

Optimum Reduced-Order DSE for Power Systems with PMU Measurements

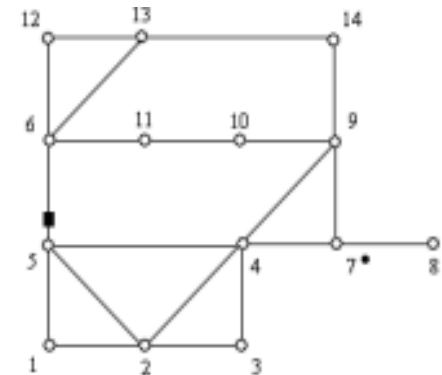
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Introduction

- Using noisy measurements and topology to estimate the states of the power system.
- State: voltage and angle of every bus in the power system

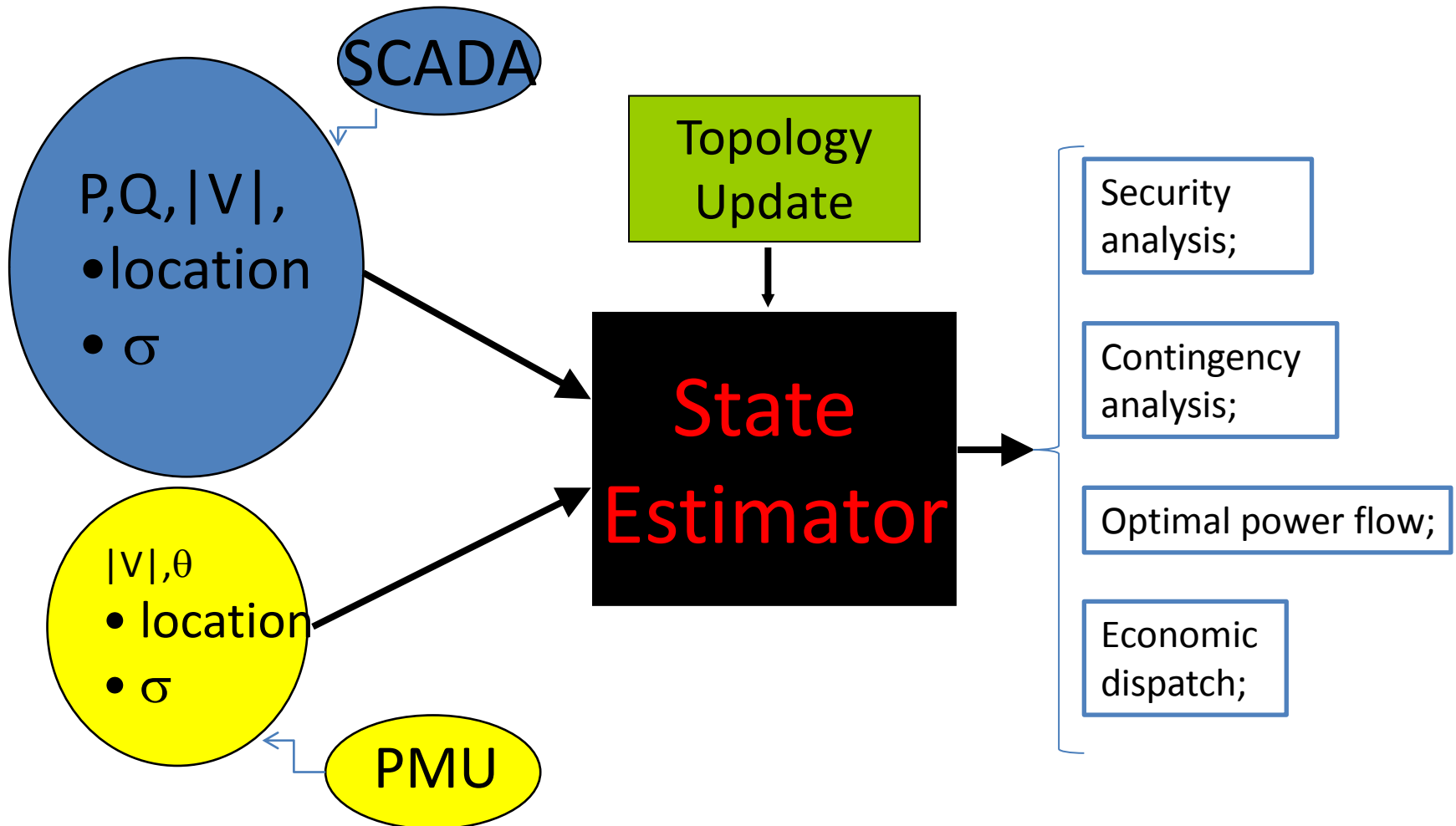


- SCADA: supervisory control and data acquisition
- PMU: synchronized phasor measurement unit

Why State Estimation?

