# Volatility in Real-Time Electricity Markets: efficiency or manipulation?

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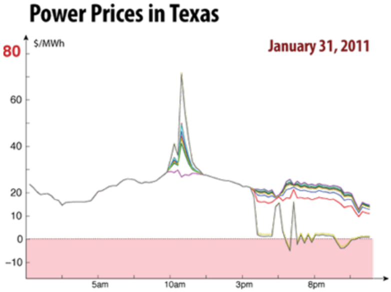
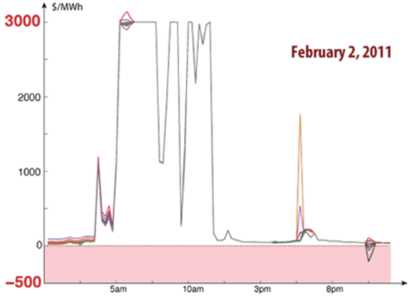
# Is it price manipulation or an *efficient* market?

Source: Meyn 2012.

Prices ($/MWh)




Time of the day




Time of the day

# Motivation and (quick) related work

## Control by prices and distributed optimization

- *PowerMatcher: multiagent control in the electricity infrastructure* – Kok et al. (2005)
- *Real-time dynamic multilevel optimization for demand-side load management* – Ha et al. (2007)
- *Theoretical and Practical Foundations of Large-Scale Agent-Based Micro-Storage in the Smart Grid* – Vytelingum et al (2011)
- *Dynamic Network Energy Management via Proximal Message Passing* – Kraning et al (2013)

## Fluctuations of prices in real-time electrical markets

- *Dynamic competitive equilibria in electricity markets* – Wang et al (2012)

# Issue: The electric grid is a large, complex system

# We study an idealistic real-time market model that includes demand-response and storage

**Question 1.** Is there a contradiction between observed prices and "Market efficiency"?

**Question 2.** Can real-time prices can be used for control?

# We study an idealistic real-time market model that includes demand-response and storage

**Question 1.** Is there a contradiction between observed prices and "Market efficiency"?

- No.
  - Any price equilibrium leads to a socially optimal allocation.

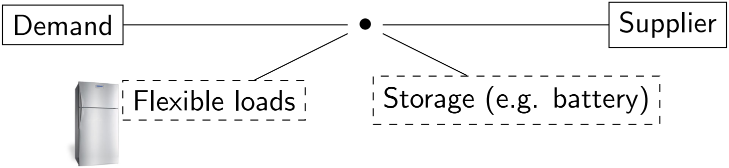
**Question 2.** Can real-time prices can be used for control?

- Yes and no:
  - Provable and decentralized methods (Lagrangian decomposition)
  - There is a high price fluctuation

# Outline

# Outline

# We consider the simplest model that takes the dynamical constraints into account (extension of Wang et al. 2012)




Each player is selfish and has internal utility/constraints. It exchanges energy.

# We assume perfect competition

Users are selfish and price-takers:

$$\underset{E_i \in \text{internal constraints of } i}{\arg\max}\ \mathbb{E}\left[\int_0^\infty \underbrace{W_i(t)}_{\text{internal utility}} - \underbrace{P(t)E_i(t)}_{\text{bought/sold energy}} dt\right]$$

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Players share a common probabilistic forecast model

Players cannot influence $P(t)$.

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## Definition

A competitive equilibrium is a price for which players selfishly agree on what should be bought and sold:

- For any player $i$, $E_i^e$ is a selfish best response to $P$:
- $\sum_{i \in \text{players}} E_i^e(t) = 0.$

# Two examples of internal utility functions and constraints

- Generator: generates $G(t)$ units of energy at time $t$.
  - Cost of generation: $cG(t)$.
  - Ramping constraints: $\zeta^- \leq G(t+1) - G(t) \leq \zeta^+$.

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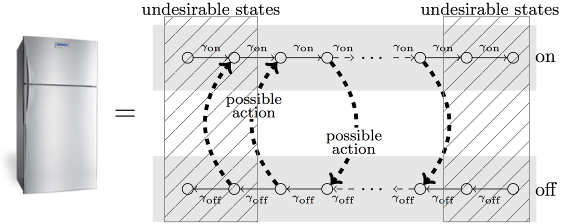
- Flexible loads: population of $N$ thermostatic loads.




  - Consumption can be anticipated/delayed

# The market is efficient (first welfare theorem)

**Theorem**

*For any installed quantity of demand-response or storage, any competitive equilibrium is socially optimal.*

If players agree on what should be bought or sold, then it corresponds to a socially optimal allocation.

