Energy efficiency investment and management for subway stations

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Optimization for subway stations

Paris subway system energy consumption $=$
$1/3$ stations $+ \ 2/3$ trains

Subway stations have recoverable energy ressources

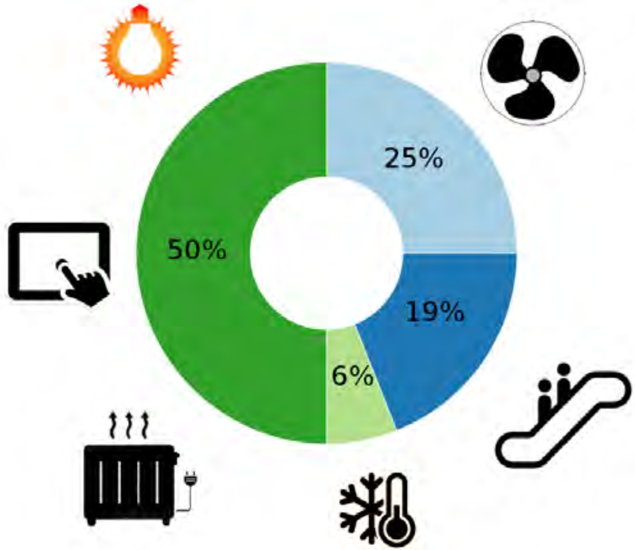
We use optimization to harvest unexploited energy ressources and manage the energy efficiency investments

Outline

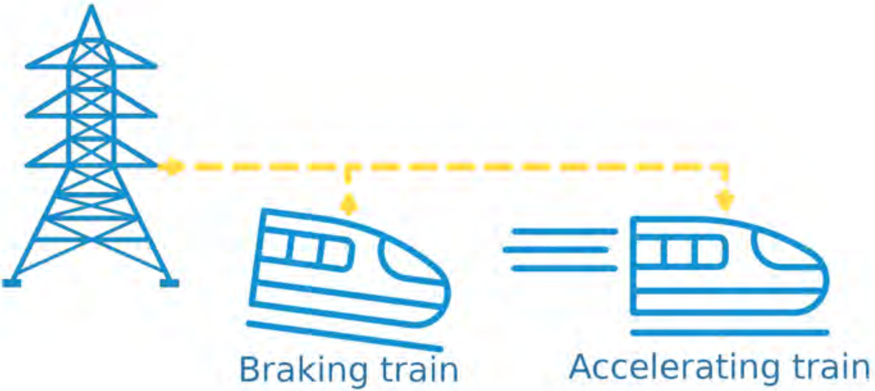
1. Improving energy efficiency of subway stations
   - Subway stations energy mix
   - Energy management system
2. Stochastic optimal batteries management
   - Battery intraday control
   - Investment management
   - Investment/Control decomposition
3. Time decomposition strategy and first results
   - Resolution method: Bilevel Stochastic Dynamic Programming
   - Preliminary numerical results

Subway stations energy mix

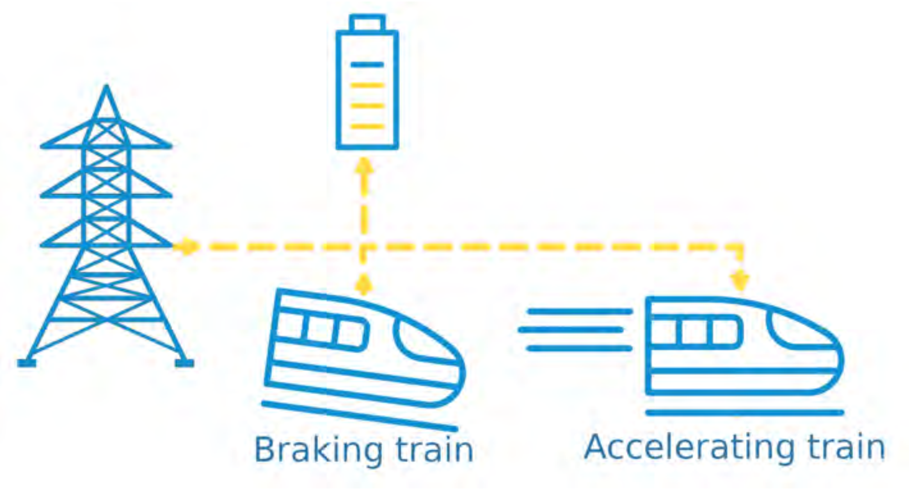
Subway stations typical energy consumption



