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Monitoring and Optimization for Smarter Power Grids

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Acknowledgement: Inst. on Renewable Energy and Environment RL-10-13

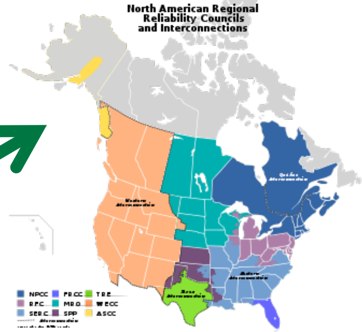
G. B. Giannakis, V. Kekatos, N. Gatsis, S.-J. Kim, H. Zhu, and B. Wollenberg, "Monitoring and Optimization for Power Grids: A Signal Processing Perspective," *IEEE SP Magazine*, Sept. 2013.

Aging infrastructure

Edison: light bulbs
Tesla: AC system

Deregulation started

Enron, blackouts



1888

Natural monopolies
Single commodity
Grew rapidly in the 2 world wars

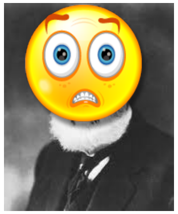
1980-90s

2000s

1876

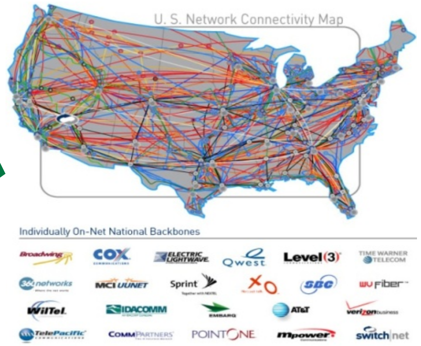
1980-90s

Bell: telephone



Deregulation started

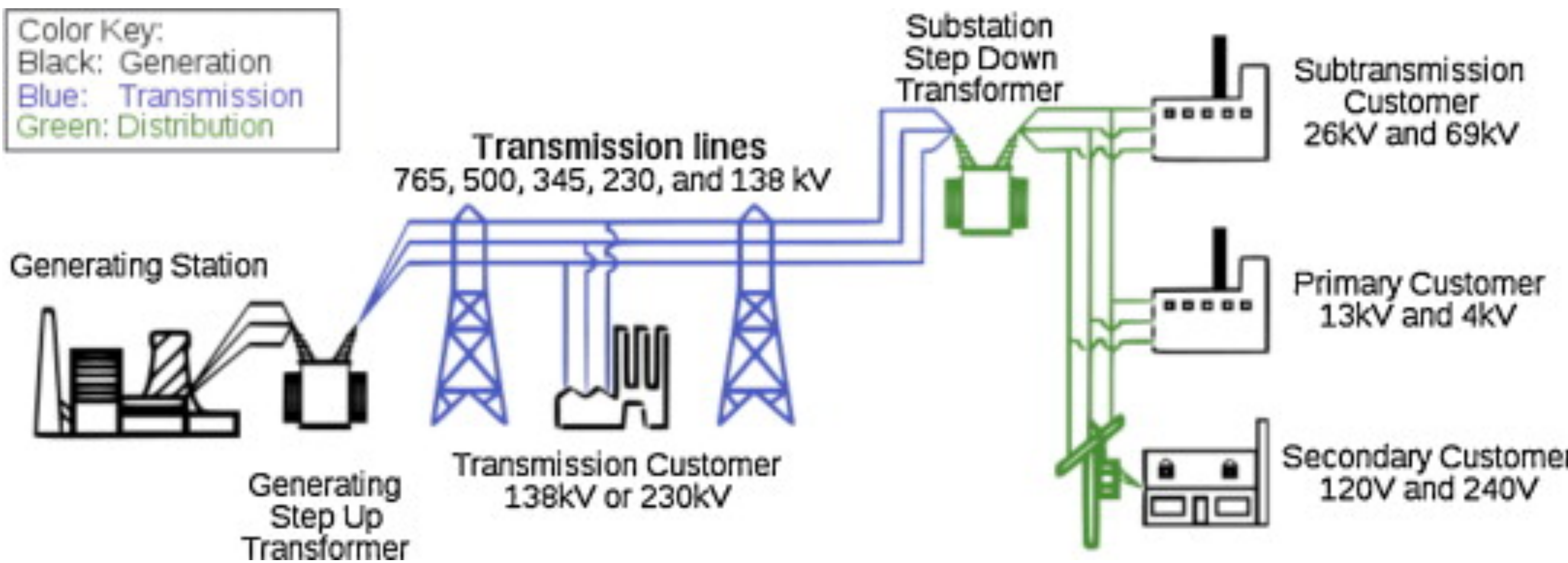
1969: DARPAnet



- Power outages cost: inadequate system understanding
- 2009 US Recovery Act includes $43 billion for energy
- 2008 PA Act 129 for energy efficiency ~ $1 billion in 4 years

The grid then, now, and ahead

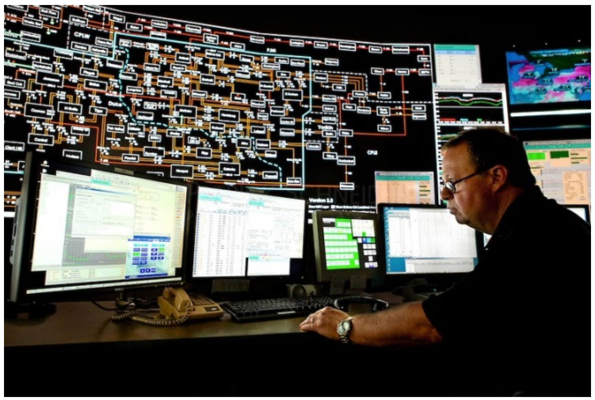
"Most significant engineering achievement of 20th century" [NAE Report'10]



- Several challenges ahead
  - 99.97% reliable, but power outages still cost $150 billion/year
  - Customer engagement and environmental concerns

Picture source: FERC. "Final Report on the Aug. 14, 2003 Blackout in the US and Canada," Apr. 2004.

Smart Grid: Advanced infrastructure and information technologies to enhance the current electrical power network



controllable

resilient

efficient

participation

sustainable

self-healing

green

situational awareness

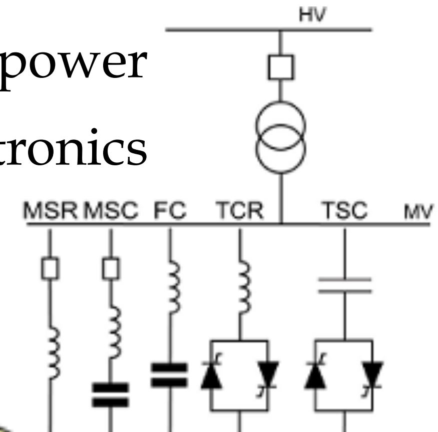
Dept. of Energy, "The smart grid: an introduction"

Enabling technology advances

renewables

power

electronics



distributed generation

micro-grids

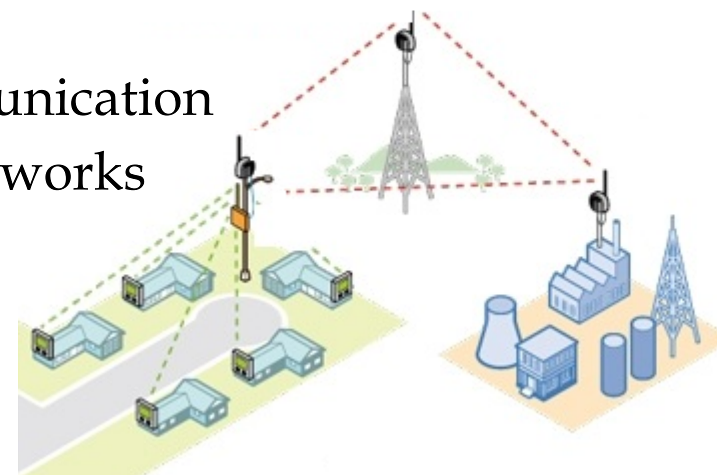
optimization, learning, and signal processing toolbox

electric vehicles

sensing/metering

demand response

communication networks



Outline

- Modeling
- Grid monitoring
  - Power system state estimation
  - Observability and cyber attacks
  - Phasor measurement units (PMUs)
  - Learning and inference
- Optimal grid operation
  - Economic operation
  - Demand response
  - Electric vehicles
  - Renewables
- Open issues

Power grid modeling

A. R. Bergen and V. Vittal, *Power System Analysis*, Prentice Hall, 2000.

Preliminaries

- Power grids as electric circuits

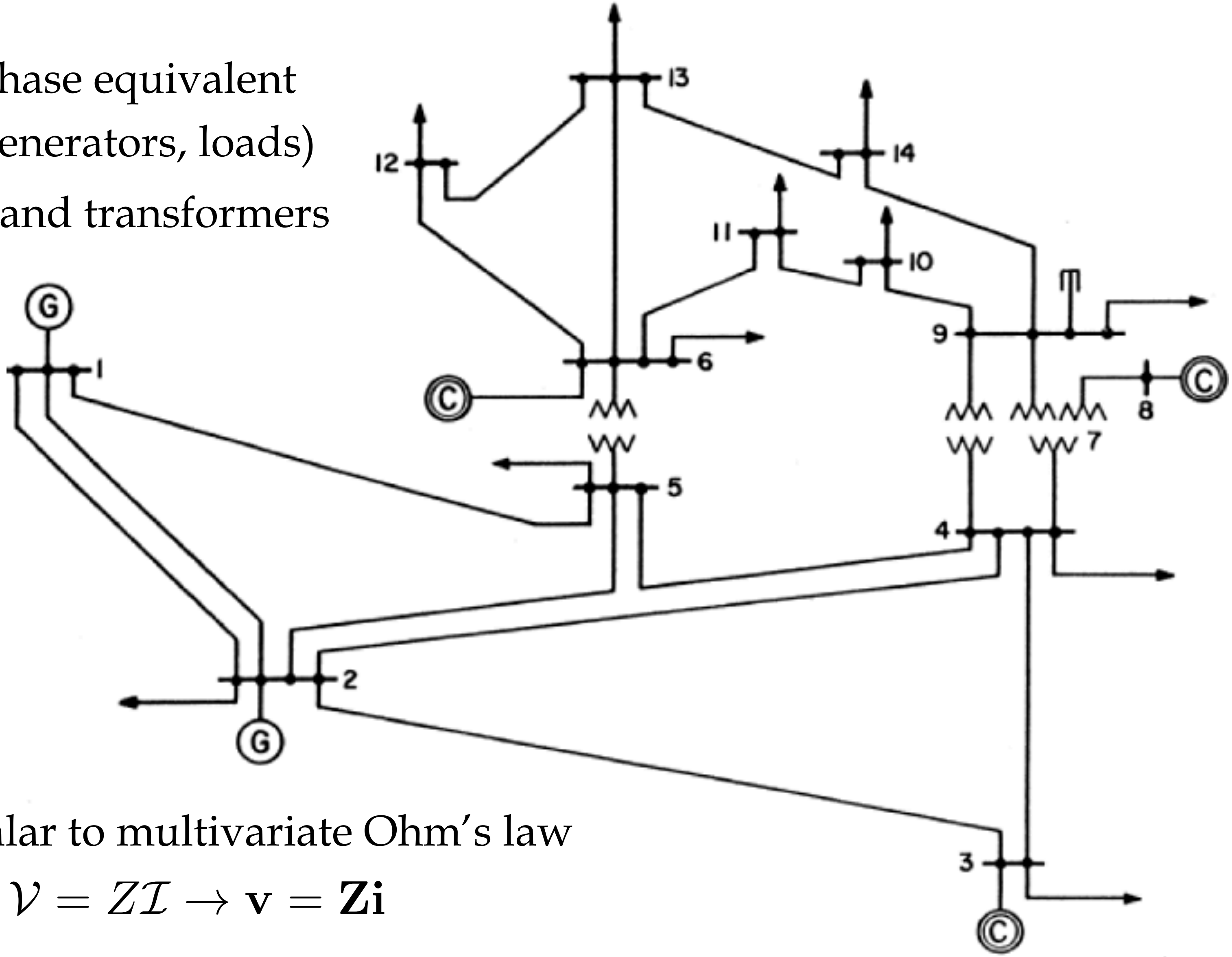
- AC voltages, currents, and powers are sinusoids (in steady state)

- Phasor representation (at nominal frequency)
  - Polar and rectangular coordinates:

$$\boxed{\mathcal{V} = Ve^{j\theta} = V_r + jV_i}$$

IEEE 14-bus benchmark

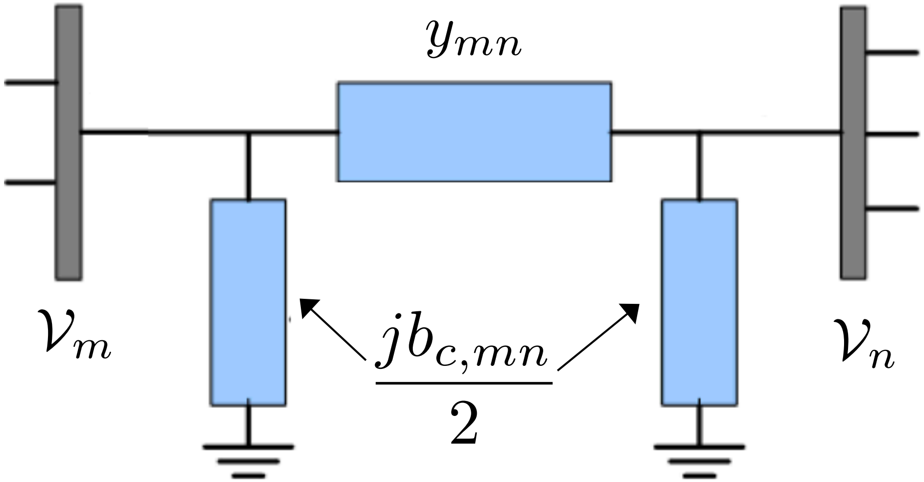
- Single-phase equivalent
- Buses (generators, loads)
- Tx lines and transformers



- From scalar to multivariate Ohm's law

$$\mathcal{V} = Z\mathcal{I} \rightarrow \mathbf{v} = \mathbf{Zi}$$

Transmission lines



equivalent π model

- Line series *impedance*

$$z_{mn} = r_{mn} + jx_{mn} \ (x_{mn} > 0)$$

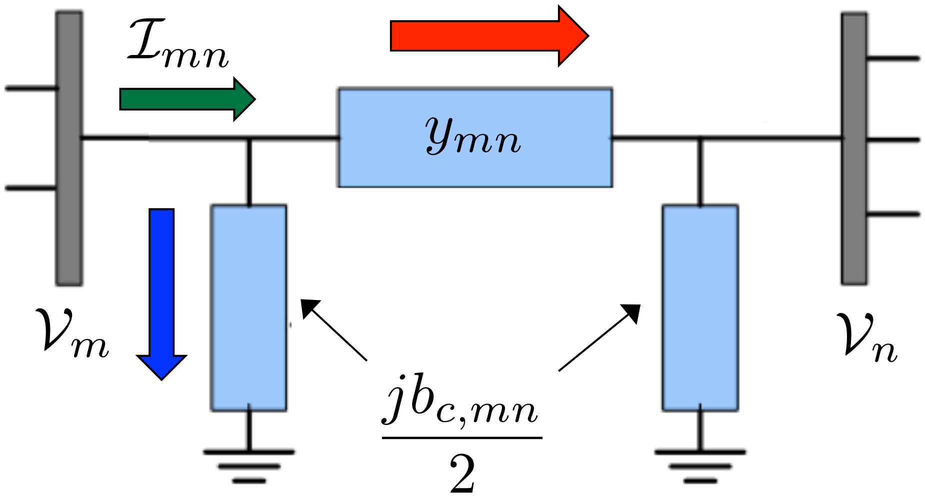
- Line series *admittance*

$$y_{mn} = \frac{1}{z_{mn}} = g_{mn} + jb_{mn}$$

$$g_{mn} = \frac{r_{mn}}{r_{mn}^2 + x_{mn}^2}, \ b_{mn} = -\frac{x_{mn}}{r_{mn}^2 + x_{mn}^2} < 0$$

- Total charging susceptance $\quad b_{c,mn} > 0$

Line currents

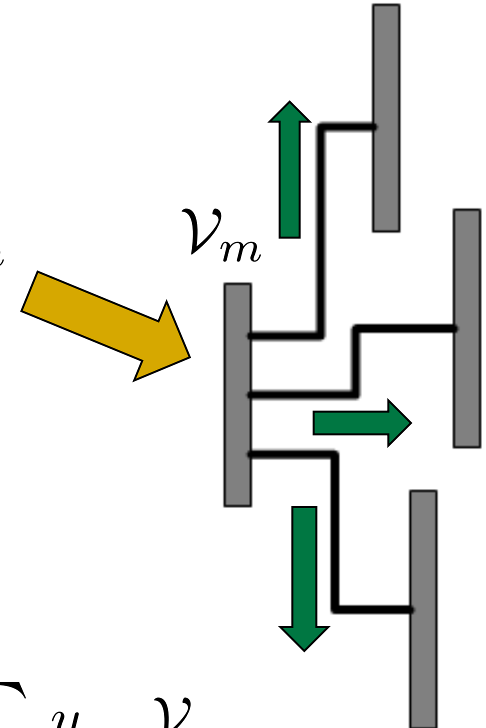


$$\mathcal{I}_{mn} = y_{mn}(\mathcal{V}_m - \mathcal{V}_n) + j\frac{b_{c,mn}}{2}(\mathcal{V}_m - 0)$$

$$\mathcal{I}_{mn} = (jb_{c,mn}/2 + y_{mn})\mathcal{V}_m - y_{mn}\mathcal{V}_n$$

Bus injection currents

$$\mathcal{I}_m = \sum_{n \in \mathcal{N}_m} \mathcal{I}_{mn}$$



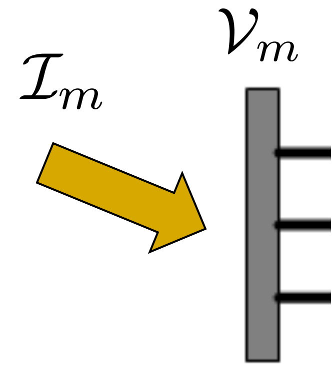
- Kirchoff's current law (KCL)

$$\mathcal{I}_m = \left(\sum_{n \neq m} y_{mn} + j \sum_{n \neq m} b_{c,mn}/2 \right) \mathcal{V}_m - \sum_{n \neq m} y_{mn} \mathcal{V}_n$$

Multivariate Ohm's law

- Concatenating all injection currents $\mathcal{I}'_m$s $\boxed{\mathbf{i} = \mathbf{Y}\mathbf{v}}$
- *Bus admittance matrix* $[\mathbf{Y}]_{mn} = \begin{cases} \sum_{k \neq m} y_{mk} + j\frac{b_{c,mk}}{2} & , m = n \\ -y_{mn} & , m \neq n \end{cases}$
  - Symmetric and non-Hermitian
  - Sparse → efficient computations and storage
  - *Fundamental* for monitoring and optimization
- *Bus impedance matrix* $\mathbf{Z} := \mathbf{Y}^{-1}$ $\boxed{\mathbf{v} = \mathbf{Z}\mathbf{i}}$
  - Nonsparse
  - Not the matrix of line impedances
- *Bottomline*: Currents linearly expressed in terms of nodal voltages

Complex power



- Power injection to bus *m*

$$\boxed{\mathcal{S}_m = \mathcal{V}_m \mathcal{I}_m^* = P_m + jQ_m}$$

- (Re)active power generated or consumed at a bus
- Power flow over line *(m,n)* $\quad \mathcal{S}_{mn} = \mathcal{V}_m \mathcal{I}_{mn}^*$
- Multivariate power model $\quad \boxed{\mathbf{s} = \mathrm{diag}(\mathbf{v})\mathbf{i}^* = \mathrm{diag}(\mathbf{v})\mathbf{Y}^*\mathbf{v}^*}$
- **Y** in rectangular coordinates $\quad \boxed{\mathbf{Y} = \mathbf{G} + j\mathbf{B}}$
- Polar versus rectangular coordinates for **v**

Power flow equations

- **Case 1: Polar coordinates**

$$P_m = \sum_n V_m V_n \left(G_{mn} \cos(\theta_m - \theta_n) + B_{mn} \sin(\theta_m - \theta_n)\right)$$
$$Q_m = \sum_n V_m V_n \left(G_{mn} \sin(\theta_m - \theta_n) - B_{mn} \cos(\theta_m - \theta_n)\right)$$

- Power depends only on phase differences
- Reference (slack or swing) bus $\theta_1 = 0$

- **Case 2: Rectangular coordinates**

$$P_m = V_{r,m} \sum_n (V_{r,n} G_{mn} - V_{i,n} B_{mn}) + V_{i,m} \sum_n (V_{i,n} G_{mn} + V_{r,n} B_{mn})$$
$$Q_m = V_{i,m} \sum_n (V_{r,n} G_{mn} - V_{i,n} B_{mn}) + V_{r,m} \sum_n (V_{i,n} G_{mn} + V_{r,n} B_{mn})$$

- Quadratic equations

Power flow problem

- No. of buses: N_b
- No. of equations: $2N_b$
- No. of variables: $4N_b$ $\Longrightarrow$ $\{(P_m, Q_m, V_m, \theta_m)\}_{m=1}^{N_b}$

Goal: *Given values of $2N_b$ variables, find the rest $2N_b$ unknown variables by solving the nonlinear power flow equations*

- Typically, given values come from
  - Generators (PV buses) (P_m, V_m)
  - Loads (PQ buses) (P_m, Q_m)
  - Reference bus $(V_1, \theta_1 = 0)$

DC flow model

$$P_m = \sum_n V_m V_n \left(G_{mn} \cos(\theta_m - \theta_n) + B_{mn} \sin(\theta_m - \theta_n)\right)$$
$$Q_m = \sum_n V_m V_n \left(G_{mn} \sin(\theta_m - \theta_n) - B_{mn} \cos(\theta_m - \theta_n)\right)$$

(A1) Lossless lines $\quad r_{mn} \ll x_{mn} \rightarrow \mathbf{G} \simeq \mathbf{0}$

(A2) Small angle differences $\quad \theta_m - \theta_n \simeq 0$

(A3) Unit voltage magnitudes $\quad V_m \simeq 1$

$$P_m \simeq -\sum_{n \neq m} b_{mn}(\theta_m - \theta_n)$$
$$Q_m \simeq -b_{mm} - \sum_{n \neq m} b_{mn}(V_m - V_n)$$

DC bus admittance model

- Power injections (and flows) ***linearly*** related to phase differences

$$P_m = -\sum_{n \neq m} b_{mn}(\theta_m - \theta_n)$$

- Multivariate model

$$\mathbf{p} = \mathbf{B}\boldsymbol{\theta}$$

$$[\mathbf{B}]_{mn} = \begin{cases} \sum_{n \neq m} x_{mn}^{-1} & , m = n \\ -x_{mn}^{-1} & , m \neq n \end{cases}$$

  - Symmetric and positive semidefinite
  - Lossless lines $\mathbf{B}\mathbf{1}_{N_b} = \mathbf{0}_{N_b} \Rightarrow \mathbf{p}^T \mathbf{1}_{N_b} = 0$
  - Weighted Laplacian of power grid graph

Power system state estimation (PSSE)

Motivation for PSSE

Goal: Given meter readings and grid parameters, find state vector $\mathbf{v}$

- Quantities of interest expressible as a function of bus voltages $\mathbf{v}$
- PSSE is of paramount importance for
  - situational awareness
  - reliability analysis and planning
  - load forecasting
  - economic operations and billing
- Statistical problem formulation [Schweppe et al'70]

F. C. Schweppe, J. Wildes, and D. Rom, "Power system state estimation: Parts I, II, and III," *IEEE Trans. Power App. Syst.*, Jan. 1970.

