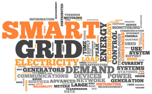
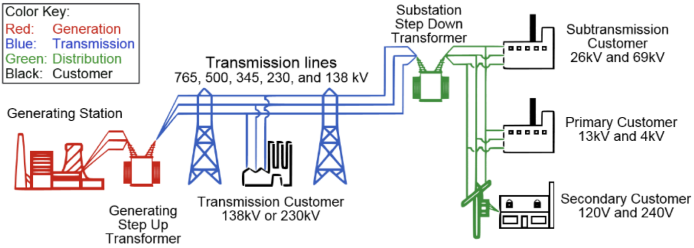
Demand Response Pricing Problems for Energy Management

Luce Brotcorne



Outline

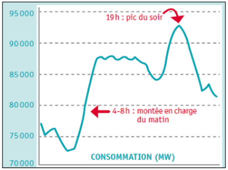
Centralized system



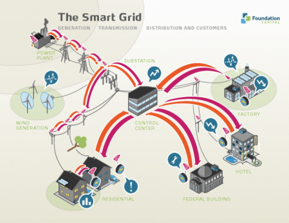
Anjos (2015)

Motivation

- Demand for energy is largely uncontrollable and varies with time of day and season.



Motivation (2)



- Energy resources are more and more spatially scattered
- Wind and solar energies are highy variable and intermittent
- Supply-demand balance failure $\rightarrow$ system instability
- Total capacity of installed generation must be $\geq$ max demand to ensure the security of supply.

New challenges in demand and offer

- Demand for energy is largely uncontrollable and varies with time of day and season.
- Energy resources are more and more spatially scattered.
- Wind and solar energies are highly variable and intermittent.
- Supply-demand balance failure $\rightarrow$ system instability.
- Deregulation

Demand Side Management

Why Necessary?

- DSM: **control** and **manipulate** the demand to meet capacity constraints.

Major DSM Techniques

- Direct load control, load limiters, load switching.
- Commercial/industrial programs.
- Demand bidding.
- Time-of-use pricing to induce load shifting.
- Smart grid
  "The smart grid is expected to revolutionize electricity generation, transmission, and distribution allowing two-way flows for both electrical power and information. Moreover it can complement the current electric grid system by including renewable energy sources." (Bari et al.)

Bilevel Programming

To deal with decision processes involving two decision-makers with a hierarchical structure:

- Two decision levels: a leader and a follower.
- The leaders sets his decision variables first. Then the follower reacts based on the choices of the leader.
- Each decision-maker controls a set of variables subject to constraints and seeks to optimize a given objective function.
- Objective functions usually are in conflict and decision-makers do not cooperate.

Related to Principal Agent Paradigm, Equilibrium constrained Mathematical Program, Stackelberg Game

Mathematical Formulation

$$\max_{x} \; f(x) \quad \text{s.t.} \quad x \in X$$

$$\begin{aligned}
\min_{x_1} \;\; & f_1(x_1, x_2) \\
\text{s.t.} \;\; & \\
& x_1 \in S_1 \\
& x_2 \text{ solves } \min_{x_2} \;\; f_2(x_1, x_2) \\
& \text{s.t.} \\
& (x_1, x_2) \in S
\end{aligned}$$

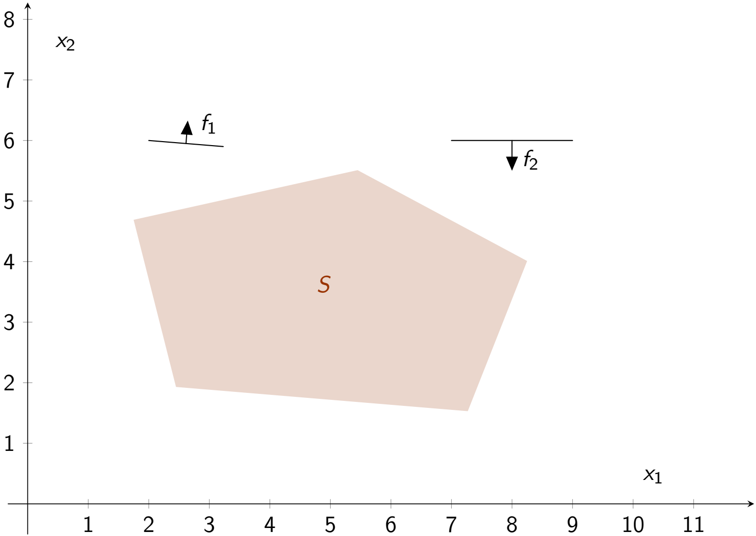
The feasible region of the leader's problem is implicitly determined by an optimization problem.