- Distributed integration of renewable sources and PHEVs as new loads will make the power grid's operation more stressed, increasing the possibility of blackouts and brownouts;
- The system operators will therefore need more reliable, timely and even predicable knowledge of the system (maintain situational awareness). More accurate and timely SE will be an important tool to help achieving that goal;
- SE is the foundation for many numbers of “smart grid” applications on the distribution system, e.g., voltage control, reactive power management, demand response, etc;
- SE = a mitigator + an economic monitor + an arbitrator;

SE Diagram



PMU vs SCADA measurements

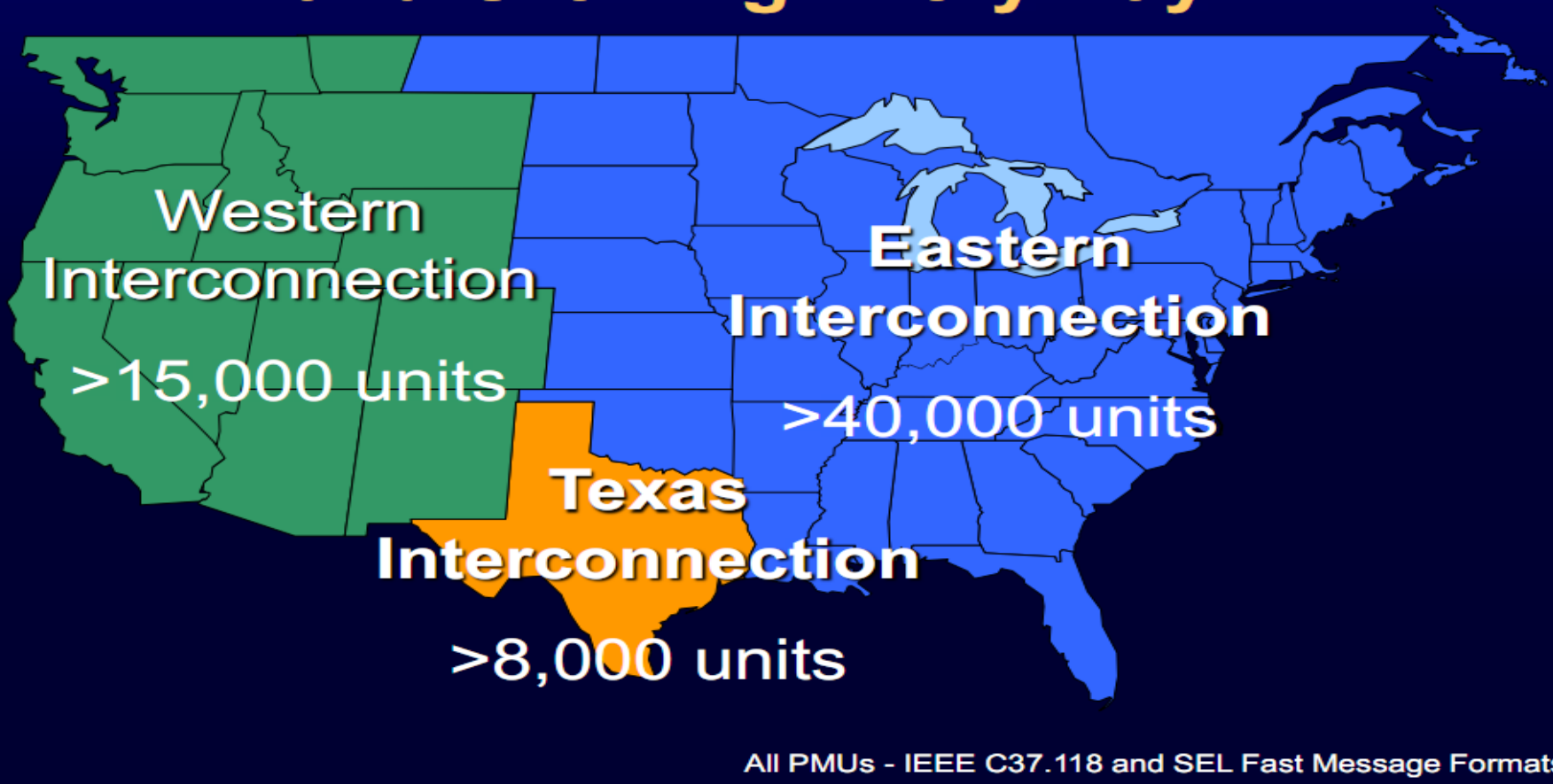
- SCADA (usually) measures
 - Power flow; power injection; voltage magnitude
 - Update slowly,
- PMU can directly measure
 - All measurements are synchronized by GPS signal
 - Voltage (current) magnitude and phase angle
 - Update very quick
 - Higher precision than SCADA,

