Inter-Area Oscillations: Monitoring and Optimization Solutions

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Acknowledgements

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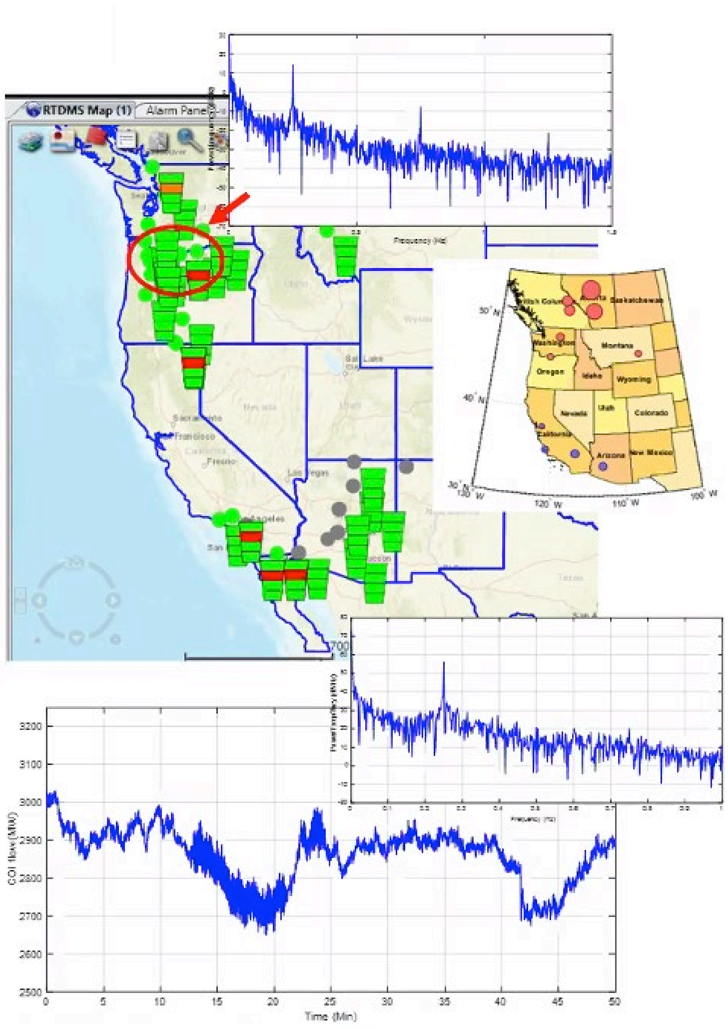
A continent-wide dynamical system

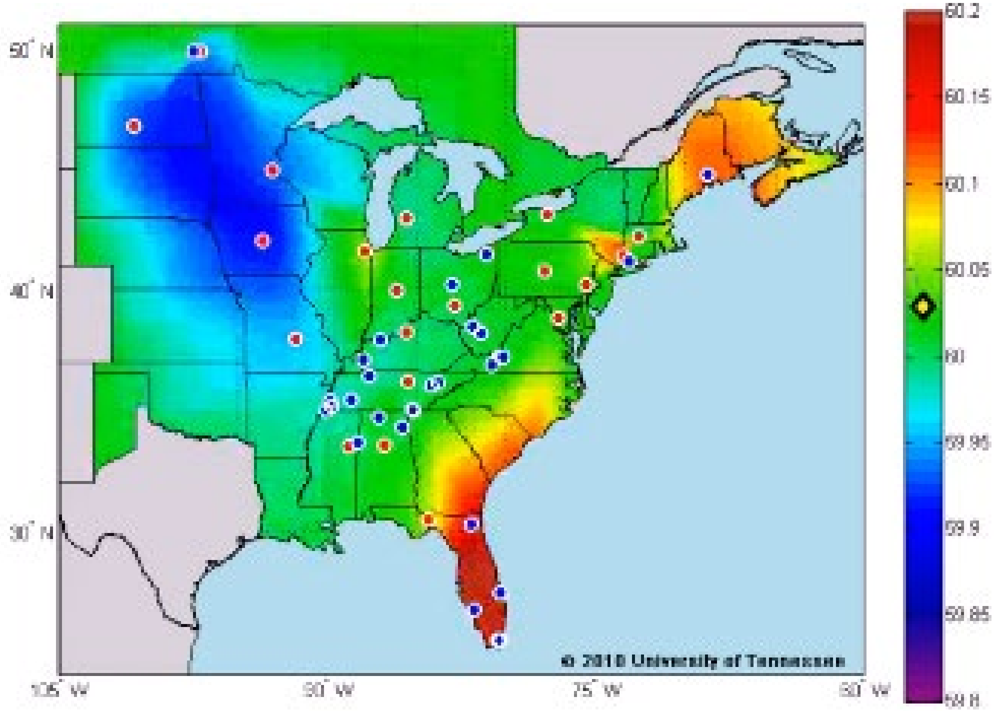


hidden sources California ISO

inter-area oscillations

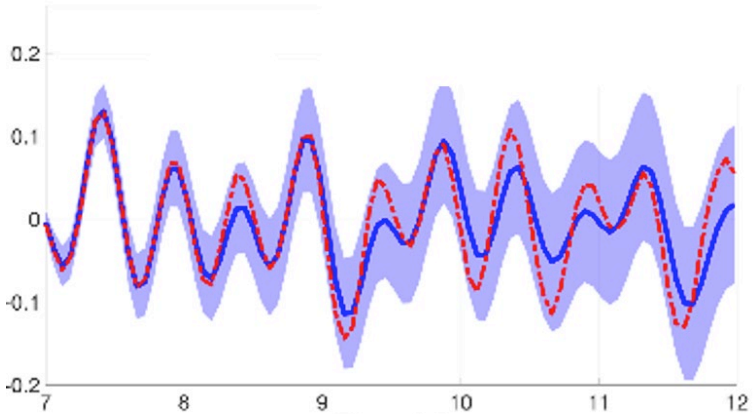
Motivation

- Maintaining grid stability requires
  - identifying undamped oscillations
  - locate hidden sources
- Learn grid dynamics from PMU data
  - non-metered buses
  - missing or compromised data
  - minimal system information
- Dispatch system to suppress oscillations
  - generation $$$ vs. stability
  - cost-benefit analysis

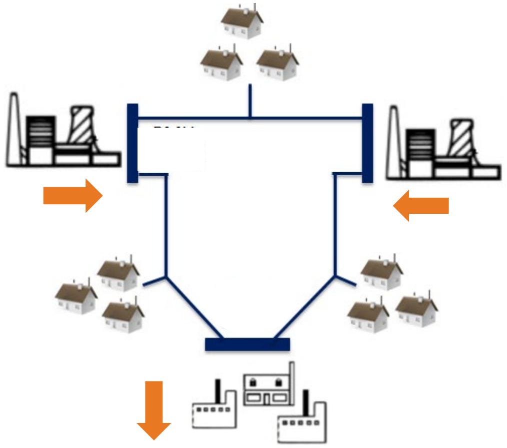


Outline

- *Monitoring inter-area oscillations*



- *Optimizing to suppress inter-area oscillations*

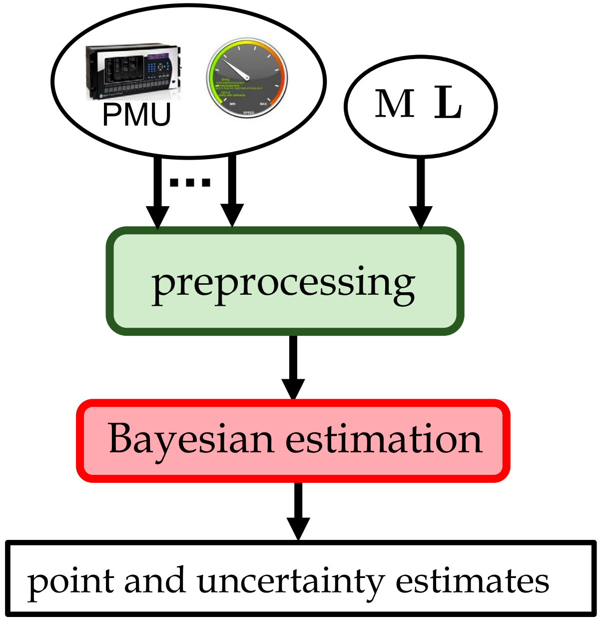


Problem statement

- Swing equation (approximate linearized grid dynamics)