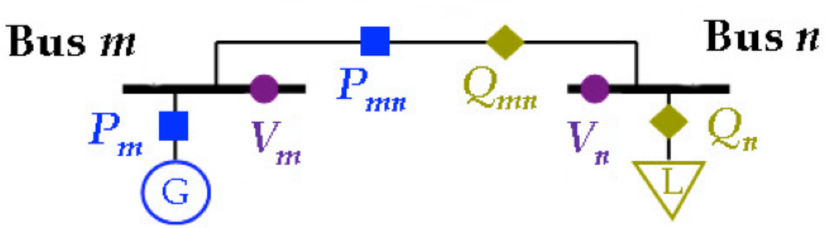
SCADA-based PSSE

- Supervisory control and data acquisition (SCADA)
  - Terminals forward readings to control center (~4 secs)
  - Phases cannot be used due to timing mismatches

- Available measurements (M)

$$\{V_m, P_m, Q_m, P_{mn}, Q_{mn}, I_{mn}\}$$

$$\mathbf{z} = \mathbf{h}(\mathbf{v}) + \boldsymbol{\epsilon}$$



- Nonlinear (weighted) least-squares

$$\hat{\mathbf{v}} := \arg\min_{\mathbf{v}} \|\mathbf{z} - \mathbf{h}(\mathbf{v})\|^2$$

- Possible constraints
  - Zero-injection buses $P_m = Q_m = 0$
  - Feasible ranges $V_m^{\min} \leq V_m \leq V_m^{\max}$

Popular solvers

$$\hat{\mathbf{v}} := \arg\min_{\mathbf{v}} \|\mathbf{z} - \mathbf{h}(\mathbf{v})\|^2$$

(M1) Gauss-Newton iterations

- Approximate $\mathbf{h}(\mathbf{v}) \simeq \mathbf{h}(\mathbf{v}_k) + \mathbf{J}_k(\mathbf{v} - \mathbf{v}_k), \ \mathbf{J}_k : \text{Jacobian at } \mathbf{v}_k$
- Linear LS in closed form $\mathbf{v}_{k+1} = \mathbf{v}_k + (\mathbf{J}_k^T \mathbf{J}_k)^{-1} \mathbf{J}_k^T (\mathbf{z} - \mathbf{h}(\mathbf{v}_k))$

- QR-based remedies for numerical stability
- Convergence to local minimum

(M2) Fast decoupled solver

- Active powers depend only on $\{\theta_m\}$; reactive only on $\{V_m\}$
- Approximate $(\mathbf{J}_k^T \mathbf{J}_k)^{-1}$ at *flat voltage profile* $\mathbf{v} = \mathbf{1} + j\mathbf{0}$

A. Monticelli and A. Garcia, "Fast decoupled state estimators," *IEEE Trans. Power Syst.*, May 1990.

Semidefinite relaxation

- Rectangular coordinates: measurements are ***quadratic*** in $\mathbf{v}$

$$P_m + jQ_m = \mathcal{V}_m \mathcal{I}_m^* = \mathbf{e}_m^T \mathbf{v} (\mathbf{Y}\mathbf{v})^H \mathbf{e}_m = \mathrm{Tr}(\underbrace{\mathbf{Y}^H \mathbf{e}_m \mathbf{e}_m^T}_{\mathbf{H}_m} \mathbf{v}\mathbf{v}^H)$$

- Yet ***linear*** in $\mathbf{V} = \mathbf{v}\mathbf{v}^H$

$$\min_{\mathbf{v}} \sum_{m=1}^{M} (z_m - h_m(\mathbf{v}))^2 \quad \Rightarrow \quad \begin{aligned} &\min_{\mathbf{V}} \sum_{m=1}^{M} (z_m - \mathrm{Tr}(\mathbf{H}_m \mathbf{V}))^2 \\ &\text{s.to} \;\; \mathbf{V} \succeq \mathbf{0} \text{ and } \cancel{\mathrm{rank}(\mathbf{V}) = 1} \end{aligned}$$

- It can be cast as an SDP (PSSE convexified)
- SDR in SP and communications [Goemans et al '95], [Luo et al'10]
- SDR for optimal power flow [Bai et al '08]
- $\hat{\mathbf{V}} \rightarrow \hat{\mathbf{v}}$: Dominant eigenvector approximation or randomization

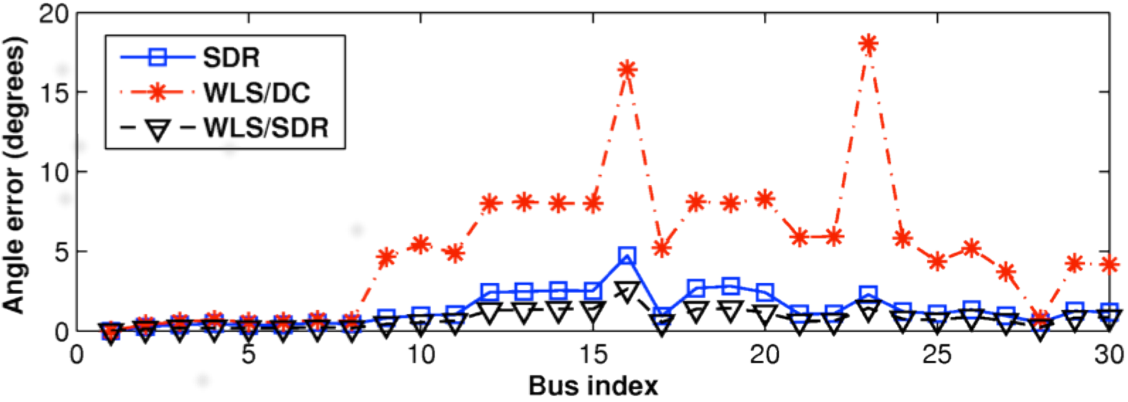
H. Zhu and G. B. Giannakis, "Estimating the state of AC power systems using semidefinite programming," in *Proc. of North American Power Symposium*, Aug. 2011.

Numerical tests

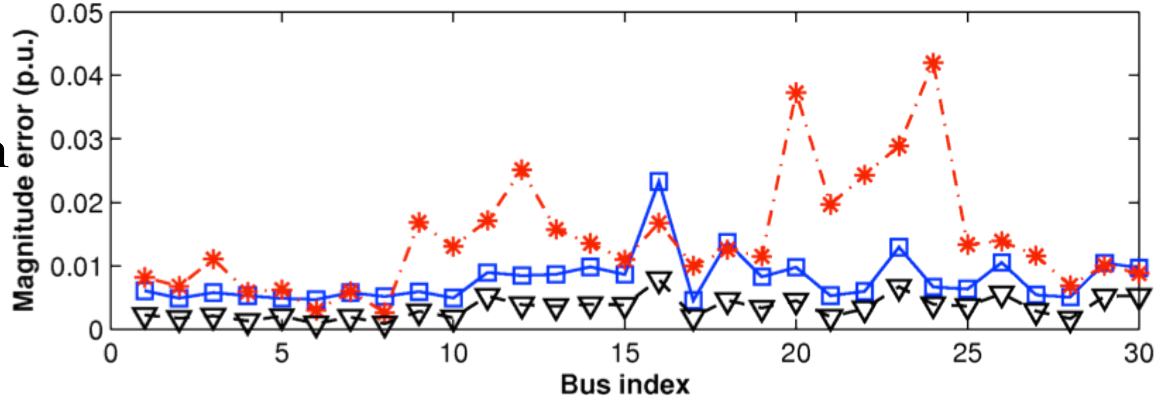
- IEEE 30-bus benchmark grid
- $V_m \sim \mathcal{N}(1, 0.01), \;\; \theta_m \sim \mathcal{U}[-\theta, \theta]$

Average running time in secs.

# of buses	WLS	SDR
30	0.216	1.62
57	0.558	4.32
118	2.87	21.6



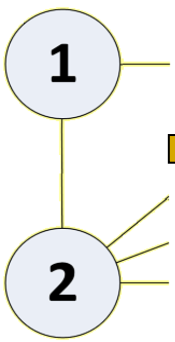
- Closer to global optimum at higher complexity



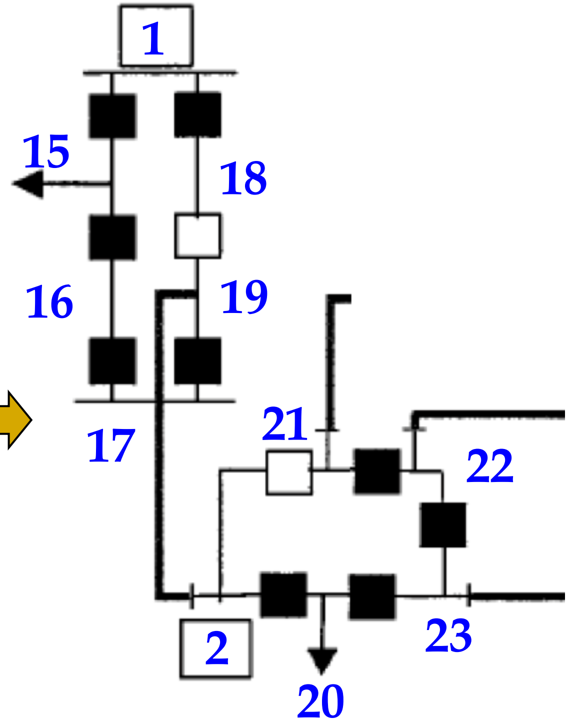
Dynamic PSSE

- Well-motivated due to load and renewable variability
- Challenged by unknown *system dynamics*
  - Random walk state model [Monticelli' 00] $$\mathbf{v}(t+1) = \mathbf{v}(t) + \mathbf{w}(t)$$
  - With exogenous load [Blood-Krogh-Ilic' 08] $$\mathbf{v}(t+1) = \mathbf{F}(t)\mathbf{v}(t) + \mathbf{e}(t) + \mathbf{w}(t)$$
- Common *prediction* step; *correction* step options
  - Extended Kalman filter (EKF) [Monticelli' 00]
  - Unscented KF: more accurate but also complex [Valverde-Terzija'11]
  - Particle filters if affordable by real-time PSSE requirements

Circuit breakers



bus/branch model



bus section/switch model

- Protection and grid reconfiguration

Superbowl 2013

- Zero-impedance elements
- Modeling
  - closed: $\mathcal{V}_{15} = \mathcal{V}_{16}$
  - open: $\mathcal{I}_{18,19} = 0$

Generalized state estimation

- Network topology processor collects circuit breaker (CB) statuses
- Topology errors easily detected, but hardly identified by PSSE
- Generalized state estimation (GSE) seeks state and grid topology

GSE:
$$\begin{aligned} \min_{\mathbf{x}} \quad & \|\mathbf{z} - \mathbf{H}\mathbf{x}\|_2^2 \\ \text{s.to} \quad & \mathbf{C}\mathbf{x} = \mathbf{0} \end{aligned}$$

- Augmented state vector **x**: bus section voltages ***and*** CB flows
- CB statuses effect constraints to ensure identifiability

A. Monticelli, "Electric power system state estimation," *Proc. of the IEEE*, Feb. 2000.

Identifying topology errors

- Validate the status of suspected/un-instrumented CBs
  - Least-absolute value (LAV) [Singh-Alvarado'95]
  - Largest normalized residual test (LNRT) [Clements-Costa'98]
  - Probabilistic modeling [Korres-Katsikas '02]
  - Mixed-integer nonlinear program [Caro et al'10]

- Account for CB status: **C (S)** for (un)-instrumented
- ***Block-sparsity*** (Group-Lasso penalty) for suspected CBs

$$\min_{\mathbf{x}} \quad \|\mathbf{z}-\mathbf{H}\mathbf{x}\|_2^2 + \lambda \sum_{m\in\mathcal{S}} \|\mathbf{S}_m\mathbf{x}\|_2$$

$$\text{s.to} \quad \mathbf{C}\mathbf{x} = \mathbf{0}$$

V. Kekatos and G. B. Giannakis, "Joint power system state estimation and breaker status identification," in *Proc. IEEE PES North American Power Symposium*, Sept. 2012.

IEEE 14-bus grid

65 bus sections

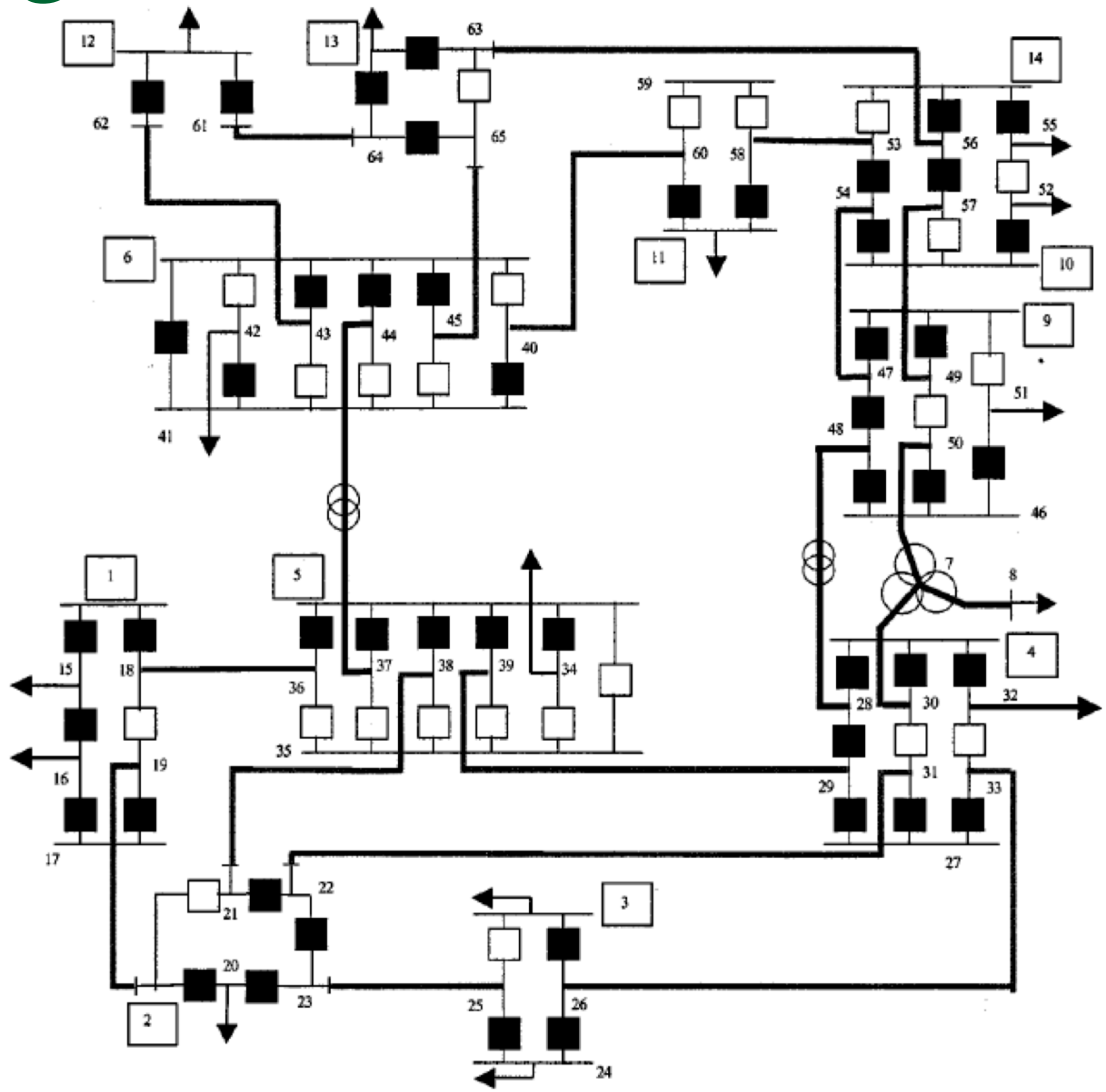
73 CBs

276 states

316 measurements

Suspected CBs: 10-70

- 80% correct
- 20% erroneous

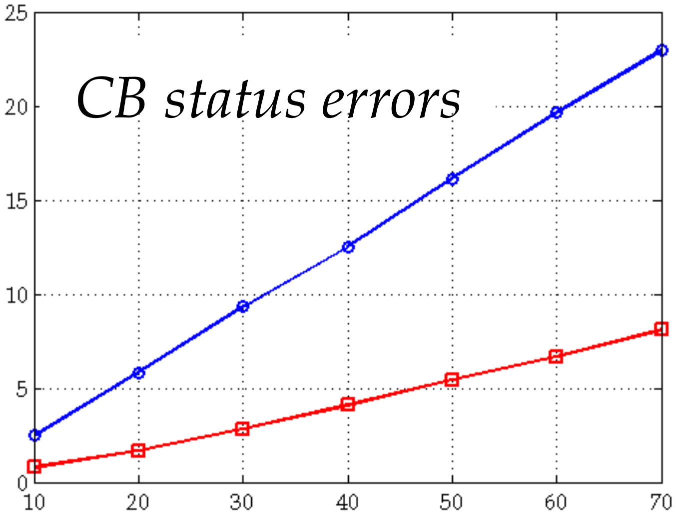


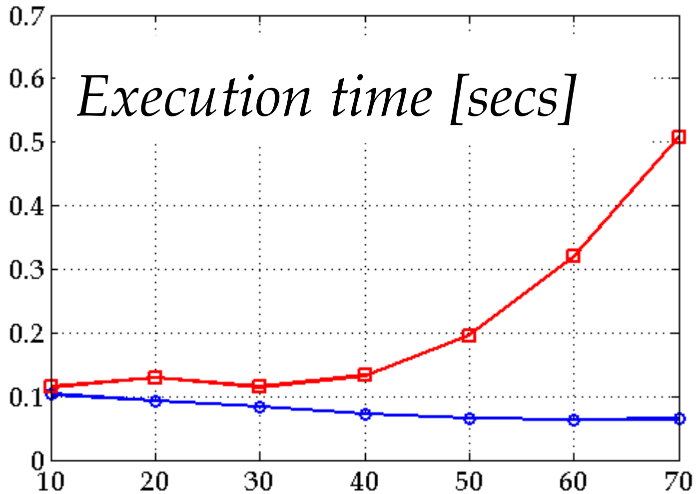
A. Gomez-Exposito and A. de la Villa Jaen, "Reduced substation models for generalized state estimation," *IEEE Trans. Power Syst.*, Nov. 2001.

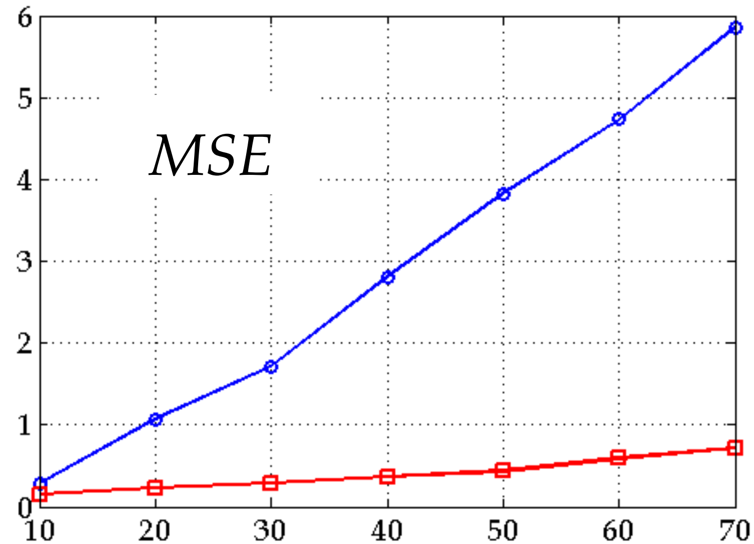
Numerical results

Generalized state estimator

Novel method







No. of suspected CBs

V. Kekatos and G. B. Giannakis, "Joint Power System State Estimation and Breaker Status Identification," in *Proc. IEEE PES North American Power Symposium*, Sept. 2012.