Subway stations have unexploited energy ressources

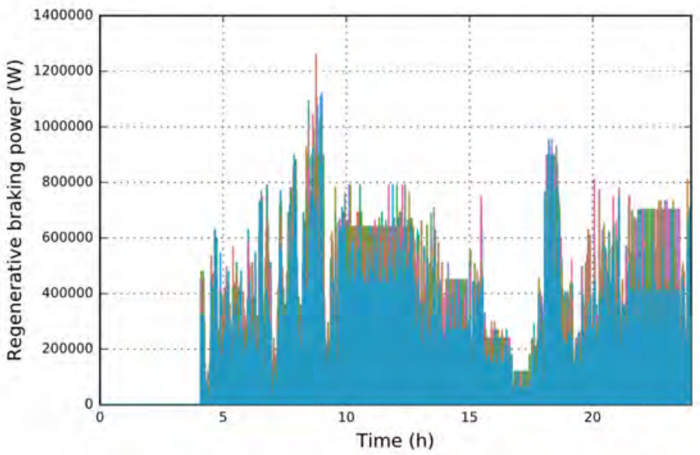


Energy recovery requires a buffer



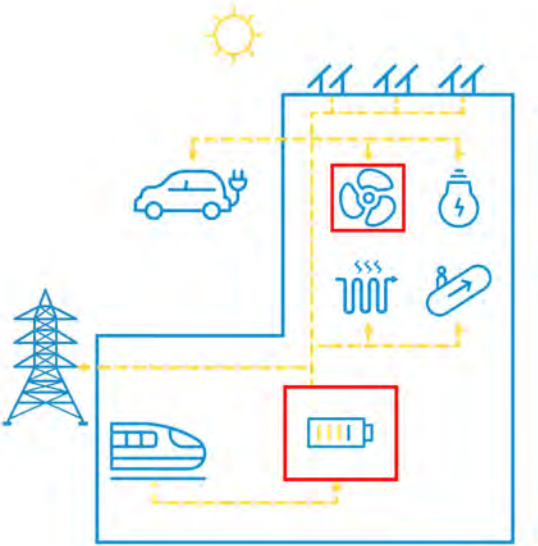
Subways braking energy is unpredictible

Multiple braking energy realizations



Energy management system

Microgrid concept for subway stations



Previous results of stations energy management

We control ventilations and a battery

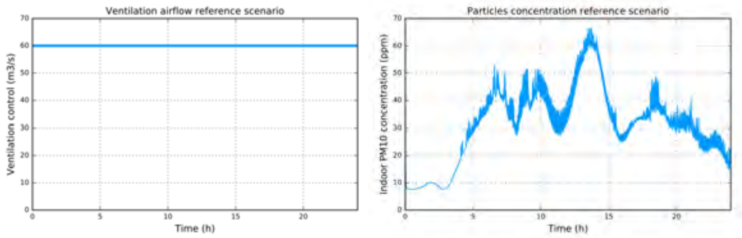
- Time horizon: 24h
- Time discretization: 20 seconds
- Battery capacity: 80kWh
- Uncertainty: 100 braking energy scenarios, deterministic demand

Comparison of 2 algorithms:

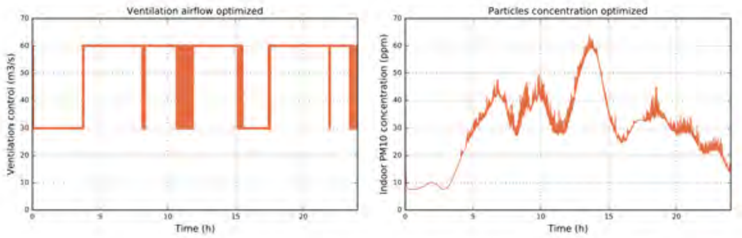
	MPC	**SDP**
Offline comp. time	0	1h
Online comp. time	[10s,200s]	[0s,1s]
Av. economic savings	-27.3%	-30.7%

Air quality comparaison

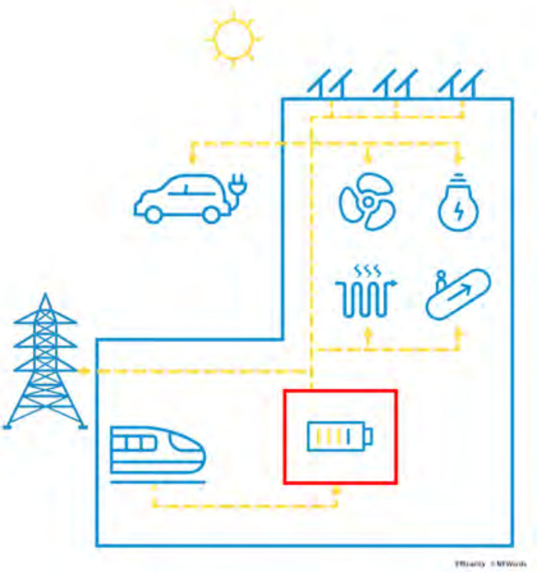
Reference case:



