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

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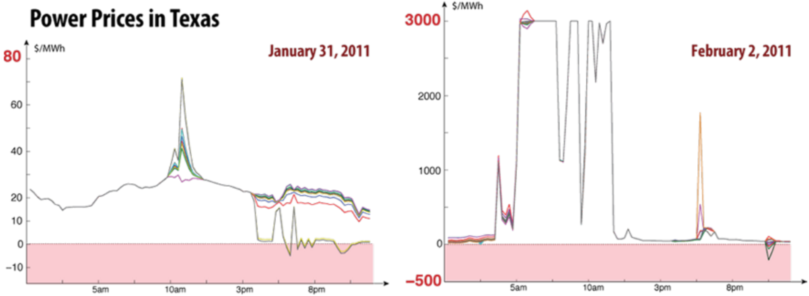
Can we understand real-time electricity prices?

Prices in $/MWh



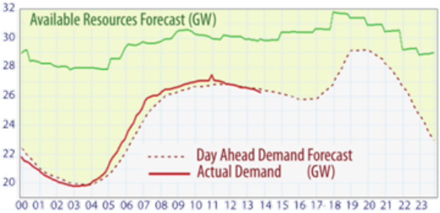
Time of the day Time of the day

Is it price manipulation or an efficient market?

Issue 1: The electric grid is a large, complex system

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

Issue 2: Mix of forecast (day-ahead) and real-time control



Mean error: 1–2%

Mean error: 20%

Main message

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

- Real-time prices can be used for control
  - Decentralized control
  - Socially optimal
- 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

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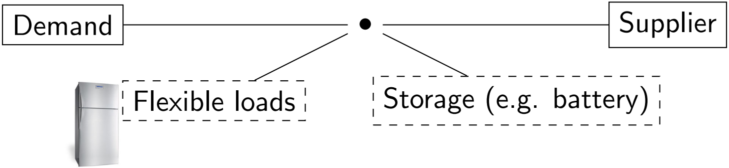
We consider the simplest model that takes the dynamical constraints into account (extension of Wang et al. 2012)



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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  - Cost of generation: $cG(t)$.
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- Flexible loads: population of N thermostatic appliances
  - Internal cost: temperature deadband.
  - Constraints: applicances can be switched on or off

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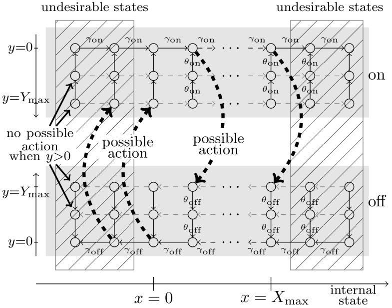

Appliance = Markov chain

Consumption can be anticipated/delayed but

- ★ Fatigue effect
- ★ Mini-cycle avoidance

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)

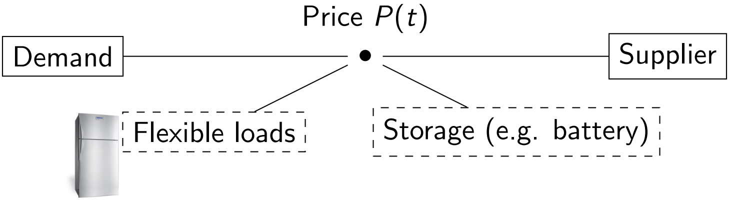
Theorem

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.

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

1. forecast price $P(1), \dots, P(T)$, $\bar{E}$

Demand

Price $P(t) \xrightleftharpoons[\textbf{2. } \text{forecasts consumption } E]{\textbf{1. } \text{forecast price } P(1),\dots,P(T),\ \bar{E}}$

$\vdots$

2. forecasts consumption E

3. Update price

Fridges

Theorem

The algorithm converges.

We use ADMM iterations.

Augmented Lagrangian:

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

ADMM (alternating direction method of multipliers):

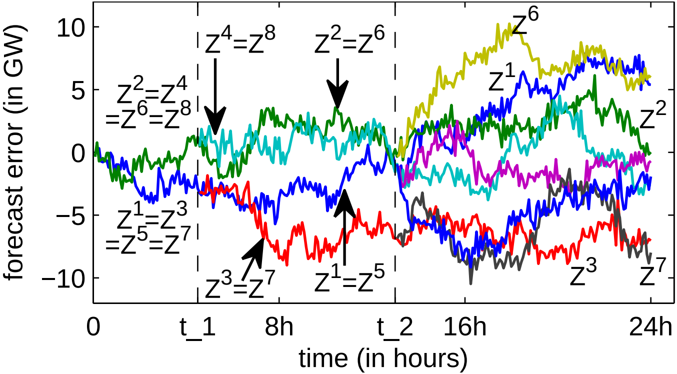
$$\begin{aligned}
E^{k+1} &\in \arg\max_E L_\rho(E,\bar{E}^k,P^k) && \text{for each player (distributed)}\\
\bar{E}^{k+1} &\in \arg\max_{\bar{E}\text{ s.t. }\sum_i \bar{E}_i=0} L_\rho(E^{k+1},\bar{E},,P^k) && \text{projection (easy)}\\
P^{k+1} &:= P^k - \rho(\sum_i E_i^{k+1}) && \text{price update}
\end{aligned}$$

