Data-Driven Analysis of Power System Dynamic Performances via Koopman Mode Decomposition

Yoshihiko Susuki
Department of Electrical Engineering
Kyoto University
JST-CREST

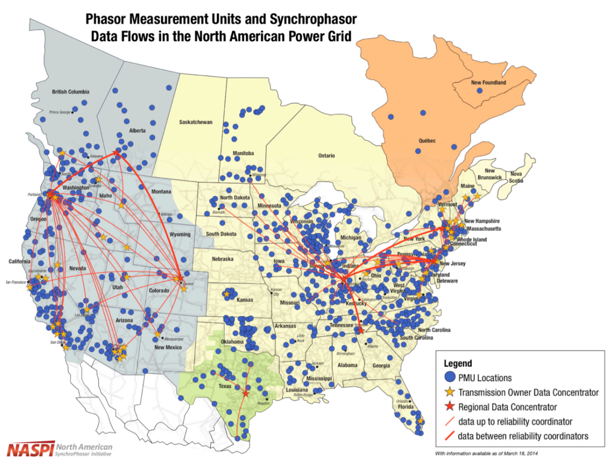
ENERGY Management SYSTEM

April 21, 2015
JST-NSF-DFG-RCN Workshop
Arlington, Washington DC

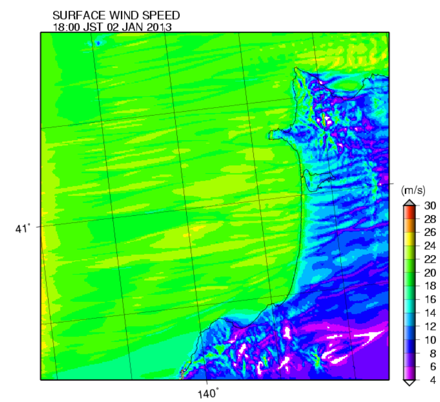
KYOTO UNIVERSITY
KYOTO JAPAN
FOUNDED 1897

Challenging Issue

- How do we utilize massive quantities of ***data*** for analysis and control of muliti-scale power systems?
  - Measured: voltage, phase, power flow
  - Predicted: wind speed (renewable output), demand power, EV-sharing (movement of multiple EVs with batteries in space- and time-domain)



from https://www.naspi.org/



from Nagoya Univ. HyARC

at Anjo-City, Japan

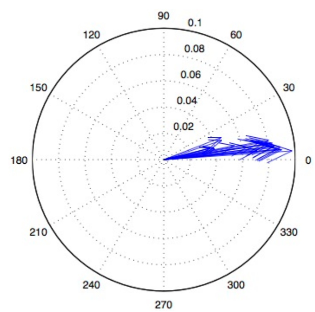
Purpose and Contents

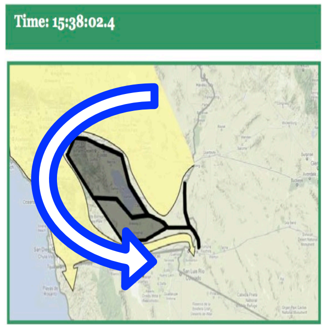
Data-Driven Analysis of Power System Dynamic Performances

- Application of Koopman Mode Decompostion
  - A (nonlinear) generalization of linear oscillatory modes, guided by operator theory of nonlinear dynamical systems---Koopman Operator

----

1. Brief Summary of the Underlying Theory
2. Two Applications:
   1. Modal Identification
   2. Power Flow Diagnostic
3. Message and Ongoing Work





Koopman Mode Decomposition

Mathematical Formulation:

$$x_{k+1} = T(x_k) \quad x \in M$$

- Finite-dimensional nonlinear model, which describes internal state dynamics of a power system

$$g : M \to \mathbb{R}$$

- Observable or output of the model, which describes measurement or sampling of the dynamics

$$Ug(x) = g \circ T(x)$$

- Koopman operator (**linear!**) that describes time evolution of the measured quantity

Decomposition of Time Evolution of Vector-valued Observable :

$$g(x_k) = \sum_i \lambda_i^k \phi_i(x_0) V_i$$

Koopman mode

Measured quantity (multi-dim.)

