Inter-area Oscillations in Power Systems

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Editor

Inter-area Oscillations in Power Systems

A Nonlinear and Nonstationary Perspective

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Preface

The study of complex dynamic processes governed by nonlinear and nonstationary characteristics is a problem of great importance in the analysis and control of power system oscillatory behavior. Power system dynamic processes are highly random, nonlinear to some extent, and intrinsically nonstationary even over short time intervals as in the case of severe transient oscillations in which switching events and control actions interact in a complex manner.

Phenomena observed in power system oscillatory dynamics are diverse and complex. Measured ambient data are known to exhibit noisy, nonstationary fluctuations resulting primarily from small magnitude, random changes in load, driven by low-scale motions or nonlinear trends originating from slow control actions or changes in operating conditions. Forced oscillations resulting from major cascading events, on the other hand, may contain motions with a broad range of scales and can be highly nonlinear and time-varying.

Prediction of temporal dynamics, with the ultimate application to real-time system monitoring, protection and control, remains a major research challenge due to the complexity of the driving dynamic and control processes operating on various temporal scales that can become dynamically involved. An understanding of system dynamics is critical for reliable inference of the underlying mechanisms in the observed oscillations and is needed for the development of effective wide-area measurement and control systems, and for improved operational reliability.

Complex power system response data can contain nonlinear and possibly strong local trends, noise, and may exhibit sudden variations and other nonlinear effects associated with large and abrupt changes in system topology or operating conditions that make the extraction of salient features difficult. Accounting for nonlinear and time-varying features can not only provide a better description of the data but can also reveal crucial information on system's oscillatory behavior such as modal properties and moving patterns. By tracking the evolving dynamics of the underlying oscillations, the onset of system instability can be determined and the critical stages for analysis and control can be identified.

Recent years have seen a flourishing of activity in various techniques for the analysis of power system dynamic behavior. Foremost among linear analysis tools, Prony's method has been widely applied to estimate small-signal dynamic properties from measured and simulated data. Applications of linear techniques in the context of power oscillations include, for example, modal extraction from ringdowns, the analysis of dynamic tests, and the identification of transfer functions. Ongoing research into the study of modal behavior in the presence of high noise levels and possibly nonstationary situations has resulted in variations to these approaches that extend their practical use to the realm of near-real-time stability assessment and control, and has stimulated the development of enhanced monitoring systems. This in turn, has sparked a resurgence of interest in the development of new algorithms that use the available online information to estimate modal properties.

Advances in signal processing algorithms, along with continuously growing computational resources and monitoring systems are beginning to make feasible the analysis and characterization of transient processes using real-time information. Much of the recent work has been driven by interest in near real-time estimation of electromechanical modal properties from measured ambient data. This effort has resulted in various signal processing methods with the capability of tracking the evolving dynamics of critical system modes.

Complementary, time–frequency analysis techniques that explicitly acknowledge and incorporate nonlinearity or nonstationarity in both the time and frequency domain are emerging as subjects of research and application in engineering investigations. Adaptive, nonlinear time-varying methods with the ability to capture the temporal evolution of critical modal parameters, promise to enhance our understanding of the physical mechanisms that underlie system oscillatory dynamics and have the potential to be applied to more general transient oscillations, governed by multiscale, time-varying processes.

A significant element of this major thrust is the development of wide-area measurement systems. Extracting the salient features of interest from a widely dispersed and usually large number of system observations is a complex problem. In the analysis of large models, where a significant amount of observational data is available, the development of data-based statistical models with the capacity to process the vast wealth of information and extract relevant, physically independent patterns is appealing. For many of the above developments, a complete framework for temporal characterization of system behavior, however, is still evolving.

The combined utilization of temporal, modal information and advanced measurement and control techniques holds also enormous potential to provide critical information for early detection, mitigation, and avoidance of large-scale cascading failures and could form the basis of smart, wide-area automated analysis and control systems. Analysis and characterization of time-synchronized system measurements requires mathematical tools that are adaptable to the varying system conditions, accurate and fast, while reducing the complexity of the data to make them comprehensible and useful for control and real-time decisions. Experience with the analysis of complex inter-area oscillations from measured data, shows that issues such as noise, time-varying behavior, data measurement errors, and nonlinear effects have to be addressed if these tools are to be of practical use. Further, the applicability of these techniques to both, ambient from online system measurements and large-scale transient oscillations has to be fully investigated because some techniques are better suited for a specific type of behavior.

This book deals with the development and application of advanced measurement-based signal processing techniques to the study, characterization, and control of complex transient processes in power systems. Recent advances in understanding, modeling and controlling system oscillations are reviewed. Specific attention is given to the modeling and control of complex time-varying (and possibly nonlinear) power system transient processes which have not been present in previous work. Techniques that explicitly address and treat nonlinearity and nonstationarity are given and efficient methods to generate time-varying system approximations from both measured and simulated data are discussed. Attention is also given to the vital new ideas of dynamic security assessment in real-time implementations and the development of smart, wide-area measurement and control systems incorporating FACTS (flexible AC transmission system) technology. Application examples include the analysis of real data collected on grids in western North America, Australia, Italy, and Mexico. These studies are expected to stimulate the interest of other researchers, toward the investigation of complex nonstationary power system oscillations and may form the basis of more advanced computational algorithms.

The book is organized into eight chapters written by leading researchers who are major contributors to knowledge in this field.

Chapter 1 demonstrates and examines the performance of several methods for estimating small-signal dynamic properties from measured responses. The theoretical basis for these methods is described as well as application, properties, and performance. Examples include computer simulations and actual system experiments from the western North American power grid. Analysis goals center on estimating the modal properties of the system including modal frequency, damping, and shape.

