INFORMATION AND COMPUTATION HIERARCHY

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Caveats

This talk

- ❑ does not addressing practical and challenging issues of today;
- ❑ is not comprehensive coverage of the topic
- ❑ covers a few problems whose solutions are likely deemed to be too expensive, intractable, too general and high level, too detailed and special….

Goal: In the spirit of "broader analysis," we examine a few hypotheses; should the hypothesized needs arise, what are the issues to consider, insights to gain, and tradeoffs to make.

Outlines

- Motivations
- Computation hierarchy: is cloud the right architecture?
  - Birman’s estimates & Brewer’s CAP conjecture
- Information hierarchy in time
  - Risk limiting dispatch (a story from the generation side)
  - Deadline scheduling (a story from the demand side)
- Information hierarchy in space
  - Impacts of data quality on LMP
- Concluding remarks

Motivation

- The electrical grid as we know now.
- The need of transformative changes.
- Emerging new operating regimes.
- New technological drivers

Can the current computation, communication, and networking paradigms support the required changes?

Birman-Ganesh-van Renesse estimates

- 10K PMUs with 400 PDCs are deployed.
- 30 measurements per sec and 256 B per measurement
- Total data rate per PDC:

  $25 \times 256 \times 30 = 192$ KB/sec
- Combined rate for 400 PDCs is about 615MB/sec
- National scale sharing of information gives 15Gb/sec

Cloud as a computation architecture:

- Scalability and computation power
- Robustness against failure and elasticity
- Unifying architecture that incorporates web-based participants:
  - Community based micro-grids
  - Home energy management
  - Large scale EV charging

Cloud over smart grid: challenges

- ❑ Time criticality
- ❑ Data consistency
- ❑ Security & trustworthiness

Are we asking too much?

CAP and Brewer’s Conjecture

CAP definition

- **C**onsistency: atomic, linearizable data (all nodes should see the same data at the same time)
- **A**vailability: every request receives a response
- **P**artition tolerance: system continues to operate despite arbitrary message loss.

Brewer’s conjecture:

- At most two of the CAP properties can be achieved at the same time

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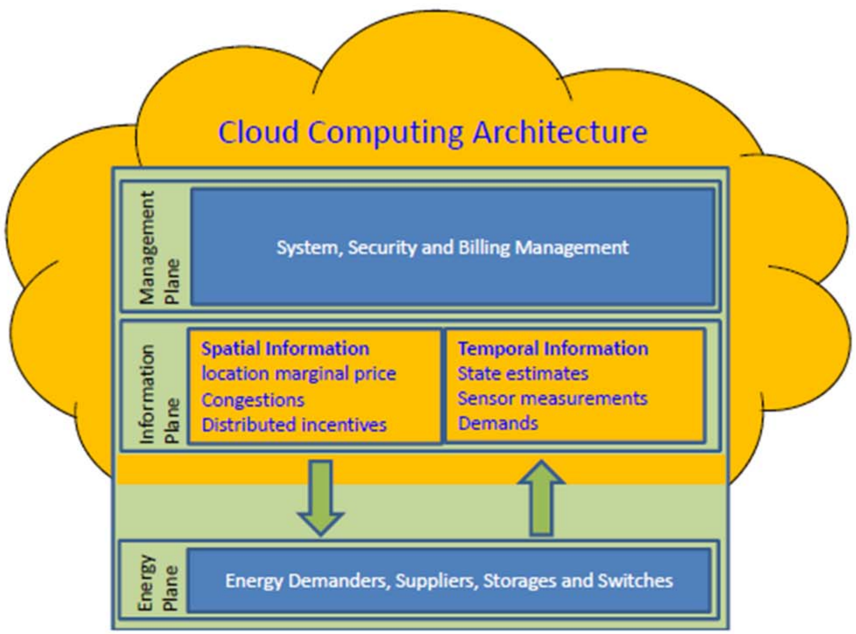
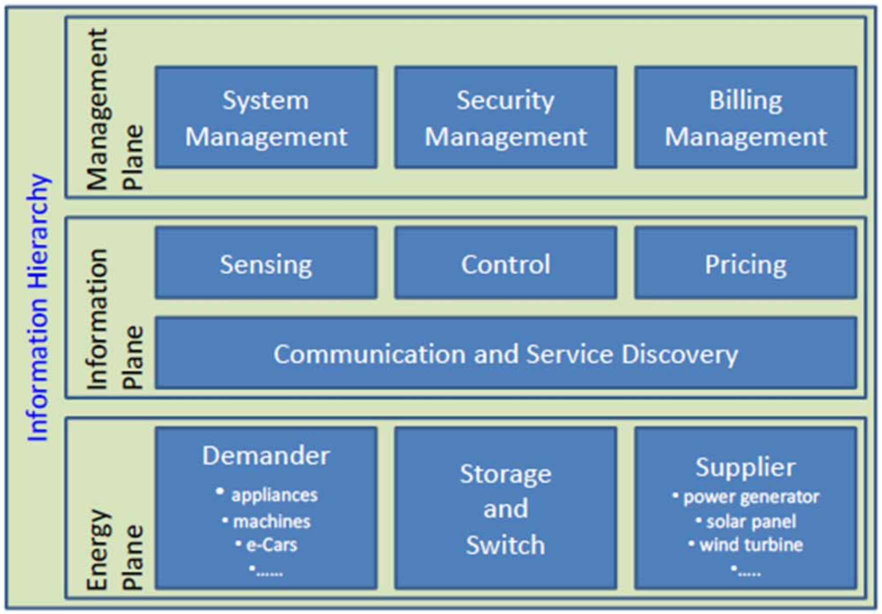
Information hierarchy on a cloud architecture



(a) Computation and Information hierarchy overlay.



(b) Components of an information hierarchy.

Information hierarchy defines where, when, and what information is made available for decision making.

Information hierarchy in time

- Time sensitive operation decisions are required for high level integration of stochastic generations and demand side participation at faster time scales.
- Information hierarchy in time addresses the problem of what kind of information is required and by what time decisions have to be made.
- Two illustrative stories:
  - Stochastic economic dispatch with renewable resources (Varaiya-Wu-Bialek)---a generation side story
  - Large scale EV charging---a demand side story

Generation under uncertainties

Classical paradigm:

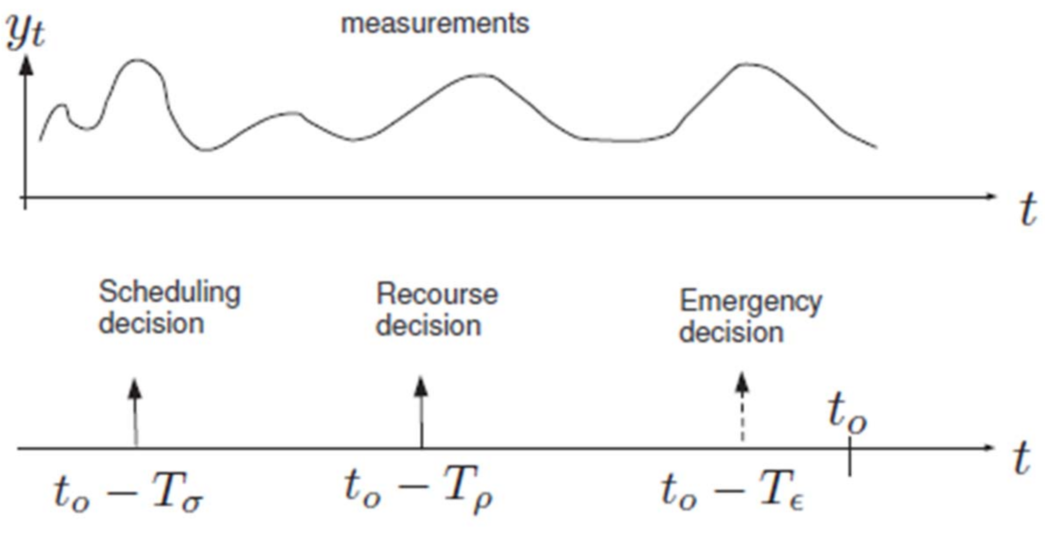
- Future load is uncertain
- Generation is firm and controllable
- Two stage decisions:
  - Day ahead dispatch via the day ahead market
  - Real-time adjustment via the real-time market

What happens with renewable integration?