Optimized with SDP:



We are focusing on the battery



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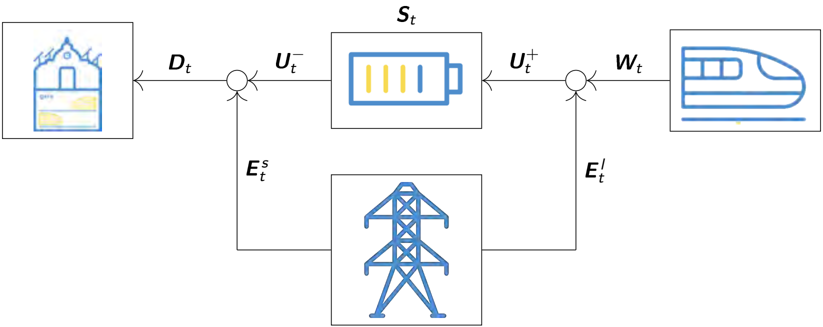
Batteries intraday control

Electrical network representation



Station node

- D_t: Demand station
- E_t^s: Energy from grid to station
- U_t^-: Discharge battery

Subways node

- W_t: Braking energy
- E_t^l: Energy from grid to battery
- U_t^+: Charge battery

Intraday control problem

For a given battery we want a control maximizing the expected savings:

$$\max_{\boldsymbol{U}_\cdot} \mathbb{E}\Big[\sum_{t=0}^{T} c_t^e \underbrace{\left(\boldsymbol{U}_t^- - \boldsymbol{E}_t^l\right)}_{\text{saved energy}}\Big]$$

$$\begin{aligned}
\text{s.t} \quad & \boldsymbol{S}_{t+1} = \boldsymbol{S}_t - \frac{1}{\rho_d}\boldsymbol{U}_t^- + \rho_c sat(\boldsymbol{U}_t^+ \vee \boldsymbol{W}_t) && \Big\} \text{SOC dynamic} \\
& \alpha_m C \leq \boldsymbol{S}_t \leq \alpha_M C && \} \text{SOC bounds} \\
& \boldsymbol{U}_t^+ - \boldsymbol{W}_t \leq \boldsymbol{E}_t^l && \Big\} \text{Supply/demand balance} \\
& 0 \leq \boldsymbol{D}_t - \boldsymbol{U}_t^- && \} \text{No selling constraint} \\
& 0 \leq \boldsymbol{E}_t^l && \Big\} \text{No selling constraint} \\
& \boldsymbol{S}_0 = s_0 && \} \text{Initial SOC}
\end{aligned}$$

Investment management

Batteries investments valuation difficulties

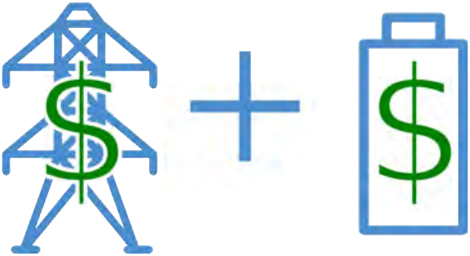
- Control strategy: Daily savings and batteries aging depend on the way we control them
- Market uncertainties: Batteries and electricity costs are uncertain
- Investment management uncertainties: We can postpone our first investment, replace our batteries or abandon the project in reaction to market observation
- External impacts: Environmental incentives are not direct financial benefits

