Impact of Demand-Response on the Efficiency and Prices in Real-Time Electricity Markets

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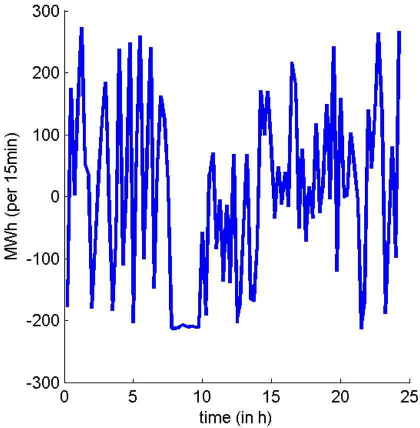
[1] Joint work with Jean-Yves Le Boudec (EPFL), Alexandre Proutiere (KTH) and Dan-Cristian Tomozei (EPFL)

Quiz: what is the value of energy?



Average price is 20\$/MWh.
Average production is 0.

1. 0\$.
2. $150k\$$
3. $-150k\$$.

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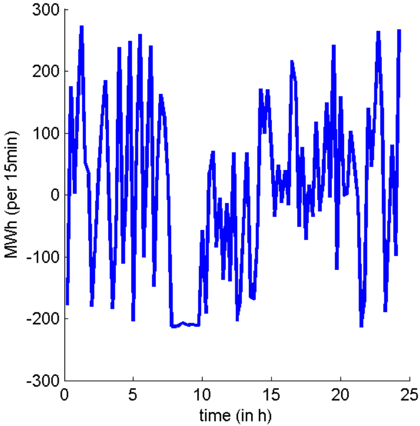

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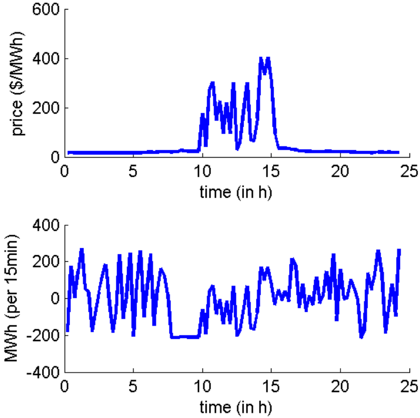

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   YES: If you buy on the real-time electricity market (Texas, mar 3 2012)
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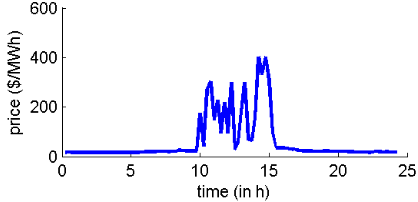

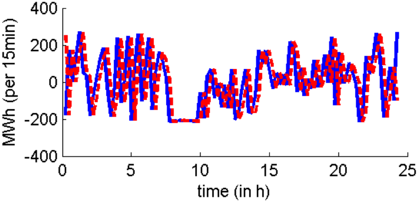

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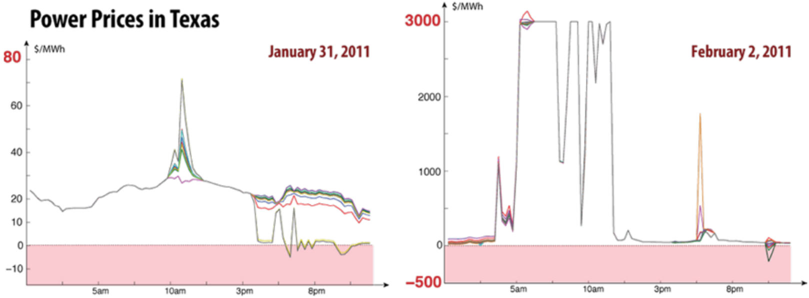
1. 0\$.
   YES: If you are a private consumer.
2. 150k\$
   YES: If you buy on the real-time electricity market (Texas, mar 3 2012)
3. $-150k$\$.
   NO (but YES for the red curve! Texas, march 3rd 2012)

Can we understand real-time electricity prices?

Source: Cho-Meyn 2006.

Prices in $/MWh



Time of the day Time of the day

Is it price manipulation or an efficient market?

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

It is governed by a mix of economics (efficiency) and regulation (safety).

Our contribution

We study a simple real-time market model that includes demand-response.

