REAL-TIME PRICE FORECAST WITH BIG DATA

A STATE SPACE APPROACH

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August 7, 2013

CERTS Review

DATA QUALITY AND ITS EFFECTS ON MARKET OPERATIONS

DENY OF SERVICE ATTACK ON REAL-TIME ELECTRICITY MARKET
COVER UP PROTECTION AGAINST TOPOLOGY ATTACK

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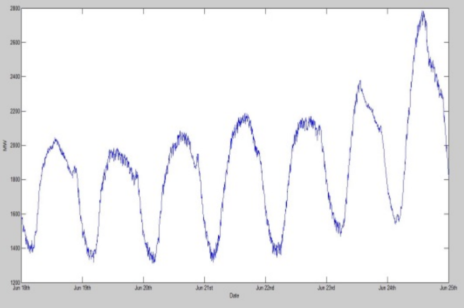
Project overview

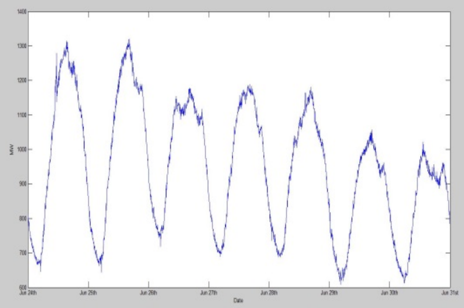
- Objectives
  - Accurate short-term probabilistic forecasting of real-time LMP.
  - Incorporate real-time measurements (e.g. SCADA/PMU).
  - Scalable computation techniques.
- Summary of results
  - A real-time LMP model with forecasting and measurement uncertainties.
  - A Markov chain abstraction of real-time LMP computation.
  - Monte Carlo sampling techniques.
  - Preliminary simulations.

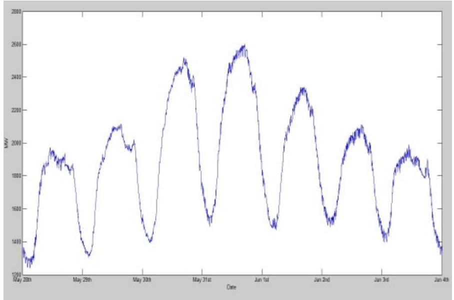
Outline

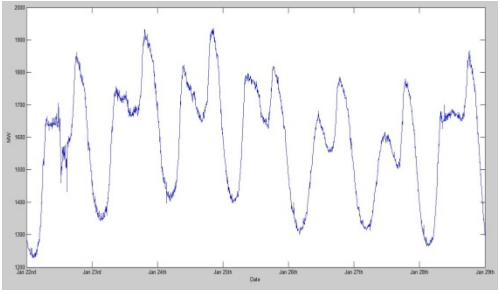
- Motivation
  - Load and real-time LMP as random processes
  - Benchmark techniques
  - Comments on the state of the art.
- Probabilistic forecasting of real-time LMP
- Simulation studies
- Summary and future work

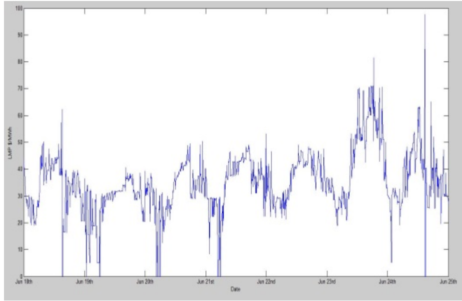
Sample paths of load and LMP

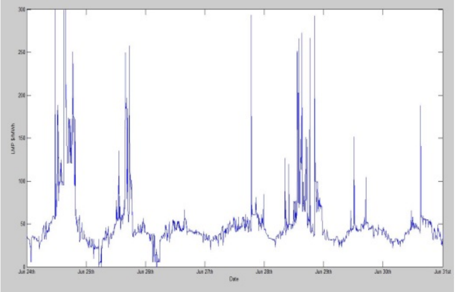


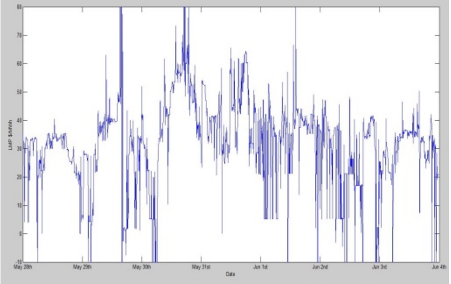


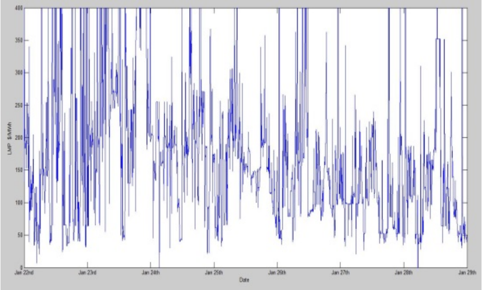




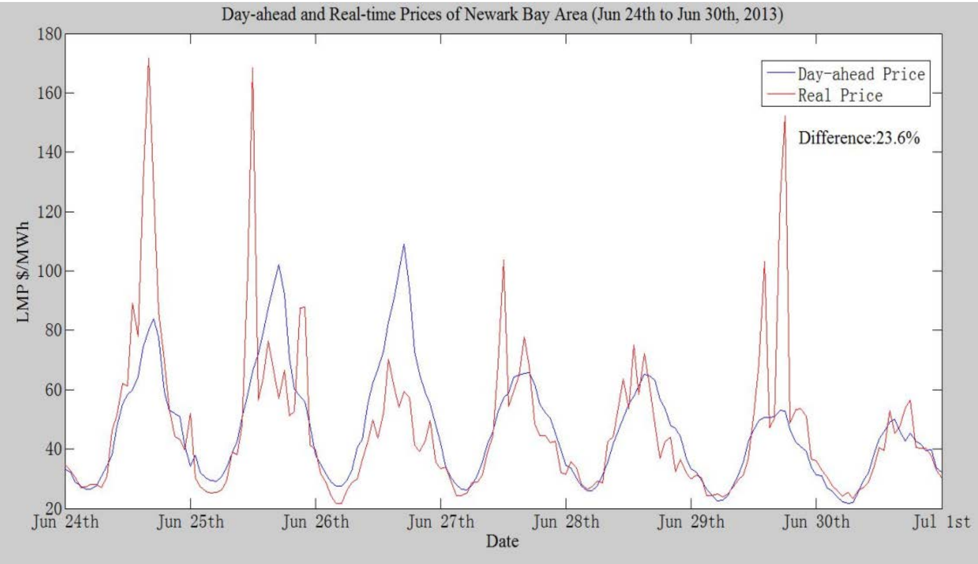


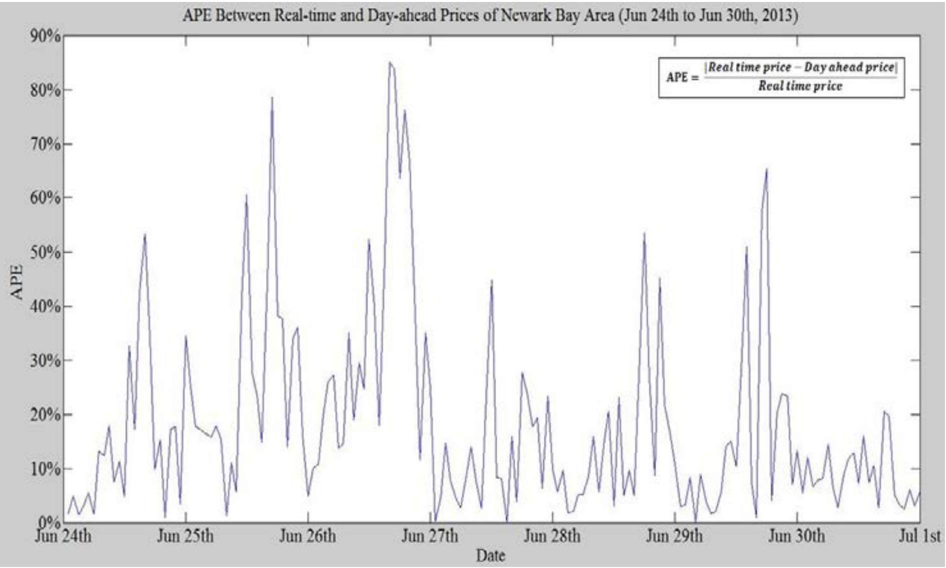






Day ahead vs. real-time

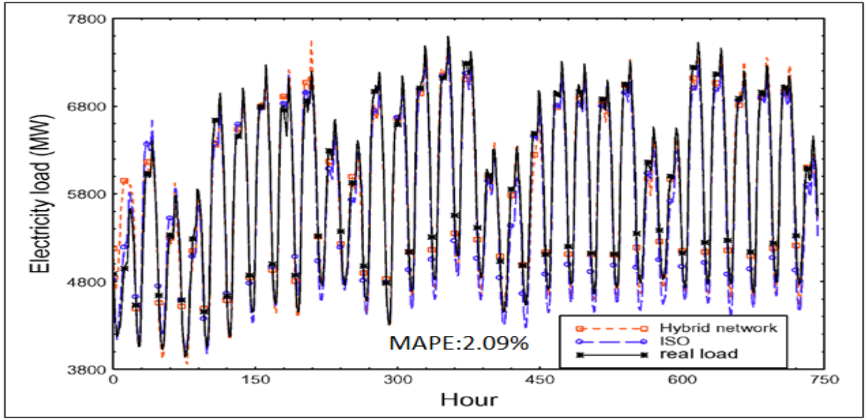


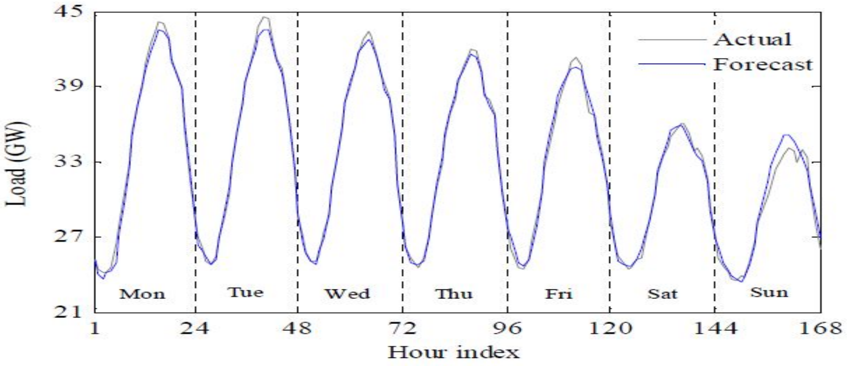


Benchmark techniques

- Time series
  - ARMA, ARIMA, ARMAX, GARCH
- Machine learning
  - Neural networks, support vector machines (SVM)
- Hybrid techniques
  - Jump (switching) models