Observability analysis

Given measurement set and grid parameters, assess state identifiability;
if non-identifiable, find observable ***islands*** *(maximally connected subgrids)*

- Q: Why bother? A: To select *(pseudo-)measurement* sites
  - generation schedules, load predictions, historical data
- Runs online to cope with meter failures, terminal delays, grid changes

DC model

$$P_m = -\sum_{n \neq m} b_{mn}(\theta_m - \theta_n)$$

$$Q_m = -b_{mm} - \sum_{n \neq m} b_{mn}(V_m - V_n)$$

- $P-\theta$ results carry over to $Q-V$
- Pairs of active-reactive meters

A. Monticelli, "Electric power system state estimation," *Proc. of the IEEE*, Feb. 2000.

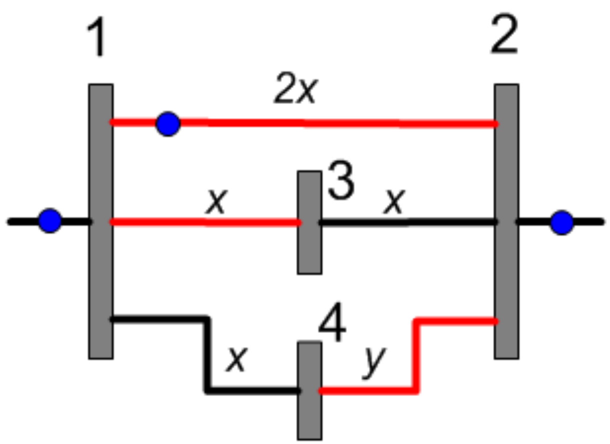
Numerical observability

- Identifiability (DC model): $\mathbf{z} = \mathbf{H}\boldsymbol{\theta} \Leftrightarrow$ $\mathbf{H}$ is full column rank
- Voltage phase shift ambiguity anyway
- Branch-bus incidence matrix $\mathbf{A}^{N_l \times N_b}$: $[\mathbf{A}]_{ln} = \begin{cases} 1 & , l : n \to m \\ -1 & , l : m \to n \\ 0 & , \text{o.w.} \end{cases}$
- *Observable:* If $\text{null}(\mathbf{H}) \subseteq \text{null}(\mathbf{A}) = \{c \cdot \mathbf{1}_{N_b}, c \in \mathbb{R}\}$
- For $\boldsymbol{\theta} \in \text{null}(\mathbf{H})$, the non-zeros of $\mathbf{A}\boldsymbol{\theta}$ define unobservable lines
- Systematic removal of unobservable branches reveals observable islands

A. Monticelli and F. F. Wu, "Network observability," *IEEE Trans. Power App. Syst.*, May 1985.

Topological observability

- Graph-theoretic approach
- Builds a maximal spanning tree (o.w. forest)
  - branches directly measured or incident to a metered bus
  - every branch corresponds to a different measurement



- Numerical observability implies topological observability
- Converse does not necessarily hold (x=y) [Monticelli'00]

K. A. Clements, P. R. Krumpholz, and G. W. Davis, "PSSE with measurement deficiency: An observability/measurement placement algorithm," *IEEE Trans. Power App. Syst.*, July 1983.

Bad data

- *Sources:* time-skews, parameter uncertainty, uncalibrated meters, reverse wiring
- Preprocessing (polarity and range tests)

- DC (or linearized AC) model without bad data

$$\boxed{\mathbf{z} = \mathbf{H}\mathbf{x} + \boldsymbol{\epsilon}} \qquad \mathbf{H} \in \mathbb{R}^{M \times N}$$

  - LSE $\hat{\mathbf{x}} = \left(\mathbf{H}^T\mathbf{H}\right)^{-1}\mathbf{H}^T\mathbf{z}$
  - LSE residual $\mathbf{r} := \mathbf{z} - \mathbf{H}\hat{\mathbf{x}} = \mathbf{P}_{\mathbf{H}}^{\perp}\mathbf{z} = \mathbf{P}_{\mathbf{H}}^{\perp}\boldsymbol{\epsilon}$
  - For $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, $\mathbf{r} \sim \mathcal{N}(\mathbf{0}, \mathbf{P}_{\mathbf{H}}^{\perp})$, $\mathrm{rank}(\mathbf{P}_{\mathbf{H}}^{\perp}) = M - N$

A. Abur and A. Gomez-Exposito, *Power System State Estimation: Theory and Implementation*, Marcel Dekker, 2004.

Revealing outliers

Chi-squared test *(detection)*

- Because $\mathbf{r} \sim \mathcal{N}(\mathbf{0}, \mathbf{P}_{\mathbf{H}}^{\perp})$, then $\|\mathbf{r}\|_2^2 \sim \chi^2_{M-N}$
- If $\|\mathbf{r}\|_2^2 > F^{-1}_{\chi^2_{M-N}}(0.05)$, declare bad data

Largest normalized residual test-LNRT *(identification)*

- $r_i/\sqrt{P_{ii}} \sim \mathcal{N}(0,1)$, P_{ii} is the *i*-th diagonal entry of $\mathbf{P}_{\mathbf{H}}^{\perp}$
- If $\max_i \frac{|r_i|}{\sqrt{P_{ii}}} > t$, the *i*-th measurement is bad
- Remove bad datum and re-compute LSE (efficient RLS update)
- Equivalent to leave-one-out validation

F. C. Schweppe et al, "Power system state estimation: Part II," *IEEE Trans. Power App. Syst.*, Jan. 1970.

Robust PSSE

- Least-absolute deviations (LAV) $\hat{\mathbf{x}}_{\text{LAV}} := \arg\min_{\mathbf{x}} \|\mathbf{z} - \mathbf{H}\mathbf{x}\|_1$
- Least-median of squares (LMS) $\hat{\mathbf{x}}_{\text{LMS}} := \arg\min_{\mathbf{x}} \text{med}_i (z_i - \mathbf{h}_i^T \mathbf{x})^2$
- Huber estimator $\hat{\mathbf{x}}_{\text{H}} := \arg\min_{\mathbf{x}} \sum_{i=1}^{M} h\left(z_i - \mathbf{h}_i^T \mathbf{x}\right)$

- Additive outlier model

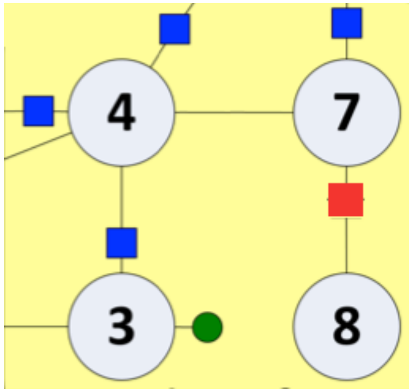
$$\boxed{\mathbf{z} = \mathbf{H}\mathbf{x} + \boldsymbol{\epsilon} + \mathbf{o}}$$

- Systematic bad data cleansing
  - decentralized algorithms
  - correlated noise, (block-)sparse
  - link to compressed sensing

$$\boxed{\min_{\mathbf{x},\mathbf{o}} \|\mathbf{z} - \mathbf{H}\mathbf{x} - \mathbf{o}\|_2^2 + \lambda \sum_{l=1}^{L} \|\mathbf{o}_l\|_2}$$

V. Kekatos and G. B. Giannakis, "Distributed Robust Power System State Estimation," *IEEE Trans. Power Syst.*, May 2013.

Critical measurements



The i-th measurement is critical if once removed from the measurement set, the power system becomes unobservable

- *Claim:* The i-th column of $\mathbf{P}_{\mathbf{H}}^{\perp}$ is zero; hence, $r_i = 0 \quad (\mathbf{r} = \mathbf{P}_{\mathbf{H}}^{\perp}\boldsymbol{\epsilon})$
- For a critical measurement
  - undefined NRT $|r_i|/\sqrt{P_{ii}}$
  - no cross-validation (blindly trusted)
- Bad data processing vulnerable to critical measurements
- Multiple corrupted readings
  - communication link failures, cyber-attacks

O. Kosut, L. Jia, J. Thomas, and L. Tong, "Malicious data attacks on smart grid," *IEEE Trans. Smart Grid*, Dec. 2011.

Cyber-attacks

- Grid is a continent-size *cyber-physical* system
- No. of cyber-incidents on power SCADA: 3 (2009), 25 (2011)
- Challenged by increased sensing and networking
- *Types:* GPS spoofing, generator controls, CB tripping
- Focus on PSSE (situational awareness, markets)

$$\boxed{\mathbf{z} = \mathbf{H}\mathbf{x} + \boldsymbol{\epsilon} + \mathbf{a}}$$

- Compromised meters at non-zero entries of **a**
- *Stealth attacks* can arbitrarily mislead PSSE by $\mathbf{a} = \mathbf{H}\mathbf{v}$
- Deleting related rows of **H** deems the system unobservable

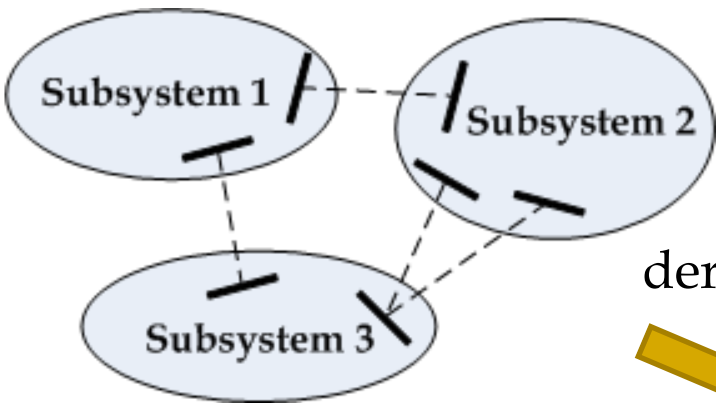
Liu, Ning, and Reiter, "False data injection attacks against state estimation in electric power grids," *ACM Trans. Info. and System Security*, May 2011.

Non-stealth attacks

- Caveats
  - attacker knows **H**
  - linearization around **x**
- Designs for attacker and defender [Kosut-Jia-Thomas-Tong'11]
  - defender solves an l_1-norm penalized GLRT
  - attacker trades identifiability for state divergence
- Topology attacks [Kim-Tong'13]
- Nonlinear AC model attacks [Zhu-GG'12]
- *Summary on PSSE*

Distributed PSSE

vertically organized markets

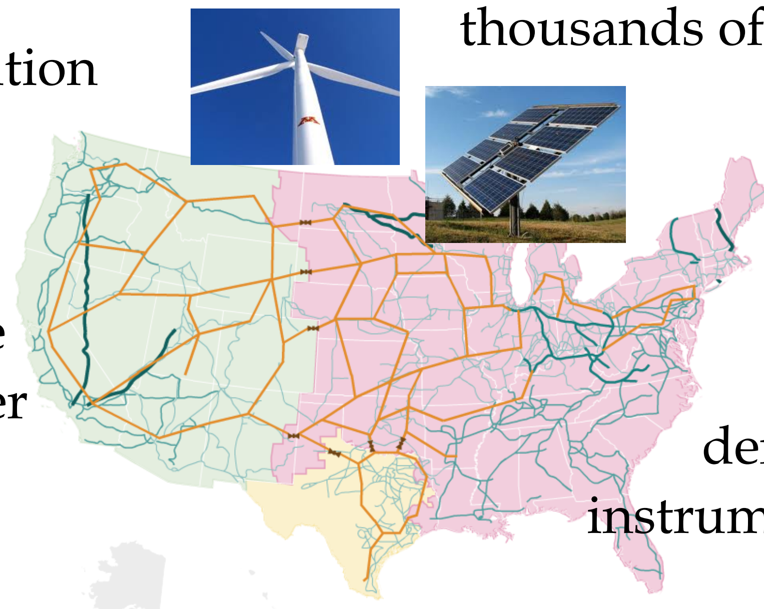


tie lines

deregulation

long-distance power transfer

control areas with thousands of buses



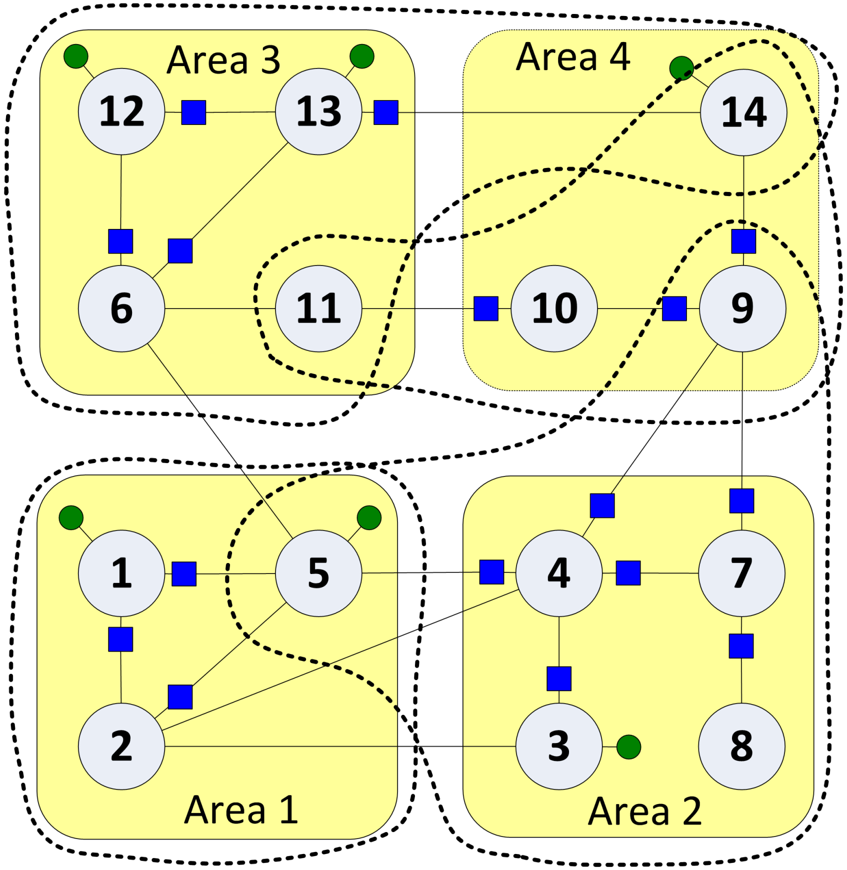
dense instrumentation

privacy policies

A. Gomez-Exposito, A. Abur, A. de la Villa Jaen, and C. Gomez-Quiles, "A multi-level state estimation paradigm for smart grids," *Proc. of the IEEE*, June 2011.

Setups

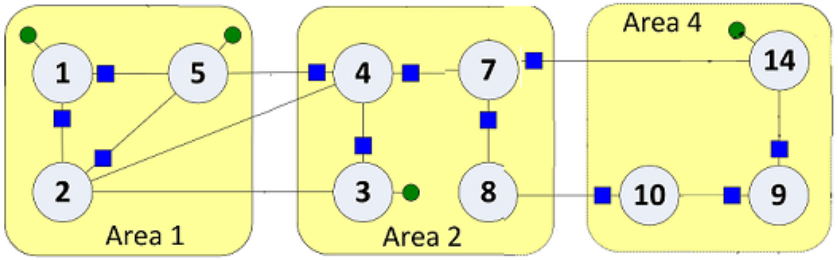
- IEEE 14-bus grid with 4 control areas
- Area 2 states (buses): *{3,4,7,8}*
- Area 2 collects flow measurements *{(4,5), (4,9), (7,9)}…*



- *Option 1:* Ignore tie-line meters
  - statistically suboptimal
  - observability at risk (bus 11)
  - tie-line mismatches (trading)
- *Option 2:* Augment $\mathbf{v}_2$ to *{3,4,7,8,5,9}*
  - consent with neighbors on shared states

G. Korres, "Distributed multi-area state estimation," *IEEE Trans. Power Syst.*, Feb. 2011.

Distributed solvers

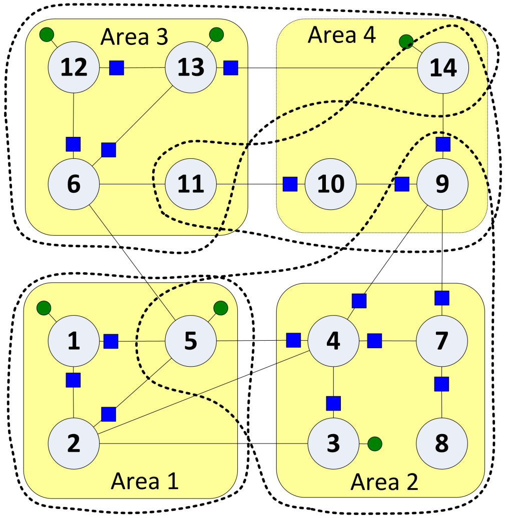


- Parallel and cascade (KF-type) solvers [Schweppe et al' 70]
- Arbitrary interconnection graph
  - Coordinator needed [Zhao-Abur' 05], [Korres et al '11]
- Decentralized solvers
  - Block Jacobi [Conejo et al' 07]; consensus averaging [Xie et al' 11]
- *Caveats:* Local observability, shared interconnection states, slow convergence (if ensured), parameter tuning

A. Gomez-Exposito, A. de la Villa Jaen, C. Gomez-Quiles, P. Rousseaux, T. V. Cutsem, "A taxonomy of multi-area state estimates," *Electric Power Systems Research*, 2011.

ADMM solver

- Local linear(ized) model $\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{n}_k$



- Regional PSSEs $$\min_{\mathbf{x}_k \in \mathcal{X}_k} \quad f_k(\mathbf{x}_k)$$

- Coupled local problems $$\min_{\{\mathbf{x}_k\}} \quad \sum_{k=1}^{K} f_k(\mathbf{x}_k)$$ $$\text{s.t.} \quad \mathbf{x}_k[l] = \mathbf{x}_l[k]$$

- Framework features: minimum inter-area exchanges, linear convergence guaranteed, disclosure policies

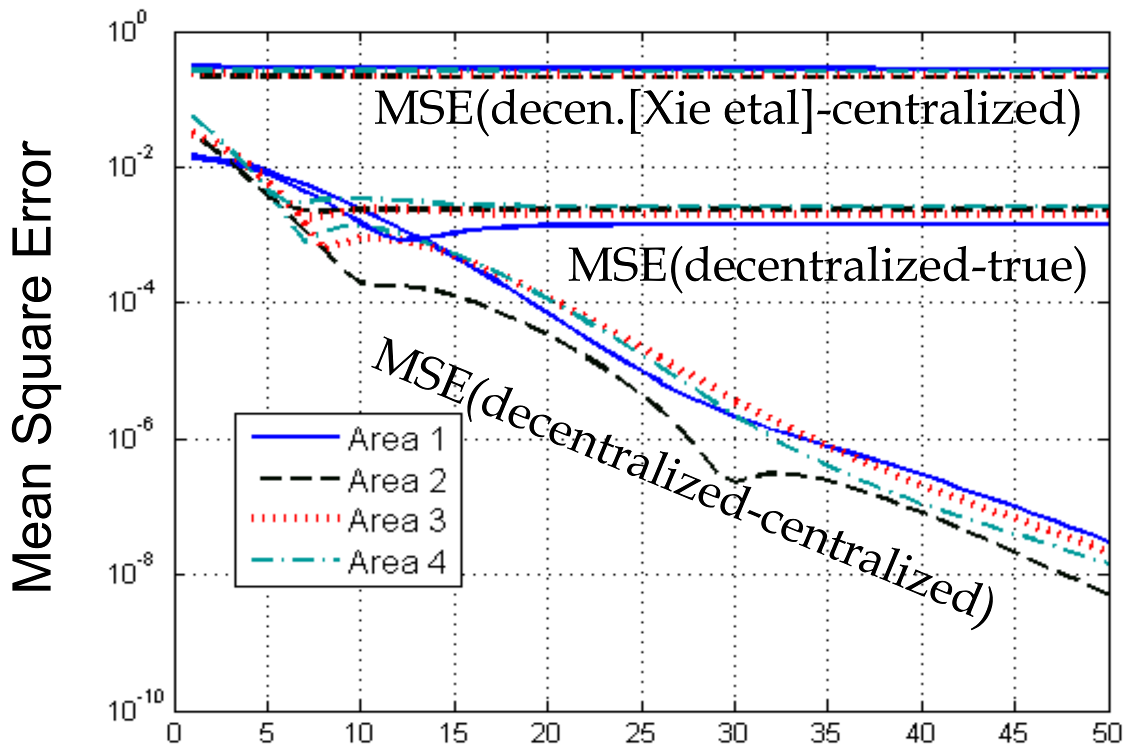
- ADMM-based semidefinite programming (SDP) [Zhu-GG' 12]
  - inter-area dependency graph affects decomposability

V. Kekatos and G. B. Giannakis, "Distributed Robust Power System State Estimation," *IEEE Trans. on Power Syst.*, May 2013.

Decentralized LS-based PSSE

S1. $\mathbf{x}_k^{t+1} \Leftarrow \left(\mathbf{H}_k^T\mathbf{H}_k + c \cdot \mathbf{D}_k\right)^{-1}\left(\mathbf{H}_k^T\mathbf{z}_k + c \cdot \mathbf{D}_k\mathbf{p}_k^t\right)$

S2. $p_k^{t+1}(i) \Leftarrow p_k^t(i) + \left(x_l^{t+1}[i] - \frac{x_k^t(i) + x_l^t[i]}{2}\right)$



L. Xie, C. Choi, and S. Kar, "Cooperative distributed state estimation: local observability relaxed," *Proc. IEEE PES General Meeting*, July 2011.