Chapter 2 revisits some of the fundamental assumptions of the recently introduced Hilbert–Huang transform. The ability of empirical mode decomposition (EMD) to yield monocomponent intrinsic mode functions is examined in the context of power system oscillations. Some enhancements to the EMD are proposed to enhance its ability to better discriminate between closely spaced frequency components. Additionally, frequency demodulation is suggested, to extract physically relevant instantaneous frequency from the Hilbert transform. Synthetic data as well as real life data are used to demonstrate the validity of the enhancements.

Chapter 3 discusses some refinements to the Hilbert–Huang technique to analyze time-varying multicomponent oscillations. Improved masking signal techniques for the EMD are proposed and tested on measured data of a real event in northern Mexico. Based on this framework, a novel approach to the computation of instantaneous damping is suggested and a local implementation of the Hilbert transform is also described. The accuracy of the method is demonstrated by comparisons to Prony and Fourier analysis.

Chapter 4 investigates the applicability of Hilbert–Huang analysis technique to extract modal information in the presence of noise and possibly nonstationary situations. Application of Hilbert analysis is examined relative to the more established Prony analysis, with particular reference to the considerable structural differences which exist between the two methods. Factors affecting the performance of the techniques including noise tolerance, performance in the case of closely spaced frequency components and changes in the underlying system dynamics are discussed and investigated using synthetic and measured data.

In Chapter 5 a real-time centralized controller for addressing small-signal instability related events in large electric power systems is proposed. Using wide-area monitoring schemes to identify the emergence of growing or undamped oscillations related to interarea and/or local modes, rules are developed for increasing multi-Prony method's observability and dependability. This information is then utilized to initiate static VAR compensation controls to enhance the damping of a critical mode; the algorithms are tested in a two-area power system and in a large-scale simulation example.

Chapter 6 discuses the use of multivariate data analysis techniques to extract and identify dynamically independent spatiotemporal patterns from time-synchronized data. By seeing the snapshots of system data as a realization of random fields generated by some kind of stochastic process, a statistical approach to investigate propagating phenomena of different spatial scales and temporal frequencies is proposed and tested on real noisy measurements from the Mexican system. The method provides accurate estimation of nonstationary effects, modal frequency, time-varying shapes, and time instants of intermittent transient behavior.

Chapter 7 proposes new techniques for detection and estimation of nonstationary power transients. Attention is focused on two aspects of small signal models: the detection of change in the system and the identification of the new operating parameters. Techniques to detect significant changes in system dynamics by analyzing the dynamic response to continual load changes based on detection theory are proposed. Approaches based on time–frequency analysis techniques are then used to yield improved modal estimates in nonstationary environments. Applications to measurement data from the Australian connected system are presented.

Finally, Chapter 8 discusses the development of advanced monitoring and control approaches for enhancing power system security. The monitoring structure is based on wavelet analysis of wide-area measurements systems targeted to extract the critical damping of critical oscillation modes. A hierarchical response-based control strategy that may incorporate FACTS technologies and special protection systems is developed and tested on a dynamic model of the Italian interconnected system to provide effective stabilization of critical modes.

The book is the first comprehensive, systematic account of current analysis methods in power system oscillatory dynamics in both time and frequency domains ranging from modal analysis, to data-driven time-series models and statistical approaches. The procedures can be used in various disciplines other than power engineering, including signal and time analysis, process identification and control, and data compression and has wide applications to many important problems covering engineering, biomedical, physical, geophysical, and climate data.

This is a book intended for advanced undergraduate and graduate courses, as well as for researchers, utility engineers, and advanced teaching in the fields of power engineering, signal processing, and identification and applied control.

Guadalajara, Mexico A.R. Messina

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Chapter 1
Signal Processing Methods for Estimating Small-Signal Dynamic Properties from Measured Responses

Daniel Trudnowski and John Pierre

Abstract Power system small-signal electromechanical dynamic properties are often described using linear system concepts. The underlying hypothesis is that small motions of the system can be described by a set of ordinary differential equations. Modal analysis of these governing equations provides considerable insight into the stability properties of the system. Over the past two decades, many signal processing techniques have been developed to conduct modal analysis using only time-synchronized actual system measurements. Some techniques are appropriate for transient signals, others are for ambient signal conditions, and some are for conditions where a known probing signal is exciting the system. In this chapter, an overview of many of the more successful analysis techniques is presented. The theoretical basis for these methods is described as well as application properties and performance. Examples include computer simulations and actual system experiments from the western North American power system. Analysis goals center on estimating the modal properties of the system including modal frequency, damping, and shape.

1.1 Introduction

Time-synchronized measurements provide rich information for estimating a power system's electromechanical modal properties via advanced signal processing. This information is becoming critical for the improved operational reliability of interconnected grids. A given mode's properties are described by its frequency, damping, and shape. Modal frequencies and damping are useful indicators of power system stress, usually declining with increased load or reduced grid capacity. Mode shape provides critical information for operational control actions. Over the past two decades, many signal processing

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techniques have been developed and tested to conduct modal analysis using only time-synchronized actual system measurements. Some techniques are appropriate for transient signals while others are for ambient signal conditions.

Many of the signal processing algorithms described in this chapter are the basis for several evolving software tools. The majority of these tools are used to conduct engineering analysis of the grid in an off-line or post disturbance setting [1]. More recently, online real-time software tools and applications are evolving [2] and will likely continue to be a research focus area for the power system community.

Near-real-time operational knowledge of a power system's modal properties may provide critical information for control decisions and thus enable reliable grid operation at higher loading levels. For example, modal shape may someday be used to optimally determine generator and/or load-tripping schemes to improve the damping of a dangerously low damped mode. The optimization involves minimizing load shedding and maximizing improved damping. The two enabling technologies for such real-time applications are a reliable real-time-synchronized measurement system and accurate modal analysis signal processing algorithms.

