A Complex LASSO-Approach for Localizing Forced Oscillations in Power Systems

A brief reiteration

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Introduction

Forced Oscillations in Power Systems

Natural Oscillations	Forced Oscillations
natural	forced
naturla	forced
natural	forced



Theory

State Space Representation

Express Power System Dynamics in State Space:

$$\dot{\mathbf{x}}(t) = \underset{n \times n}{\mathbf{A}} \mathbf{x}(t) + \underset{n \times m}{\mathbf{B}} \mathbf{u}(t)
\mathbf{y}(t) = \underset{p \times n}{\mathbf{C}} \mathbf{x}(t)
\forall t \ge 0$$
(1)

 $\mathbf{x}(t)$: internal state variables + controller variables vector

 $\mathbf{u}(t)$: forced oscillation vector



Forced Oscillation Vector

Express Forced Oscillations based on locations of origin and signal composition:

$$\mathbf{u}(t) = \begin{bmatrix} u_{1}(t) \\ u_{2}(t) \\ \vdots \\ u_{m}(t) \end{bmatrix} = \begin{bmatrix} \sum_{l=1}^{M_{1}} a_{1,l} \sin(\omega_{2,l}t + \phi_{1,l}) \\ \sum_{l=1}^{M_{2}} a_{2,l} \sin(\omega_{2,l}t + \phi_{2,l}) \\ \vdots \\ \sum_{l=1}^{M_{m}} a_{m,l} \sin(\omega_{m,l}t + \phi_{m,l}) \end{bmatrix}$$
(2)

$$a_{r,l} \geq 0$$

$$\omega_{r,l} = 2\pi f \geq 0$$
 (r,l) refer to the l^{th} sinusoid at the r^{th} location



Sparsity Assumption

Let $a_r(t)$ be the vector representation of the sinusoids at the r^{th} location.

$$a_r(t) = \begin{bmatrix} a_{r,1} \sin(\omega_{r,1}t + \phi_{r,1}) & \dots & a_{r,M_r} \sin(\omega_{r,M_r}t + \phi_{r,M_r}) \end{bmatrix}$$

Assumption 1: Both u(t) and $a_r(t)$ are sparse vectors. That implies most locations are FO free and for the locations that do have FO, the number of distinct sinusoidal components of the local FO is small.

$$||u(t)||_0 << m$$

 $||a_r(t)||_0 << M_r$



Discrete State Space Representation

Most PMUs sample at 30Hz or 60Hz. So the sampling time period is T=1/30s or 1/60s.

Let
$$A_d = \exp(AT)$$
 and $B_d = \{\int_0^T \exp(A(T-s))ds\}B$.

Let k = 0, 1, ... and define $\mathbf{x}[k] \triangleq \mathbf{x}(kT)$, $\mathbf{u}[k] \triangleq \mathbf{u}(kT)$ and $\mathbf{y}[k] \triangleq \mathbf{y}(kT)$. Suppose that $\mathbf{u}(t)$ is piece-wise constant during $kT \leq t \leq (k+1)T$. Then

$$x[k+1] = A_{d}x[k] + B_{d}u[k]$$

$$y[k] = C_{p \times 1} x[k]$$

$$y[k] = \sum_{p \times 1} x[k]$$
(3)

We assume x[0] = 0 as our focus is only on inputs triggered by FOs.



Transfer Function from Discrete State Space Representation

Let
$$H_z = \underset{p \times m}{\mathsf{C}} [zI - A_d]^{-1} B_d$$
.

representation for the system:

From standard Linear System Analysis, we may conclude that Y[z] = H[z]U[z] where Y[z], U[z] are the Z-Transforms of y[n] and u[n]. Replacing z with $\exp(j\Omega)$, where $\Omega \in (0,2\pi)$, we get the DTFT

$$Y[\Omega] = H[\Omega]U[\Omega]$$

$$\underset{p \times 1}{\underset{p \times m}{\prod}} \underset{m \times 1}{\underset{m \times 1}{\prod}}$$
(4)



