Energy Pricing Problems for Demand side and Revenue Management

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INVENTEURS DU MONDE NUMÉRIQUE

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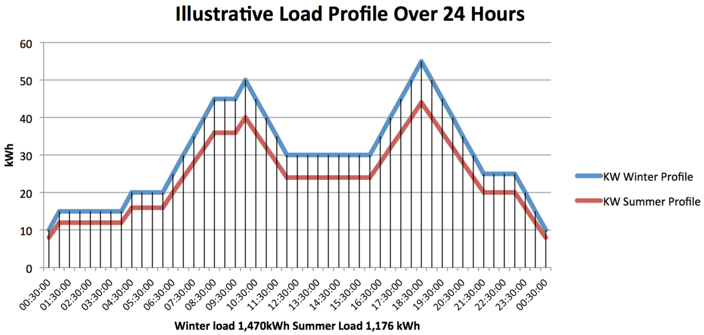
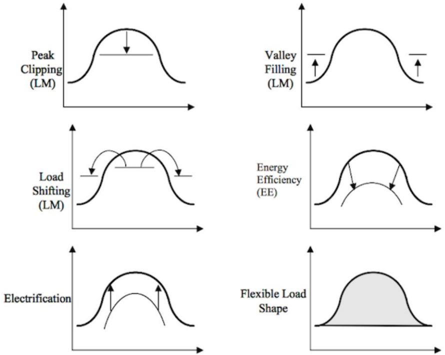
OUTLINE

MOTIVATION : PEAK LOAD



Source : Sustainable Energy Society Southern Africa,
www.sessa.org.za/about-sessa/chairman-s-blog/490-getting-a-handle-on-the-cost-of-solar-pv

DSM Techniques



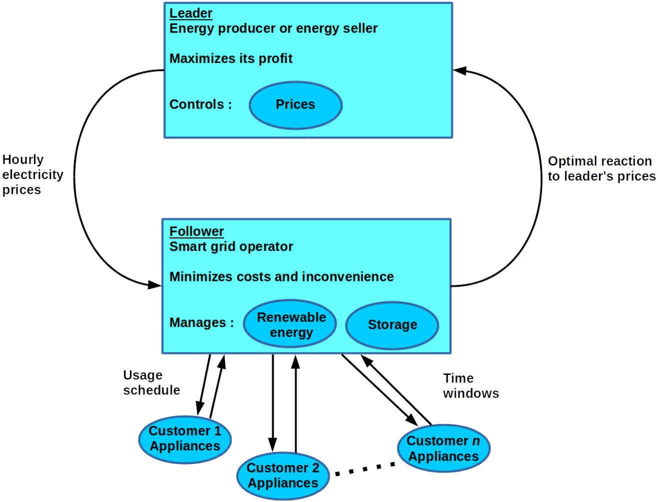
Source: Primer on Demand-Side Management, World Bank Document CRA No. D06090, 02/2005

- Our tool : time-of-use pricing.

Motivation : Smart Grids

- Scattered energy resources.
- Communication facilitated by smart meters.

Energy Pricing Problem



Bilevel Programming

Decision process involving two decision-makers with a hierarchical structure :

- Two decision levels : a leader and a follower, controlling their decision variables, seeking to optimize their objective function.
- The leader sets his decision variables first. Then the follower reacts based on the choices of the leader.

Bilevel programming is strongly NP-hard.
Originated from Stackelberg games, related to principal-agent problem, mathematical programs with equilibrium constraints.

Energy Pricing Problem

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.

Energy Pricing Problem

Assumptions

The smart grid operator has four energy sources :

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

The renewable energy production is known in advance.

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 :

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

Follower's objective function :

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

Bilevel Model : Constraints of the follower

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

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

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

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

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

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

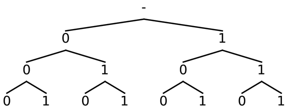
Stochastic approach

Motivation

Renewable energy production is by nature unpredictable → λ^h_{max} not known in advance.