# **Proof.** The first welfare theorem is a Lagrangian decomposition

For any price process $P$:

social planner's problem

$$\boxed{\max_{\substack{E_i \text{ satisfies constraints } i \\ \forall t : \sum_i E_i(t) = 0}} \mathbb{E}\left[\sum_{i \in \text{players}} \int W_i(t)dt\right]}$$

selfish response to prices

$$\leq \sum_{i \in \text{players}} \boxed{\max_{E_i \text{ satisfies constraints } i} \mathbb{E}\left[\int (W_i(t) + P(t)E_i(t))dt\right]}$$

If the selfish responses are such that $\sum_i E_i(t) = 0$, the inequality is an equality.

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If the selfish responses are such that $\sum_i E_i(t) = 0$, the inequality is an equality.

# Outline

**Reminder:** If there exists a price such that selfish decisions leads to energy balance, then these decisions are optimal.

### Theorem

*For any installed quantity of demand-response or storage:*

- *There exists such a price.*
- *We can compute it (convergence guarantee).*

# We design a decentralized optimization algorithm based on an iterative scheme

**Iterative algorithm based on ADMM**

Price $P(t)$ $\underset{\textbf{2.}\ \text{forecasts consumption } E}{\overset{\textbf{1.}\ \text{forecast price } P(1),\dots,P(T),\ \bar{E}}{\rightleftarrows}}$ Generator / Demand / $\vdots$ / Fridges

**3.** Update price

**Theorem**

*The algorithm converges.*

# We use ADMM iterations.

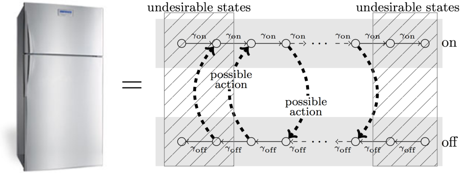
Augmented Lagrangian:

$$L_\rho(E,P) := \sum_{i\in\text{players}} W_i(E_i) + \sum_t P(t)\left(\sum_i E_i(t)\right) - \frac{\rho}{2}\sum_{t,i}\left(E_i(t)-\bar{E}_i(t)\right)^2$$

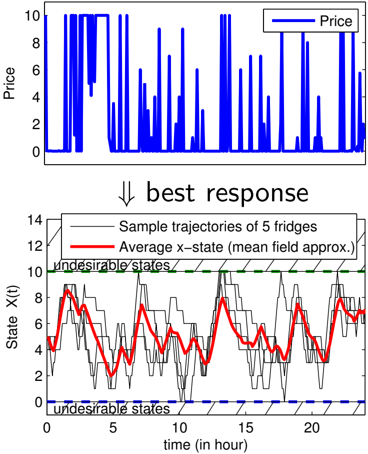
ADMM (alternating direction method of multipliers):

$$\begin{aligned} E^{k+1} &\in \arg\max_E L_\rho(E,\bar{E}^k,P^k) && \text{for each player (distributed)} \\ \bar{E}^{k+1} &\in \arg\max_{\bar{E}\text{ s.t. } \sum_i \bar{E}_i=0} L_\rho(E^{k+1},\bar{E},,P^k) && \text{projection (easy)} \\ P^{k+1} &:= P^k - \rho(\sum_i E_i^{k+1}) && \text{price update} \end{aligned}$$

# The algorithm is distributed: each flexible appliance computes its best-response to price



Object $=$ Markov chain



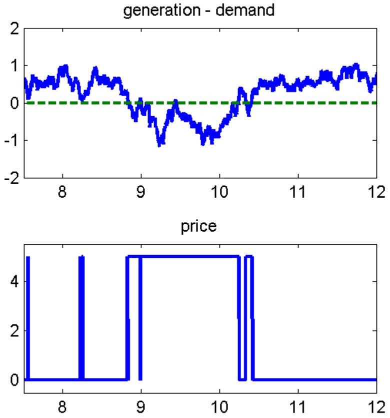
# Outline

**Reminder:** we know how to compute a price such that selfish decision leads to a social optimum.

We can evaluate the effect of more flexible load / more storage.

- Is the price smooth?
- Impact on social welfare.

# Without storage or DR, prices are never equal to the marginal production cost (Wang et al. 2012)




No storage

- Reason is ramping constraint of generation.