A subset of variables are constrained to be an optimal solution of another optimization problem parameterized by the remaining variables

Main properties of bilevel programs

- Bilevel programs are intrinsically hard to solve being typically non convex and non differentiable.
- One of its main features is that bilevel problem may not possess a solution even when the objective functions of the leader and the follower are continuous and S is compact.
- Optimal solutions are non Pareto-optimal.

Example:Geometry of linear bilevel program



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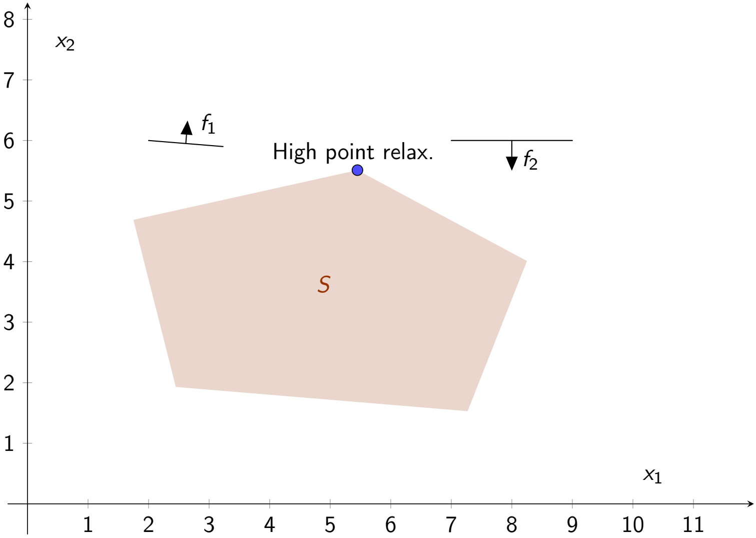

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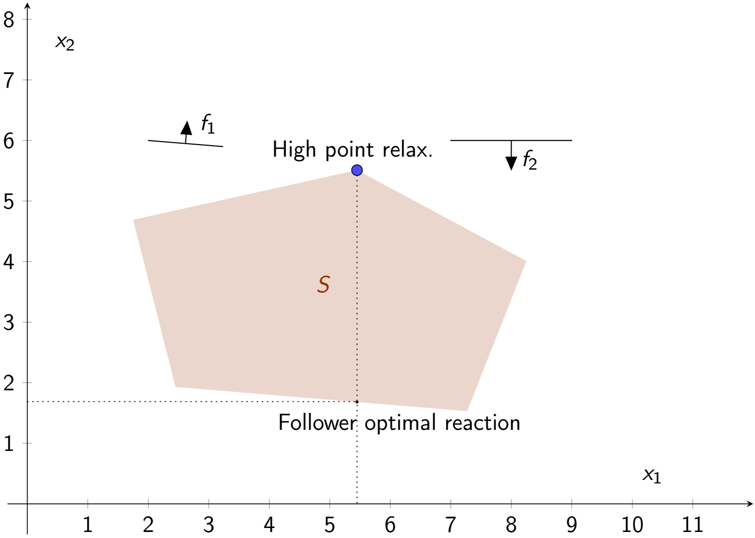

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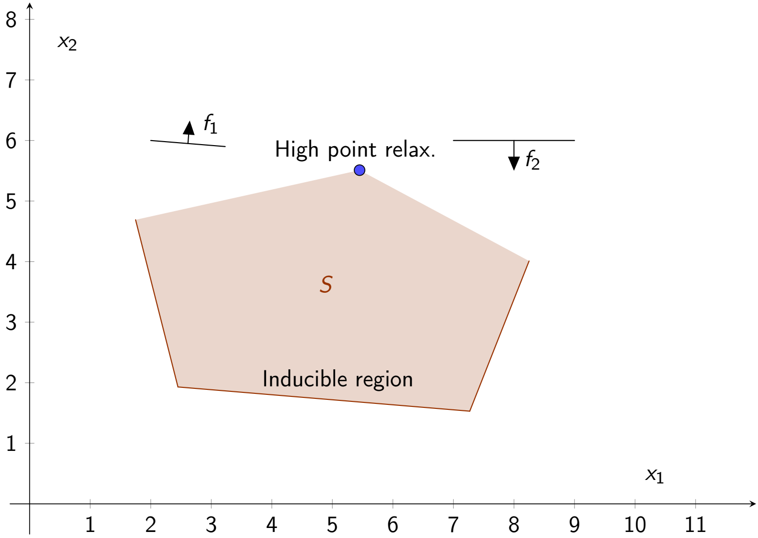