Two sides of PMU measurements

- PMU measurements can be added to the traditional SCADA measurements to improve DSE performance
- The inclusion of PMU measurements leads to
 - increased computational burden;
 - combined linear and nonlinear measurements;
 - ill-conditioned measurement noise covariance matrix.

We propose a reduced-order DSE.

Synchrophasors Are Everywhere, and Growing Every Day!



- The number of PMUs is growing fast!

* Source: David Costello, "Synchrophasors and the Smart Grid", GCPA Fall Conference, 2009.
available: <http://www.gulfcoastpower.org/default/f09wkshpcostello.pdf>

Dynamic vs. Static

- Static state estimation
 - Consumes a great deal of computing resource, ignores the dynamics of the system (one shot estimation, no forecasting);
- Dynamic state estimation
 - Enhances computation speed;
 - Integrates the system dynamics information (power grid mostly runs in quasi-static status, and its dynamics can be well captured by historical data);
 - Has prediction capability and more accurate;

Why Reduced-order DSE

- If the PHEV penetration reaches a significant level (maybe coming soon), the states of the system will change more quickly, making it important to shorten consecutive SE interval and have faster SE algorithm;
- With more PMUs, the dimension of SE will significantly increase, so does the complexity for traditional DSE. The problem of ill-conditioned matrix will increase the possibility of non-convergence of traditional DSE.

System Model

- The dynamic model is given by

$$x(k+1) = F(k)x(k) + g(k) + w(k),$$

k : time instant

state trans-
ition matrix

Trend
behavior

Additive
noise

$$x(k) = [\theta_2(k) \cdots \theta_N(k) \ V_1(k) \cdots V_N(k)]$$

θ : voltage
phase angle

V : voltage
magnitude

Measurement equation

- The equation observes the system:

$$\begin{bmatrix} Z_1(k) \\ Z_2(k) \end{bmatrix} = \begin{bmatrix} h_1[x(k)] \\ h_2[x(k)] \end{bmatrix} + \begin{bmatrix} V_1(k) \\ V_2(k) \end{bmatrix}$$

Z: Measurement vector
h: nonlinear measurement equation,
determined by the topology
V: noise (error) vector

- Note: h_1 for SCADA measurements is always nonlinear, while h_2 can be linear

Dynamic State Estimation

- DSE usually can be divided into two steps:
 - Prediction step: calculate the state of one time instant ahead based on the state evolution function; (many prediction techniques have been proposed, e.g., Artificial Neural Networks and Fuzzy Logic techniques, etc.)
 - Filtering step: synthesize the predicted states and the measurements of the current instant to achieve better (in statistics) estimates

Reduced Order DSE

- The reduced order DSE first decouples those states that are directly observable by PMU measurements from the rest of the states;
- Use those PMU-observable states to help estimate the rest of the states;
- The proposed algorithm then performs those two categories of state estimation separately:
 - Linearly estimates the PMU states
 - Optimally estimates the rest states

Reduced Order DSE

- The N dimension state vector is decoupled into N_1 , and $(N-N_1)$ dimension state vectors;
- The estimated PMU states are treated as deterministic input for estimating the remaining states;
- The estimation of the remaining states is optimal with the performance metric being the trace of the error covariance matrix (the same as Kalman filtering scheme).