Load forecasting

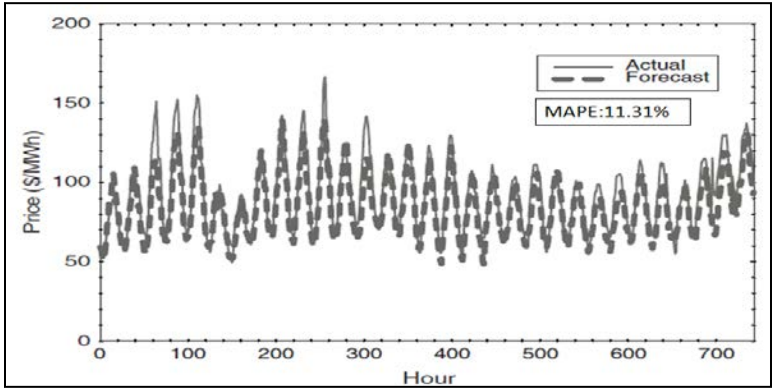


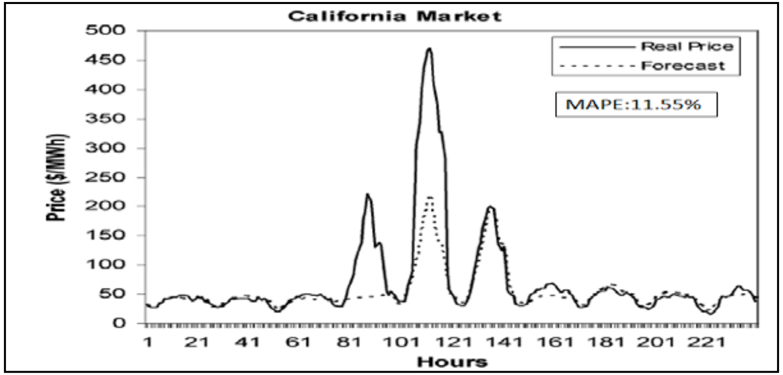


Forecasting Method	MAPE
ANN [1] ANN [2]	1.46% 1.24%
SVM [3]	2.09%

[1] P. Mandal, T. Senjyu, N. Urasaki, and T. Funabashi, "A neural network based several-hour-ahead electric load forecasting using similar days approach," Int. Journal. of Electric Power and Energy System, vol. 28, no. 6, pp. 367–373, July 2006.
[2] P. Mandal, T. Senjyu, N. Urasaki, and T. Funabashi, "Short-Term Price Forecasting for Competitive Electricity Market," Power Symposium, 2006. NAPS 2006. 38th North.
[3] S. Fan, C. Mao and L. Chen, "Next-day electricity-price forecasting using a hybrid network," IET Generation, Transmission & Distribution, Volume 1, Issue 1, January, 2007.

Day ahead LMP forecasting

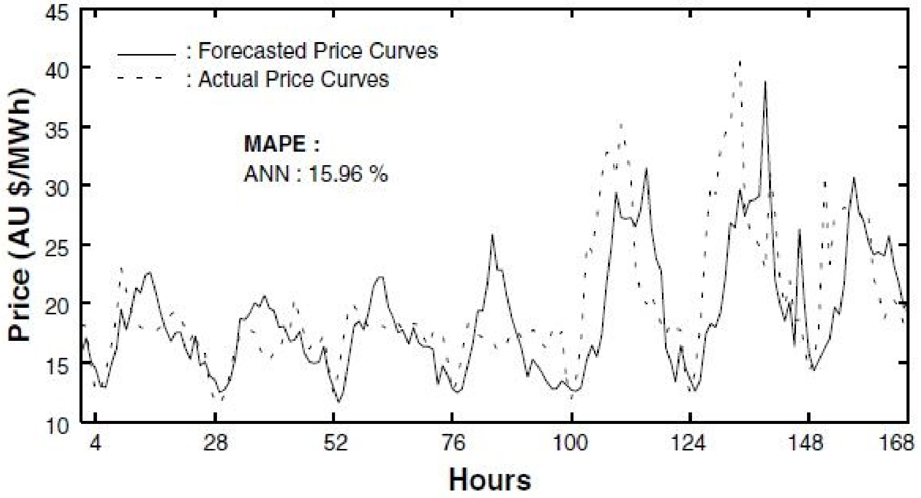




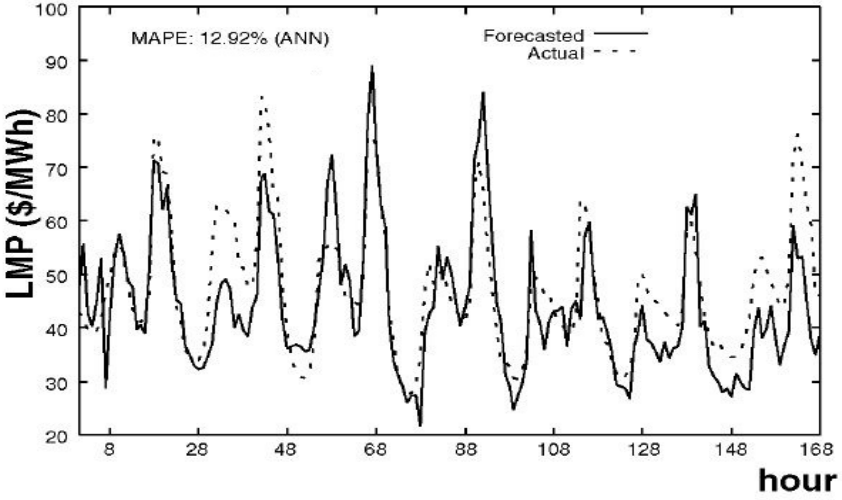
Forecasting Method	MAPE
ANN [1] ANN [2] ANN [4]	15.96% 12.92% 8.67%
SVM [3]	11.31%
GARCH [5]	11.55%
ARMAX [6]	9.01%

[4] P. Mandal, T. Senjyu, N. Urasaki, and T. Funabashi, “A neural network based several-hour-ahead electric load forecasting using similar days approach,” Int. Journal. of Electric Power and Energy System, vol. 28, no. 6, pp. 367–373, July 2006.
[5] R. Garcia, J. Contreras, “A GARCH Forecasting Model to Predict Day-Ahead Electricity Prices,” Int. Journal of Electric Power and Energy System, vol. 20, no. 2, MAY 2005.
[6] J. Zhang, C. Yu, G. Hou, “Application of Chaotic Particle Swarm Optimization in the Short-term Electricity Price Forecasting,” Int. Journal of Electric Power and Energy System, vol. 28, no. 6, pp. 367–373, July 2006.

Real-time LMP forecasting



Actual and forecast six-hours-ahead electricity price for Victorian electricity market (Nov 1st to 7th, 2003).



Actual and forecast six-hours-ahead electricity price for PJM market (Jan 8th to 14th, 2006).

[4] F. Sarafraz, H. Ghasemi, H. Monsef, "Locational Marginal Price Forecasting by Locally
Linear Neuro-Fuzzy Model," EEEIC, 2011 10th, Rome

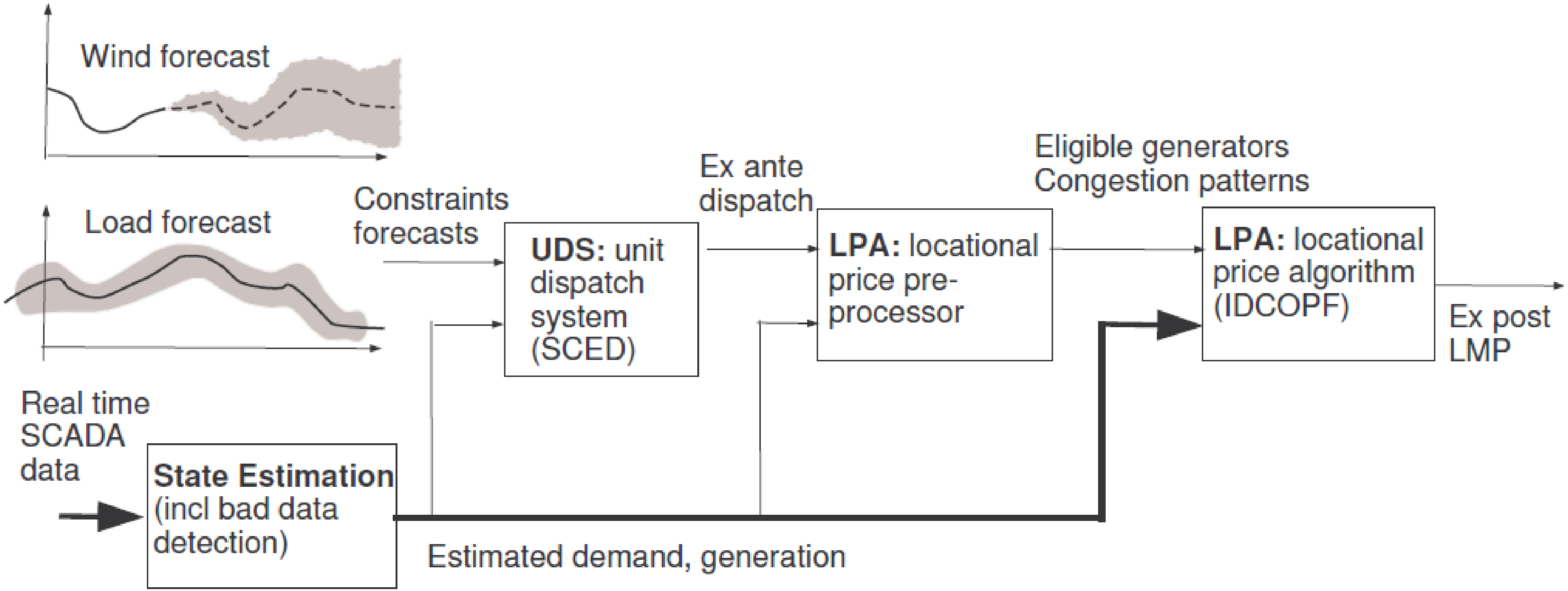
Summary of the state-of-the-art

- Extensive literature:
  - Mostly black box techniques
  - Primarily providing point forecasting
  - Rarely deal with on LMP and network effects
- Extremely accurate load forecasting (1-3%)
- Relatively poor price forecasting (10-20%)