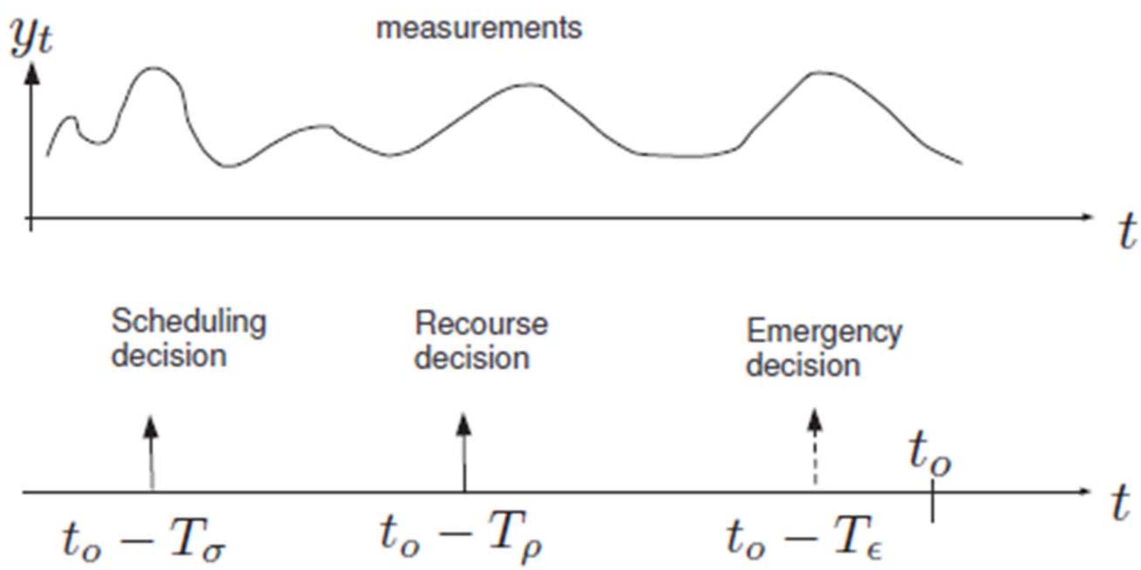
- Future load is uncertain
- Generation is stochastic and only partially controllable
- But short-term supply/demand is more “predictable”

A paradigm for a "smart grid"

- Assuming real-time measurements
- Exploit sophisticated prediction and real-time control
- Limiting risk from stochastic uncertainties
- Multi-stage stochastic optimization over scheduling, recourse, and emergency decisions.



Risk Limited Dispatch



Risk-limiting constraints:

$$
\begin{aligned}
&\Pr\{g(x(t), u_\sigma) = 0, && h(x(t), u_\sigma) \le 0 && \mid Y_{t-T_\sigma}\} && \ge p^*_\sigma,\\
&\Pr\{g(x(t), u_\sigma, u_\rho) = 0, && h(x(t), u_\sigma, u_\rho) \le 0 && \mid Y_{t-T_\rho}\} && \ge p^*_\rho,\\
&\Pr\{g(x(t), u_\sigma, u_\rho, u_\epsilon) = 0, && h(x(t), u_\sigma, u_\rho, u_\epsilon) \le 0 && \mid Y_{t-T_\epsilon}\} && \ge p^*_\epsilon.
\end{aligned}
$$

Objective:

$$C(u_\sigma, u_\rho, u_\epsilon) = \mathbb{E}(u_\sigma) + \mathbb{E}(u_\rho) + \mathbb{E}(u_\epsilon)$$

Risk limiting dispatch: Insights

- The role of information manifests itself via "conditioning." Different information hierarchies provide different conditioning mechanisms.
- In some simple cases, the "value of information" can be assessed, providing
  - economic justifications of a particular form of information hierarchy.
  - justifications of who should pay for such costs
- For some simple cases, optimal policy has an informative structure.
  - For example, threshold policy on generation is optimal.

Risk limiting dispatch: challenges

- The role of information manifests itself via "conditioning." Different information hierarchies provide different conditioning mechanisms.
- Often there is no analytical solution available; approximations in both information structure and optimal decisions are necessary. How good are such approximations?
- Impact of networking imperfections (e.g. delay, data inconsistency) are not known. How robust are such techniques?
- Information hierarchy in time and space: synchronization, local vs. global decisions, fusion rules, capacity requirements on information networks

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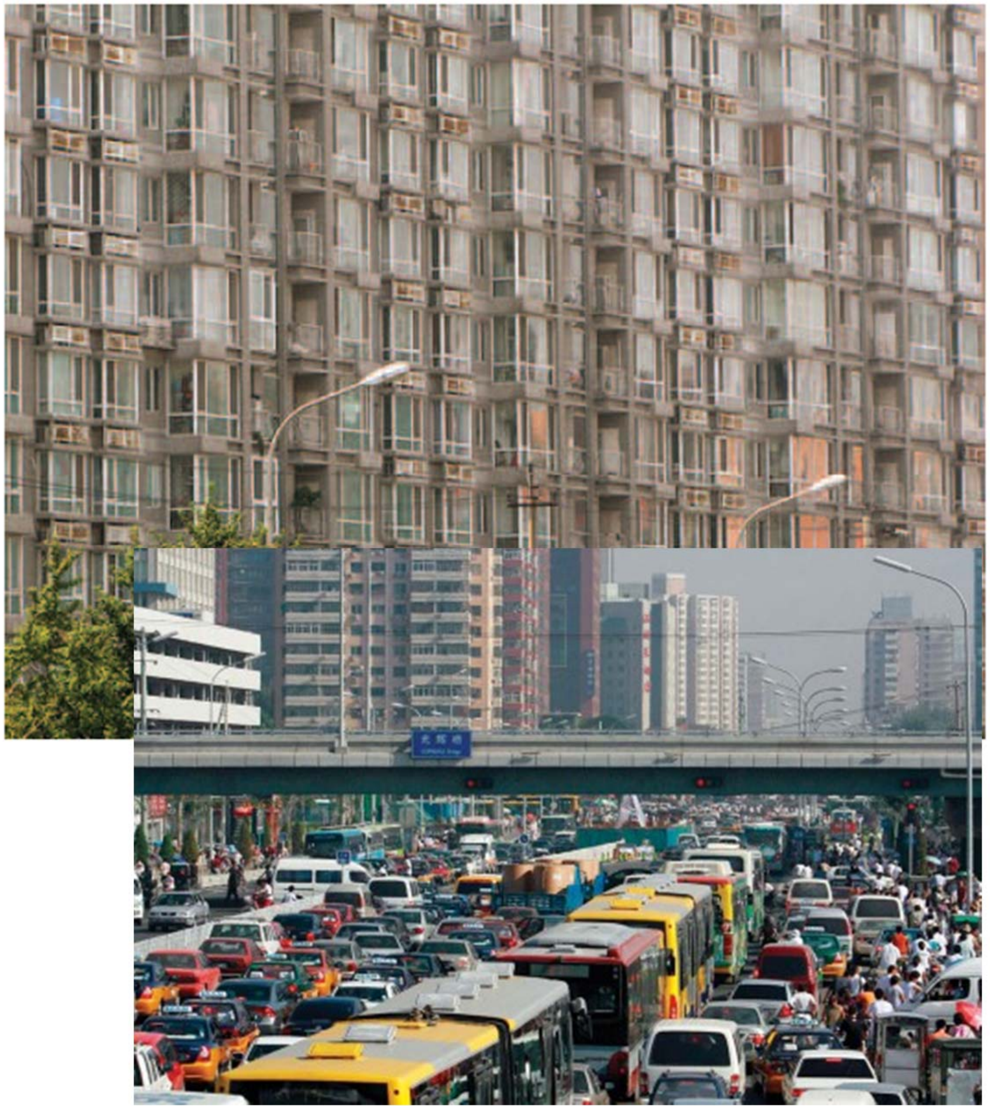
  - Large scale EV charging---a demand side story