Eigen-values and eigen-functions of U:

$$U\phi_i = \lambda_i \phi_i$$

Ref.) C. Rowley et al., *J. Fluid Mechanics,* vol.641, pp.309-325 (2009).

Computation of Koopman Modes

Arnoldi-like Algorithm to compute an approximation of the Koopman eigenvalues and modes *directly from* ***data***:

$\{g_0, \dots, g_m\}$ Finite-time data obtained in experiments or simulations under uniform sampling

~ Koopman Eigenvalue

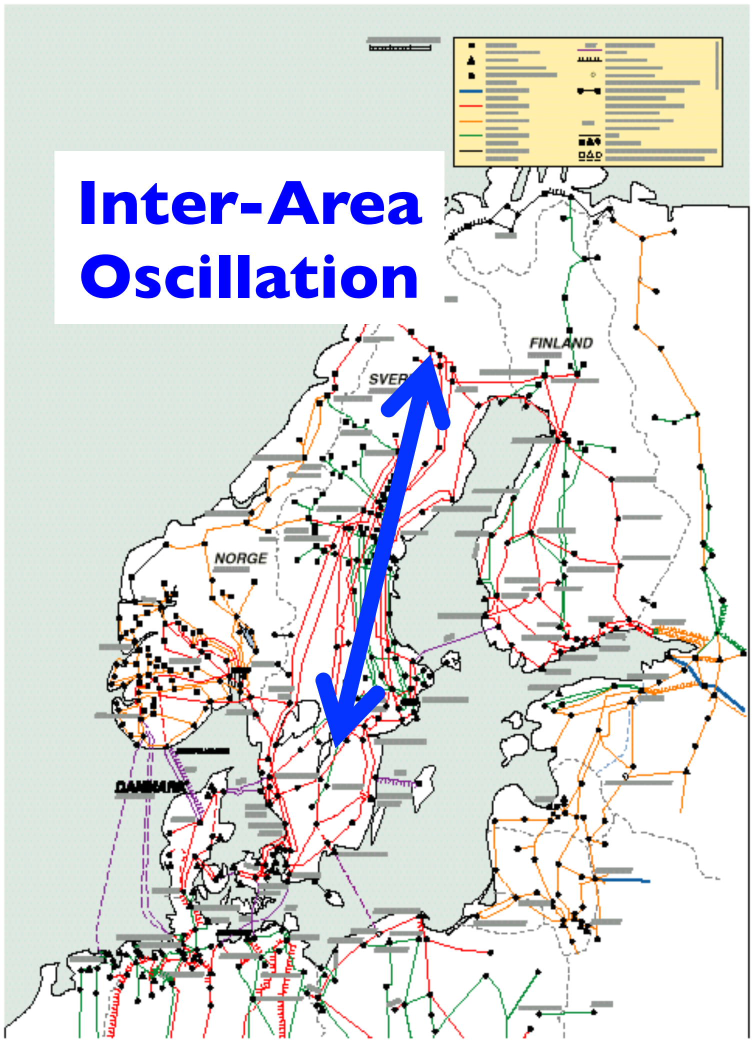
~ Koopman Mode (scaled by a constant value)

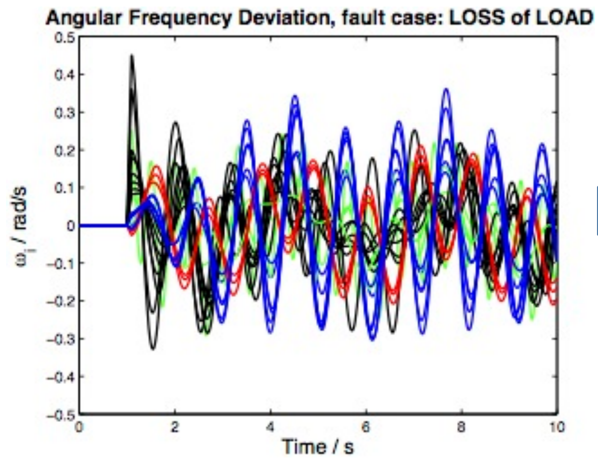
$$g_k = \sum_{j=1}^{m} \tilde{\lambda}_j^k \tilde{V}_j, \quad g_m = \sum_{j=1}^{m} \tilde{\lambda}_j^m \tilde{V}_j + \eta_m$$

$$k = 0, \dots, m-1$$

For details, see the paper [C. Rowley, I. Mezic, *et al.*, *J. Fluid Mech.*, vol.641, pp.115-127 (2009)].