In this chapter, an overview of many of the more successful analysis techniques is presented. The theoretical basis for these methods is described as well as application and performance properties. Examples include computer simulations and actual system experiments from the western North American power system (wNAPS). Analysis goals center on estimating the modal properties of the system including modal frequency, damping, and shape.

The chapter is organized as follows. Section 1.2 discusses system basics. An overview of mode estimation algorithms is provided in Section 1.3. Section 1.4 discusses the use of probing signals to improve mode estimates. Section 1.5 provides some examples. Model validation and estimation assessment is discussed in Section 1.6, and Section 1.7 covers mode-shape estimation. Finally, conclusions are discussed in Section 1.8.

1.2 System Basics

Analyzing and estimating power system electromechanical dynamic effects are a challenging problem because the system:

1. is nonlinear, high order, and time varying;
2. contains many electromechanical modes of oscillation close in frequency; and
3. is primarily stochastic in nature.

Design of signal processing algorithms requires that one address each of these issues. Fortunately, the system behaves relatively linear when at a steady-state operating point [3].

As has been established in one of the many excellent books that address the properties and nature of electromechanical dynamics in power systems (e.g., see [4, 5]), electromechanical modes are typically classified as either local or inter-area in nature. Local modes occur when a single generator or plant swings against the system while an inter-area mode occurs when several generators in an area swing against generators in another area. Because local modes are characterized by larger inertias and lower impedance paths, their frequencies tend to be higher. In general, local modes tend to be in the 1–2 Hz range while inter-area modes tend to be in the 0.2–1.0 Hz range. Typically, the inter-area modes are more troublesome.

Consistent with power system dynamic theory, we assume that a power system can be linearized about an operating point [4, 5]. The underlying assumption is that small motions of the power system can be described by a set of ordinary differential equations of the form

$$\begin{aligned} \dot{\mathbf{x}}(t) &= A\mathbf{x}(t) + B_{\mathrm{L}}\mathbf{q}(t) + B_{\mathrm{E}}\mathbf{u}_{\mathrm{E}}(t) \\ \mathbf{y}(t) &= C\mathbf{x}(t) + D_{\mathrm{L}}\mathbf{q}(t) + D_{\mathrm{E}}\mathbf{u}_{\mathrm{E}}(t) + \boldsymbol{\mu}(t) \end{aligned} \tag{1.1}$$

where $\mathbf{q}$ is a hypothetical random vector perturbing the system, vector $\mathbf{x}$ contains all system states including generator angles and speeds, and t is time. Control actions that can be described as smooth functions of the state $\mathbf{x}$ are embedded in the system A matrix, and all other actions are represented by the exogenous input vector $\mathbf{u}_{\mathrm{E}}$. These include set-point changes, low-level probing signals (e.g., a low-level probing signal into a DC converter), and load pulses that are applied to examine system dynamics. Measurable signals are represented by $\mathbf{y}$ which contains measurement noise $\boldsymbol{\mu}$ that includes effects from instruments, communication channels, recording systems, and similar devices. In general, measurement noise has a relatively small amplitude when quality instrumentation is employed. Changes which are breaker actuated may produce system topology changes that alter the system A matrix to various degrees.

The assumption for $\mathbf{q}$ is that it is a vector of small-amplitude random perturbations typically conceptualized as noise-produced load switching. It has been hypothesized that the load switching is primarily integrated stationary Gaussian white noise with each element of $\mathbf{q}$ independent [6]. This assumption is certainly open to more research.

An expanded perspective of the system is shown in Fig. 1.1 where y_i is the ith element of $\mathbf{y}$ [7]. Multiple-input and multiple-output (MIMO) system G is assumed linear. Network topology changes are represented by switches in dynamic gain matrices K and K', which may or may not be deliberate.

We classify the response of the system in Fig. 1.1 as one of two types: transient (sometimes termed a ringdown) and ambient. The basic assumption for the ambient case is that the system is excited by low-amplitude variations at $\mathbf{q}$ and $\mathbf{u}_{\mathrm{E}}$ and that the variations are typically random or pseudorandom in nature. This results in a response at y that is colored by the dynamics G.

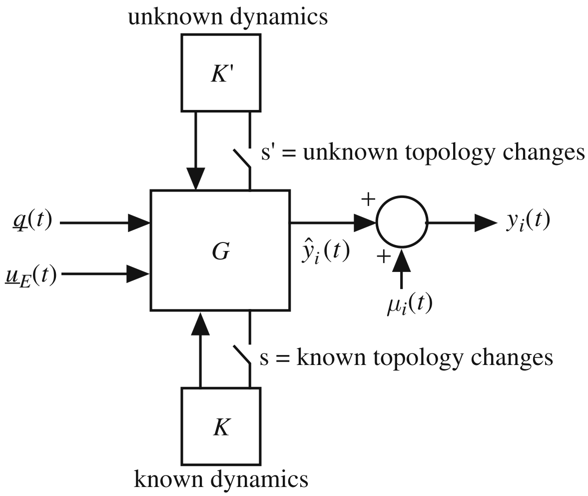

Fig. 1.1 A structure for information sources in process identification

A transient response is typically larger in amplitude and is caused by a sudden switch at **s** or **s**′, or a sudden step or pulse input at $\mathbf{u}_E$. The resulting time-domain response is a multimodal oscillation superimposed with the underlying ambient response.

The different types of responses are shown in Fig. 1.2, which shows a widely published plot of the real power flowing on a major transmission line during a breakup of the wNAPS in 1996. Prior to the transient at the 400 s point, the system is in an ambient condition. After the ringdown at the the 400 s point, the system returns to an ambient condition. The next event in the system causes an unstable oscillation.

