Dealing with Uncertainty in the Smart Grid: A Learning Game Approach

Hélène Le Cadre (helene.le_cadre@mines-paristech.fr)

Jean-Sébastien Bedo (jean-sebastien.bedo@m4x.org)

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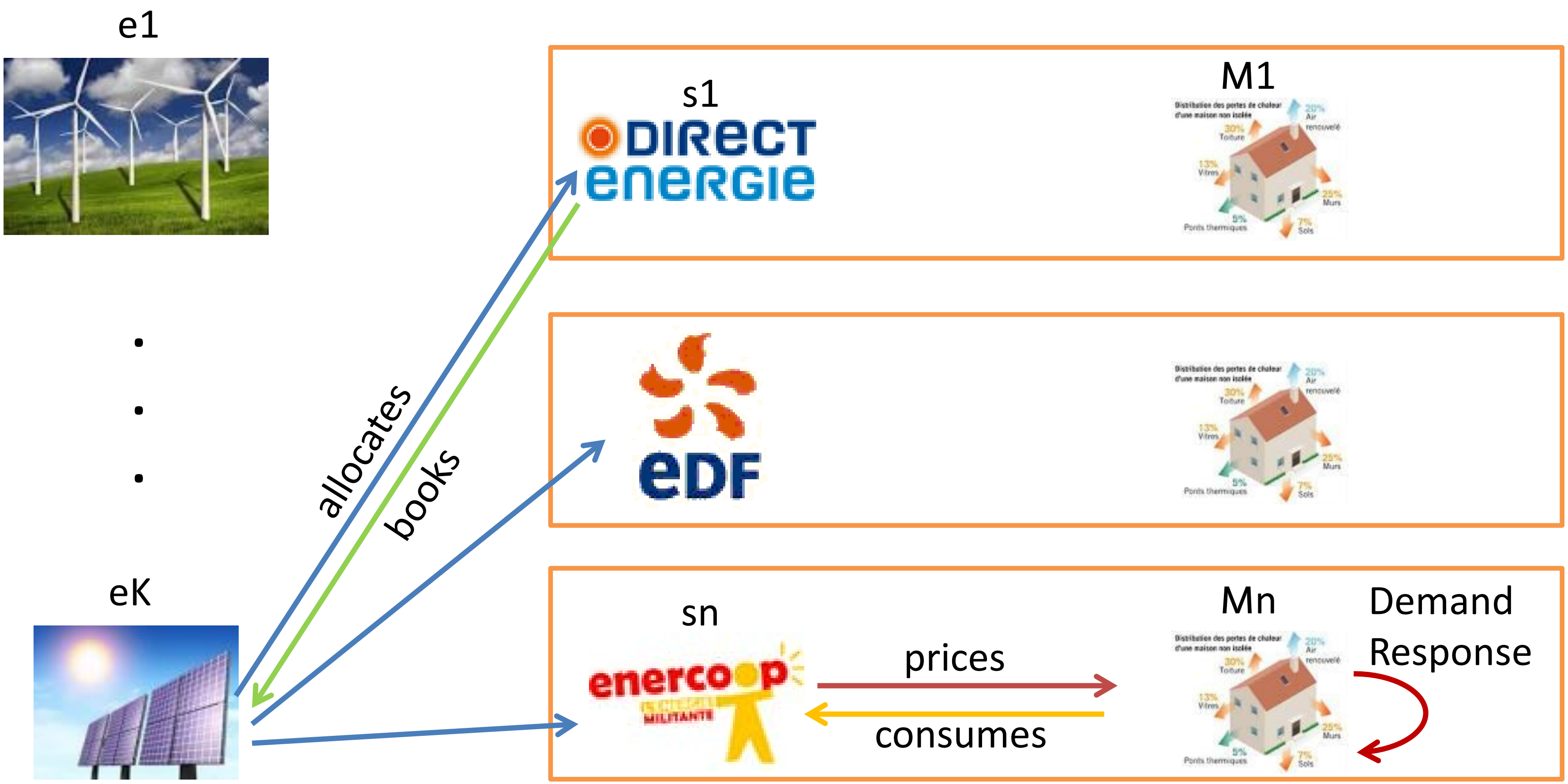
Objectives