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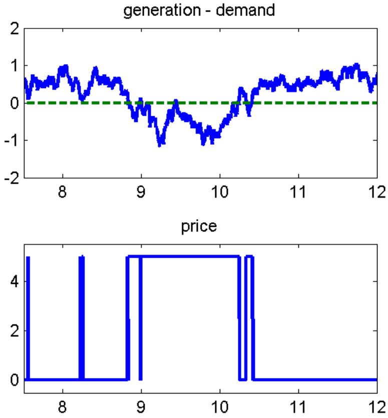


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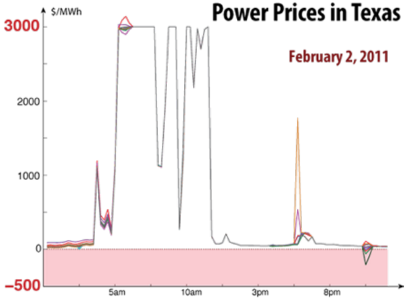
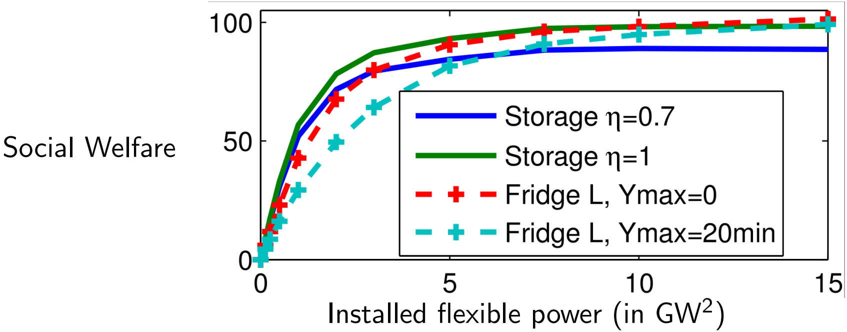



- Reason is ramping constraint of generation.

# With perfect information, demand-response is better than storage



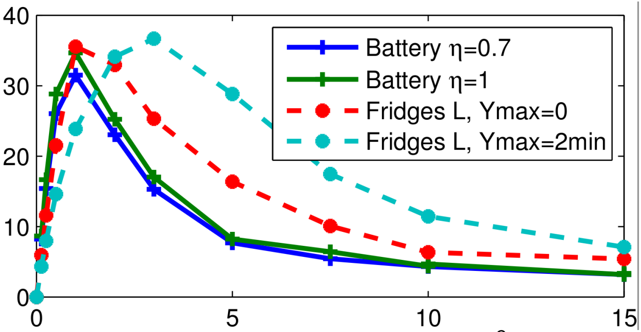

- Delaying or anticipating consumption has no charge/discharge inefficiency.

[2] The forecast errors correspond to a total wind capacity of 26GW.

# Problem of the market structure: perfect storage or DR lead to a price concentration

Incentive to install less demand-response than the social optimal.

Welfare for storage owner / demand-response operator




Installed flexible power (in GW[3])

[3] The forecast errors correspond to a total wind capacity of 26GW.

# Outline

# Summary

**1.** Real-time market model (generation dynamics, flexible loads, storage)
A price such that selfish decisions are feasible leads to a social optimum.

**2.** We know how to compute the price.

- Trajectorial forecast, mean field and ADMM

**3.** Benefit of demand-response: flexibility, efficiency
Drawbacks: non-observability, under-investment

# Perspectives

- Distributed optimization in smart-grid
  - Methodology:
    - Distributed Lagrangian (ADMM) is powerful
    - Use of trajectorial forecast makes it computable
  - In distribution networks.
- Optimization in Systems with many small agents.
  - Virtual prices and/or virtual markets:

## Nicolas Gast — http://mescal.imag.fr/membres/nicolas.gast/

Model and Forecast


- Dynamic competitive equilibria in electricity markets, G. Wang, M. Negrete-Pincetic, A. Kowli, E. Shafieepoorfard, S. Meyn and U. Shanbhag, *Control and Optimization Methods for Electric Smart Grids*, 35–62 2012,
- From probabilistic forecasts to statistical scenarios of short-term wind power production. P. Pinson, H. Madsen, H. A. Nielsen, G. Papaefthymiou, and B. Klockl. *Wind energy*, 12(1):51-62, 2009


Storage and Demand-response


- Impact of storage on the efficiency and prices in real-time electricity markets. N Gast, JY Le Boudec, A Proutière, DC Tomozei, e-Energy 2013
- Impact of Demand-Response on the Efficiency and Prices in Real-Time Electricity Markets. N Gast, JY Le Boudec, DC Tomozei. e-Energy 2014


ADMM


- Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein. Foundations and Trends in Machine Learning, 3(1):1-122, 2011.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