Decentralized bad data cleansing

- Pertinent *bad data-aware* model

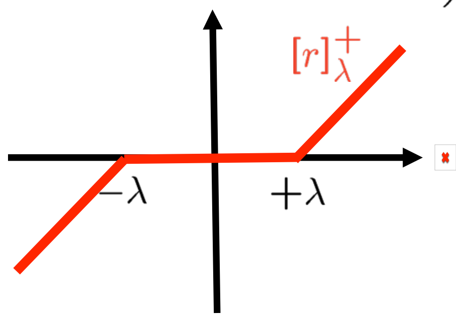
$$\mathbf{z} = \mathbf{H}\mathbf{x} + \mathbf{n} + \mathbf{o}$$

- Reveal outliers via

$$f(\mathbf{x}) := \min_{\mathbf{o}} \ \frac{1}{2}\|\mathbf{z} - \mathbf{H}\mathbf{x} - \mathbf{o}\|_2^2 + \lambda\|\mathbf{o}\|_1$$
$$= \sum_{m=1}^{M} h(z_m - \mathbf{h}_m^T\mathbf{x})$$

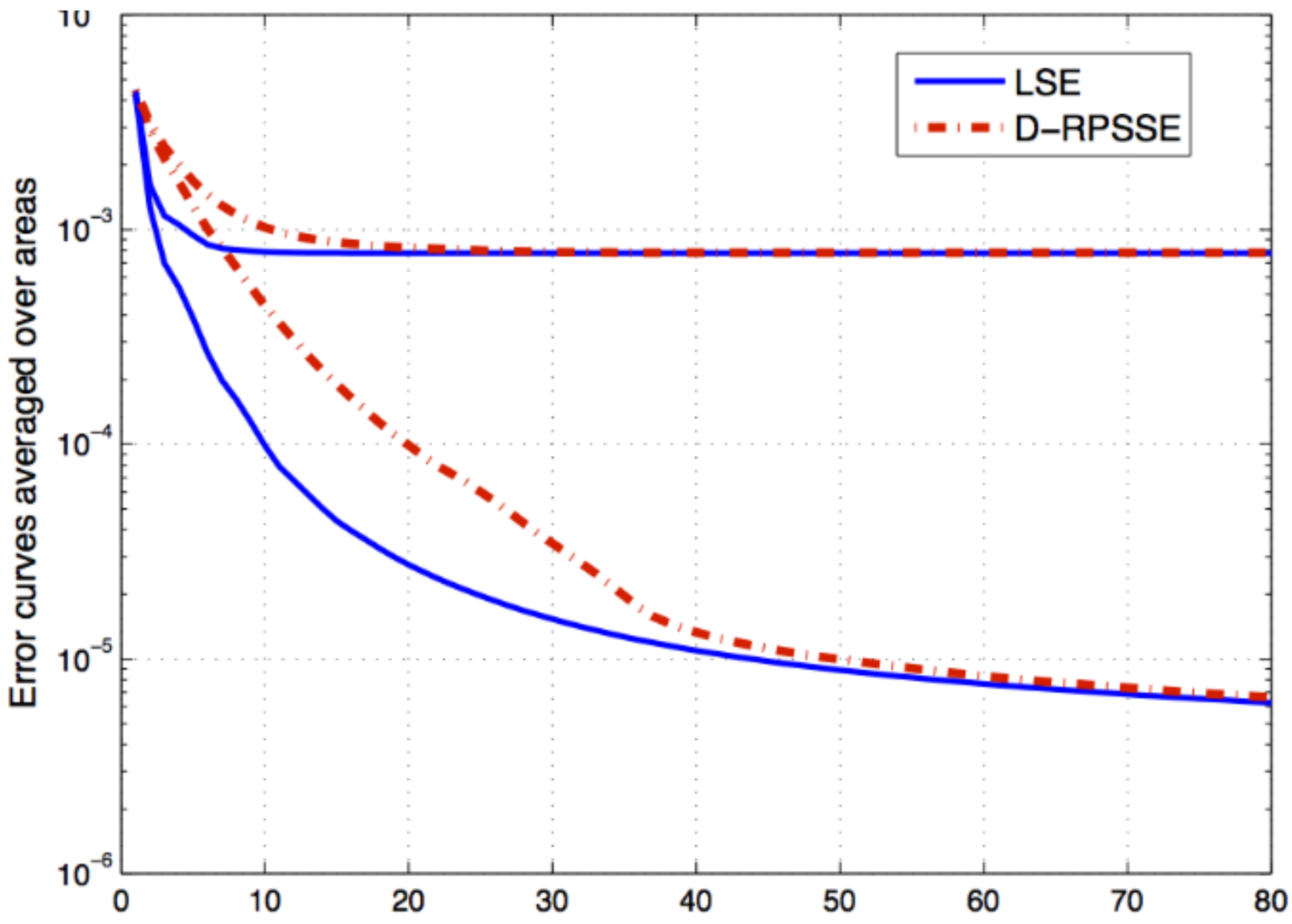
S1. $\mathbf{x}_k^{t+1} \Leftarrow \left(\mathbf{H}_k^T\mathbf{H}_k + c \cdot \mathbf{D}_k\right)^{-1} \left(\mathbf{H}_k^T(\mathbf{z}_k - \mathbf{o}_k^t) + c \cdot \mathbf{D}_k\mathbf{p}_k^t\right)$

S2. $\mathbf{o}_k^{t+1} \Leftarrow \left[\mathbf{z}_k - \mathbf{H}_k\mathbf{x}_k^{t+1}\right]_\lambda^+$



S3. $p_k^{t+1}(i) \Leftarrow p_k^t(i) + \left(x_l^{t+1}[i] - \frac{x_k^t(i) + x_l^t[i]}{2}\right)$

D-PSSE on a 4,200-bus grid



Phasor measurement units (PMUs)

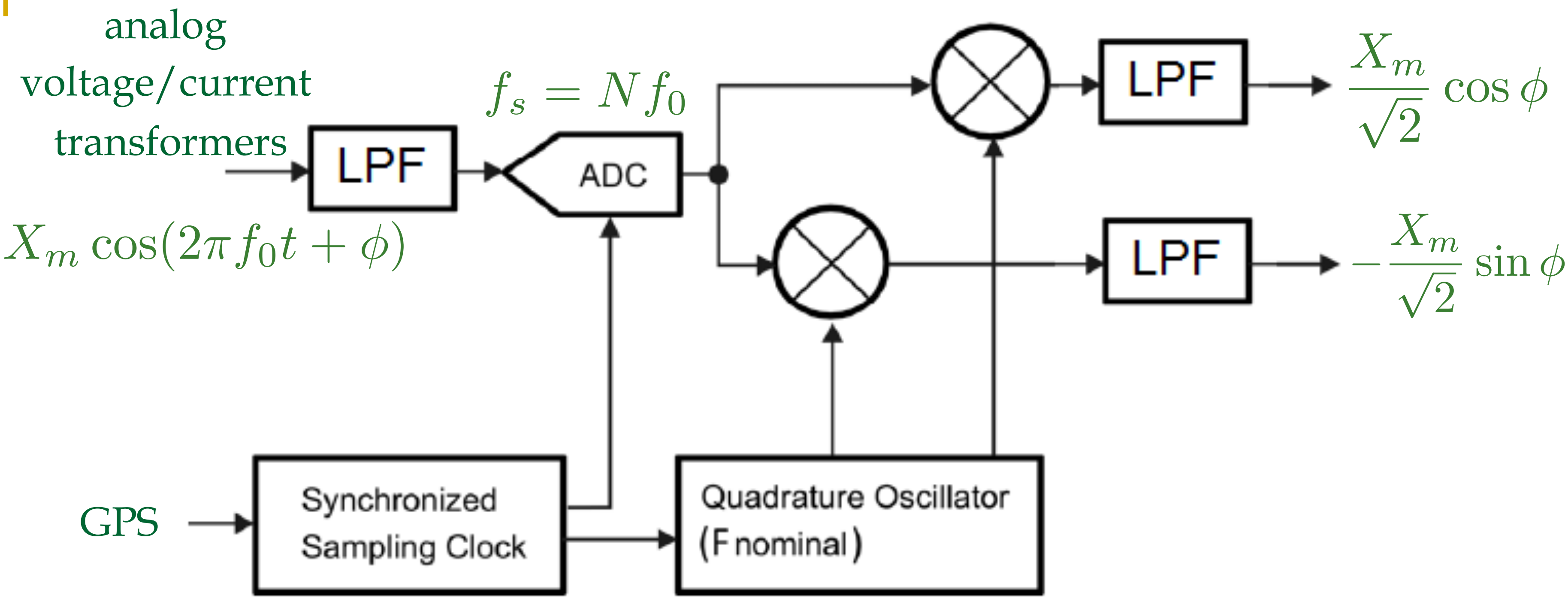
PMU versus SCADA

	SCADA	**PMU**
measurements	power, voltage, current *magnitude*	voltage & current *phasors*, frequency (derivative)
meas. model	non-linear	linear
reporting rate	one every 1-4 sec	30-60/sec
wide-area sync	poor	precise (GPS signal)

"It's like going from an X-ray to an MRI of the grid," Terry Boston, PJM CEO

A. G. Phadke and J. S. Thorp, *Synchronized Phasor Measurements and their Applications*, Springer, 2008.

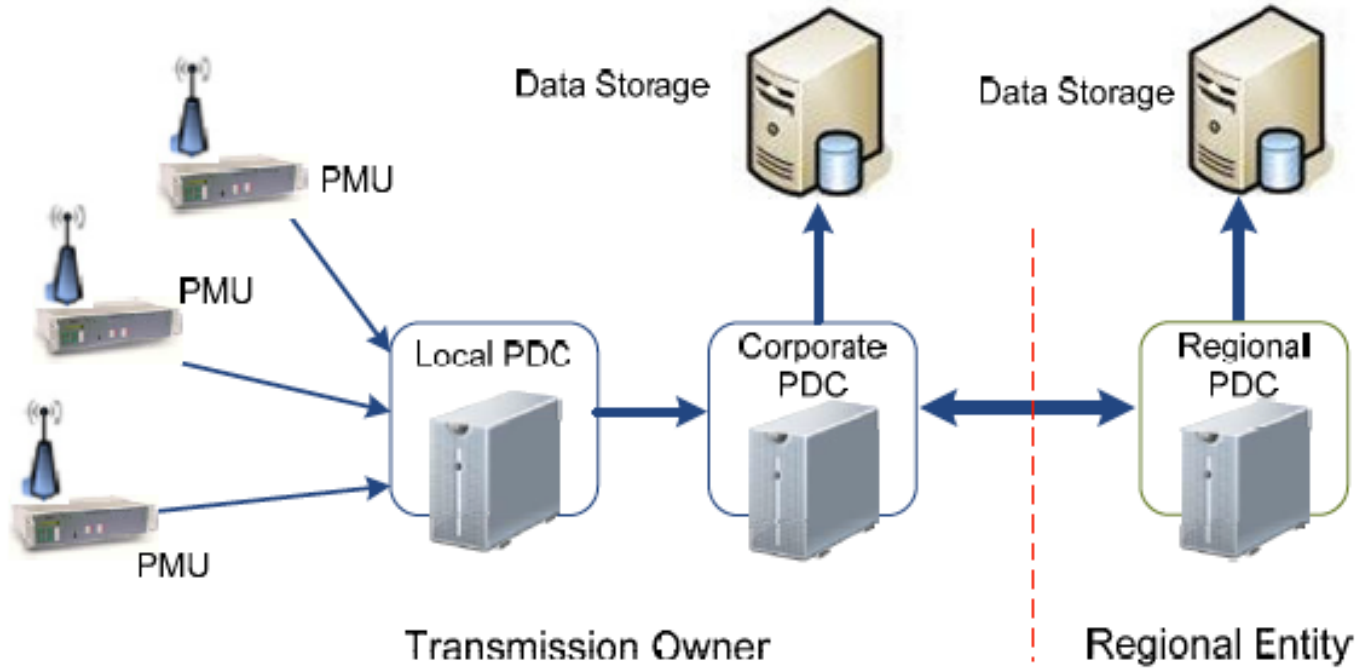
PMU architecture



- Correlation or (sliding) DFT
- Frequency offset estimation also of interest
- Other unknowns: DC and damping effects

IEEE Standard for Synchrophasor Measurements for Power Systems, *IEEE Std. C37.118*, Dec. 2011.

System architecture



- Single PMU can measure voltage and several line currents
- Phasor data concentrator (PDC)
  - collects data streams from several PMUs
  - time-alignment, local cleansing, data compression

PMU uses

Power system state estimation

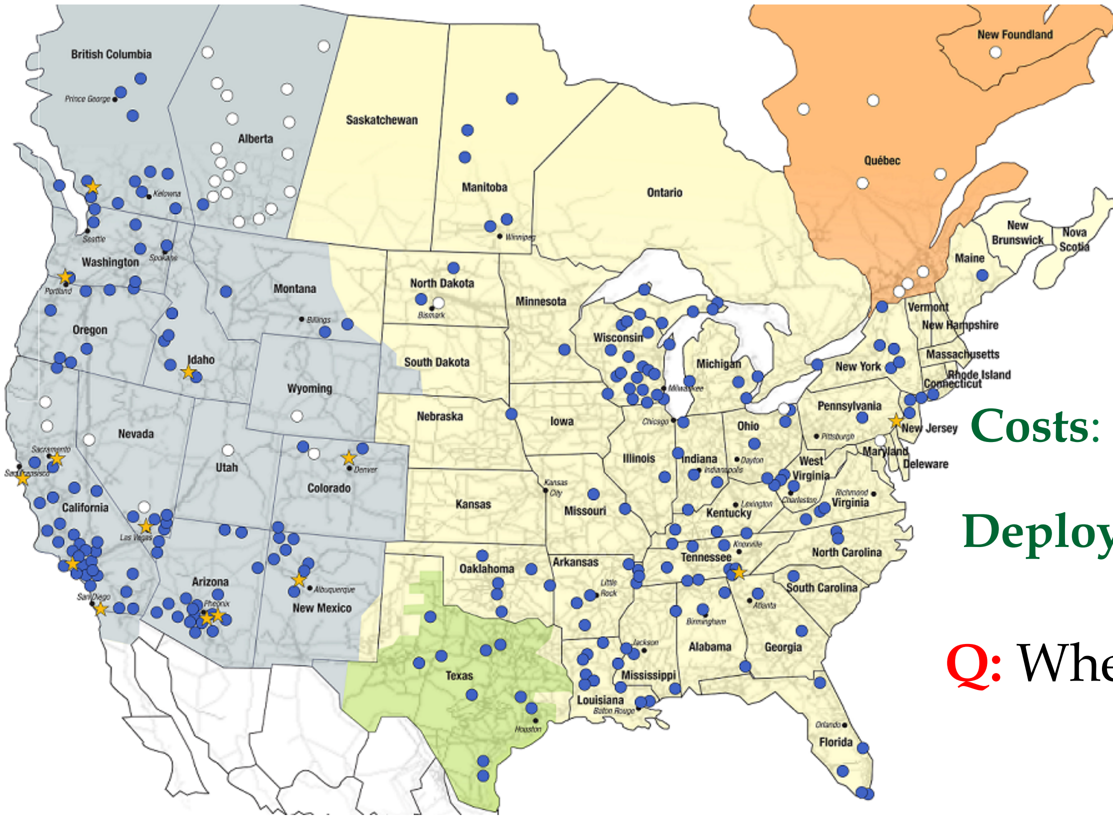
- Challenges
  - different rates
  - (non)linear models (rect./polar)
  - phase alignment
- Solutions
  - SCADA estimates as priors
  - PMU at reference bus

Monitoring, control, and protection (local and wide-area)

- Voltage stability
- Parameter estimation and dynamic line rating
- Oscillation and angular separation monitoring
- Visualization

A. G. Phadke and J. S. Thorp, *Synchronized Phasor Measurements and their Applications*, Springer, 2008.

Deployment of PMUs



Costs: acquisition, installation, networking

Deployment: 2009: ~100; 2014: ~500

Q: Where should new PMUs be placed?

- Criteria: topological observability [Emami-Abur'10]
  estimation accuracy [Li-Negi-Ilic'11]

North American Synchrophasor Initiative, www.naspi.org

Optimal experimental design

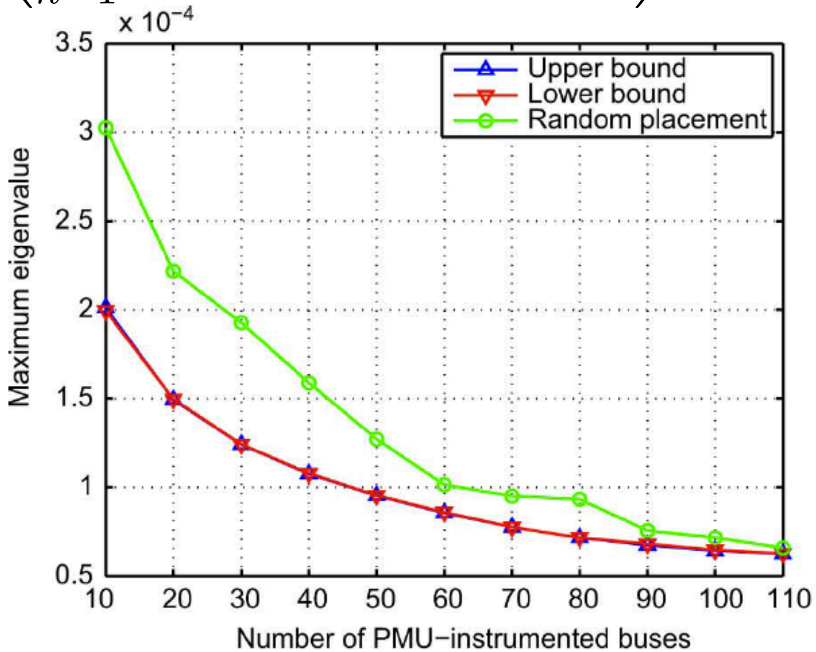
- PMU measurement model $\mathbf{z}_n = \mathbf{H}_n \mathbf{x} + \boldsymbol{\epsilon}_n$
  - SCADA prior $\mathbf{x} \sim \mathcal{N}(\hat{\mathbf{x}}_{\text{SCADA}}, \boldsymbol{\Sigma}_s)$
  - MMSE covariance $\boldsymbol{\Sigma}(\mathbf{a}) = \left(\sum_{n=1}^{N} a_n \mathbf{H}_n^T \boldsymbol{\Sigma}_n^{-1} \mathbf{H}_n + \boldsymbol{\Sigma}_s^{-1} \right)^{-1}$
- E-optimal design (NP-hard)

$$\min_{\mathbf{a}} \left\{ \lambda_{\max}(\boldsymbol{\Sigma}(\alpha)) : \mathbf{a} \in \{0,1\}^N, \mathbf{a}^T \mathbf{1} = k \right\}$$

  - SDP relaxation

$$\min_{\mathbf{a}} \left\{ \lambda_{\max}(\boldsymbol{\Sigma}(\alpha)) : \mathbf{a} \in [0,1]^N, \mathbf{a}^T \mathbf{1} = k \right\}$$

- Scalable projected gradient algorithm

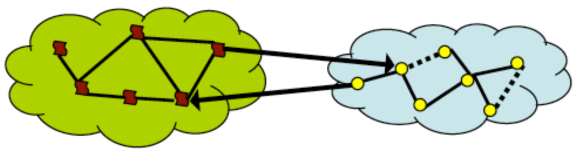


V. Kekatos, G. B. Giannakis, and B. Wollenberg, "Optimal Placement of Phasor Measurement Units via Convex Relaxation," *IEEE Trans. on Power Systems*, vol. 27, pp. 1521-1530, Aug. 2012.

Additional learning and inference issues

Cascading failures

- Blackouts cost $150 billion/year
- ***Cascading:*** Lines exceed ratings and successively fail
- Linear DC model $\mathbf{p} = \mathbf{B}\boldsymbol{\theta}$
  - Internal-external states $\boldsymbol{\theta}^T = [\boldsymbol{\theta}_I^T \ \boldsymbol{\theta}_E^T]$
  - Pre- and post-outage graph $(\mathcal{N}, \mathcal{E}) \rightarrow (\mathcal{N}, \mathcal{E}')$



Problem: *Given pre- and post-outage internal states* $\boldsymbol{\theta}_I$, $\boldsymbol{\theta}'_I$, *and basecase topology* $\mathbf{B}$, *find the line outage set* $\tilde{\mathcal{E}} := \mathcal{E} \setminus \mathcal{E}'$

- Exhaustive search [Tate-Overbye'09], [Emami-Abur'10]; GMRF [He-Zhang'11]

Linear DC model with outages

- Nodal power injections remain *unchanged* $\mathbf{p}' = \mathbf{p} + \mathbf{n}$

- Post-/pre-outage DC model $\mathbf{B}'\boldsymbol{\theta}' = \mathbf{B}\boldsymbol{\theta} + \mathbf{n} \;\Rightarrow\; \mathbf{B}\tilde{\boldsymbol{\theta}} = \tilde{\mathbf{B}}\boldsymbol{\theta}' + \mathbf{n}$

$$\tilde{\mathbf{B}} := \mathbf{B}' - \mathbf{B}$$
$$\tilde{\boldsymbol{\theta}} := \boldsymbol{\theta}' - \boldsymbol{\theta}$$

- Exploit $\tilde{\mathbf{B}} = \sum_{l \in \tilde{\mathcal{E}}} \frac{1}{x_l} \mathbf{a}_l \mathbf{a}_l^T$

- *Sparse representation* over all transmission lines

$$\tilde{\mathbf{B}}\boldsymbol{\theta}' = \sum_{l \in \mathcal{E}} \mathbf{a}_l m_l + \mathbf{n}, \quad m_l := \begin{cases} \frac{\mathbf{a}_l^T \boldsymbol{\theta}'}{x_l} & , l \in \tilde{\mathcal{E}} \\ 0 & , l \notin \tilde{\mathcal{E}} \end{cases}$$

H. Zhu and G. B. Giannakis "Sparse overcomplete representation for efficient identification of power line outages," *IEEE Trans. Power Syst.*, Nov. 2012.

Grid Laplacian

- Linear DC model $\boxed{\mathbf{p} = \mathbf{B}\boldsymbol{\theta} + \mathbf{n}}$

nodal powers

bus admittance matrix

nodal voltage phases

$$[\mathbf{B}]_{mn} = \begin{cases} \sum_{n \neq m} x_{mn}^{-1} & , m = n \\ -x_{mn}^{-1} & , m \neq n \end{cases}$$

- From nodes to lines: weighted grid Laplacian

$$(m, n) \leftrightarrow l$$

$$\mathbf{B} = \sum_{l \in \mathcal{E}} x_l^{-1} \mathbf{a}_l \mathbf{a}_l^T = \sum_{(m,n) \in \mathcal{E}} x_{mn}^{-1} \cdot \begin{array}{c} \begin{array}{cccccc} & m & & n & & \end{array} \\ \left[\begin{array}{cccccc} \ddots & \vdots & & \vdots & & \\ \cdots & +1 & \cdots & -1 & \cdots & \\ & \vdots & \ddots & \vdots & & \\ \cdots & -1 & \cdots & +1 & \cdots & \\ & \vdots & & \vdots & \ddots & \end{array}\right] \begin{array}{c} \\ m \\ \\ n \\ \\ \end{array} \end{array}$$

$$(\mathbf{a}_l := \mathbf{e}_m - \mathbf{e}_n)$$

Lassoing line outages

$$\boxed{\mathbf{B}\tilde{\theta} = \mathbf{A}\mathbf{m} + \mathbf{n}}$$

$\mathbf{A} := [\mathbf{a}_1 \ \cdots \ \mathbf{a}_{|\mathcal{E}|}]$ branch-bus incidence matrix

- Given only $(\mathbf{B}, \tilde{\boldsymbol{\theta}}_I)$, solve for $\tilde{\boldsymbol{\theta}}_I = [\mathbf{B}^\dagger]_I \mathbf{A}\mathbf{m} + [\mathbf{B}^\dagger]_I \mathbf{n}$
- Sparse linear regression model with colored noise
  - Orthogonal matching pursuit (greedy)
  - l_1-norm penalized regression (coordinate descent)

IEEE 300-bus (detection probability)

	ES	OMP	CD
Single (5%)	82.0	82.0	81.4
Double (10%)	61.8	62.0	63.1
Double (5%)	70.5	71.0	70.6
Double (2%)	85.1	85.3	84.8

Running times (secs.)

