Managing electricity consumption by providing dynamic tariff incentives
To make a better use of renewable energy

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Context / Motivation

Industrial partner: EDF

Aim: maintain balance between production and consumption

Current solution: forecast consumption and adapt production

Prospective solution: encourage/discourage consumption by dynamically setting prices

Advantage: better use of renewable energy
**Data set**

“SmartMeter Energy Consumption Data in London Households”

https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households

Public dataset – by UK Power Networks (subbranch of EDF)

Individual consumptions at half-hourly frequency in year 2013

About 1,000 customers with tariff incentives

K=3 tariffs: Low (L), Normal (N), High (H)

Tariff incentives indeed have an impact on consumption!
Quantitative approach → Design a specific pricing policy

Exploration–exploitation dilemma: Need to simultaneously
  Discover the behaviors of customers (≡ exploration)
  Optimize incentives sent (≡ exploitation)

Of course behaviors may change over time!

Bandit monitoring

  We only observe the outcome of the tariff(s) picked
  Not of what would have happened with different choices

Aim: Design pricing strategies (with theoretical guarantees)
  Test them on data

Issue: Historical data obtained for a given sequence of choices

Solution: Construct first a realistic data generator
Methodology

1. Estimate a model / Build a data generator based on 2013 data (consumption + context)

2. Get historical contexts for 2014 + January 2015
   Generate realistic consumptions
   2.1. Use normal tariff only in 2014
   2.2. Then use a machine learning algorithm for January 2015 and pick among all $K$ tariff levels
Modeling of the consumption $\rightarrow$ known and effective methodology designed by EDF

Population assumed to be homogeneous (as a first approach)

(Mean) consumption $Y$ depends on context $x_t \in \mathbb{R}^d$

Context = temperature, season, day of the week, hour of the day, etc.

Also depends on tariff $k \in \{1, \ldots, K\}$

\[ Y_t = f_1(\text{temperature}) + f_2(\text{position in the year}) + f_3(\text{hour}) + f_4(\text{tariff}) + \ldots + \text{noise} \]

If single tariff $k$ picked:

\[ Y_{t,k} = \gamma_k + \sum_{i=1}^{d} f_i(x_{t,i}) + \text{noise} \]
First model/generator: With a single tariff at any given time

Parametric model for \( Y_{t,k} = \gamma_k + \sum_{i=1}^{d} f_i(x_{t,i}) + \text{noise} \)

given by a

Generalized additive model (Wood, 2006) based on so-called cubic splines

\[ Y_{t,k} = \gamma_k + \beta^T \varphi(x_t) + \varepsilon_{t,k} \]

where \( \beta \) and \( \gamma_k \) are unknown, but \( \varphi(x_t) \) is known

→ Need to extend this modeling to \( K \) tariffs
Final model/generator: With various tariffs at the same time

If tariffs \{1, \ldots, K\} are distributed in shares \( p = (p_1, \ldots, p_K) \)

Then (cf. homogeneous population), mean consumption:

\[
Y_{t,p} = \sum_{k=1}^{K} p_k Y_{t,k} = \sum_{k=1}^{K} p_k (\beta^T \varphi(x_t) + \gamma_k + \varepsilon_{t,k})
= \theta^T \phi(x_t, p) + p^T \varepsilon_t
\]

with \( \theta \) unknown, but \( \phi(x_t, p) \) is known (and linear in \( p \))

Noise: \( \varepsilon_t \) iid vectors, \( \mathbb{E}[\varepsilon_t] = 0 \), sub-Gaussian
\[
\Gamma = \text{Var}(\varepsilon_t) \text{ estimated on data}
\]

In-sample performance: good, \( r^2 = 92\% \) and MAPE = 8.82\%
Methodology (reminder)

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New machine-learning problem defined:
**Target tracking** for contextual bandits

Known parameters
- $K$ tariffs
- Context set $\mathcal{X}$
- Transfer function $\phi : \mathcal{X} \times \mathcal{P} \to \mathbb{R}^m$
- Bound $C$ on consumptions $Y$

