Application of Oscillation Monitoring Data for the Detection of Event Signatures

K. M. Rogers, *Student Member, IEEE*, and T. J. Overbye, *Fellow, IEEE*

***Abstract*—Disturbances in power systems cause oscillations which can be observed in measured signals throughout the network. This paper examines the relationship between events in the system and the measured modal content of the oscillations. Identifying patterns or distinguishing characteristics from oscillation monitoring data is examined in the context of linear system theory and control theory. Our results show that with knowledge of the nominal modes of certain generators, it is often possible to distinguish an event at one of these generators.**

***Index Terms*—oscillations, Prony, signal analysis, eigenvalues, data mining**

I. Introduction

DISTURBANCES cause oscillations in power system signals, also referred to as "ringdowns," which commonly appear as exponentially-damped sinusoids. When oscillations are present, it is often desirable to characterize the signal with respect to its frequency content. An oscillation monitoring system (OMS) [1] can provide operators with an indicator that, for example, the system has poor damping (~3%). Estimates are computed of the frequency, damping, amplitude, and phase of the components in the signal [2]. An OMS evaluates the modal content of measured oscillations in power system signals, cross-checks the results using several methods, and generates alerts when poorly damped modes are discovered [1]. Such an OMS can serve as an early warning of serious events. Useful information about operational reliability is obtained from the estimated modes.

The purpose of this work is to facilitate the use of OMS modal estimates for the discovery of event signatures in the ringdown data. We seek to uncover mappings between the estimated modal content and events in the system. The premise is that different events have different impacts on the system and thus produce different ringdowns. Thus, certain changes may impact modal estimates in distinct, predicable ways. An interesting relationship between the modal content of angle measurements and increased wind generation in Texas is recognized in [3]. Changes in modal content associated with significant events motivate our work of to recognize and classify patterns in oscillation data. In this paper, we examine the relationship of the observed oscillations to known power system modes.

Power systems are constantly changing. Small disturbances include load changes, while large disturbances include network topology changes and faults. In this work, we are predominately interested in what occurs during large disturbances. Suppose, for example, a fault occurs at the terminals of a generator. A phasor measurement unit (PMU) suitably located in the system will capture oscillation data that occurs as a result of this event. The question is whether we can take the ringdown data of the event as viewed from the PMU measurements and ascertain which possible events may have caused the ringdown.

The goal is to characterize ringdowns in terms of time and frequency domain signatures and to pick out these signatures in incoming data. To characterize a ringdown, it is necessary to find attributes which can serve as unique, identifying characteristics of an event. Analysis is needed on the extent to which certain events are distinguishable from other events. The inherent limitations of signature-searching must be examined. For example, do generator outages appear distinct in OMS results? Furthermore, what circumstances are necessary to assure that certain events will present distinct signatures? If associations between OMS modes and certain events can be made, engineers can identify the occurrence of these events from measurement data. Event types of interest may include faults, generator trips, system topology changes, as well as significant wind events.

In this paper, the focus is on recognizing events occurring at specific generators. For a generator fault, the goal is to use oscillation data to identify which generators are likely to have been involved. It may be the case that key eigenvalues and associated generators are known *a priori*, especially if a transient stability model of the system is available. Our analysis and study system results indicate that if modes of certain generators are known, it is often possible to distinguish an event at one of those generators. The paper presents experimental results of events at several locations and examines the identifying information that is present in the ringdowns from these events.

II. Power System Oscillations

In power systems, it is imperative to obtain information about damping and stability, and this information is present in the oscillations. The GSO 37-bus study system [4] used in this paper is shown in Figure 1. The angle reference is the average of all generator angles.

This material is based upon work supported by the Department of Energy under Award Number DE-OE0000097.

The authors are with the University of Illinois at Urbana-Champaign (e-mail: krogers6@illinois.edu, overbye@illinois.edu).

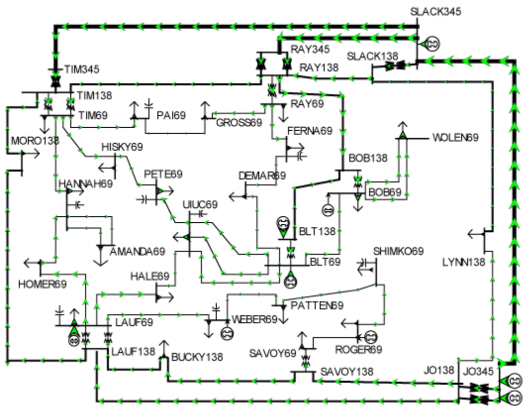

Figure 1. GSO 37-Bus System

We seek interesting patterns which relate the modal content of measured oscillations to the modes of particular generators. In this section, we discuss the content of oscillation signals.