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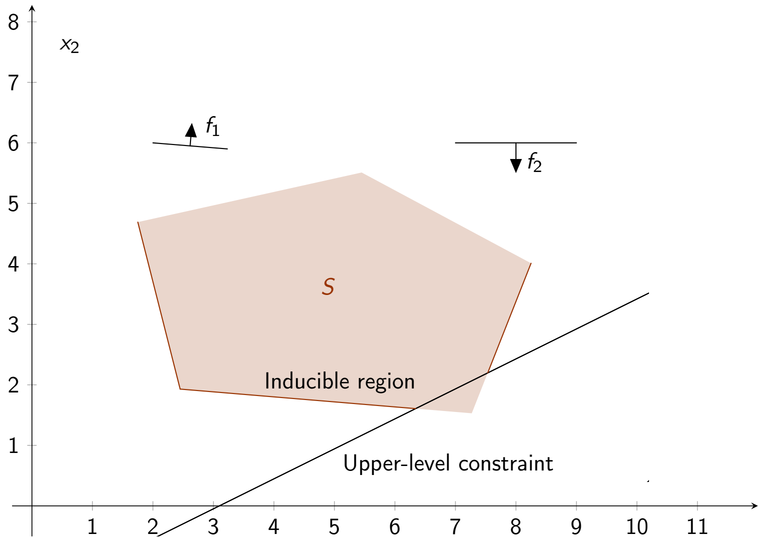

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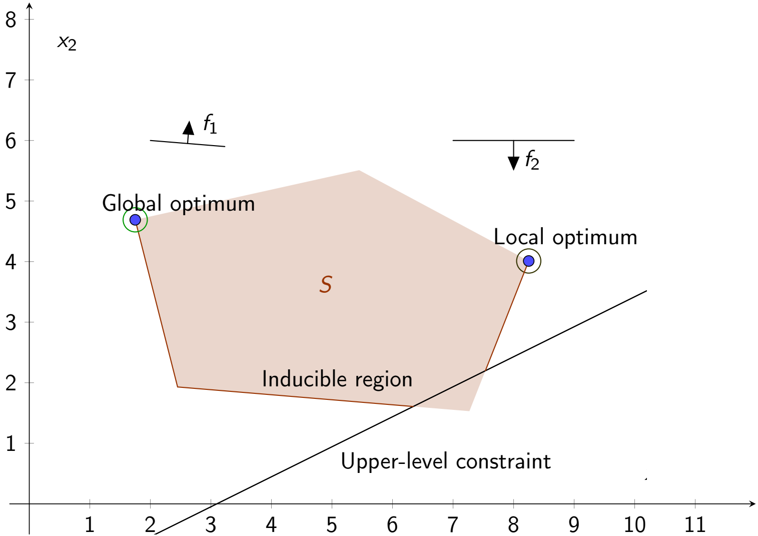
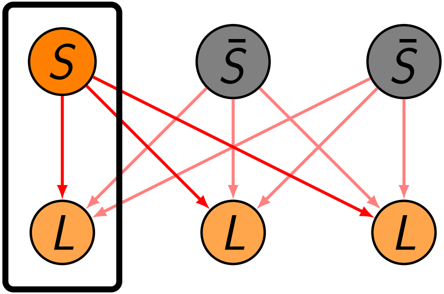
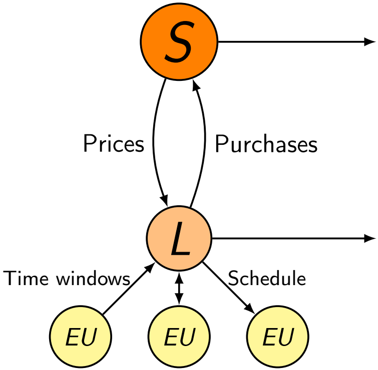


Time of use Pricing - Single leader, Single follower



- Brotcorne L., Lepaul S., Von Niederhausern L., A rolling horizon approach for a demand response stochastic bilevel pricing model , working paper.

Time of use Pricing - Single leader, Single follower



Controls prices
Maximizes profit

Controls usage schedule
Manages RE and storage
Minimizes generalized cost

Time of use Pricing - Single leader, Single follower

Objectives

- Leader maximizes (revenue - buying cost on the spot market) by deciding on prices,
- Follower minimizes (billing cost + inconvenience cost) by deciding on the schedule of consumption.

Assumptions

- 24-hours cycles,
- Demand is fixed,
- Every customer has a set of appliances with preferred time windows,
- All appliances have power consumption limits,
- All appliances are preemptive.

Time of use Pricing - Single leader, Single follower

Characteristics

The smart grid operator has four energy sources:

- Electricity bought from leader,
- Electricity bought from competitor,
- Renewable energy,
- Stored energy.

