

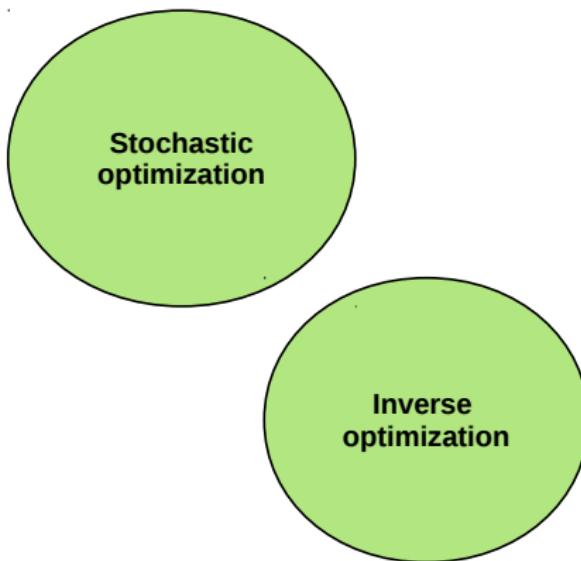
# Inverse Optimization and Forecasting Techniques Applied to Decision-making in Electricity Markets

Javier Saez-Gallego

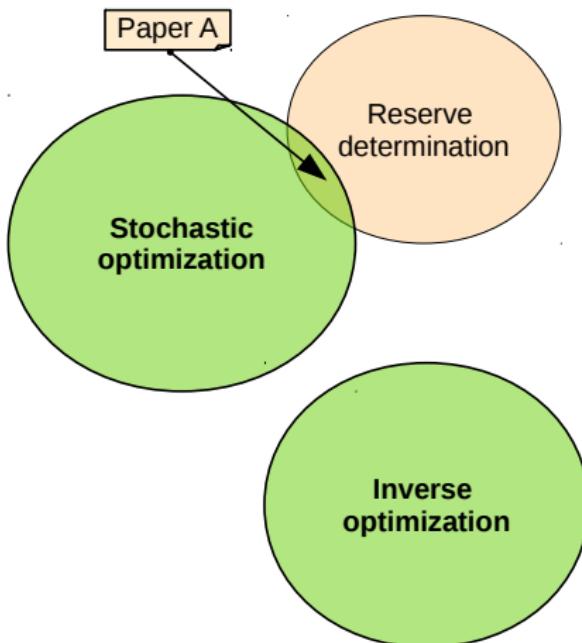
November 22<sup>nd</sup>, 2016



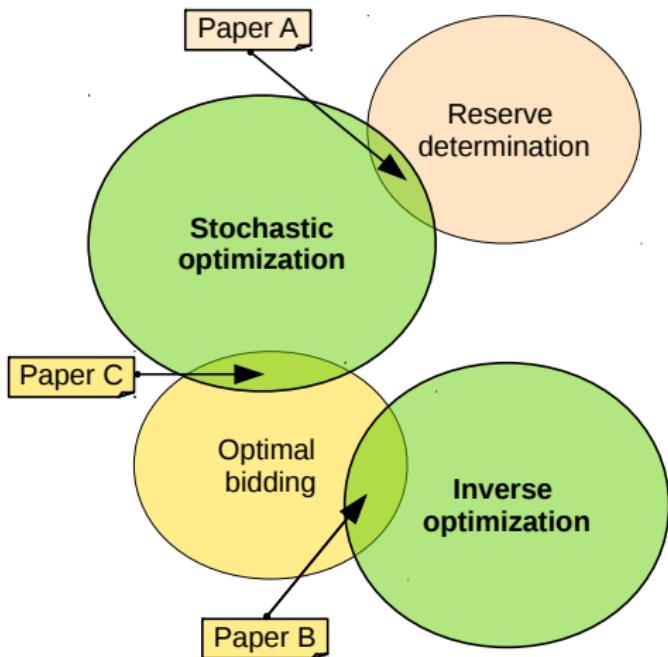
# Papers included in the thesis



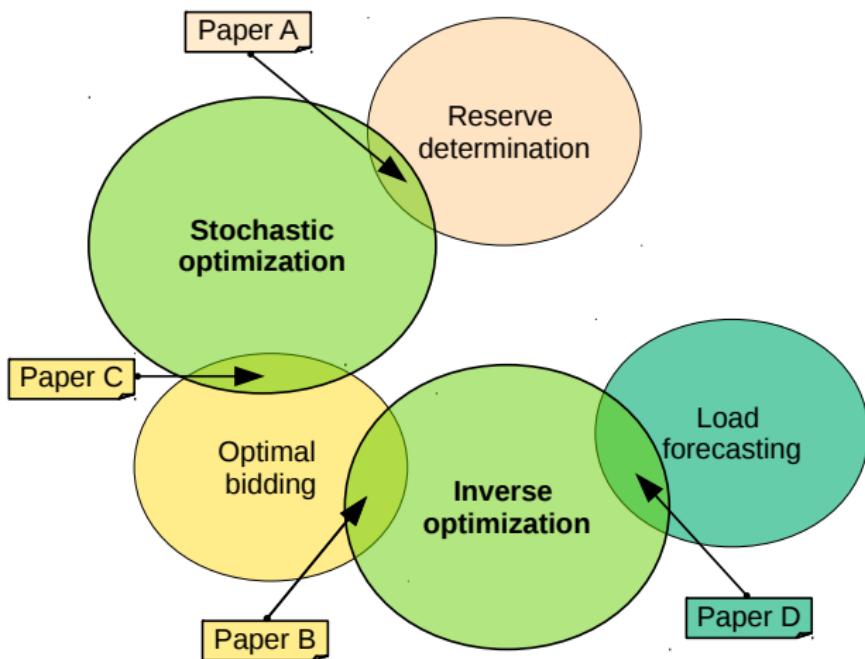