Outline

- Motivation
- Probabilistic forecasting of real-time LMP
  - A stylized real-time ex post LMP model
  - Information structure
  - LMP states and Markov chain representations
  - Probabilistic forecast
- Preliminary simulations
- Summary and future work

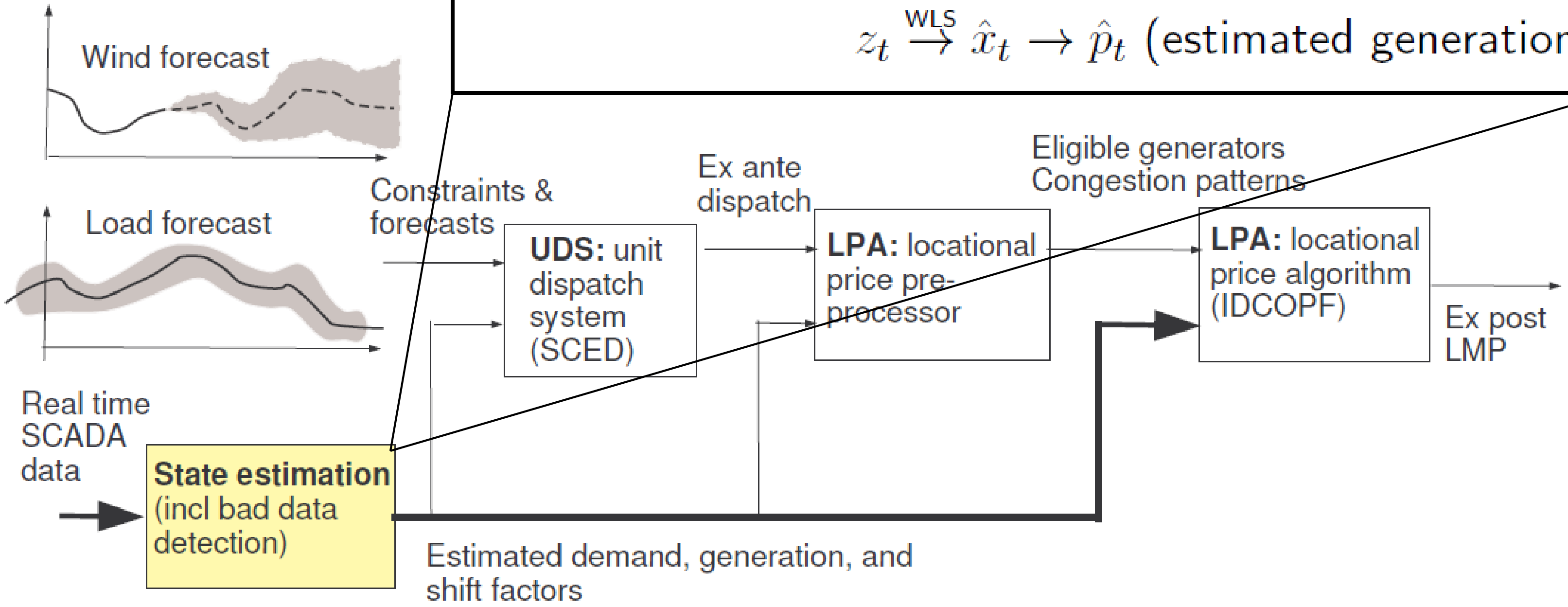
A stylized real-time ex post LMP model



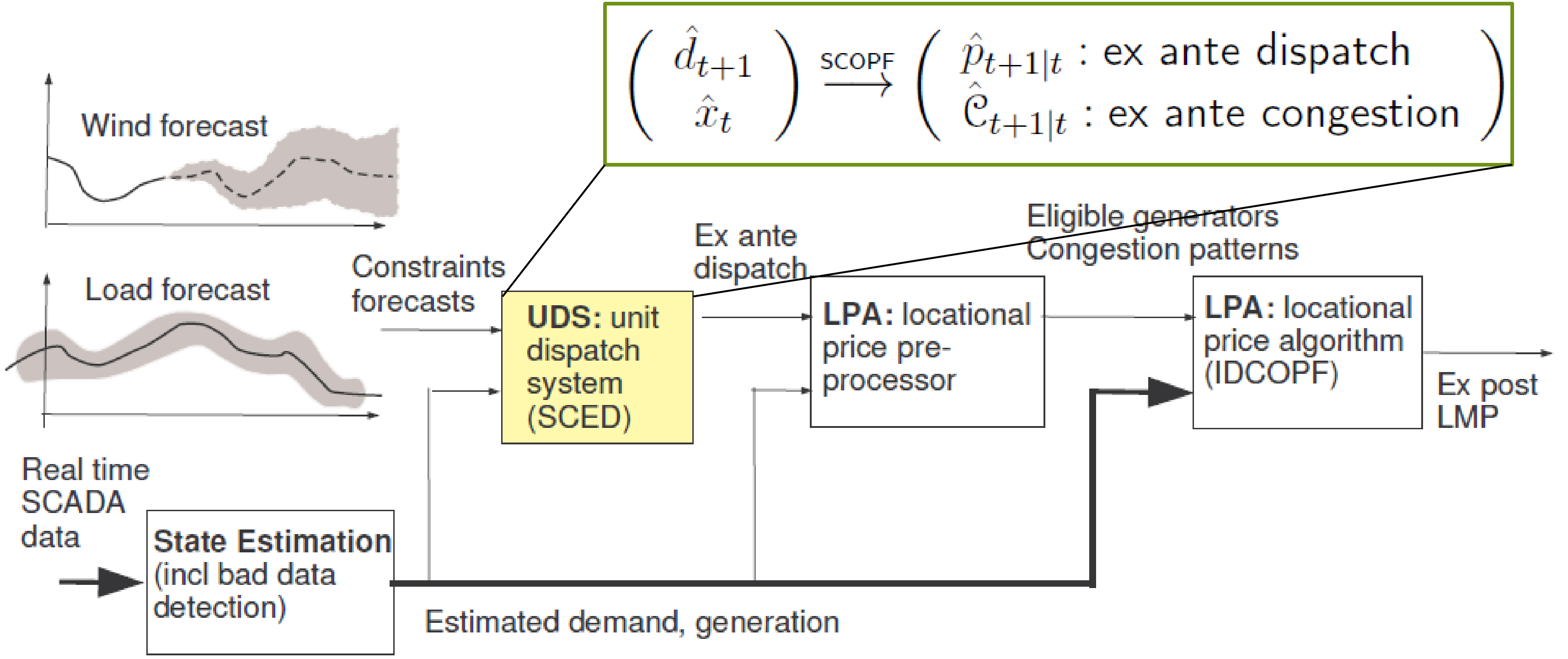
State estimation

- Power system as a graph: $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$
- SCADA measurement model: $z_t = h(x_t, \mathcal{G}) + e_t$

$$z_t \overset{\text{WLS}}{\longrightarrow} \hat{x}_t \rightarrow \hat{p}_t \text{ (estimated generation)}$$