Bilevel Model

Exogenous data

- H: Set of time slots,
- K: Energy cost for the leader for time slot h,
- $\bar{p}^h$: Competitor's price for time slot h,
- N: Set of customers,
- A_n: Set of devices for customer n,
- $\beta_{n,a}^{\max}$: Power limit of appliance a for customer n,
- $E_{n,a}$: Demand of customer n for appliance a,
- $T_{n,a} = \{T_{n,a}^{first}, \ldots, T_{n,a}^{last}\}$: Time window for appliance a of customer n ,
- $C_{n,a}(h)$: Inconvenience cost for customer n if appliance a is used at time h,
- λ_{max}^h: Hourly production of renewable energy,
- S^{min}, S^{max}: Lower and upper bounds for battery capacity,
- ρ^c: Charging coefficient.

Bilevel Model

Decision variables of the leader

- p^h: Energy price for time slot h.

Decision variables of the follower

- $x^h_{(n,a)}$: Energy bought from the leader,
- $\bar{x}^h_{(n,a)}$: Energy bought from the competitor,
- $\lambda^h_{(n,a)}$: Energy taken from the renewable energy production,
- $s^h_{(n,a)}$: Energy taken from the battery,
- S^h: Energy storage state at time h,
- λ^h_s: Renewable energy transferred to the battery,
- x^h_s: Energy bought from the leader and transferred to the battery,
- $\bar{x}^h_s$: Energy bought from the competitor and transferred to the battery.

Bilevel Model: Objective Functions

Leader's objective function:

$$\max_{p} \sum_{n\in \boldsymbol{N}} \sum_{a\in \boldsymbol{A_n}} \sum_{h\in T_{n,a}} p^h x^h_{(n,a)} + \sum_{h\in \boldsymbol{H}} \left(p^h x^h_s - K \left(h, x^h_s + \sum_{n\in \boldsymbol{N}} \sum_{a\in \boldsymbol{A_n}} x^h_{(n,a)} \right) \right).$$

Follower's objective function:

$$\min_{x,\bar{x},\lambda,s,S} \quad \sum_{n\in \boldsymbol{N}} \sum_{a\in \boldsymbol{A_n}} \sum_{h\in T_{n,a}} \left(p^h x^h_{(n,a)} + \bar{p}^h \bar{x}^h_{(n,a)} + C^h_{(n,a)} \left(x^h_{(n,a)} + \bar{x}^h_{(n,a)} + \lambda^h_{(n,a)} + s^h_{(n,a)} \right) \right)$$
$$+ \sum_{h\in \boldsymbol{H}} \left(p^h x^h_s + \bar{p}^h \bar{x}^h_s \right).$$

Bilevel Model: Constraints of the follower

$$\sum_{h \in T_{n,a}} \left(x^h_{(n,a)} + \bar{x}^h_{(n,a)} + \lambda^h_{(n,a)} + s^h_{(n,a)} \right) \geq E_{(n,a)} \qquad \forall n \in N, a \in A_n$$

$$x^h_{(n,a)} + \bar{x}^h_{(n,a)} + \lambda^h_{(n,a)} + s^h_{(n,a)} \leq \beta^{max}_{(n,a)} \qquad \forall n \in N, a \in A_n, h \in T_{n,a}$$

$$\lambda^h_s + \sum_{n \in N} \sum_{a \in A_n} \lambda^h_{(n,a)} \leq \lambda^h_{max} \qquad \forall h \in H$$

$$S^{h+1} = S^h - \sum_{n \in N} \sum_{a \in A_n} s^h_{(n,a)} + \rho^c (\lambda^h_s + x^h_s + \bar{x}^h_s) \qquad \forall h \in H$$

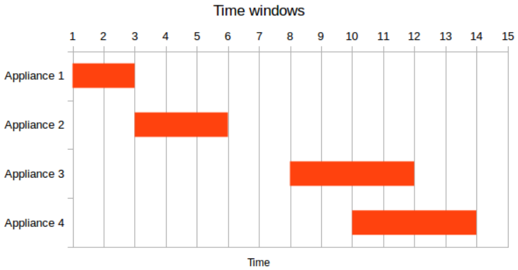
$$\sum_{n \in N} \sum_{a \in A_n} s^h_{(n,a)} \leq S^h \qquad \forall h \in H$$

$$S^{min} \leq S^h \leq S^{max} \qquad \forall h \in H.$$

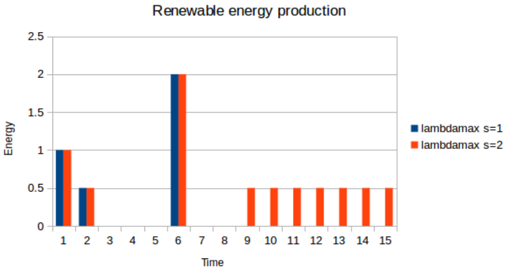
Example

Four appliances $\{1,2,3,4\}$:

- Appliance 1, $\beta_1^{max} = 1,\ E_1 = 1.5,$
- Appliance 2, $\beta_2^{max} = 1,\ E_2 = 2,$
- Appliance 3, $\beta_3^{max} = 1,\ E_3 = 2.5,$
- Appliance 4, $\beta_4^{max} = 1,\ E_4 = 3.$



Two scenarios, similar up to $h = 7$.