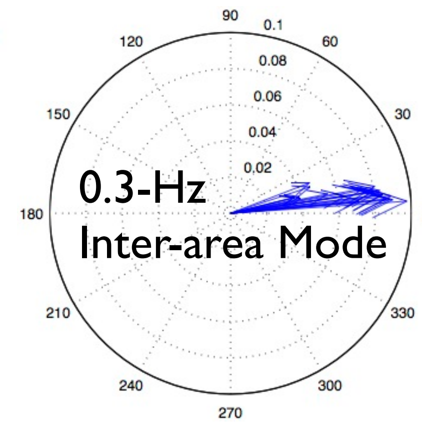
Modal Identification (1/2) - NORDEL Grid





Simulation data with nonlinear swing equation of Nordic 32-bus test system w/ 22 generators

Koopman Mode Decomposition

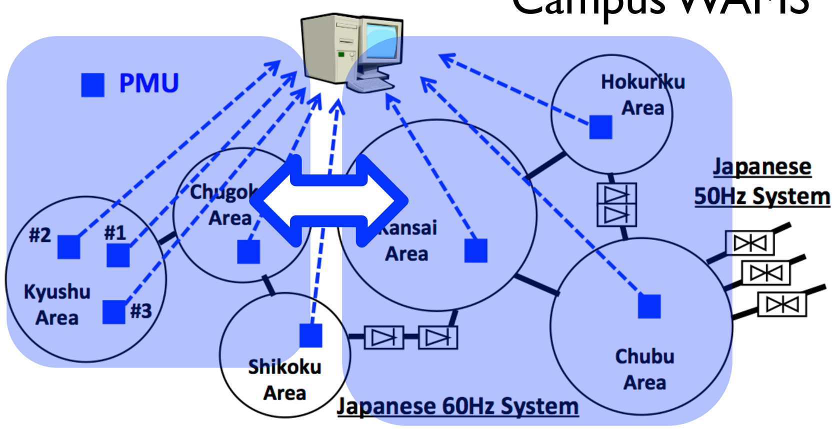


- *No* similar mode is identified by linearization of the swing equation.
- The inter-area mode is **inherently nonlinear!**

Ref.) F. Raak, Y. S., and T. Hikihara, *Proc. Annual Conference of IEEJ*, Nagoya University, March (2013).