- Define an optimal learning algorithm to deal with renewable energies uncertainty
  - Calculate bounds on the profit risk linked to forecast errors
  - Estimate learning speed
- Evaluate the incentives for energy providers to enter into a coalition in a learning context

Agents overview

- Energy producers (e1,…,eK)
  - We focus on renewable energy (wind, solar, etc.) which are unpredictable
  - We denote the energy productions by $\upsilon_k^e(t)$, which are individual sequences
- Energy service providers (s1,…,sn)
  - We do not take into account energy transport costs and constraints
- Captive consumers ($\mathscr{M}$1,…,$\mathscr{M}$n)
  - We consider both local energy production and demand response mechanisms
  - We denote the energy net demands by $\upsilon_i^s(t)$, which are individual sequences

Our model is based on a Stackelberg Game



Customers optimization program

- $\mathcal{M}$i net demand reaches $v_i^s(t)$ energy units for time period t
- $\mathcal{M}$i decides to perform Demand Response by
  - postponing the consumption of ai(t) energy units
  - buying the rest $v_i^s(t)$ – ai(t) to provider si
- The quantity of DR is chosen so as to minimize the total cost of energy $\underbrace{\left(v_i^s(t)\text{-}a_i(t)\right)p_i(t)}_{\text{Consumption cost}} + \underbrace{c(a_i(t))}_{\text{DR cost}}$
- Under a quadratic DR cost, we find that, at equilibrium, $a_i(t) = p_i(t)$

Service providers optimization program 1/2

- The energy procurement market is divided in 2 steps
  1. Each provider si books qik(t) energy units to ek.
  2. ek allocates its production $v_k^e(t)$ proportionally to the bookings. We denote $\alpha_{ki}(t)$ the share obtained by si.
- The profit of service provider si at each time period t is then the sum of three components:

1	the revenues from the retail market	$\left(v_i^s(t) - a_i(t)\right)p_i(t)$
2	the costs of energy booking towards producers	$-\sum_{k=1\ldots K} q_{ik}(t)\widetilde{p_k}(t)$
3	a cost related to energy shortage if the energy provided by renewable producers is not sufficient to satisfy the demand of si customers	$-\gamma_i\left[\left(v_i^s(t) - a_i(t)\right) - \sum_{k=1\ldots K} \alpha_{ki}(t)v_k^e(t)\right]_+$

Service providers optimization program 2/2

- Under fair energy shortage costs, if energy shortage is nearly certain, i.e. $\upsilon_i^s(t) \geq \gamma_i + 2\alpha_i \sum_{k=1\ldots K} \upsilon_k^e(t)$, si will define its price and energy bookings such that

$$\begin{cases} p_i(t) = \dfrac{\nu_i^s(t) + \gamma_i}{2} \\ q_{ik}(t) = \dfrac{\nu_k^e(t)}{\tilde{p}_k(t)} \dfrac{n-1}{\delta \tilde{\gamma}_i} \alpha(i) \end{cases}$$

- Else, si will book a minimum of energy and decrease its price to avoid energy shortage

➢ We assume that we are in the first case, which fits well to today situation, where renewable energy is the minority

Energy producers optimization program

- The profit of energy producer ek at each time period is the sum of two components:

1 the revenues of energy bookings

$$\widetilde{p_k}(t) \sum_{i=1 \dots n} q_{ik}(t)$$

2 a cost related to energy shortage if the energy provided to each si is lower than its previous booking

$$-\widetilde{\gamma_i}[q_{ik}(t) - \alpha_{ki}(t) v_k^e(t)]_+$$

The energy producers can avoid energy shortage costs by fixing their price to $\frac{n-1}{\delta \, min \widetilde{\gamma_i}}$, which is independent of production and demand.