We maximize a finite horizon discounted expected cost

$$\max_{\boldsymbol{U}_\cdot, \boldsymbol{R}_\cdot} \mathbb{E}\Big[\sum_{t=0}^{T_{tot}} \underbrace{\gamma_t}_{\text{Discount rate}} \Big(c^e_t \big(\underbrace{\boldsymbol{U}^-_t - \boldsymbol{E}^l_t}_{\text{Saved energy}} \big) - \underbrace{\boldsymbol{C}^b_t \boldsymbol{R}_t}_{\text{Battery purchase cost}} \Big) \Big]$$

$$T_{tot} = N \times T$$

Using our energy savings to cover our investments



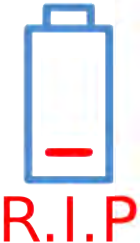
Controlling the batterie state of charge $\boldsymbol{S}_t$

$$\boldsymbol{S}_{t+1} = \chi_{\boldsymbol{R}_t}\Big(\underbrace{\boldsymbol{S}_t}_{SOC} - \frac{1}{\rho_d}\underbrace{\boldsymbol{U}_t^-}_{Discharge} + \rho_c \underbrace{sat(\boldsymbol{U}_t^+ \vee \boldsymbol{W}_t)}_{Charge}\Big) + \underbrace{S_t^{ini}(\boldsymbol{R}_t)}_{SOC_0 \text{ at replacement}}$$

$$\chi_{\boldsymbol{R}_t} = \mathbb{1}_{\boldsymbol{R}_t=0}$$

The batterie state of health $\boldsymbol{H}_t$

$$\boldsymbol{H}_{t+1} = \chi_{\boldsymbol{R}_t}\Big(\underbrace{\boldsymbol{H}_t}_{SOH} \underbrace{-\boldsymbol{U}_t^- - sat(\boldsymbol{U}_t^+ \vee \boldsymbol{W}_t)}_{\text{Exchanged energy}}\Big) + \underbrace{H_t^{ini}(\boldsymbol{R}_t)}_{SOH_0 \text{ at replacement}}$$



The batterie capacity C_t renewal/purchase

$$C_{t+1} = \chi_{R_t} \underbrace{C_t}_{\text{Current battery capacity}} + \underbrace{R_t}_{\text{New battery purcharse}}$$

Ensuring some states/control constraints

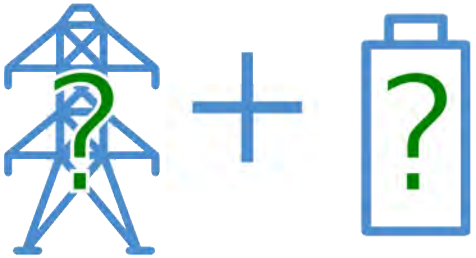
$$\underbrace{\alpha_m \boldsymbol{C}_t \leq \boldsymbol{S}_t \leq \alpha_M \boldsymbol{C}_t,\ 0 \leq \boldsymbol{H}_t}_{\text{SOC and health bounds}}$$

$$\underbrace{\boldsymbol{U}_t^+ - \boldsymbol{W}_t \leq \boldsymbol{E}_t^l,\ 0 \leq \boldsymbol{E}_t^l,\ 0 \leq \boldsymbol{D}_t - \boldsymbol{U}_t^-}_{\text{Supply/Demand balance}}$$

$$\underbrace{\boldsymbol{S}_0 = s_0,\ \boldsymbol{C}_0 = c_0,\ \boldsymbol{H}_0 = h_0}_{\text{Intial state}}$$

And the non-anticipativity constraint

$$\sigma(\boldsymbol{U}_t), \sigma(\boldsymbol{R}_t) \subset \sigma(\boldsymbol{W}_0, \boldsymbol{C}_0^b, ..., \boldsymbol{W}_{t-1}, \boldsymbol{C}_{t-1}^b)$$



Investment/control problem

$$\max_{\boldsymbol{U}_\cdot, \boldsymbol{R}_\cdot} \mathbb{E}\Big[\sum_{t=0}^{T_{tot}} \gamma_t \Big(c_t^e \Big(\boldsymbol{U}_t^- - \boldsymbol{E}_t^l \Big) - \boldsymbol{C}_t^b \boldsymbol{R}_t \Big) \Big]$$

$$\text{s.t} \quad \boldsymbol{S}_{t+1} = \chi_{\boldsymbol{R}_t} \Big(\boldsymbol{S}_t - \frac{1}{\rho_d} \boldsymbol{U}_t^- + \rho_c sat(\boldsymbol{U}_t^+ \vee \boldsymbol{W}_t) \Big) + S_t^{ini}(\boldsymbol{R}_t)$$

$$\boldsymbol{H}_{t+1} = \chi_{\boldsymbol{R}_t} \Big(\boldsymbol{H}_t - \boldsymbol{U}_t^- - sat(\boldsymbol{U}_t^+ \vee \boldsymbol{W}_t) \Big) + H_t^{ini}(\boldsymbol{R}_t)$$

$$\boldsymbol{C}_{t+1} = \chi_{\boldsymbol{R}_t} \boldsymbol{C}_t + \boldsymbol{R}_t$$