A second story….

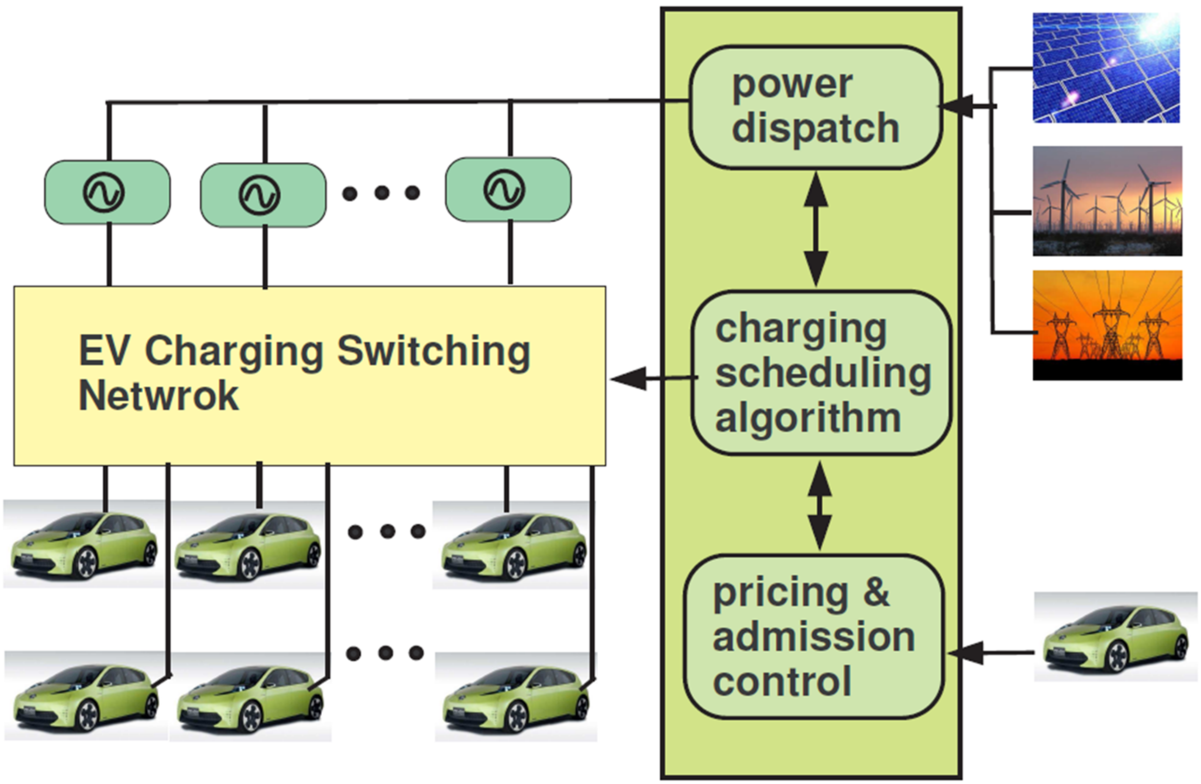


Large scale of charging of EVs

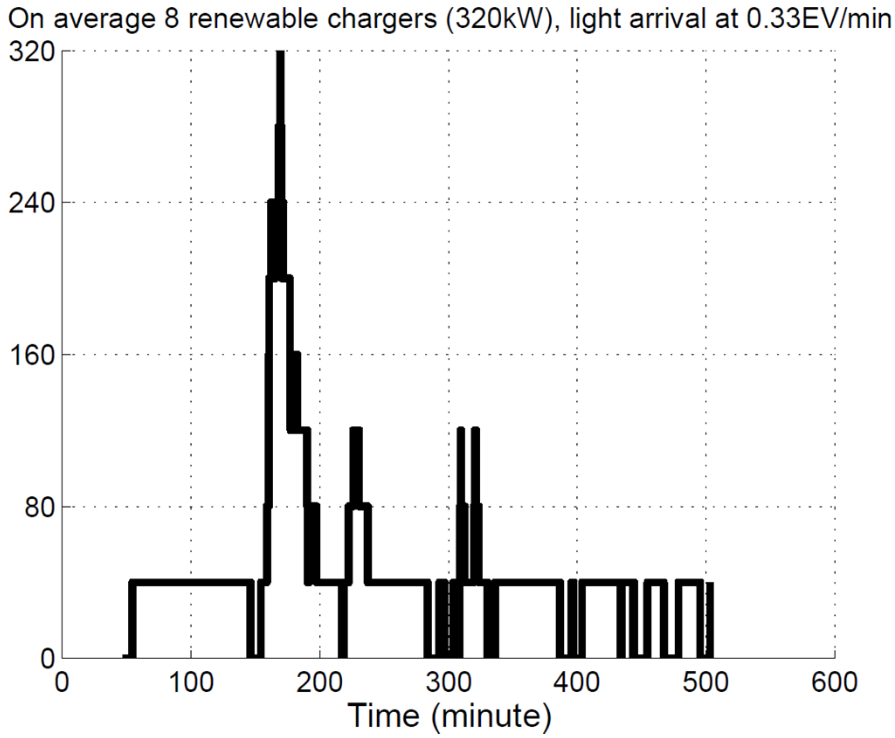
Power supply	Voltage	Max current	Charging time
1 phase 3kW	230 VAC	16A	6-8 hours
1 phase 7kW	230 VAC	32A	3-4 hours
3 phase 10kW	400 VAC	16A	2-3 hours
3 phase 24kW	400 VAC	32A	1-2 hours
3 phase 43kW	400 VAC	63A	20-30 min
DC 50kW	400-500 VDC	100-125A	20-30 min