Learning Game Description

- Only service providers must forecast energy demand and energy production to optimize their profit

- We denote by
  - $f_i(x)$ the forecast made by si for the value x
  - $f_i(t)$ all the forecasts made by si at time period t
  - $f_{-i}(t)$ all the forecasts made by other service providers than si at time period t
  - $f(t) = (f_i(t), f_{-i}(t))$
  - $\nu(t)$ the vector of energy productions and demands at time period t
  - $\pi_i(f_i(t), f_{-i}(t), \nu(t))$ the profit of service provider si

Optimal learning strategies

- Loss: the difference between the profit obtained with an exact forecast and the observed profit
  - $l_i(f(t), \nu(t)) = \pi_i(\nu(t), f_{-i}(t), \nu(t))$ - $\pi_i(f(t), \nu(t))$
- External regret: the difference between the observed cumulative loss and the cumulative loss of the best constant prediction (pure strategy)
  - $R_i(T) = \sum_{t=1}^{T} l_i(f(t), \nu(t)) - \min_{y} \sum_{t=1}^{T} l_i(y, f_{-i}(t), \nu(t))$
- A Hannan consistent learning strategy is such that

$$\lim_{T \to +\infty} \frac{1}{T} R_i(T) = 0$$

A Hannan consistent learning strategy exists for each provider si.

External regret Learning Algorithm

Initialization. For $t = 0$, we set: $w_0(x) = \frac{1}{|\mathcal{E}|}$, $\forall x \in \mathcal{E}$.

Step 1 *to* T. The updating rules are the following:

$$
\begin{aligned}
d_t(x) &= \frac{w_t(x)}{\sum_{x \in \mathcal{E}} w_t(x)}, \; \forall x \in \mathcal{E} \\
w_{t+1}(x) &= \exp\left(\eta_{t+1} \sum_{s=1}^{t} H_X(x,s)\right) \\
&= w_t(x)^{\frac{\eta_{t+1}}{\eta_t}} \exp\left(\eta_{t+1} H_X(x,t)\right), \; \forall x \in \mathcal{E} \\
\eta_{t+1} &= \min\left\{\frac{1}{2\max\{|H_X|\}}; \sqrt{\frac{2(\sqrt{2}-1)}{e-2}}\sqrt{\frac{\ln|\mathcal{E}|}{\vartheta_t}}\right\} \\
\vartheta_{t+1} &= \vartheta_t + Var\Big(H_X(X_{t+1}, t+1)\Big)
\end{aligned}
$$

where H_X is the payoff function associated to the forecast made by si for the value X. It corresponds to the terms of provider si profit equation depending only on X. H_X(y,t) is the payoff value for making the forecast y at time period t.

The external regret learning algorithm is a Hannan consistent forecasting strategy for si.

Coalition learning strategy

- A coalition of providers is a group of providers who collaborate to learn the hidden energy productions. They align their predictions on a common value.
- Independent learning payoff

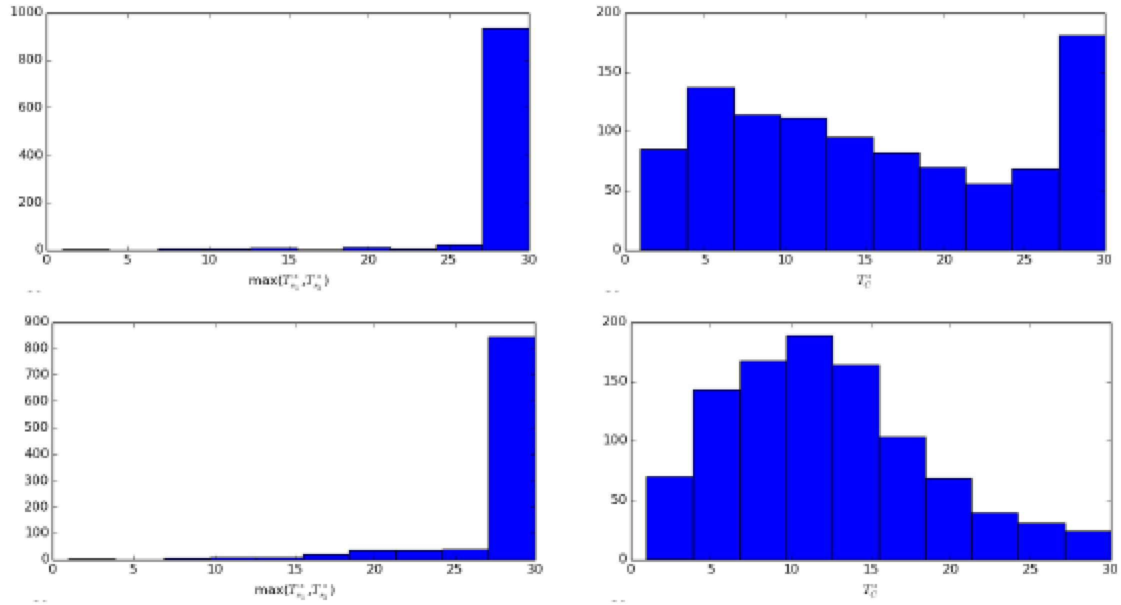
$$H_{f_i(\nu_k^e)}(x,t) = -\frac{\alpha(i)}{\tilde{\gamma}_i}\frac{n-1}{\delta}x - \gamma_i\Big(\nu_i^s(t) - \frac{f_i(\nu_i^s,t)+\gamma_i}{2} - \sum_{l \neq k}\frac{\alpha(i) f_i(\nu_l^e,t)}{\sum_{j=1,\dots,n}\alpha(j) f_j(\nu_l^e,t)}\nu_l^e(t) - \frac{\alpha(i)x}{\sum_{j\neq i}\alpha(j) f_j(\nu_k^e,t)+\alpha(i)x}\nu_k^e(t)\Big)_+$$