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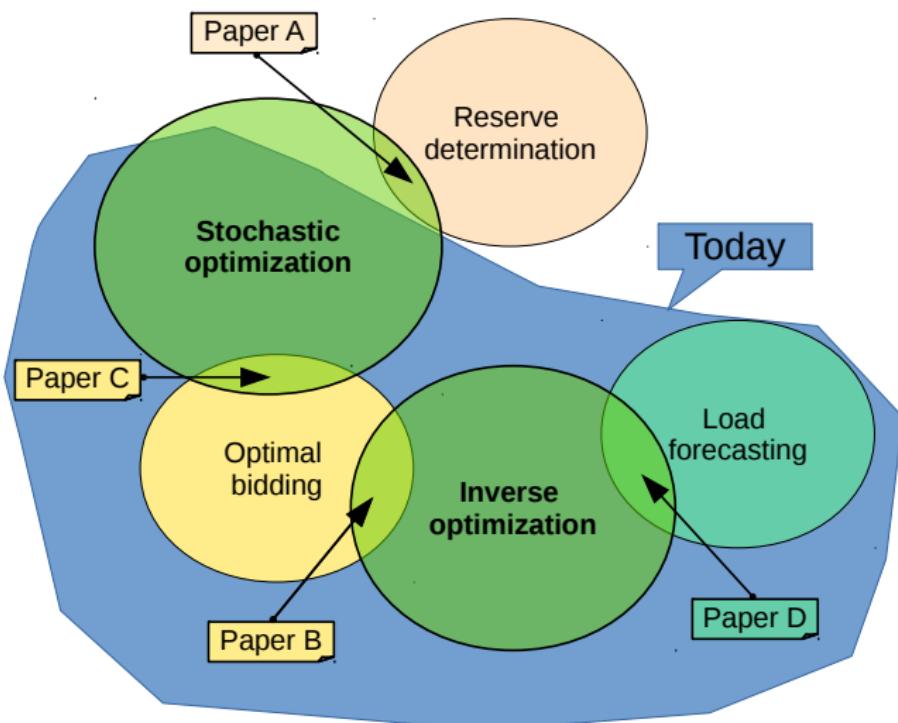
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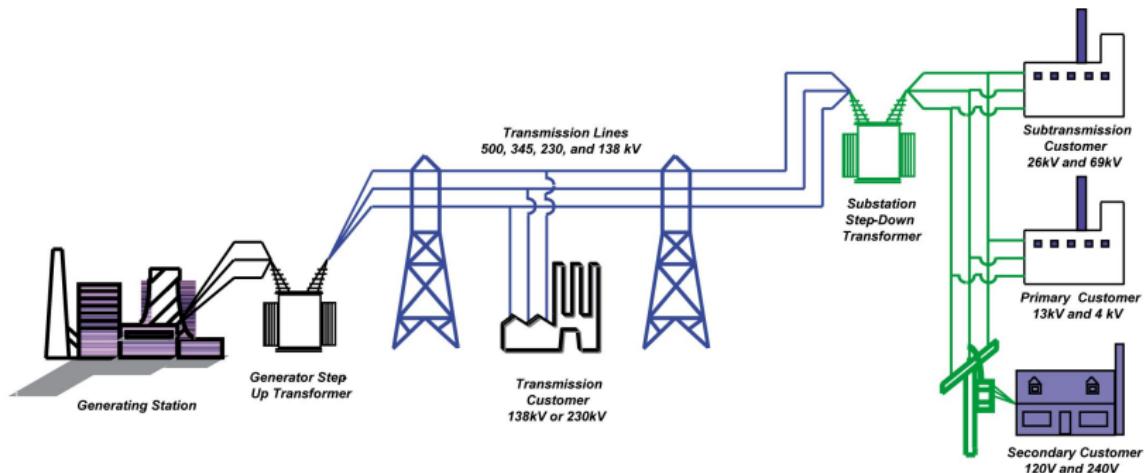
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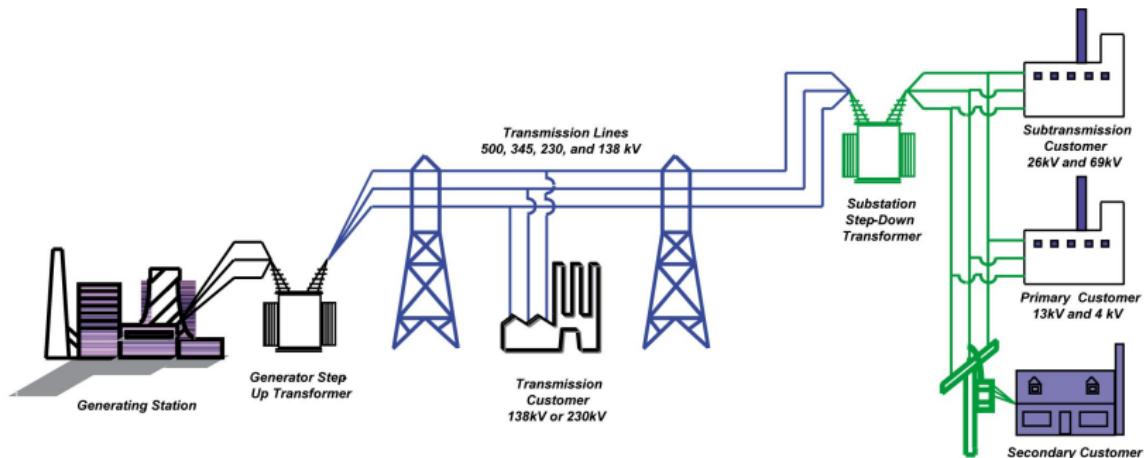
# Papers included in the thesis