A. Power System Ringdowns

When a disturbance is applied and then removed to a linear time-invariant system, the system will "ring down" according to the solution of the system differential equations

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} \tag{1}$$

where $\mathbf{A}$ is the linearized system matrix from the dynamic equations in the power system. The eigenvalues, right eigenvectors, and left eigenvectors of $\mathbf{A}$ can be represented respectively as λ_i ,$\mathbf{p_i}$, and $\mathbf{q_i}$. Then, as discussed in [2], the state of the system as a function of time $\mathbf{x}(t)$ may be written as

$$\mathbf{x}(t) = \sum_{i=1}^{n} \left(\mathbf{q_i}^{\mathbf{T}} \mathbf{x_o}\right) \mathbf{p_i} e^{\lambda_i t} \tag{2}$$

where $\mathbf{x_0}$ is the initial system state and n is the true dimension of the system.

The total system response is the sum of a zero-input component and a zero-state component [5]. This should not be confused with the natural response and the forced response, which is a similar decomposition but not the same. The zero-input portion is the response of a linear system when there is no input. This response reveals the inherent behavior of the system. The zero-input component is the solution of the following equation for $x_\phi(t)$.

$$(D^N + a_1 D^{N-1} + ... + a_{N-1} D + a_N) x_\phi(t) = 0 \tag{3}$$

where the symbol D represents the derivative operator d/dt. Equation (3) is satisfied by a solution of the following form:

$$x_\phi(t) = c e^{\lambda t} \tag{4}$$

Then, (3) can be written as

$$c e^{\lambda t} \left(\lambda^N + a_1 \lambda^{N-1} + ... + a_{N-1} \lambda + a_N \right) = 0 \tag{5}$$

A non-trivial solution requires that the polynomial in (5) be equal to zero,

$$\lambda^N + a_1 \lambda^{N-1} + ... + a_{N-1} \lambda + a_N = 0 \tag{6}$$

$$\left(\lambda - \lambda_1\right)\left(\lambda - \lambda_2\right)...\left(\lambda - \lambda_N\right) = 0 \tag{7}$$

so there are N possible solutions. Thus, (4) can be any of the exponential solutions,

$$c_1 e^{\lambda_1 t}, c_2 e^{\lambda_2 t}, ..., c_N e^{\lambda_N t} \tag{8}$$

where any linear combination of these exponentials is also a possible solution (for proof, see [5]). These exponentials represent the poles, eigenvalues, roots, or characteristic modes of the system [5], [6]. Which one of the infinite number of possible solutions we actually obtain as the response is dependent upon the system input and upon the initial conditions.

Since $\mathbf{A}$ is determined by the differential equations of generators and represents the eigenvalues or modes associated with the generators, it follows that a measured ringdown in the system will contain information about those modes. A measurement signal, such as line flow deviation or voltage deviation, is a linear combination of the states [7],

$$s(n) = \sum_k w_k x_k(n) \tag{9}$$

where w_k are weights, and samples are taken at $t=nT$, where T is the sample period. Thus, a measured signal contains information about the system modes and is also a sum of damped exponentials.

For a linear system, the characteristic modes of the system are completely determined from the system impulse response. That is, if the input into a linear system is the Dirac delta function, $\delta(t)$, then the response of the system is a linear combination of all the modes of the system. So, ideally, if the system could be perturbed by this input, the characteristic modes of the system would be clearly present in the response. The zero-state component assumes an initial state equal to zero and is the result of convolving the system input with the impulse response. This portion of the response will generally contain both characteristic modes and non-characteristic modes of the system.

When considering power system oscillations, the response will not be ideal for several reasons. Power systems are not linear systems. Also, it is impossible to perturb the system by a delta function because it would have to have infinite magnitude and an infinitely small duration. Theoretically, a delta function perturbs the system by an infinitely short amount of time at all the frequencies, and then it is suddenly removed as the input. Thus, the way the system responds to a delta function is completely governed only by its own characteristic modes, so these characteristic modes may be retrieved. In a real power system, the input is obviously not a delta function, so non-characteristic modes may be present.

The behavior of a more general system near an equilibrium point $\mathbf{x_e}$ is governed by

$$\begin{aligned} \Delta\dot{\mathbf{x}} &= \mathbf{A}\Delta\mathbf{x} + \mathbf{B}\Delta\mathbf{u} \\ \Delta\mathbf{y} &= \mathbf{C}\Delta\mathbf{x} + \mathbf{D}\Delta\mathbf{u} \end{aligned} \tag{10}$$

where matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, and $\mathbf{D}$ represent the system equations linearized around $\mathbf{x_e}$, and the transfer function is

$$\mathrm{H(s)} = \frac{\mathrm{Y(s)}}{\mathrm{U(s)}} = \mathbf{C}(s\mathbf{I} - \mathbf{A})^{-1}\mathbf{B} + \mathbf{D} \tag{11}$$

which represents the modes expected in the oscillations.

Additionally, a ringdown can be considered to be in one of three categories. (1) The system is stable and the value returns to the equilibrium value $\mathbf{x_e}$. (2) The system is stable but returns to some new equilibrium point, denoted $\mathbf{x_{e,new}}$. (3) The system is unstable. The focus of this work is on the oscillations for the first two types. Future work is possible to obtain more information by simultaneously considering the steady-state changes that occur in situation (2).

