Dealing with Information in New Energy Systems

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Content

Dealing with Information in Decentralized Systems

Standard Optimization

Let $U \subset \mathbb{U}$ and define a single criterion: $j : \mathbb{U} \to \mathbb{R}$.

Standard Optimization Problem

$$\begin{aligned} \max \quad & j(u), \\ s.t. \quad & u \in U. \end{aligned}$$

Game Theory to model interactions between agents

Game: abstract model of a scenario in which self-interested rational agents interact.

Agents and decision space

- A finite space of agents
- $a \in A \to$ decision $u_a \in \mathbb{U}_a$
- $\mathbb{U}_a$ set of decisions for agent a equipped with σ-field $\mathcal{U}_a$
- decision space $\mathbb{U}_A := \prod_{a \in A} \mathbb{U}_a$ equipped with the product decision field $\mathcal{U}_A := \bigotimes_{a \in A} \mathcal{U}_a$

Strategic Form Game Representation

$$\mathcal{G} := \Big(A, (\mathbb{U}_a)_{a \in A}, (j_a)_{a \in A} \Big) \; ,$$

where $j_a : \prod_{b \in A} \mathbb{U}_b \to \mathbb{R}$.

Strategies for agent a

- pure strategies space $\mathbb{U}_a$
- randomized strategies space $\Delta(\mathbb{U}_a)$: set of probability distributions $\gamma_a \in \Delta(\mathbb{U}_a)$
- agents choose their strategies simultaneously and independently

Expected utility of agent a

$$J_a(\gamma_{-a}, \gamma'_a) = \sum_{u \in \mathbb{U}} \Big(\prod_{b \in A \setminus \{a\}} \gamma_b(u_b) \Big) \, \gamma'_a(u_a) \, j_a(u) \; .$$

Solutions

Nash equilibrium

Strategy γ is a Nash equilibrium (NE) of $\mathcal{G}$ if

$$J_a(\gamma) \geq J_a(\gamma_{-a}, \gamma'_a) \quad \forall a \in A \quad \forall \gamma'_a \in \Delta(\mathbb{U}_a) \, .$$

NE obtained at the intersection of Best Responses $u_a^{BR}\Big((u_b)_{b \in A \setminus \{a\}}\Big), \forall a \in A$.

Sequential decision making: Stackelberg game equilibrium

i) agent a (leader) $\rightarrow$ $u_a^\star \in \mathbb{U}_a = \arg\max_{u_a \in \mathbb{U}_a} j_a(u_a, u_{-a})$,
ii) observing the leader's action $u_a^\star$, follower $b \in A \setminus \{a\} \rightarrow$
$u_b^\star \in \mathbb{U}_b = \arg\max_{u_b \in \mathbb{U}_b} j_b\Big(u_a^\star, u_b, (u_c)_{c \in A \setminus \{a,b\}}\Big)$
$\rightarrow$ Stackelberg game equilibrium $\Big(u_a^\star, (u_b^\star)_{b \in A \setminus \{a\}}\Big)$.

Algebraic Information Representation

- Ω measurable set equipped with σ-field $\mathcal{F}$
- $\omega \in \Omega$ state of Nature
- History space $\mathbb{H} := \mathbb{U}_A \times \Omega = \prod_{b \in A} \mathbb{U}_b \times \Omega$ equipped with product history field $\mathcal{H} := \mathbb{U}_A \otimes \mathcal{F} = \bigotimes_{b \in A} \mathbb{U}_b \otimes \mathcal{F}$
- Let $C \subset A$ we introduce the subfield $\mathbb{U}_C := \bigotimes_{b \in C} \mathbb{U}_b \otimes \bigotimes_{b \notin C} \{\emptyset, \mathbb{U}_b\} \otimes \mathcal{F} \subset \mathbb{U}_A$
- information provided by the decisions of the agents in C $\mathcal{D}_C := \mathcal{U}_C \otimes \{\emptyset, \Omega\} = \bigotimes_{b \in C} \mathcal{U}_b \otimes \bigotimes_{b \notin C} \{\emptyset, \mathbb{U}_b\} \otimes \{\emptyset, \Omega\} \subset \mathcal{U}_A \otimes \mathcal{F} \subset \mathcal{H}$
- Information field of agent $a \in A$: $\mathcal{I}_a \subset \mathcal{H}$

Stochastic system definition

Stochastic system $\{\mathbb{U}_a, \mathcal{U}_a, \mathcal{I}_a\}_{a \in A}$.