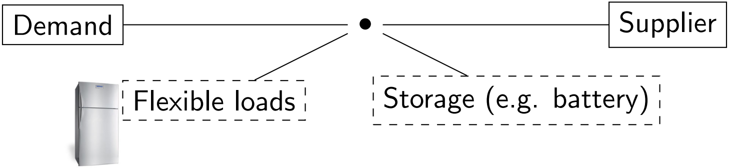
- Real-time prices can be used for control
  - Socially optimal
  - Provable and decentralized methods
- However:
  - There is a high price fluctuation
  - Demand-response makes forecast more difficult
  - Market structure provide no incentive to install large demand-response capacity

Outline

1. Real-Time Market Model and Market Efficiency
2. Numerical Computation and Distributed Optimization
3. Consequences of the (In)Efficiency of the Pricing Scheme
4. Summary and Conclusion

Outline

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



Each player has internal utility/constraints and exchange energy

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 appliances: Markov model

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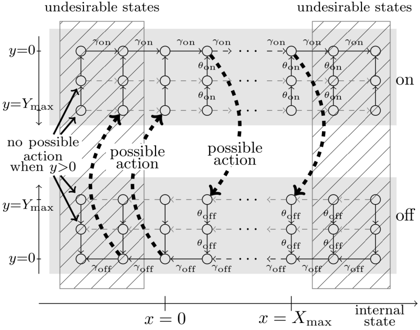

Consumption can be anticipated/delayed but

- Fatigue effect
- Mini-cycle avoidance

  - Internal cost: temperature deadband.
  - Constraints: Markov evolution and temperature deadband, switch on/off.

We assume perfect competition between 2, 3 or 4 players

(supplier, demand, storage operator, flexible demand aggregator)

Player i maximizes:

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

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Players share a common probabilistic forecast model

Players cannot influence $P(t)$.

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

$(P^e, E_1^e, \dots, E_j^e)$ is a competitive equilibrium if:

- For any player i, E_i^e is a selfish best response to P:

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

- The energy balance condition: for all t:

$$\sum_{i \in \text{players}} E_i^e(t) = 0.$$

An (hypothetical) social planner's problem wants to maximize the sum of the welfare.

$(E_1^e, \dots, E_j^e)$ is socially optimal if it maximizes $\mathbb{E}\left[\int_0^\infty \underbrace{\sum_{i\in \text{ players}} W_i(t)\, dt}_{\text{social utility}}\right]$,

subject to

- For any player i, E_i^e satisfies the constraints of player i.
- The energy balance condition: for all t:

$$\sum_{i\in\text{players}} E_i^e(t) = 0.$$

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

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

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

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selfish response to prices

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What is the price equilibrium? Is it smooth?

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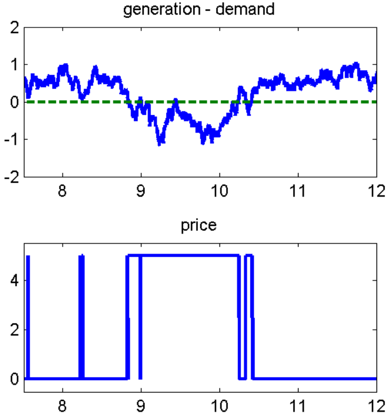
- Production has ramping constraints,
- Demand does not.

Fact 1. Without storage or DR, prices are never equal to the marginal production cost (Wang et al. 2012)



No storage

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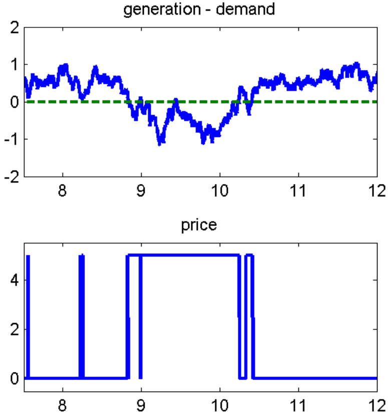