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

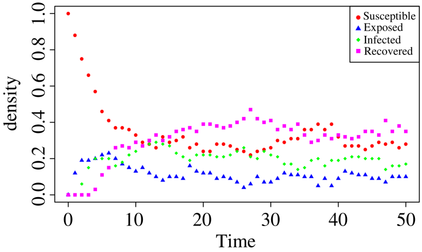
1. Utility functions and constraints are convex
2. We represent forecast errors by multiple trajectories



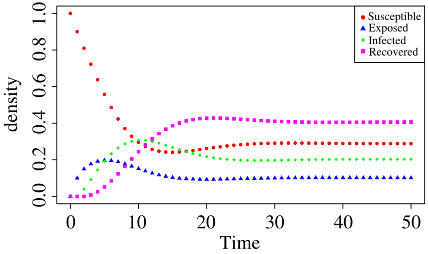
- Extension of Pinson et al (2009).
- Using covariance of data from the UK

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



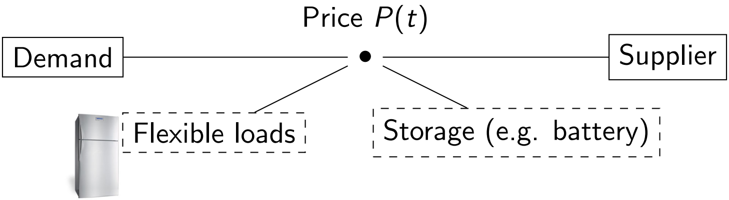
Original system



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

Outline

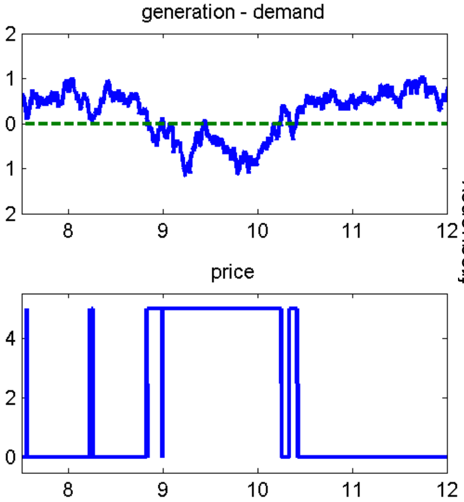
Reminder: we know how to compute a price such that selfish decision leads to a social optimum.



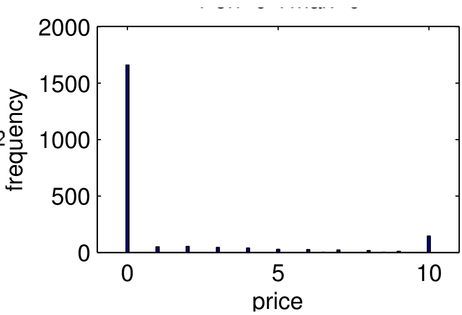
We can evaluate the effect of more flexible load / more storage.

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

Without demand-response or storage, the price fluctuates. It is never equal to the marginal production cost

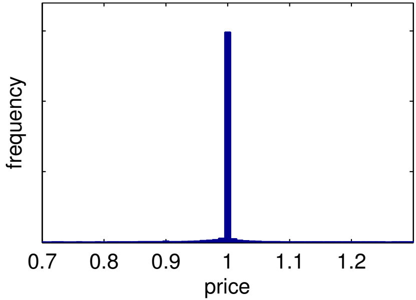


Evolution vs time

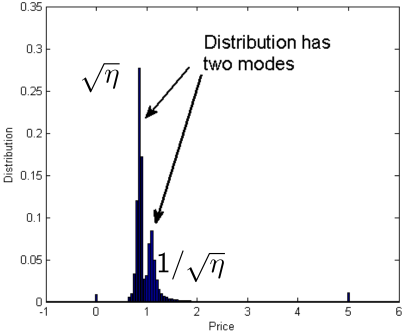


Histogram of prices

Demand-response or perfect storage smooths the price. Real storage does not.