B. Single-Machine-Infinite-Bus Eigenvalues

Single-machine-infinite-bus (SMIB) eigenvalues are calculated by modeling one machine in detail while modeling the rest of the system as an infinite bus [8]. SMIB eigenvalues can be obtained for each generator if the dynamic models are known. Thus, a SMIB model allows the local modes of a generator to be examined and can greatly simplify analysis. Detailed investigation of SMIB models is found in [9].

A linearized second order model of a synchronous generator can be used to represent its electromechanical modes (machine angle and rotor speed),

$$\begin{aligned} \Delta\dot{\partial} &= \Delta\omega \\ \Delta\dot{\omega} &= -k_s\Delta\partial - k_D\Delta\omega \end{aligned} \tag{12}$$

where k_s is the synchronizing coefficient and k_D is the damping coefficient. In general, such a second order system is represented as

$$s^2 + 2\zeta\omega_n s + \omega_n^{\ 2} = 0 \tag{13}$$

where the poles may be expressed as

$$s = \sigma + j\omega \tag{14}$$

$$\omega = \omega_n\sqrt{1-\zeta^2} \tag{15}$$

$$\sigma = \zeta\omega_n \tag{16}$$

where ζ is the damping ratio, ω_n is the natural frequency, and ω_d is the damped natural frequency. The Laplace transform pair, from [10], is given by the following:

$$Ae^{-\sigma t}\cos(\omega t + \phi) \leftrightarrow \frac{a_1 s + a_0}{(s+\sigma)^2 + \omega^2} \tag{17}$$

$$A = \left[a_1^{\ 2} + (a_1\sigma - a_0)^2 / \omega^2\right]^{1/2} \tag{18}$$

$$\phi = \tan^{-1}\left(\frac{(a_1\sigma - a_0)/\omega}{a_1}\right) \tag{19}$$

The eigenvalues of (12) are

$$\lambda = \frac{-k_D}{2} \pm \frac{1}{2}\sqrt{k_D^{\ 2} - 4k_s} \tag{20}$$

These electromechanical modes associated with angle and frequency tend to be the most prominent in the ringdown for three-phase faults at the generator terminals. Thus, the modes in (20) are of particular interest. For a SMIB system, these modes can be found by examining participation factors.

Participation factors are essentially a measure of the effect of a particular state on a particular eigenvalue,

$$p_{ki} = \frac{\partial\lambda_i}{\partial a_{kk}} = \frac{\mathbf{w_{ki}v_{ki}}}{\mathbf{w_i^T v_i}} \tag{21}$$

and they relate the kth state variable to the ith eigenvalue. These are determined from right and left eigenvectors **v** and **w** respectively. Eigenvectors may be chosen with any convenient scaling such as to make $\mathbf{w^T v}$= 1. Thus, participation factors show which state variables reflect or capture certain modes, and one can determine which modes represent the angle and speed states by inspection.

Two distinctions should be made before proceeding. First, a two-bus equivalent system can be constructed based on a SMIB model: one bus represents the machine, while the other bus and transmission line represent the rest of the system. Ringdowns in the two-bus equivalent represent modes of the particular generator more clearly since the dynamics of all other generators are not modeled, whereas ringdowns in the full system contain the impact of all generators. It is useful to compare the modal content of a ringdown in the two-bus system to that of the full system. Additionally, it is important to distinguish between the rotor angle and the bus angle. In simulation, it is possible to obtain the internal rotor angle which is a state of the generator, and this angle often more clearly preserves certain modes. Conversely, the bus angle, which is possible to measure, is a function of solving the network's algebraic equations.

In summary, a relationship exists between the system eigenvalues, which may be associated with certain generators, and the modes in a ring-down. Measurement data can be used to characterize these relationships to facilitate event detection and classification. How well the SMIB eigenvalues of a generator are preserved in a ringdown partially depends on how linear the differential equations are as well as the coupling between generators. If an entry in the system matrix **A** depends on the state, the system is nonlinear, and the computed eigenvalues may change considerably as the system state changes.

III. Approach

The methods in this section are used to investigate the extent to which events at different generators have distinct signatures in OMS results. Results on estimating oscillation parameters of power systems in [7] corroborate our theory that for a small disturbance, a measurement can be modeled as the output of a linear system excited by a delta function. Then, the signal is completely characterized by the coefficients of the numerator and denominator polynomial. The coefficients of this transfer function are termed a linear predictive code (LPC) or model (LPM). This LPM gives a model of the signal, and from this signal model we can compute various signal attributes. Important attributes are frequency, presence or absence of critical modes, degree of damping, and amplitude of signal components. The future evolution of the signal can also be predicted from the LPM.

Approaches for LPM characterization of the signal are discussed and demonstrated in this section. Differences are often present in how the coefficients of the LPM are estimated. Understanding the benefits and limitations of particular identification methods with respect to signature-seeking is important. The methods explored in this section are the Prony method [2], the Steiglitz-McBride algorithm [11] with initial mode estimates, and mode-matching least-squares (LS) estimation. Signatures of different events are evident. These approaches illustrate the feasibility of distinguishing different events from each other in the resulting ringdown data. Research on techniques to further characterize the signatures and to appropriately distinguish between events is in progress.