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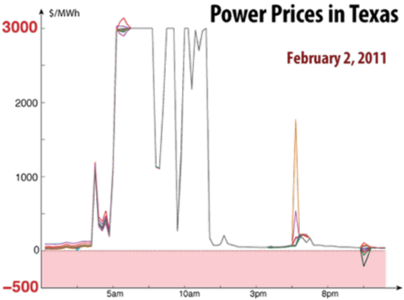
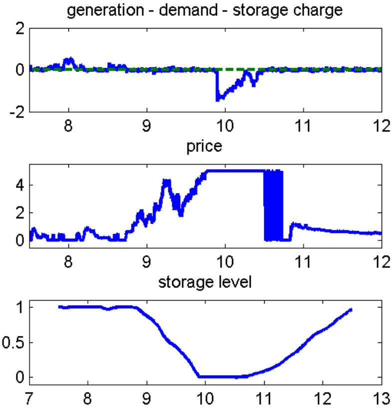
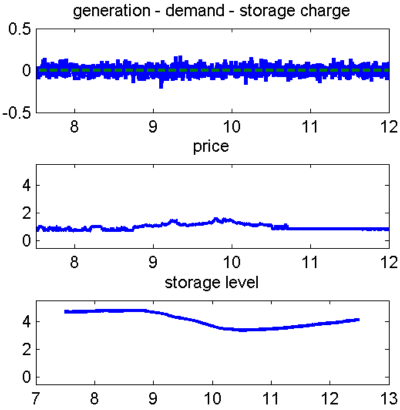


Fact 2. Perfect storage leads to a price concentration

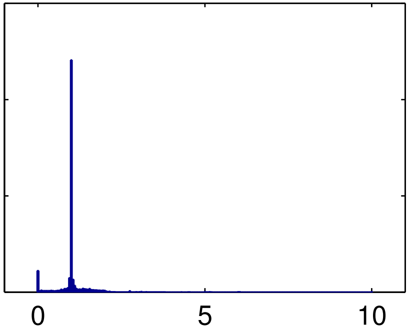


Small storage

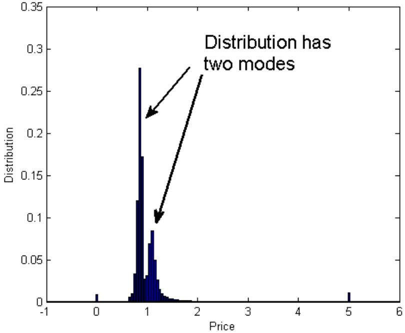


Large storage

Fact 3. Because of (in)efficiency, the price oscillates, even for large storage



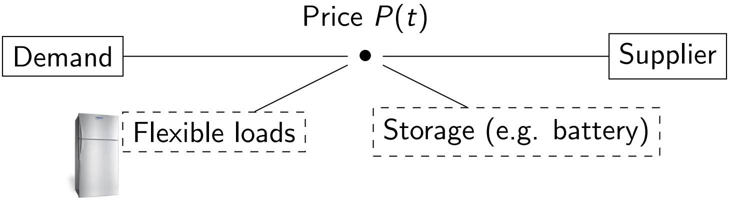
Perfect storage: price becomes equal to the marginal production cost



Realistic storage: two modes in $\sqrt{\eta}$ and $1/\sqrt{\eta}$

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

Generator

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

$\vdots$

3. Update price

Fridges

Theorem

The algorithm converges.

We use ADMM iterations.

Augmented Lagrangian:

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

ADMM (alternating direction method of multipliers):

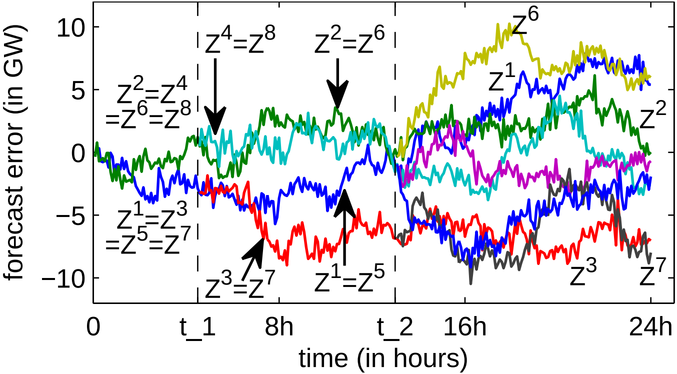
$$\begin{aligned}
E^{k+1} &\in \arg\max_E L_\rho(E, \bar{E}^k, P^k) && \text{for each player (distributed)}\\
\bar{E}^{k+1} &\in \arg\max_{\bar{E}\text{ s.t. } \sum_i \bar{E}_i = 0} L_\rho(E^{k+1}, \bar{E}, , P^k) && \text{projection (easy)}\\
P^{k+1} &:= P^k - \rho(\sum_i E_i^{k+1}) && \text{price update}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