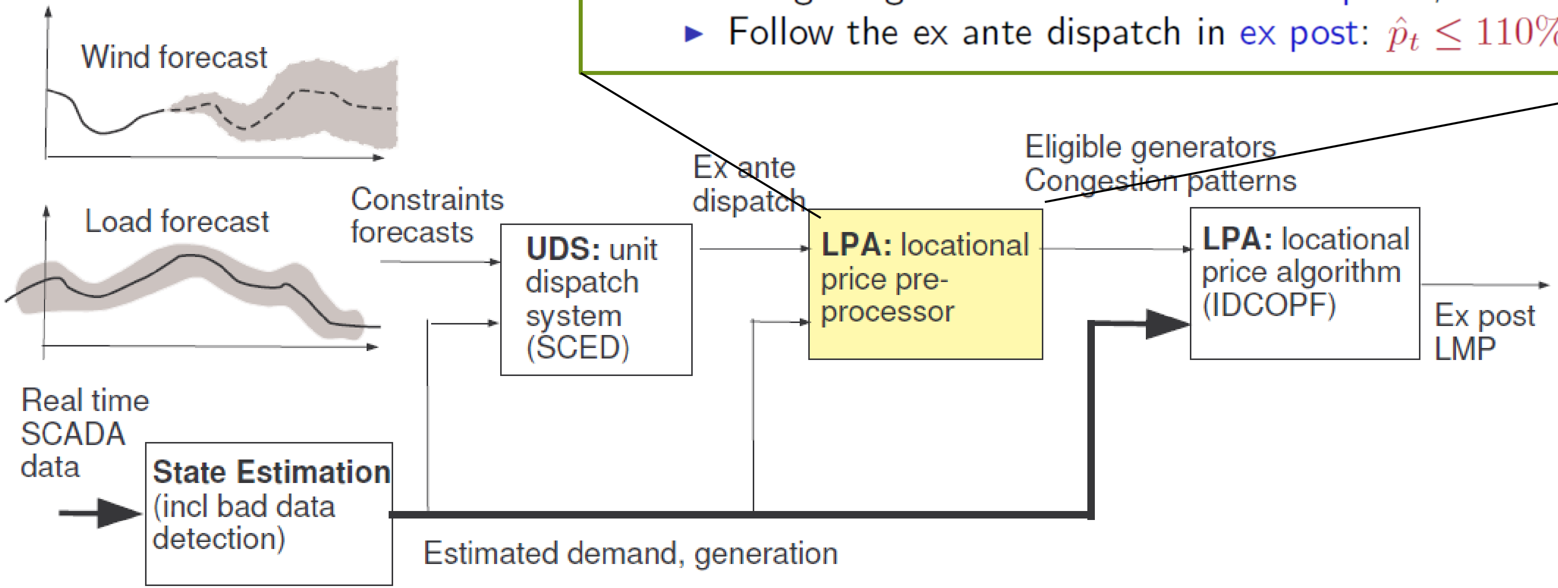


Ex ante dispatch

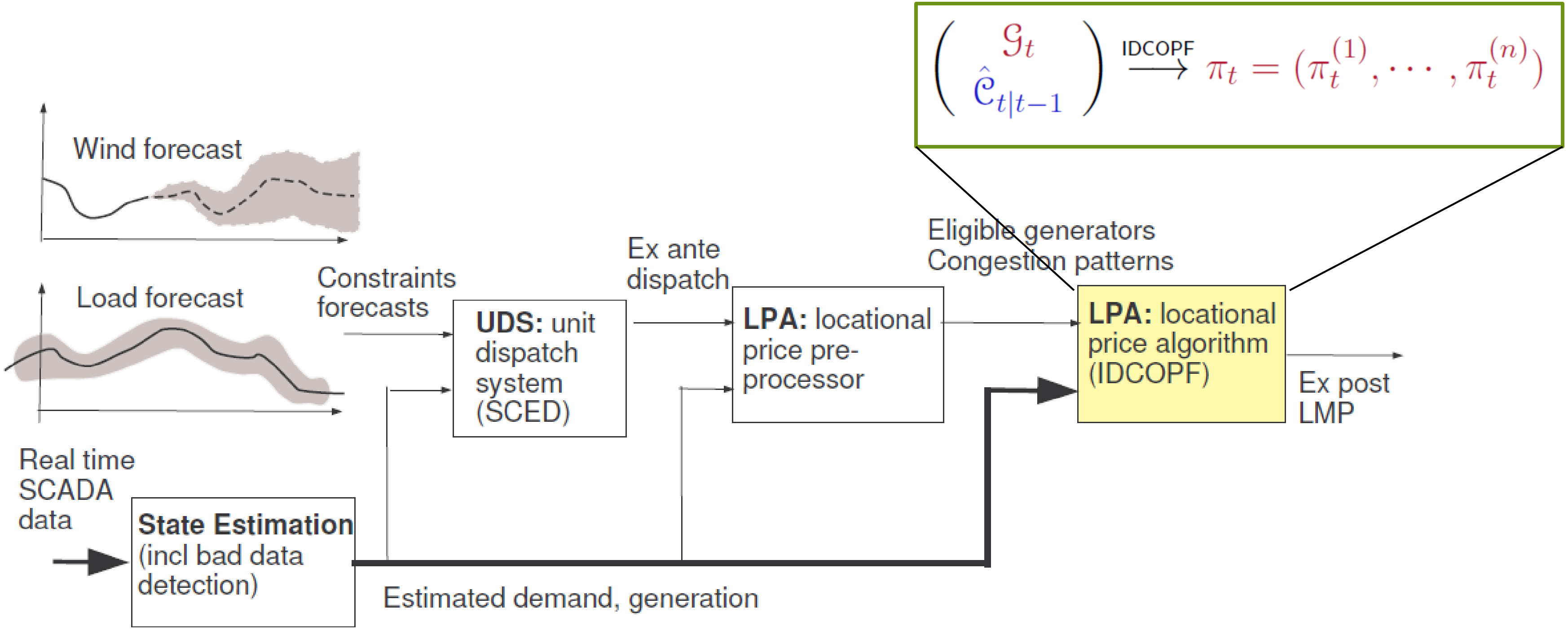


Ex post eligible generators

- Ex ante dispatch from SCOPF @ $t-1$: $\hat{p}_{t|t-1}$
- Ex post generation from state estimation @ t : $\hat{p}_t$
- Determine the set of eligible (flexible) generators $\mathcal{G}_t$:
  - Marginal generator in the ex ante dispatch;
  - Follow the ex ante dispatch in ex post: $\hat{p}_t \leq 110\% \times \hat{p}_{t|t-1}$



Ex post LMP



$\begin{pmatrix} \mathcal{G}_t \\ \hat{\mathcal{C}}_{t|t-1} \end{pmatrix} \xrightarrow{\text{IDCOPF}} \pi_t = (\pi_t^{(1)}, \cdots, \pi_t^{(n)})$
Wind forecast
Load forecast
Constraints forecasts
UDS: unit dispatch system (SCED)
Ex ante dispatch
LPA: locational price pre-processor
Eligible generators Congestion patterns
LPA: locational price algorithm (IDCOPF)
Ex post LMP
Real time SCADA data
State Estimation (incl bad data detection)
Estimated demand, generation

Ex post LMP via IDCOPF

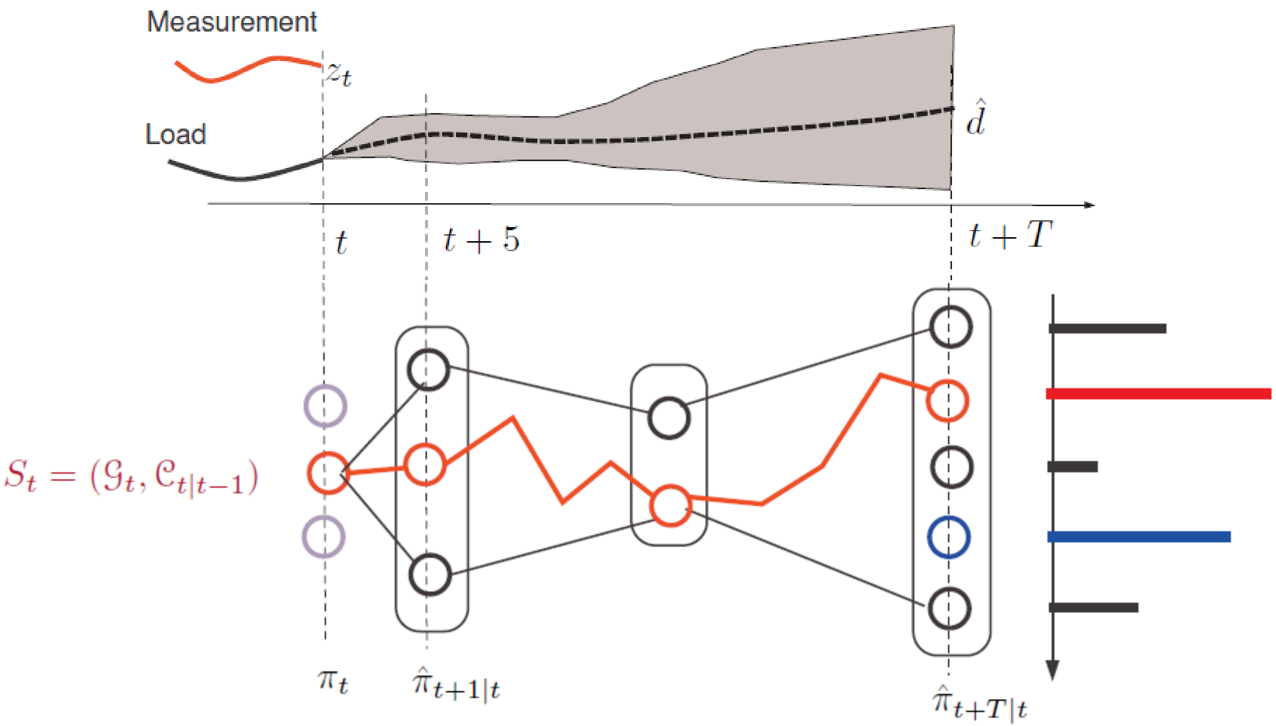
- Obtain the set of eligible generators $\mathcal{G}_t$ and the ex ante congestion $\hat{\mathcal{C}}_{t|t-1}$
- Compute an incremental DC OPF (Idcopf):

$$\begin{array}{llll} \text{minimize} & \sum_{i\in\mathcal{G}_t} c_i \Delta p_i & & \\ \text{subjcet to} & \sum_i \Delta p_i = 0 & & (\hat{\lambda}) \\ & \Delta p_{\text{min}} \leq \Delta p_i \leq \Delta p_{\text{max}} & i \in \mathcal{G}_t; & \\ & \sum_{i\in\mathcal{G}_t} A_{ki} \Delta p_i \leq 0; & k \in \mathcal{C}_{t|t-1} & (\hat{\mu}_k) \end{array}$$

- The vector LMP is given by

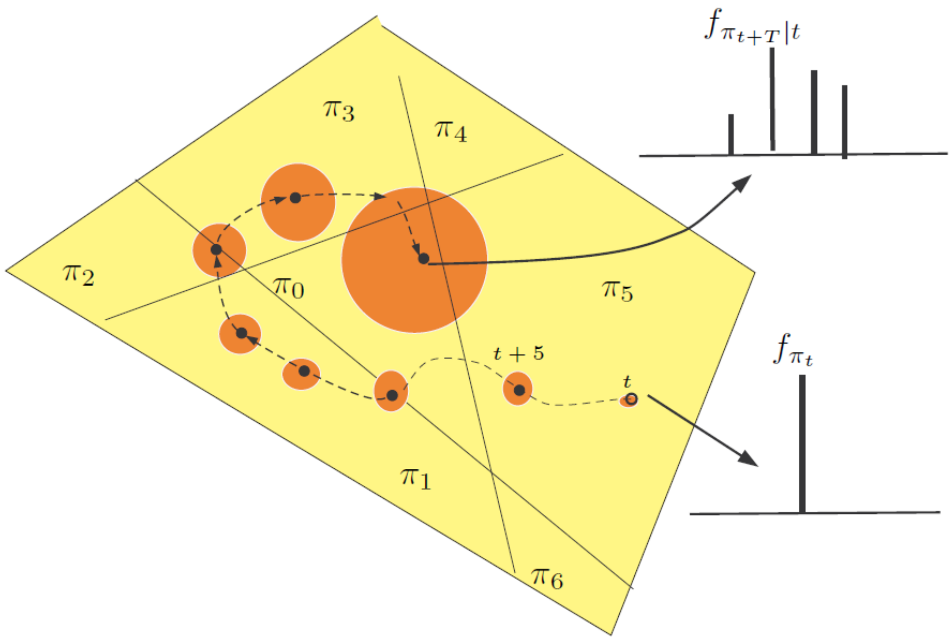
$$\hat{\pi} = \hat{\lambda}^* \mathbf{1} - A\hat{\mu} \triangleq \text{Idcopf}(\mathcal{G}_t, \mathcal{C}_{t|t-1})$$