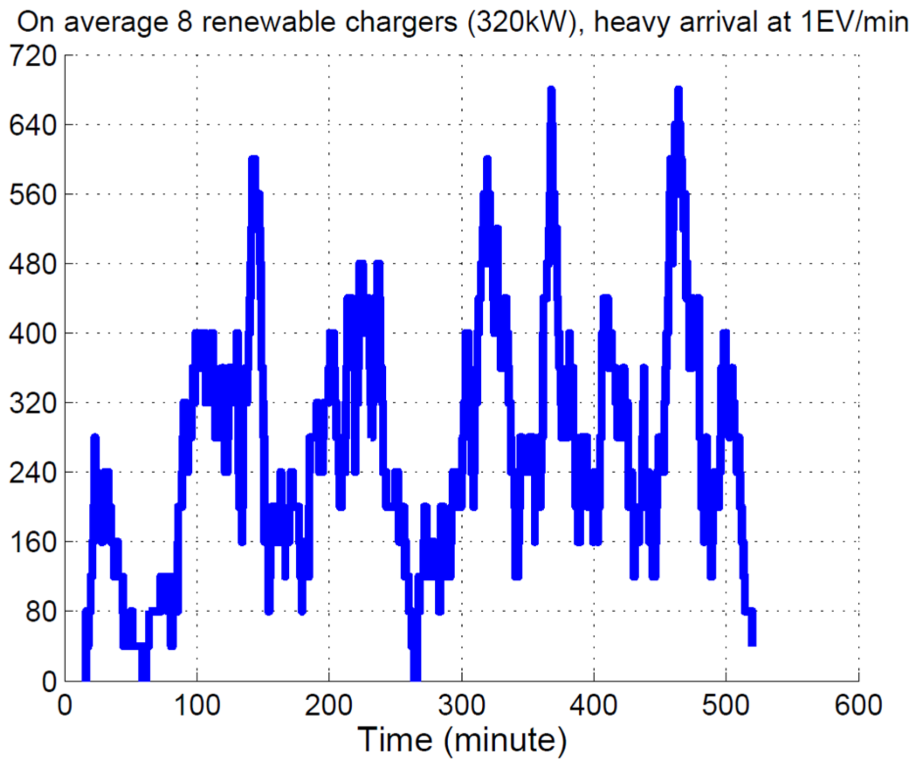
What does it take to support the charging of 5M EVs?