ADMM converges because the problem is convex

1. Utility functions and constraints are convex
   - *e.g.*, Ramping constraints, batteries capacities, flexible appliances

ADMM converges because the problem is convex

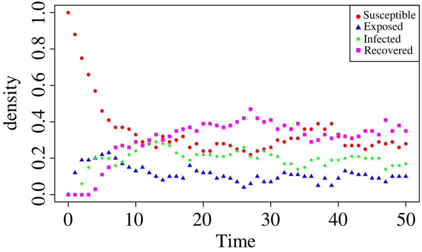
1. Utility functions and constraints are convex
2. We represent forecast errors by multiple trajectories



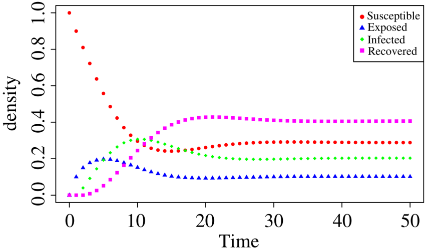
- Extension of Pinson et al (2009).
- Using covariance of data from the UK

ADMM converges because the problem is convex

1. Utility functions and constraints are convex
2. We represent forecast errors by multiple trajectories
3. We approximate the behavior of the flexible appliances by a mean-field approximation



Original system



Mean-field approximation
(limit as number of appliances is large)

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

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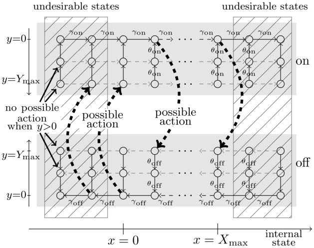
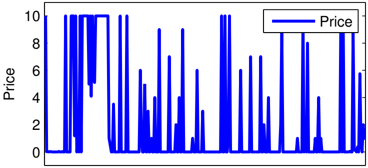
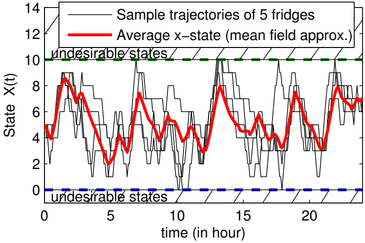


Object = Markov chain

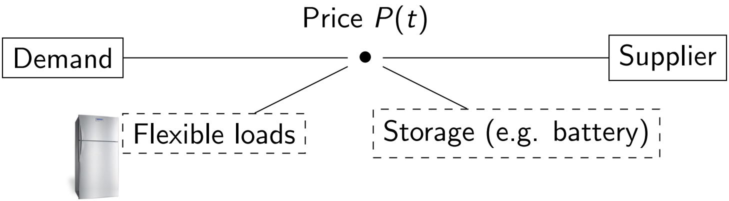


⇓ best response



Outline

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

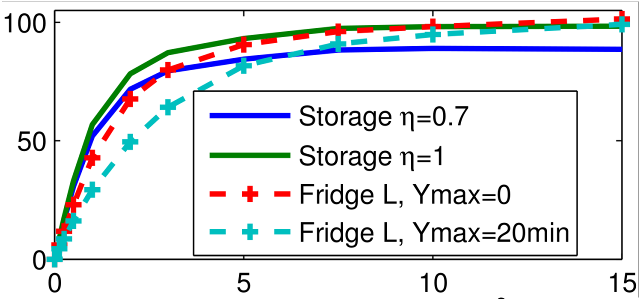


We can evaluate the effect of more flexible load / more storage.

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

In a perfect world, the benefit of demand-response is similar to perfect storage

Social Welfare



Installed flexible power (in GW[2])

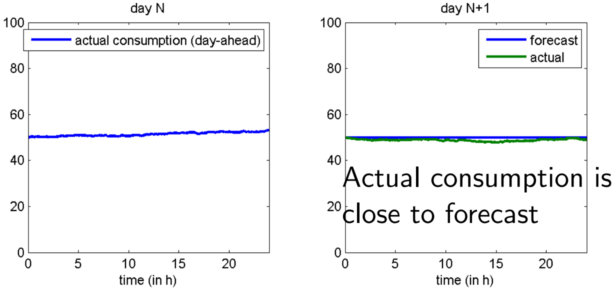
- No charge/discharge inefficiencies for demand-response (we can only anticipate or delay consumption).