Information structure and Markov chain



Probabilistic forecasting

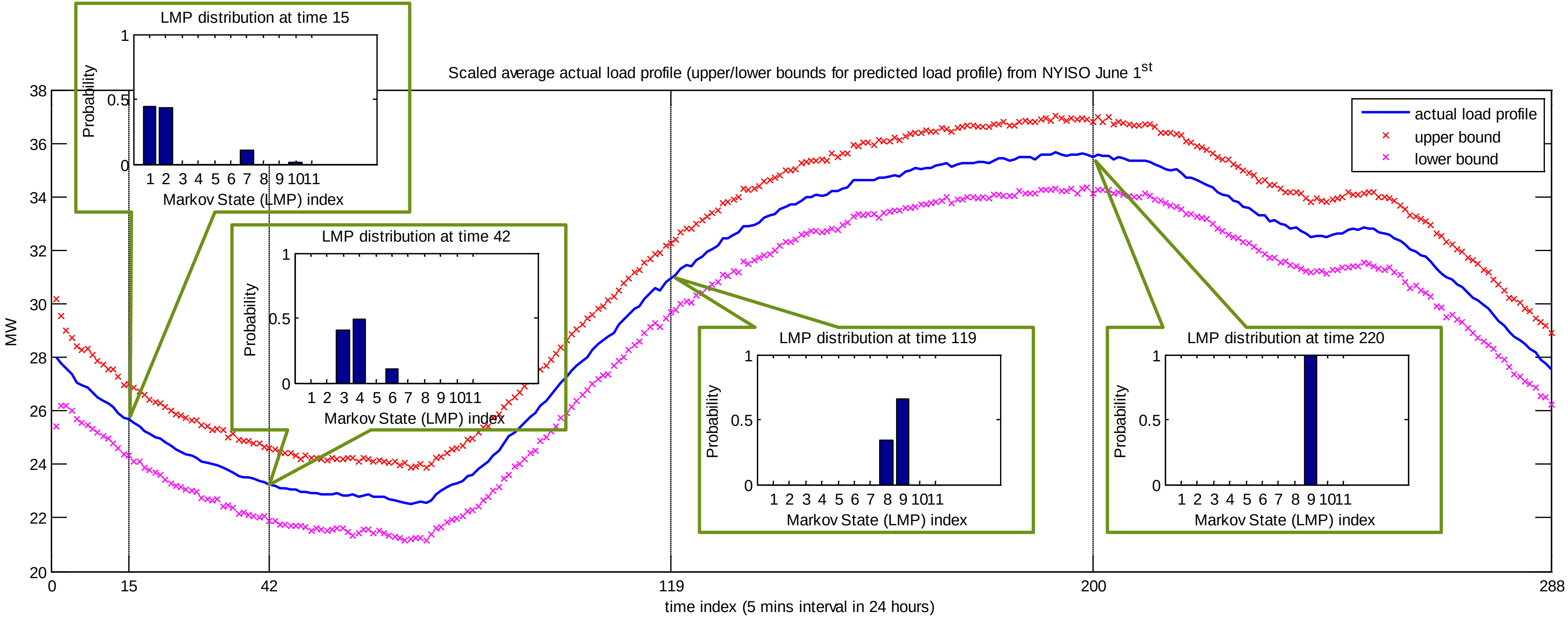
$$f_{\pi_{t+T}|t} = \delta_{\pi_t} \times P_t \times P_{t+5} \times \cdots \times P_{t+T-1}$$



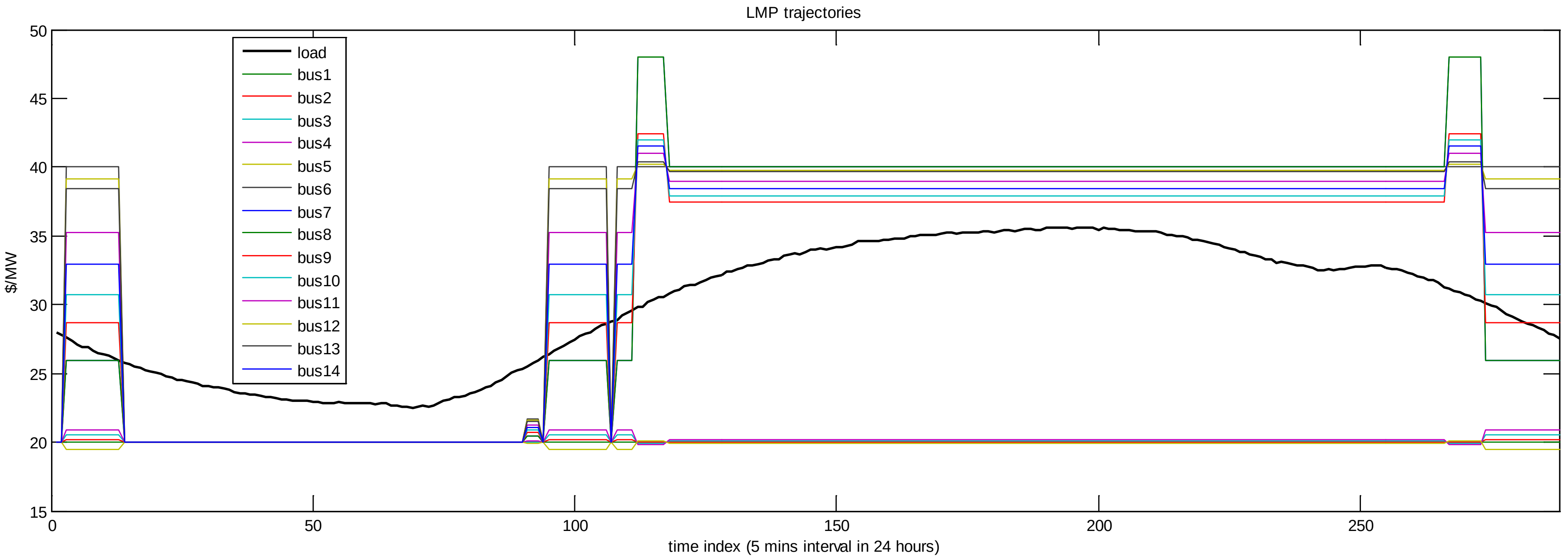
Outline

- Motivation
- Probabilistic forecasting of real-time LMP
- Preliminary simulations
  - IEEE 16 bus with NYISO sample load profiles
  - Varying load errors and correlations
  - Monte Carlo techniques to estimate transition matrices
- Summary and future work