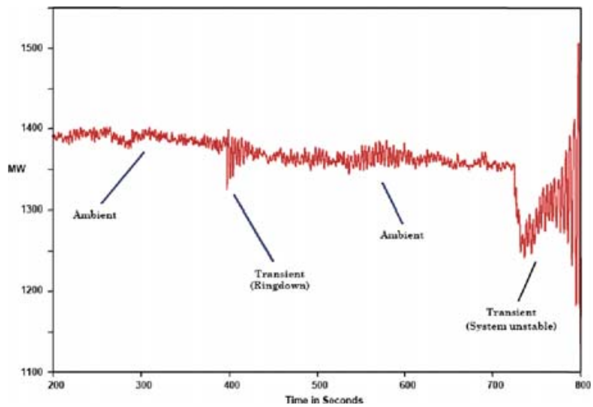

Fig. 1.2 Real power flowing on a major transmission line during the western North American power system breakup of 1996

In developing and applying measurement-based modal analysis algorithms, it is imperative that one considers the stochastic nature of the system. Power systems are continually excited by random inputs with high-order independence. This is modeled by $\mathbf{q}(t)$ in our formulation. Because of this stochastic nature, no algorithm can exactly estimate the modal properties of the system from finite-time measurements. There will always be an error associated with the estimate. When evaluating estimation algorithms, one must address these error properties. This includes the bias error as well as the variance of the estimate.

In terms of application, we classify modal frequency and damping estimation algorithms into two categories: (1) ringdown analyzers and (2) mode meters. A ringdown analysis tool operates specifically on the ringdown portion of the response; typically the first several cycles of the oscillation (5–20 s). Alternatively, a mode meter is applied to any portion of the response: ambient, transient, or combined ambient/transient. Ultimately, a mode meter is an automated tool that estimates modal properties continuously and without reference to any exogenous system input.

1.3 Signal Processing Methods for Estimating Modes

Many parametric methods have been applied to estimate power system electromechanical modes. As stated above, we classify these methods into two categories: ringdown analyzers and mode meters. In this section, we provide an overview of some of the algorithms that have been used to solve these problems.

1.3.1 Ringdown Algorithms

Ringdown analysis for power system modal analysis is a relatively mature science. The underlying assumed signal model for these algorithms is a sum of damped sinusoids. The most widely studied ringdown analysis algorithm is termed Prony analysis. The pioneering paper by Hauer, Demeure, and Scharf [8] was the first to establish Prony analysis [9] as a tool for power system ringdown analysis. Expansion to transfer function applications, multiple outputs, and improved numerics were progressively established in [10–17]. Other ringdown analysis algorithms have been successfully applied to power system applications. These include the minimal realization algorithm first introduced in [18], the eigenvalue ralization algorithm (ERA) in [19], the matrix pencil method [20], and the Hankel total least squares (HTLS) [20]. The conclusions and discussions in [21] point to the vast similarities between Prony analysis and the ERA. A comparative analysis between matrix pencil, HTLS, and Prony analysis in [20] conclude that HTLS and matrix pencil estimate the mode damping more accurately. These conclusions are certainly subject to the example case and the parameters chosen for the analysis.

It is beyond the scope of this chapter to provide the equations for all the ringdown methods. As an overview, we provide the basic equations for Prony analysis. The reader is directed to the above references for more details.

While ignoring noise content and assuming nonrepeated poles, if one applies an impulse input to the system in (1.1), the response at the ith output can be written as

$$y_j(t) = \sum_{i=1}^{n} B_i e^{\lambda_i t} \tag{1.2}$$

where λ_i is the ith pole (mode). If we let $t = kT$, where T is the constant sample period, this equation can be converted to discrete-time form as

$$y_j(kT) = \sum_{i=1}^{n} B_i z_i^k, \quad \text{for } k = 0, 1, \ldots, m \tag{1.3}$$

where $z_i = e^{\lambda_i T}$ is the discrete-time pole. Equation (1.3) is expanded into matrix form as

$$\begin{bmatrix} y(0) \\ y(T) \\ \vdots \\ y(mT) \end{bmatrix} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ z_1 & z_2 & \cdots & z_n \\ \vdots & \vdots & \ddots & \vdots \\ z_1^m & z_2^m & \cdots & z_n^m \end{bmatrix} \begin{bmatrix} B_1 \\ B_2 \\ \vdots \\ B_n \end{bmatrix} \tag{1.4}$$

It is relatively easy to show [9] that

$$\begin{bmatrix} y(nT) \\ y((n+1)T) \\ \vdots \\ y(mT) \end{bmatrix} = \begin{bmatrix} y((n-1)T) & y((n-2)T) & \cdots & y(0) \\ y(nT) & y((n-1)T) & \cdots & y(T) \\ \vdots & \vdots & \ddots & \vdots \\ y((m-1)T) & y((m-1)T) & \cdots & y((m-n)T) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \tag{1.5}$$

where the a_i's are the coefficients of the characteristic equation

$$z^n - \left(a_1 z^{n-1} + a_2 z^{n-2} + \cdots + a_n\right) = 0 \tag{1.6}$$

The solution of (1.6) are the z_i poles.

Prony analysis involves solving (1.5) for the a_i characteristic equation coefficients. Then (1.6) is rooted to obtain the z_i discrete-time poles. Lastly, (1.4) is solved for the B_i's. As described in the above references, these equations can be extended to the multioutput case. Selection of model order n, sample period T, and number of data points $m+1$ are also addressed throughout the literature.