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

Problem of demand-response: synchronization might lead to forecast errors

No Demand-response

Total consumption



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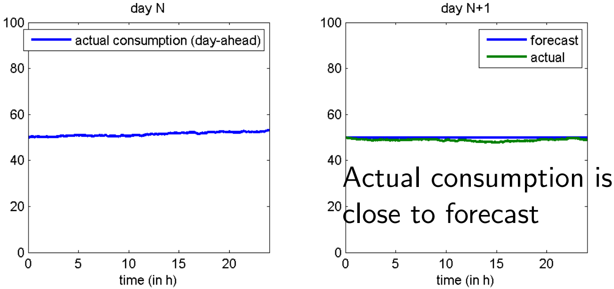
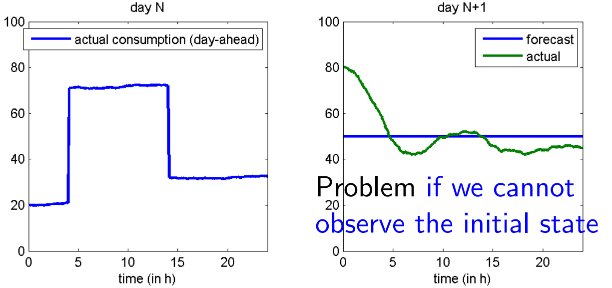


Actual consumption is close to forecast

With Demand-response

Total consumption



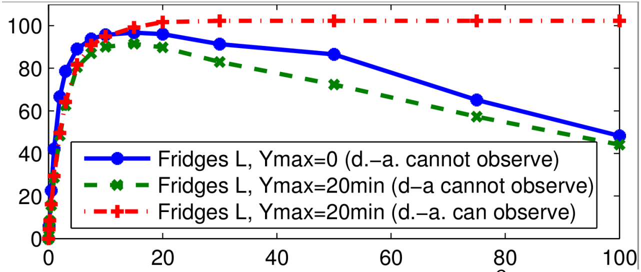
Problem if we cannot observe the initial state

Problem of demand-response. Non-observablity is detrimental if the penetration is large

We assume that:

- The demand-response operator knows the state of its fridges
- The day-ahead forecast does not.

Social Welfare

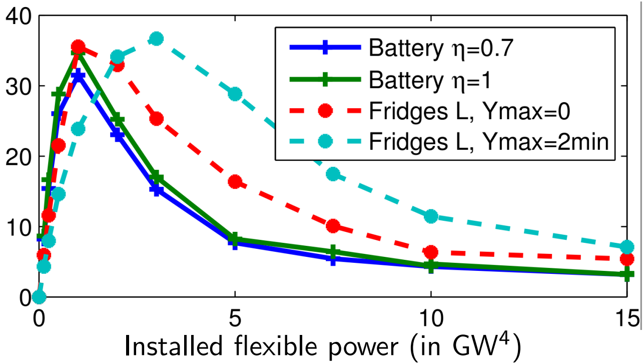


Installed flexible power (in GW[3])

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

Problem of the market structure. Incentive to install less demand-response than the social optimal.

Welfare for storage owner / demand-response operator

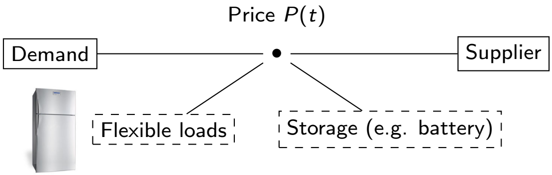


[4]The forecast errors correspond to a total wind capacity of 26GW.

Outline

Summary

1. Real-time market model (generation dynamics, flexible loads, storage)



2. A price such that selfish decisions are feasible leads to a social optimum.

3. We know how to compute the price.

- Trajectorial forecast, mean field and ADMM

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

Perspectives

- Distributed optimization in smart-grid
  - In distribution networks.
  - Methodology:
    - Distributed Lagrangian (ADMM) is powerful
    - Use of trajectorial forecast makes it computable
- Optimization in Systems with many small agents.
- Virtual prices and/or virtual markets:
  - Bike-sharing systems (to solve the optimization problem but not to define prices for users).

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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

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- 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.

Supported by the EU project quanticol — http://www.quanticol.eu