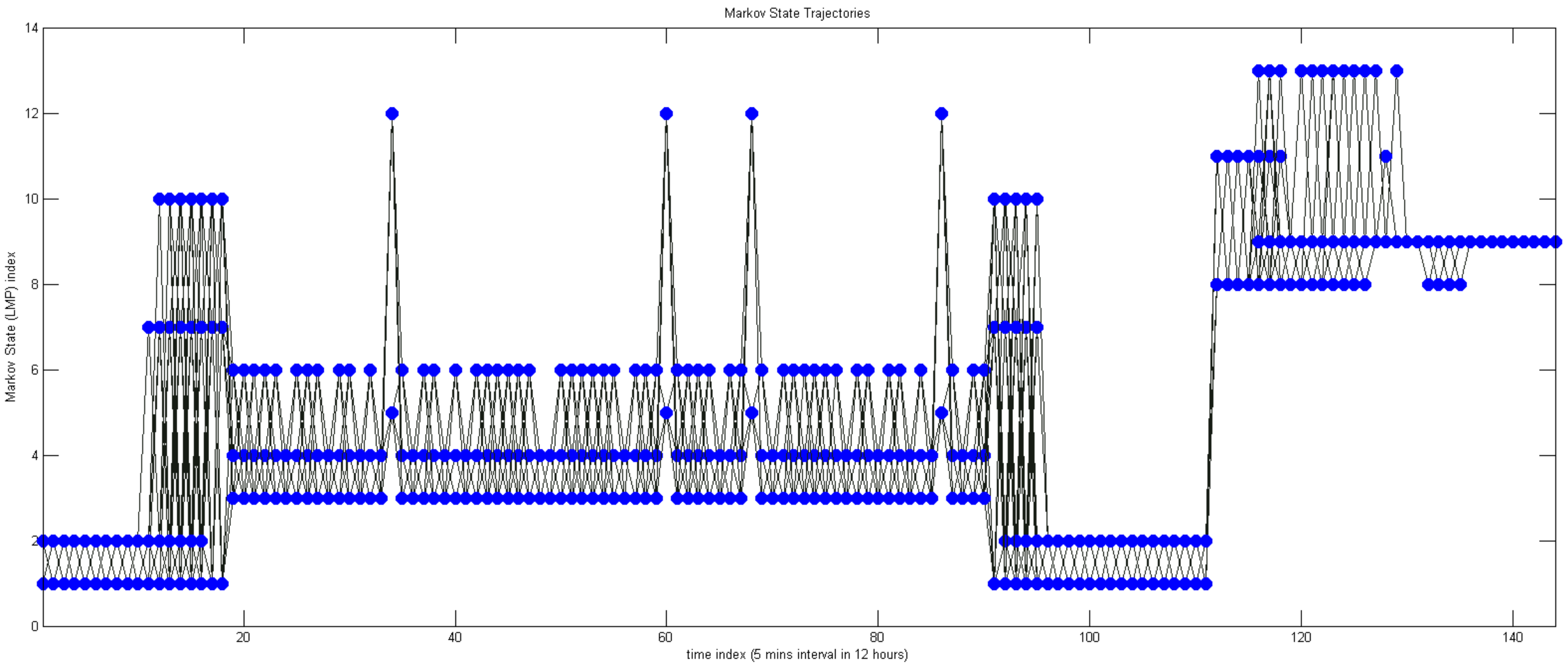
Load and price distributions



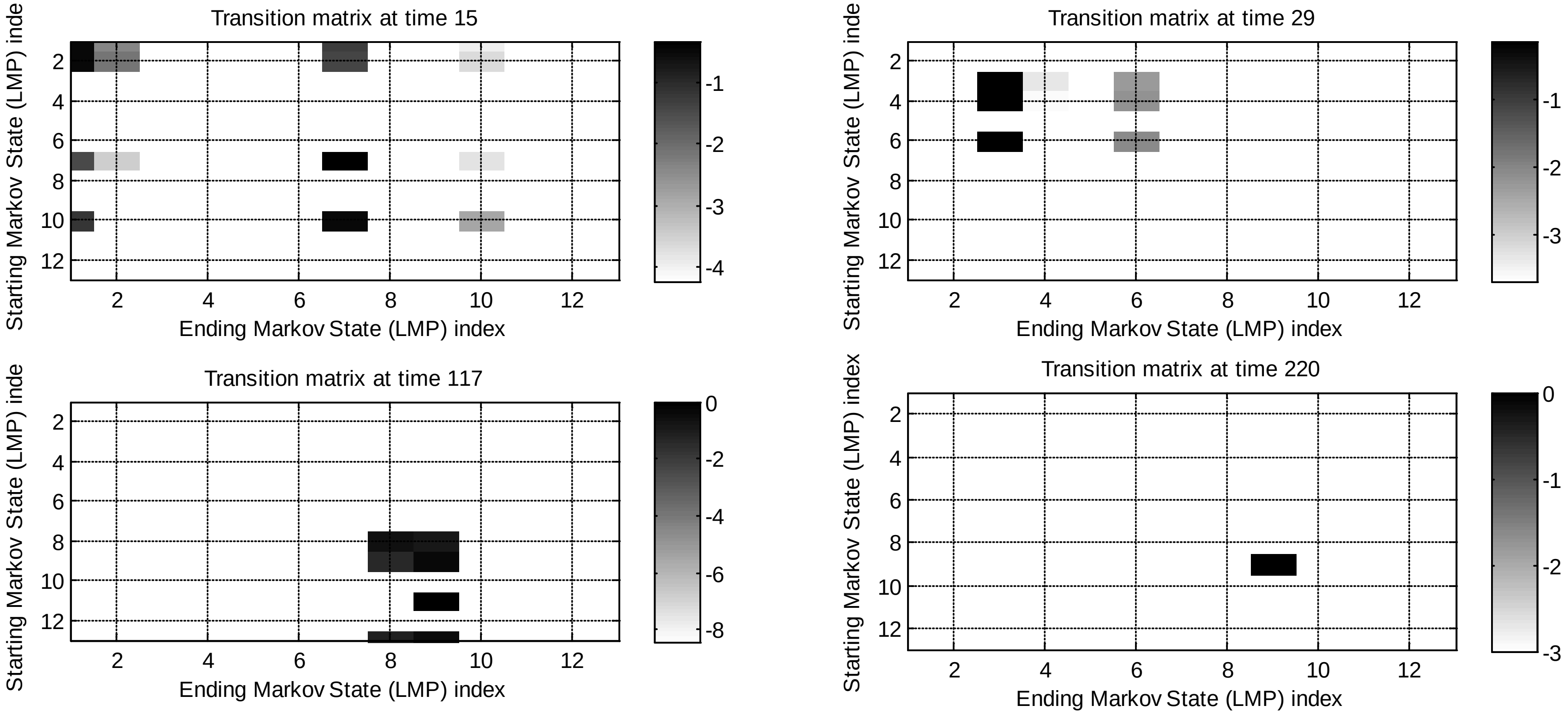
LMP trajectories



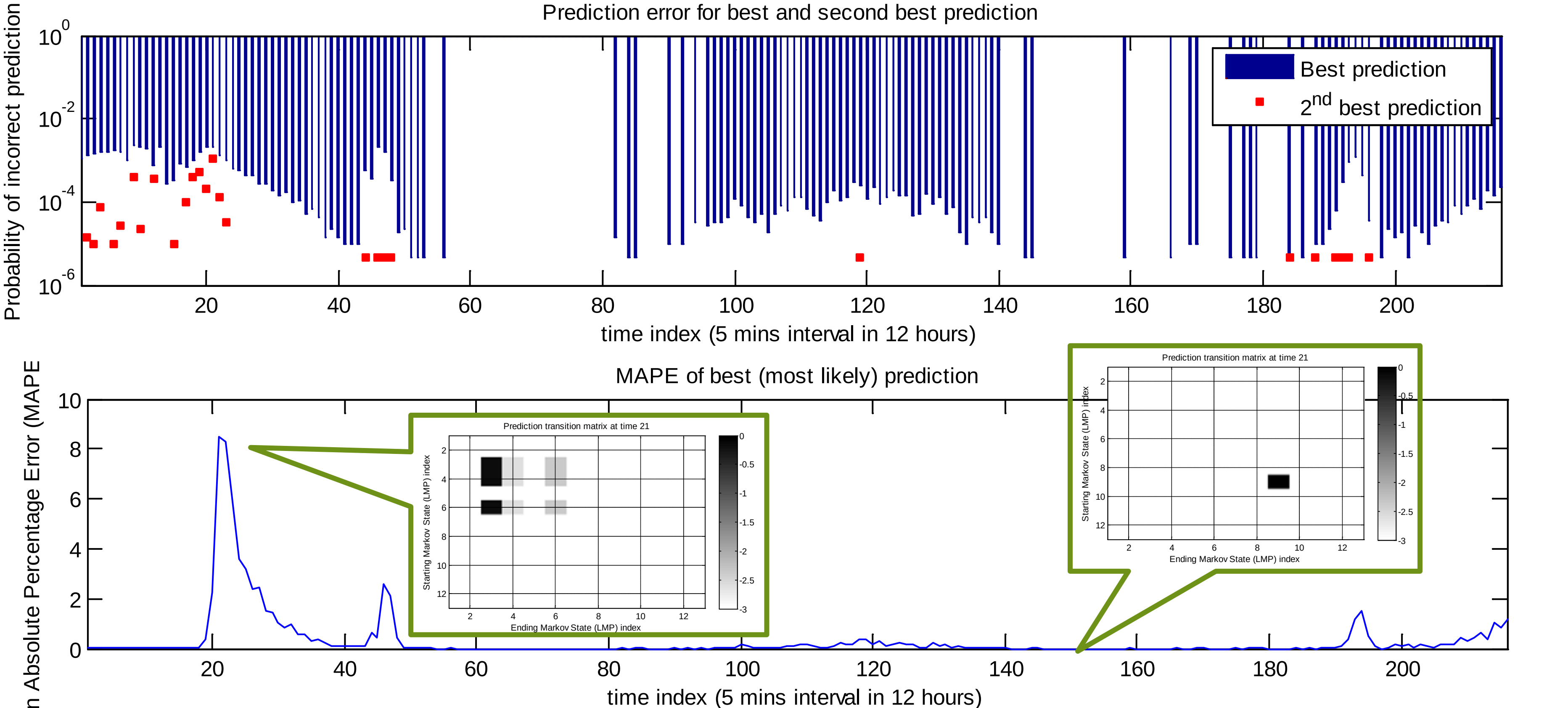
Time inhomogeneous Markov Chain



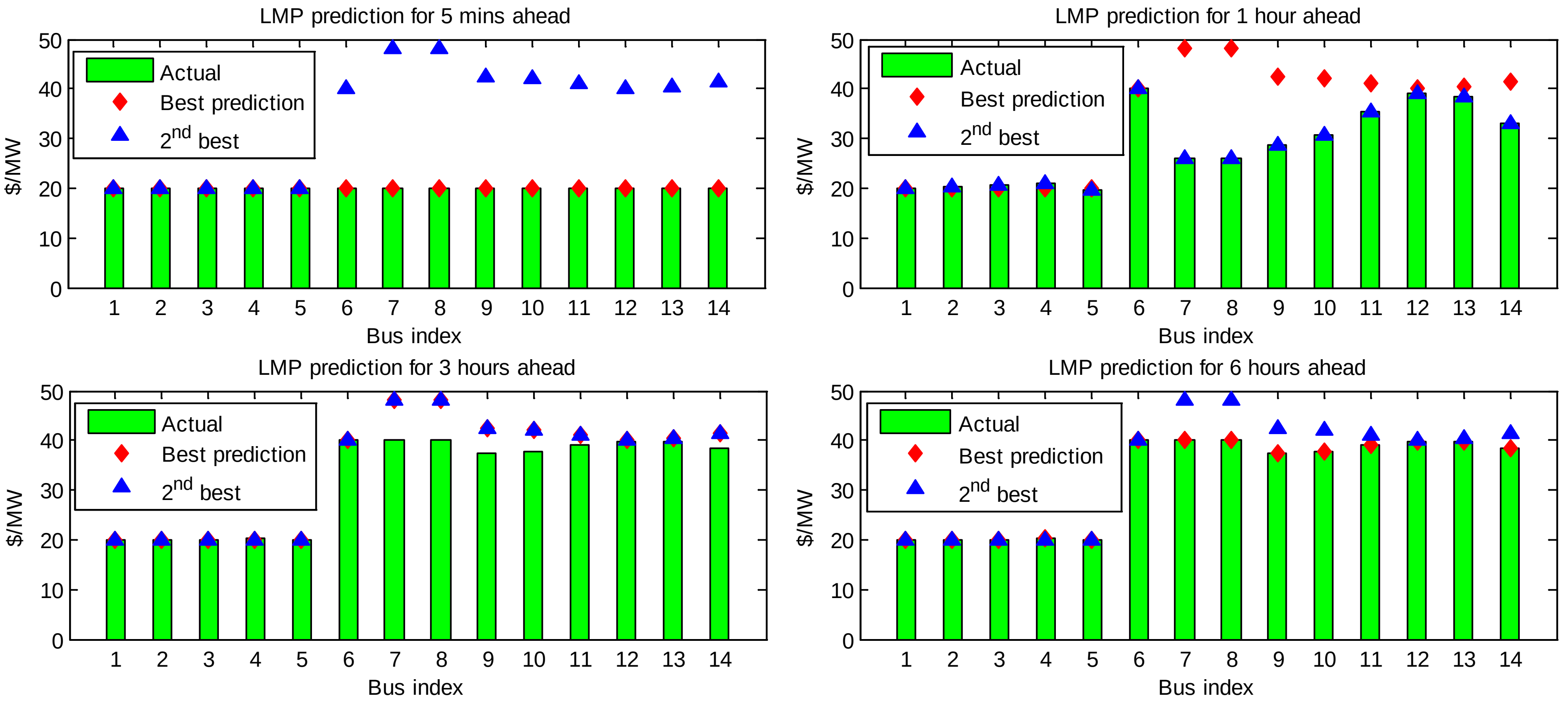
Transition Matrices



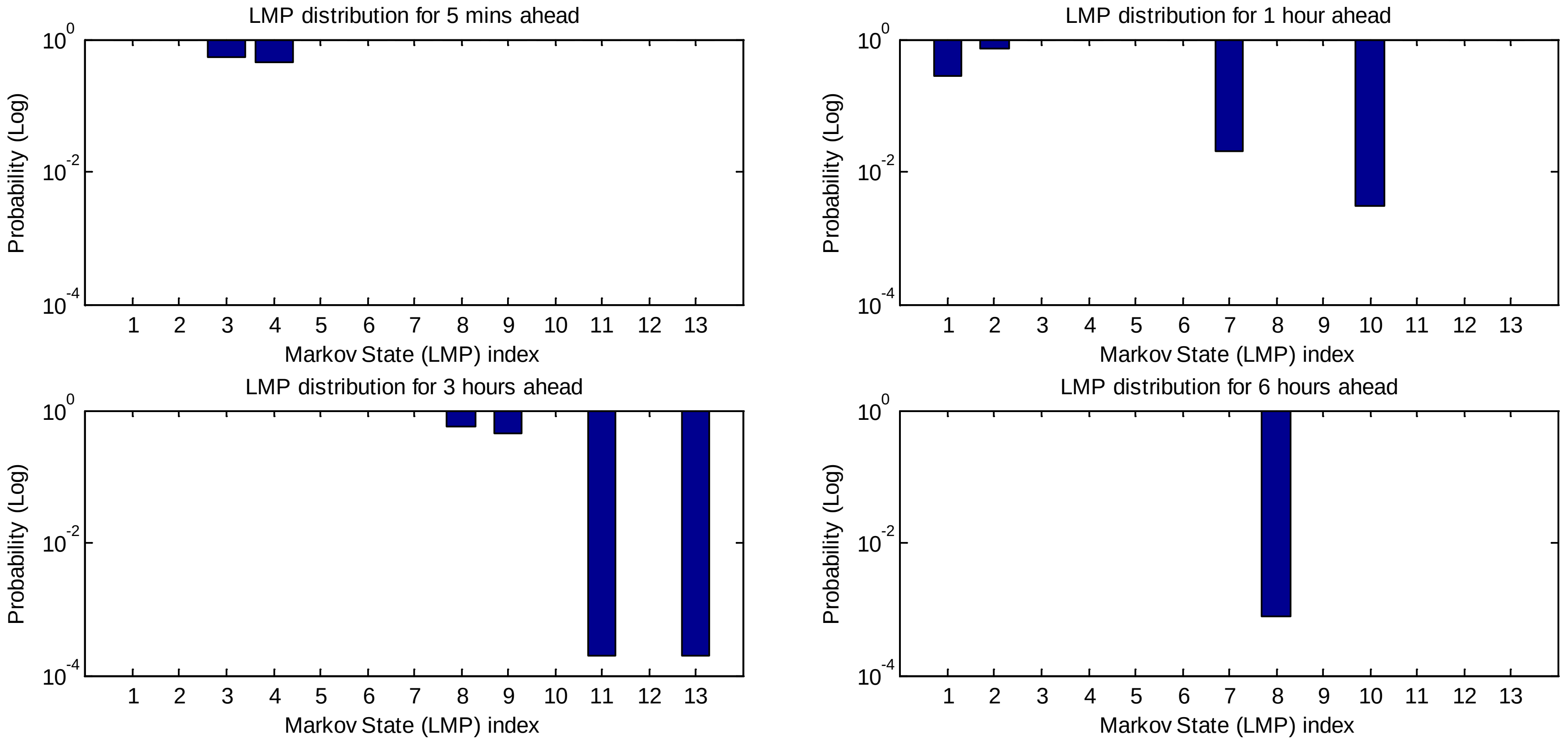
6 hours ahead prediction error



LMP prediction for different time horizon



LMP distribution for different prediction horizons



Planned research

- Forecasting techniques
  - Incorporating load models
  - More sophisticated Monte Carlo techniques (important sampling, MCMC)
  - Generator behavior models
  - Forecasting with renewable sources
  - Demand response
- Extensive simulation studies and comparisons

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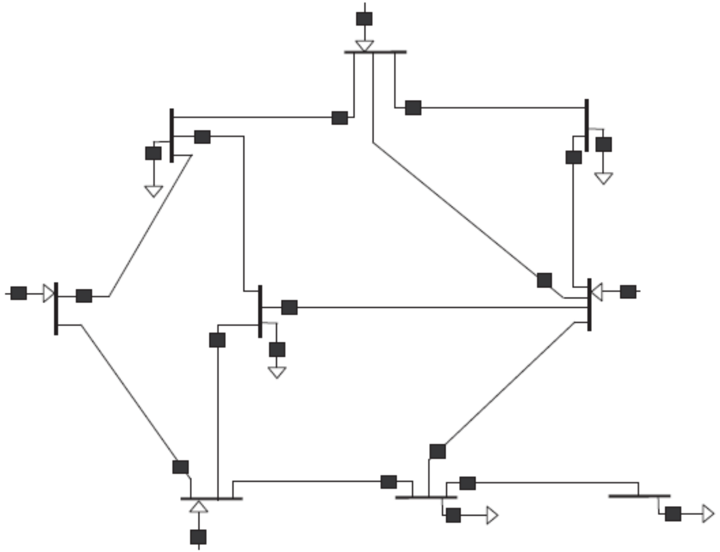
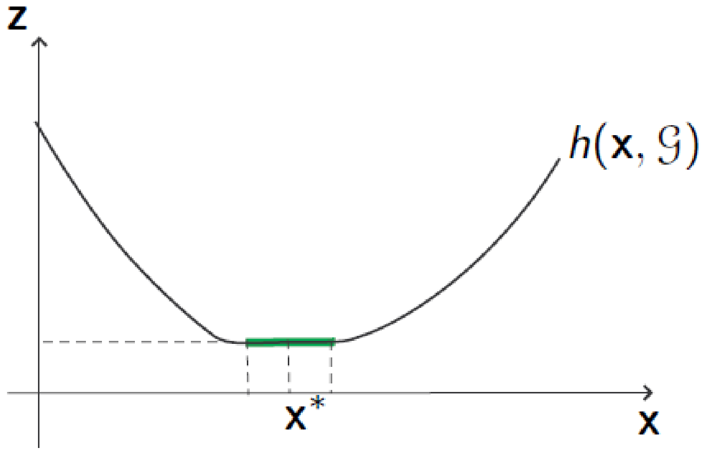
Observability