Witsenhausen's intrinsic model

Agents make decisions in an order which is not fixed in advance.

Solvability and Causality

- Solvability: for each state of Nature, agents' decisions are uniquely determined by their strategies.
- Causality: agents are ordered, one playing after the other with available information depending only on agents acting earlier but the order may depend upon history.

Binary relations between agents

1) precedence
2) subsystem
3) information-memory relation
4) decision-memory relation

→ Typology of systems.

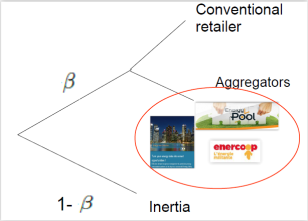
Competition and Coalition for Smart Energy Supply

Agents

- conventional retailer
- aggregator
- consumers organized in *coalition*

Definition 1

A *coalition* is a set of end users who agree on a joint demand profile to be contracted in the wholesale electricity market with the mediation of an aggregator.



Problem: pricing the aggregator's services

Aggregator's tasks are *nested*:

- forward positioning in the day-ahead electricity market to compensate the uncertainty associated with load estimation,
- supply service pricing.

Questions:

- How should the aggregator price his services so as to reach a targeted expected profit?
- How should the targeted expected profit be defined to prevent consumers from switching to conventional retailer[a]?

[a] Stability criterion relevant for *cooperative of local renewable producers* (ex. Enercoop).

A Bilevel Game

n days, T time periods per day,

$\Pi_{agg} \geq 0$ targeted expected profit,

$p^\star(t)$ aggregator's price at time period t,

$\boldsymbol{p^\star} = \left(p^\star(t)\right)_{t=0}^{nT-1}$ aggregator's price profile.

Bilevel game between aggregator and consumers:

1. aggregator $\rightarrow$ price profile $\boldsymbol{p^\star} = \left(p^\star(t)\right)_{t=0}^{nT-1}$ so as to reach his targeted expected profit,
2. each consumer $i \in \mathcal{G} \rightarrow$ load profile $\boldsymbol{x_{i,l}} = \left(x_{i,l}(t)\right)_{t=0}^{nT-1}, \forall l \in \mathcal{L}_i$ to minimize his energy bill under reservation price constraints.

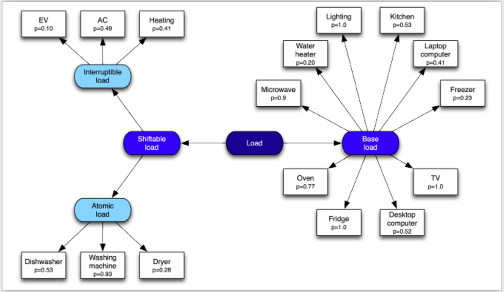
Remark: Π_{agg} can be optimized to prevent consumers from switching to conventional retailer.

Consumer i Load Classification

consumer i loads can be classified

- shiftable loads $\mathcal{L}_i = \mathcal{B}_i \cup \mathcal{I}_i$
  - interruptible loads $l \in \mathcal{I}_i$
  - block loads $l \in \mathcal{B}_i$

  $\rightsquigarrow$ (shiftable) load profile $\boldsymbol{x_{i,l}} = (x_{i,l}(t))_{t=0}^{nT-1}, l \in \mathcal{L}_i$
- base load $d_i(t) = \hat{d}_i(t) - \epsilon_i(t)$ where $\epsilon_i(t) \sim \boldsymbol{f_i}(0; \sigma_i^2)$



[Vasirani et al.]

Load Characteristics

For each consumer i and load l, we define:

- earliest time period for the load to start $\underline{t_{i,l}} \in [\![0; nT-1]\!]$,
- latest time period for the load to finish $\overline{t_{i,l}} \in [\![0; nT-1]\!]$ with $\underline{t_{i,l}} \leq \overline{t_{i,l}}$,
- duration of the load $\mu_{i,l} \in [\![0; nT]\!]$, with $0 \leq \mu_{i,l} \leq \overline{t_{i,l}} - \underline{t_{i,l}}$,
- load power rate (kW) $w_{i,l} \in \mathbb{R}_*^+$ (constant over each time slot over which the load is activated),
- load priority level $k_{i,l} \in [\![1; K]\!]$.

