A Data-driven Bidding Model for a Cluster of Price-responsive Consumers of Electricity

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Outline

- Motivation
- Capturing the consumers' price-response in a market bid
- Defining the estimation problem
- Leveraging auxiliary information
- Solving the estimation problem
- Case study: The Olympic Peninsula experiment
- Concluding remarks

Market Barriers

Three major barriers to entry to wholesale electricity markets for the small consumer:

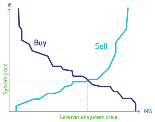
1. The consumer must be able to see the electricity price and react to it

The *Smart Grid* Revolution

2. The high capital cost of communication infrastructure and regulatory requirements

Aggregation to join forces

3. The market speaks its own language: Selling offers and *purchasing bids*



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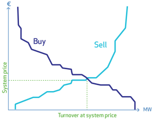
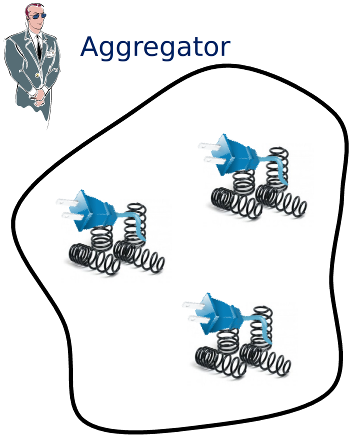


The Market-Bidding Problem



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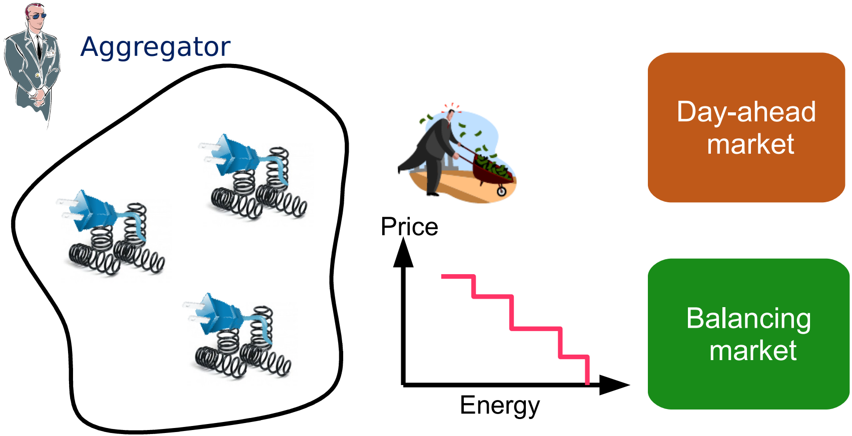


Background Material

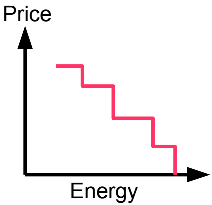
- A number of works address the load scheduling problem under real-time/dynamic pricing:
  - ✓ Often follow the principles of Model Predictive Control
  - ✓ *Rational-behavior models*: the price-response of the pool seeks to minimize the electricity cost
  - ✓ A variety of different types of power loads, e.g., a refrigeration system [Hovgaard et al., 2013], an electric vehicle [Iversen et al., 2014], or the HVAC system of a building [Qureshi et al., 2014, Zugno et al., 2013]
- *Statistical models*: the price-response of the pool is inferred from observed data [Corradi et al., 2013, Hosking et al., 2013]
  - ✓ Also econometric models that rely on the concept of price elasticities [De Jonghe et al., 2012]
- Bidding models for large consumers and for retailers that supply an inelastic and uncertain demand [Conejo et al., 2010b, Ch. 8 and 9]
- Bids often boil down to offering load reduction or to buying the price-based predicted consumption of the pool [Parvania et al., 2013, Qureshi et al., 2014]

The Market Bid

The bid should capture the price-response of the aggregation of flexible consumers

Parameters θ of the *complex* bid:

- Step-wise marginal utility function ($a_{b,t}$)



- Maximum load pick-up and drop-off limits (r_t^u,r_t^d) (similar to the ramping limits of a conventional generating unit)
- Maximum and minimum power consumption ($\overline{P}_t$,$\underline{P}_t$)

The Market Bid ⇔ The Price-Response Model

$$\text{Maximize}_{x_{b,t}} \sum_{t \in \mathcal{T}} \left(\sum_{b \in \mathcal{B}} a_{b,t} x_{b,t} - p_t \sum_{b \in \mathcal{B}} x_{b,t} \right)$$

Subject to

$$\underline{P}_t + \sum_{b \in \mathcal{B}} x_{b,t} - \underline{P}_{t-1} - \sum_{b \in \mathcal{B}} x_{b,t-1} \leq r_t^u \qquad t \in \mathcal{T}_{-1} \qquad (1a)$$

$$\underline{P}_{t-1} + \sum_{b \in \mathcal{B}} x_{b,t-1} - \underline{P}_t - \sum_{b \in \mathcal{B}} x_{b,t} \leq r_t^d \qquad t \in \mathcal{T}_{-1} \qquad (1b)$$

$$0 \leq x_{b,t} \leq \frac{\overline{P}_t - \underline{P}_t}{B} \qquad b \in \mathcal{B}, t \in \mathcal{T} \qquad (1c)$$

with the total consumption given by $\underline{P}_t + \sum_{b \in \mathcal{B}} x_{b,t}$

The Market Bid ⇔ The Price-Response Model

Many assume that the consumption behavior of a cluster of flexible loads can be modeled by an optimization problem of the type of (1) with the aim of:

- Studying the economic impact of flexible demand [Borenstein, 2005] (including its role in the large-scale integration of renewable energy sources [Sioshansi and Short, 2009])
- Building energy management systems [Conejo et al., 2010a, Ferreira et al., 2012, Mohsenian-Rad and Leon-Garcia, 2010, Rahimiyan et al., 2014]
- Offering demand-response services [Parvania et al., 2013]
- Operating a distribution network [Kraning et al., 2013]
- Designing stochastic unit commitment models [Khodaei et al., 2011, Papavasiliou and Oren, 2014, Wang et al., 2013]
- ...

But how do we determine the set of characteristic parameters θ that define the market bid?

The Estimation Problem

- We estimate the bid parameters θ from observational price-consumption data

Time	Price	Load
t_1	p_1	x_1^{meas}
t_2	p_2	x_2^{meas}
...	...	...

- **Inverse optimization**: the parameters of the bid are the parameters of an optimization problem
- We cast the inverse optimization problem as a **bilevel programming problem**

The Estimation Problem as a Bilevel Program

Upper-level problem

$$\underset{x,\theta}{\text{Minimize}} \ \|x - x^{meas}\|$$

$s.t.$ Constraints on bid parameters

Lower-level problem

$$\underset{x}{\text{Maximize}} \ \text{Utility}(a_b) \ - \text{Cost}$$

$s.t.$ Power bounds $(\overline{P}, \underline{P})$

Maximum pick-up rate (r^u)

Maximum drop-off rate (r^d)

$$\theta = \{a_b, r^u, r^d, \overline{P}, \underline{P}\}$$

Equivalent Single-level Optimization Problem

Parameter estimation

$$\underset{x,\theta}{\text{Minimize}} \sum_{t\in\mathcal{T}} w_t \left| \underline{P}_t + \sum_{b\in\mathcal{B}} x_{b,t} - x_t^{meas} \right|$$

subject to

$$a_{b,t} \geq a_{b+1,t} \quad b \in \mathcal{B}, t \in \mathcal{T}$$

KKT conditions of lower-level problem

Equivalent Single-level Optimization Problem

Parameter estimation

$$\underset{x,\theta}{\text{Minimize}} \sum_{t \in \mathcal{T}} w_t \left| \underline{P}_t + \sum_{b \in \mathcal{B}} x_{b,t} - x_t^{meas} \right|$$

subject to

$$a_{b,t} \geq a_{b+1,t} \quad b \in \mathcal{B}, t \in \mathcal{T}$$

KKT conditions of lower-level problem

The weight w_t has a threefold purpose:

1. If the market bid is intended for a forward (e.g., day-ahead) market, then w_t could represent the cost of imbalances at time t
2. The most recent observations can be given larger weights
3. Zero weight for missing or wrong measurements

Equivalent Single-level Optimization Problem

Parameter estimation

$$\underset{x,\theta}{\text{Minimize}} \sum_{t\in\mathcal{T}} w_t \left(e_t^+ + e_t^-\right)$$

subject to

$$\underline{P}_t + \sum_{b\in\mathcal{B}} x_{b,t} - x_t^{meas} = e_t^+ - e_t^- \qquad t\in\mathcal{T}$$

$$e_t^+, e_t^- \geq 0 \qquad t\in\mathcal{T}$$

$$a_{b,t} \geq a_{b+1,t} \qquad b\in\mathcal{B}, t\in\mathcal{T}$$

KKT conditions of lower-level problem

Including Auxiliary Information (Features Z)

Time	Price	Load	External Info.
t_1	p_1	x_1^{meas}	z_1
t_2	p_2	x_2^{meas}	z_2
...	...	...	...

Generalized framework for inverse optimization:

- x^{meas} needs not be optimal or even feasible for the lower-level problem
- Auxiliary information on features is leveraged

Upper-level problem

$$\underset{x,\theta(Z)}{\text{Minimize}} \; \|x - x^{meas}\|$$

$$s.t. \quad \boxed{\theta(Z) \in \Xi, \forall Z}$$

Lower-level problem

$$\underset{x}{\text{Maximize}} \; \text{Utility } (a_b(Z)) \; - \text{Cost}$$

$$s.t. \quad \text{Power bounds } \left(\overline{P}(Z), \underline{P}(Z)\right)$$

$$\text{Maximum pick-up rate } (r^u(Z))$$

$$\text{Maximum drop-off rate } \left(r^d(Z)\right)$$

Including Auxiliary Information (Features Z)

We assume that the bid parameters are affine functions of the features, e.g.,

$$\underline{P}_t(Z) = \underline{P} + \sum_{i \in \mathcal{I}} \alpha_i^{\underline{P}} Z_{i,t}, \quad t \in \mathcal{T}$$

The bid must make sense for any plausible value of the features, in particular,

- The minimum consumption limit must be lower than or equal to the maximum consumption limit
- The minimum consumption limit must be non-negative
- The maximum pick-up rate must be greater than or equal to the negative maximum drop-off rate

Including Auxiliary Information (Features Z)

For example,

$$\underline{P} + \sum_{i\in\mathcal{I}} \alpha_i^{\underline{P}} Z_{i,t} \leq \overline{P} + \sum_{i\in\mathcal{I}} \alpha_i^{\overline{P}} Z_{i,t}, \quad t \in \mathcal{T}, \text{for all } Z_{i,t}$$

Assume that $Z_{i,t} \in [\overline{Z}_i, \underline{Z}_i]$, then

$$\underline{P} - \overline{P} + \underset{\substack{Z'_{i,t} \\ \text{s.t. } \underline{Z}_i \leq Z'_{i,t} \leq \overline{Z}_i \\ i\in\mathcal{I}}}{\text{Maximize}} \left\{ \sum_{i\in\mathcal{I}} (\alpha_i^{\underline{P}} - \alpha_i^{\overline{P}}) Z'_{i,t} \right\} \leq 0, \quad t \in \mathcal{T}.$$