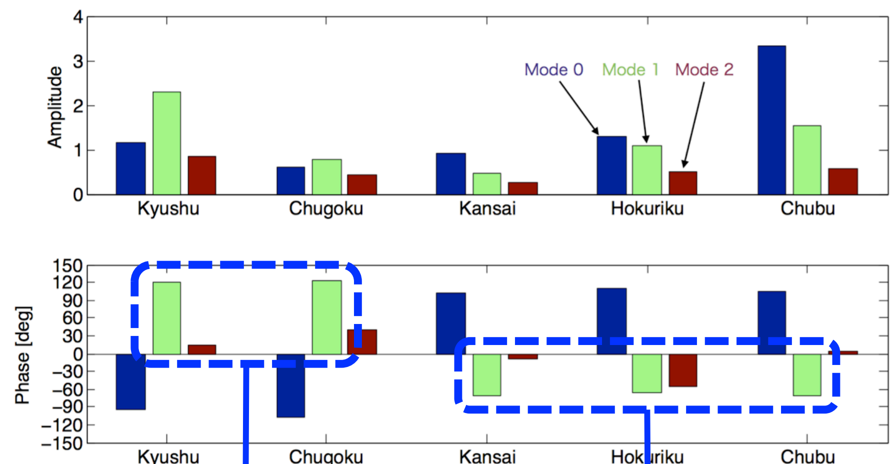
Modal Identification (2/2) - West Japan

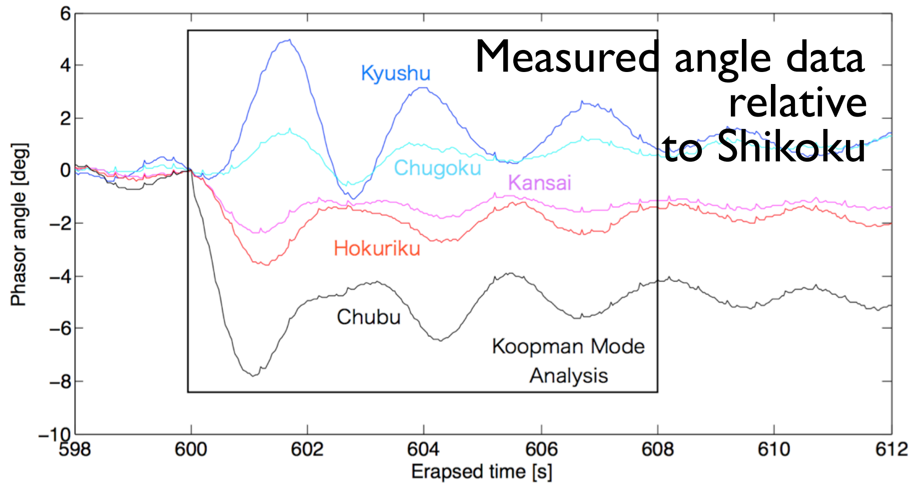
Campus WAMS



Koopman modes derived from the data

Mode	Growth rate	Argument	Frequency	Norm
0	0.9986	±0.0066[rad]	0.0316[Hz]	15.1540
1	0.9919	±0.0826[rad]	0.3944[Hz]	9.5207
2	0.9890	±0.1147[rad]	0.5474[Hz]	1.5193