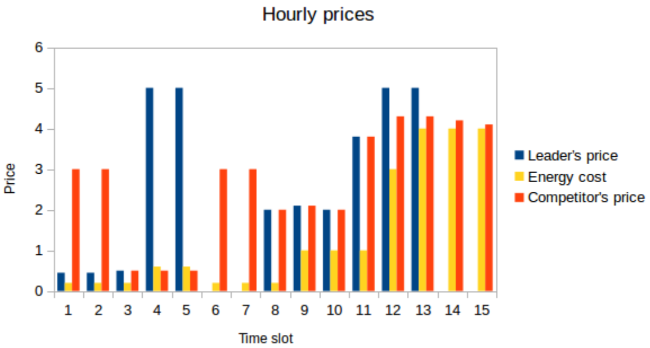


Energy storage capacity: $S^h \in [0, 1]$, $\rho^c = 0.9$.

Energy supply costs for the leader, one competitor.

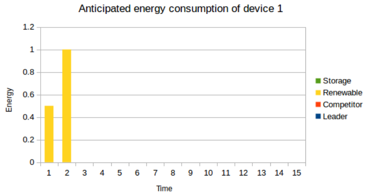
Example

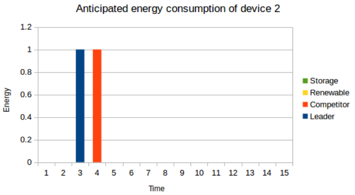
Leader's optimal prices, competitor's prices and energy supply costs.



Example

What we expected:





Example

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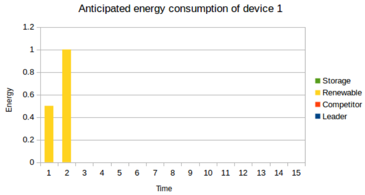
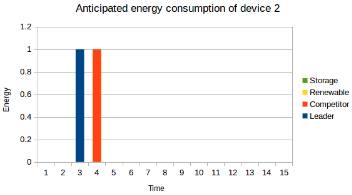
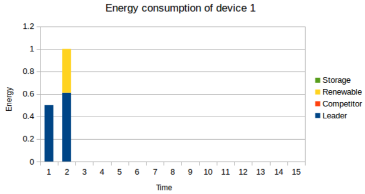
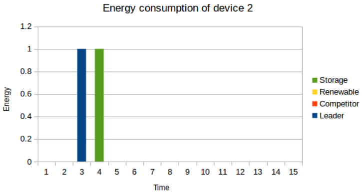




What really happens:





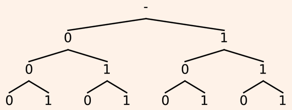
Stochastic approach

Motivation

Renewable energy production is by nature unpredictable $\rightarrow \lambda^h_{max}$ not known in advance.

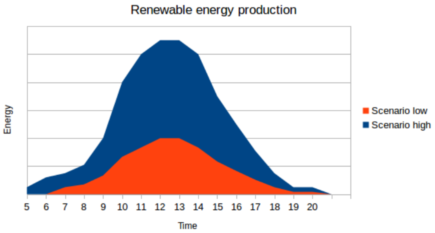
Properties

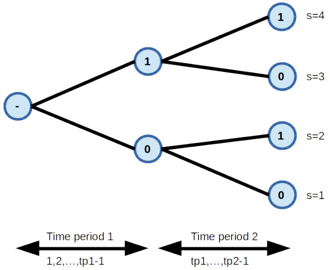
- Scenario tree-based approach,



- Every leaf is a scenario,
- Every scenario happens with given probability.

Scenario trees





- Time separated in time periods (around 3 hours),
- One set of variables per scenario,
- Nonanticipativity constraints,
- Expected values of the objective functions.