# Challenges in the electricity supply service



# Challenges in the electricity supply service



Renewables

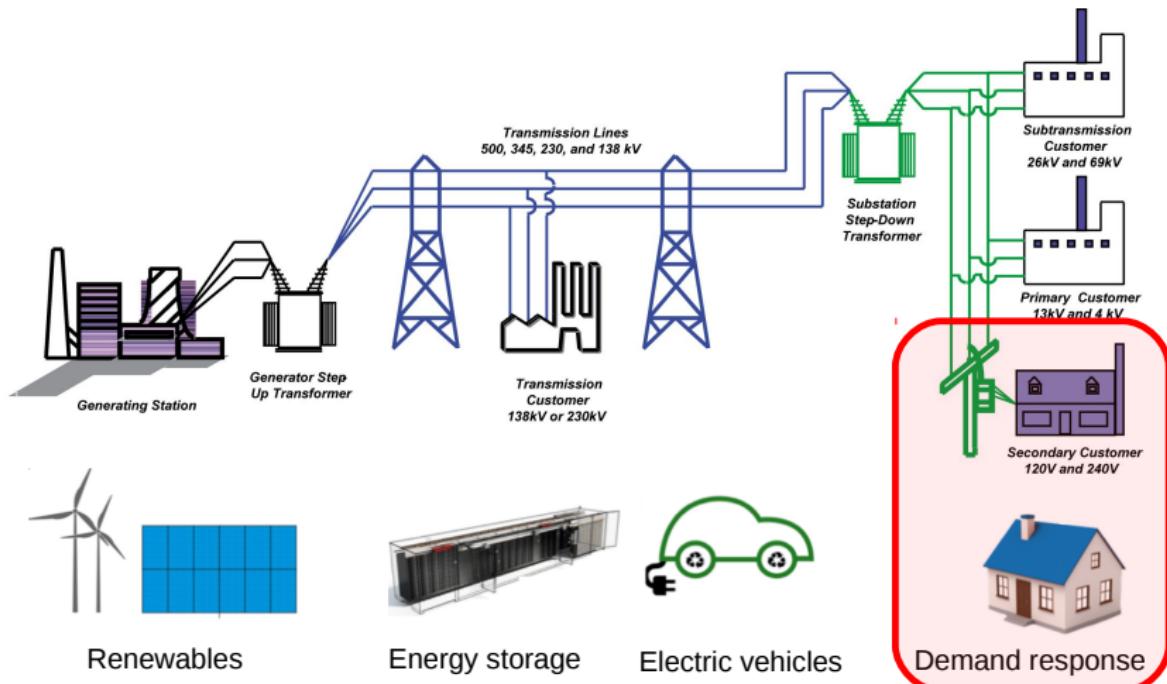


Electric vehicles

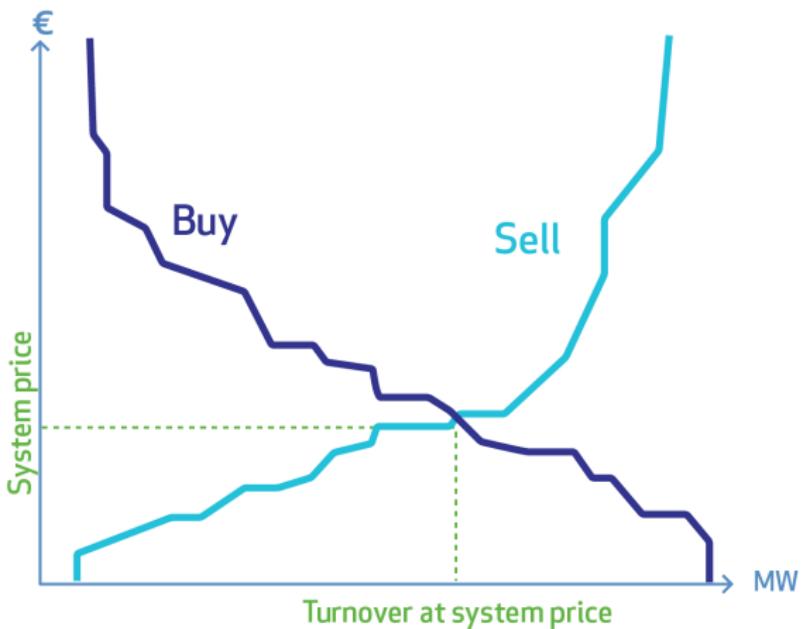


Demand response

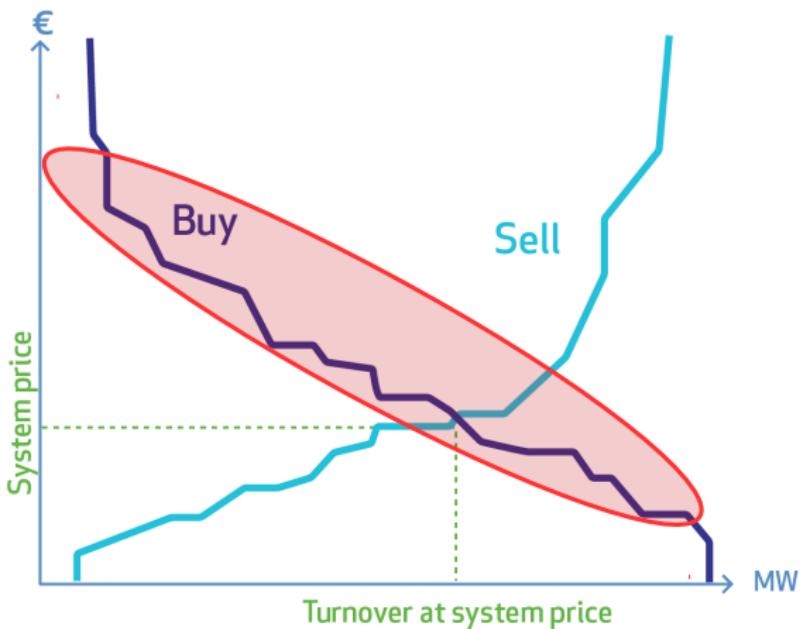
# Challenges in the electricity supply service