Unknown parameters
(They model the behaviors)
- Coefficients $\theta \in \mathbb{R}^m$
- Covariance matrix $\Gamma = \text{Var}(\varepsilon_t)$

For each round $t = 1, 2, \ldots$

1. Observe a context $x_t \in \mathcal{X}$ and a target $c_t \in [0, C]$
2. Choose an allocation of tariffs $p_t = (p_{t,1}, \ldots, p_{t,K})$
3. Observe a mean consumption $Y_{t,p_t} = \theta^T \phi(x_t, p_t) + p_t^T \varepsilon_t$
4. Encounter an error $(Y_{t,p_t} - c_t)^2$

→ **Algorithm constructed:** based on a LinUCB-approach
Realistic simulations

$K = 3$ tariff levels

Consider attainable targets: $\theta^T \phi(x_t, 1) \leq c_t \leq \theta^T \phi(x_t, 3)$

Aim: smooth out consumption
Reminder of the experiment design → provider changing its policy

- Pick the “normal” tariff for 1 year, i.e., $p_t = (0, 1, 0)$
- Then start picking different allocations with at most 2 tariffs (either 1+2 or 2+3)

Repeat this 200 times

Jan 1, 2015 (= first day of demand management)
Low−tariff mean consumption  
Normal−tariff mean consumption  
High−tariff mean consumption  

Top: January 1, 2015  
Bottom tariff allocations based on a single run  
Bottom: January 30, 2015
What’s next? [Work in progress]

– The case of inhomogeneous consumers
  Create clusters of clients according to their profiles
  Tailor allocations picked to each cluster

– Rebound effect

And now, some dirty details about the algorithm...
Estimation of $\theta$ as for the LinUCB algorithm 
(Li et al., 2010; Chu et al., 2011; Abbasi-Yadkori et al., 2011)

For some $\lambda > 0$: at the beginning of round $t \geq 2$,

$$
\hat{\theta}_{t-1} \in \arg \min_{\tilde{\theta} \in \mathbb{R}^m} \left\{ \lambda \| \tilde{\theta} \| + \sum_{s=1}^{t-1} (Y_{s,p_s} - \tilde{\theta}^\top \phi(x_s, p_s))^2 \right\}
$$

$\hat{\theta}_{t-1}$ is essentially $1/\sqrt{T}$–close to the real parameter $\theta$

Variance $\Gamma$ also needs to be estimated online

Thus, conditional error

$$
\mathbb{E}[(Y_{t,p_t} - c_t)^2 \mid F_{t-1}] = \left( \theta^\top \phi(x_t, p_t) - c_t \right)^2 + p_t^\top \Gamma p_t
$$

estimated by the confidence interval

$$
\left( \left[ \hat{\theta}^\top_{t-1} \phi(x_t, p) \right]_C - c_t \right)^2 + p^\top \hat{\Gamma} p \pm \alpha_{t,p}
$$
Confidence intervals \( \left( \left[ \hat{\theta}_{t-1}^T \phi(x_t, p) \right]_c - c_t \right)^2 + p^T \hat{\Gamma} p \pm \alpha_{t,p} \)

Play optimistically
(it is a trade-off between exploitation and exploration):

Pick \( \arg \min_{p \in \mathcal{P}} \left\{ (\hat{\theta}_{t-1}^T \phi(x_t, p) - c_t)^2 + p^T \hat{\Gamma} p - \alpha_{t,p} \right\} \)

Theoretical guarantee:

\[
\sum_{t=1}^{T} (Y_{t,p_t} - c_t)^2 \lesssim O\left( T^{2/3} \right) + \sum_{t=1}^{T} \min_{p \in \mathcal{P}} \left\{ (\theta^T \phi(x_t, p) - c_t)^2 + p^T \Gamma p \right\}
\]

Cumulative error \( \lesssim \) Regret + Performance of the best constant \( p \)
Technological support for startups

By Agence maths–entreprises

Helps connecting with academic researchers in machine learning and funding projects (50%–50%, even more) to develop/improve your core technology

Up to 30 kE (e.g., for 1–year shared postdoc)

Recent example: UncharTech (Sébastien Toth, H16)

Contact: I’m a board member, come and talk to me!