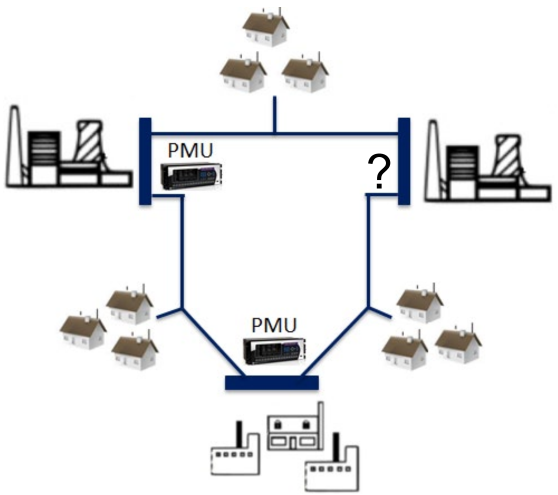
$$\mathbf{M}\dot{\boldsymbol{\omega}} + \mathbf{D}\boldsymbol{\omega} + \mathbf{L}\boldsymbol{\delta} = \mathbf{p}$$

Given approx. grid model $(\mathbf{M}, \mathbf{L})$ *and partial PMU data of any type* $(\delta_n, \omega_n, \dot{\omega}_n, p_n)$, *learn any type of dynamic grid signal that has not been metered*

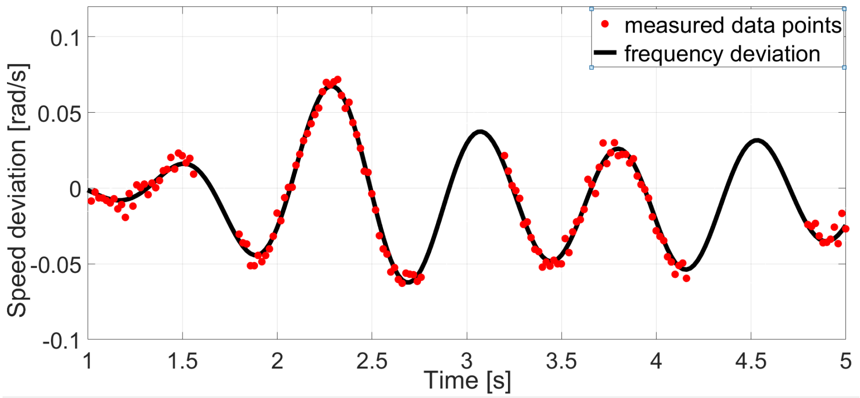


Prior work

- Data-based approaches [Gao+'14, Zhang-Wang'19, Osipov-Chow'20]
  - low-rank in PMU data matrices/tensors
  - model-free
  - cannot extrapolate at non-metered buses



- Dynamic state estimation [Zhao-Mili'19, Wang'12, Zhou+'13]
  - Kalman filters presume
    - measured inputs
    - uniformly sampled data
  - derivatives approximated with finite differences



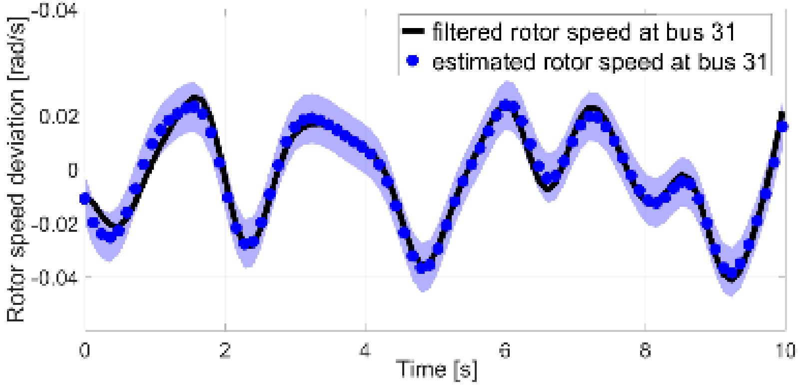
Bayesian inference

- Suppose jointly Gaussian random vectors $\begin{bmatrix} \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \begin{bmatrix} \mathbf{\Sigma}_{11} & \mathbf{\Sigma}_{21}^\top \\ \mathbf{\Sigma}_{21} & \mathbf{\Sigma}_{22} \end{bmatrix} \right)$

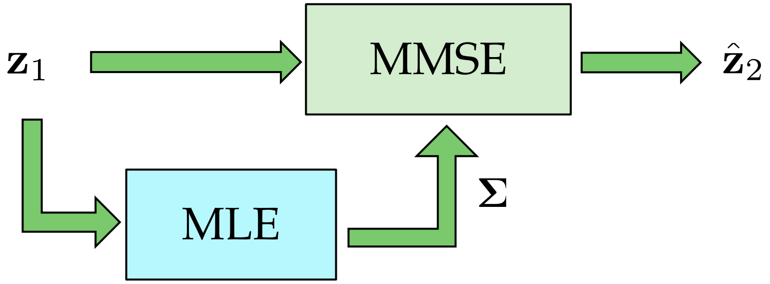
- Given $\mathbf{z}_1$, find MMSE of $\mathbf{z}_2$

point prediction $\quad \mathbb{E}[\mathbf{z}_2|\mathbf{z}_1] = \mathbf{\Sigma}_{21}\mathbf{\Sigma}_{11}^{-1}\mathbf{z}_1$

uncertainty $\quad \mathrm{Cov}[\mathbf{z}_2|\mathbf{z}_1] = \mathbf{\Sigma}_{22} - \mathbf{\Sigma}_{21}\mathbf{\Sigma}_{11}^{-1}\mathbf{\Sigma}_{21}^\top$



- Parameterize $\mathbf{\Sigma}$ and find parameters via ML using $\mathbf{z}_1$



C. M. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006.

Gaussian processes for dynamical systems

- Consider SISO LTI system $\ddot{y}(t) + \gamma\dot{y}(t) + \lambda y(t) = x(t)$

- Model $y(t)$ as a Gaussian process (GP) $\mathbf{y} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$ $[\mathbf{\Sigma}]_{ij} = \mathbb{E}[y(t_i)y(t_j)] = k(t_i, t_j)$

  any collection of $y(t)$ samples

- Derivative of a GP is a GP! $\dot{\mathbf{y}} \sim \mathcal{N}(\mathbf{0}, \ddot{\mathbf{K}})$ $[\ddot{\mathbf{K}}]_{ij} = \mathbb{E}\left[\frac{\partial y(t_i)}{\partial t_i}\frac{\partial y(t_j)}{\partial t_j}\right] = \frac{\partial^2 \mathbb{E}[y(t_i)y(t_j)]}{\partial t_i \partial t_j} = \frac{\partial^2 k(t_i,t_j)}{\partial t_i \partial t_j}$

- All involved signals $\ddot{y}(t), \dot{y}(t), y(t), x(t)$ become GPs

- *Q:* How to extend to MIMO swing setup?