# Challenges in the electricity supply service

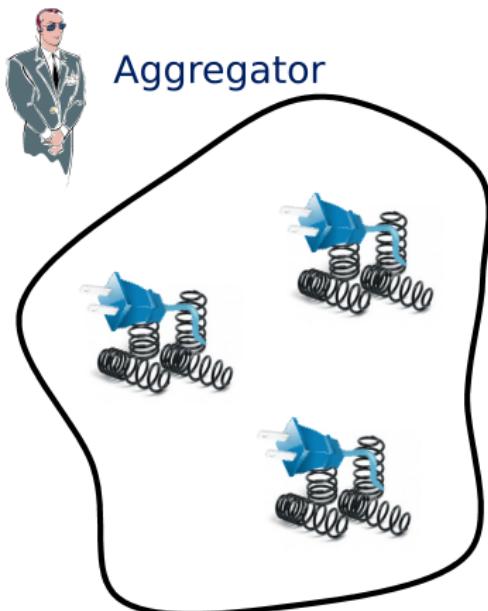


# Challenges in the electricity supply service



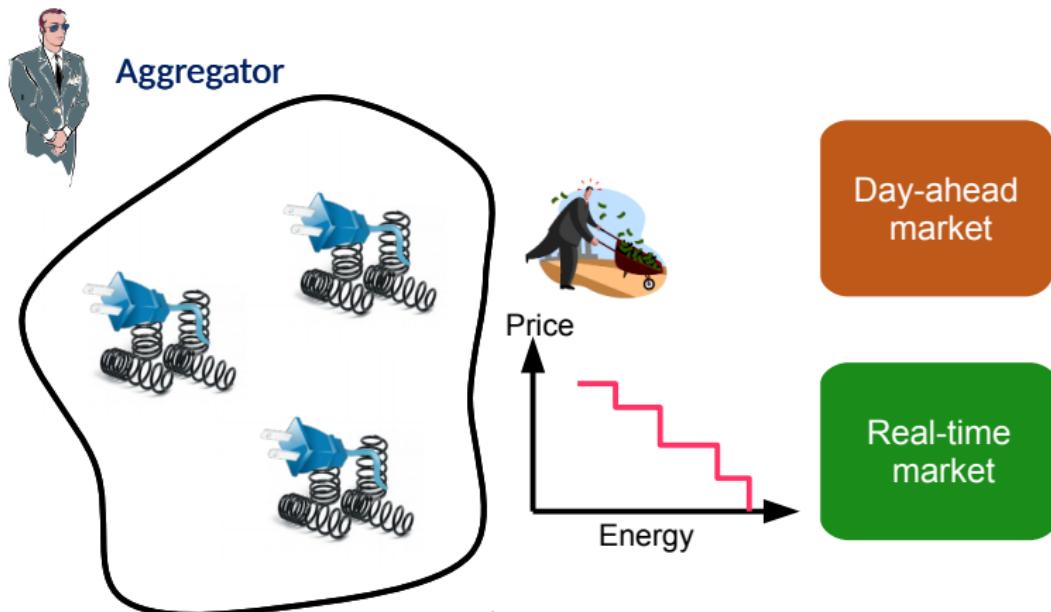
# Optimal bidding

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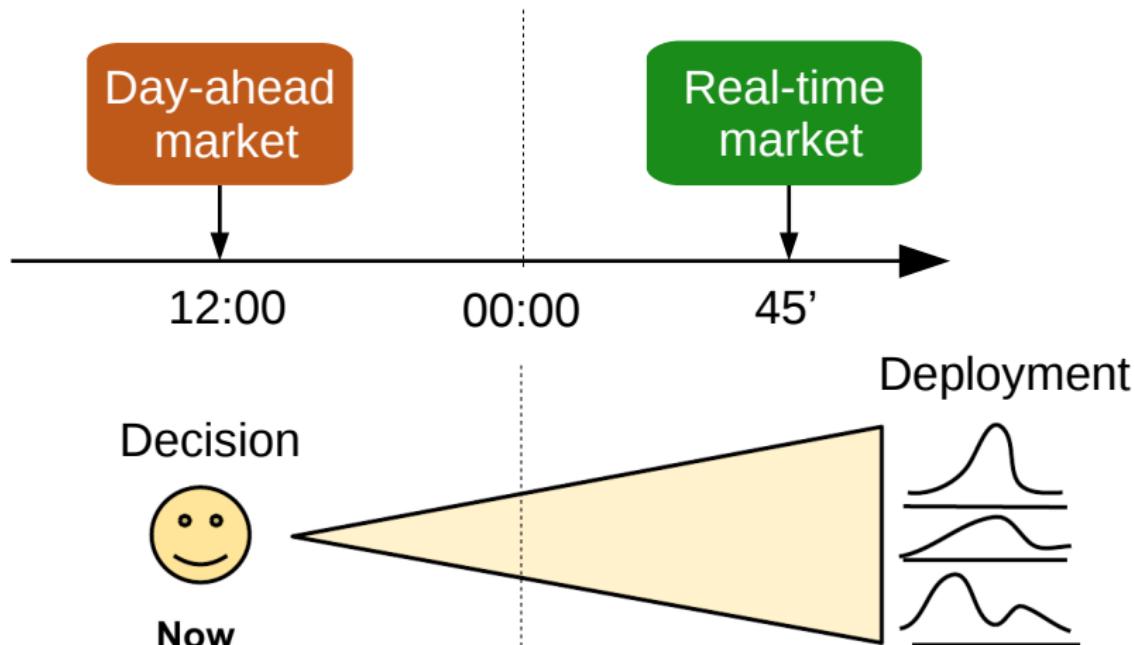


- Price-responsive units (households)
- Too small to participate in the Wholesale electricity market

# Optimal bidding



# Optimal bidding



# The data

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

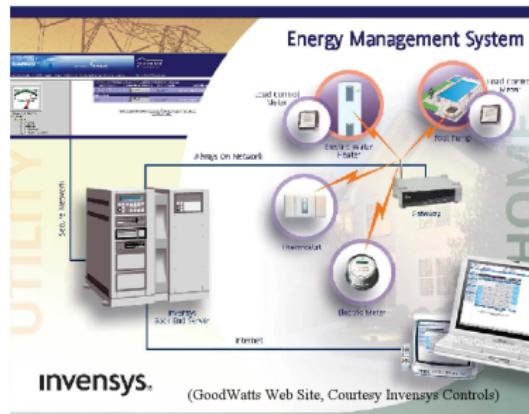
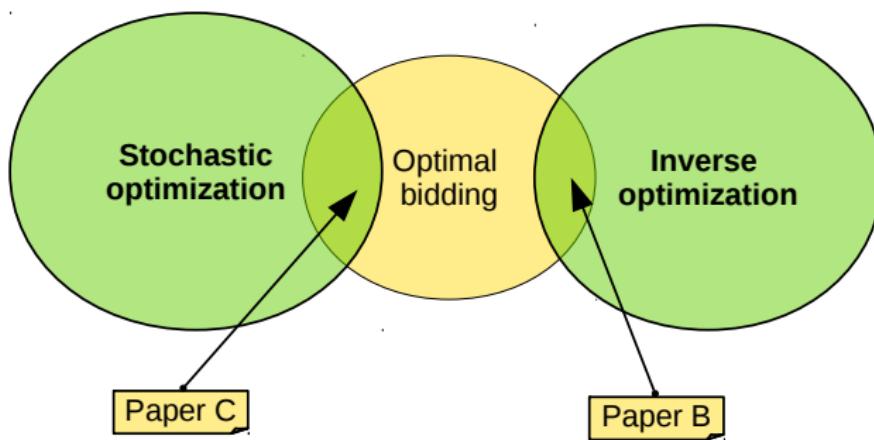


Figure 3.2. Invensys GoodWatts™ System Components

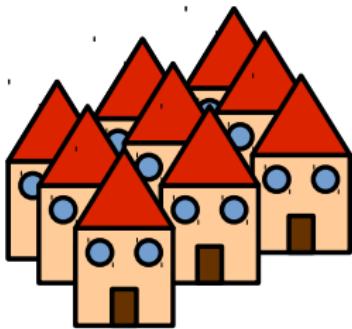
# Two approaches



J. Saez-Gallego, M. Kohansal,  
A. Sadeghi-Mobarakeh and  
J. M. Morales  
**"Optimal Price-energy Demand Bids  
for Aggregate Price-responsive  
Loads"**  
Submitted to *IEEE Transactions on  
Smart Grid*, 2016

J. Saez-Gallego, J. M. Morales, M.  
Zugno, and  
H. Henrik,  
**"A data-driven bidding model for a  
cluster of price-responsive  
consumers of electricity"**  
In: *IEEE Transactions on Power  
Systems*, February, 2016