	ES	OMP	CD
Single, 118-bus	5.9e-2	1.3e-4	4.9e-2
Double, 118-bus	4.1	2.7e-4	9.7e-2
Single, 300-bus	0.15	4.0e-4	0.39
Double, 300-bus	22.5	1.1e-3	0.97
Single, 2383-bus	1.2	1.4e-2	2.6
Double, 2383-bus	$\sim$	2.9e-2	4.2

Electromechanical modes

- Oscillations in voltage, frequency, and power flows (grid breakup)
- Inter-area oscillations in 0.1-1 Hz

- Challenges in retrieving harmonics
  - nonlinearity
  - time-varying power systems
  - closely-spaced frequencies

- Linearized continuous-time differential equations

$$\dot{\mathbf{x}}(t) = \mathbf{A}_x \mathbf{x}(t) + \mathbf{B}_u \mathbf{u}(t) + \mathbf{w}(t)$$

- Probing signal $\mathbf{u}(t)$

- Modes described by the eigenvalues of $\mathbf{A}_x$

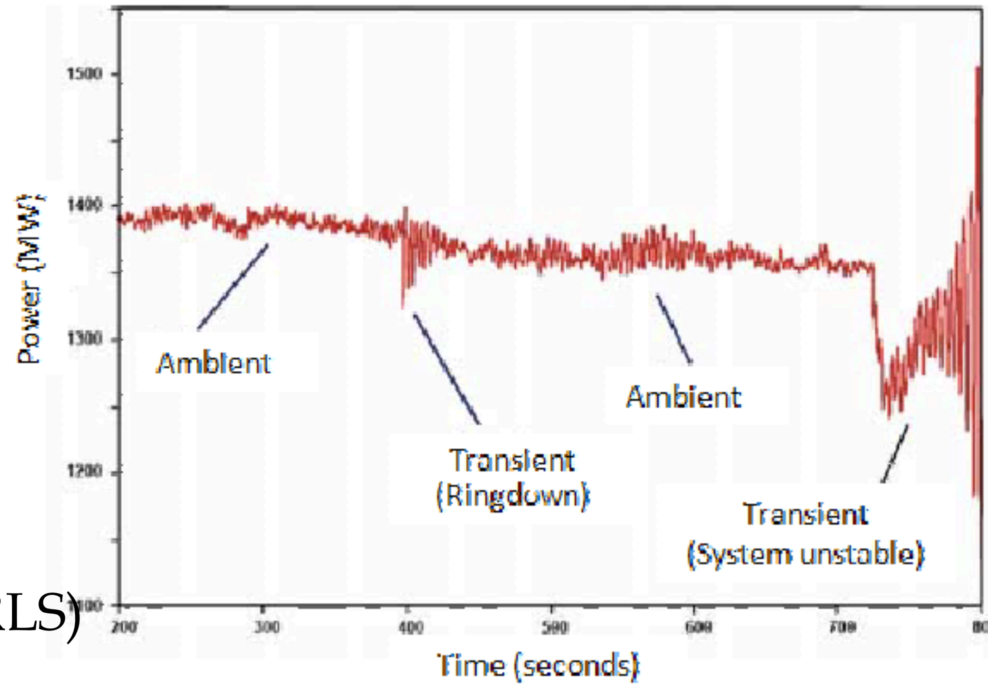
P. Kundur, *Power System Stability and Control*, McGraw-Hill, 1994.

Mode estimation

(M1) Build $\mathbf{A}_x$ based on grid model (scalability issues)

(M2) Spectral estimates using measured $\mathbf{x}(t)$

- Measurement types
  - ambient (regular)
  - ring-down (disturbance)
  - probing (engineered $\mathbf{u}(t)$)
- Batch modal analysis (Prony's)
- Adaptive nodal analysis (LMS, RLS)



- Probing signal design for improved accuracy and minimal grid impact

D. Trudnowski and J. Pierre, *Signal processing methods for estimating small-signal dynamic properties from measured responses*, Springer, 2009.

Load forecasting

- Based on historical load data and other (e.g., weather) predictors
- Data exhibit cycles (daily, weekly, seasonal)
- Outliers due to extreme weather, events, and strikes
- Time scales depend on application
  - minute and hour (economic dispatch)
  - week (reliability assessment)
  - year (generation and transmission planning)
- Spatial scales per substation, utility, and interconnection
- *Challenges:* deregulation, demand response, electric vehicles

Popular load predictors

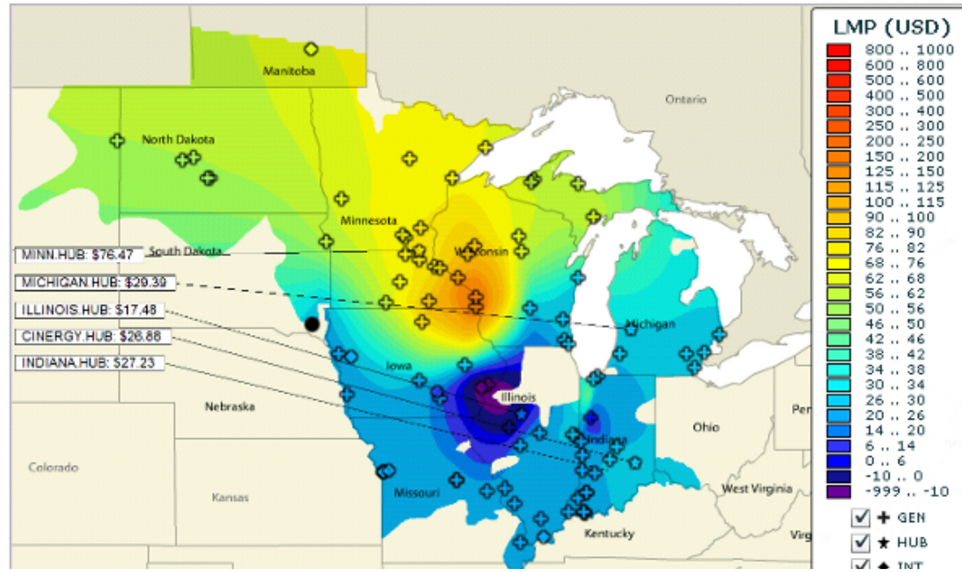
- Ordinary LS
- Kernel-based regression and SVMs
- Time series analysis (ARMA, ARIMA, ARIMAX)
- State-space models with KF and particle filtering
- Neural networks and artificial intelligence
- Low-rank models for load cleansing [Mateos-GG'12]

M. Shahidehpour, H. Yamin, and Z. Li, *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Management*, Wiley Interscience, 2002.

Electricity price forecasting

- Important for asset owners, system operators, government

- Challenges
  - weather and load
  - hedging strategies
  - outages and security



MISO market

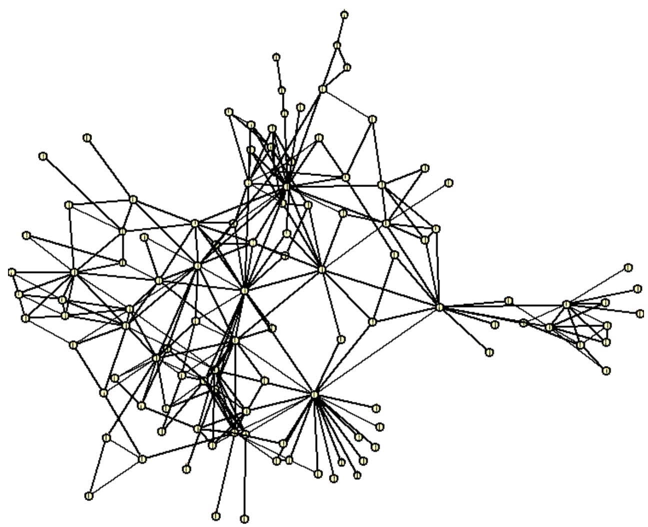
- Approaches
  - Time-series based predictors [Contreras et al'03], [Conejo et al'05]
  - Neural networks [Gonzalez et al'05], [Li et al'07], [Wu-Shahidehpour'10]
  - Nearest-neighbor approach [Lora-Exposito'07]
  - QP with outage combinations [Zhou-Tesfatsion-Liu'11]

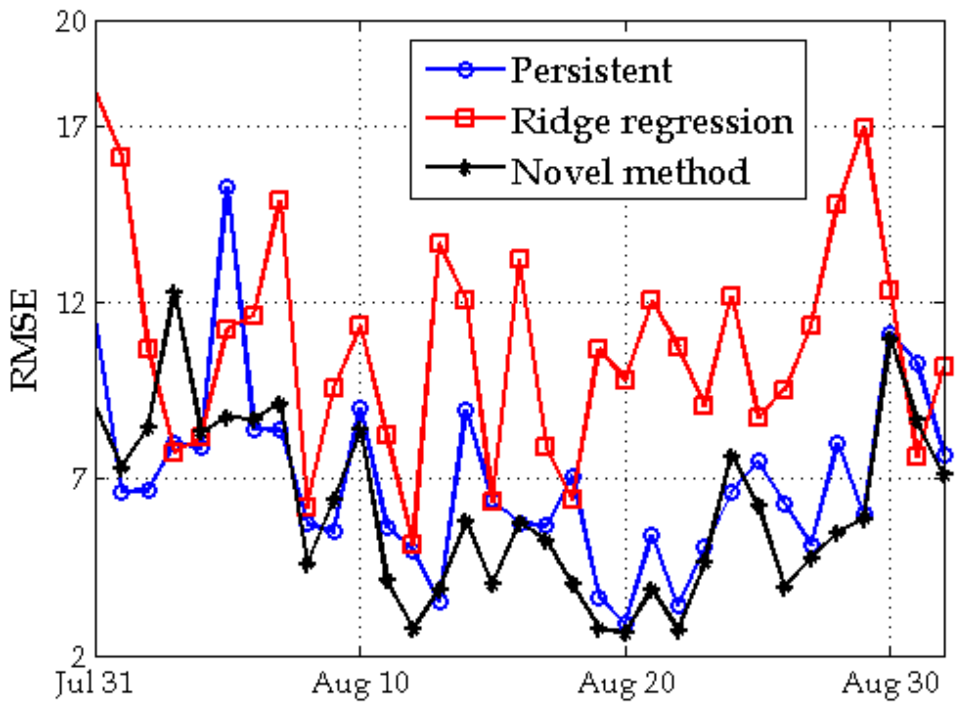
M. Amjady and N. Hemmati, "Energy price forecasting," *IEEE Power Energy Mag.*, Apr. 2006.

V. Kekatos, S. Veeramachaneni, M. Light, and G. B. Giannakis, "Day-Ahead Electricity Market Forecasting using Kernels," *Proc. of Innovative Smart Grid Technologies*, Feb. 2013.

Spatiotemporal price forecasting

- Learning over *pricing network* $\hat{f} := \arg\min_{f \in \mathcal{H}} \sum_{t,n} (p(t,n) - f(\mathbf{x}_t, n))^2 + \lambda \|f\|_{\mathcal{H}}^2$
- Separable kernel $k((t_i, n_i), (t_j, n_j)) = k_t(\mathbf{x}_{t_i}, \mathbf{x}_{t_j}) k_s(n_i, n_j)$
- k_t : Gaussian kernel
- k_s : inverse Laplacian of balancing authority graphs



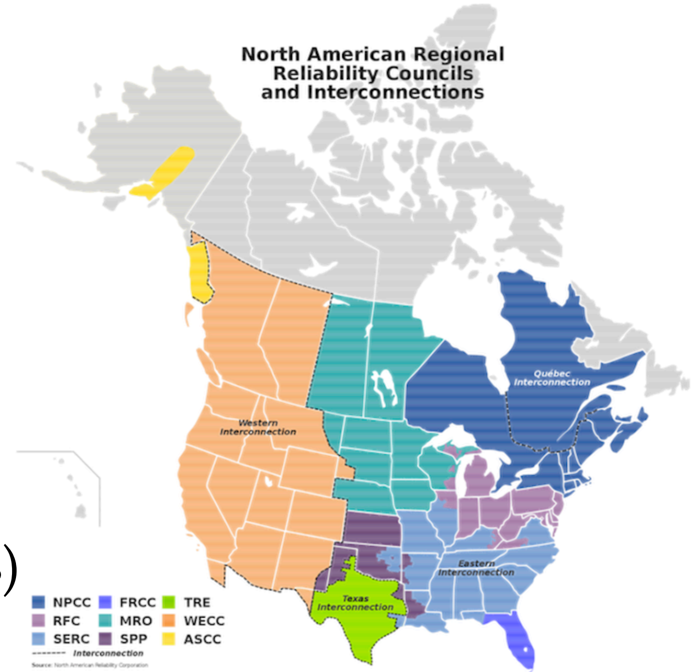


MISO; Jun-Aug 2012; 1732 nodes

V. Kekatos, Y. Zhang, and G. B. Giannakis, "Electricity Market Forecasting via Low-Rank Multi-Kernel Learning," *IEEE Journal of Selected Topics in Signal Processing (submitted).*

Clustering the grid

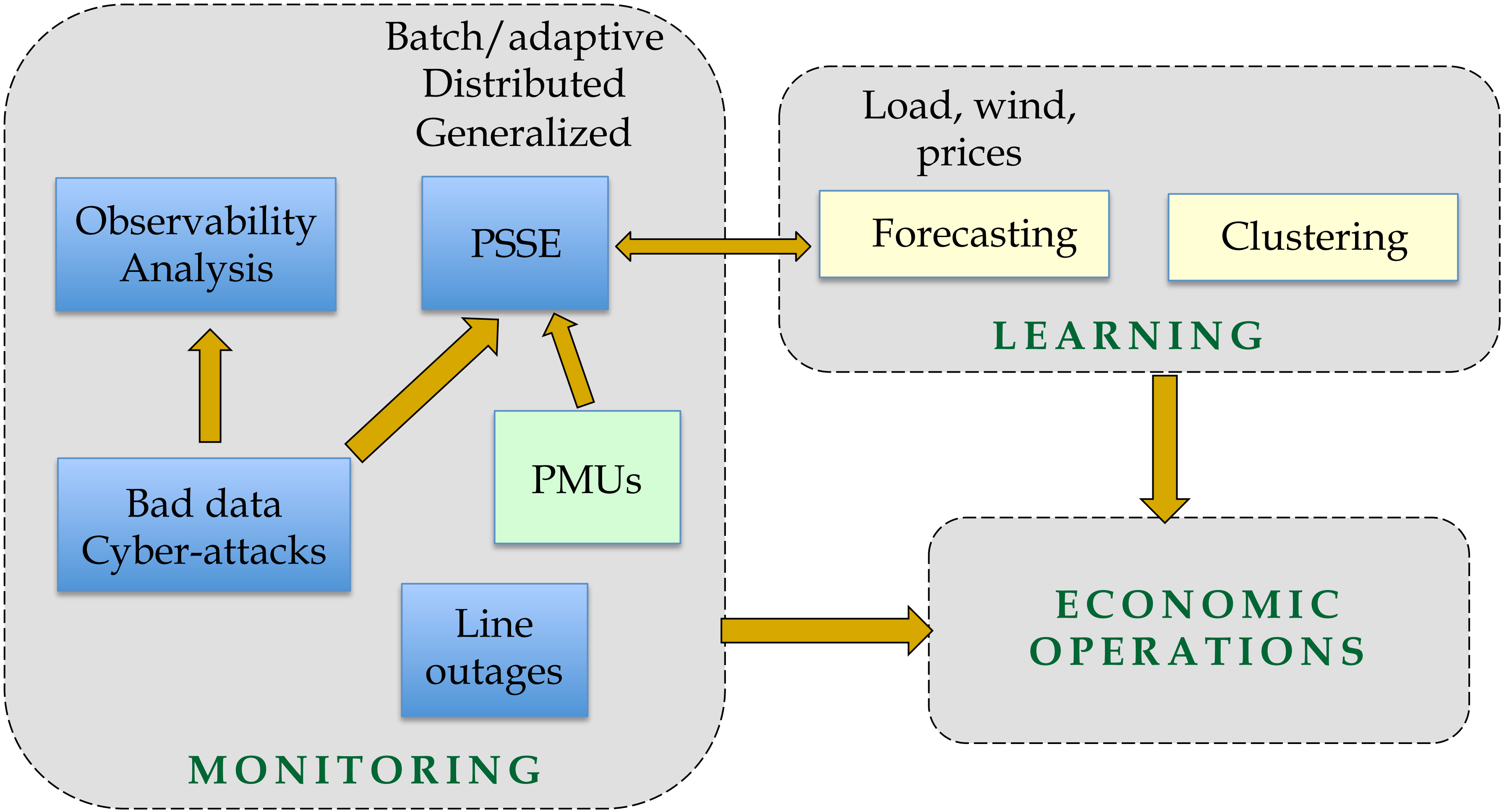
- Static partitioning into reliability regions
- Modularization facilitates
  - decentralized and parallel computing
  - minimum communication
- "Self-healing" (islanding under contingencies)
  - active power balance (frequency stability)
  - reactive power balance (voltage stability)



- Zonal analysis via spectral clustering (reliability planning, market)
  - bus adjacency (*"small-world effect"* [Watts-Strogatz'98])
  - bus electrical adjacency (admittance matrix)

J. Li, C.-C. Liu, and K. Schneider, "Controlled partitioning of a power network considering real and reactive power balance," *IEEE Trans. Smart Grid*, Dec. 2010.

Grid monitoring and learning



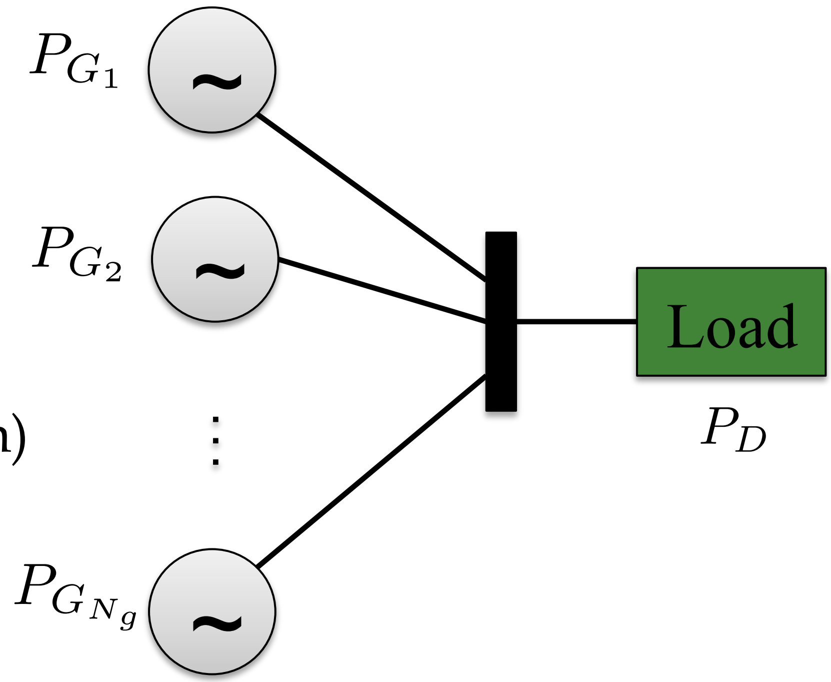
Economic Operation of Power Systems

A. Gomez-Exposito, A. J. Conejo, and C. Canizares, *Electric Energy Systems: Analysis and Operation*, CRC Press, 2009.

A. J. Wood and B. F. Wollenberg, *Power Generation, Operation, and Control*, 2nd ed., Wiley, 1996.

Generation cost

- Thermal generators
- Power output P_{G_i} (MW)
- Generation cost $C_i(P_{G_i})$ (\$/h or €/h)

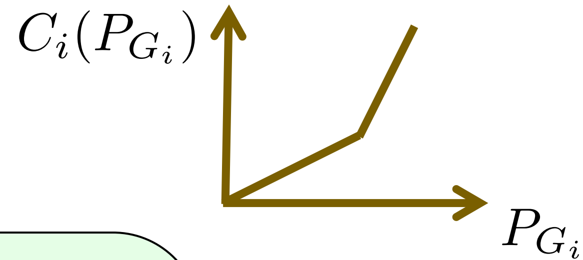


***Economic dispatch (ED):** Find most economically generated power output to serve given load*

- ED typically solved every 5-10 minutes

Optimizing ED

- Generation cost $C_i(P_{G_i})$ typically convex and strictly increasing
  - Piecewise linear or quadratic



$$\min_{\{P_{G_i}\}} \sum_{i=1}^{N_g} C_i(P_{G_i})$$

$$\text{subj. to } \sum_{i=1}^{N_g} P_{G_i} = P_D$$

$$P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max}$$

- ED balances supply and demand most economically
- Convex optimization problem

Marginal price

- Lagrange multiplier λ for supply-demand balance

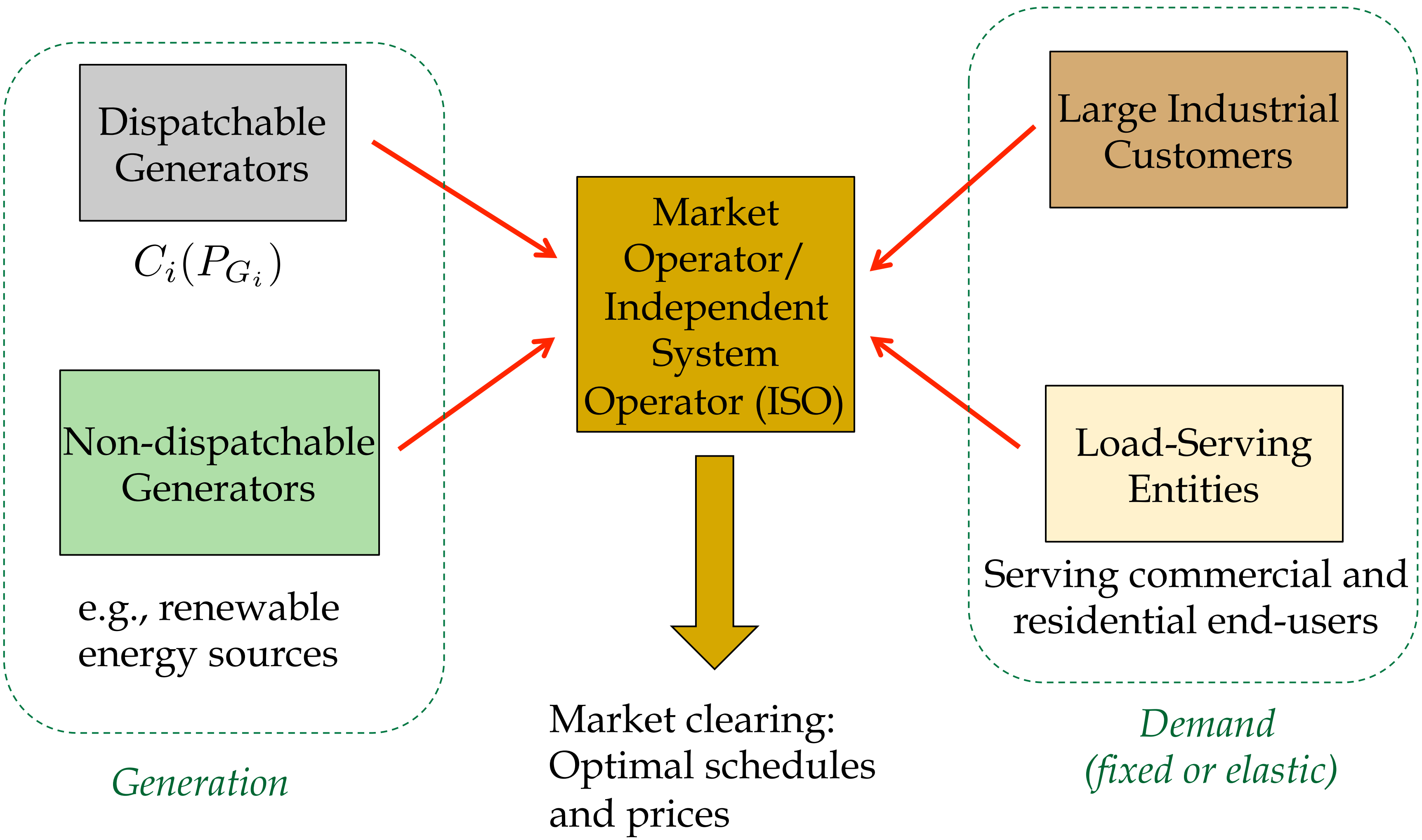
$$\sum_{i=1}^{N_g} P_{G_i} = P_D$$

- Optimal generation output

$$P_{G_i}^* = \underset{P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max}}{\arg\min} \{C(P_{G_i}) - \lambda^* P_{G_i}\}$$