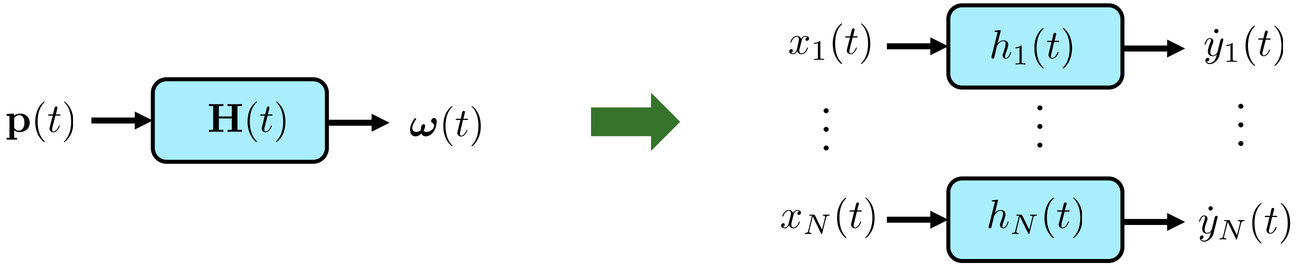
  A: Model spatiotemporal covariance using swing dynamics $\mathbb{E}[\omega_n(t+\tau)\omega_m(t)]$

Graepel, "Solving noisy linear operator equations by GPs: Application to ordinary and partial differential equations", *ICML* 2003.
Raissi, Perdikaris, and Karniadakis, "Inferring solutions of differential equations using noisy multi-fidelity data," *J. of Comp. Physics*, 2017.

Linearized grid dynamics

- Decouple MIMO dynamics to SISO *eigensystems* if $\mathbf{D} = \gamma \mathbf{M}$

$$\mathbf{M}\dot{\boldsymbol{\omega}} + \mathbf{D}\boldsymbol{\omega} + \mathbf{L}\boldsymbol{\delta} = \mathbf{p} \quad \Rightarrow \quad \ddot{\mathbf{y}} + \gamma\dot{\mathbf{y}} + \boldsymbol{\Lambda}\mathbf{y} = \mathbf{x}$$



  - define EVD: $\mathbf{L}_M = \mathbf{M}^{-1/2}\mathbf{L}\mathbf{M}^{-1/2} = \mathbf{V}\boldsymbol{\Lambda}\mathbf{V}^\top$
  - transform $\mathbf{x} = \mathbf{V}^\top\mathbf{M}^{-1/2}\mathbf{p}$ and $\dot{\mathbf{y}} = \mathbf{V}^\top\mathbf{M}^{1/2}\boldsymbol{\omega}$

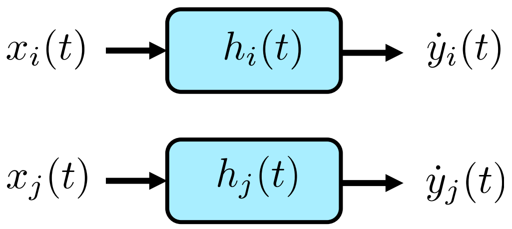
- Model $\dot{\mathbf{y}}(t)$ as GPs to learn grid dynamics

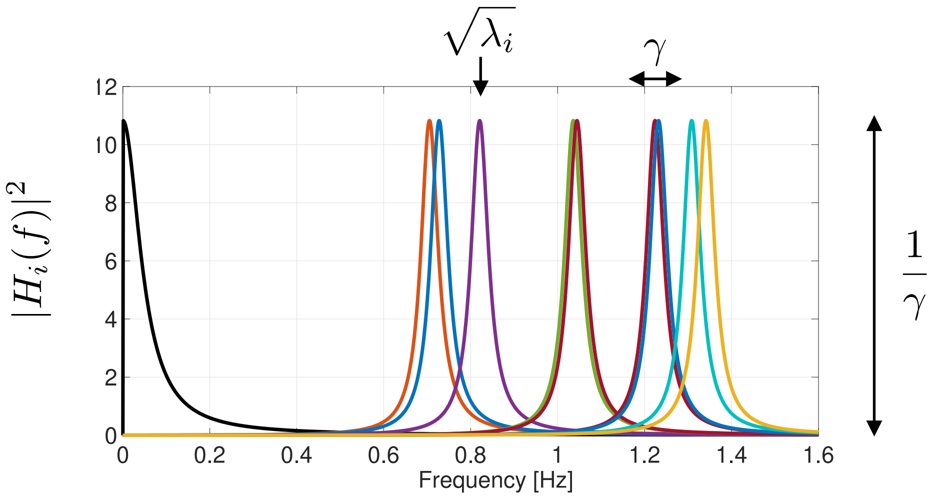
$$\mathbb{E}[\boldsymbol{\omega}(t+\tau)\boldsymbol{\omega}^\top(t)] = \mathbf{M}^{-1/2}\mathbf{V}\mathbb{E}[\dot{\mathbf{y}}(t+\tau)\dot{\mathbf{y}}^\top(t)]\mathbf{V}^\top\mathbf{M}^{-1/2}$$

Paganini and Mallada, "Global analysis of synchronization performance for power systems: bridging the theory-practice gap", *IEEE TAC*, Sep. 2019.
Huynh, Zhu, Chen, Elbanna, "Data-driven estimation of frequency response from ambient synchrophasor measurements," *IEEE TPWRS*, Nov. 2018.

Eigenstate covariances

- Each eigensystem is a second-order LTI





Freq. response of eigensystems of IEEE 300-bus system (first 10)

- Input/output second-order statistics

$$R_{\dot{y}_i\dot{y}_j}(\tau) = h_i(\tau) * h_j(-\tau) * R_{x_ix_j}(\tau) \iff S_{\dot{y}_i\dot{y}_j}(f) = H_i(f) \cdot H_j^*(f) \cdot S_{x_ix_j}(f)$$

time domain (correlation) *frequency domain (spectra)*

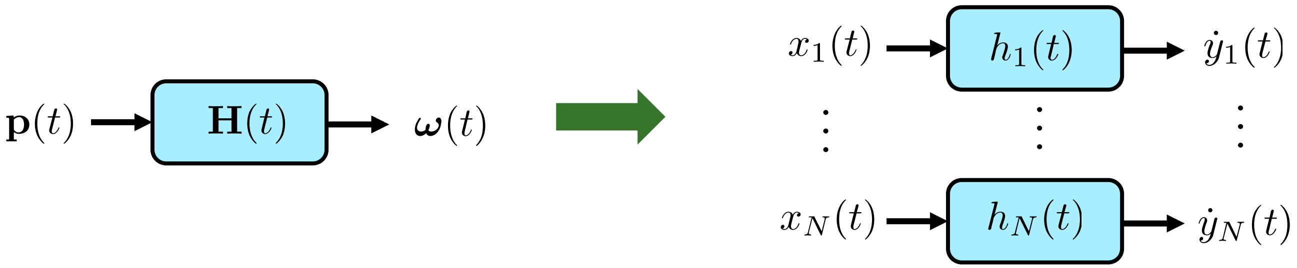
- Due to small overlap (if any), approximate $S_{x_ix_j}(f) \simeq S^0_{x_ix_j} \Longrightarrow R_{\dot{y}_i\dot{y}_j}(\tau) = S^0_{x_ix_j} h_i(\tau) * h_j(-\tau)$

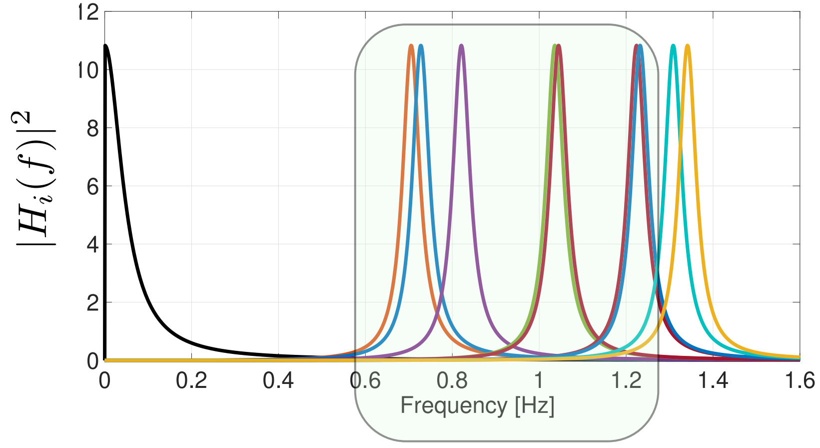
find by MLE for few overlapping pairs *(i,j)*

Jalali, Kekatos, Bhela, Zhu, "Inferring Power System Frequency Oscillations using Gaussian Processes," *IEEE CDC*, Dec. 2021.