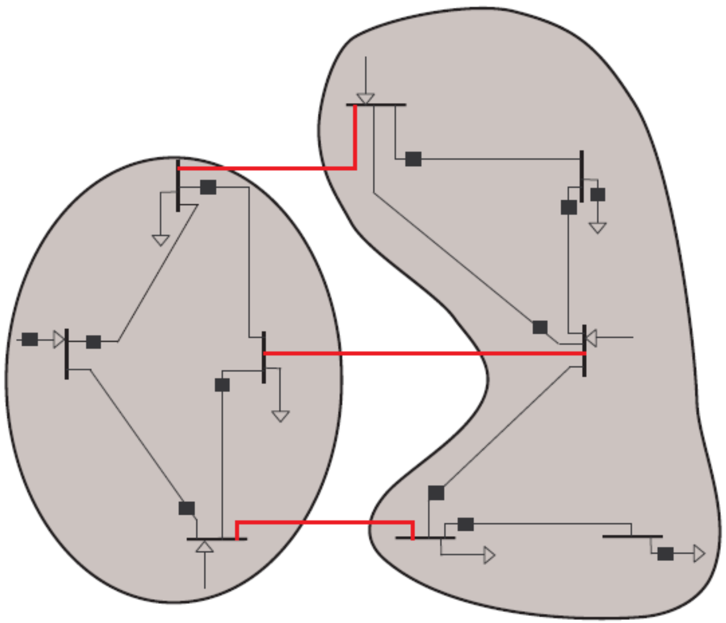


- Power system as a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$
  - System state x: voltage phasors at buses (vertices)
  - Observation equation: $z = h(x, \mathcal{G})$

- Locally unobservable at $\mathbf{x}^*$:



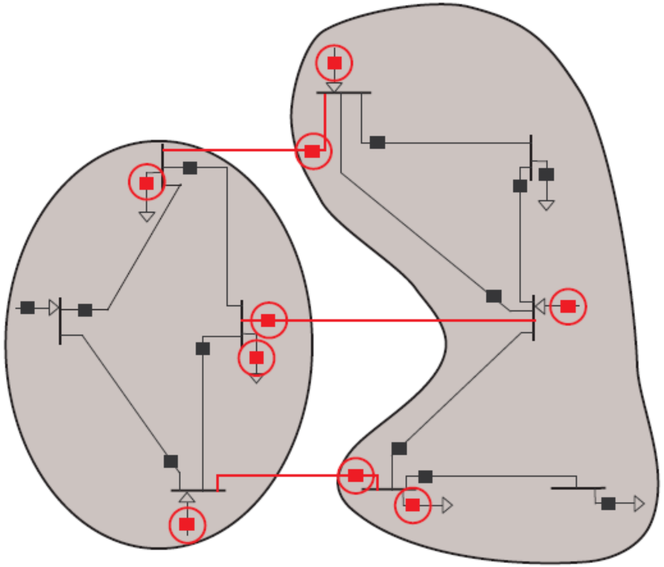
A graph theoretic condition (KCD'80)



Theorem

A network is observable if and only if $\exists$ *a spanning tree with an assigned meter on each edge.*

Undetectable attack (KJTT'11)

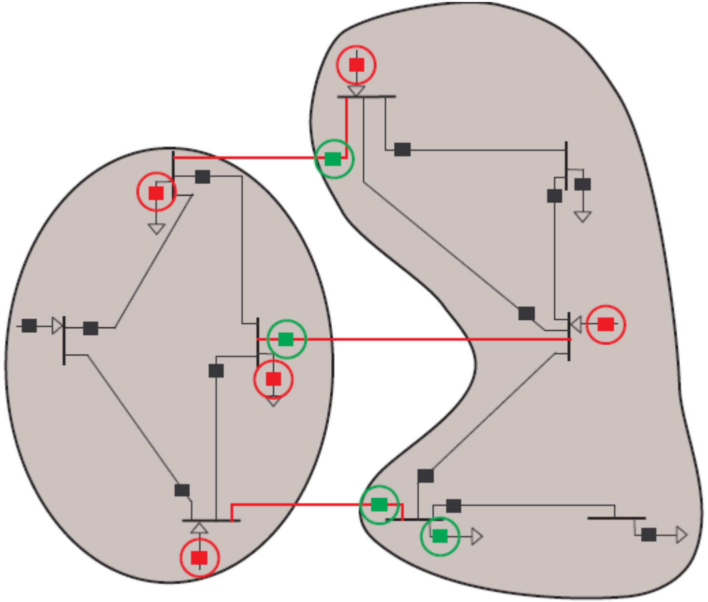


Theorem

The attacker can make the power system unobservable by controlling a set of meters associated with a cut without being detected by the control center.

- The minimum number of meters accessible to the attacker is $\Theta(|\text{min-cut}|)$.

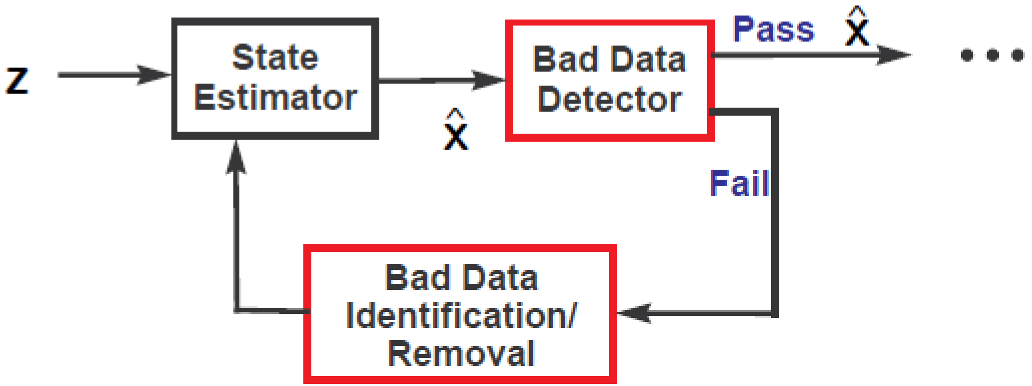
Only half of the meters are needed!