- ED optimizes net cost: Generation cost minus revenue
- Price λ^* ($/MWh or €/MWh)
- Prices $\longleftrightarrow$ Lagrange multipliers

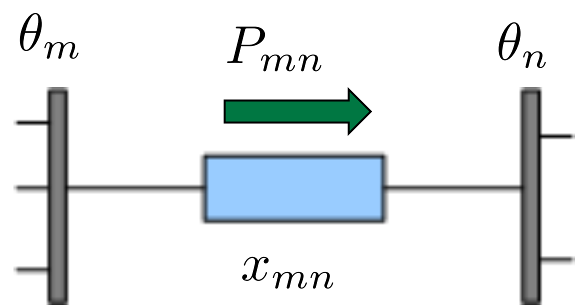
Market participants



A. J. Conejo, M. Carrion, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*, Springer, 2010, ch. 1.

DC power flow

- ED must account for transmission network constraints
  - DC approximation



- Generator P_{G_m} and load P_{D_m} per bus m
  - At all buses: $\mathbf{p}_G$ and $\mathbf{p}_D$
- Power flow from bus m to bus n

$$P_{mn} = x_{mn}^{-1}(\theta_m - \theta_n)$$

- Define the $N_l \times N_b$ matrix

$$\mathbf{F} = \mathbf{DA}$$

$\mathbf{A} = \text{branch-bus incidence matrix}$

$\mathbf{D} = \text{diag}(\{x_{mn}^{-1}\}_{(m,n)\in\mathcal{E}})$

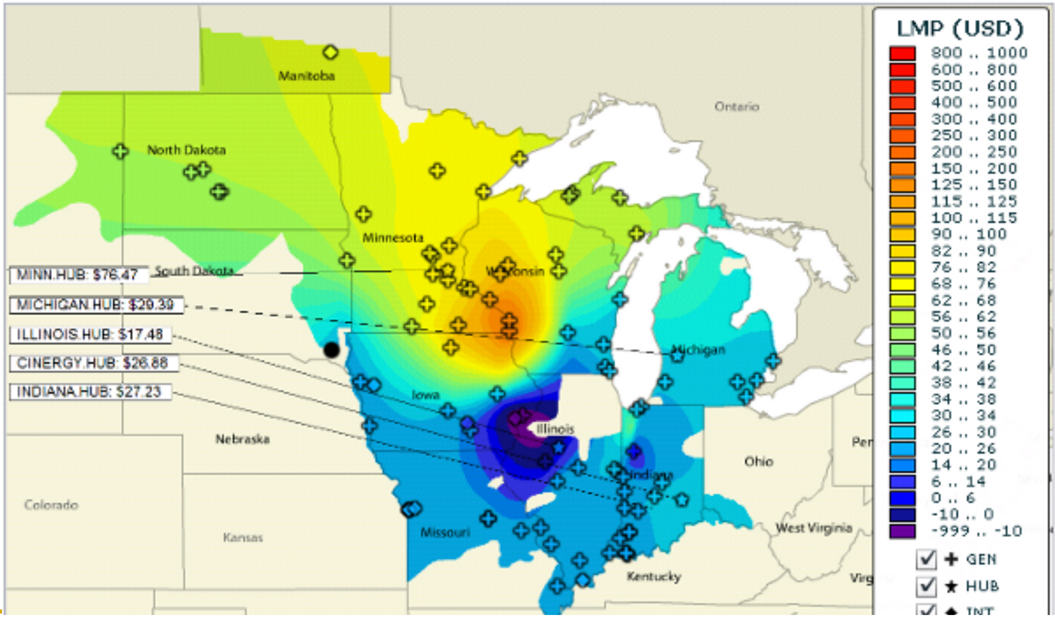
- Power flows at all lines $\mathbf{f} = [P_{mn}] = \mathbf{F}\boldsymbol{\theta}$

DC optimal power flow

- Power balance per bus; flow limit per line

$$
\begin{aligned}
\min_{\mathbf{p}_G,\,\boldsymbol{\theta}} \quad & \sum_{m=1}^{N_b} C_m(P_{G_m}) \\
\text{subj. to} \quad & \mathbf{p}_G - \mathbf{p}_D = \mathbf{B}\boldsymbol{\theta} \\
& |\mathbf{F}\boldsymbol{\theta}| \leq \mathbf{f}^{\max} \\
& \mathbf{p}_G^{\min} \leq \mathbf{p}_G \leq \mathbf{p}_G^{\max}
\end{aligned}
$$

- Convex optimization problem
- Locational marginal prices (LMPs)
  - Multipliers for nodal balance



MISO market

R. D. Christie, B. F. Wollenberg, and I. Wangensteen, “Transmission management in the deregulated environment,” *Proc. of the IEEE*, Feb. 2000.

Contingencies

- System security must be ensured even under unplanned events
  - Line flow and bus voltage limits

- Set of credible contingencies $\mathcal{K}$
- Contingency $k \in \mathcal{K}$ may include any of the following:
  - Generation loss $P_{G_m}^{\max,k} = P_{G_m}^{\min,k} = 0$
  - Generation derating $P_{G_m}^{\max,k} = P_{G_m}^{\max} - \Delta P_{G_m}^{k}$
  - Demand variation $P_{D_m}^{k} = P_{D_m} + \Delta P_{D_m}^{k}$
  - Line outage gives rise to $\mathbf{B}^k$, $\mathbf{F}^k$, $\mathbf{f}^{\max,k}$

- Notation for generation limits and demand $\boxed{(\mathbf{p}_G^{\max,k}, \mathbf{p}_G^{\min,k}, \mathbf{p}_D^{k}) \in \mathcal{C}^k}$

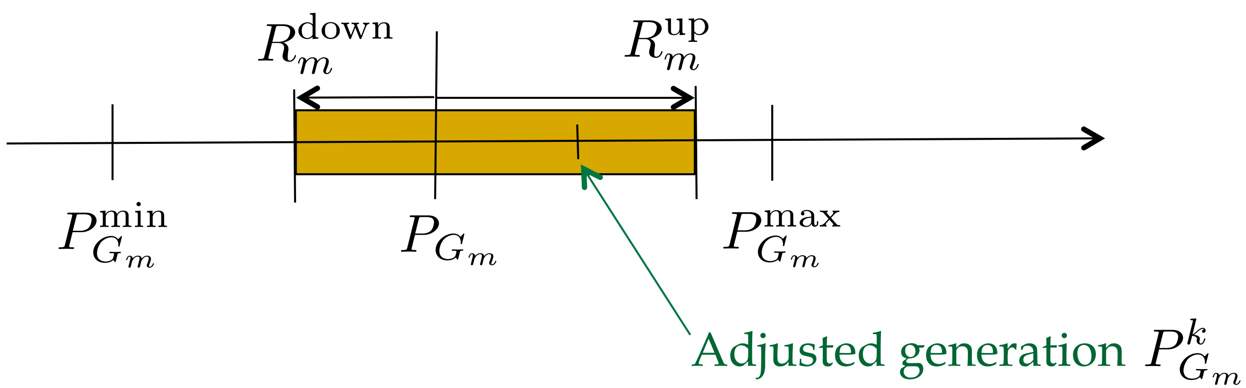
- North American Electric Reliability Council (NERC) *N*-1 security rule

Reserves

- Spinning reserve: Online generation capacity available to be deployed under contingencies

- Scheduling of reserves
  - Up-spinning R_m^{up} ; down-spinning R_m^{down}

- Reserve level available depends on generation schedule P_{G_m}



Security-constrained DC OPF

- Decide reserve levels and adjustments for each contingency

$$\min_{\substack{\mathbf{p}_G,\,\boldsymbol{\theta},\,\mathbf{r}^{\text{up}},\,\mathbf{r}^{\text{down}}\\ \{\mathbf{p}_G^k,\,\boldsymbol{\theta}^k\}_{k\in\mathcal{K}}}} \sum_{m=1}^{N_b} \left[C_m(P_{G_m}) + C_m^{\text{up}}(R_m^{\text{up}}) + C_m^{\text{down}}(R_m^{\text{down}})\right]$$

subj. to

$$\begin{aligned} &\mathbf{p}_G - \mathbf{p}_D = \mathbf{B}\boldsymbol{\theta}\\ &|\mathbf{F}\boldsymbol{\theta}| \leq \mathbf{f}^{\max}\\ &\mathbf{p}_G^{\min} \leq \mathbf{p}_G \leq \mathbf{p}_G^{\max} \end{aligned}$$

Network constraints in base case

$$\begin{aligned} &\mathbf{p}_G^k - \mathbf{p}_D^k = \mathbf{B}^k\boldsymbol{\theta}^k && \forall\, k \in \mathcal{K}\\ &|\mathbf{F}^k\boldsymbol{\theta}^k| \leq \mathbf{f}^{\max,k} && \forall\, k \in \mathcal{K}\\ &\mathbf{p}_G^{\min,k} \leq \mathbf{p}_G^k \leq \mathbf{p}_G^{\max,k} && \forall\, k \in \mathcal{K}\\ &(\mathbf{p}_G^{\max,k}, \mathbf{p}_G^{\min,k}, \mathbf{p}_D^k) \in \mathcal{C}^k && \forall\, k \in \mathcal{K} \end{aligned}$$

Network constraints at every contingency

$$\begin{aligned} &\mathbf{r}^{\text{down}} \leq \mathbf{p}_G - \mathbf{p}_G^{\min};\;\; \mathbf{r}^{\text{up}} \leq \mathbf{p}_G^{\max} - \mathbf{p}_G\\ &\mathbf{p}_G - \mathbf{r}^{\text{down}} \leq \mathbf{p}_G^k \leq \mathbf{p}_G + \mathbf{r}^{\text{up}} \quad \forall\, k \in \mathcal{K} \end{aligned}$$

Reserve levels and adjustment constraints

F. D. Galiana, F. Bouffard, J. M. Arroyo, and J. F. Restrepo, "Scheduling and pricing of coupled energy and primary, secondary, and tertiary reserves," *Proc. of the IEEE*, Nov. 2005.

AC power flow

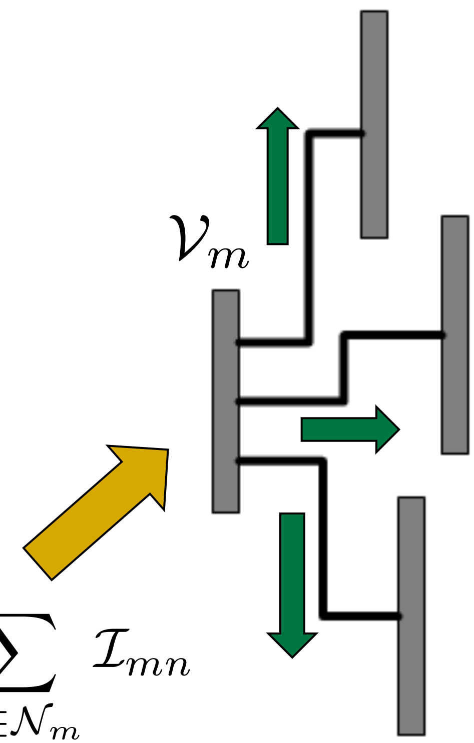
- Incorporate AC transmission network into ED
  - AC model is exact
  - Ohmic losses - typically 5% of total load
  - Bus voltage constraints

- Real power injection: $P_{G_m} - P_{D_m}$
- Reactive power injection: $Q_{G_m} - Q_{D_m}$

- Complex power flowing over line (m, n)

$$\mathcal{S}_{mn} = \mathcal{V}_m \mathcal{I}_{mn}^*$$

- Current injections $\mathbf{i} = \mathbf{Y}\mathbf{v}$



$$\mathcal{I}_m = \sum_{n \in \mathcal{N}_m} \mathcal{I}_{mn}$$

AC optimal power flow

$$\begin{aligned}
\min_{\mathbf{p}_G,\mathbf{q}_G,\mathbf{v}} \quad & \sum_{m=1}^{N_b} C_m(P_{G_m}) \\
\text{subj. to} \quad & \mathbf{p}_G - \mathbf{p}_D + j(\mathbf{q}_G - \mathbf{q}_D) = \operatorname{diag}(\mathbf{v})(\mathbf{Y}\mathbf{v})^* \\
& |\mathrm{Re}\{\mathcal{S}_{mn}\}| \leq f_{mn}^{\max}; \; |\mathcal{S}_{mn}| \leq S_{mn}^{\max} \\
& V_m^{\min} \leq |\mathcal{V}_m| \leq V_m^{\max} \\
& \mathbf{p}_G^{\min} \leq \mathbf{p}_G \leq \mathbf{p}_G^{\max}; \;\; \mathbf{q}_G^{\min} \leq \mathbf{q}_G \leq \mathbf{q}_G^{\max}
\end{aligned}$$

- Quadratic equality constraints $\Rightarrow$ nonconvex problem
- Typical approaches rely on KKT conditions

SDP relaxation

- Canonical basis $\{\mathbf{e}_m\}_{m=1}^{N_b}$ of $\mathbb{R}^{N_b}$

$$\mathcal{V}_m \mathcal{I}_m^* = \mathbf{e}_m^H \mathbf{v} (\mathbf{Y}\mathbf{v})^H \mathbf{e}_m = \mathrm{tr}[\mathbf{e}_m^H \mathbf{v}\mathbf{v}^H \mathbf{Y}^H \mathbf{e}_m] = \mathrm{tr}[\mathbf{Y}^H \mathbf{e}_m \mathbf{e}_m^H \mathbf{v}\mathbf{v}^H]$$

- Nodal balance constraint linear in $\boxed{\mathbf{V} := \mathbf{v}\mathbf{v}^H}$

$$\boxed{P_{G_m} - P_{D_m} + j(Q_{G_m} - Q_{D_m}) = \mathrm{tr}[\mathbf{Y}^H \mathbf{e}_m \mathbf{e}_m^H \mathbf{V}]}$$

- Line flow and bus voltage constrains also linear in $\mathbf{V}$

- AC OPF with variables $\mathbf{p}_G, \mathbf{q}_G, \mathbf{V}$ and additional constraints

$$\boxed{\mathbf{V} \succeq \mathbf{0}} \qquad \boxed{\mathrm{rank}[\mathbf{V}] = 1}$$ ⇒ Nonconvex ⇒ Drop

- Works in many practical OPF instances and IEEE benchmarks
- Optimal in (three-phase) tree networks [Lam et al'12] [Dall'Anese et al'13]

X. Bai, H.Wei, K. Fujisawa, and Y.Wang, "Semidefinite programming for optimal power flow problems," *Int. J. Elect. Power Energy Syst.*, 2008.
J. Lavaei and S. Low, "Zero Duality Gap in Optimal Power Flow Problem," *IEEE TPS*, Feb. 2012.

Multi-period scheduling

- Scheduling horizon $\{1,\ldots,T\}$
- Unit commitment (UC) solved every day in many ISOs
- Binary variable: $u_m^t = 1$ if gen. m is ON at slot t, 0 otherwise
- Practical constraints for thermal generators
- Ramp-up/down $\boxed{P_{G_m}^t - P_{G_m}^{t-1} \leq \mathsf{U}_m}$ $\boxed{P_{G_m}^{t-1} - P_{G_m}^t \leq \mathsf{D}_m}$
- Minimum up/down time
  - If a generator is turned on, it must remain on for the next T_m^{up} slots

$$\boxed{u_m^t - u_m^{t-1} \leq u_m^\tau,\ \tau = t+1,\ldots,\min\{t+T_m^{\text{up}}, T\}}$$

  - If a generator is turned off, it must remain off for T_m^{down} slots

Unit commitment

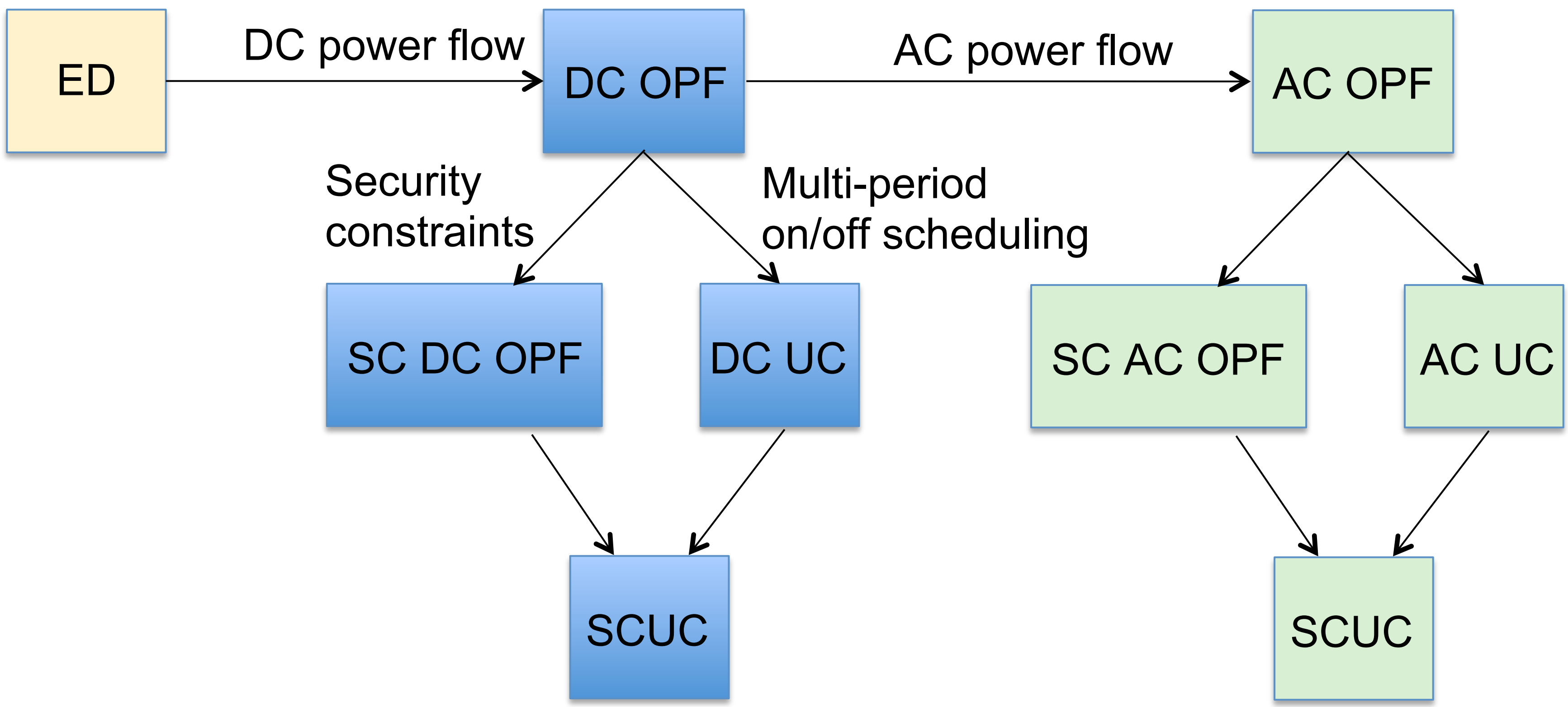
- Start-up/shut-down costs $S_m^t(\{u_m^\tau\}_{\tau=0}^t)$
  - Depend on previous on/off activity

$$\begin{aligned}
\min_{\{p_{G_m}^t, \theta_m^t, u_m^t\}_{m,t}} \quad & \sum_{t=1}^{T} \sum_{m=1}^{N_b} \left[C_m^t(P_{G_m}^t) + S_m^t(\{u_m^\tau\}_{\tau=0}^t) \right] \\
\text{subj. to} \quad & u_m^t P_{G_m}^{\min} \leq P_{G_m}^t \leq u_m^t P_{G_m}^{\max}; \; u_m^t \in \{0,1\} \\
& \text{nodal balance constraints for every } t \\
& \text{line flow limits for every } t \\
& \text{ramp-up/down limits} \\
& \text{minimum up/down time constraints}
\end{aligned}$$

Solution approaches

- UC is a mixed-integer program [Padhy'04]
  - Further complication: Coupling of on/off status across time
- Classical approach [Takriti-Birge'00]
  - Dualize nodal balance and line flow constraints
  - Lagrangian minimization can by solved by dynamic programming
  - Commitments from optimal multipliers
  - After commitments are set, solve DC OPF
- Benders decomposition [Shahidehpour et al'02]
- Duality gap vanishes as number of generators increases [Bertsekas et al'83]

Economic operations



- SCUC is solved for day-ahead market clearing in many ISOs

Demand response

Demand response

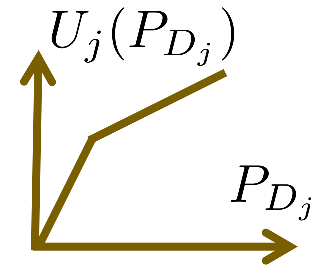
- Changes in electricity consumption by end-users in response to
  - Changes in electricity prices over time
  - Incentive payments at times of high wholesale prices or jeopardized system reliability
- Demand-side management, load control

- Incentive-based programs
  - Direct load control/interruptible loads
    - Large customers enter into contracts with utility
    - Utility takes full control of their loads
  - Demand-side bidding (DSB)

M. Albadi and E. F. El-Saadany, "Demand Response in Electricity Markets: An Overview," *IEEE PES GM*, 2007.
K. Hamilton and N. Gulhar, "Taking Demand Response to the Next Level," *IEEE PES Mag.*, May 2010.