Inter-area oscillations

- Key to monitor *low-frequency eigen-systems* (0.2 to 1.2 Hz)
  - wide-area thus hard-to-control
  - cause hidden oscillations
  - intra-area may be unobservable anyway





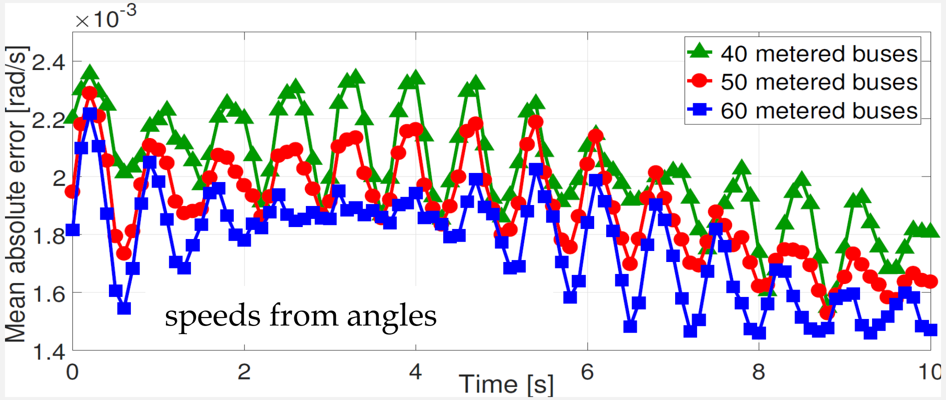
inter-area eigensystems $\mathcal{A}$

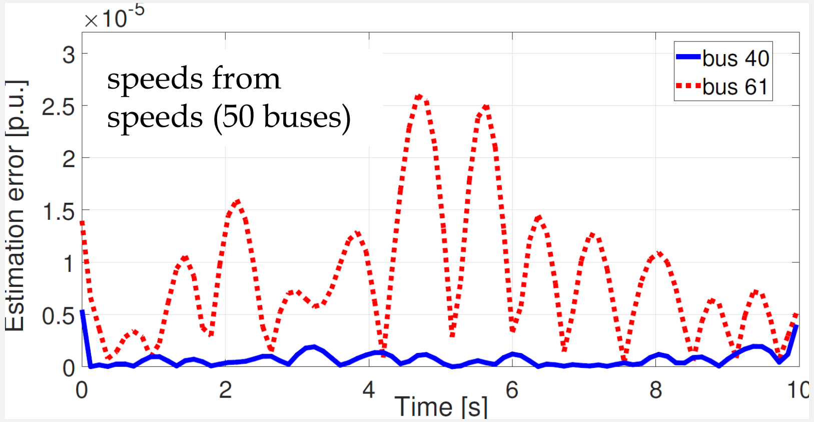
- Keep only *inter-area eigensystems* by low-pass filtering data

$$\boldsymbol{\omega} = \mathbf{M}^{-1/2}\mathbf{V}_{\mathcal{A}}\dot{\mathbf{y}}_{\mathcal{A}} + \mathbf{M}^{-1/2}\mathbf{V}_{\bar{\mathcal{A}}}\dot{\mathbf{y}}_{\bar{\mathcal{A}}} \quad \xrightarrow{\text{LPF}} \quad \boldsymbol{\delta}_{\mathcal{A}} = \mathbf{M}^{-1/2}\mathbf{V}_{\mathcal{A}}\mathbf{y}_{\mathcal{A}}$$

Ramakrishna and Scaglione, "Grid-graph signal processing: A graph signal processing framework for the power grid," *IEEE TSP*, 2021

Linearized 300-bus Kron-reduced to 69 buses



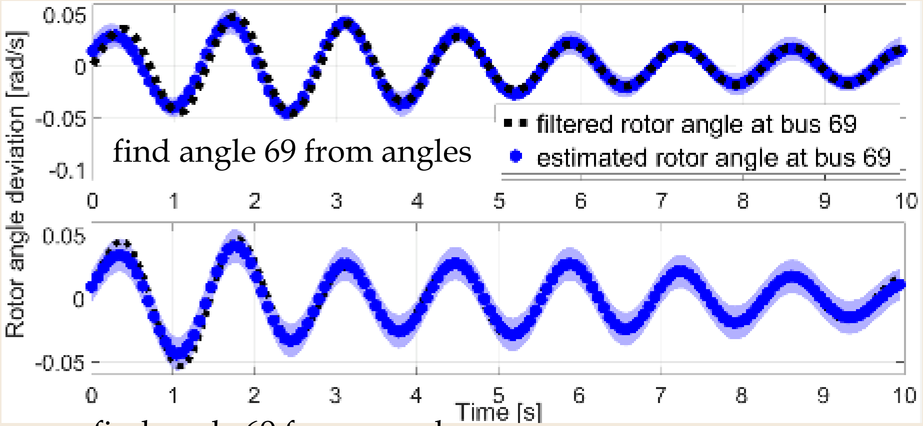


ambient conditions

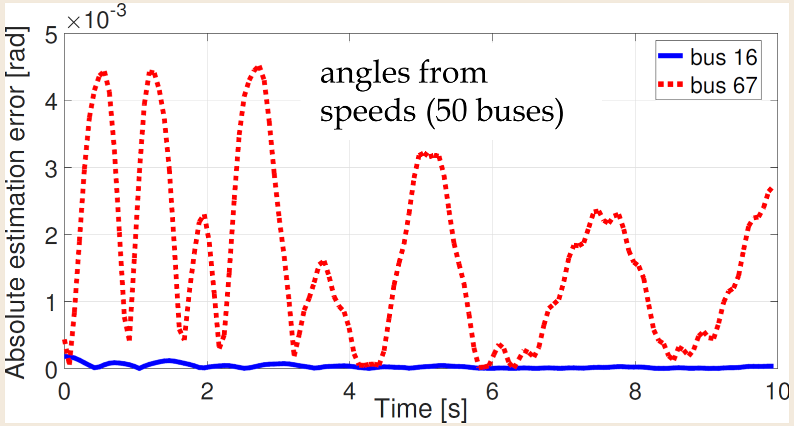
(WGN input)