which is equivalent to

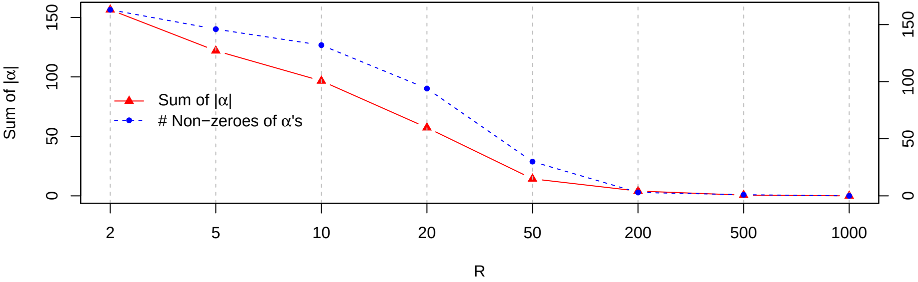
$$\begin{aligned}
&\overline{P} - \underline{P} + \sum_{i\in\mathcal{I}} (\overline{\phi}_{i,t}\overline{Z}_i - \underline{\phi}_{i,t}\underline{Z}_i) \leq 0 && t \in \mathcal{T} \\
&\overline{\phi}_{i,t} - \underline{\phi}_{i,t} = \alpha_i^{\overline{P}} - \alpha_i^{\underline{P}} && i \in \mathcal{I}, t \in \mathcal{T} \\
&\overline{\phi}_{i,t}, \underline{\phi}_{i,t} \geq 0 && i \in \mathcal{I}, t \in \mathcal{T}.
\end{aligned}$$

LASSO regularization

Add the following term to the objective function

$$R\left(\sum_{i\in\mathcal{I}}\left(|\alpha_i^a| + |\alpha_i^d| + |\alpha_i^{\overline{P}}| + |\alpha_i^{\underline{P}}|\right)\right)$$

- Penalize the affine terms α
- Feature selection & better prediction capabilities
- Choose R by way of model validation



Two-step Procedure

Step 1: Solve a linear relaxation of the estimation problem (which is an MPEC)

Step 2: Recompute the parameters defining the utility function with the parameters defining the constraints of the lower-level problem fixed at the values estimated in Step 1

L-Penalty Method

We relax the complementarity conditions [Siddiqui and Gabriel, 2013]

$$\begin{aligned}&\underset{x,\lambda}{\text{Minimize}}\ \mathrm{cx}\\ &\mathrm{Ax}-\mathrm{b}\geq 0 \perp \lambda \geq 0\end{aligned} \quad\Longrightarrow\quad \begin{aligned}&\underset{x,\lambda}{\text{Minimize}}\ \mathrm{cx}+\mathrm{L}(\mathrm{Ax}-\mathrm{b}+\lambda)\\ &\mathrm{Ax}-\mathrm{b}\geq 0\\ &\lambda \geq 0\end{aligned}$$

- Parameter *L* penalizes violations of the complementarity constraints
- Optimality is not guaranteed - practical usefulness proved
- Model validation to tune *L*

Step 1: Solution to the relaxed estimation problem

$$\underset{\substack{x_t,\theta_t,e_t^+,e_t^-,\alpha_i^u,\alpha_i^d\\ \alpha_i^{\overline{P}},\alpha_i^{\underline{P}},\psi_t^{\overline{P}},\psi_t^{\underline{P}},\lambda_t^u,\lambda_t^d\\ \overline{\phi}_{i,t},\underline{\phi}_{i,t}\overline{\varphi}_{i,t},\underline{\varphi}_{i,t},\overline{\eta}_{i,t},\underline{\eta}_{i,t}}}{\text{Minimize}} \quad \overbrace{\sum_{t\in\mathcal{T}} w_t(e_t^+ + e_t^-)}^{\text{Estimation error}} + \overbrace{R\left(\sum_{i\in\mathcal{I}}\left(|\alpha_i^u| + |\alpha_i^d| + |\alpha_i^{\overline{P}}| + |\alpha_i^{\underline{P}}|\right)\right)}^{\text{Lasso regularization}} +$$

$$\overbrace{L\left(\sum_{\substack{b\in\mathcal{B}\\ t\in\mathcal{T}}} w_t\left(\psi_{b,t}^{\overline{P}} + \psi_{b,t}^{\underline{P}} + \frac{\overline{P}_t - \underline{P}_t}{B}\right) + \sum_{t\in\mathcal{T}_{-1}} w_t\left(\lambda_t^u + \lambda_t^d + r_t^u + r_t^d\right)\right)}^{\text{Penalization of complementarity conditions}}$$

subject to:

1. Upper-level constraints (linear reformulation of absolute value, constraints on bid parameters and the α's)
2. Lower-level constraints (price-response model)
   - Primal feasibility
   - Dual feasibility

Step 2: Refining the marginal utilities $a_{b,t}$

- Reformulate the inverse problem using primal-dual formulation [Chan et al., 2014, Keshavarz et al., 2011]
- In the lower-level, fix the parameters appearing in the constraints at the values estimated in Step 1
- Replace the estimated load (x) by the measured one (x^{meas})

Inverse problem
(relaxed)
Estimate:
$\widehat{\theta} = \{\widehat{a}_{b,t}, \widehat{r}_t^d, \widehat{r}_t^u, \widehat{\overline{P}}_t, \widehat{\underline{P}}_t\}$

Fix $\{\widehat{r}_t^d, \widehat{r}_t^u, \widehat{\overline{P}}_t, \widehat{\underline{P}}_t\}$

Refining problem
Re-estimate $a_{b,t}$

Minimize $w\epsilon$ = Weigthed Duality Gap

subject to

Primal Ojective = Dual Objective + ϵ
Primal Constraints
Dual Constraints

Step 2: Refining the marginal utilities $a_{b,t}$

$$\underset{a_{b,t},\lambda_t^u,\lambda_t^d,\psi_t^{\overline{P}},\psi_t^{\underline{P}},\underline{\psi}_{b,t},\overline{\psi}_{b,t},\epsilon_t}{\text{Minimize}} \sum_{t\in\mathcal{T}} w_t\epsilon_t \tag{3}$$

$$\sum_{b\in\mathcal{B}} a_{b,1}x_{b,1}^{meas'} - p_1\sum_{b\in\mathcal{B}} x_{b,1} + \epsilon_1 = \sum_{b\in\mathcal{B}}\left(\frac{\overline{P}_1 - \underline{P}_1}{B}\right)\overline{\psi}_{b,1} \tag{4}$$

$$\sum_{b\in\mathcal{B}} a_{b,t}x_{b,t}^{meas'} - p_t\sum_{b\in\mathcal{B}} x_{b,t} + \epsilon_t = \sum_{b\in\mathcal{B}}\left(\frac{\overline{P}_t - \underline{P}_t}{B}\right)\overline{\psi}_{b,t} +$$

$$\left(r_t^u - \underline{P}_t + \underline{P}_{t-1}\right)\lambda_t^u + \left(r_t^d + \underline{P}_t - \underline{P}_{t-1}\right)\lambda_t^d \qquad t\in\mathcal{T}_{-1}$$

$$a_{b,t} \geq a_{b+1,t} \qquad t\in\mathcal{T}$$

$$\lambda_t^u, \lambda_t^d \geq 0 \qquad t\in\mathcal{T}_{-1}$$

$$\psi_t^{\overline{P}}, \psi_t^{\underline{P}}, \underline{\psi}_{b,t}, \overline{\psi}_{b,t} \geq 0 \qquad t\in\mathcal{T}$$