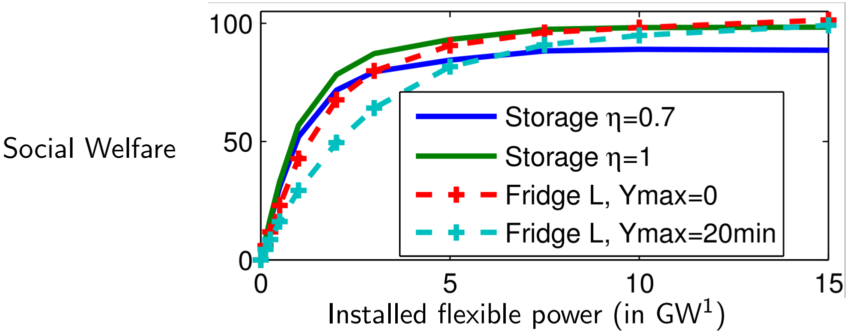


Large amount of 100% efficient storage or demand-response



Storage with efficiency $\eta < 1$

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



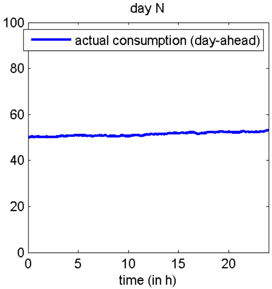
- No charge/discharge inefficiencies for demand-response (we can only anticipate or delay consumption).

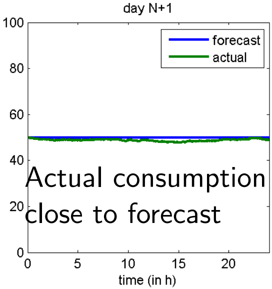
[1]The forecast errors correspond to a total wind capacity of 26GW.

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

No Demand-response

Total consumption



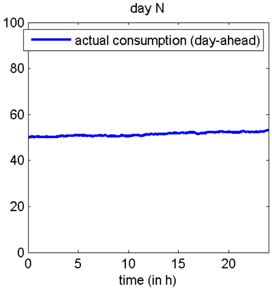


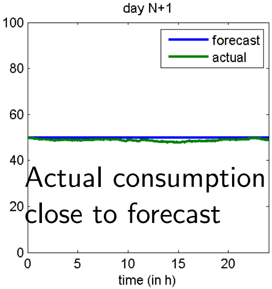
Actual consumption is close to forecast

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

No Demand-response

Total consumption

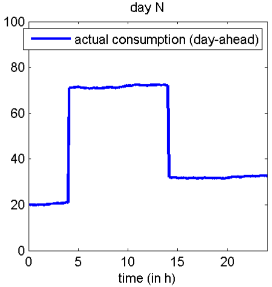


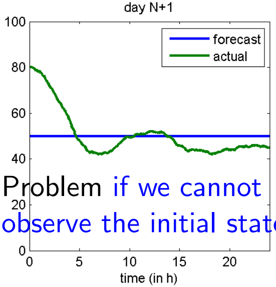


Actual consumption is close to forecast

With Demand-response

Total consumption





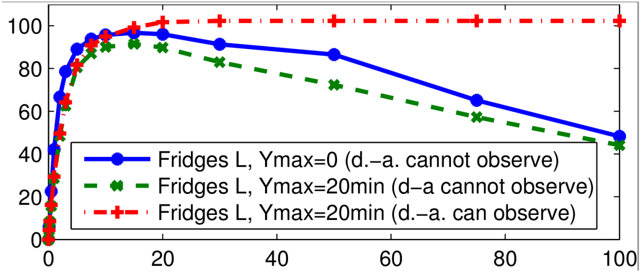
Problem if we cannot observe the initial state

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.

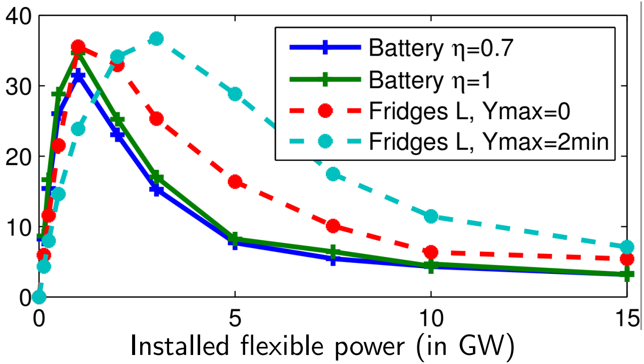
Social Welfare



Installed flexible power (in GW)

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

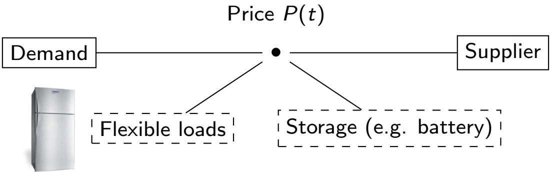
Welfare for storage owner / demand-response operator



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

- Real-time Market
  - Efficient but not robust
    - Efficiency disregards safety, security, investment,...
  - Methodology:
    - Distributed Lagrangian (ADMM) is powerful
    - Use of trajectorial forecast makes it computable
    - Can be used for learning
- Virtual prices and/or virtual markets:
  - Interesting applications: electric cars, voltage control

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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

- 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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