Framing attack:

- Let $\mathcal{J}$ be a set of meters on a cut with partition $\mathcal{J} = \mathcal{J}_1 \bigcup \mathcal{J}_2$.
- The attacker injects bad data on $\mathcal{J}_1$ such that the control center (i) detects bad data; (ii) identifies bad data occur at $\mathcal{J}_2$.

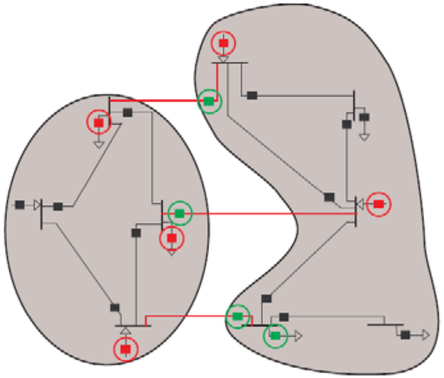
Bad data identification and removal

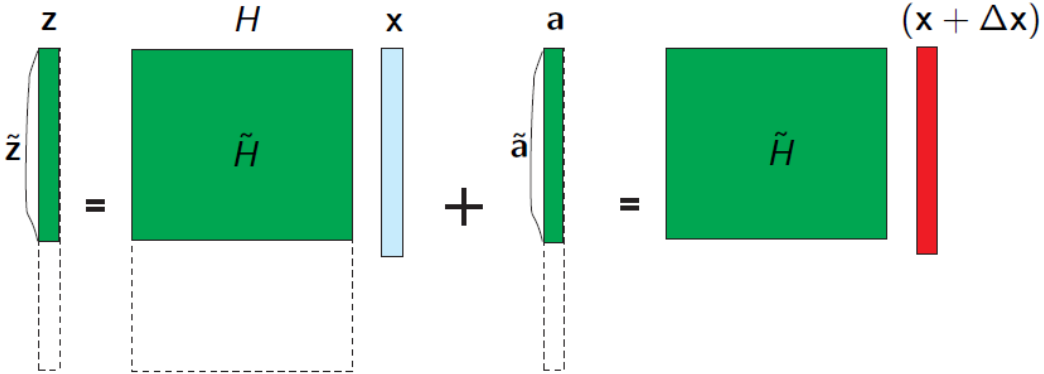


- State estimate: $\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} (\mathbf{z} - h(\mathbf{x}))^T \Sigma^{-1} (\mathbf{z} - h(\mathbf{x}))$
- Residue: $\mathbf{r} \triangleq \mathbf{z} - h(\hat{\mathbf{x}})$; $\quad \mathbf{r}^N \triangleq \Omega^{-1}\mathbf{r}$.
- Bad data identification and removal:
  - If $\mathbf{r}^T \Sigma^{-1} \mathbf{r} \leq \tau$, accept $\hat{\mathbf{x}}$;
  - If $\mathbf{r}^T \Sigma^{-1} \mathbf{r} > \tau$, remove the meter i with the largest $|r_i^N|$.

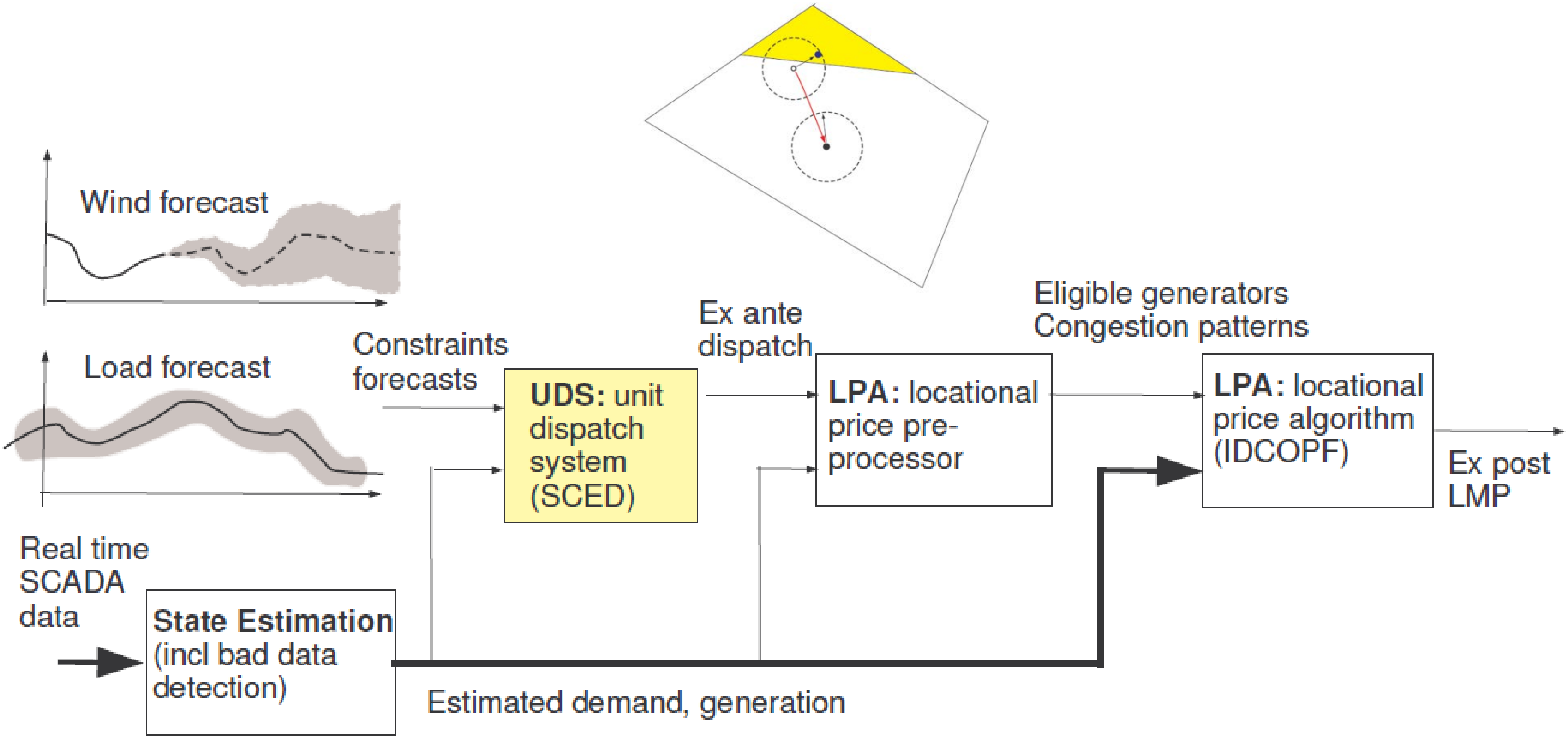
Framing attack via QCQP

maximize	$\mathbb{E}\{\sum_{i\in\mathcal{I}_T}(r_i^N)^2\} = \|R\mathbf{a}\|_2^2$	maximizing residue energy of target meters.
subject to	$\|\mathbf{a}\|_2 = 1, \mathbf{a} \in \mathcal{A}$	find target direction
	$\tilde{\mathbf{a}} \in \text{Col}(\tilde{H})$	$(\tilde{\mathbf{a}} = \tilde{H}\Delta\mathbf{x})$.

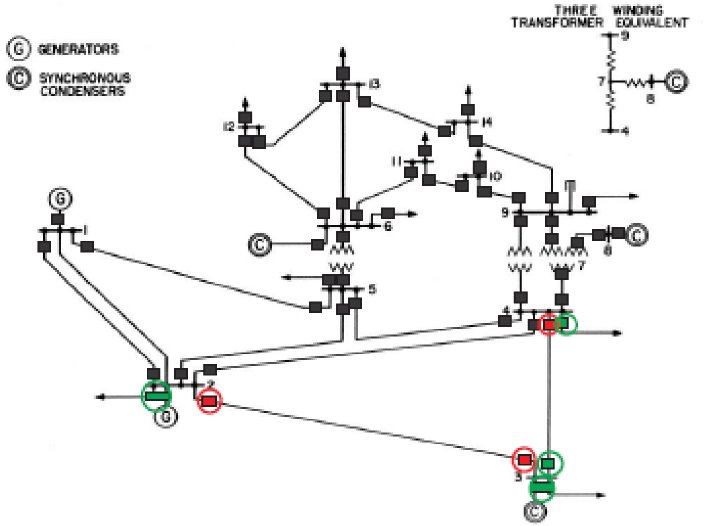


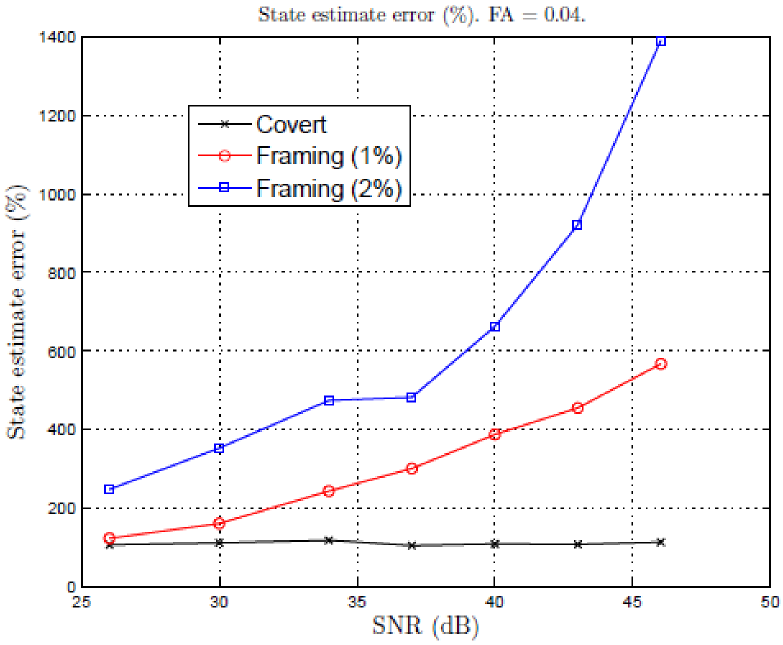


DoS attack on real-time operations



Simulation examples (AC)





Conclusion

- Attacks on cyber physical systems (power systems) are real:
  - State attacks
  - Topology attacks
  - Dispatch attacks
- A key step toward protection is deploy authentication mechanisms.