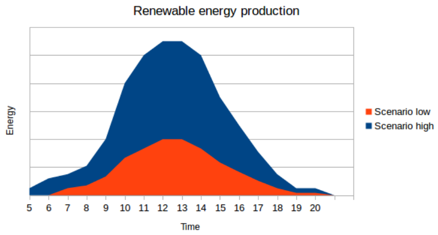
Properties

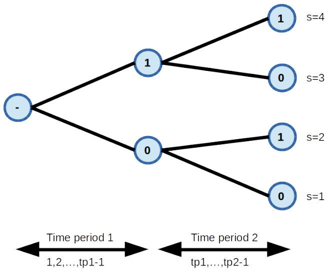
- Scenario tree-based approach,



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

SCENARIO TREES





Impact on the model

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

Exact Solution Method

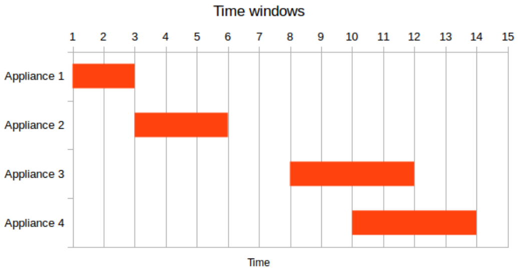
Single Level formulation

- Optimality conditions (primal,dual and complementarity constraints) of the follower,
- Complementary slackness constraints → linearized using binary variables,
- Objective function is linearized using the follower's dual objective function,
- Single level MIP.

Base example

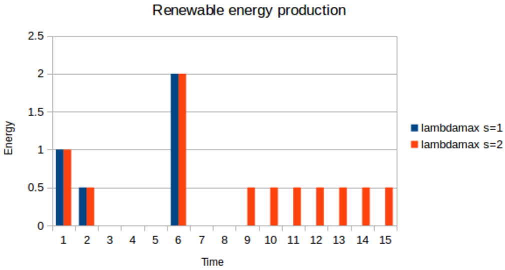
Four appliances $\{1, 2, 3, 4\}$:

- 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, $\beta_4^{max} = 1$, $E_4 = 3$.



BASE EXAMPLE

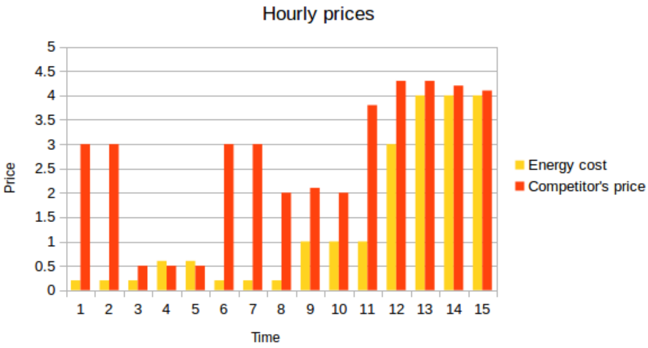
Two scenarios, similar up to $h = 7$.



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

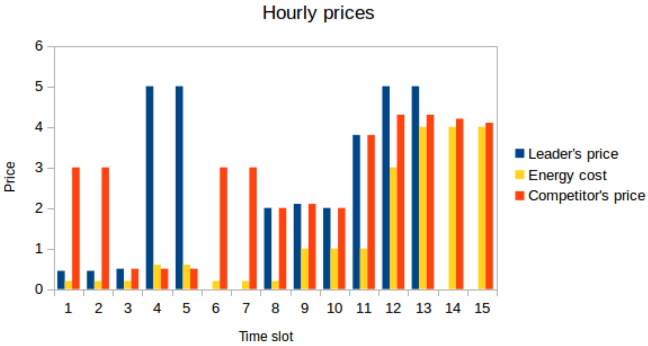
Base example

Energy supply costs for the leader, one competitor.



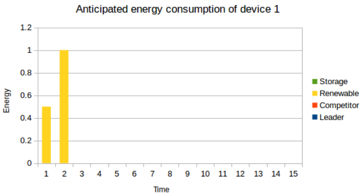
Base example

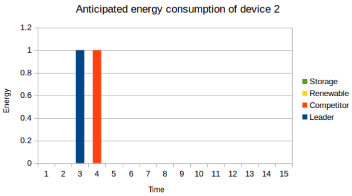
Leader's optimal prices, competitor's prices and energy supply costs.