generator trip

@ bus #69

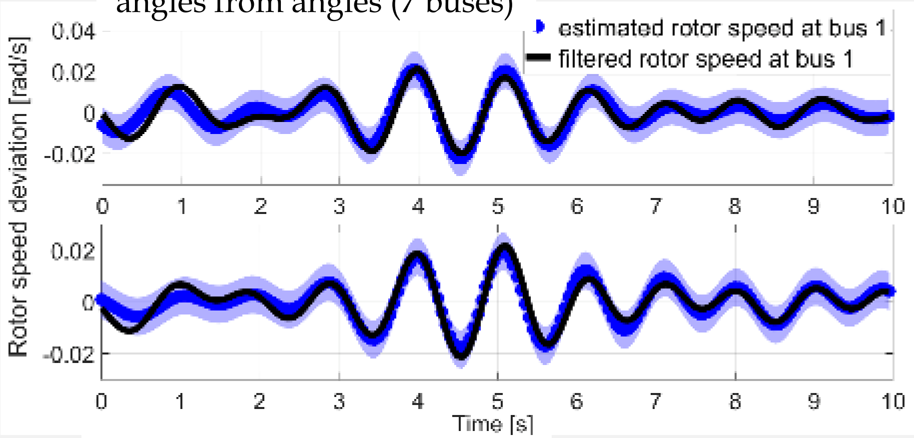


find angle 69 from speeds



Nonlinear 39-bus Kron-reduced to 10 buses

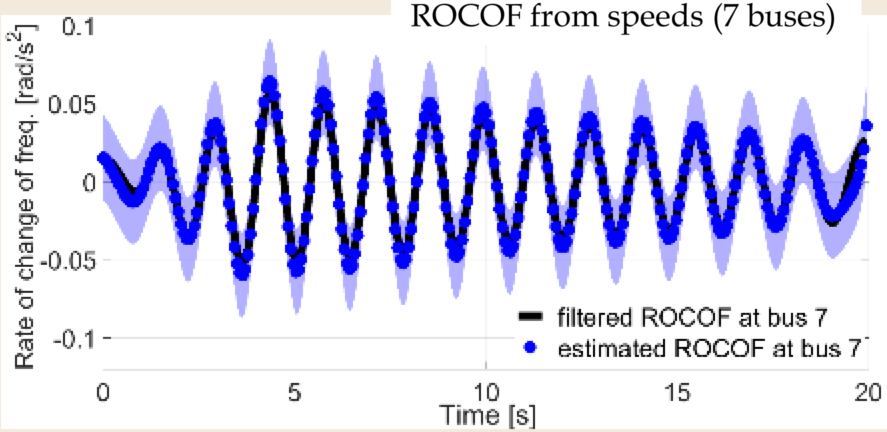
angles from angles (7 buses)



angles from speeds (7 buses)

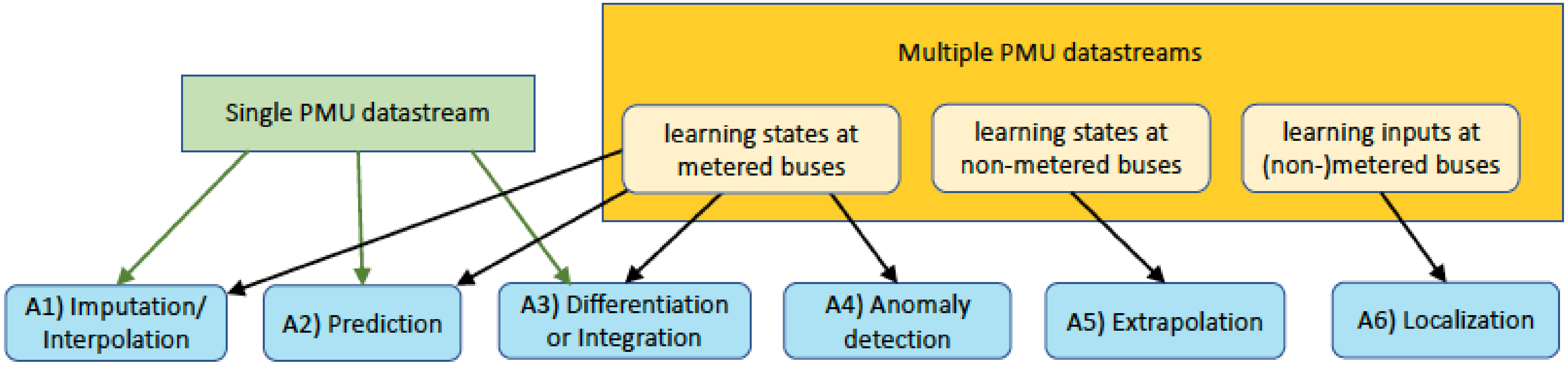
ambient conditions

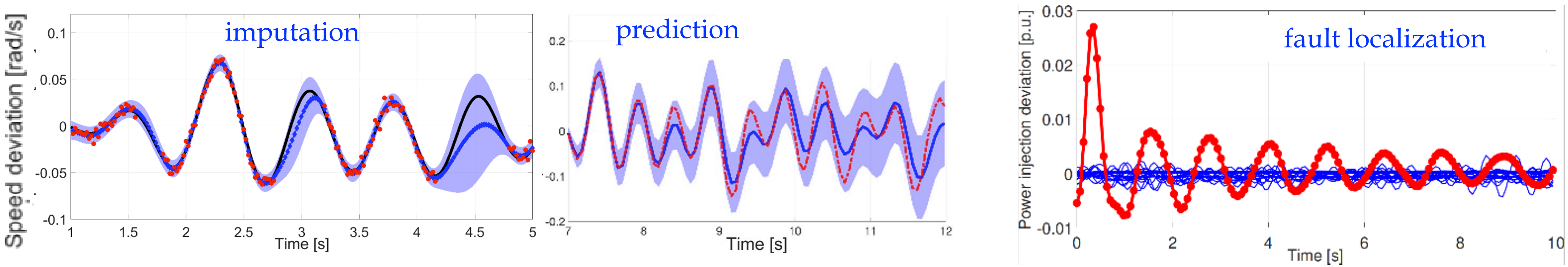
ROCOF from speeds (7 buses)



fault near bus #7

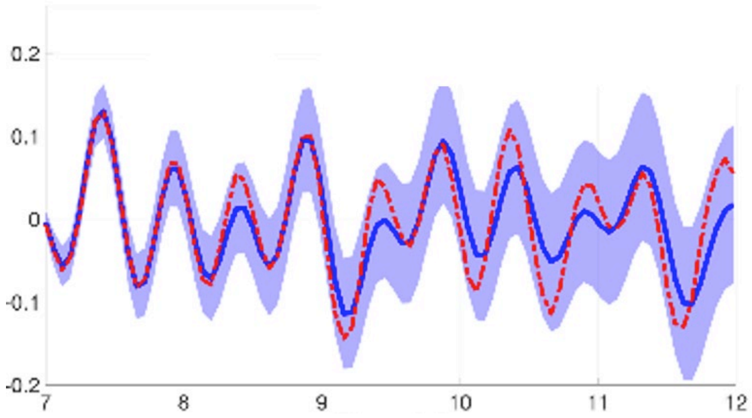
Learning grid dynamics



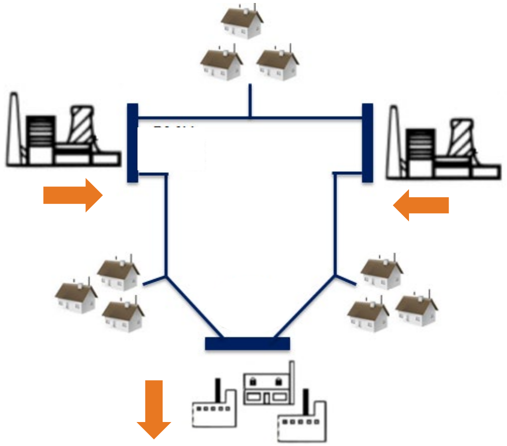


Outline

- *Monitoring inter-area oscillations*



- *Optimizing to suppress inter-area oscillations*



Improving rotor-angle stability

- Classical yet modern topic

- *Transient stability* (large disturbance)
  - simulations or direct methods
  - assess stability [Chow+'20], [Turitsyn'16]
  - ensure stability [Gan+'00], [Chen+'20]