Decoupling the states

$$\begin{bmatrix} \mathbf{x}_1(k+1) \\ \mathbf{x}_2(k+1) \end{bmatrix} = \begin{bmatrix} \tilde{\mathbf{F}}_{11}(k) & \tilde{\mathbf{F}}_{12}(k) \\ \tilde{\mathbf{F}}_{21}(k) & \tilde{\mathbf{F}}_{22}(k) \end{bmatrix} \begin{bmatrix} \mathbf{x}_1(k) \\ \mathbf{x}_2(k) \end{bmatrix} \\ + \begin{bmatrix} \mathbf{Q}_1(k+1) \\ \mathbf{Q}_2(k+1) \end{bmatrix} \mathbf{g}(k) + \begin{bmatrix} \mathbf{Q}_1(k+1) \\ \mathbf{Q}_2(k+1) \end{bmatrix} \mathbf{w}(k)$$

$$\begin{bmatrix} \mathbf{z}_1(k) \\ \mathbf{z}_2(k) \end{bmatrix} = \begin{bmatrix} \tilde{\mathbf{H}}_{11}(k) & \tilde{\mathbf{H}}_{12}(k) \\ \mathbf{0} & \tilde{\mathbf{H}}_{22}(k) \end{bmatrix} \begin{bmatrix} \mathbf{x}_1(k) \\ \mathbf{x}_2(k) \end{bmatrix} + \begin{bmatrix} \mathbf{v}_1(k) \\ \mathbf{v}_2(k) \end{bmatrix}$$

- $\mathbf{Q}(k)$ is a permutation matrix, grouping the PMU states to be $\mathbf{x}_2(k)$, and remaining states to be $\mathbf{x}_1(k)$

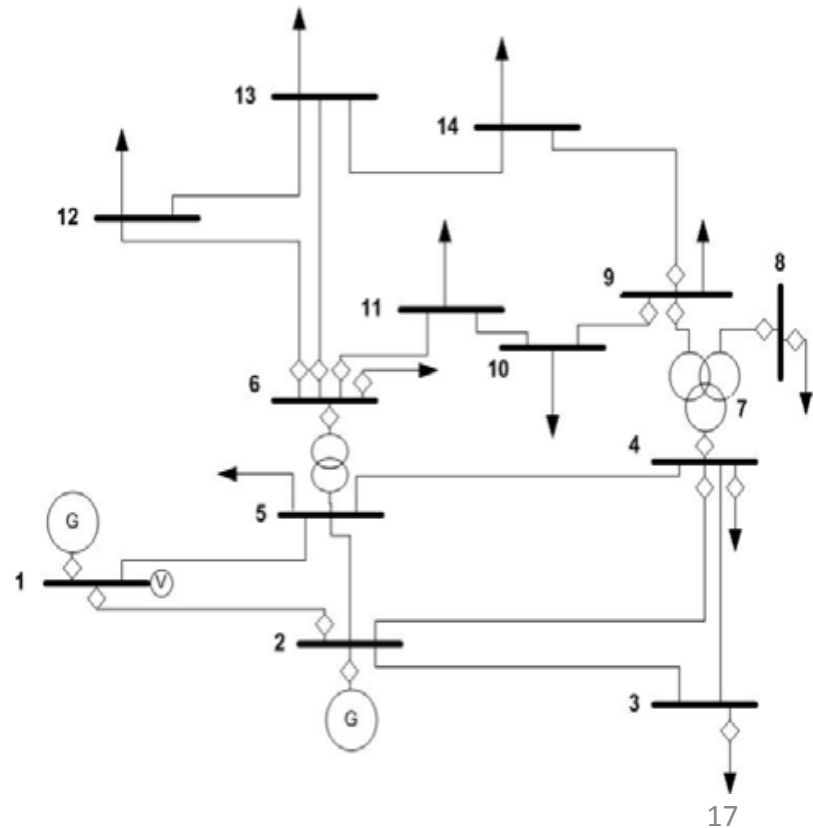
Constrained optimization

- The optimal estimation of $x_1(k)$ can now be cast as a constrained optimization problem;
- Solving the constrained optimization problem is done in two steps:
 - Find the optimal predictor;
 - Find the optimal filter.

Simulation Configuration

- To compare the performance of the reduced-order scheme with the traditional extended Kalman filter scheme.