A. Prony Analysis

Prony analysis can be used to quantify the modal content of a ringdown by determining a best-fit reduced-order model both in time and frequency domains. Similar methods for estimating a LPM in power systems include least squares (LS) and generalized least squares (GLS) [12]. Prony analysis can be considered a variation on the linear LS method, while GLS is an iterative approach to allow online updating of modal estimates. Following Section II, power system oscillations can be approximated by a sum of damped exponentials:

$$y(t)=\sum_{i=1}^{p} B_i e^{\lambda_i t} \tag{22}$$

Prony analysis [2] estimates the parameters B_i and λ_i of (22), where (22) is also expressed as

$$y(t)=\sum_{i=1}^{q} A_i e^{\sigma_i t}\cos\left(\omega_i t+\phi_i\right) \tag{23}$$

and σ_i is the damping, A_i is the amplitude, ω_i is the frequency in radian/s, and ϕ_i is the phase in radians. This estimated modal content can provide a useful summary of transient stability runs as well as of measured data.

Many variations exist in Prony analysis implementations. In this paper, all Prony analysis is performed following the implementation of the Prony toolbox for Matlab [13], which is described in detail in [14] in its original context for analyzing modes in reactor measurements.

In Figure 2a, SMIB eigenvalues with low damping for generators BLT138, LAUF69, ROGER69, BLT69, and BOB69 are shown. Prony analysis results for simulated events of three-phase faults to ground followed by the generator tripping at BLT138, LAUF69, ROGER69, BLT69, and BOB69 are shown in Figure 2b, where the angle at BUCKY138 is the simulated PMU signal.

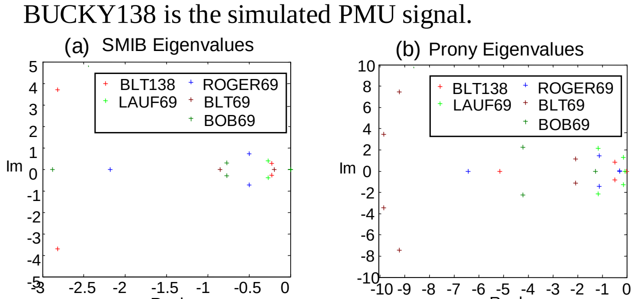

Figure 2. (a) SMIB eigenvalues for generators (b) Prony analysis of events at generators

Each set of eigenvalues in Figure 2b represents a ringdown. For example, the angle response at BUCKY138 to the event at BLT138 is given in Figure 3.

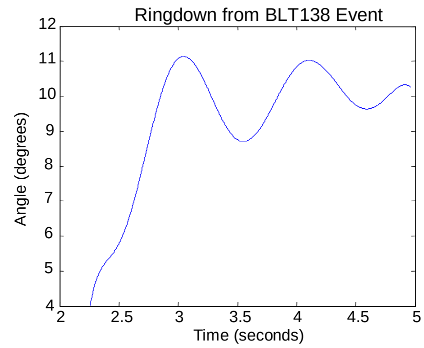

Figure 3. Angle response to BLT138 event

By inspection of Figure 2a and b, there is some similarity in structure, but more analysis is needed.

B. Stiglitz-McBride Algorithm with Initial Parameters

The Steiglitz-McBride (SM) algorithm, introduced in [11], iteratively computes Kalman estimates. The algorithm identifies a transfer function N(z)/D(z) where

$$\mathrm{N(z)}=\alpha_0+\alpha_1\mathrm{z}^{-1}+\ldots+\alpha_{n-1}\mathrm{z}^{n-1} \tag{24}$$

$$\mathrm{D(z)}=1+\beta_1\mathrm{z}^{-1}+\ldots+\beta_n\mathrm{z}^{n} \tag{25}$$

Each iteration of the algorithm determines updates of the coefficients $\alpha_0,\ldots,\alpha_{n-1}$, and $\beta_1,\ldots\ \beta_n$ until the estimated response converges to the true response. Convergence properties of the algorithm are examined in [15].

The applicability of the SM algorithm in power systems for the purpose of studying low frequency electromechanical oscillations and for identifying low-order models from simulation data is examined in [16] and [17]. Performance comparisons of the Steiglitz-McBride algorithm, the Eigensystem Realization Algorithm, and the Prony method are given in [17]. As explained in [16], the estimated transfer function can be written as a sum of the residues r_i over the poles.

$$\mathrm{H(s)}=\sum_{i=1}^{n}\frac{r_i}{s-\lambda_i} \tag{26}$$

The SM method can be executed in two forms, either with or without the use of initial parameters [11]. Executing the SM algorithm with specific initial parameters is advantageous for cases where certain modes seem to be of interest, as in our application. The SM algorithm is especially useful because we can specify modes to serve as an initial estimate for the denominator coefficients of the LPM. The SM algorithm implementation used in this paper is the Seiglitz-McBride function in Matlab's Signal Processing Toolbox [18].