# Paper C. Optimal Price-energy Demand Bids for Aggregate Price-responsive Loads



## The setup

A cluster of price-responsive units under variable price of electricity

## The goal

Obtain optimal bid in the day-ahead market that maximizes the profit of the retailer

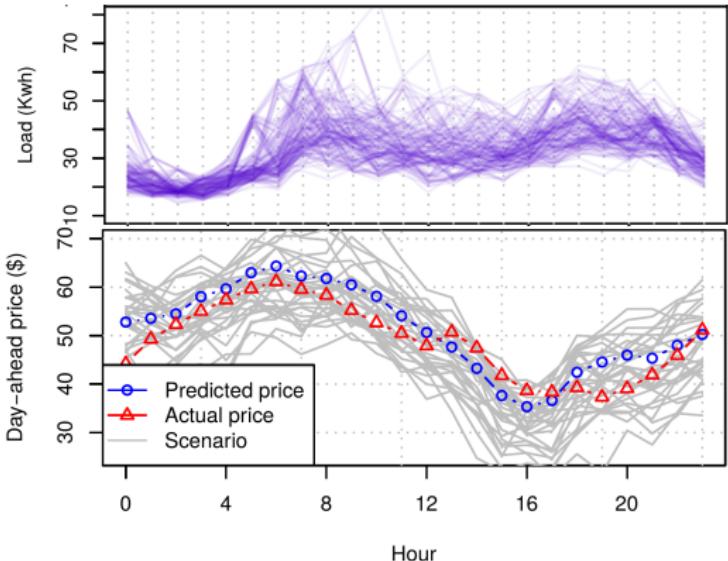
# Paper C. Optimal Price-energy Demand Bids for Aggregate Price-responsive Loads

$$\underset{X_t^D, u_{t,b}}{\text{Maximize}} \quad \mathbb{E} \left\{ \sum_{t=1}^{24} \left( \Pi_t X_t - \Lambda_t^D X_t^D - \Lambda_t^R (X_t - X_t^D) \right) \right\}$$

Total profit =  $\begin{matrix} \text{revenue} \\ \text{from} \\ \text{selling} \end{matrix} - \begin{matrix} \text{purchase} \\ \text{cost in the} \\ \text{day ahead} \end{matrix} - \begin{matrix} \text{purchase} \\ \text{cost/selling} \\ \text{profit in the} \\ \text{real-time} \end{matrix}$

- **No risk considered:** analytic solution given
- **Risk constraints:** limit the probability of purchasing certain fraction of the load in the real-time market.

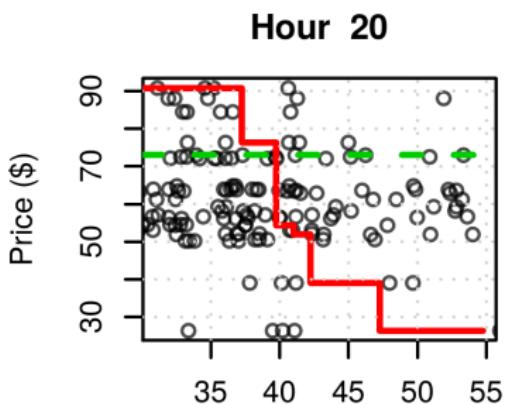
# Paper C. Optimal Price-energy Demand Bids for Aggregate Price-responsive Loads



## The solution

- Dynamic price-responsive behavior of consumers is modeled based on scenarios
- Scenarios based on non-parametric models

# Paper C. Optimal Price-energy Demand Bids for Aggregate Price-responsive Loads



## Results

- Risk-unconstrained bidding results in flat curve with highest expected profits
- Risk-averse bids are more steep with lower expected profits and lower variance too

# Inverse optimization

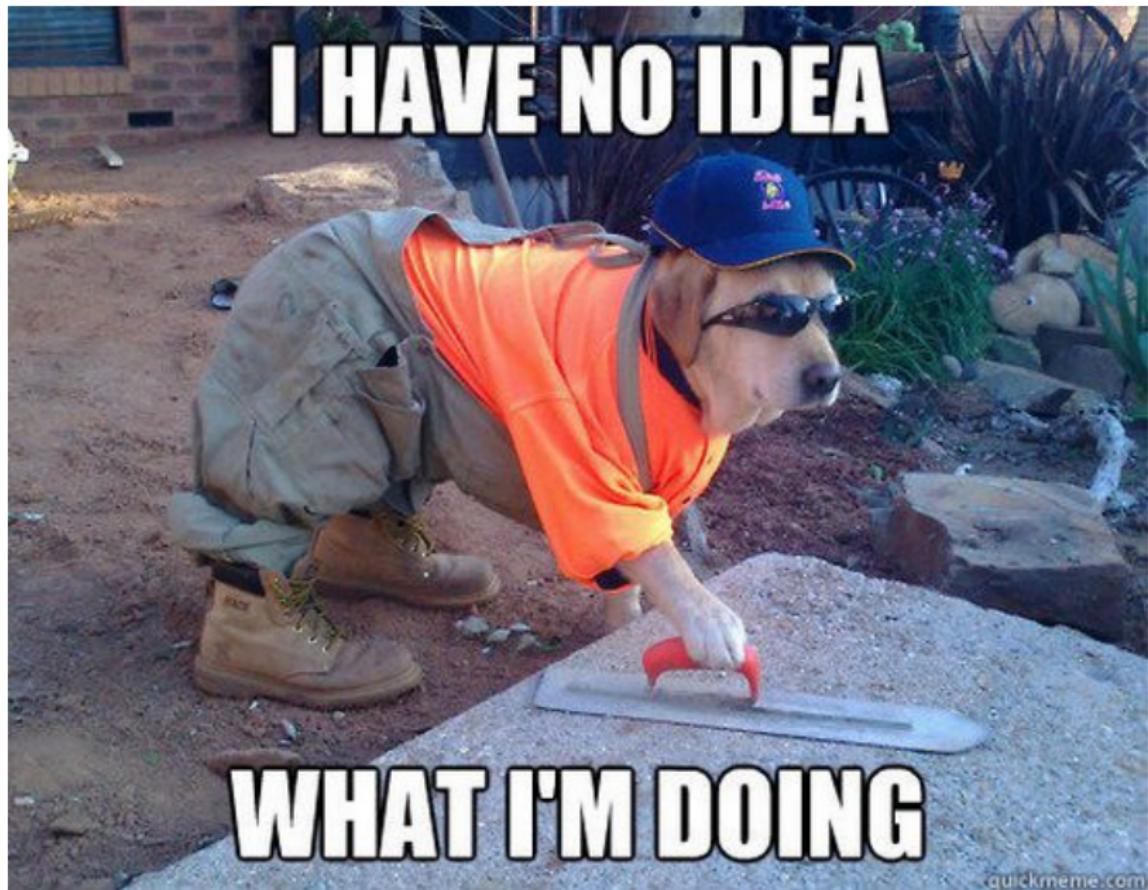
**Introduction**  
○○○○○

**C: Optimal bidding**  
○○○○

**B: Inverse optimization**  
○●○○○○○○○

**D: Load Forecasting**  
○○○○○○○○

**Conclusions**  
○○



# I HAVE NO IDEA



# WHAT I'M DOING

# Basics of inverse optimization

*Traditional* constrained optimization problems find the decision variable  $x$  that maximize (or minimize) a function