$$\alpha_m \boldsymbol{C}_t \leq \boldsymbol{S}_t \leq \alpha_M \boldsymbol{C}_t, \ 0 \leq \boldsymbol{H}_t$$

$$\boldsymbol{U}_t^+ - \boldsymbol{W}_t \leq \boldsymbol{E}_t^l, \ 0 \leq \boldsymbol{E}_t^l, \ 0 \leq \boldsymbol{D}_t - \boldsymbol{U}_t^-$$

$$\boldsymbol{S}_0 = s_0, \ \boldsymbol{C}_0 = c_0, \ \boldsymbol{H}_0 = h_0$$

$$\sigma(\boldsymbol{U}_t), \sigma(\boldsymbol{R}_t) \subset \sigma(\boldsymbol{W}_0, \boldsymbol{C}_0^b, ..., \boldsymbol{W}_{t-1}, \boldsymbol{C}_{t-1}^b)$$

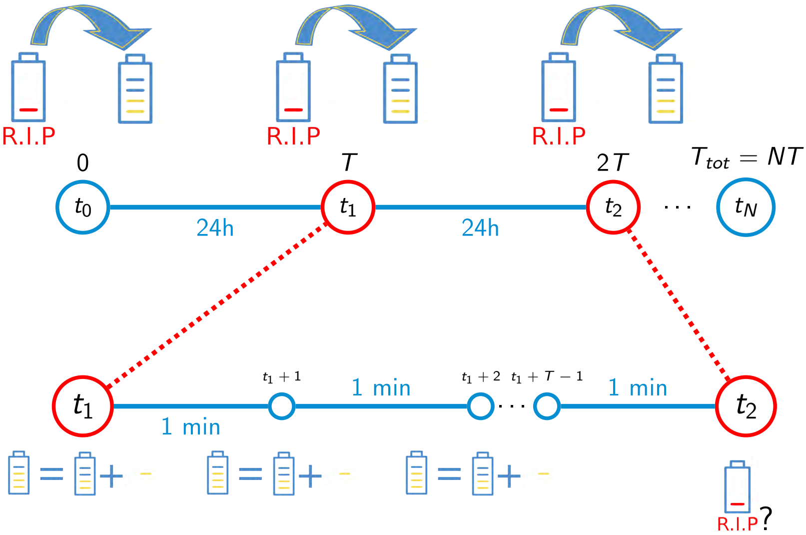
Model assumptions

- Daily electricity contract: c_t^e is T-periodic
- No intraday battery renewal: $\forall t \neq kT,\ \boldsymbol{R}_t = 0$
- Braking energy probability law is T-periodic:
  Let $\xi_k^W = \left(\boldsymbol{W}_t\right)_{t=t_k..t_k+T-1}$ then $(\xi_k^W)_{k\in 0,..,N}$ are i.i.d.
- Cost of batteries is constant intraday:
  $\forall k, \forall t \in \{kT, .., (k+1)T - 1\},\ \boldsymbol{C}_t^b = \boldsymbol{C}_{kT}^b$

`We note k-th day first time step:` $t_k = kT$

Investment/Control decomposition

Two decision time scales



How to decompose the investment problem into:

an intraday control problem

and

a daily investment problem?

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Resolution method: Bilevel Stochastic Dynamic Programming

Intraday control problem parametrized value function

$\forall k \in \{0, .., N\}$ we define:

$$Q_0^{\mu}(s_0, c_0, h_0;\ \boldsymbol{S}_d, \boldsymbol{H}_d) =$$

$$\max_{\boldsymbol{U}_\cdot} \mathbb{E}\Big[\sum_{t=t_k+1}^{t_{k+1}-1} c_t^e \Big(\boldsymbol{U}_t^- - \boldsymbol{E}_t^l \Big) \Big]$$