Demand-side bidding

- Large customers adjust consumption (ED with DSB) [Christie et al'00]
- Concave utility function $U_j(P_{D_j})$: willingness-to-buy
  - Piecewise linear or quadratic



$$\min_{\{P_{G_i}\},\{P_{D_j}\}} \quad \sum_{i=1}^{N_g} C_i(P_{G_i}) - \sum_{j=1}^{N_d} U_j(P_{D_j})$$

Maximize social welfare

$$\text{subj. to} \quad \sum_{i=1}^{N_g} P_{G_i} = \sum_{j=1}^{N_d} P_{D_j}$$

Supply-demand balance

$$P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max}$$

$$P_{D_j}^{\min} \leq P_{D_j} \leq P_{D_j}^{\max}$$

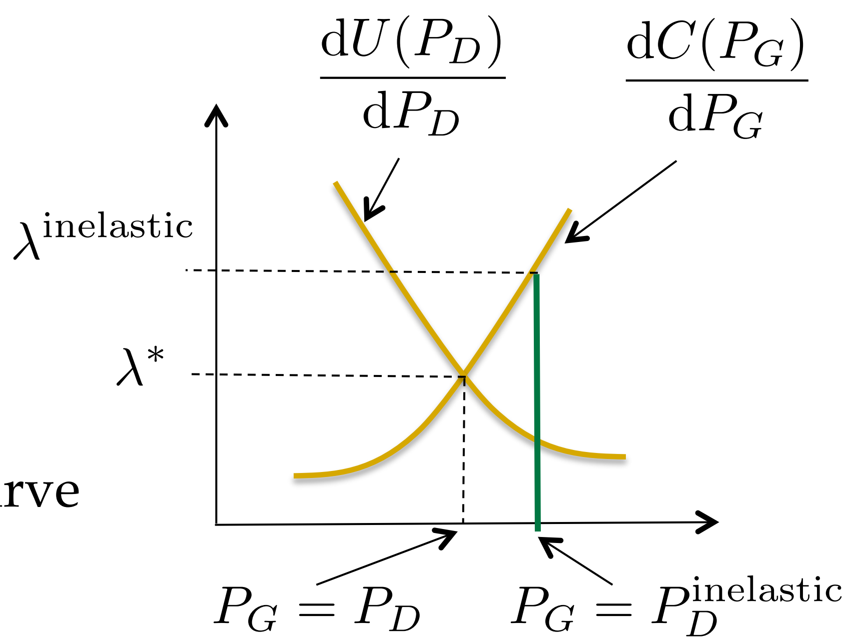
DSB can reduce marginal price

- Consider one generator and one load
- Lagrangian function

$$L(P_G, P_D, \lambda) = C(P_G) - U(P_D) - \lambda(P_G - P_D)$$

- Marginal price

$$\boxed{\lambda^* = \frac{\mathrm{d}C(P_G)}{\mathrm{d}P_G} = \frac{\mathrm{d}U(P_D)}{\mathrm{d}P_D}}$$



- DSB → elastic demand
- Slide from right to left on $\mathrm{d}C/\mathrm{d}P_G$ curve
- DSB tends to decrease marginal price

Price-based programs

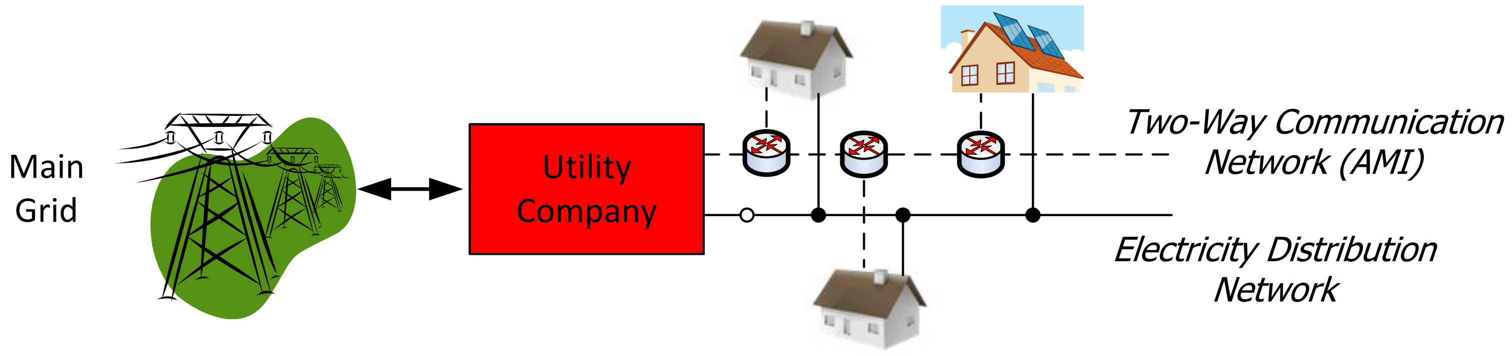
- Time of use (TOU)
  - Prices vary throughout the day, e.g., peak and off-peak
  - TOU rates announced long time ahead ➡ not dynamic

- Critical peak pricing (CPP)/extreme day pricing (EDP)
  - Higher prices on top of TOU for certain days
  - Called during emergencies/high wholesale prices
  - Effect may be announced a day in advance

- Real-time pricing (RTP)
  - Typically hourly prices reflecting wholesale prices
  - Day-ahead or hour-ahead

Advanced metering infrastructure

- Real-time pricing enabled by the AMI
- Two-way communication network
- Utility $\longleftrightarrow$ smart meters at end-user premises
- Smart meter measures power consumption with frequency e.g., 15min
- "Prices to devices" $\longrightarrow$ Energy consumption scheduling



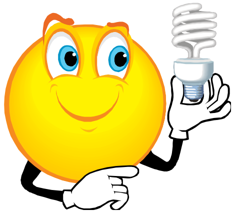
Adjustable power appliances

- Scheduling horizon $\{1, \ldots, T\}$
- Power consumption p_a^t of appliance a
- Concave utility function $U_a(\mathbf{p}_a)$

- Elastic loads, e.g., lights

$$U_a(\mathbf{p}_a) = \sum_{t=1}^{T} U_a^t(p_a^t)$$

$$p_a^{\min} \le p_a^t \le p_a^{\max}$$



- Energy loads, e.g., PHEV charging

$$U_a(\mathbf{p}_a) = U_a\left(\sum_{t=1}^{T} p_a^t\right)$$

$$E_a^{\min} \le \sum_{t=1}^{T} p_a^t \le E_a^{\max}$$

$$p_a^{\min} \le p_a^t \le p_a^{\max}$$

L. Chen, N. Li, L. Jiang, and S. Low, "Optimal Demand Response: Problem Formulation and Deterministic Case," in *Control and Optimization Methods for Smart Grids*, Springer, 2012.

Additional types of appliances

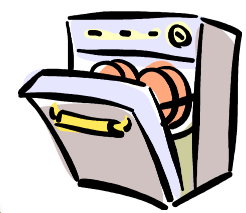
- Thermostatically controlled loads, e.g., AC

$$\vartheta^t = (1-\gamma)\vartheta^{t-1} - \gamma\vartheta^{\mathrm{amb},t} - \eta p_a^t$$

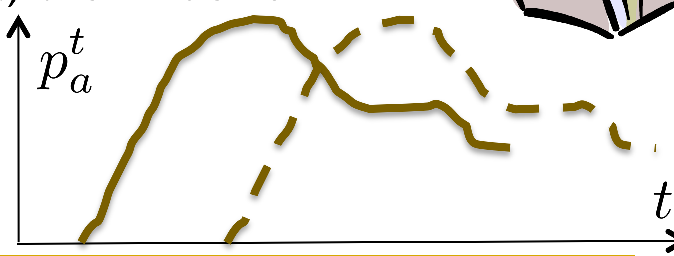
  - Room temperature ϑ^t; ambient (external) $\vartheta^{\mathrm{amb},t}$
  - Preferred temperature $\vartheta^{\min} \leq \vartheta^t \leq \vartheta^{\max}$

- Interruptible loads: If on, they consume nonzero power

$$p_a^t = 0 \quad \text{or} \quad p_a^{\min} \leq p_a^t \leq p_a^{\max}$$



- Noninterruptible and deferrable loads, e.g., dishwasher
  - Fixed load profile, can be shifted
  - Integer constraints



Energy consumption scheduling

- Cost of power for end-user: typically (piecewise) linear
- Tradeoff cost with utility

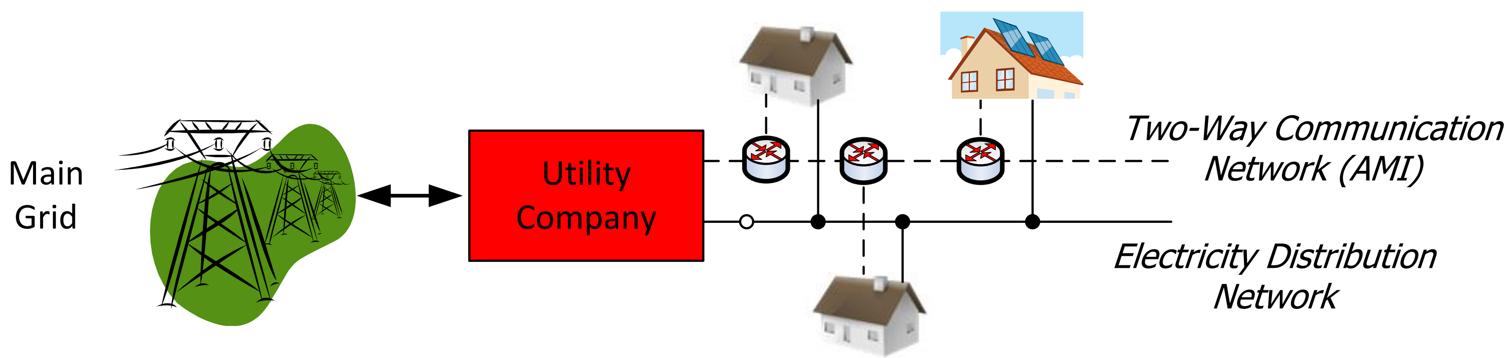
$$
\begin{aligned}
\min_{\{\mathbf{p}_a\}} \quad & \sum_{t=1}^{T} c^t \sum_{a\in\mathcal{A}} p_a^t - \sum_{a\in\mathcal{A}} U_a(\mathbf{p}_a) \\
\text{subj. to} \quad & \mathbf{p}_a \in \mathcal{P}_a, a \in \mathcal{A}
\end{aligned}
$$

- Convexity depends on $\mathcal{P}_a$
- Solved by the smart meter with processor

- With interruptible appliances: Vanishing duality gap when horizon length increases [Gatsis-GG'11]
- Price uncertainty: Prediction methods, robust/stochastic optimization [Mohsenian-Rad,Leon-Garcia'10], [Conejo et al'10], [Kim-Poor'11], [Kim-GG'13]

Cooperative DR

- Set of users $\{1, \ldots, R\}$ served by the same utility company
- Set of smart appliances $\mathcal{A}_r$ per user r
- Power consumption p_{ra}^t
- End-user utility function $U_{ra}(\mathbf{p}_{ra})$
- Cost of power procurement for utility company $C^t\left(\sum_{r=1}^{R}\sum_{a\in\mathcal{A}_r} p_{ra}^t\right)$



Social welfare maximization

$$\min_{\{\mathbf{p}_{ra}\}} \quad \sum_{t=1}^{T} C^t \left(\sum_{r=1}^{R} \sum_{a \in \mathcal{A}_r} p_{ra}^t \right) - \sum_{r=1}^{R} \sum_{a \in \mathcal{A}_r} U_{ra}(\mathbf{p}_{ra})$$

$$\text{subj. to} \quad \mathbf{p}_{ra} \in \mathcal{P}_{ra},\ a \in \mathcal{A}_r,\ r = 1 \ldots, R$$

- **Motivation:** Reduce peak demand respecting users' preferences

- Convexity depends on $\mathcal{P}_{ra}$
- Challenges
  - Distributed scheduling over AMI
  - Privacy issues

Solution approaches

- Gradient projection, block coordinate descent, dual decomposition, Vickrey-Clark-Groves mechanism
  [Chen et al'12], [Mohsenian-Rad et al'10], [Papavasiliou et al'10], [Samadi et al'11], [Gatsis-GG'12]

- **Dual decomposition:** Introduce variable s^t for total provided power

$$\boxed{\sum_{r=1}^{R}\sum_{a\in\mathcal{A}_r} p_{ra}^t \leq s^t}$$

Supply-demand balance

  - Lagrange multiplier λ^t for supply-demand balance
- **Upshot**
  - Separate subproblems for utility and smart meters
  - Privacy respect

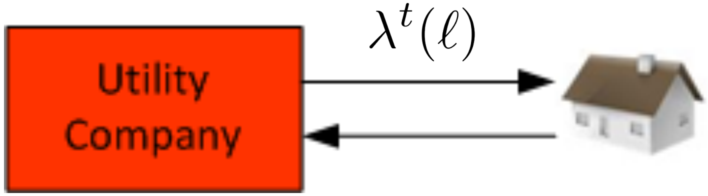
Distributed algorithm

- **Schedule update:** At the utility company and smart meters

$$\min_{0 \le s^t \le s^{\max}} \{C^t(s^t) - \lambda^t(\ell) s^t\}$$

prices

$\lambda^t(\ell)$



$$\min_{\mathbf{p}_{ra} \in \mathcal{P}_{ra}} \left\{ \sum_{t=1}^{T} \lambda^t(\ell) p_{ra}^t - U_{ra}(\mathbf{p}_{ra}) \right\}$$

$\sum_{a \in \mathcal{A}_r} p_{ra}^t(\ell)$

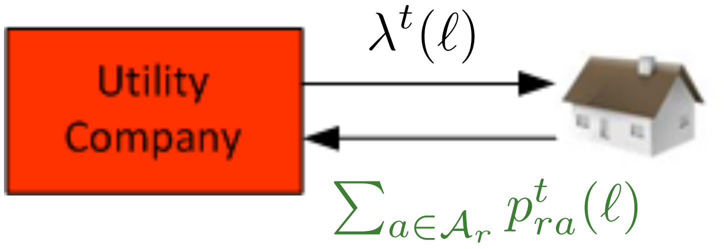
total hourly consumption

- **Multiplier update:** At utility company

$$\lambda^t(\ell+1) = \left[\lambda^t(\ell) + \beta \left(\sum_{r=1}^{R} \sum_{a \in \mathcal{A}_r} p_{ra}^t(\ell) - s^t(\ell) \right) \right]^+$$

Lost AMI messages

- Messages in both ways may be lost
  - Not transmitted, due to failure
  - Not received, due to noise
  - Cyber-attacks



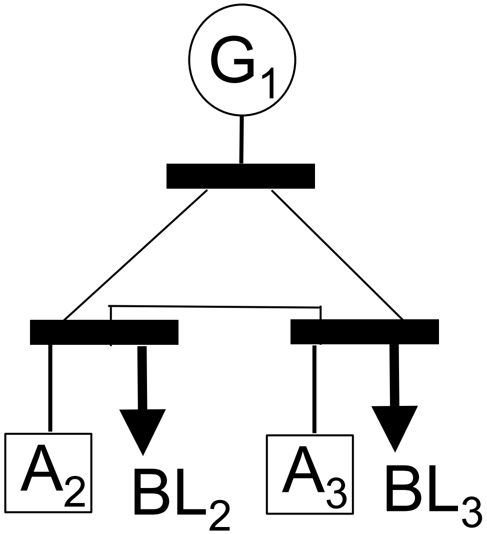
- Use the latest message available
- Convergence established for different lost-message patterns
  - Asynchronous subgradient method

- **Benefit:** Resilience to communication network outages

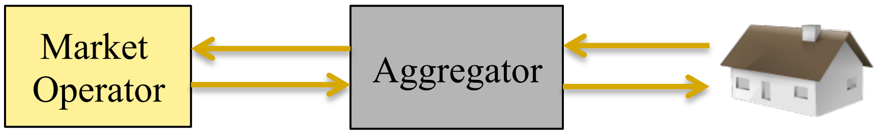
N. Gatsis and G. B. Giannakis, "Residential load control: Distributed scheduling and convergence with lost AMI messages," *IEEE Trans. Smart Grid*, June 2012.

Scheduling with DR aggregators

- **Goal:** DR from small-scale end-users into day-ahead scheduling
- **Challenges**
  - User preferences are private
  - Large-scale problem



- **Approach:** Decomposition algorithms
  - Subproblems for market operator and aggregators



- **Outcome**: Scalable distributed solution

N. Gatsis and G. B. Giannakis, "Decomposition algorithms for market clearing with large-scale demand response," *IEEE Trans. Smart Grid*, 2013.

Y. Zhang, N. Gatsis, and G. B. Giannakis, "Disaggregated bundle methods for distributed market clearing in power networks," in *Proc. IEEE Global Conf. Signal and Information Process.*, Dec. 2013.

Plug-in (Hybrid) Electric Vehicles

Plug-in electric vehicles

- PEVs feature batteries that can be plugged in
  - at end-user premises
  - at charging stations

- Hybrid: Also consume fuel (PHEV)

- Benefits of high P(H)EV penetration
  - environmental: reduce carbon emissions
  - economic: reduce dependency on oil

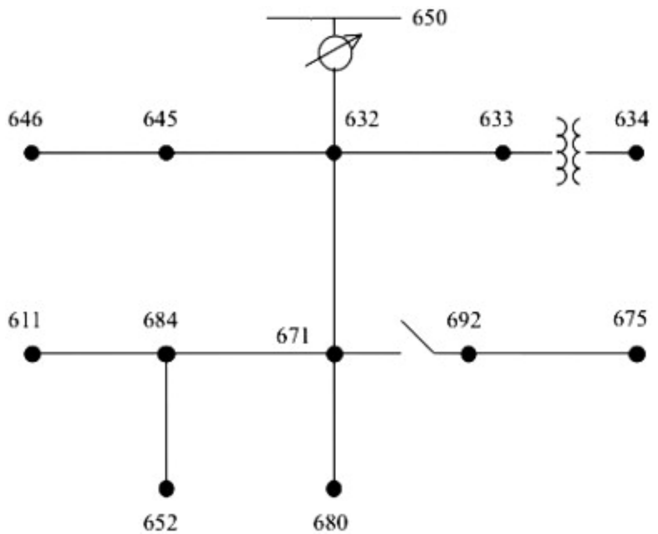
Opportunities and challenges

- PHEV battery charging is a controllable load

- Charging coordination required to avoid
  - overloading of distribution networks [Clement-Nyns et al'10]
  - accentuating (or creating new) peaks

- Aggregator provides charging services to end-users [Wu et al'12]
  - Can offer reserves [Sortomme et al'12], [Bessa et al'12]
- Vehicle-to-grid (V2G) [Kempton-Tomic'05]
  - Unidirectional V2G: Modulation of charging rate ⇨ system reserves
  - Bidirectional V2G: Discharge batteries to feed power in the grid
- Mitigation of renewable energy intermittency
- Spatiotemporal prediction of demand [Lojowska et al'12], [Bae-Kwasinski'12]

Load factor



IEEE 14-node feeder

- Power provided at the substation at slot t

  $s^t = \text{base load} + \text{PHEV charging} + \text{losses}$

- Load factor (LF) $0 \leq \text{LF} \leq 1$

$$\text{LF} = \frac{\sum_{t=1}^{T} s^t}{\max_{t=1,\ldots,T} s^t \cdot T}$$

- LF closer to 1 ⇒ Total power consumption smoother
  - Lower peak, higher valley

Charging coordination

- Fleet of vehicles $n = 1, \ldots, N$
- Charging rate r_n^t at slot t
  - Vehicle plugged in at different slots $\Rightarrow$ $r_n^{t,\min} \leq r_n^t \leq r_n^{t,\max}$
- Total power (ignoring losses)

$$s^t = L^t + \sum_{n=1}^{N} r_n^t$$

- Charging coordination

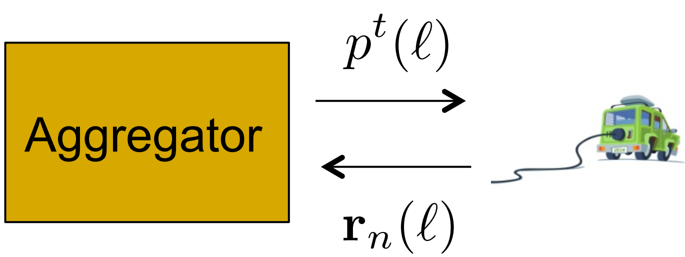
$$\begin{aligned} \min_{\{\mathbf{r}_n\}} \quad & \sum_{t=1}^{T} C\left(L^t + \sum_{n=1}^{N} r_n^t\right) \\ \text{subj. to} \quad & \mathbf{r}_n^{\min} \leq \mathbf{r}_n \leq \mathbf{r}_n^{\max} \\ & \sum_{t=1}^{T} r_n^t = E_n \end{aligned}$$

Distributed charging

- Quadratic cost $C(s^t) = (s^t)^2$
  - Under certain conditions, $\boxed{\max \mathrm{LF} \Leftrightarrow \min (s^t)^2}$ [Sortomme et al'11]

- Charging coordination problem similar to cooperative DR
- Pricing signal $p^t(\ell)$; initialization $p^t(1) = L^t$
- Schedule update $\mathbf{r}_n(\ell)$ at smart charger
  - Approximation of objective $C(s^t) = (s^t)^2$
- Price update at aggregator

$$p^t(\ell+1) = L^t + \sum_{n=1}^{N} r_n^t(\ell)$$

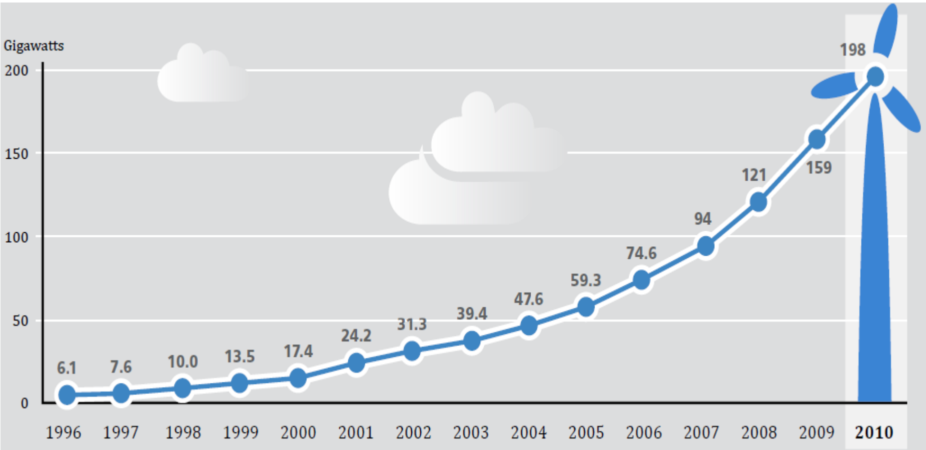


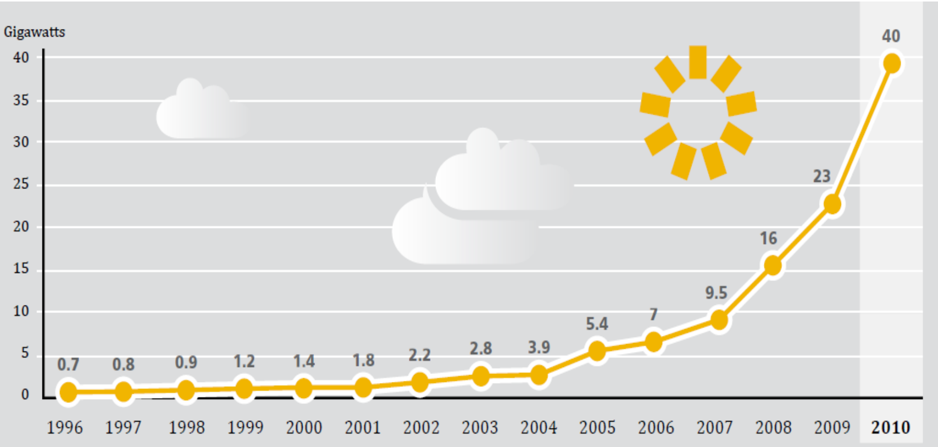
L. Gan, U. Topcu, and S. Low, "Optimal decentralized protocol for electric vehicle charging," in *Proc. Control and Decision Conf.*, Dec. 2011.