Energy management system for LSC

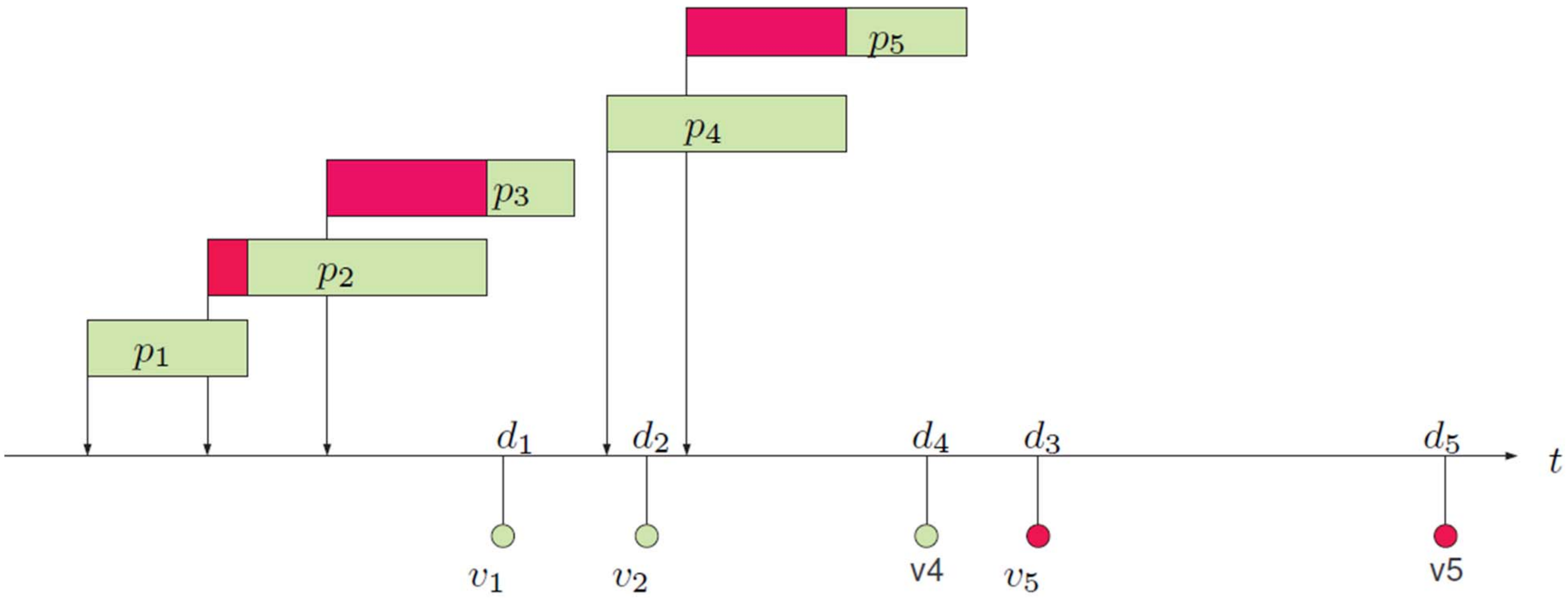


Power profile of unmanaged charging

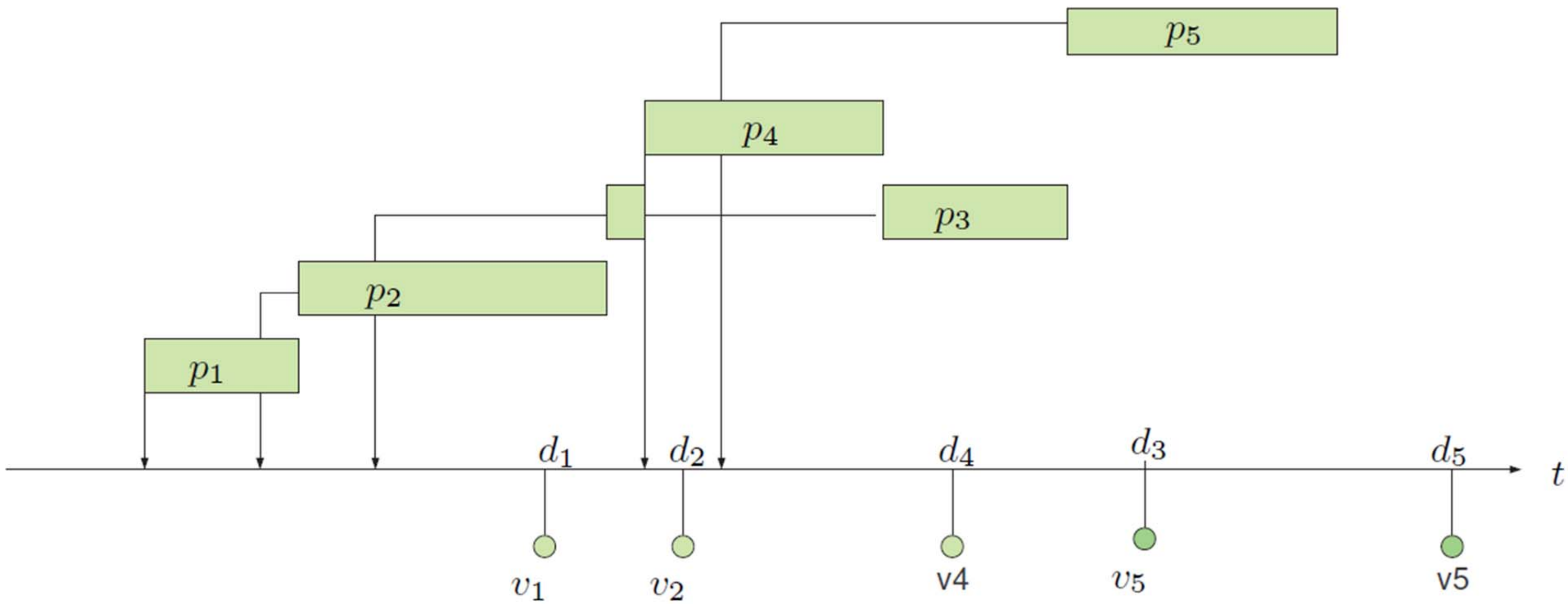




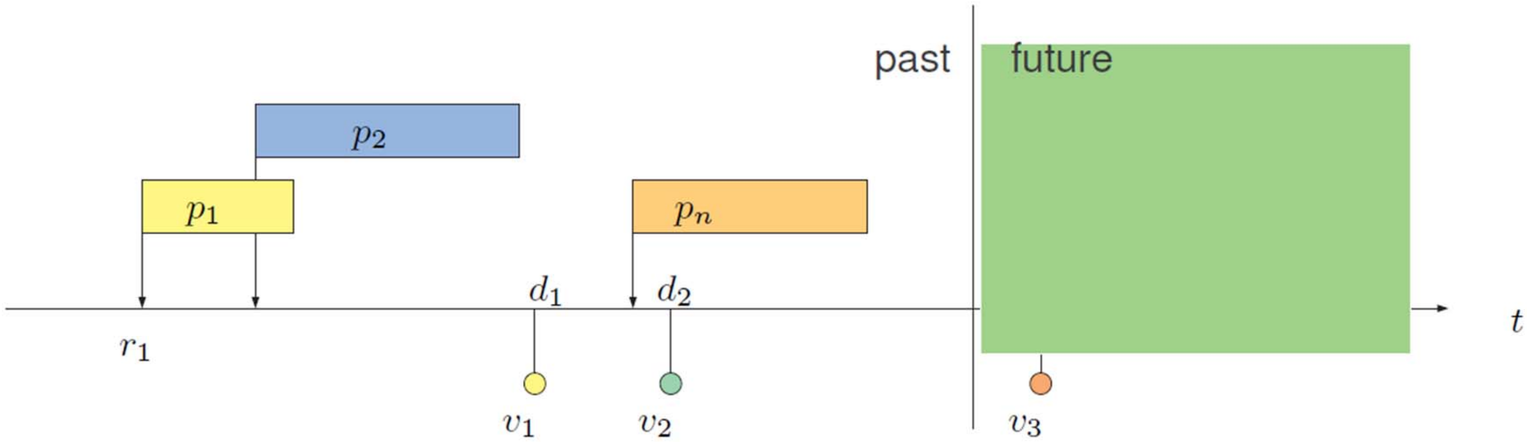
Unmanaged charging



Managed charging by deadlines (EDF)



Information hierarchy and VoI



- Given a job instance $\mathcal{J}$, compare profit $V_\pi(\mathcal{J})$ of an online policy π with that of the optimal offline policy $V^*_{\text{off}}(\mathcal{J})$
- An online scheduling algorithm π is α-competitive for a collection of job instances $\mathcal{J}$ if

$$C(\pi, \mathcal{J}) = \min_{\mathcal{J} \in \mathcal{J}} \frac{V_\pi(\mathcal{J})}{V^*_{\text{off}}(\mathcal{J})} = \alpha$$

Value of information: how good is EDF?

- A job instance $\mathcal{J}$ is underloaded if there is an offline algorithm that completes all jobs on time in $\mathcal{J}$.
- If $\mathfrak{J}$ is a collection of underloaded job instances, then

$$\max_{\pi} C(\pi, \mathfrak{J}) = C(\pi_{\mathsf{EDF}}, \mathfrak{J}) = C(\pi_{\mathsf{LLF}}, \mathfrak{J}) = 1.$$

EDF (Liu&Layland'73) and LLF (Dertouzos'74, Mok'83).

- For general load cases,

$$\max_{\pi} C(\pi, \mathcal{I}) = \frac{1}{4}$$

Baruah&etal'92, Koren&Shasha'95. Optimal policy: EDF + LLF.

Optimal competitive ratio

Theorem (single level pricing)

Suppose that the marginal cost of purchasing electricity from the grid is normalized to 1 *and the offered charging price is* $\gamma \leq 1$*, then for the case of* m*-renewable chargers*

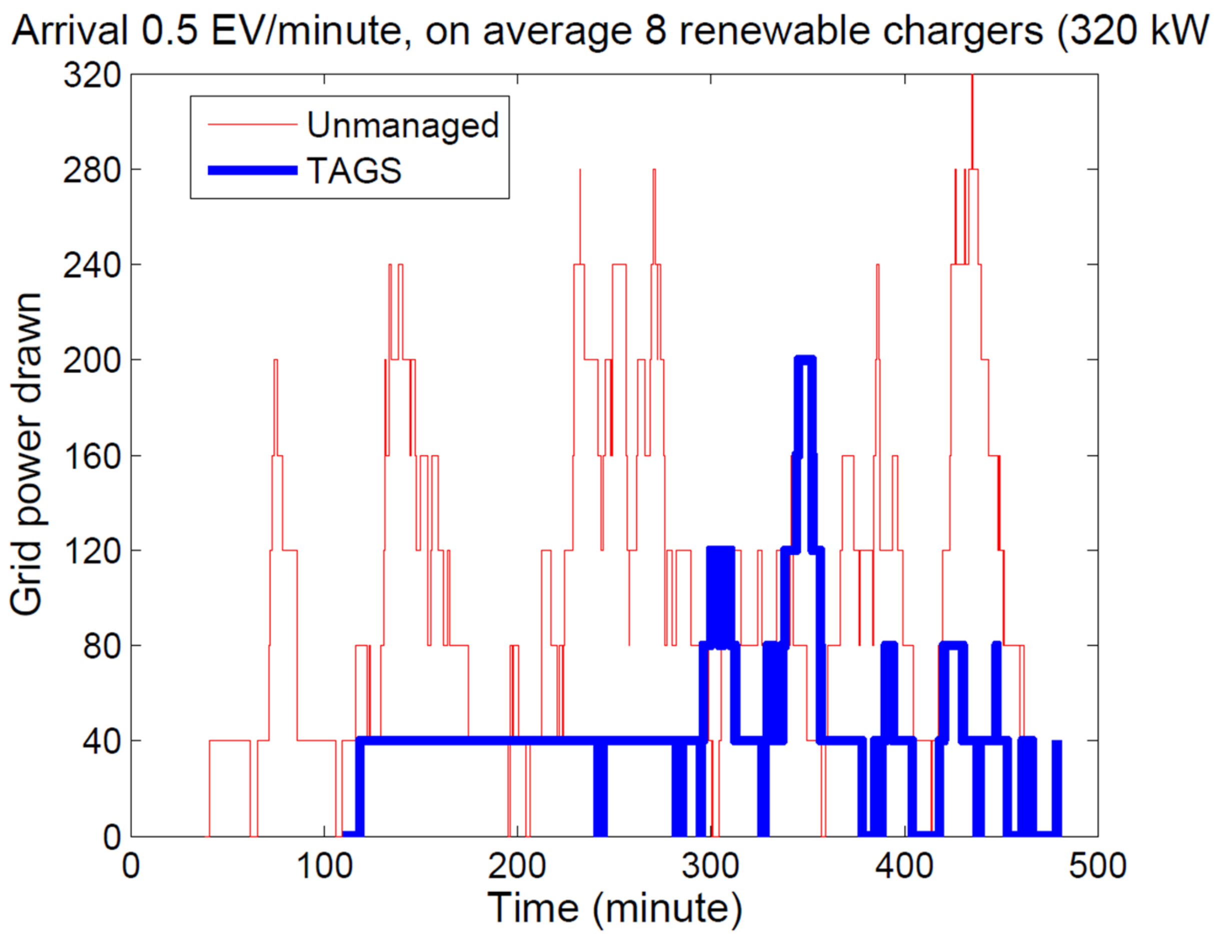
$$\max_{\pi} C^{purchase}(\pi) = \frac{1}{z(\gamma, m)}$$