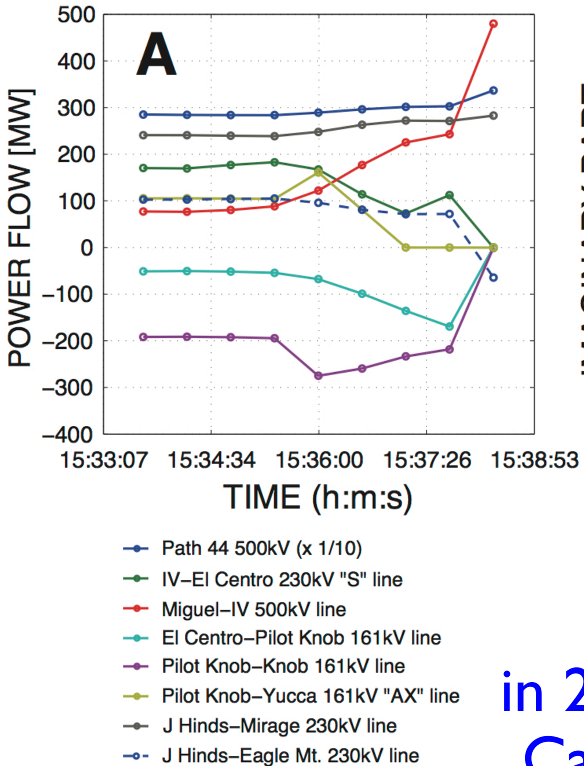


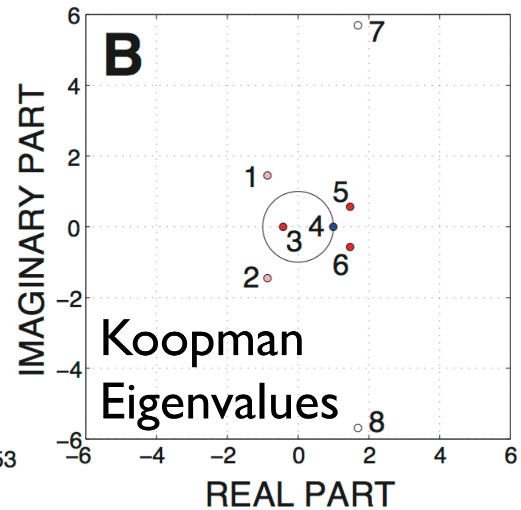


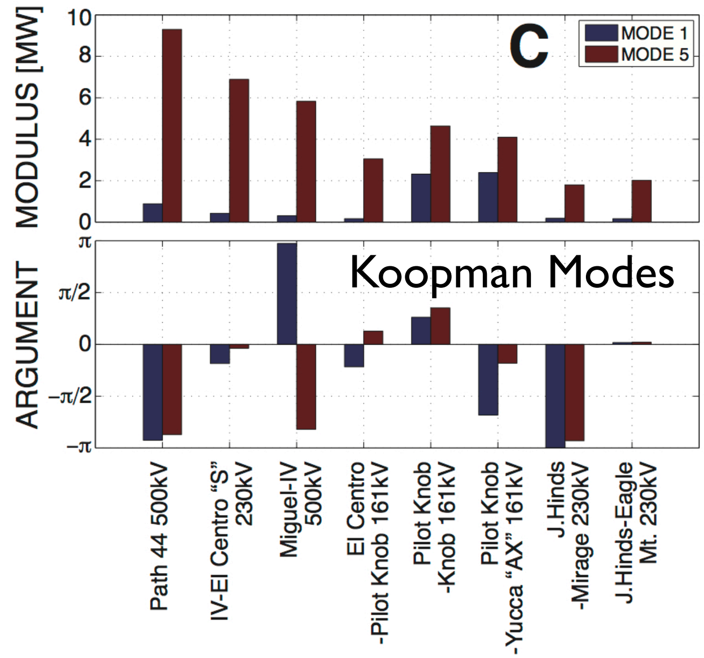
Inter-area mode (0.39 Hz "Chubu-Hokuriku-Kaisai v.s. Chugoku-Kyushu") with small damping is detected.

Ref.) Y. Ota, Y.S., F. Raak, and I. Mezic, *Proc. Annual Conference of IEEJ*, Tokyo City University, March (2015).

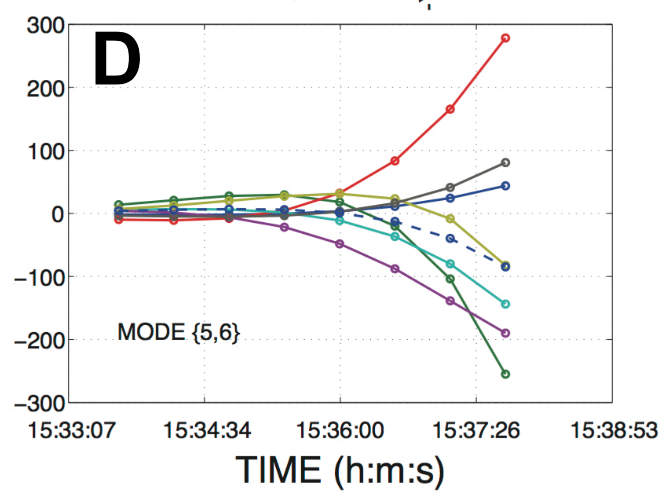
Power Flow Diagnostic (1/2)