Reservation price

Consumer i's reservation price for load l of priority $k_{i,l} \in [\![1; K]\!]$: maximum price consumer i is willing to pay per unit of load $p_{\max,i}(k_{i,l}) \geq 0$.
Priority rule:
$k_{i,l} \prec k_{i,l'} \Rightarrow p_{max,i}(k_{i,l}) > p_{max,i}(k_{i,l'}), \forall l, l' \in \mathcal{L}_i, l \neq l'$.

Consumer i Load Scheduling

A linear optimization program under load constraints

$$
\begin{aligned}
\min_{\left(\mathbf{x_{i,l}}\right)_{l\in\mathcal{L}_i}} \quad & \sum_{l\in\mathcal{L}_i} \boldsymbol{p^\star}^T \mathbf{x_{i,l}}, \\
s.t. \quad & x_{i,l}(t) \in \{0; w_{i,l}\}, \forall t \in [\![0; nT-1]\!], \forall l \in \mathcal{L}_i, \\
& \sum_{\{t<\underline{t_{i,l}}\}\cup\{t>\overline{t_{i,l}}\}} x_{i,l}(t) = 0, \forall l \in \mathcal{L}_i, \\
& \sum_{t=\underline{t}_{i,l}}^{\overline{t}_{i,l}} x_{i,l}(t) = \mu_{i,l} w_{i,l}, \forall l \in \mathcal{L}_i, \\
& x_{i,l}(t) + x_{i,l}(t+2) < 2w_{i,l} + x_{i,l}(t+1), \forall t \in [\![\underline{t_{i,l}}; \overline{t_{i,l}} - 2]\!], \\
& \forall l \in \mathcal{B}_i.
\end{aligned}
$$

Reservation Price Constraint and Instance Description

The load profiles $\boldsymbol{x_{i,l}}$ that do not check

$$\boldsymbol{p}^{\star T}\mathbf{x_{i,l}} \leq p_{\max,i}(k_{i,l})\mu_{i,l}w_{i,l} \ ,$$

are cancelled.

Example 2

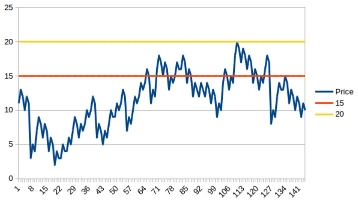
$T = 144$ (10 min time slots [ts]), $n = 1$, $K = 3$

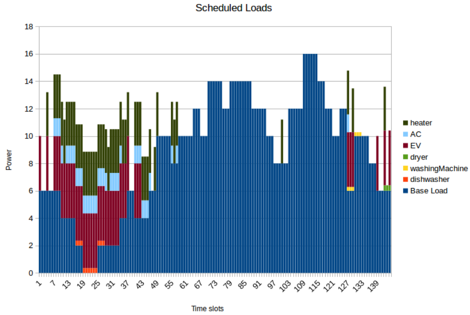
- Block loads
  - l='dishwasher', $k_{i,l} = 1$, $\mu_{i,l} = 12$ ts, $\underline{t_{i,l}} = 126$ ts, $\overline{t_{i,l}} = 36$ ts, $w_{i,l} = 0.35$ kW
  - l='washing machine', $k_{i,l} = 2$ ts, $\mu_{i,l} = 6$ ts, $\underline{t_{i,l}} = 108$ ts, $\overline{t_{i,l}} = 132$ ts, $w_{i,l} = 0.26$ kW
  - l='dryer', $k_{i,l} = 3$, $\mu_{i,l} = 3$ ts, $\underline{t_{i,l}} = 132$ ts, $\overline{t_{i,l}} = 144$ ts, $w_{i,l} = 0.4$ kW
- Interruptible loads
  - l='EV', $k_{i,l} = 1$, $\mu_{i,l} = 42$ ts, $\underline{t_{i,l}} = 42$ ts, $\overline{t_{i,l}} = 108$ ts, $w_{i,l} = 4$ kW
  - l='AC', $k_{i,l} = 3$, $\mu_{i,l} = 36$ ts, $\underline{t_{i,l}} = 0$ ts, $\overline{t_{i,l}} = 144$ ts, $w_{i,l} = 1.3$ kW
  - l='heater', $k_{i,l} = 2$, $\mu_{i,l} = 48$ ts, $\underline{t_{i,l}} = 0$ ts, $\overline{t_{i,l}} = 144$ ts, $w_{i,l} = 3.2$ kW