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What is the solution?

$$\underset{x,y}{\text{Maximize}} \quad 3x + y$$

Subject to

$$x + y \leq 7$$

$$0 \leq x \leq 5$$

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# Basics of inverse optimization

## Inverse optimization

What are the values of  $a$  and  $b$  such that  $x^* = 5$  and  $y^* = 2$ ?

$$\underset{a,b}{\text{Maximize}} \quad a x^* + y^*$$

Subject to

$$x^* + y^* \leq b$$

$$0 \leq x^* \leq 5$$

$$0 \leq y^*$$

# Basics of inverse optimization

## Inverse optimization

What are the values of  $a$  and  $b$  such that  $x^* = 5$  and  $y^* = 2$ ?

$$\underset{a,b}{\text{Maximize}} \quad a x^* + y^*$$

Subject to

$$x^* + y^* \leq b$$

$$0 \leq x^* \leq 5$$

$$0 \leq y^*$$

The solution is  $a > 1$  and  $b = 7$ .

# Optimal bidding



The bid represents the behavior of the aggregated pool in the market.



## Parameters $\theta$ of the bid:

- Marginal utility ( $a_{b,t}$ )
- Maximum and minimum power consumption ( $\bar{P}_t, P_t$ )
- Pick-up and drop-off limits ( $r_t^u, r_t^d$ ) (equivalent to ramp limits)

# The Bid



Unit-like problem

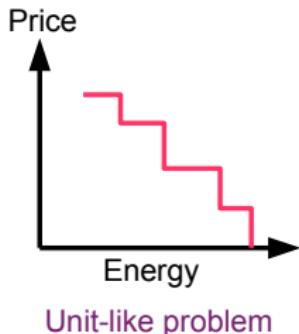
Maximize  $\underset{x}{\text{Total utility}} - \text{cost energy}$

Pick-up limit ( $r^u$ )

Drop-off limit ( $r^d$ )

Power bounds ( $P, \bar{P}$ )

# The Bid



Maximize  $\sum_x$  (Total utility – cost energy)

Pick-up limit ( $r^u$ )

Drop-off limit ( $r^d$ )

Power bounds ( $\underline{P}, \bar{P}$ )

- The energy assigned to each block is  $x_{bt}$
- And the total estimated load as  $x_t^{tot} = \underline{P}_t + \sum_{b \in \mathcal{B}} x_{b,t}$

$$\underset{x_{b,t}}{\text{Max}} \sum_{t \in \mathcal{T}} \left( \sum_{b \in \mathcal{B}} a_{b,t} x_{b,t} - \text{price}_t \sum_{b \in \mathcal{B}} x_{b,t} \right)$$

Subject to

$$-r_t^d \leq x_t^{tot} - x_{t-1}^{tot} \leq r_t^u$$

$$0 \leq x_{b,t} \leq \frac{\bar{P}_t - \underline{P}_t}{B}$$

# The Estimation Process



Time	Price	Load	External Info.
$t_1$	$\text{price}_1$	$x_1^{\text{meas}}$	$z_1$
$t_2$	$\text{price}_2$	$x_2^{\text{meas}}$	$z_2$
...	...	...	...

# The Estimation Process



Estimation problem:  
inverse optimization and  
bilevel programming

Upper-level problem

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

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

$$A\theta \leq b$$

Lower-level problem

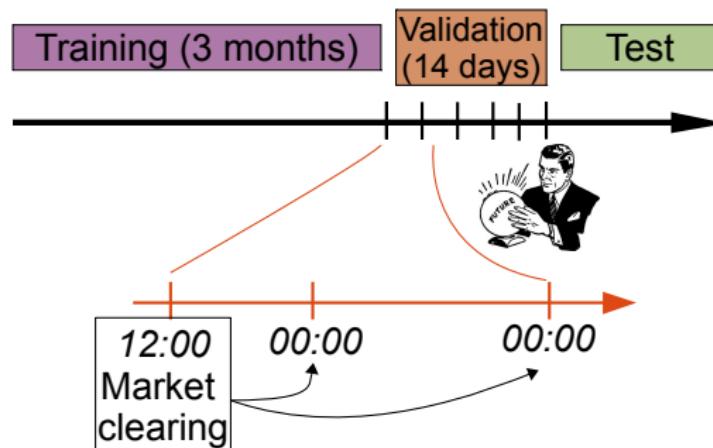
$$\begin{aligned} & \text{Maximize } (Total \text{ utility} \\ & \quad - \text{cost energy}) \\ & \text{Pick-up limit } (r^d) \\ & \text{Drop-off limit } (r^u) \\ & \text{Power bounds } (\underline{P}, \bar{P}) \end{aligned}$$

Time	Price	Load	External Info.
$t_1$	$\text{price}_1$	$x_1^{\text{meas}}$	$z_1$
$t_2$	$\text{price}_2$	$x_2^{\text{meas}}$	$z_2$
...	...	...	...