- *Small-signal stability* (small disturbance)
  - linearized model, eigen-based H_2/H_∞-norms
  - ensure stability [Chung+'04], [Zarate-Minano+'11], [Inoue+'21]
  - inertia placement, line switching [Poolla'17], [Song'18], [Bhela'19,'21]

Definition and Classification of Power System Stability

TPWRS '04

IEEE/CIGRE Joint Task Force on Stability Terms and Definitions

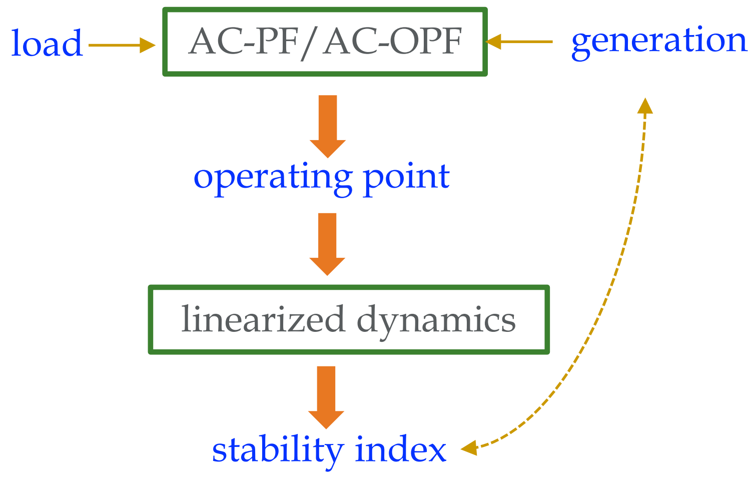
Prabha Kundur (Canada, Convener), John Paserba (USA, Secretary), Venkat Ajjarapu (USA), Göran Andersson (Switzerland), Anjan Bose (USA), Claudio Canizares (Canada), Nikos Hatziargyriou (Greece), David Hill (Australia), Alex Stankovic (USA), Carson Taylor (USA), Thierry Van Cutsem (Belgium), and *Vijay Vittal (USA)*

Definition and Classification of Power System Stability – Revisited & Extended

TPWRS '20

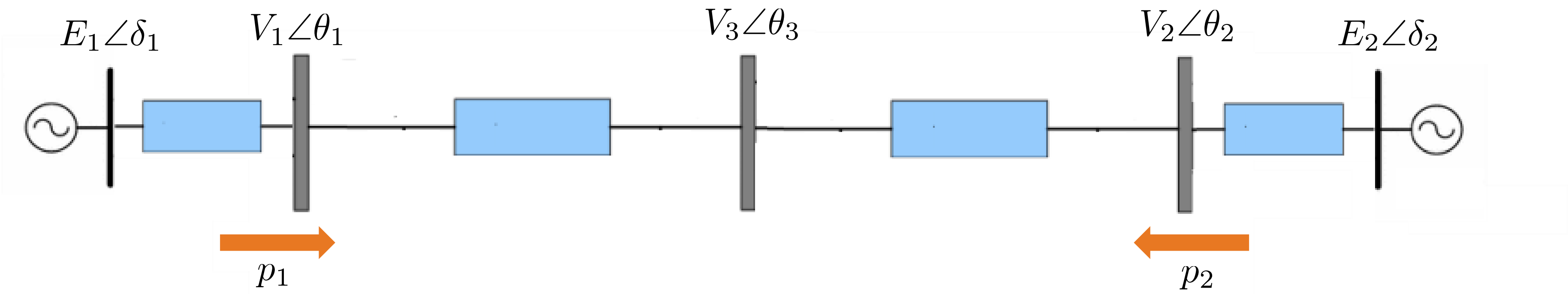
Chairman: N. Hatziargyriou Co-Chairman: J. V. Milanović Secretary: C. Rahmann

Contributors: N. Hatziargyriou, *Fellow, IEEE*, J. V. Milanović, *Fellow, IEEE*, C. Rahmann, *Senior Member, IEEE*, V. Ajjarapu, *Fellow, IEEE*, C. Cañizares, *Fellow, IEEE*, I. Erlich†, *Senior Member, IEEE*, D. Hill, *Fellow, IEEE*, I. Hiskens, *Fellow, IEEE*, I. Kamwa, *Fellow, IEEE*, B. Pal, *Fellow, IEEE*, P. Pourbeik, *Fellow, IEEE*, J. J. Sanchez- Gasca, *Fellow, IEEE*, A. Stanković, *Fellow, IEEE*, T. Van Cutsem, *Fellow, IEEE*, V. Vittal, *Fellow, IEEE*, C. Vournas, *Fellow, IEEE*.



Effective network model

- Network reduced to set of dynamic buses $\mathcal{S}$



- OPF deals with external voltages $\mathbf{v}$
- Dynamics depend on internal voltages $\mathbf{e}$

linearly related!

$$\mathbf{v}_{\mathcal{S}} = \mathbf{\Gamma}_{\mathcal{S}}\mathbf{e}$$

Dynamics and operating point

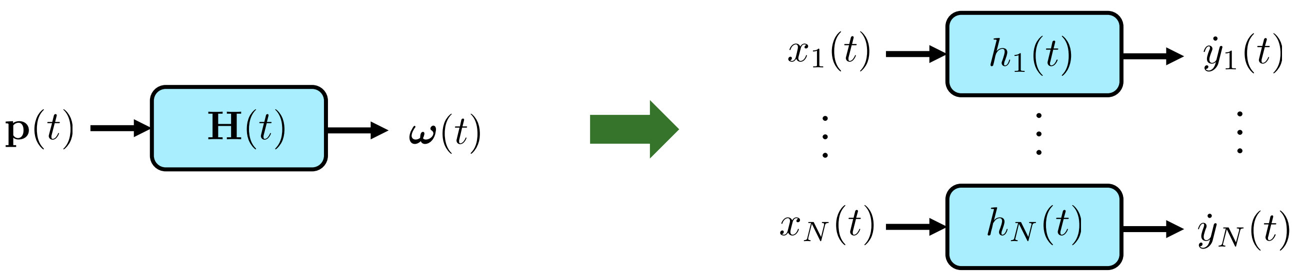
- Swing dynamics depend on operating point $\mathbf{M}\dot{\boldsymbol{\omega}} + \mathbf{D}\boldsymbol{\omega} + \mathbf{L_0}\boldsymbol{\delta} = \mathbf{p}$
- Jacobian matrix of PF equations $[\mathbf{L}_0]_{nm} = [\nabla_{\boldsymbol{\delta}}\mathbf{p}]_{nm} = \begin{cases} \sum_{k\neq n} \gamma_{nk} E_n E_k \cos\left(\delta_n^0 - \delta_k^0\right) & , m = n \\ -\gamma_{nm} E_n E_m \cos\left(\delta_n^0 - \delta_m^0\right) & , m \neq n \end{cases}$
- *Variable lifting* $\mathbf{E} = \mathbf{e}\mathbf{e}^H$ ➡ $E_n E_m \cos\left(\delta_n^0 - \delta_m^0\right) = \mathrm{Re}\{\mathbf{E}_{nm}\}$
- Matrix **L** depends linearly on **E,** or the SDP-OPF variable **V**