Parameters of the test instances

- 1 client owning 5, 10 or 20 appliances (500-3000W each),
- 1 to 4 time periods on 6 or 12 hours,
- Energy costs based on SPOT market prices: 40-70/MWh,
- Competitor's prices from 0.1 to 0.2 /kWh,
  Renewable energy production:
  smartflower™ POP+,
  2.31 kWp $\rightarrow$ 2-3 MWh/year,
  Storage size: 2,3 kWh,

Value of stochastic solution (VSS) and expected value of perfect information (EVPI)

VSS

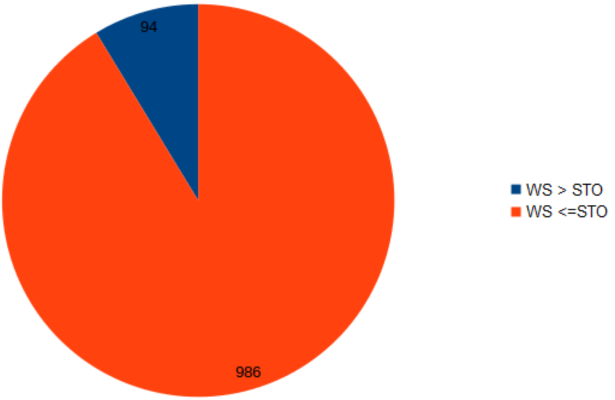
- Optimal solution on an average scenario.
- 1. Optimal prices on the average scenario.
  2. Follower's optimal reaction to these prices $\rightarrow EEV$.
  3. $VSS = STO - EEV$.

EVPI

- The decision-makers know which scenario will occur.
- 1. Optimal solution for each scenario.
  2. Expected value on all scenarios $\rightarrow WS$.
  3. $EVPI = WS - STO$.

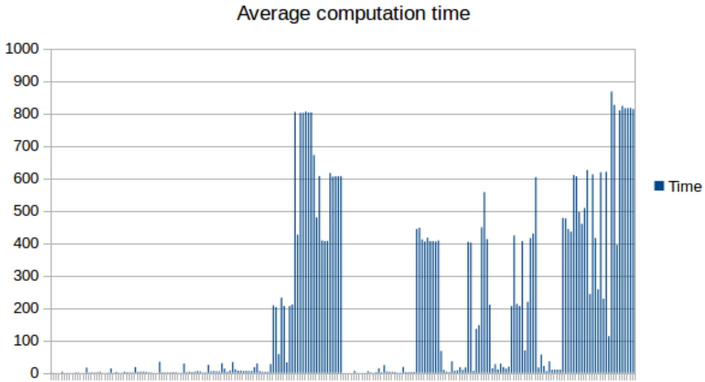
$$EEV \leq STO \leq WS.$$

WS



Counter-intuitive, but normal in a bilevel context.

Computation time

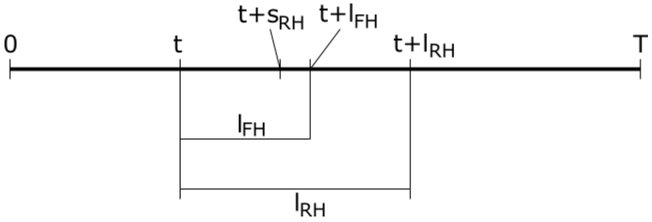


Time limit: 1000 s.
Larger times on larger instances: 12 hours, 4 time periods (16 scenarios), 20 appliances.

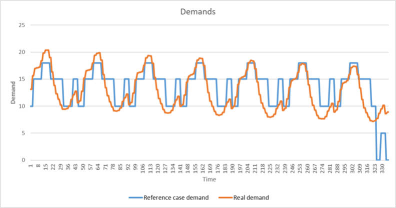
Rolling horizon method

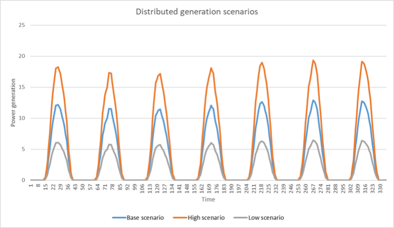
New parameters:

- l_{RH} is the length of the *rolling* horizon,
- l_{FH} is the length of the *frozen* horizon,
- s_{RH} is the *step size*.



Base instance





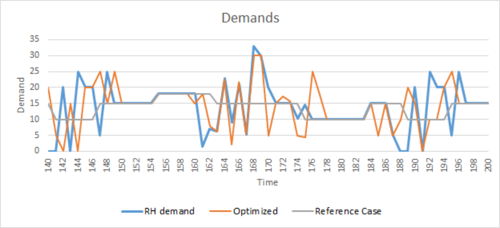
All data retrieved from EDF.

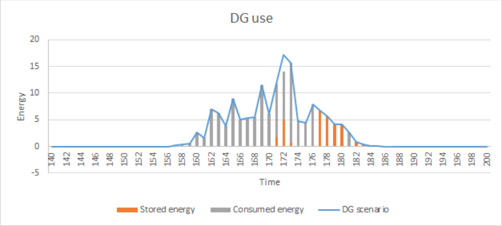
RH results

Tests with $s_{RH} = 1$, $l_{RH} = 12$, and $l_{FH} = 6$.