where $z(\gamma, m) > 1$ *is the unique such positive real root of*

$$f(z) = \gamma(z+m)^{m+1} - z(m+1)^{m+1}$$

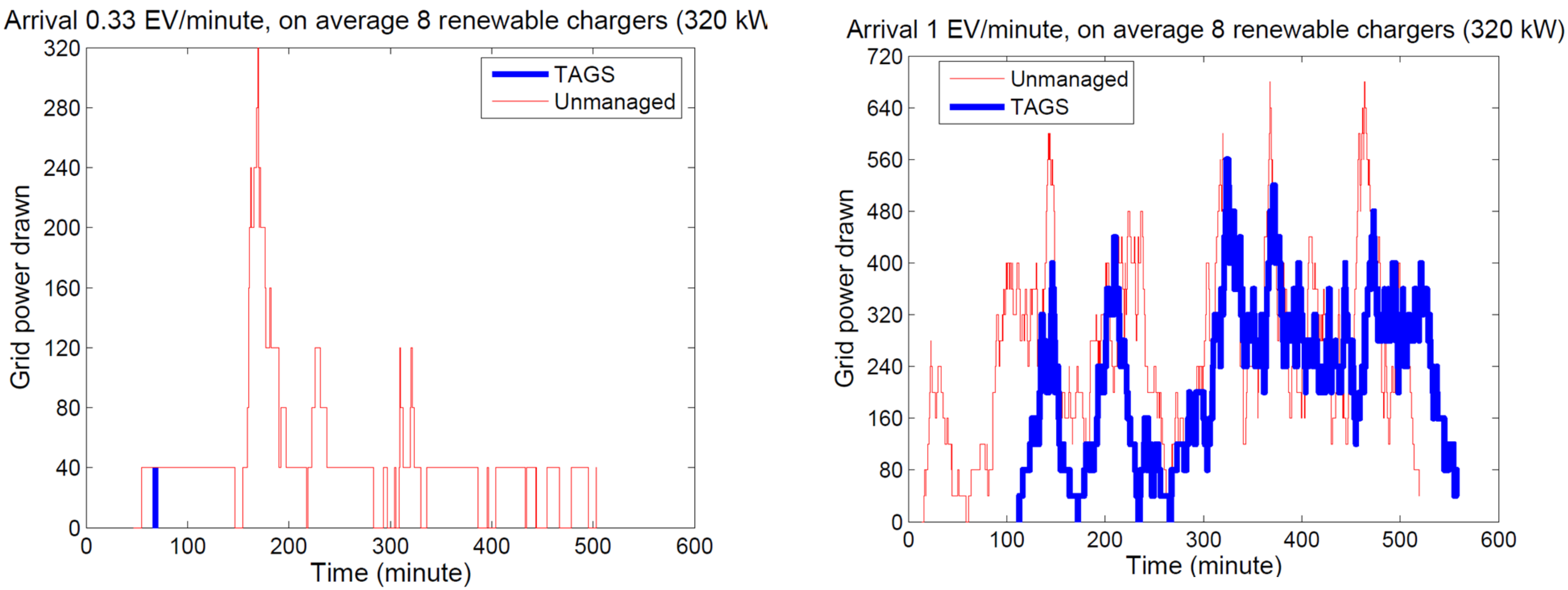
- Achievability: **TAGS**—Threshold Assignment and Greedy Scheduling.
- Converse: adversary manipulated job instances.

Power profile: managed vs. unmanaged



25% reduction of peak power consumption on average

Power profile: managed vs. unmanaged



71% reduction (1/3 EV/min) and 12% reduction (1EV/min)

Information hierarchy for LSC: Insights

- Large scale charging has to be managed, of course!
- The key is to exploit available laxity by casting the problem as one of deadline scheduling.
- Load information (deadline and the amount of charge) becomes available at different time scale: day ahead estimates, traffic conditions, and in real-time.
- The service provider should provide pricing incentives for customers: lower price for more flexible customers.
- Significant gain can be realized by managed charge.
- There is value for reservation.

Information hierarchy for LSC: challenges

- What is the impact of large scale charging on the grid? How much smart charging can help?
- What are the interactions between the grid and smart charging facilities?
- Interacting information structures and decisions:
  - There are very few charging facility, why I buy an EV?
  - There are so few EVs, why do I invest in charging facilities

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Information hierarchy in space

- Information hierarchy in space addresses the problem of collecting and disseminating information for certain decision functions from and to a large geographical area: where to collect, what are the networking requirements, data resolution, and latency.
- Information generated at different spatial locations may be inconsistent, erroneous, out of date, even malicious. (Recall the Brewer's conjecture and CAP Theorem)
- A fundamental question is how the quality of data affects the quality of grid operation (state estimation, real-time market operations, etc.)

Power system state estimation

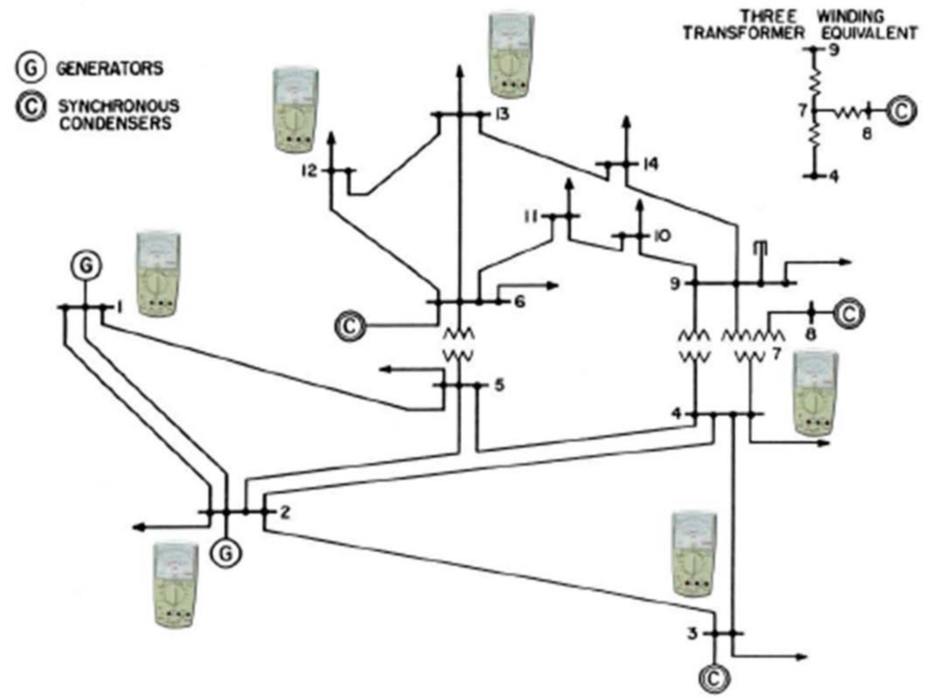
- We consider static state estimation

$$Z = h(X) + W$$

where

- Z: vector of measurements
- X: the state vector
- W: the measurement noise.

- The state vector X (conventionally) is the vector of bus voltage phasors or, equivalently, the generation and load vector.