$\triangle$

First instance - High reservation prices

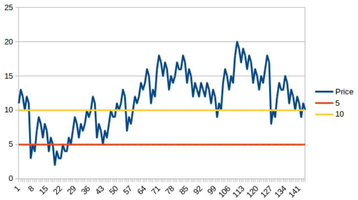
$$p_{\max,i}(1) = 10^3,\ p_{\max,i}(2) = 20,\ p_{\max,i}(3) = 15$$

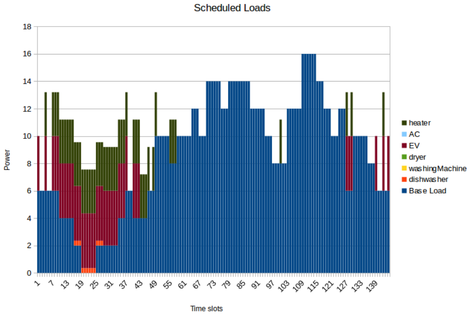




Second instance - Low reservation prices

$$p_{\max,i}(1) = 10^3,\ p_{\max,i}(2) = 10,\ p_{\max,i}(3) = 5$$





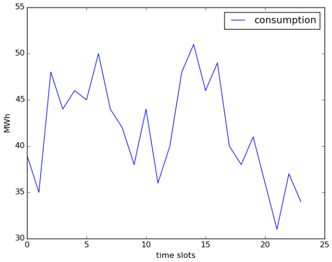
Aggregator's Profit and Interaction with the Market

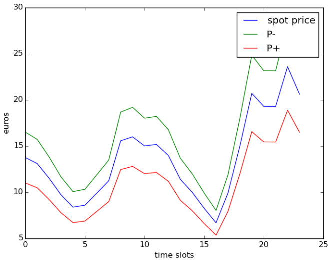
$$\Pi_{agg} = \sum_{t=0}^{nT-1} \Big\{ \underbrace{p^{\star}(t)\big(x_{\mathcal{G}}(t) + \hat{d}_{\mathcal{G}}(t)\big) + \sum_{i \in \mathcal{G}} \mathbb{E}\left[IB_i(t)\right]}_{\sum_{i\in\mathcal{G}} y_i \quad \text{total cost paid by coalition } \mathcal{G}} - \mathbb{E}\Big[c(\mathcal{G}, t)\Big] \Big\},$$

where:

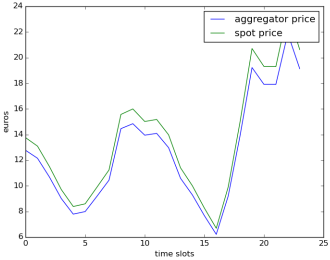
- Π_{agg} targeted expected profit,
- $p^{+}(t)$ excess power price on balancing, $p^{-}(t)$ missing power price on balancing, $p^{f}(t)$ day-ahead price s.t. $p^{+}(t) < p^{f}(t) < p^{-}(t)$
- $x_{\mathcal{G}}(t) = \sum_{i\in\mathcal{G}} \sum_{l\in\mathcal{L}_i} x_{i,l}(t)$,
- $\hat{d_{\mathcal{G}}}(t) = \sum_{i\in\mathcal{G}} \hat{d}_i(t)$,
- imbalance penalty $IB_i(t) = p^{-}(t)\Big(\hat{d}_i(t) - d_i(t)\Big)_{-} + \Big(p^{f}(t) - p^{+}(t)\Big)\Big(\hat{d}_i(t) - d_i(t)\Big)_{+}$,
- aggregator's cost
  $c(\mathcal{G}, t) = p^{f}(t)(x_{\mathcal{G}}(t) + \hat{d_{\mathcal{G}}}(t)) + p^{-}(t)\Big(\sum_{i\in\mathcal{G}}(\hat{d}_i(t) - d_i(t))\Big)_{-} - p^{+}(t)\Big(\sum_{i\in\mathcal{G}}(\hat{d}_i(t) - d_i(t))\Big)_{+}$.