Renewables

Renewable energy

- Milestones
  - US DoE: 20% of demand covered by wind energy by 2030
  - Denmark: 100% renewable energy by 2050



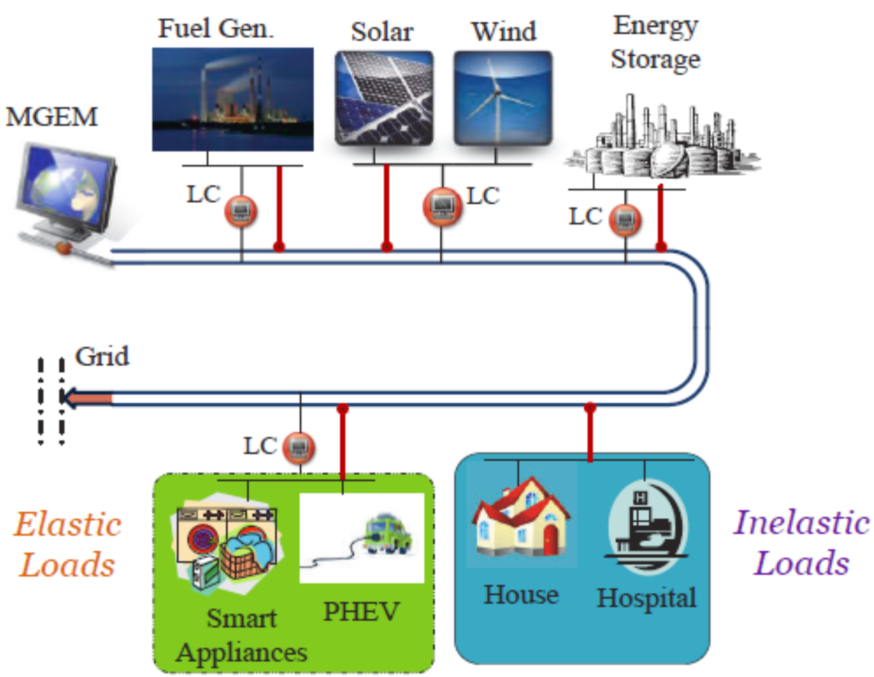


- Renewable energy production classification
  - >1 MW: utility/wholesale scale
  - 10-100 kW: microgrid scale
  - <10 kW: residential scale

Picture source: REN21, "Renewables 2011 global status report," Paris, 2011, [Online]. http://www.ren21.net/Portals/0/documents/Resources/110929_GSR2011_FINAL.pdf

Microgrids

- Small-footprint power systems
  - Distribution networks, campuses, isolated areas, military facilities
  - Distributed generation (renewable and conventional)
  - Distributed storage and controllable loads



- Why microgrids?
  - Generation closer to demand
  - Bypass transmission congestion
  - Reduced bulk generation
  - Islanded mode in disasters

LC = Local controller
MGEM = Microgrid energy manager

Challenging energy management

$$\min_{\{P_{G_m}\}} \sum_{m=1}^{N_g} C_m(P_{G_m})$$
$$\text{subj. to} \sum_{m=1}^{N_g} P_{G_m} = L$$

$$\min_{\{P_{G_m}\}} \sum_{m=1}^{N_g} C_m(P_{G_m})$$
$$\text{subj. to} \sum_{m=1}^{N_g} P_{G_m} + W = L$$

Uncertain

- Renewable energy sources (RES) are nondispatchable
- Optimization under uncertainty
  - Forecast-based; chance constraints; robust/stochastic optimization

Forecast-based methods

- RES power output forecast $\hat{W}$

$$\min_{\{P_{G_m}\}} \sum_{m=1}^{N_g} C_m(P_{G_m})$$
$$\text{subj. to} \sum_{m=1}^{N_g} P_{G_m} + \hat{W} = L$$

- Model predictive control for multi-period scheduling [Ilic et al'11]
  - Multi-period forecast; scheduling; dispatch first period only
  - Move the horizon and repeat

Risk-constrained ED

- Allow for insufficient generation at low risk level

$$\min_{\{P_{G_m}^t\}} \quad \sum_{t=1}^{T} \sum_{m=1}^{N_g} C_m(P_{G_m}^t)$$

$$\text{subj. to} \quad \text{Prob}\left[\sum_{m=1}^{N_g} P_{G_m}^t + \sum_{i=1}^{N_w} W_i^t - P_D^t \geq 0 \, (t = 1, \ldots, T) \right] \geq 1 - \alpha$$

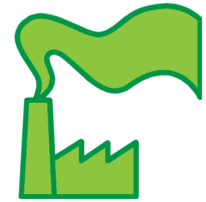
- Chance constraints intractable due to spatiotemporal correlation

- Convex approximations: Gaussian modeling, scenario approximation

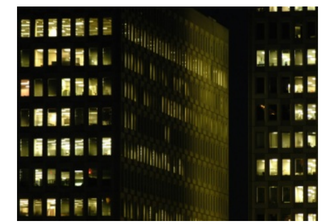
  [Liu'10], [Varaiya-Wu-Bialek'11], [Zhang-Gatsis-GG'12], [Zhang-Gatsis-Kekatos-GG'13]

Microgrid components

- Distributed generation units $P_{G_m}^t$
  - Capacity and ramp limits



- Elastic loads with concave utility $U_j(P_{D_j}^t)$



- Energy loads $\sum_{t=1}^{T} P_{E_k}^t = E_k$

- Distributed storage units
  - State of charge $B_n^t = B_n^{t-1} + P_{B_n}^t$
  - Capacity and charge rate limits

$$0 \leq B_n^t \leq B_n^{\max}$$

$$P_{B_n}^{\min} \leq P_{B_n}^t \leq P_{B_n}^{\max}$$

Renewable energy uncertainty

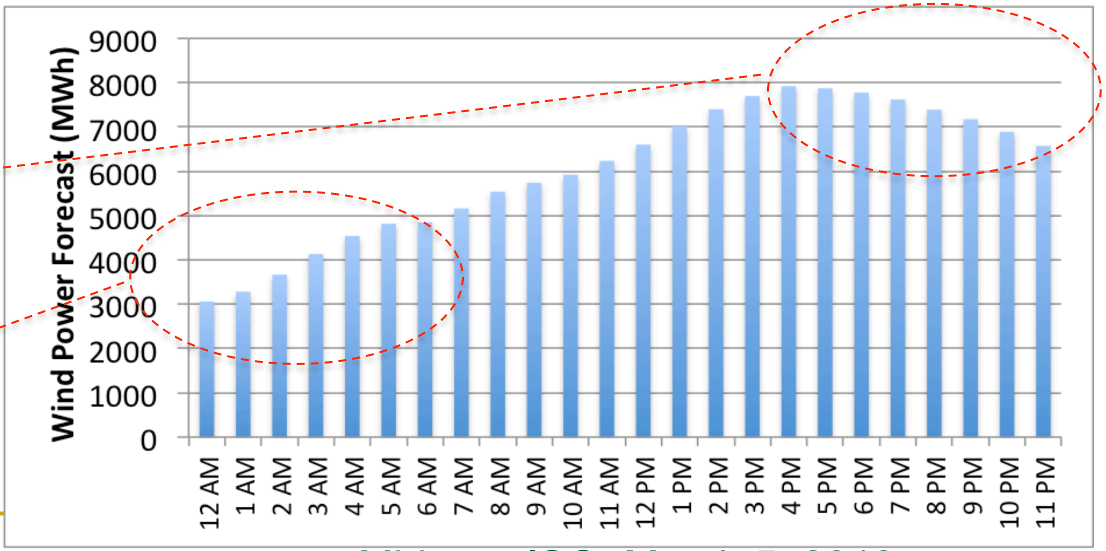
- Polyhedral uncertainty set for RES outputs W_i^t
- Split horizon $\mathcal{T} = \{1, \ldots, T\}$ into H disjoint sub-horizons

$$\mathcal{W} := \left\{ \mathbf{w} \,\middle|\, \underline{W}_i^t \leq W_i^t \leq \bar{W}_i^t, W_h^{\min} \leq \sum_{t \in \mathcal{T}_h} \sum_{i=1}^{N_w} W_i^t \leq W_h^{\max}, \bigcup_{h=1}^{H} \mathcal{T}_h = \mathcal{T} \right\}$$

  - Deterministic bounds from e.g., historical data

Higher production
in the evenings

Lower production
late night – early morning



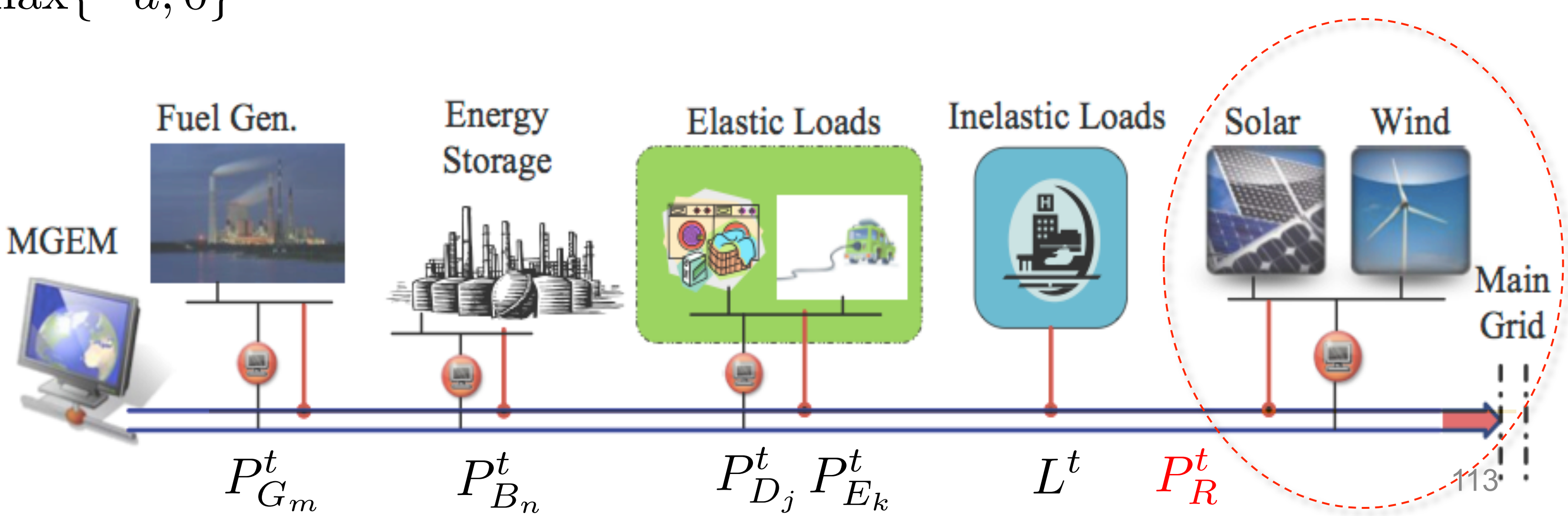
Midwest ISO, March 5, 2013

Transaction with the main grid

- Committed renewable energy P_R^t
- Worst-case transaction cost

$$G(\{P_R^t\}_{t=1}^T) := \max_{\mathbf{w}\in\mathcal{W}} \sum_{t=1}^{T} \left(\underset{\text{Import price}}{\alpha^t} \underbrace{\left[P_R^t - \sum_{i=1}^{N_w} W_i^t \right]^+}_{\text{Shortage to buy}} - \underset{\text{Export price}}{\beta^t} \underbrace{\left[P_R^t - \sum_{i=1}^{N_w} W_i^t \right]^-}_{\text{Surplus to sell}} \right)$$

$$[a]^+ = \max\{a, 0\}$$
$$[a]^- = \max\{-a, 0\}$$



Robust ED with benefits

$$\min_{\substack{\{\mathbf{p}_G,\mathbf{p}_B,\mathbf{p}_R,\\ \mathbf{p}_D,\mathbf{p}_E\}}} \quad \sum_{t=1}^{T}\sum_{m=1}^{N_g} C_m(P_{G_m}^t) - \sum_{t=1}^{T}\sum_{j=1}^{N_d} U_j(P_{D_j}^t) + G(\{P_R^t\}_{t=1}^T)$$

$$\text{subj. to} \quad \text{generation, load, storage contraints}$$

$$\sum_{m=1}^{N_g} P_{G_m}^t - \sum_{n=1}^{N_s} P_{B_n}^t + P_R^t = \sum_{j=1}^{N_d} P_{D_j}^t + \sum_{k=1}^{N_e} P_{E_k}^t + L^t$$

$$t = 1, \ldots, T$$

Supply-demand balance

- Computational challenge: Maximization over uncertainty set
- Unit commitment, transmission network, reserves
  [Zhao-Zheng'12], [Bertsimas et al'13]

Y. Zhang, N. Gatsis, and G. B. Giannakis, "Robust energy management with high-penetration renewables," *IEEE Trans. Sustainable Energy*, 2013.

Stochastic programming

- Two-stage approach
  - First stage: Unit commitments in a day-ahead fashion
  - Second stage: Generation dispatch when uncertainty is revealed

- Uncertainty is RES output here
- Postulate plausible scenarios $s = 1, \ldots, S$ of RES output $\{W_i^t(s)\}_{i,t}$
- Scenario s has probability $\pi(s)$

- First-stage decision variables: Commitments $\mathbf{u}$
- Second-stage decision variables: Generation dispatch $\mathbf{p}_G(\mathbf{u}, s)$; $\boldsymbol{\theta}(\mathbf{u}, s)$
  - Second-stage variables depend on first-stage decisions and scenario

Second-stage problem

- Consider a single period
- For fixed $\mathbf{u}$ and $\mathbf{w}(k)$, solve DC OPF

$$
\begin{aligned}
\mathcal{Q}(\mathbf{u}, s) = \min_{\mathbf{p}_G(\mathbf{u},s),\, \boldsymbol{\theta}(\mathbf{u},s)} \quad & \sum_{m=1}^{N_b} C_m(P_{G_m}(\mathbf{u}, s)) \\
\text{subj. to} \quad & \mathbf{p}_G(\mathbf{u}, s) - \mathbf{p}_D + \mathbf{w}(s) = \mathbf{B}\boldsymbol{\theta}(\mathbf{u}, s) \\
& |\mathbf{F}\boldsymbol{\theta}(\mathbf{u}, s)| \leq \mathbf{f}^{\max} \\
& u_m P_{G_m}^{\min} \leq P_{G_m}(\mathbf{u}, s) \leq u_m P_{G_m}^{\max}
\end{aligned}
$$

- Convex problem
- Multi-period extension includes ramp constraints

First-stage problem

- Decide unit commitments
  - Start-up/shut-down costs and expected cost of dispatch

$$\begin{aligned} \min_{\mathbf{u}} \quad & \sum_{t=1}^{T} \sum_{m=1}^{N_b} S_m^t(\{u_m^t\}_{\tau=0}^{t}) + \sum_{s=1}^{S} \pi(s) \mathcal{Q}(\mathbf{u}, s) \\ \text{subj. to} \quad & u_m^t \in \{0,1\} \\ & \text{minimum up/down time constraints} \end{aligned}$$

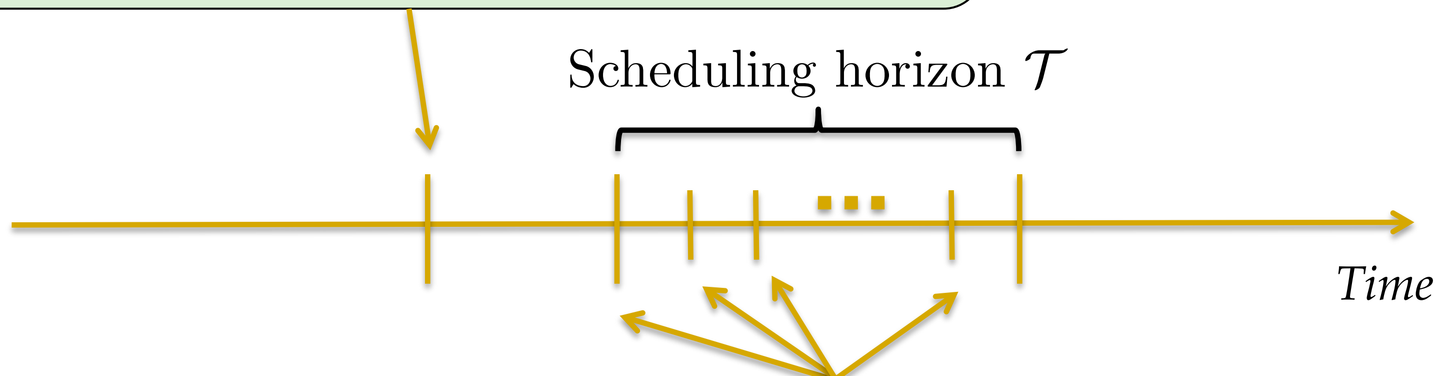
- First stage includes second-stage decisions in $\mathcal{Q}(\mathbf{u}, s)$
- First stage decides commitments ahead of time
- At the beginning of the horizon, $\mathbf{w}$ becomes known through forecast
- Solve second-stage problem for generation dispatch
- Extensions: DSB, reserves, demand uncertainties [Bouffard-Galiana'08]

Stochastic optim. for microgrids

- Two-stage stochastic programming for energy planning in microgrids

➢ First-stage decisions: Ahead of the horizon

1. Generation setpoints $P^t_{G_m}$
2. Load setpoints $P^t_{D_j}$



➢ Second-stage decisions: Real-time

1. Load adjustments A^t_j --- negative load adjustment penalized with price δ^t_j
2. Transaction with the main grid --- energy import/export at prices α^t, β^t

➢ Scenarios $s = 1, \ldots, S$ for RES output $\mathbf{w}^t(s)$

The two stages

- Second stage: Convexity ensured if $\alpha^t \geq \beta^t$ for all t

$$\mathcal{Q}^t(\mathbf{p}_G^t, \mathbf{p}_D^t, \mathbf{w}^t) = \min_{\mathbf{a}^t, \mathbf{p}_R^t} \underbrace{\sum_{j=1}^{N_d} \delta_j^t [A_j^t]^-}_{\text{Load adjustment cost}} + \underbrace{\alpha^t \left[P_R^t - \sum_{i=1}^{N_w} W_i^t \right]^+ - \beta^t \left[P_R^t - \sum_{i=1}^{N_w} W_i^t \right]^-}_{\text{Transaction cost}}$$

$$\text{subj. to} \quad \sum_{m=1}^{N_g} P_{G_m}^t + P_R^t = \sum_{j=1}^{N_d} (P_{D_j}^t + A_j^t) + L^t$$

$$P_{D_j}^{\min} \leq P_{D_j}^t + A_j^t \leq P_{D_j}^{\max}$$

- First stage is convex as long as second stage is convex

$$\min_{\mathbf{p}_G, \mathbf{p}_D} \sum_{t=1}^{T} \sum_{m=1}^{N_g} C_m(P_{G_m}^t) - \sum_{t=1}^{T} \sum_{j=1}^{N_d} U_j(P_{D_j}^t) + \sum_{s=1}^{S} \pi(s) \sum_{t=1}^{T} \mathcal{Q}^t(\mathbf{p}_G^t, \mathbf{p}_D^t, \mathbf{w}^t(s))$$

$$\text{subj. to} \quad \text{generation and load constraints}$$

G. Martinez, N. Gatsis, and G. B. Giannakis, "Stochastic programming for energy planning in microgrids with renewables," in *Proc. IEEE Workshop Comput. Advances in Multi-Sensor Adaptive Process.*, Dec. 2013.

Robust vs. stochastic optimization

	Robust	Stochastic
Approach	Worst-case (conservative)	On the average
Modeling requirements	Uncertainty set, typically polyhedral	Set of scenarios and corresponding probabilities
Main computational challenge	Maximization over uncertainty set	Large number of scenarios required

- Solution approaches entail decomposition methods

Open issues

Big Data grid informatics

- Energy analytics: statistical learning
- Data deluge at different system levels
- Forecasting of loads, RES, prices, consumer patterns, PEV charging

	Large-scale systems	**Microgrids**	**Smart Buildings**
Measurement data	SCADA, PMUs	Voltage and power across distribution system	Power meter readings, ambient condition sensors
Needs and objectives	Situational awareness, reliability, cyber-security, economic operation	Self-sustainability, operation in connected or islanded modes	Energy conservation, anomalous consumption pattern detection

Renewables and PEVs

- Renewable energy enabled consumers
  - Increased demand response capabilities

- Aggregator participation in markets
  - Increased uncertainty

- Predicting consumer patterns and response
- Dynamic learning of consumer elasticity in PEV charging

- Interconnections: from transmission systems to microgrids
- Leverage SP expertise for resource management

Thank you!