SMIB eigenvalues and modal estimates from other methods can serve as useful initial conditions. When the modes obtained from Prony analysis are used as the initial transfer function poles, the SM method approximation more closely matches the true signal than the Prony approximation. For a 0.1 second balanced three-phase to ground fault at BLT138 in the two-bus equivalent, the bus angle ringdowns using Prony and SM methods are shown in Figure 4, for 30 modes:

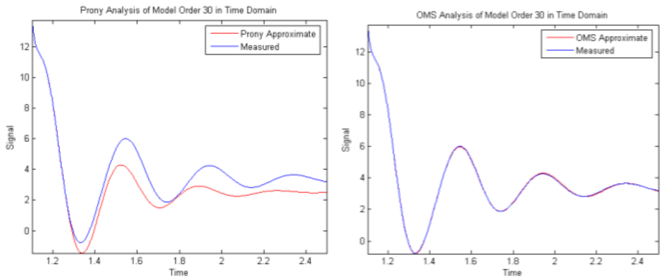

Figure 4. 30-mode estimate for BLT138 fault in two-bus equivalent – Prony method (left), SM method (right)

When only four modes are estimated, the discrepancy between the two methods is even more obvious, as shown in Figure 5.

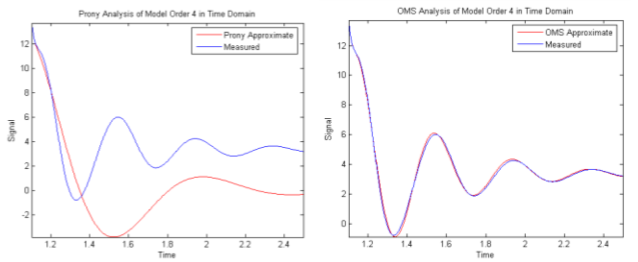

Figure 5. Four-mode estimate for BLT138 fault in two-bus equivalent – Prony method (left), SM method (right)

However, when no initial parameters for the SM method are specified, its results essentially match the Prony method.

Thus, the insight for the SM approach is to choose initial parameters, since a noteworthy improvement in the results is observed. Suggestions include choosing the largest-amplitude eigenvalues from an initial Prony analysis or choosing the SMIB eigenvalues. We generally see this effect for all of the studied fault signals.

C. Mode-Matching Least Squares Estimation

The approach in this section seeks a direct mapping between the estimated modes of the response and the SMIB eigenvalues. Least-squares estimation is used to force the estimate to include certain known or specified modes. Specified modes (damping and frequency) are held fixed while their amplitudes and initial phases are estimated. The objective is to solve the following,

$$\min_{A_i,\phi_i} \left\| \mathbf{f(t)} - \mathbf{y(t)} \right\|^2 \quad (27)$$

where $\mathbf{f(t)}$ is a vector of the estimated signal and $\mathbf{y(t)}$ is a vector of the true signal. The estimate $\mathbf{f(t)}$ is a summation of unknown coefficients multiplied by known sinusoids:

$$\mathbf{f(t)} = \sum_{i=1}^{q} A_i e^{\sigma_i t} \cos\left(\omega_i t + \phi_i\right) = \sum_{i=1}^{q} \underbrace{A_i e^{j\phi_i}}_{unknown} \underbrace{e^{\sigma_i t} \cos\left(\omega_i t\right)}_{known} \quad (28)$$

Therefore, if we know the dampings and frequencies, we can estimate the amplitudes and initial phases by solving the following linear matrix equation for **a**:

$$\mathbf{Ea} = \mathbf{y(t)} \quad (29)$$

Matrix **E** and vector **a** have the following structures:

$$\mathbf{E} = \begin{bmatrix} e^{\gamma_1(0\Delta t)} & \cdots & e^{\gamma_n(0\Delta t)} \\ \vdots & \ddots & \vdots \\ e^{\gamma_1(N\Delta t)} & \cdots & e^{\gamma_n(N\Delta t)} \end{bmatrix} \quad (30)$$

$$\mathbf{a} = \left[A_1 e^{j\theta_1}, \ldots, A_n e^{j\theta_n} \right]^T \quad (31)$$

where n is the number of modes and N is the number of time points. Then, the least-squares solution is

$$\mathbf{a} = [\mathbf{E}^{\mathbf{T}}\mathbf{E}]^{-1}\mathbf{E}^{\mathbf{T}}\mathbf{y} \quad (32)$$

where **a** is a vector of complex numbers which, in polar notation, give the magnitude and initial angle of the signal.

The quality of the approximation depends on which modes are specified. If a careful choice of representative modes is made initially, then $\mathbf{f(t)}$ is approximately equal to the original signal. Conversely, if the modes are poorly selected, a meaningful approximation may not be found. As with the SM algorithm, the authors have experimented with several ways of choosing the initial modes for this algorithm. Suggestions include the SMIB eigenvalues and estimates from other methods.

Once the amplitudes and initial phases of the selected modes are determined, one may examine the amplitudes of the modes to find generators with significant contributions to the event. Generators with electromechanical modes corresponding to the highest estimated amplitudes should be noted. The identified generator or generators may serve as an indication of the likely source of the event.

Consider again the event at BLT138 corresponding to Figure 3. Following the method described, SMIB eigenvalues are chosen to be the specified modes. Figure 6 shows a fit of 29 generator SMIB eigenvalues to the ringdown and also plots the Prony estimate.