Measured Data on Power Flows in 2011 Arizona-Southern California Grid Outages

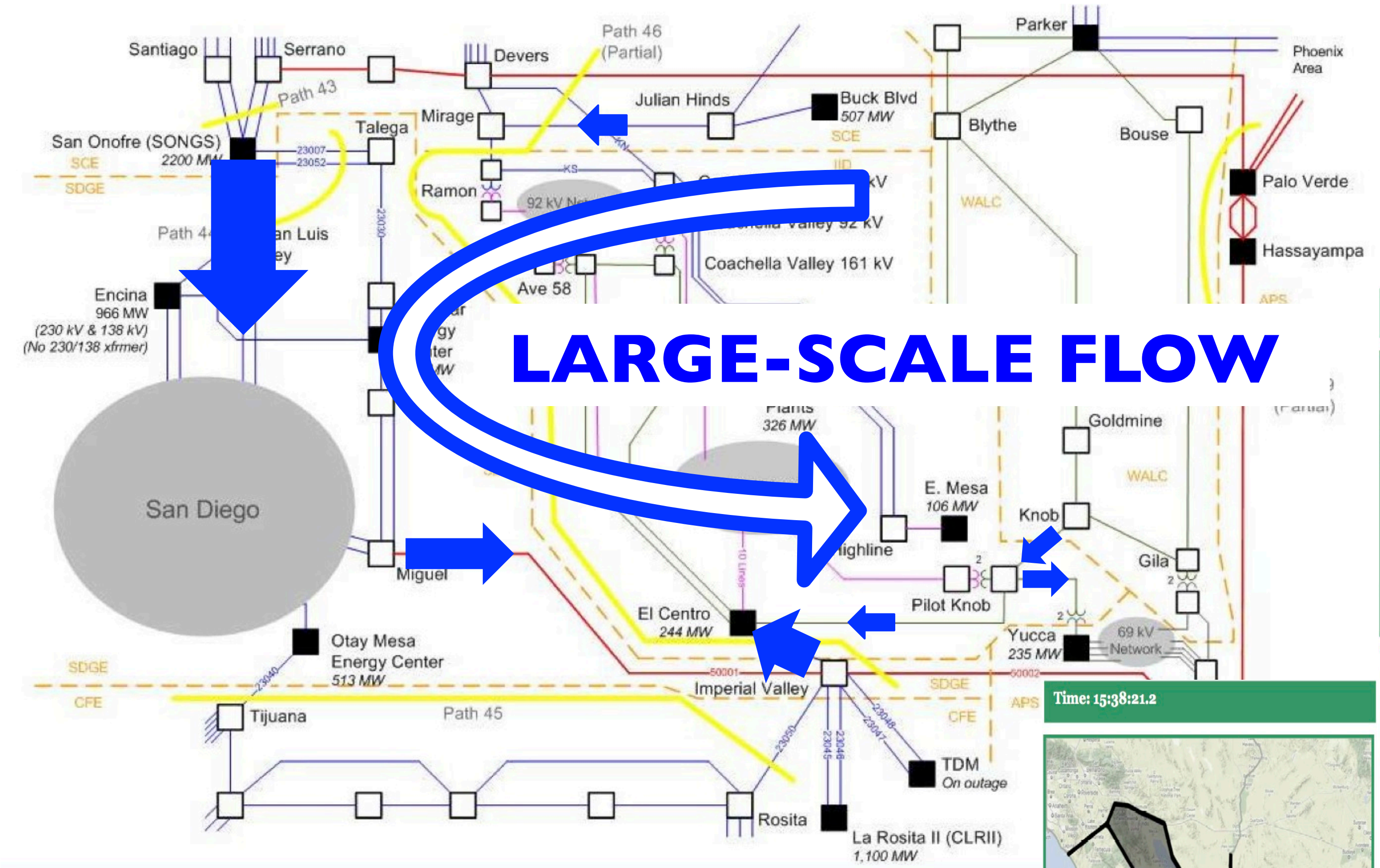


Ref.) FERC and NERC, Arizona-Southern California Outages on September 8, 2011, Causes and Recommendation, 2012.