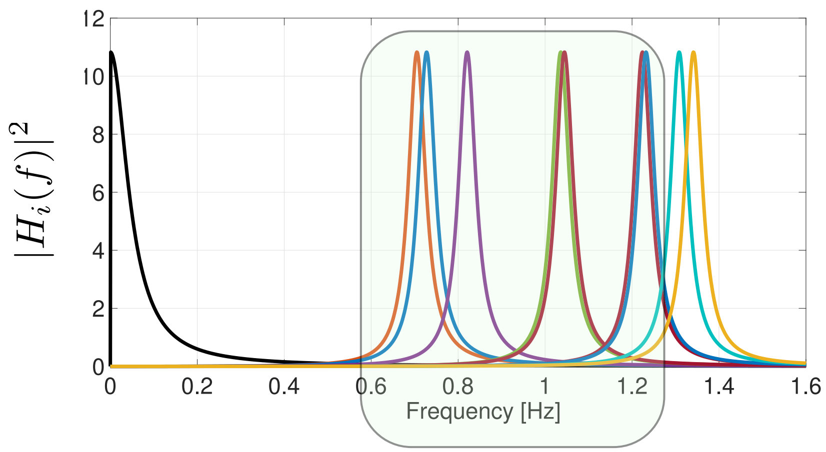
$$\mathbf{v}_{\mathcal{S}} = \boldsymbol{\Gamma}_{\mathcal{S}}\mathbf{e} \quad \Rightarrow \quad \mathbf{V}_{\mathcal{S}\mathcal{S}} = \boldsymbol{\Gamma}_{\mathcal{S}}\mathbf{E}\boldsymbol{\Gamma}_{\mathcal{S}}^H$$

- How does small-signal stability relate to **L**?

Wang, Cui, Wang, and Gu, "SDP-Based Optimal Power Flow With Steady-State Voltage Stability Constraints," *IEEE TSG*, July 2019.

Stability metric





K inter-area eigensystems $\mathcal{A}$

- If $\mathbf{p} \sim \mathcal{N}(\mathbf{0}, \alpha \mathbf{M})$, *eigen-outputs* are independent $y_i(t) \sim \mathcal{N}\left(0, \frac{1}{2\gamma\lambda_i}\right)$ ← eigenvalue of $\mathbf{L}_M = \mathbf{M}^{-1/2}\mathbf{L}\mathbf{M}^{-1/2}$

- Suppress energy of inter-area eigensystems $f_s = \sum_{i \in \mathcal{A}} \mathbb{E}[y_i^2(t)] \propto \sum_{i \in \mathcal{A}} \frac{1}{\lambda_i}$

- Convex function of **L**!

$$f_s(\mathbf{L}_M) = \min_{s, \mathbf{Z} \succeq 0} \operatorname{Tr}(\mathbf{Z}) + Ks$$
$$\text{s.to} \begin{bmatrix} \mathbf{Z} + s\mathbf{I} & \mathbf{W} \\ \mathbf{W} & \mathbf{L}_M \end{bmatrix}$$

Stability-improving OPF

$$\min \quad (1-\mu) f_g(\mathbf{p}^g) + \mu f_s(\mathbf{L}_M)$$
$$\text{over} \quad \mathbf{v}, \mathbf{e}, \mathbf{L}, \{p_n^g, q_n^g\}$$

subject to…

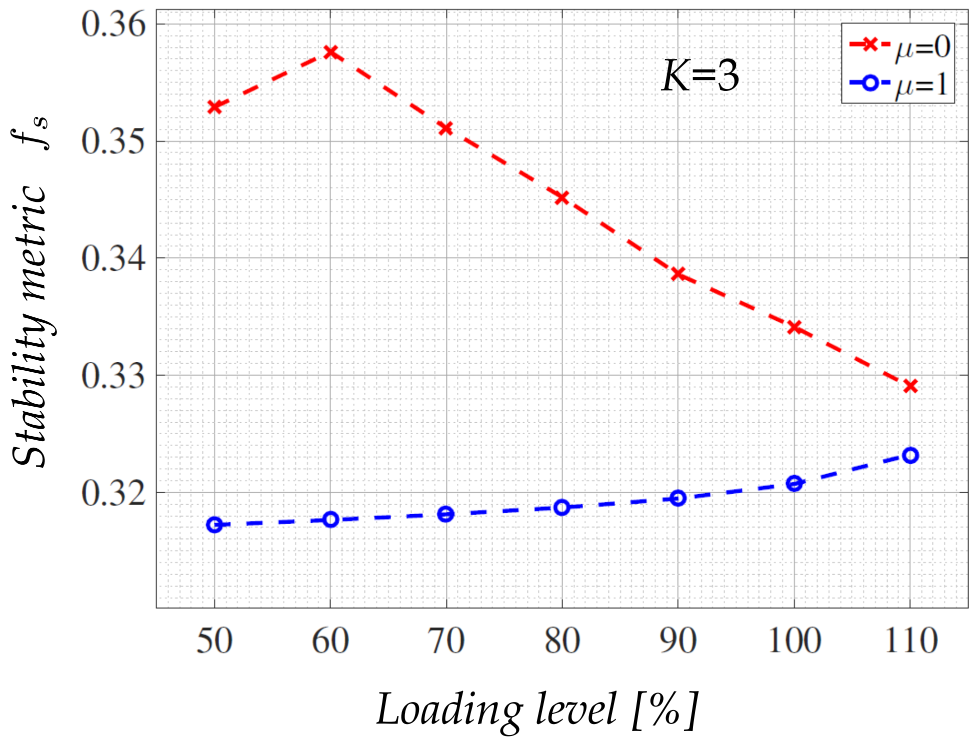
$$\mathbf{v}^H \mathbf{M}_{p_n} \mathbf{v} = p_n^g - p_n^d$$
$$\mathbf{v}^H \mathbf{M}_{q_n} \mathbf{v} = q_n^g - q_n^d$$
$$\underline{p}_n^g \leq p_n^g \leq \bar{p}_n^g$$
$$\underline{q}_n^g \leq q_n^g \leq \bar{q}_n^g$$
$$\underline{v}_n \leq \mathbf{v}^\top \mathbf{M}_{v_n} \mathbf{v} \leq \bar{v}_n$$
$$\mathbf{v}^H \mathbf{M}_{i_{mn}} \mathbf{v} \leq \bar{i}_{mn}$$
$$\mathbf{v}_{\mathcal{S}} = \mathbf{\Gamma}_{\mathcal{S}} \mathbf{e}$$
$$[\mathbf{L}_{\delta^0}]_{n,m} = \begin{cases} \sum_{k \neq n} \frac{E_n E_k}{\gamma_{nk}} \cos\left(\delta_n^0 - \delta_k^0\right), m = n \\ -\frac{E_n E_m}{\gamma_{nm}} \cos\left(\delta_n^0 - \delta_m^0\right), m \neq n \end{cases}$$