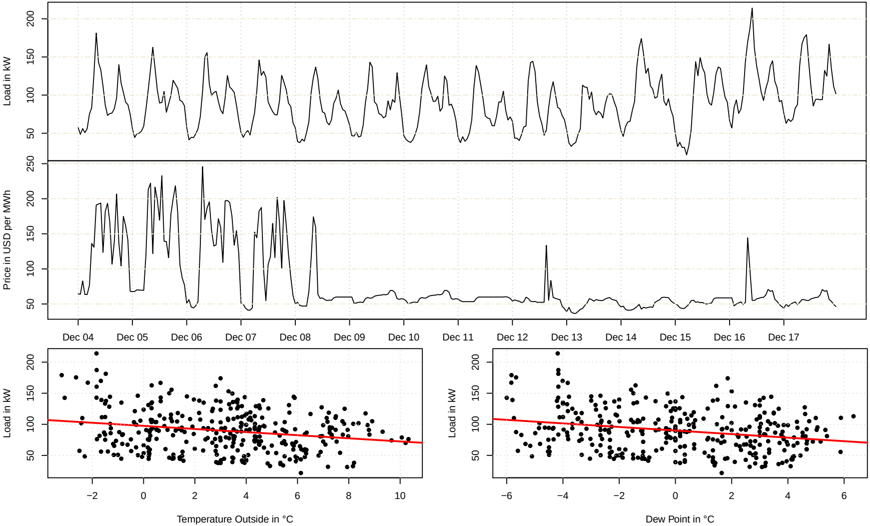
Dual feasibility constraints

Case Study

- Data of price-responsive households from Olympic Peninsula project from May 2006 to March 2007
- Decisions made by the home-automation system based on occupancy modes, comfort settings, and price
- The price was sent out every 15 minutes to 27 households

Case Study

- Load, price, temperature and dew point during december



Benchmark models

ARX: Auto-Regressive model with eXogenous inputs [Dorini et al., 2013, Corradi et al., 2013]

$$x_t = \boldsymbol{\vartheta}_x \boldsymbol{X}_{t-n} + \boldsymbol{\vartheta}_z \boldsymbol{Z}_t + \epsilon_t,$$

with $\epsilon_t \sim \mathrm{N}(0,\sigma^2)$ and σ^2 is the variance.

$\boldsymbol{Z}_t$: outside temperature, solar irradiance, wind speed, humidity, dew point (up to 36 hours in the past), plus binary indicators for the hour of the day and the day of the week.

Simple Inv: Only the marginal utilities are estimated (12 blocks) as in Step 2, the rest of bid parameters to historical maximum/minimum values observed in the last seven days. Inspired from Keshavarz et al. [2011], Chan et al. [2014].

Benchmark models

Inv Few: Our inverse optimization scheme only with the outside temperature and hourly indicator variables as features.

$$w_t = gap_t \left(\frac{t}{T}\right)^E, t \in \mathcal{T}$$

$E \geq 0$, forgetting factor.

T: total number of periods.

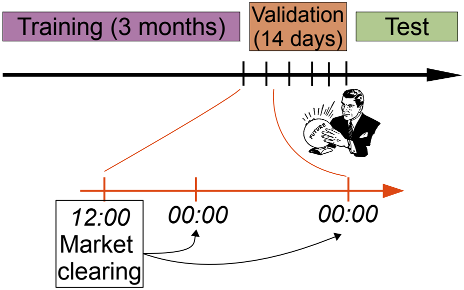
gap indicates whether the observation was correctly measured ($gap = 1$) or not ($gap = 0$).

Inv All: The same as **Inv Few**, but including all features and regularization.

Case Study

Rolling-horizon validation for model tuning (based on MAPE)

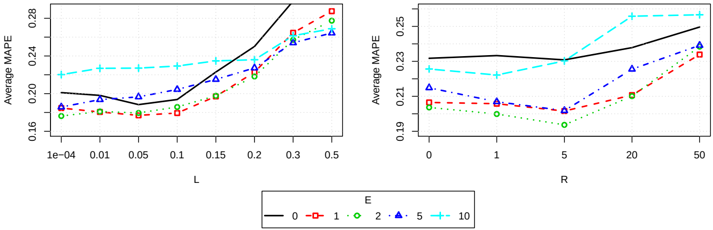
- Penalization parameter L
- Regularization parameter R
- Forgetting factor E