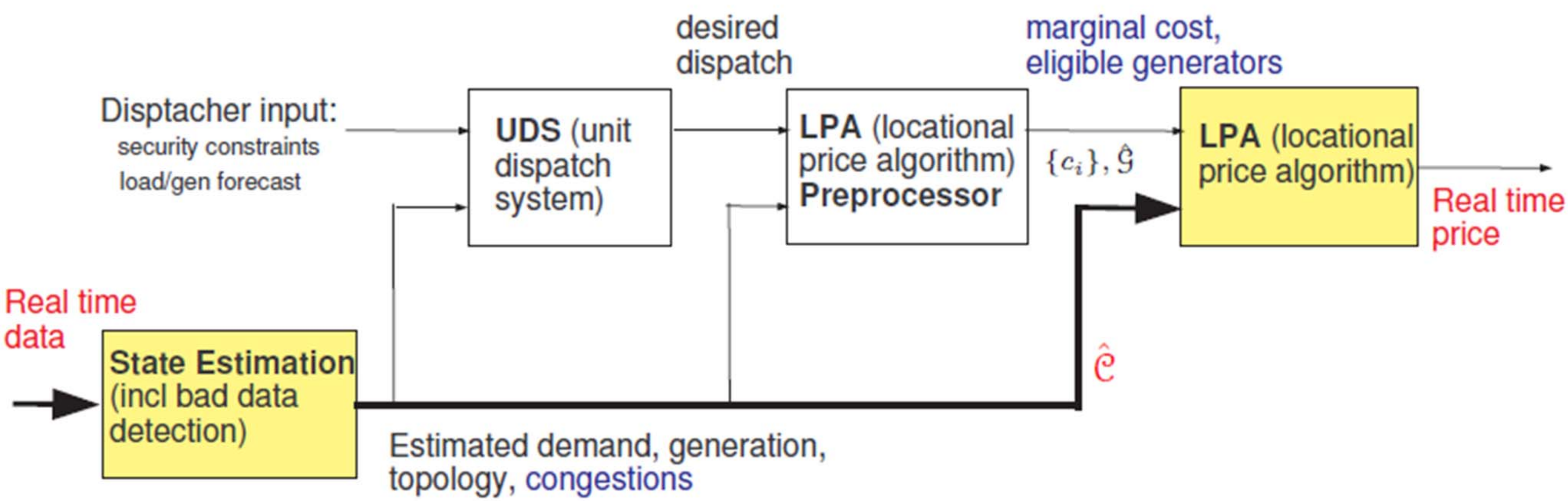


- One common approach is the weighted least squares (WLS) estimator:

$$\hat{x}_{\text{WLS}}(z) = \arg\min_{x}(z - h(x))^{\mathsf{T}} \Sigma_W^{-1} (z - h(x))$$

- An alternative is to pursue a Bayesian approach.

Data in real-time market operations

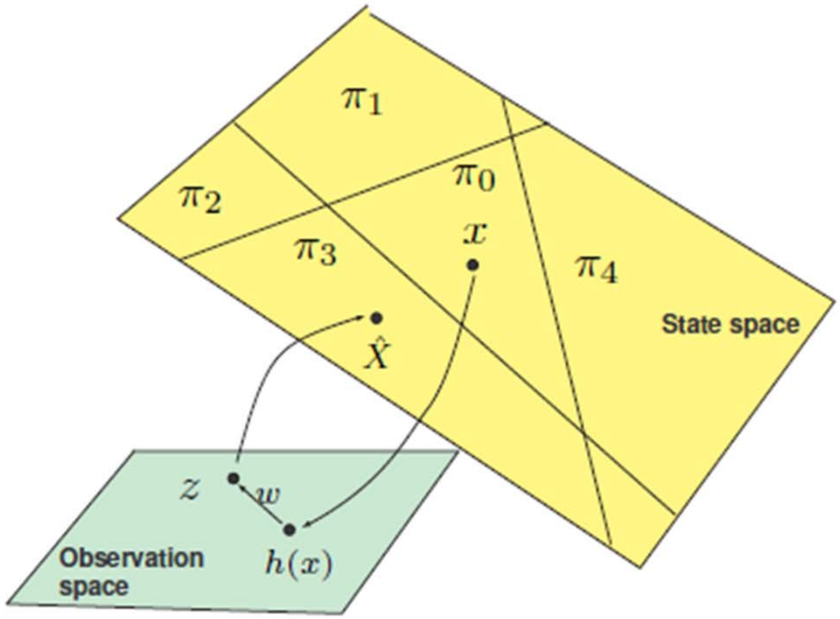


From data to real-time LMP

- The state space is partitioned by hyperplanes into price regions.
- The real time LMP is random, and it forms a Markov chain:

$$Z \rightarrow \hat{X} \rightarrow \pi$$

- If data are to affect price, they have to move $\hat{x}$ to a different price region.



Data quality models

We consider a simple perturbation model

$$Z_t = h(X_t) + W_t + A_t, \quad A_t \in \mathcal{A}$$

where $\mathcal{A}$ characterizes the nature of the perturbation.

- Some examples:
  1. Static perturbation: $A_t = a \in \mathcal{A} = \{a : \|a\|_0 \leq T\}$.
  2. Perturbation with memoryless data dependency: $A_t = Q(Z_t) \in \mathcal{A}$.
  3. Dynamic perturbation: $A_t = Q(Z_t, Z_{t-1}, \cdots)$.
- We focus on the worst case analysis for (1-2).

Bad data detection

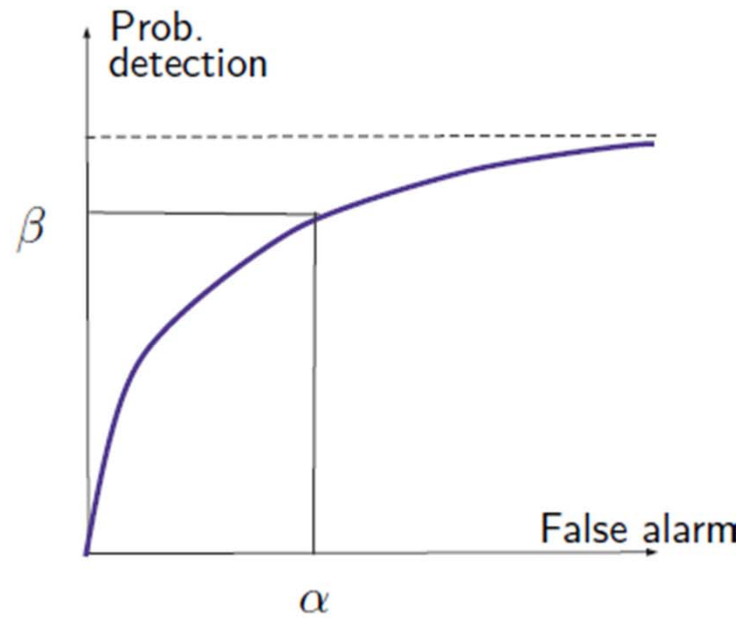
- State estimation:

$$\hat{x}_{\mathrm{WLS}}(z) = \arg\min_{x} \|z - h(x)\|^2_{\Sigma_W^{-1}}$$

- Bad data detection: Typical detector:

$$\|z - h(\hat{x}_{\mathrm{WLS}}(z))\| \underset{\text{good}}{\overset{\text{bad}}{\gtrless}} \tau$$

where the choice of τ determines the operating point.