# Results

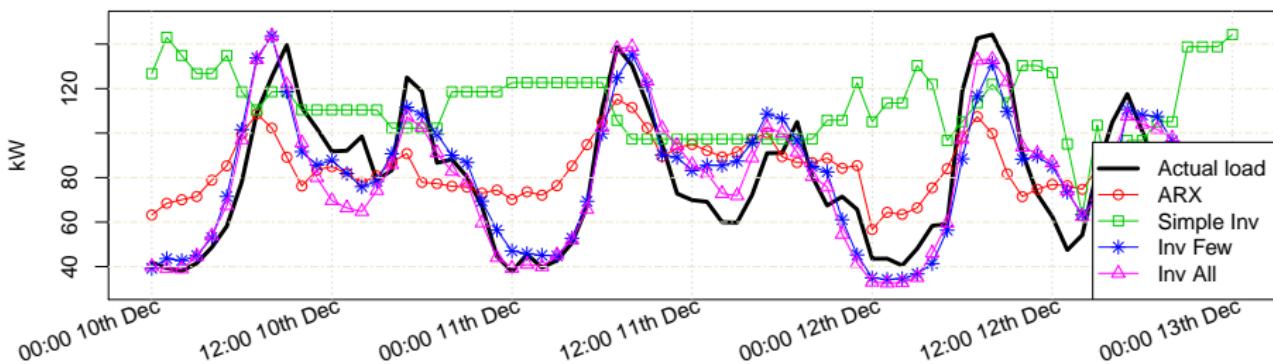
Cross-validation: In a rolling-horizon manner

- ① Compute optimal bid
- ② Input the price
- ③ Error: estimated load vs actual load.



# Results

Prediction capabilities of different benchmarked methods



MAPE	
ARX	0.2752
Inv Few	0.1846
Inv All	0.1987

# Load forecasting

**Paper D:** J. Saez-Gallego and J. M. Morales,  
“Short-term Forecasting of Price-responsive Loads Using Inverse Optimization”. Under review in *IEEE Transactions on Smart Grid*, 2016.

# Energy demand forecasting as solution



- Plan grid expansion
- Mitigating grid congestions
- Minimizing cost of over or under contracting
- Facilitating adoption of demand response

# Energy demand forecasting as solution



- A cluster of price-responsive buildings is considered
- Economic Model Predictive Control (EMPC)

# Forecasting the demand

Model the hourly demand using a linear problem

Unknown variables:

- the **marginal utility**  $u_{b,t}$
- the **bounds of the power**  
 $\bar{P}_t, \underline{P}_t$

Available historical information:

- measured load  $x_{b,t}$
- electricity price  $price_t$
- external variables

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- the **bounds of the power**  $\bar{P}_t, \underline{P}_t$

Available historical information:

- measured load  $x_{b,t}$
- electricity price  $price_t$
- external variables

$$\underset{x_t}{\text{maximize}} \quad \sum_{b=1}^B x_{b,t} (u_{b,t} - price_t)$$

$$\text{subject to} \quad \underline{P}_t \leq \sum_{b=1}^B x_{b,t} \leq \bar{P}_t$$

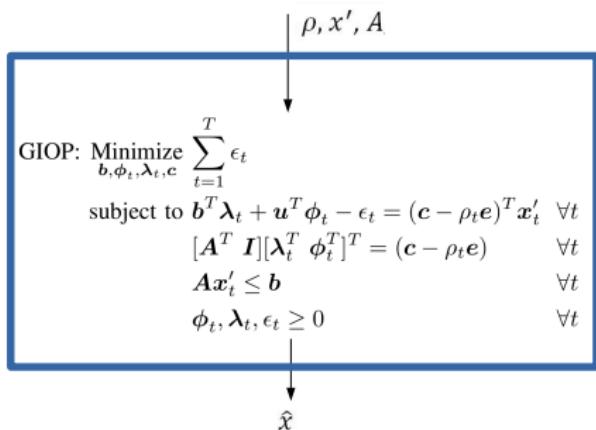
$$0 \leq x_{b,t} \leq E_{b,t}$$



# Forecasting the demand

## Challenges

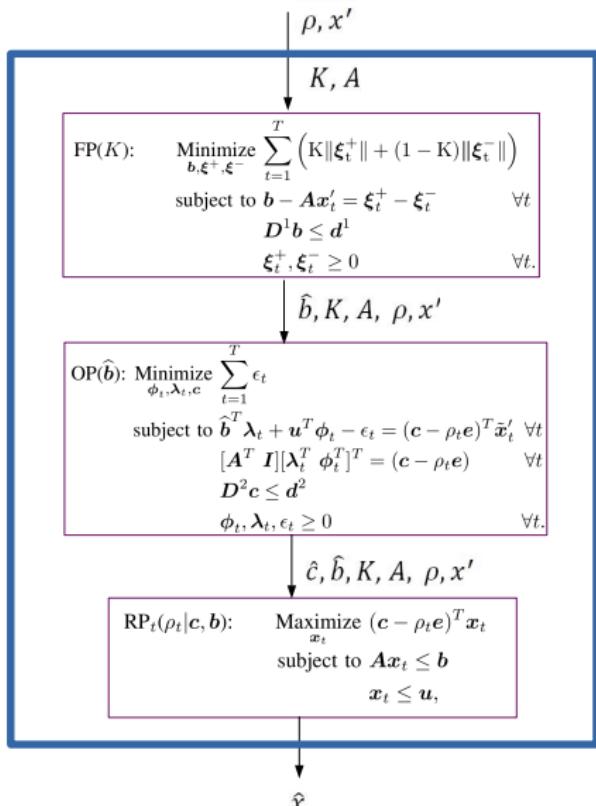
- Non-linear nature of the original problem
- Issues with feasibility and optimality
- Unable to solve for small-to-medium sized datasets



# Forecasting the demand

## Solution

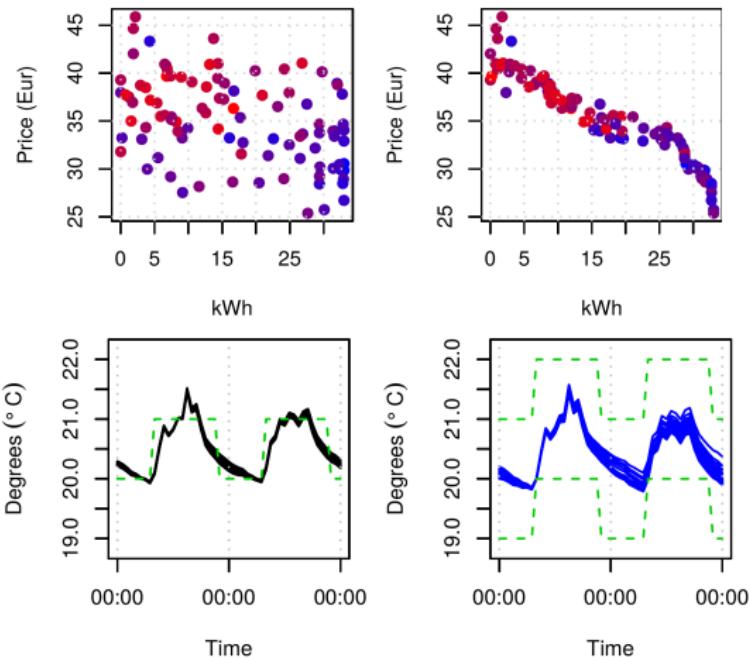
- Iterative estimation process: single linear problems
- Fast to solve (10 seconds)
- Attractive statistical properties: suited for out-of-sample estimation