Base example

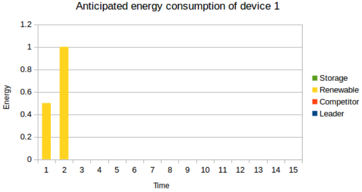
What we thought :

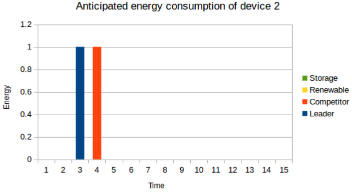




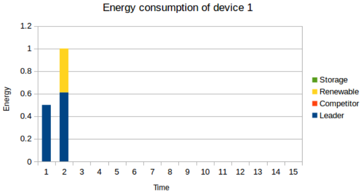
Base example

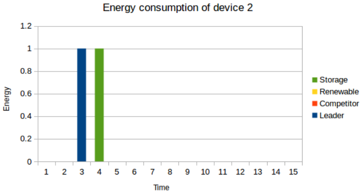
What we thought :





What happened :





Parameters of the test instances

- 1 customer 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 → 2-3 MWh/year,
  Storage size : 2,3 kWh,
  3 sizes, 3 starting states

- 5 instances for each parameter setting → 1080 instances.

VSS and EVPI

Two usual bounds in stochastic programming.

VSS

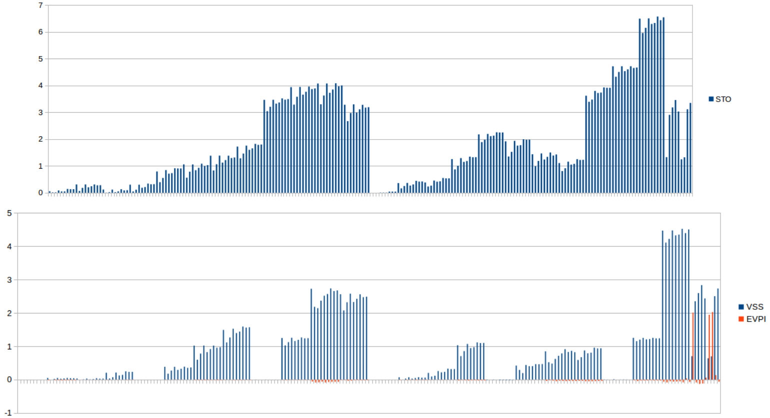
- Value of stochastic solution.
- Optimal solution on an average scenario.
- 1. Optimal prices on the average scenario.
  2. Follower's optimal reaction to these prices $\rightarrow EEV$.
  3. $VSS = STO - EEV$.

EVPI

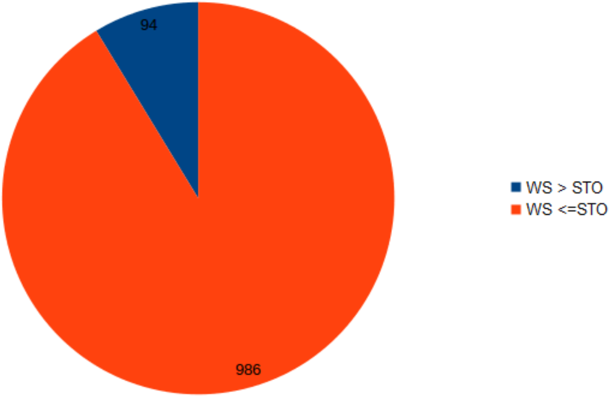
- Expected value of perfect information.
- The decision-makers know which scenario will occur.
- 1. Optimal solution for each scenario.
  2. Expected value on all scenarios $\rightarrow WS$.
  3. $EVPI = WS - STO$.

Usually, $EEV \leq STO \leq WS$.

STO-VSS-EVPI

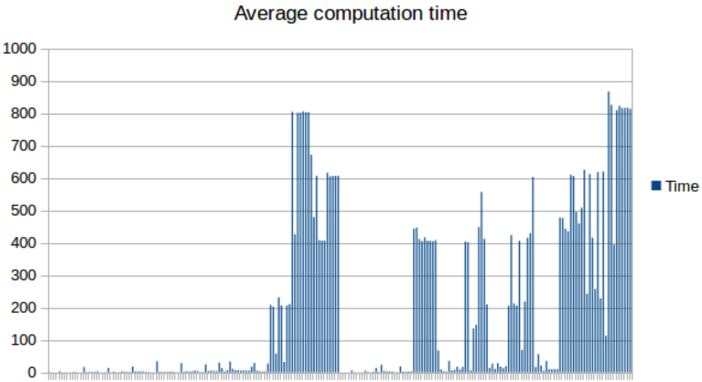


WS



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.