1.3.2 Mode-Meter Algorithms

Ambient analysis of power system data estimates the modes when the primary excitation to the system is random load variations, which results in a low-amplitude stochastic time series (ambient noise). A good place to begin ambient analysis is with nonparametric spectral estimation methods, which are very robust as they make very few assumptions. The most widely used nonparametric method is the Welch periodogram [22, 23] spectrum which provides an estimate of a signal's strength as a function of frequency. Thus, usually the dominate modes are clearly visible as peaks in the spectral estimate. The estimates of the mode frequencies are identifiable in the locations of the peaks. The narrower the peaks, the lighter is the damping. Welch spectral estimates are also used in estimating mode shape as will be discussed in Section 1.7. While robust and insightful, nonparametric methods do not provide direct numerical estimates of a mode's damping ratio and frequency. Therefore, to obtain further information parametric methods are applied.

Ambient-based mode estimation can be conducted in the time domain or frequency domain. Time-domain algorithms operate directly on the sampled data while frequency-domain methods require the estimation of the power spectral density (PSD) function (usually using Welch's method). The first available ambient-based mode estimation work [6] used a frequency-domain strategy. The method described in [6] was applied to actual system measurements. With this approach, Welch periodogram averaging is used to estimate the PSD of a signal. Frequency-domain identification is then used to estimate the system modes. A disadvantage of the approach in [6] is that the frequency-domain identification process used requires an initial estimate of the system modes prior to analysis which is difficult to automate.

There are two basic types of parametric mode estimation algorithms: block processing and recursive. With block processing algorithms, the modes are estimated from a window of data. For each new window of data, a new estimate is calculated. For example, assume one is using a 5 min window length. For each window of data, a single set of modes is calculated. All data in the 5 min block are equally weighted. A new mode estimate can be calculated as often as required, but each calculation requires 5 min of the most recent data. The first application of block processing is contained in [24] where the Yule–Walker (YW) algorithm is used to estimate modes using an autoregressive (AR) model. The method is extended to the overdetermined modified YW method [35] to estimate an autoregressive moving average (ARMA) model in [25]. The approach is further extended to multiple signals in [26], which can improve the performance. Block processing methods using subspace methods CVA (canonical variate algorithm) and N4SID (numerical algorithm for subspace state–space system identification) were first introduced in [27] and [34], respectively. A variation of the YW approach that estimates the autocorrelation function using a frequency-domain calculation is introduced in [28]; this method is termed the Yule–Walker spectrum (YWS) method. Also in [28], the YW, YWS, and N4SID algorithms are compared. Another frequency-domain method is the frequency-domain decomposition (FDD) method described in [29], which decomposes the signals' estimated power spectrum.

For recursive methods, the estimated modes are updated for each new sample of the data. The new estimate is obtained using a combination of the new data point and the previous mode estimate. A forgetting factor is used to discount information based on previous data; therefore, new data is weighted more in each calculation. Similar to the block processing methods, all recursive methods tested to date require many minutes of data to converge to a steady-state solution. Published results include the least-mean squares (LMS) method [30] and the regularized robust recursive least-squares (R3LS) method [31, 32].

The R3LS method described in [32] offers several advances to previous algorithms. First, it accommodates an autoregressive moving average exogenous (ARMAX) model to account for ambient noise as well as a known input, which can enhance performance during probing. Second, it has a robust objective function to reduce the impact of missing or outlier data, and third, it can incorporate a priori knowledge of the modes. The full impact of these advances is the subject of current and future research.

An important component of a mode meter is the automated application of the algorithm. With all algorithms, several modes are estimated and many of them are "numerical artifacts." Typically, "modal energy" methods are used to determine which of the modes in the frequency range of the inter-area modes have the largest energy in the signal [28]. It is then assumed that this is the mode of most interest.

It is beyond the scope of this chapter to provide the equations for all the mode-meter methods described above. The reader is directed to the above references for more details and for information on preprocessing the data before application of the mode-meter algorithms.

1.4 Power System Identification Using Known Probing Signals

It is absolutely imperative to understand that because of the stochastic nature of the system, the accuracy of any mode estimation is limited. It is possible to significantly improve the estimation by exciting the system with a probing signal. A signal may be injected into the power system using a number of different actuators such as resistive brakes, generator excitation, or modulation of DC intertie signals. For example, operators of the wNAPS use both the 1,400 MW Chief Joseph dynamic brake and modulation of the Pacific DC intertie (PDCI) to inject known probing signals into the system. The wNAPS is shown in Fig. 1.3 with the PDCI being the DC line flowing from Oregon to southern California. The PDCI has been modulated with a number of different signals including short duration mid-level probing resulting in transient