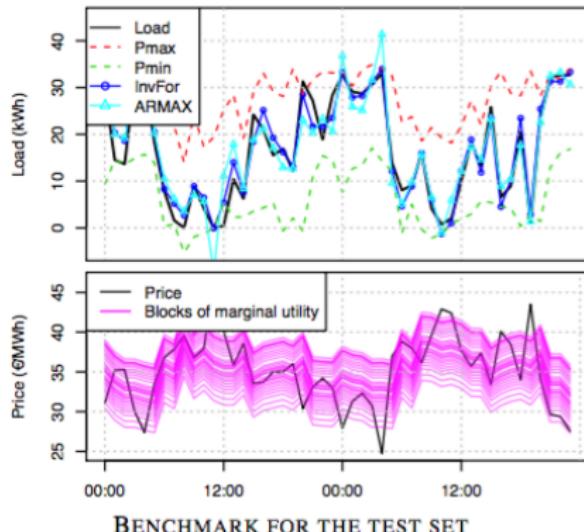
# Case study



**100 buildings equipped with heat pumps**



# Case study



BENCHMARK FOR THE TEST SET

	No Flex		Flex	
	NRMSE	SMAPE	NRMSE	SMAPE
<i>Persistence</i>	0.1727	0.1509	0.3107	-
<i>ARMAX</i>	0.10086	0.08752	0.13107	0.08426
<i>InvFor</i>	0.10093	0.0886	0.08903	0.07003

# Summary of contributions



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- Inverse optimization

- ① Formulation of generalized inverse optimization models
- ② Practical solution methods
- ③ Application to optimal bidding and time series forecasting
- ④ Use historical data and external variables

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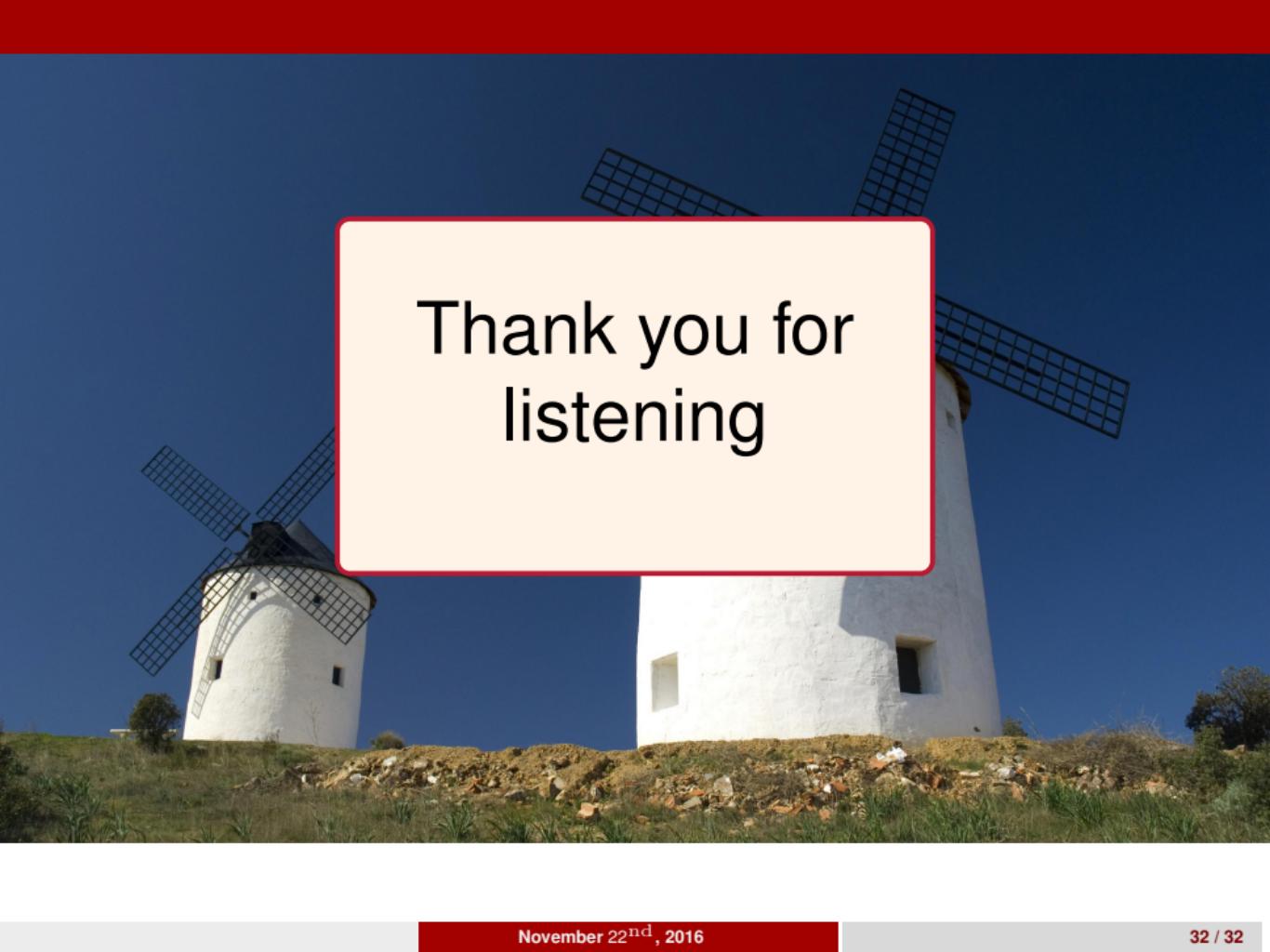
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- Inverse optimization
  - ① Formulation of generalized inverse optimization models
  - ② Practical solution methods
  - ③ Application to optimal bidding and time series forecasting
  - ④ Use historical data and external variables
- A **probabilistic framework** to determine the total reserve requirements using a **stochastic programming**
- All the proposed solutions are benchmark and tested in a realistic manner

# Future perspectives

- Further application of inverse optimization modeling: finance, health care, transport, etc.
- From a mathematical perspective, extend the concept of inverse optimization to allow
  - larger amounts of data
  - non-linear relationships
  - robust solutions
- Study reserve capabilities of demand under the smart grid paradigm

A photograph of two traditional white windmills with dark wooden blades, set against a clear, deep blue sky. The windmills are positioned on a grassy hillside with some scattered rocks at the base.

Thank you for  
listening