Base Load and Market Prices

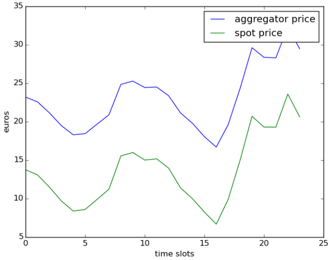




Impact of Greediness

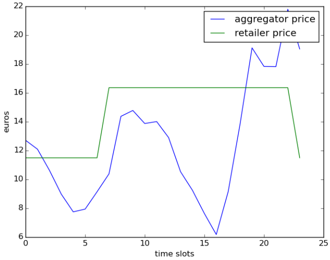


Low Π_{agg}

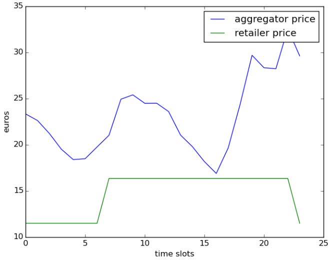


High Π_{agg}

Balancing Greediness and Stability



Low Π_{agg}



High Π_{agg}

Coalition Stability

γ-model characteristic function game:

- $v(\mathcal{G}) = \Pi_{agg} + \sum_{t=0}^{nT-1} \mathbb{E}\Big[c(\mathcal{G}, t)\Big]$ if $\mathrm{card}(\mathcal{G}) \geq 2$,
- $v(i) = \sum_{t=0}^{nT-1} \mathbb{E}\Big[c_{retailer}(i, t)\Big], \forall i \in \mathcal{N}$ where $c_{retailer}(i, t) = p_{retailer}(t)\Big(d_i(t) + \sum_{l \in \mathcal{L}_i} x_{i,l}(t)\Big)$.

Coalition stability condition:

$$\sum_{i \in \mathcal{G}} y_i = \Pi_{agg} + \sum_{t=0}^{nT-1} \mathbb{E}\Big[c(\mathcal{G}, t)\Big],$$

$$y_i \leq \sum_{t=0}^{nT-1} \mathbb{E}\Big[c_{retailer}(i, t)\Big], \forall i \in \mathcal{G}.$$

Sharing the coalition cost

- Stand alone cost: $y_i = \kappa_i \left\{ \Pi_{agg} + \sum_{t=0}^{nT-1} \mathbb{E}\left[c(\mathcal{G}, t) \right] \right\}$ with $\kappa_i = \frac{\sum_{t=0}^{nT-1} \mathbb{E}\left[c_{retailer}(i,t) \right]}{\sum_{j \in \mathcal{G}} \sum_{t=0}^{nT-1} \mathbb{E}\left[c_{retailer}(j,t) \right]}$.
- Shapley value: $\varphi_i(v) = \frac{v(\mathcal{G})}{card(\mathcal{G})} = \frac{\Pi_{agg} + \sum_{t=0}^{nT-1} \mathbb{E}[c(\mathcal{G},t)]}{card(\mathcal{G})}$.
- Banzhaf index: $\mathcal{B}_i(v) = \frac{1}{2}\left[v(\mathcal{G}) + v(i) - \sum_{j \in \mathcal{G} \setminus \{i\}} v(j) \right]$.
- Separable and non-separable costs: $y_i = m_i + \frac{\kappa_i}{\sum_{j \in \mathcal{G}} \kappa_j} \Psi(\mathcal{G}), \forall i \in \mathcal{G}$ with $\Psi(\mathcal{G}) = \left(\Pi_{agg} + \sum_{t=0}^{nT-1} \mathbb{E}\left[c(\mathcal{G}, t) \right] \right) - \sum_{j \in \mathcal{G}} m_j$ with
    - Equal Charge Method (ECM): $\kappa_i = \frac{1}{card(\mathcal{G})}, \forall i \in \mathcal{G}$,
    - Alternative Cost Avoided Method (ACAM): $\kappa_i = \sum_{t=0}^{nT-1} \mathbb{E}\left[c_{retailer}(i, t) \right] - m_i, \forall i \in \mathcal{G}$.