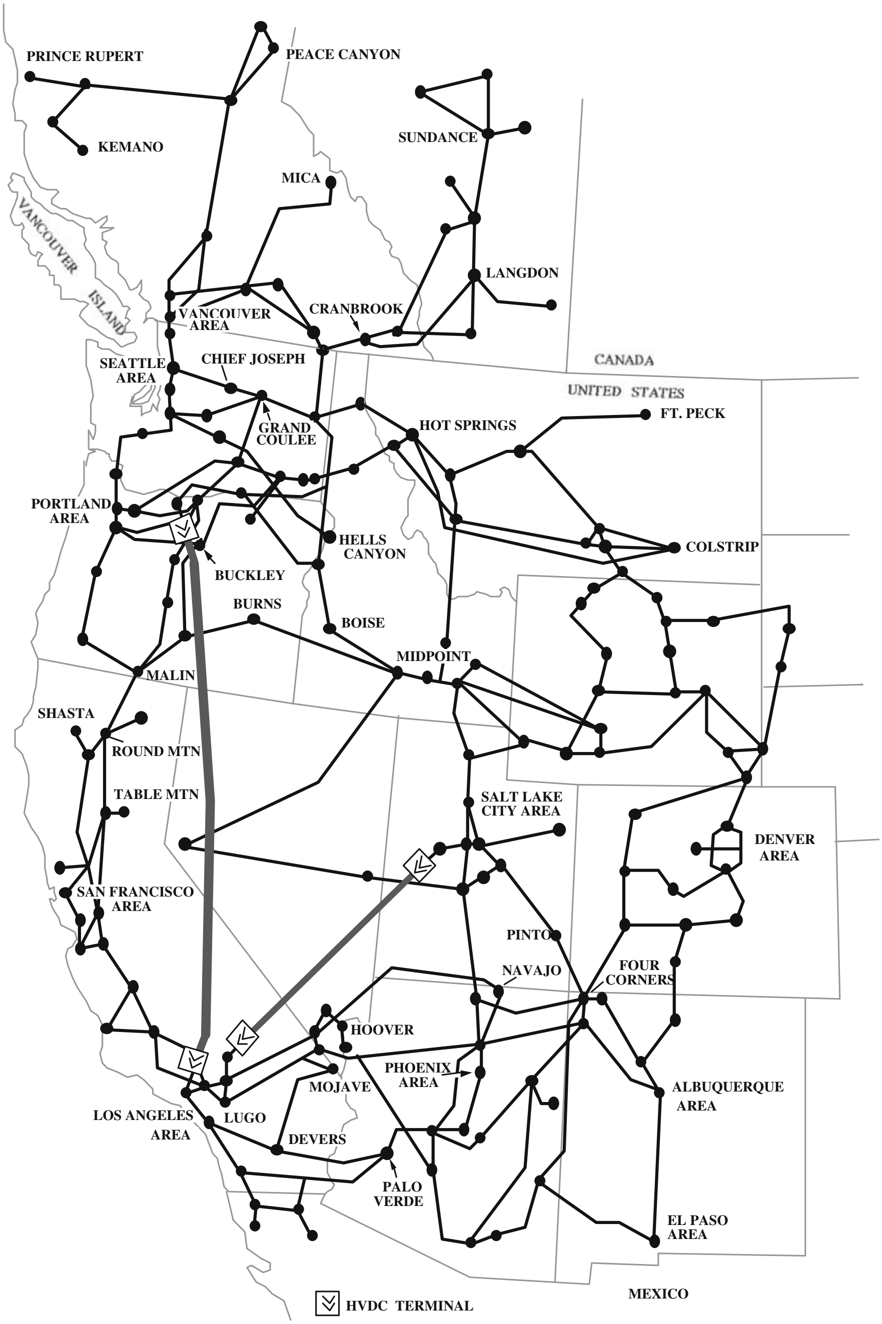

Fig. 1.3 Major buses and lines in the western North American power system

responses and long-duration low-level probing that result in measured signals only slightly above the system ambient noise floor. Low-level probing should be carried out at a level low enough to not be a significant disturbance.

The wNAPS has a long history in the use of probing signals for electromechanical mode identification [7, 33]. During the 1980s and 1990s the Chief Joseph brake was frequently used to benchmark system characteristics. In the late 1990s, with synchronized wide-area measurements becoming readily available, modulating the PDCI became more common. In 1999, mid-level probing signals were used to characterize the mode damping. In 2000, low-level pseudorandom noise was injected into the system. The application of system identification methods to the input and output data from that test showed great promise for mode estimation [34]. In 2005, 2006, and 2008, a number of extensive tests were carried out using low-level multisine probing signals modulate at the PDCI. The synchronized measurements of the system response to those tests proved to be rich in information about the system's dynamic characteristics.

With known input signals, not only can the electromechanical modes be identified with improved performance, but complete input/output system models, such as transfer functions and state–space models, can be estimated from the input location to the measured output locations. Many different system identification methods can be used. This includes extending the R3LS [32] and N4SID [34] methods described previously. There is a tremendous amount of literature on system identification given measured inputs and outputs. Some of these algorithms work on the time-domain data while other algorithms utilize the frequency-domain data. The literature is too extensive to review here; the reader is referred to one of many textbooks (e.g., see [36]). Classical nonparametric methods such as ETFE (empirical transfer function estimation) and spectral methods [36] may be used to estimate the system magnitude and phase response. The advantage of the nonparametric methods is that they make very few assumptions about the underlying system model. Thus, they play an important role in validating parametric system models where one looks for consistency from the frequency response identified from a parametric method and the nonparametric methods. The parametric methods provide much more information about the system such as a state–space model or a transfer function equation. It is important that the parametric algorithm chosen matches well with the underlying condition. For example, if an algorithm designed to analyze a transient response (i.e., a sum of damped sinusoids) is applied to ambient data, which is not the sum of damped sinusoids, then poor results are expected.

1.4.1 Probing Signal Selection

In choosing a low-level probing signal to inject into the system, many factors come into play. The objective in probing signal design is to create an input that will result in accurate estimates of the electromechanical inter-area modes and possibly other system dynamic characteristics while maintaining safe operation of the power system. The choice of probing signals has a very substantial influence on the observed measured data. The protection of the power system is of the utmost importance. Other important considerations include the shape, amplitude, duration, and repetition of the injected signal. Some identification techniques were developed for specific input signals.

A few limitations on the input design are specific to the power system application. It is desirable not to have too many sharp transitions in the modulated signal on a DC intertie. Thus, this rules out many common system identification probing signals, which typically transition from rail to rail. Also, the signal should begin and end near a value of zero creating smooth transitions when injected into the system. Second, it is desirable to keep the peak probing amplitude small when probing for a long duration. For example, with the PDCI, the maximum input magnitude has been limited to ± 20 MW for long-duration probing. Another constraint is that the probing input should not look like a single sinusoidal component as it could be mistaken for a sustained oscillation. A pseudorandom signal is preferred.