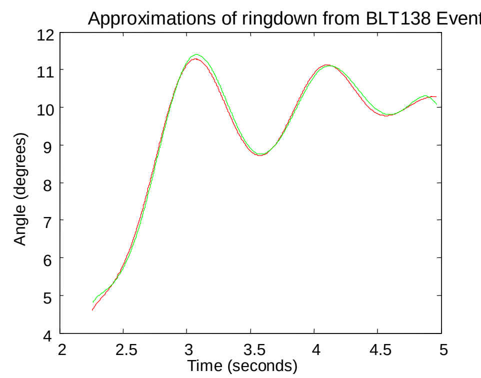

Figure 6. Approximations of Figure 3 event with Prony analysis and Mode-Matching LS

The SMIB modes with the highest amplitudes and their associated generators are found, and generators with large contributions are identified in Table 1. The SMIB modes of generator BLT 138, where the event occurred, have higher amplitudes than the other SMIB modes. Thus, the precipitating generator can be correctly identified as BLT138.

Table 1. Prony results with SMIB eigenvalue amplitudes

Amplitude	Generator	Damping	Frequency (rad)
0.0000	LAUF69	-15.142	-3.172
0.0000	LAUF69	-15.142	3.172
17525.0000	BLT138	-2.8161	3.6975
17525.0000	BLT138	-2.8161	-3.6975
9.9970	ROGER69	-1.9498	-12.603
9.9968	ROGER69	-1.9498	12.603
8.0001	LAUF69	-1.6795	14.944
7.9998	LAUF69	-1.6795	-14.944
122.1300	BLT138	-2.661	-15.716
122.1300	BLT138	-2.661	15.716

It is important to note that identification of a single contributing generator will not always be this apparent. Which modes are present in the ringdown depends on which modes are excited, and this is based on both the system input and system state.

IV. Results

In this section, we take a closer look at the signatures that occur in the ringdown results for a particular type of event. In particular, three-phase to ground faults lasting 0.1 seconds are applied at each of the eight generator buses. The ringdowns are analyzed and the results compared. The idea is to be able to pick out the characteristics that make each event appear distinct in a ring down.

For the BLT138 fault in the two-bus equivalent, the Prony analysis of ringdowns for both the rotor angle and the bus angle are given in the top two plots of Figure 7. Note how the signals change when the system is interconnected. The bottom plots of Figure 7 show the ringdowns in the full system for the same event.

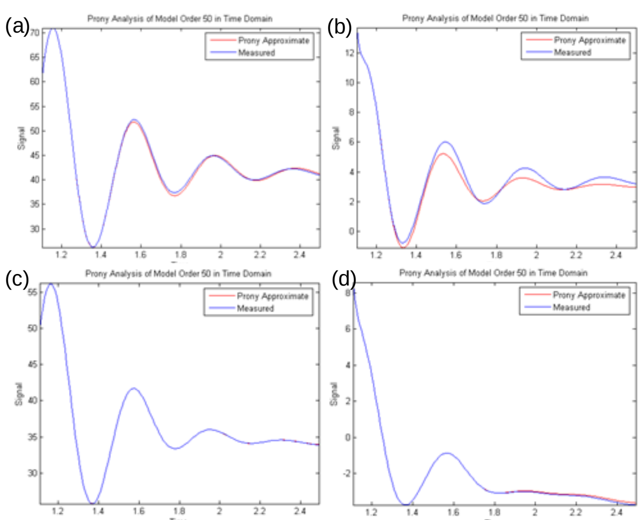

Figure 7. Fault at BLT138 – Two-bus equivalent rotor angle (a) and bus angle (b); Full system rotor angle (c) and bus angle (d)

Table 2 provides a summary of the results for each event at each generator bus in the full system. It is important here to point out an inherent challenge, which is how best to quantify similarity of modes. In these results, we examined both the Euclidean distance and the Manhatten distance in the $j\omega$ direction. The latter is simply the SMIB eigenvalue frequency minus the estimated frequency, in radians. The value of the frequency term may be of greater significance than the value of the damping term. The reasoning is that frequency is based on physical characteristics of the generator whereas damping may more readily change based on controls in the system.

The first row in each portion of the table denotes the generator and its electromechanical SMIB modes. The most significantly contributing mode estimates are given, obtained from the three methods described in this paper. Beneath each mode are two numbers, indicated in the *(d:a,b)* term, where *a* is the Euclidean distance and *b* is the Manhatten distance of each mode to the SMIB mode. Low distance values indicate an estimate which is well-matched to the SMIB electromechanical mode. More research is needed to better quantify the "closeness" of modes.