Π_{agg} upper-bound

Solutions	**Π_{agg} upper-bound**
Equitable	$card(\mathcal{G}) \min_{i \in \mathcal{G}} v(i) - \sum_{t=0}^{nT-1} \mathbb{E}[c(\mathcal{G}, t)]$
Stand-alone	$\sum_{i \in \mathcal{G}} v(i) - \sum_{t=0}^{nT-1} \mathbb{E}[c(\mathcal{G}, t)]$
Shapley	$card(\mathcal{G}) \min_{i \in \mathcal{G}} v(i) - \sum_{t=0}^{nT-1} \mathbb{E}[c(\mathcal{G}, t)]$
Banzhaf	$\sum_{i \in \mathcal{G}} v(i) - \sum_{t=0}^{nT-1} \mathbb{E}[c(\mathcal{G}, t)]$
Separable and non-separable	$\min_{i \in \mathcal{G}} \left\{ \frac{\sum_{j \in \mathcal{G}} \kappa_j}{\kappa_i} \Big(v(i) - \big(1 + \frac{\kappa_i}{\sum_{j \in \mathcal{G}} \kappa_j}$ $-card(\mathcal{G})\big) v(\mathcal{G}) - \sum_{j \in \mathcal{G} \setminus \{i\}} v(\mathcal{G} \setminus \{j\}) \Big) \right\}$

Mapping Cost Sharing to Price Profile

- Choose a cost sharing mechanism.
- Π_{agg} equals the upper-bound.
- Find algorithmically the mapping:

$$\underbrace{(y_i)_{i \in \mathcal{G}}}_{\text{cost sharing}} \quad \rightarrow \quad \underbrace{\boldsymbol{p}^{\star}}_{\text{price profile}} \quad .$$

Aggregator's Price Profile Computation

$$y_i - \sum_{t=0}^{nT-1} \mathbb{E}[IB_i(t)] = \sum_{t=0}^{nT-1} p^\star(t) \Big(\sum_{l \in \mathcal{L}_i} x_{i,l}(t) + \hat{d}_i(t) \Big), \forall i \in \mathcal{G}.$$

Matricially: $\boldsymbol{A}\boldsymbol{p}^\star = \boldsymbol{b}$. Let A^+ be the Penrose-Moore pseudo inverse of A.

1. If $card(\mathcal{G}) = nT$ then $A^+ = A^{-1}$ if A is full rank $\rightsquigarrow$ unicity of the solution
2. If $card(\mathcal{G}) > nT$ A^+ minimizes $\|\boldsymbol{p}^\star - \boldsymbol{A}^+\boldsymbol{b}\|$ $\rightsquigarrow$ no exact solution
3. If $card(\mathcal{G}) < nT$ A^+ is the solution which minimizes $\|\boldsymbol{p}^\star\|$ $\rightsquigarrow$ no unicity of the solution

Problem

$\boldsymbol{p}^\star$ may have negative coefficients.

Spanning the Kernel

Any $\boldsymbol{p}$ in $\mathbb{R}^{nT}$ can be split in $\boldsymbol{p} = \boldsymbol{p}^{Im} + \boldsymbol{p}^{Ker}$ where

- $\boldsymbol{p}^{Ker} \in Ker(\boldsymbol{A}) = \{\boldsymbol{p} | \boldsymbol{Ap} = \boldsymbol{0}\}$ and $\boldsymbol{p}^{Im} \in Im(\boldsymbol{A})$
- $\boldsymbol{p}^{Im}$ orthogonal to $\boldsymbol{p}^{Ker}$

Any $\boldsymbol{p}$ such that $\boldsymbol{Ap} = \boldsymbol{b}$ must check

$$\|\boldsymbol{p}\|^2 = \|\boldsymbol{p}^{\boldsymbol{Im}} + \boldsymbol{p}^{\boldsymbol{Ker}}\|^2 = \|\boldsymbol{p}^{\boldsymbol{Im}}\|^2 + \|\boldsymbol{p}^{\boldsymbol{Ker}}\|^2.$$

$\rightsquigarrow$ Moore-Penrose solution is the one such that $\boldsymbol{p}^{Ker} = \boldsymbol{0}$.

$$\begin{aligned} \min \quad & \sum_{k \in Ker(A)} \alpha_k^2 \\ s.t. \quad & \boldsymbol{A}^+ \boldsymbol{b} + \sum_{k \in Ker(A)} \alpha_k \boldsymbol{p}^{\boldsymbol{Ker,k}} \geq 0, \end{aligned}$$

has a unique solution if, and only if, the square matrix having as coefficient $(i,j) \in [\![0; nT-1]\!]^2$ $\sum_{k \in Ker(A)} p_i^{Ker,k} p_j^{Ker,k}$, is invertible.
$\rightsquigarrow$ Idea: span $Ker(\boldsymbol{A})$ of dimension $\max\{0; nT - rank(\boldsymbol{A})\}$.