Transfer Function of Forced Oscillation Vector

Applying DTFT on u(t) to get $U[\Omega]$:

$$\mathbf{U}(\Omega) = \begin{bmatrix} \sum_{l=1}^{M_{1}} a_{1,l} \{ \exp(-j\phi_{1,l}) \delta(\Omega + \omega_{1,l}) + \exp(j\phi_{1,l}) \delta(\Omega - \omega_{1,l}) \} \\ \sum_{l=1}^{M_{2}} a_{2,l} [\exp(-j\phi_{2,l}) \delta(\Omega + \omega_{2,l}) + \{ \exp(j\phi_{2,l}) \delta(\Omega - \omega_{2,l}) \} \\ \vdots \\ \sum_{l=1}^{M_{m}} a_{m,l} \{ \exp(-j\phi_{m,l}) \delta(\Omega + \omega_{m,l}) + \exp(j\phi_{m,l}) \delta(\Omega - \omega_{m,l}) \} \end{bmatrix}$$

$$(5)$$

$$\omega_{r,l}$$
 can be substituted by $\frac{1}{T}\tilde{\omega}_{r,l}$



Introduction to My Work

Transient vs Steady State Stability

Transient Stability	Steady State Stability
A sudden, out-of-trend, high	Accumulation of several
magnitude change in a state	seemingly minor trends in
variable(s) causes blackouts.	state variables over time,
	ultimately leading to a critical
	point where a small change
	could cause blackouts.
Chief parameters of concern	Autocorrelation and
are ROCOF, frequency nadir,	covariance are some of the
steady-state frequency	commonly used parameters
deviation.	for prognosis.
Inertia is a fundamental	Inertia plays a minor role
parameter here.	here.

Bifurcations and Critical Slowing Down

Bifurcation: A qualitative change in the 'motion' of a dynamical System due to a quantitative change in one of its parameters. Serious bifurcations, called **Critical Bifurcations**, cause the system to become unstable from stable.



Bifurcations and Critical Slowing Down

Critical Slowing Down: Dynamical Systems exhibit early statistical warning signs before collapsing:

- · Increased recovery times from perturbations.
- · Increased signal variance from the mean trajectory.
- · Increased flicker and asymmetry in the signal

The above three properties can be identified by increasing variance and autocorrelation in time-series measurements taken from the system.



Procedure

Procedure

- Accessed a bunch of real-world frequency time-series data and plotted their:
 - bulk distribution (pdf)
 - · auto-correlation curves

in order to demonstrate that:

 grid frequencies often exhibit significant deviation from gaussianity

autocorrelation can be a reasonable indication of grid steady-state stability.

- · Obtained explanation for the signature dynamics of each grid.
- Then implemented and tested the IEEE 9 Bus System in PSSE for symptoms of Critical Slowing Down as an Early Warning System.

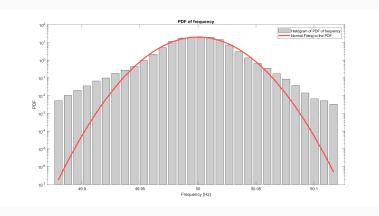


Figure 1: Continental European Grid frequency PDF: Heavier tails than a Gaussian Distribution.



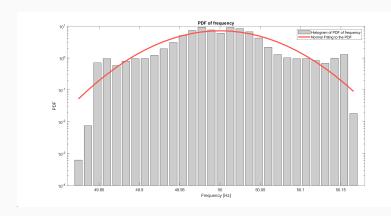


Figure 2: Mallorcan (an islanded Spanish grid) frequency pdf



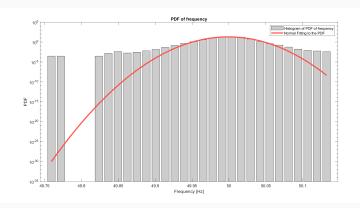


Figure 3: French grid frequency pdf including a blackout



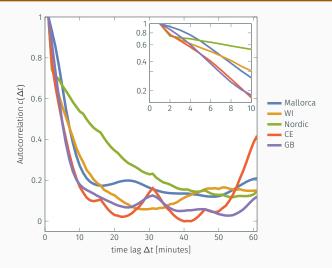


Figure 4: Autocorrelation decay of different synchronous regions.



Table 1: Inverse-correlation values for different grids

Grid name	Inverse-correlation value T^{-1} [min ⁻¹]
Mallorca	0.0654
Western Interconnection	0.0498
Nordic	0.0235
Continental Europe	0.0829
Great Britain	0.0879

Figure 5: Inverse correlation time is proportional to the damping constant of the grid.