System identification theory gives much guidance for input design. It is important to keep in mind that when probing, the measured outputs are a combination of the response to the probing signal and the ambient signal, which is always present in the measured outputs. The ambient signal is stochastic (random) in nature. Thus, when the probing signal is present, only a portion of the measured output is the system response to the probing signal, and the other portion is the ambient noise process. When it comes to the quality of the estimated parameters, it is the spectrum of the probing signal which is most important, not the particular time-domain wave shape. The general idea is to place the content of the probing signal in the frequency band of interest, in this case the frequency range of the inter-area electromechanical modes.

The amplitude and time duration of the low-level injected signal are critical. Clearly, the amplitude needs to be small enough not to interfere with the normal operation of the power system. Yet, there is a well-known trade-off in system identification between the observation time and the signal strength. Performance of system identification algorithms improves with signal-to-noise ratio (SNR) and with observation time. The repeatability of the pseudonoise is important to fully take advantage of the repetition of the injected signal. Also, knowing the specific frequency content is critical.

An important quality of a probing signal is its crest factor. The crest factor of a zero mean waveform $u[n]$ is defined as

$$C_{\mathrm{r}} \triangleq \sqrt{\frac{\max_n u^2[n]}{(1/N)\sum_{n=1}^{N} u^2[n]}} \tag{1.7}$$

where N is the number of samples in the waveform and n is the nth time sample. The crest factor is the ratio of the maximum magnitude of the signal to the root mean square (RMS) value. It is desirable to have a probing signal with as large an RMS value as possible for a given maximum peak magnitude. Thus, a good waveform design should have a small crest factor while maintaining the desired spectrum and power carried by the waveform. The minimum crest factor is unity and this only occurs in signals which transition from rail to rail. Because these types of signal are undesirable in this application, the minimum crest factor cannot be achieved.

There are some important advantages to using a periodic input signal. Output waveforms can be averaged over the periods giving an effective increase in the SNR by the number of periods averaged. This increase is known as the processing gain. A similar gain in SNR can be seen in the frequency domain at the frequency bins of the harmonics of the periodic input. It is very important to inject an exact integer number of cycles so that there is no leakage effect in the frequency domain. Also, periodic inputs allow for methods to estimate the noise signal. The signal period, T, is important as it determines the frequency resolution as $\Delta f = 1/T$ when conducting frequency-domain analysis. Because the inter-area electromechanical modes are usually in the frequency range from approximately 0.1 to 1.0 Hz, a frequency resolution in the neighborhood of 0.01 Hz should be adequate. Note, there is a trade-off between the frequency resolution and the number of averages. For a given input signal duration, the larger the period, the better the frequency resolution, but fewer periods of the signal are available for averaging, so the processing gain is less.

For the system tests carried out in the wNAPS in 2005, 2006, and 2008, a multisine input signal was used because of its favorable characteristics relative to the above discussion. The bottom line is that the injected signal should be chosen to not disrupt the normal operation of the power system, yet to provide an accurate system model given a specific identification method.

1.5 Mode Estimation Examples

Many papers have been published demonstrating the power system application of signal processing methods for estimating modal frequencies and damping. These papers include ringdown analysis and mode-meter applications. Many of these papers are referenced in the previous sections. In this section, we provide a few examples to emphasize some of the significant challenges. We refer the reader to the references for a complete view of the application issues.

Two types of examples are considered. With the first, a simulated system with known properties is employed. The advantage of this system is that the exact solution is known; therefore, algorithm properties can be evaluated. The second type of examples uses actual system cases from the wNAPS.

1.5.1 Simulation System

The simulation test system is shown in Fig. 1.4. A modified version of the system was originally developed as a simplified model of the western North American power grid in [37]; detailed information is presented in the appendix of [38]. It has been used in many publications as a research demonstration model for stability-limited issues and mode estimation analysis.

The system consists of major generation buses 17 through 24 and 45, and load buses 31 through 41. Each generator is represented using a detailed two-axis transient model equipped with a fast-acting voltage regulator, a power system stabilizer (PSS) unit, and a turbine governor. Two identical generators are attached to buses 17 through 24. Overall, the system order is 203. Each load is split into a portion consisting of constant impedance, constant current, constant power, and random. The random portion of both the real and reactive loads is obtained by passing independent Gaussian white noise through a 1/*f* filter. It has been hypothesized that such a filter is appropriate for load modeling [7].