Traditional measurements: 1 bus voltage magnitude, P and Q injections at 8 buses, and P and Q measured at 12 lines
PMU: directly measure voltage magnitudes and phase angles

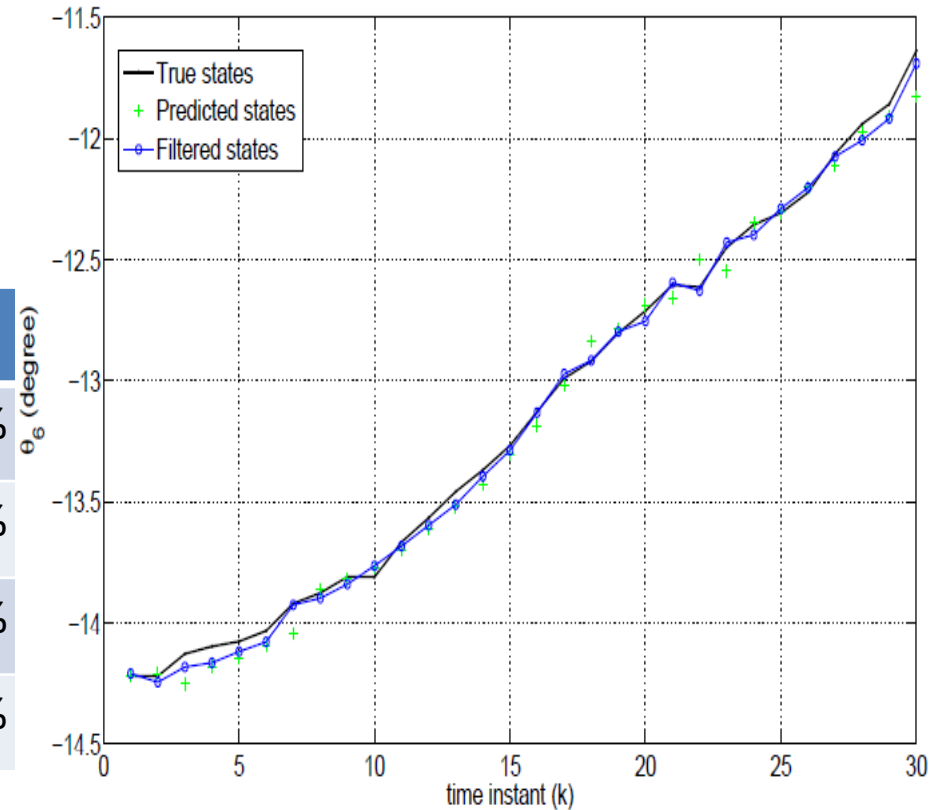


Selected Numerical Results

$$\Phi_{\theta_i}(k) = |[\theta'_i(k) - \theta_i(k)] / \theta_i(k)| * 100\%$$

$$\Phi_{v_i}(k) = | [V'_i(k) - V_i(k)] / 0.1 | * 100\%$$

Metrics	PMU	Prediction	Filtering
Φ_{θ_i}	2	0.48%/0.52%	0.23%/0.25%
	3	0.46%/0.49%	0.21%/0.23%
Φ_{v_i}	2	1.06%/1.05%	0.62%/0.64%
	3	0.99%/0.93%	0.52%/0.53%



Comments on complexity

- The proposed reduced-order DSE essentially decouples the PMU measurements from traditional measurements. They are treated as inputs to the KF whose dimension is reduced by the same number as the number of PMU measurements;
- The computational complexity for the reduced order DSE is in the same order as the traditional KF without PMU measurements.

Future work

- Extend the current work to large scale power system which may involve multiphase state estimation;
- Find and design a suitable dynamic state estimation algorithm for microgrids, which may function as an island or as part of the entire grid.

Challenges in μ -Grids SE

- SE algorithms in transmission line not applicable:
 - Very few real-time measurements are available in μ -Grids;
 - Topologies of μ -Grids change fast;
 - X/R ratio is relatively low in μ -Grids;
- Kalman state space model not available for μ -Grids.
- Complexity (both model and computational) issue is more sensitive in μ -Grids, so does the robustness of the SE algorithm.
- Integration of many DGs causes many variations in μ -Grids;
- Load forecasting is important in SE for μ -Grids: more accurate load modeling is required.

Thank you!