Detector operating characteristic

Worst/malicious data

- Under the DC model, bad data moves the state estimate

$$\hat{x}_{\text{WLS}} = Kz = \hat{x}^* + Ka$$

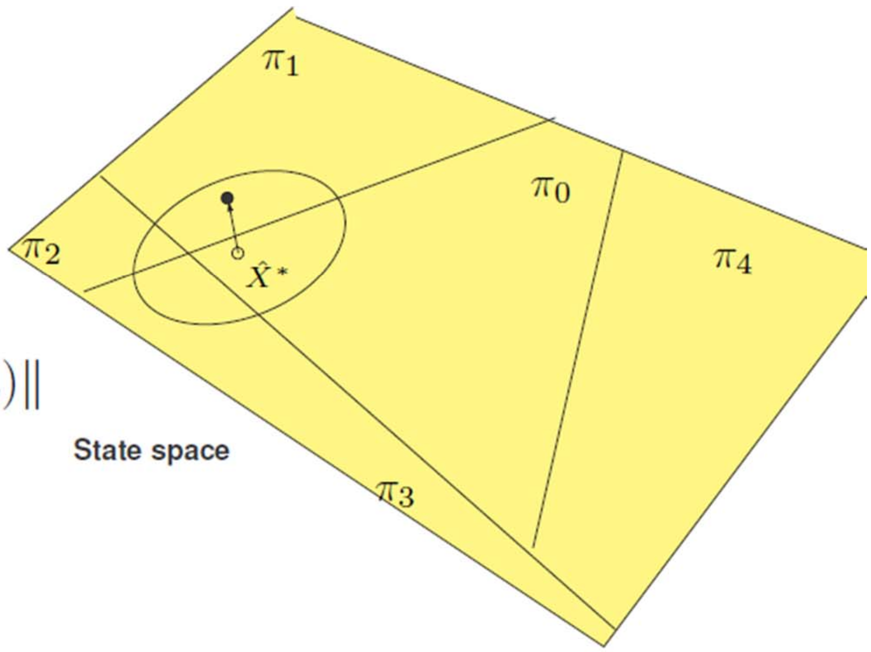
where $\hat{x}^*$ is the estimate when $a = 0$.

- The residue of WLS estimator satisfies

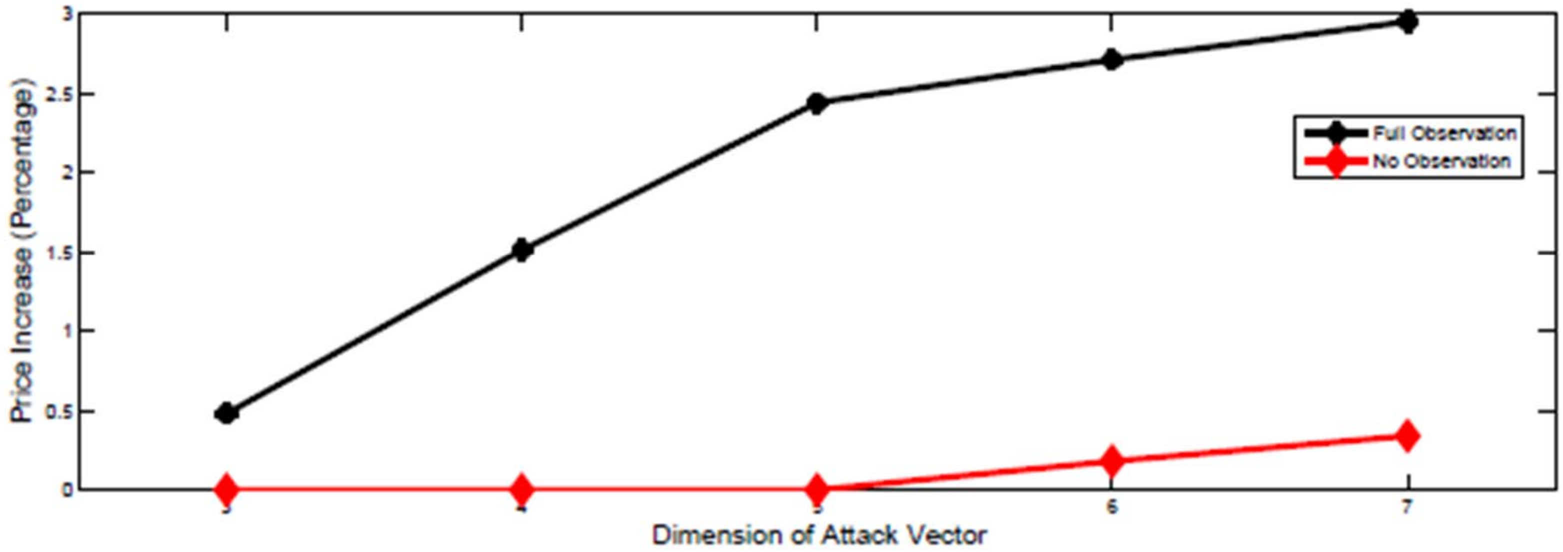
$$\|z - H\hat{x}_{\text{WLS}}(z)\| = \|(z+a)^\intercal P_H^\perp (z+a)\|$$

Thus a is not detectable if

$$\|(z+a)^\intercal P_H^\perp (z+a)\| \le \tau$$

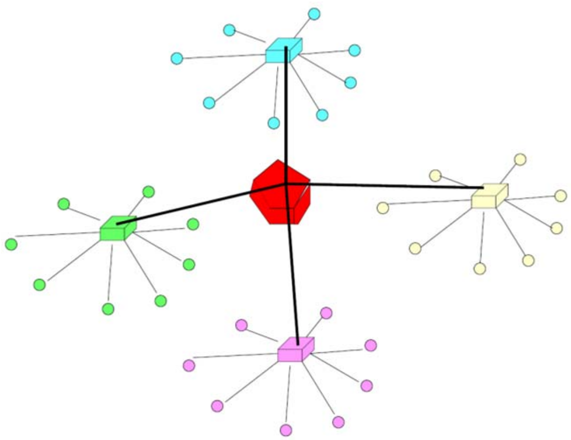


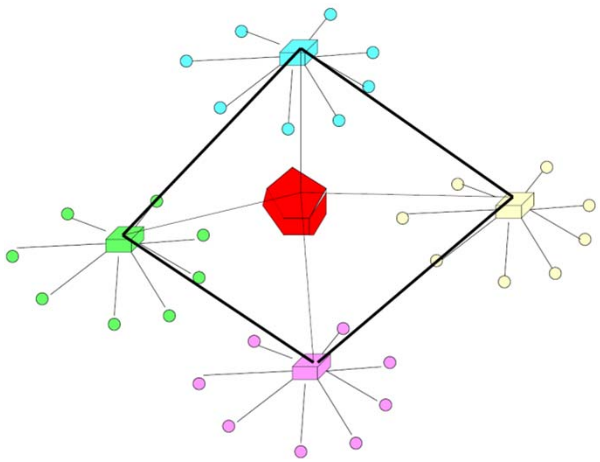
Effects of worst data (IEEE 118)



Comparison of hierarchical structures

- Two hierarchical structures under uncertainties and in changing environment:





- The role of delay and compression error of vertical information fusion vs. speed decentralized of learning.
- Network capacity requirements and rate-distortion measures

Remarks

- If the future smart grid is to include a high level of stochastic generation, to allow substantial demand response, to interact with a large number of web-based applications, to be robust against failures and attacks, it is necessary to gain a foundational understanding of the underlying computation and information hierarchy.

- Such understanding requires more than numerical studies of practical systems; analytical insights from properly simplified model may be enormously valuable.

- Such understanding will help to design scalable and highly efficient information network.