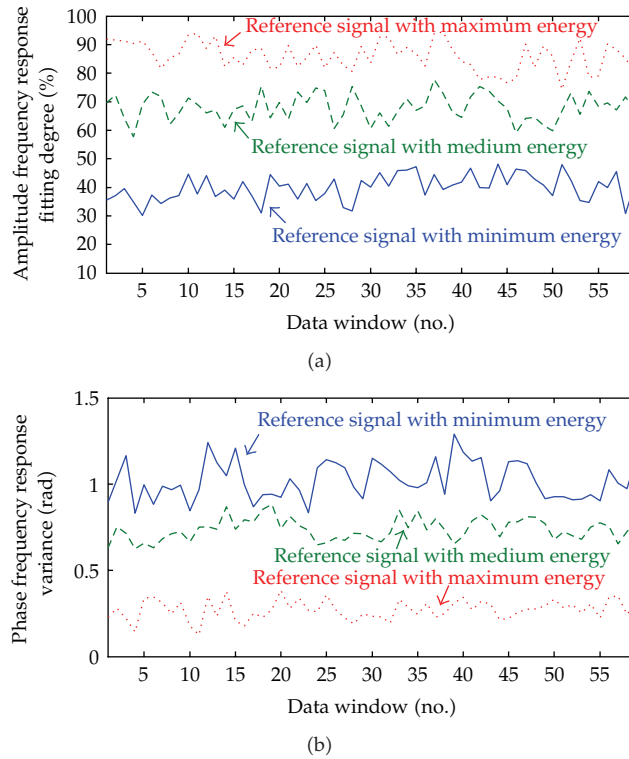


Figure 5: Closed-loop identification results with increasing energy reference signals.

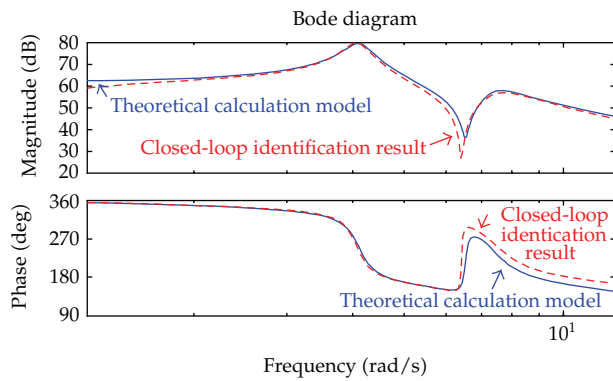


Figure 6: Bode diagram of closed-loop identification result.

8. Conclusions

Ambient signals based closed-loop identification of power system is theoretically studied in this paper, including the closed-loop identifiability, the consistency properties, and the convergence properties. It is found that a persistently exciting reference signal and a high-order complex feedback regulator are necessary for realizing the system identification in this situation. Considering that the identification bias inevitably exists, and the identification bias

and variance boosts with the increase of disturbance number, it is better to appropriately magnify the reference signal's energy and fix the noise model. At last, the theoretical results are validated by simulation examples.

Acknowledgment

This work was supported in part by the Major State Basic Research Development Program of China (2012CB215206), National Natural Science Foundation of China (51037002), Natural Science Foundation of Guangdong Province, China (2011040000995), Foundation for Distinguished Young Talents in Higher Education of Guangdong, China (LYM11108), Shenzhen Technology Research and Development Foundation (2011040000995), and Shenzhen University Basic Research Foundation (201117).