Run	RH	VPI	Ref case	Time (s)
1	35092	34848	34348	35511
2	34452	34467	33918	23594
3	34048	34034	33603	23652
4	35207	35111	34750	24251
5	34530	34528	34053	24773

Run 1: time slots 140 to 200





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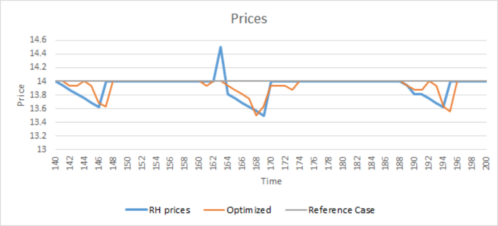
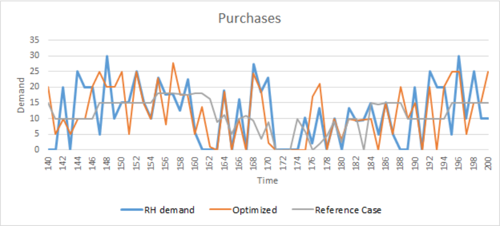
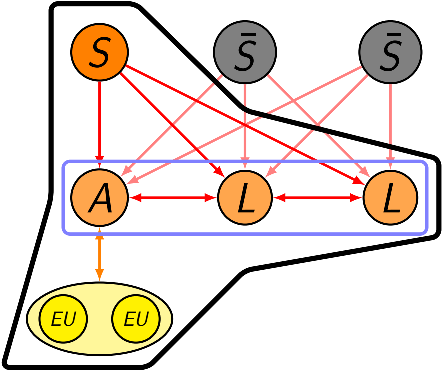


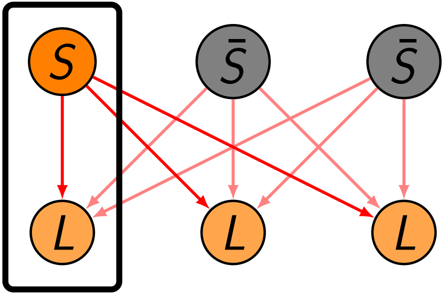


Time of use Pricing - Single leader, Multi follower



- Aussel D., Brotcorne L., Lepaul S., Von Niederhausern L., A trilevel model for a best response problem in demand side management approach of energy exchanges, submitted to EJOR .

Time and level of use Pricing - Single leader, Single follower



- TLOU pricing

  Besançon M., Anjos M., Brotcorne L.., Gomez J., A Bilevel Framework for Optimal Price-Setting of Time-and-Level-of-Use Tariffs, submitted to IEEE Transactions on Power Systems.

Time and level of use Pricing - Single leader, Single follower

Context:

- Generation planning requires information on demand
- Generation planning requires **guarantee** on consumption
- Intensify Demand Response for residential customers

Design goals:

- Reduce customers cost in exchange of a guarantee on demand
- Maintain privacy and customers flexibility
- Minimal information exchanges and customers actions

Time-and-Level-of-Use tariff (TLOU)

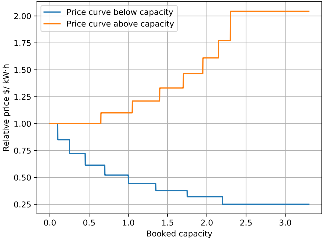
TLOU Policy (Gomez-Herrera & Anjos 2017).

For each time t

- K, booking fee
- π^L, lower tariff decreasing with capacity
- π^H, higher tariff increasing with capacity

A capacity is booked by the customers before consumption

Customer cost = Booking cost + Consumption cost



TLOU steps

Day ahead process:

1. Supplier defines pricing strategies for each time window
2. Consumers book a capacity for each time window
3. After consumption, total cost is computed

Decision variables

Supplier chooses a price policy for each time window:

- $K \geq 0$
- $\pi^L \in \mathbb{R}^{|\pi^L|} \geq 0$
- $\pi^H \in \mathbb{R}^{|\pi^H|} \geq 0$

$\pi^L(0) = \pi^H(0)$: the baseline Time-of-Use price.

Customers:

- Book capacity for the time window $c \geq 0$

Follower program

The total price paid by a customer with a booked capacity c and a consumption x for a time frame is:

$$C(c) = \begin{cases} K \cdot c + \pi^L(c) \cdot x, & \text{if } x \leq c, \\ K \cdot c + \pi^H(c) \cdot x & \text{otherwise.} \end{cases} \tag{1}$$

$\pi^L(c = 0) = \pi^H(c = 0) = \pi^0$, with π^0 the Time-of-Use price.