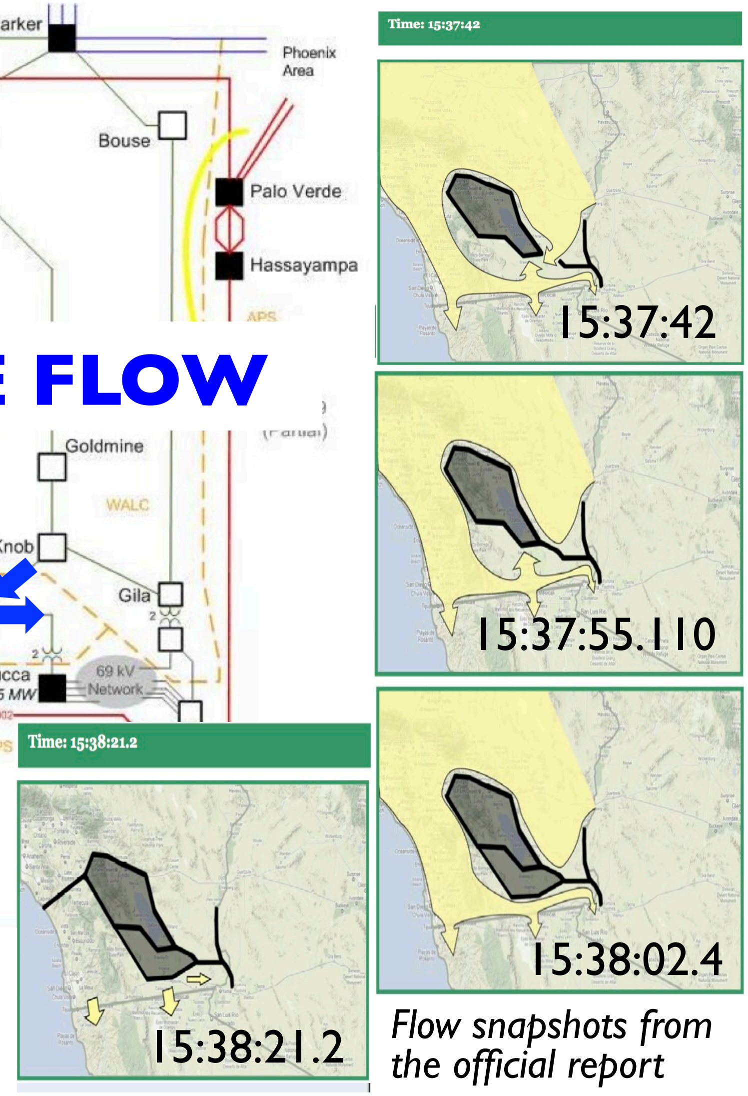
$$\boldsymbol{P}_k^{\{j,j+1\}} := \tilde{\lambda}_j^k \tilde{\boldsymbol{V}}_j + (\tilde{\lambda}_{j+1})^k \tilde{\boldsymbol{V}}_{j+1} = 2\tilde{r}_j^k \begin{bmatrix} |\tilde{V}_{j1}|\cos\{2\pi k\tilde{\nu}_j + \mathrm{Arg}(\tilde{V}_{j1})\} \\ |\tilde{V}_{j2}|\cos\{2\pi k\tilde{\nu}_j + \mathrm{Arg}(\tilde{V}_{j2})\} \\ \vdots \\ |\tilde{V}_{jm}|\cos\{2\pi k\tilde{\nu}_j + \mathrm{Arg}(\tilde{V}_{jm})\} \end{bmatrix}$$

Single-mode response ($\boldsymbol{P}_k^{\{j,j+1\}}$); modulus; argument

Power Flow Diagnostic (2/2)



A Large-scale, slow-growing mode leading to the collapse of the grid is detected.



Flow snapshots from the official report

Ref.) Y. S. and I. Mezic, *IEEE Trans. Power Syst.*, vol.29, no.2, pp.899-907, March (2014).

Conclusion - Message and Ongoing Work

Message:

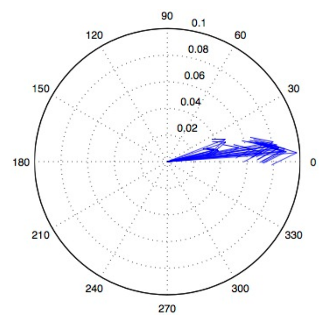
- Nonlinear Koopman modes enable the development of *fully* data-driven methodology and tools for power system analysis, which have a solid mathematical foundation---*Koopman operator.*

Ongoing Work:

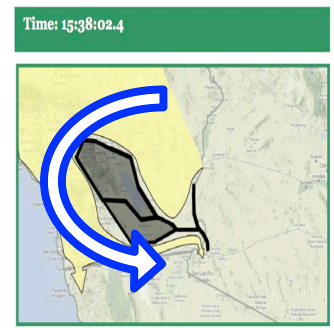
- Data-driven decision-making w/ measured and *predicted* data such as
  - Wind flow field;
  - EV-sharing (in Prof. Suzuki's Super-Team).

$$Ug(x) = g \circ T(x)$$

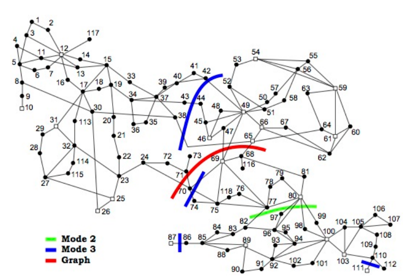
Modal identification



Power flow diagnostic



Network partitioning



Stability assessment