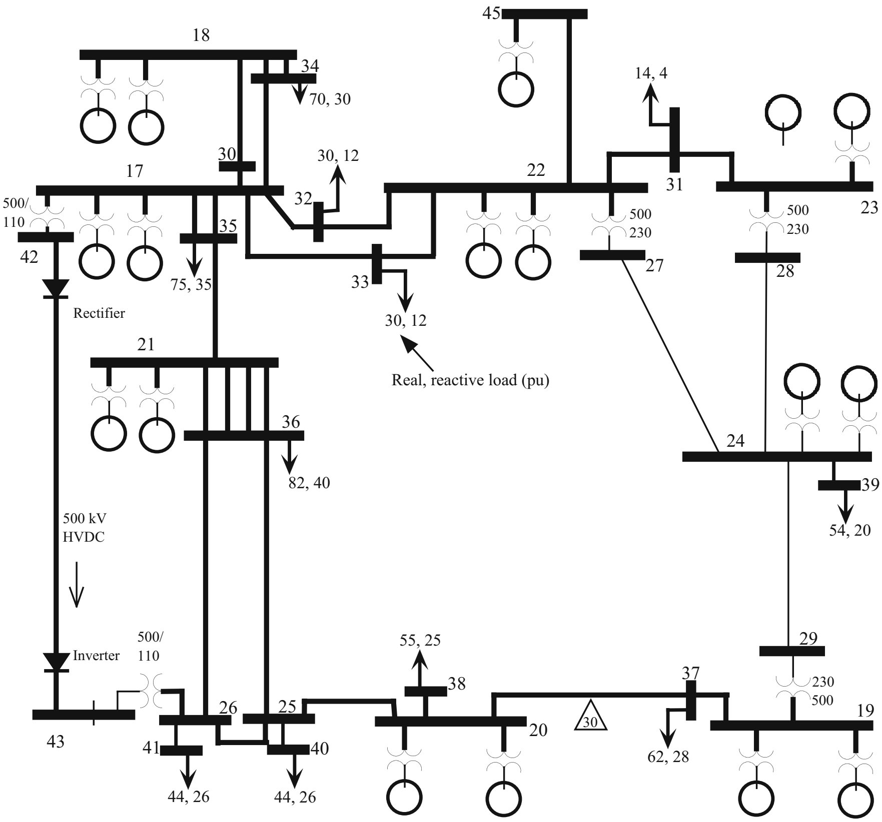

Fig. 1.4 Simulation test system

Table 1.1 Inter-area modes of 17-machine system

Frequency (Hz)	Damping (%)	Buses	vs.	Buses
0.318	10.74	North half	vs.	Southern half
0.422	3.63	North half	vs.	Southern half + bus 45
0.635	3.94	18	vs.	Rest of system
0.673	7.63	20,21	vs.	24

Two primary system operating conditions are used with the simulations that follow. With the first condition, termed the *17-machine system*, all generators are connected to the system. Under this condition, the most dominant inter-area modes are shown in Table 1.1. With the second condition, generator bus 45 is disconnected from the system; this condition is termed the *16-machine system*. Under this condition, the dominant inter-area modes are shown in Table 1.2. The modes shown in Tables 1.1 and 1.2 were calculated by conducting an eigenanalysis of the entire system's small-signal model under nominal steady-state operating conditions. The eigenanalysis was conducted using the methodology in [4].

For the examples that follow, a typical time-domain simulation consists of driving the system with independent Gaussian load variations to mimic ambient conditions. The system's response consists of small random variations in the system states. As an example, the top plot of Fig. 1.5 shows the resulting random variations of bus 22 frequency for a 10 min simulation. The frequency is calculated using the derivative of the bus phase angle.

To mimic a transient condition, a 0.5 s long load pulse is applied to bus 35. The bottom plot of Fig. 1.5 shows the system's response to a 700 MW load pulse. Figure 1.6 shows the response to a 1,400 MW pulse.

1.5.2 Ringdown Analysis Performance

As described in Section 1.3, ringdown analysis is used to estimate the modal properties from a transient. One important property we wish to emphasize is that the accuracy of the estimate is strongly related to the SNR. That is, how large the ringdown is compared to the ambient noise.

As an example, consider the ringdowns in Figs. 1.5 and 1.6. For the ringdown portion, the SNR in Fig. 1.6 is four times as large as that in Fig. 1.5. Table 1.3 compares the Prony analysis results for these two responses. For each case, the Prony analysis was conducted from 31 to 50 s into the simulation. As seen in Table 1.3, the higher SNR signal provides a more accurate mode

Table 1.2 Inter-area modes of 16-machine system

Frequency (Hz)	Damping (%)	Buses	vs.	Buses
0.361	6.59	North half	vs.	Southern half
0.618	3.57	18	vs.	Rest of system
0.673	7.66	20,21	vs.	24

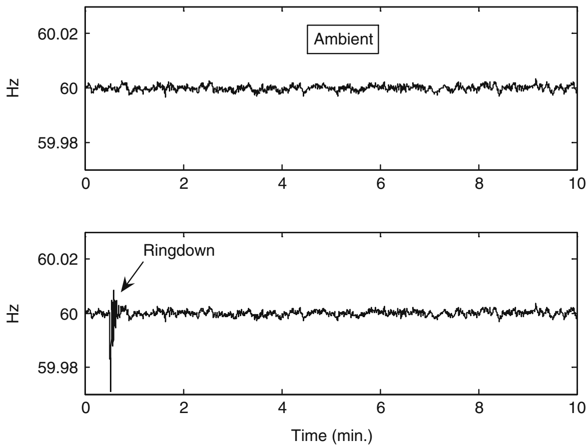

Fig. 1.5 Bus 22 frequency for 16-machine system. *Top plot*, ambient condition. *Bottom plot*, transient simulation response to a 700 MW 0.5 s load pulse at bus 35. Pulse is applied 30 s into simulation

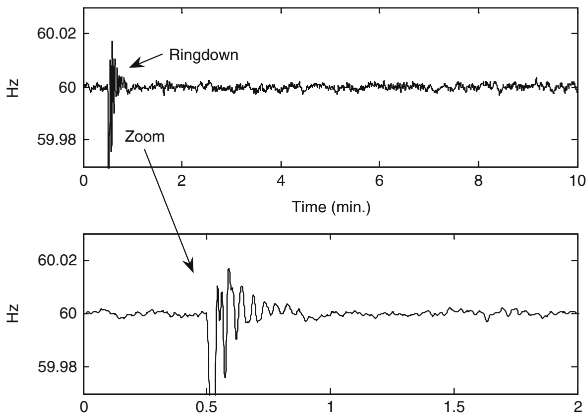

Fig. 1.6 Bus 22 frequency for 16-machine system under a transient simulation response to a 1,400 MW 0.5 s load pulse at bus 35. Pulse is applied 30 s into simulation

estimate of the dominant mode. To exactly quantify the accuracy, a Monte Carlo simulation must be conducted.

1.5.3 Mode-Meter Performance

In this example, the performance of mode-meter algorithms is demonstrated. Specifically, we consider estimation accuracy in the context of the mode damping, the analysis window size, and transient versus ambient conditions. A more extensive overview of this comparison is contained in [32, 28]. Time-domain