References

- [1] I. Kamwa, R. Grondin, J. Dickinson, and S. Fortin, "Minimal realization approach to reduce-order modelling and modal analysis for power system response signals," *IEEE Transactions on Power Systems*, vol. 8, no. 3, pp. 1020–1029, 1993.
- [2] J. R. Smith, J. F. Hauer, D. J. Trudnowski, F. Fatehi, and C. S. Woods, "Transfer function identification in power system applications," *IEEE Transactions on Power Systems*, vol. 8, no. 3, pp. 1282–1290, 1993.
- [3] I. Kamwa and L. Gérin-Lajoie, "State-space system identification-toward MIMO models for modal analysis and optimization of bulk power systems," *IEEE Transactions on Power Systems*, vol. 15, no. 1, pp. 326–335, 2000.
- [4] A. Hasanović, A. Feliachi, A. Hasanović, N. B. Bhatt, and A. G. DeGroff, "Practical robust PSS design through identification of low-order transfer functions," *IEEE Transactions on Power Systems*, vol. 19, no. 3, pp. 1492–1500, 2004.
- [5] J. W. Pierre, "Initial results in electromechanical mode identification from ambient data," *IEEE Transactions on Power Systems*, vol. 12, no. 3, pp. 1245–1251, 1997.
- [6] R. W. Wies, J. W. Pierre, and D. J. Trudnowski, "Use of ARMA block processing for estimating stationary low-frequency electromechanical modes of power systems," *IEEE Transactions on Power Systems*, vol. 18, no. 1, pp. 167–173, 2003.
- [7] N. Zhou, D. J. Trudnowski, J. W. Pierre, and W. A. Mittelstadt, "Electromechanical mode online estimation using regularized robust RLS methods," *IEEE Transactions on Power Systems*, vol. 23, no. 4, pp. 1670–1680, 2008.
- [8] C. Wu, C. Lu, T. Wang, and T. Yu, "Ambient signals based power system oscillation modes identification considering model order selection," in *Proceedings of the IEEE Power and Energy Society General Meeting (PES '09)*, pp. 1–7, Alberta, Canada, July 2009.
- [9] J. F. Hauer, W. A. Mittelstadt, K. E. Martin et al., "Use of the WECC WAMS in wide-area probing tests for validation of system performance and modeling," *IEEE Transactions on Power Systems*, vol. 24, no. 1, pp. 250–257, 2009.
- [10] D. J. Trudnowski, "Estimating electromechanical mode shape from synchrophasor measurements," *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1188–1195, 2008.
- [11] H. Ghasemi and C. A. Cañizares, "Confidence intervals estimation in the identification of electromechanical modes from ambient noise," *IEEE Transactions on Power Systems*, vol. 23, no. 2, pp. 641–648, 2008.
- [12] W. Chao, L. Chao, H. Yingduo et al., "An ARMA-P approach for estimating mode shape from ambient data," in *Proceedings of the IEEE Power and Energy Society General Meeting (PES '10)*, pp. 1–6, 2010.
- [13] L. Ljung, *System Identification-Theory For the User*, Prentice Hall, Upper Saddle River, NJ, USA, 2nd edition, 1999.
- [14] U. Forssell and L. Ljung, "Closed-loop identification revisited," *Automatica*, vol. 35, no. 7, pp. 1215–1241, 1999.
- [15] L. Ljung, "Integrated frequency-time domain tools for system identification," in *Proceedings of the American Control Conference (AAC '04)*, vol. 6, pp. 5594–5599, Boston, Mass, USA, June 2004.
- [16] X. Bombois, G. Scorletti, M. Gevers, P. M. J. Van den Hof, and R. Hildebrand, "Least costly identification experiment for control," *Automatica*, vol. 42, no. 10, pp. 1651–1662, 2006.

- [17] M. Gevers, A. S. Bazanella, and L. Mišković, *Identifiability and Informative Experiments in Open and Closed-Loop Identification*, Lecture Notes in Control and Information Sciences: Modeling, Estimation and Control, Springer, Heidelberg, Germany, 2007.
- [18] A. Karimi and I. D. Landau, "Comparison of the closed-loop identification methods in terms of the bias distribution," *Systems and Control Letters*, vol. 34, no. 4, pp. 159–167, 1998.
- [19] M. Gevers, L. Ljung, and P. V. Van Den Hof, "Asymptotic variance expressions for closed-loop identification," *Automatica*, vol. 37, no. 5, pp. 781–786, 2001.
- [20] B. Ninness and H. Hjalmarsson, "On the frequency domain accuracy of closed-loop estimates," *Automatica*, vol. 41, no. 7, pp. 1109–1122, 2005.
- [21] C. Lu, C. Li, J. He, X. Wu, and P. Li, "Optimal coordinate design of multiple HVDC modulation controllers based on MIMO system identification," in *Proceedings of the IEEE Power Engineering Society General Meeting (PES '07)*, pp. 1–8, Tampa, Fla, USA, June 2007.
- [22] J. F. Hauer, "Application of Prony analysis to the determination of modal content and equivalent models for measured power system response," *IEEE Transactions on Power Systems*, vol. 6, no. 3, pp. 1062–1068, 1991.
- [23] J. J. Sanchez-Gasca, "Performance comparison of three identification methods for the analysis of electromechanical oscillations," *IEEE Transactions on Power Systems*, vol. 14, no. 3, pp. 995–1002, 1999.
- [24] T. Söderström and P. Stoica, *System Identification*, Prentice Hall, London, UK, 1989.
- [25] P. Kundur, *Power System Stability and Control*, McGraw Hill, New York, NY, USA, 1994.
- [26] C. Yaoxiang, *Studies on Wide-Area Multi-DC Damping Coordinated Adaptive Control Based on Identifications*, Tsinghua University, Beijing, China, 2006.
- [27] L. Xingyuan, S. Zhenxia, and T. Guangfu, "Study on decentralized coordinated control for multi-infeed hvdc transmission systems," in *Proceedings of the Chinese Society for Electrical Engineering (CSEE '05)*, vol. 25, pp. 8–12, 2005.



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