Case Study

Rolling-horizon validation for model tuning (based on MAPE)

- Penalization parameter *L*
- Regularization parameter *R*
- Forgetting factor *E*



Case Study

Rolling-horizon validation for model tuning (based on MAPE)

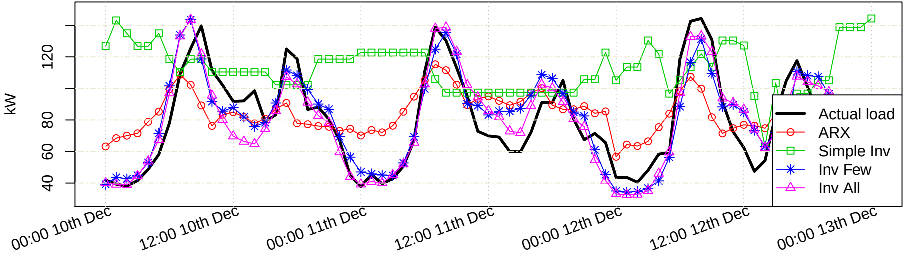
- Penalization parameter L
- Regularization parameter R
- Forgetting factor E

Month	L	R	E
September 2006	0.2	5	1
December 2006	0.1	5	2
March 2007	0.3	1	0

$L \uparrow \Rightarrow$ Price-responsiveness$\downarrow$

Case Study

Prediction capabilities of different benchmarked methods



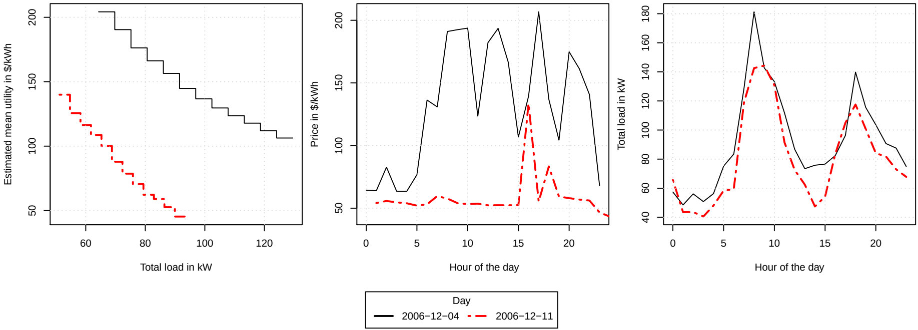
	MAE	RMSE	MAPE
ARX	22.17692	27.50130	0.2752790
Simple Inv	44.43761	54.57645	0.5858138
Inv Few	16.92597	22.27025	0.1846772
Inv All	17.55378	22.39218	0.1987778

Case Study

	September			March		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
ARX	7.6499	9.8293	0.2358	17.4397	23.3958	0.2602
Simple Inv	14.2631	17.8	0.4945	44.6872	54.6165	0.8365
Inv Few	5.5031	7.9884	0.1464	13.573	17.9454	0.2103
Inv All	5.8158	8.4941	0.1511	14.7977	19.1195	0.2391

Case Study

Estimated marginal utility for the pool of price-responsive consumers



Concluding Remarks

What we have done:

- We develop a novel approach to capture the **price-response** of the pool of flexible consumers in the form of a **market bid** using price-consumption data.
- We propose a **generalized inverse optimization framework** to estimate the market bid that best captures the price-response of the pool.
- We leverage auxiliary information on a **set of features** that may have predictive power on the consumption pattern of the cluster.
- We test our methodology using data from a **real-world experiment** and compare its performance with state-of-the-art prediction models on the same dataset.

Concluding Remarks

A preprint of the associated scientific article can be found in arXiv:
`http://arxiv.org/abs/1506.06587`

Thanks for your attention!

Website: `https://sites.google.com/site/jnmmgo/`

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