Table 2. Results for 0.1 second faults at each generator terminal

(1) Gen 53 – "BLT138," s = -2.66±j15.7162

Prony	SB	LS
s =-3.78±j10.92 *(d: 4.92, 4.80)*	s = -3.51±j16.63, *(d:1.25, -0.91)*	s = -3.78±j10.92, *(d:4.92, 4.80)*
s =-3.51±j17.13, *(d:1.65, -1.41)*	s = -2.97±j10.82, *(d: 4.91, 4.90)*	s = -3.51±j17.13, *(d:1.65, -1.41)*

(2) Gen 44 – "LAUF69," s = -1.68±j14.94

Prony	SB	LS
s =-6.02±j9.51 *(d:6.95, 5.44)*	s =-7.06±j14.97, *(d:5.38, -0.03)*	s =-6.02±j9.51, *(d:6.95, 5.44)*
s =-2.10±j16.15, *(d:1.29, -1.21)*	s =-2.13±j16.70, *(d:1.82, -1.76)*	s =-2.10±j16.15, *(d:1.29, -1.21)*

(3) Gen 50 – "ROGER69," s = -1.95±j12.60

Prony	SB	LS
s =-2.674±j12.221 *(d:0.82, 0.38)*	s =-2.862±j11.95 *(d:1.12, 0.65)*	s =-2.674±j12.221 *(d:0.82, 0.38)*

(4) Gen 54- "BLT69," s = -1.90±j11.28

Prony	SB	LS
s =-2.09±j11.09 *(d:0.27, 0.19)*	s =-1.32±j11.20 *(d:0.59, 0.08)*	s =-2.09±j11.09 *(d:0.27, 0.19)*
		s =-1.90±j11.279 *(d:0.00, 0.00)*

(5) Gen 31- "SLACK345," s = -3.68±j8.17

Prony	SB	LS
s =-2.86±j12.07 *(d:3.98, -3.90)*	s =-2.94±j10.79 *(d:2.72, -2.62)*	s =-3.683±j8.171 *(d:0.00, 0.00)*
s =-3.52±j14.45 *(d:6.28, -6.28)*	s =-1.91±j13.9 *(d:6.00, -5.73)*	

(6) Gen 28 – "JO345," s = -2.25±j14.69

Prony	SB	LS
s =-2.362±j12.74 *(d:1.95, 1.95)*	s =-2.872±j11.49 *(d:3.26, 3.2)*	s =-3.517±j14.46 *(d:1.29, 0.23)*
s =-6.224±j16.63 *(d:4.42, -1.94)*	s =-2.09±j14.40 *(d:0.33, 0.29)*	s =-2.86±j12.07 *(d:2.69, 2.62)*

(7) Gen 14- "WEBER69," s = -3.75±j15.25

Prony	SB	LS
s = -2.22±j13.30 *(d:2.48, 1.95)*	s = -2.13±j13.32 *(d:2.52, 1.93)*	s = -3.75±j15.25 *(d:0.00, 0.00)*

(8) Gen 48 – "BOB69," s = -3.37±j12.96

Prony	SB	LS
s = -3.08±j11.34 *(d:1.65, 1.62)*	s = -3.32±j11.33 *(d:1.63, 1.63)*	s = -3.37±j12.96 *(d:0.00, 0.00)*

The initial results presented here are promising, especially considering the fact that the SMIB eigenvalues are essentially two orders of approximations – firstly from the non-linear system dynamics to a linearized representation of the system, and secondly from a linearized representation of the system to generator models which are decoupled from the dynamics of other generators. The connection between SMIB models and the full system is further examined in [9].

V. Challenges

To suitably distinguish event signatures, a number of complicating issues must be confronted. As mentioned in Section IV, one challenge is to develop metrics for comparing similarity of signals based on their modal content. Another challenge is dealing with cases where strong modes excited by the event are not easily identifiable as belonging to a particular generator's local modes. Research is in progress on identifying signatures for such difficult circumstances. Rather than attempting to associate an event with one particular generator, it may be useful to determine sets of coherent generators and find the coherent group to which an event is likely to belong. Finding groups or clusters can also help make pattern-matching more tractable since rather than searching the large set of all generators, it is only necessary to search a small set of groups.

An additional challenge is that the eigenvalues of the system are changing, especially during an event, so trying to fit them to a model is trying to fit a moving target. It would be better to have an of algorithm designed to account for the expected changes over time. Studying the trajectory of eigenvalues over a window of time may provide more information about the events.

Another useful area for further investigation is system identification. The ideal method would allow certain modes to be specified as algorithm parameters while allowing the remaining modes to be selected such that a best-fit of the signal is obtained by the algorithm. More research is needed to seek direct ways to accomplish this.

Also, the number of modes, n, which should be estimated is often unknown. A number of practical issues including signal selection, filtering, and linearity assessment are discussed in [22], [19]. A primary limitation to obtaining accurate modal estimates is noise. Measurement location can also impact the estimates. It may be beneficial to consider the impact of location using relevant concepts in electromagnetic wave propagation theory [20][21]. Signals at different locations can be correlated to reflect how events move through the system. Also, utilizing a multi-signal approach in [22] provides more accurate modal estimates in the presence of noise and system nonlinearities. Including ongoing advances in OMS technology will only help to strengthen the concepts in this work.

VI. Conclusion

This work shows that different events produce ringdowns which have distinct characteristics or signatures. In this paper, a specific type of signature is studied, which relates the captured oscillation data to the generator of origin. Three identification approaches are used in Section III: the Prony method, the SM method with initial parameters, and mode-matching LS.