Ω: set of scenarios ω for load levels x_ω with a probability p_ω

Each Customer minimizes its total expected cost:

$$\min_c \; K \cdot c + \sum_{\omega \in \Omega^-(c)} \pi^L(c) \cdot p_\omega \cdot x_\omega + \sum_{\omega \in \Omega^+(c)} \pi^H(c) \cdot p_\omega \cdot x_\omega$$

Leader program

- Supplier minimizes the difference in profit between the baseline and current solution:

$$L^F(c, K, \pi^L, \pi^H) = \sum_{\omega \in \Omega} p_\omega \cdot x_\omega \cdot \pi_0 -$$

$$K \cdot c + \sum_{\omega \in \Omega^-(c)} x_\omega \cdot p_\omega \cdot \pi^L(c) + \sum_{\omega \in \Omega^+(c)} x_\omega \cdot p_\omega \cdot \pi^H(c) \quad (2)$$

- Supplier maximizes a guarantee on the consumption

$$\min_{K, \pi^L, \pi^H} L^G(c)$$

where $L^G(c) = P_\Omega[X > c]$ is decreasing with c.
$\Rightarrow$ induce good selection of c by the cutomers

TLOU: Bilevel model

$$\min_{K,\pi^L,\pi^H} (L^F(c,K,\pi^L,\pi^H), L^G(c))$$
$$s.c.\ (K,\pi^L,\pi^H) \in \Phi$$
$$\max_c L^F(c,K,\pi^L,\pi^H)$$

Exact solution method based on the structure of the problem (enumeration of feasible capacity levels) to generate the Pareto front.

Residential power consumption dataset

Study on 47-month household consumption

- Aggregation per hour
- Probability discretization using Kernel Density Estimate

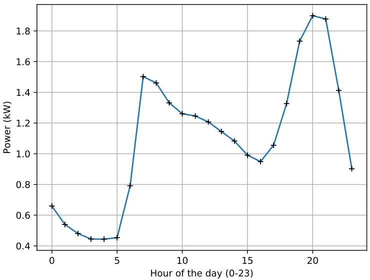


Figure: Average consumption

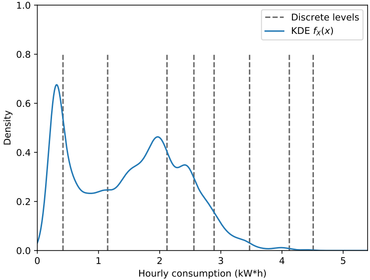
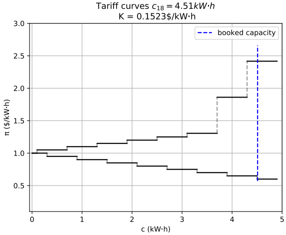


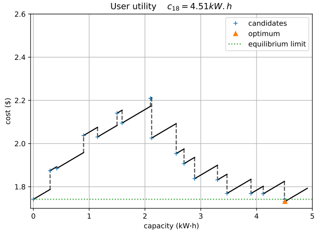
Figure: Discretization at 7AM

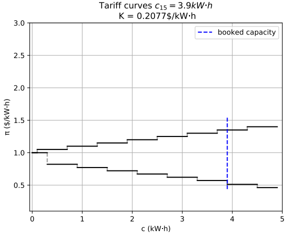
Numerical results: Pareto-optimal solutions

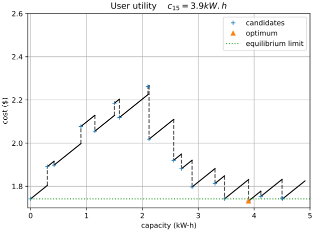
Julia, JuMP and the Coin-OR LP solver

Pareto-optimal solutions:

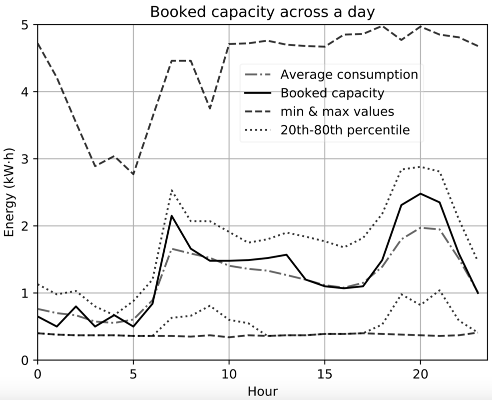








Numerical results



Conclusion

Bilevel problems

- Innovative approach for pricing problems.
- Explicitly integrated customer response into the optimization process of the supplier.
- Efficient solution methods based on the structure of the problem.

Promising research avenues:

- More efficient solution methods.
- Coupling learning approaches within optimization methods.
- Robust modeling.

Conclusion

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THANK YOU FOR LISTENING

Q & A