Algorithmic Price Computation

Goal: estimate $\boldsymbol{p}^\star$

(1) start with an estimate $\hat{\boldsymbol{x}}_i$ for each consumer $i \in \mathcal{G}$,

(2) calculate $\boldsymbol{A}\left(\hat{\boldsymbol{x}}_i, \left(\hat{d}_i(t)\right)_{t=0}^{nT-1}\right)$ and $\boldsymbol{y}\left(\hat{\boldsymbol{x}}_i, \left(\hat{d}_i(t)\right)_{t=0}^{nT-1}\right)$,

(3) Thanks to the Moore-Penrose pseudo-inverse algorithm applied to $\boldsymbol{A}\boldsymbol{p}^\star = \boldsymbol{b}$, find $\boldsymbol{p}^\star\left(\hat{\boldsymbol{x}}_i, \left(\hat{d}_i(t)\right)_{t=0}^{T-1}\right)$.

(4) Then we can deduce $\boldsymbol{x_i}\left(\boldsymbol{p}^\star\left(\hat{\boldsymbol{x}}_i, \left(\hat{d}_i(t)\right)_{t=0}^{T-1}\right)\right)$.

(5) If $\boldsymbol{x_i}\left(\boldsymbol{p}^\star\left(\hat{\boldsymbol{x}}_i, \left(\hat{d}_i(t)\right)_{t=0}^{T-1}\right)\right)$ is not equal to $\hat{\boldsymbol{x}}_{\boldsymbol{i}}$ we start again at (1) by replacing $\hat{\boldsymbol{x}}_{\boldsymbol{i}}$ by $\boldsymbol{x_i}\left(\boldsymbol{p}^\star\left(\hat{\boldsymbol{x}}_i, \left(\hat{d}_i(t)\right)_{t=0}^{T-1}\right)\right)$ until the algorithm converges.

Learning the Base Load

- $\mathcal{E}$ set of experts
- expert e forecasts $f_e(\hat{d}_i(t))_{t=0}^{nT-1}$

For each month m (nT slots) and each expert e

(1) Calculate $\hat{\boldsymbol{p}}_{\boldsymbol{e}}$ and $\boldsymbol{x}_{\mathcal{G}}(\hat{\boldsymbol{p}}_{\boldsymbol{e}})$ by running previous algorithm with $\hat{d}_i(t) = f_e(\hat{d}_i(t)), \forall t \in [\![0; nT-1]\!]$.

(2) Calculate $l(e, \hat{\boldsymbol{d}}_{\mathcal{G}}) = \Pi_{agg}|_{\hat{\boldsymbol{p}}_{\boldsymbol{e}}, \hat{\boldsymbol{d}}_{\mathcal{G}}} - \Pi_{agg}|_{\boldsymbol{p}^*, \hat{\boldsymbol{d}}_{\mathcal{G}}}$.

(3) Update the weight $\gamma_{e,.}$ of expert e thanks to the exponentially weighted forecaster rule:

$$\gamma_{e,m} = \frac{exp(-\eta \sum_{s=1}^{m} l(e, \hat{\boldsymbol{d}}_{\mathcal{G},\boldsymbol{s}}))}{\sum_{e' \in \mathcal{E}} exp(-\eta \sum_{s=1}^{m} l(e', \hat{\boldsymbol{d}}_{\mathcal{G},\boldsymbol{s}}))},$$

where $\hat{\boldsymbol{d}}_{\mathcal{G},\boldsymbol{s}}$ coincides with coalition $\mathcal{G}$ load profile evaluated over month m and η a learning parameter to be calibrated.

Main results:

- algorthmic optimization of the aggregator's price profile under demand uncertainty
- balance of aggregator's greediness (Π_{agg} definition) and coalition stability

To be done:

- determination of the coalition optimal size depending on the sharing mechanism through simulation
- introduction of capacity constraints at the consumer level
- learning algorithm performance evaluation