Examining the contributions of generator electromechanical modes to ringdowns lays the foundation for continued work in detecting and distinguishing event characteristics. This paper is an early stage in our continuing work to develop methods for signature recognition and classification in OMS data. The SMIB electromechanical modes corresponding to the faulted generator are often well-represented in the ringdown. Thus, if nominal local generator modes are known, it is often possible to correctly identify the generator where the event occurred. However, such identification may not always be easy or possible. Inherent challenges are discussed in Section V. More work is underway to deal with the numerous complicating situations that can arise.

VII. References

[1] M. V. Venkatasubramanian, M. Kezunovic, V. Vittal, “Detection, Prevention and Mitigation of Cascading Events,” Power Systems Engineering Research Center (PSERC) S-29 Final Project Report, Aug. 2008.

[2] J. F. Hauer, C. J. Demeure, L. L. Scharf, “Initial results in Prony analysis of power system response signals,” *IEEE Transactions on Power Systems*, vol. 5, no. 1, Feb. 1990, pp. 80-89.

[3] A. J. Allen, S. Santoso, W. M. Grady, "Voltage phase angle variation in relation to wind power," *2010 IEEE Power and Energy Society General Meeting*, pp.1-7, 25-29 July 2010.

[4] J. D. Glover, M. S. Sarma, T. J. Overbye, Power Systems Analysis and Design, 4th Ed., 2007.

[5] B. P. Lathi, Linear Systems and Signals, 2nd Ed., Oxford University Press, Inc., 2005.

[6] G.E. Franklin, J.D. Powell, and A. Emami-Naeni, Feedback Control of Dynamic Systems, 3rd ed., Addison-Wesley, 1994.

[7] R. Doraiswami, W. Liu, “Real-time estimation of the parameters of power system small signal oscillations,” *IEEE Transactions on Power Systems*, vol. 8, no. 1, Feb. 1993.

[8] P. W. Sauer and M. A. Pai, *Power System Dynamics and Stability*. Champaign, IL: Stipes Publishing L.L.C., 1997.

[9] R. H. Yeu, “Small signal analysis of power systems: Eigenvalue tracking method and eigenvalue estimation contingency screening for DSA,” Ph.D. dissertation, University of Illinois at Urbana Champaign, 2010.

[10] E. M. Grabbe, S. Ramo, D.E. Wooldridge, Handbook of automation, computation and control, vol. 1, Control fundamentals, John Wiley & Sons, Inc., New York, 1958.

[11] K. Steiglitz, L. E. McBridge, “A technique for the identification of linear systems,” *IEEE Transactions on Automatic Control*, vol.10, no.4, pp. 461- 464, Oct 1965.

[12] K. E. Bollinger, W. Eric Norum, “Time series identification of interarea and local generator resonant modes,” *IEEE Transactions on Power Systems*, vol. 10, no. 1, Feb. 1995.

[13] Matlab Central, Prony Toolbox, http://www.mathworks.com/matlabcentral/fileexchange/3955

[14] S. Singh, “Application of Prony Analysis to Characterize Pulsed Corona Reactor Measurements,” M.S. Thesis, ECE Department, University of Wyoming, Aug. 2003.

[15] P. Stoica, T. Soderstrom, “The Steiglitz-McBride Identification algorithm revisited- convergence analysis and accuracy

aspects," *IEEE Transactions on Automatic Control*, vol. AC-26, no. 3, June 1981, pp. 712-717.

[16] H. Okamoto, J. J. Sanchez-Gasca, K. Clark, C. A. Wegner, N. W. Miller, J. H. Chow, "Application of the steiglitz-McBride Identification algorithm to measured data from a power system simulator," *Proceedings of the American Control Conference*, Philadelphia, Pennsylvania, June 1998, pp. 2956-2962.

[17] J. J. Sanchez-Gasca, J. H. Chow, "Performance comparison of three identification methods for the analysis of electromechanical oscillations," *IEEE Transactions on Power Systems*, vol. 14, no. 3, Aug. 1999, pp. 995-1002.

[18] T. P. Krauss, L. Shore, J. N. Little, Signal Procesing Toolbox, The MathWorks, Inc., 1995.

[19] M. A. Johnson, I. P. Zarafonitis, M. Calligaris, "Prony analysis and power system stability-some recent theoretical and applications research," *IEEE Power Engineering Society Summer Meeting, 2000,* vol.3, pp.1918-1923.

[20] J.S. Thorp, C.E. Seyler, and A.G. Phadke, "Electromechanical wave propagation in large electric power systems," *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, vol. 45, no. 6, pp. 614–622, June 1998.

[21] R. Snieder and K. Wapenaar. "Imaging with ambient noise," *Physics Today*, vol. 63, no. 9, pp. 44-49, Sept. 2010.

[22] D. J. Trudnowski, J. M. Johnson, J. F. Hauer, "Making Prony analysis more accurate using multiple signals," *IEEE Transactions on Power Systems*, vol.14, no.1, pp.226-231, Feb. 1999.