- Coalition learning payoff

$$H_{f(\nu_k^e)}(x,t) = -\frac{n-1}{\delta}x\sum_i\frac{\alpha(i)}{\tilde{\gamma}_i}$$

➢ time independent

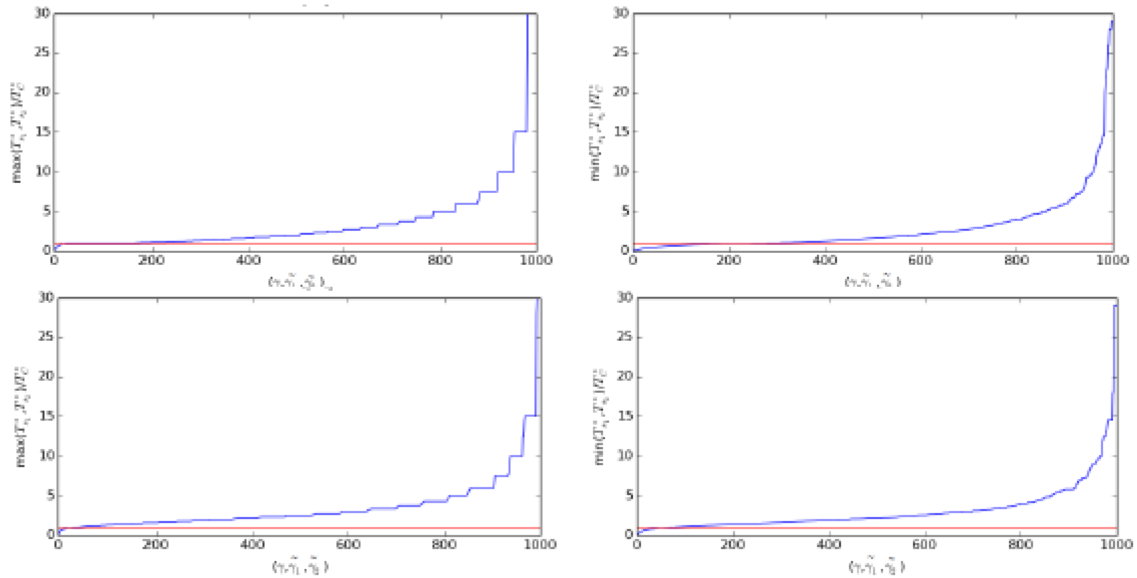
Results : convergence time



30 = not converged

- Convergence times are smaller
  - For the grand coalition than under distributed learning
  - Under internal regret minimization than under external regret minimization

Results : Will a grand coalition emerge?



- A grand coalition has 85% (resp. 98:5%) of chances to emerge under external (resp. internal) regret minimization

Conclusion

- Summary
  - We have used random individual sequences which do not require an a priori probabilistic structure.
  - Only energy service providers must forecast energy demands and productions.
  - They can decrease their average profit risk by sharing information and aligning their forecasts.
    - They often have individual incentives to do so.
    - It speeds up the market convergence.
- Ideas to be explored
  - Exogenous prices
  - Non captive consumers
  - Add transport costs and constraints
  - Use energy shortage costs to reach an energy mix target