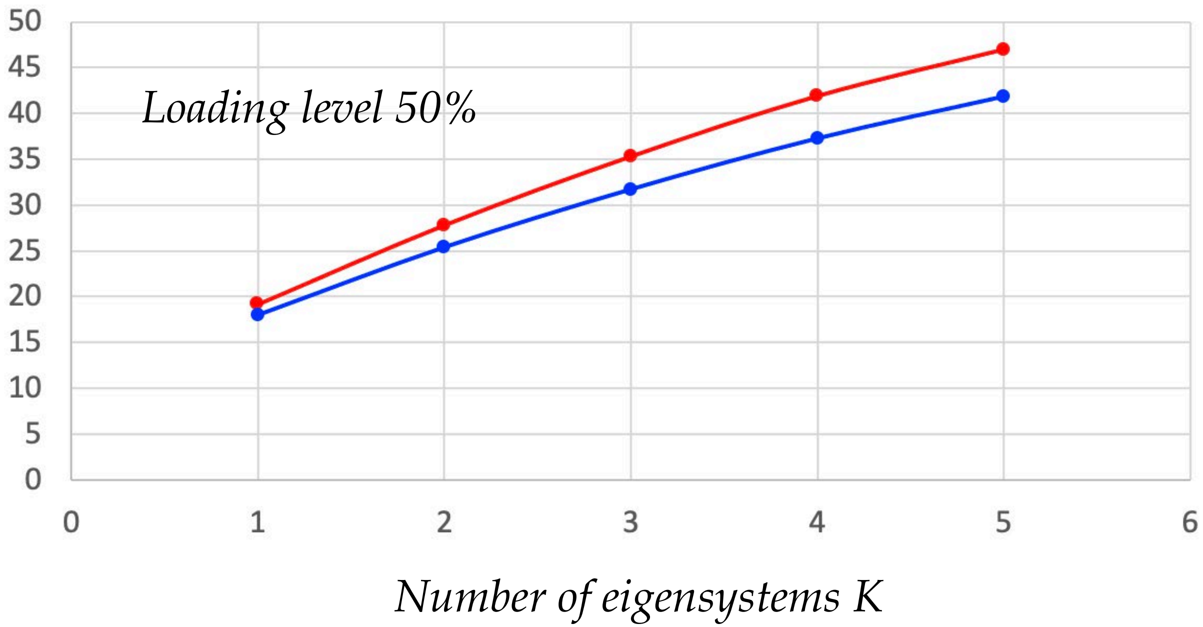
SDP relaxation →

$$\operatorname{Tr}\left(\mathbf{M}_{p_n} \mathbf{V}\right) = p_n^g - p_n^d$$
$$\operatorname{Tr}\left(\mathbf{M}_{q_n} \mathbf{V}\right) = q_n^g - q_n^d$$
$$\underline{p}_n^g \leq p_n^g \leq \bar{p}_n^g$$
$$\underline{q}_n^g \leq q_n^g \leq \bar{q}_n^g$$
$$\underline{v}_n \leq \operatorname{Tr}\left(\mathbf{M}_{v_n} \mathbf{V}\right) \leq \bar{v}_n$$
$$\operatorname{Tr}\left(\mathbf{M}_{i_{mn}} \mathbf{V}\right) \leq \bar{i}_{mn}$$
$$\mathbf{V}_{\mathcal{S},\mathcal{S}} = \mathbf{\Gamma}_{\mathcal{S}} \mathbf{E} \mathbf{\Gamma}_{\mathcal{S}}^H$$
$$[\mathbf{L}_{\delta^0}]_{n,m} = \begin{cases} \sum_{k \neq n} \frac{\operatorname{Re}\{E_{nk}\}}{\gamma_{nk}}, m = n \\ -\frac{\operatorname{Re}\{E_{nm}\}}{\gamma_{nm}}, m \neq n \end{cases}$$
$$\mathbf{V} \succeq 0$$

Exact relaxation!

Room for improvement





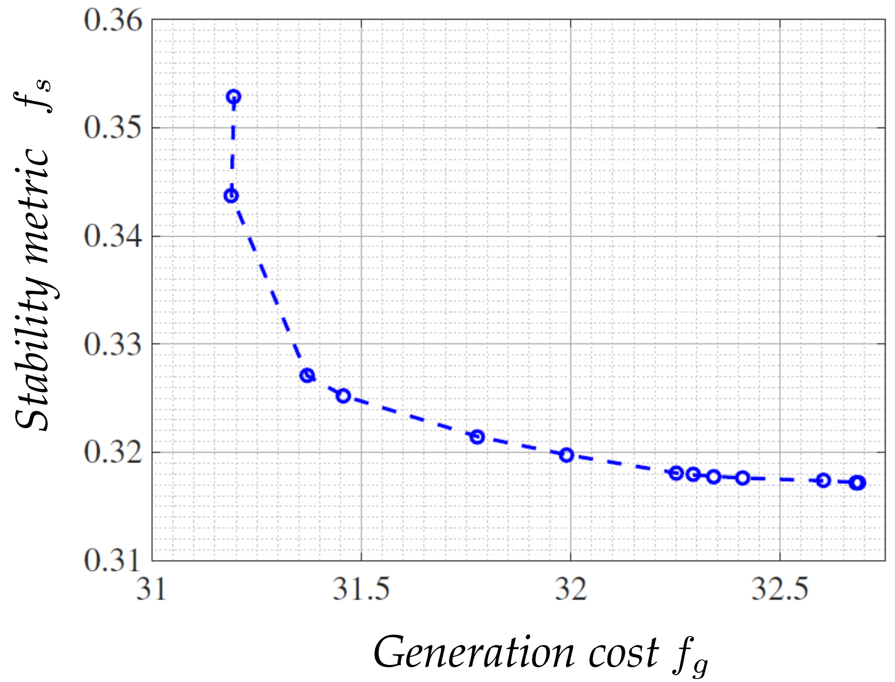
- IEEE 39-bus system (10 GENs, 10 ZIBs)

Pareto front

- Pareto analysis at 50% loading and K=3
  - stability metric ↓10% with cost ↑4.8%
  - stability metric ↓ 8% with cost ↑0.8%

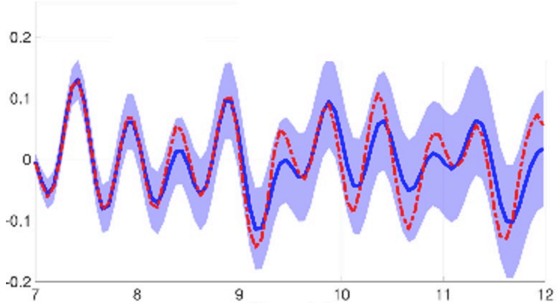
- Flexible tool for power grid dispatchers!

- Open questions
  - ☐ guarantees for exact relaxation
  - ☐ generator models
  - ☐ stability metrics
  - ☐ fix MW- and resolve for MVar/V-setpoints



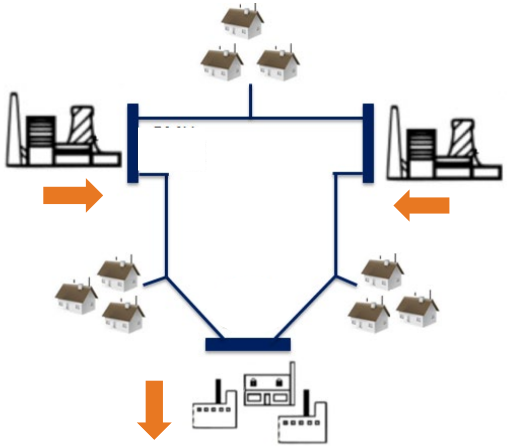
Conclusions

- *Monitoring inter-area oscillations*
  - ☑ GPs for monitoring dynamics
  - ☑ physics-informed kernel design
  - ☑ diverse PMU applications



Thank You!

- *Optimizing to suppress inter-area oscillations*
  - ☑ linked stability to OPF
  - ☑ exact SDP formulation
  - ☑ Pareto front



[1] Singh and Kekatos, "Optimal Power Flow Schedules with Reduced Low-Frequency Oscillations," *PSCC*, Porto, Portugal, June, 2022.

[2] Jalali, Kekatos, Bhela, and Zhu, "Inferring Power System Frequency Oscillations using Gaussian Processes," *IEEE CDC*, Austin, TX, Dec. 2021.

[3] Jalali, Kekatos, Bhela, Zhu, and Centeno, "Inferring Power System Dynamics from Synchrophasor Data using Gaussian Processes," *IEEE TPWRS*, (early access).