Prospects

What we did

- Innovative approach for DSM,
- Explicit integration of the customer response into the optimization process of the supplier,
- Integration of storage capacities, renewable energy and the related uncertainty,

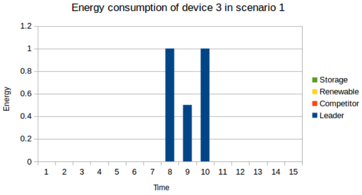
What we intend to do

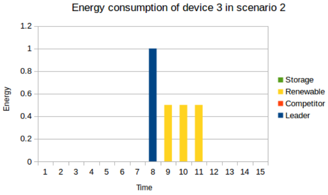
- Stochastic approach,
  - More tests,
  - Development of heuristics,
- Multi-leader approach.

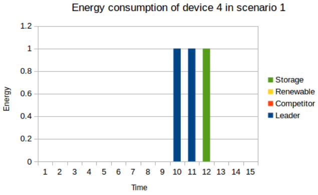
THANK YOU FOR LISTENING

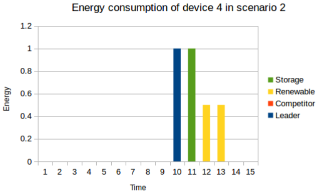
Base example

Energy consumption of appliances 3 and 4 in scenarios 1 and 2.

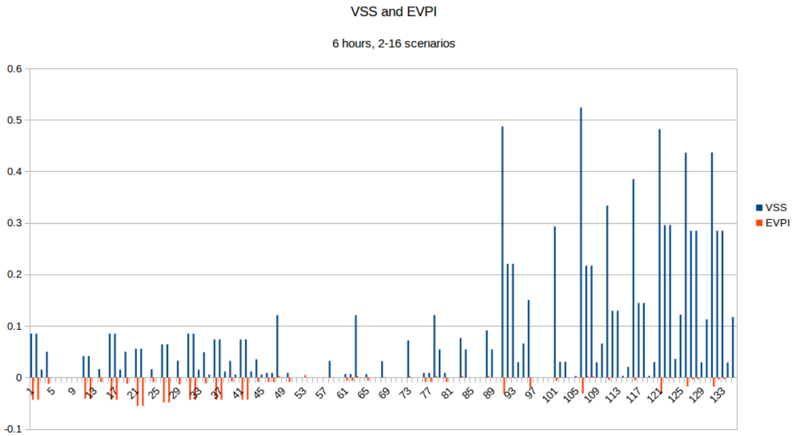






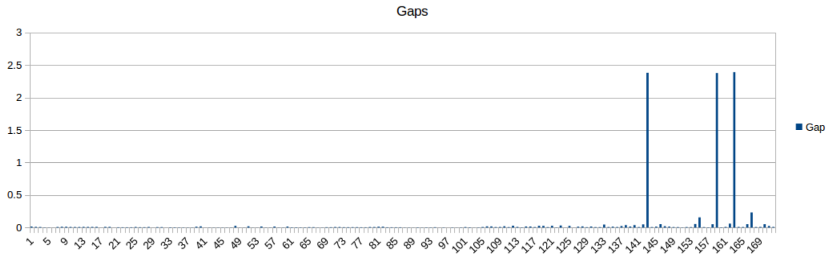


STO-VSS-EVPI

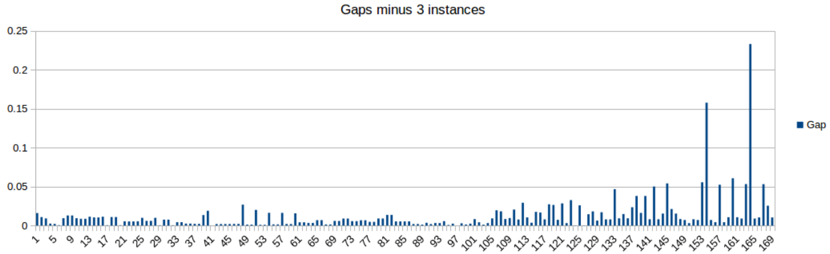


VSS and EVPI
6 hours, 2-16 scenarios
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
1 5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97 101 105 109 113 117 121 125 129 133
VSS
EVPI

Gaps



Gaps
3
2.5
2
1.5
1
0.5
0
1 5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97 101 105 109 113 117 121 125 129 133 137 141 145 149 153 157 161 165 169
Gap



Gaps minus 3 instances
0.25
0.2
0.15
0.1
0.05
0
1 5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97 101 105 109 113 117 121 125 129 133 137 141 145 149 153 157 161 165 169
Gap

Battery parameters