$$\begin{aligned}
\text{s.t}\quad & \boldsymbol{S}_{t+1} = \boldsymbol{S}_t - \frac{1}{\rho_d} \boldsymbol{U}_t^- + \rho_c sat(\boldsymbol{U}_t^+ \vee \boldsymbol{W}_t) \\
& \boldsymbol{H}_{t+1} = \boldsymbol{H}_t - \boldsymbol{U}_t^- - sat(\boldsymbol{U}_t^+ \vee \boldsymbol{W}_t) \\
& \boldsymbol{U}_t^+ - \boldsymbol{W}_t \leq \boldsymbol{E}_t^l,\ 0 \leq \boldsymbol{E}_t^l,\ 0 \leq \boldsymbol{D}_t - \boldsymbol{U}_t^- \\
& \alpha_m c_0 \leq \boldsymbol{S}_t \leq \alpha_M c_0 \\
& \boldsymbol{H}_d \leq \boldsymbol{H}_{t_{k+1}},\ \boldsymbol{S}_d \leq \boldsymbol{S}_{t_{k+1}} \\
& \boldsymbol{S}_{t_k+1} = s_0,\ \boldsymbol{H}_{t_k+1} = h_0 \\
& \sigma(\boldsymbol{U}_t) \subset \sigma(\boldsymbol{W}_{t_k+1}, ..., \boldsymbol{W}_{t_{k+1}-1})
\end{aligned}$$

Investment/Control decomposition

As suggested by Heymann et al. [2] we can extend their lemma to the stochastic case:

$$
\begin{aligned}
V_{t_k}(s_{t_k}, c_{t_k}, h_{t_k}) &= \max_{\boldsymbol{U}_\cdot, \boldsymbol{R}_\cdot} \mathbb{E}\Big[\sum_{t=t_k}^{T_{tot}} \gamma_t \Big(c^e_t\Big(\boldsymbol{U}^-_t - \boldsymbol{E}^l_t\Big) - \boldsymbol{C}^b_t \boldsymbol{R}_t\Big)\Big] \\
&= \max_{\boldsymbol{U}_{t_k}, \boldsymbol{R}_{t_k};\ \boldsymbol{S}_F, \boldsymbol{H}_F} \mathbb{E}\Big[\underbrace{\gamma_{t_k} c^e_{t_k}(\boldsymbol{U}^-_{t_k} - \boldsymbol{E}^l_{t_k})}_{\text{elec savings}} - \underbrace{\gamma_{t_k} \boldsymbol{C}^b_{t_k} \boldsymbol{R}_{t_k}}_{\text{battery renewal}} \\
&\quad + \underbrace{\gamma_{t_k} Q^\mu_0(\boldsymbol{S}_{t_k+1}, \boldsymbol{C}_{t_k+1}, \boldsymbol{H}_{t_k+1};\ \boldsymbol{S}_F, \boldsymbol{H}_F)}_{\text{intraday value}} \\
&\quad + \underbrace{V_{t_{k+1}}(\boldsymbol{S}_F, \boldsymbol{C}_{t_k+1}, \boldsymbol{H}_F)}_{\text{future investment cost}}\Big]
\end{aligned}
$$

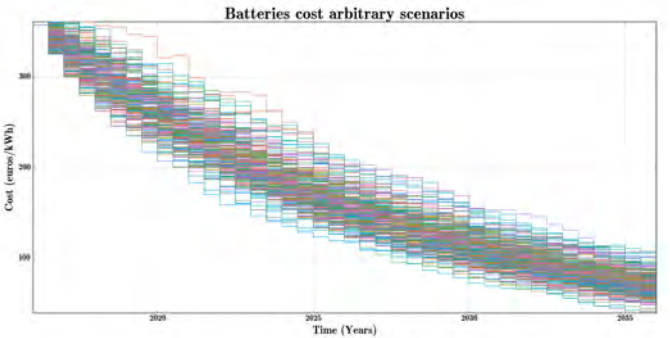
Remarks

- We need to assume time independence of the $\boldsymbol{C}_t^b$
- We need monotonicity assumptions:
  - Full battery is always preferable: $s \mapsto V_{t_k}(s, ., .)$ is non-increasing
  - Healthy battery is always preferable: $h \mapsto V_{t_k}(., ., h)$ is non-increasing
- $\boldsymbol{S}_F$ and $\boldsymbol{H}_F$ are mappings: $\sigma(\boldsymbol{S}_F),\ \sigma(\boldsymbol{H}_F) \subset \sigma(\boldsymbol{C}_{t_k}^b, \xi_k^W)$

Preliminary numerical results

Synthetic data

- Maximum exangeable energy: model proposed in Haessig et al. [1]
  $E_{exch} = 2E_{rated} * N_{cycles}$
- Discount rate: 4.5%
- Batteries cost stochastic model: synthetic scenarios that approximately coïncides with market forecasts



Comparison

We compare 3 investement strategies over 20 years, 100 $\boldsymbol{C}^b$ scenarios, 1 single capacity (80 kWh)

Straightforward approach, investment/control independence:

- Strategy 1: Buy now, replace when battery is dead, ignore aging

Bilevel Stochastic Dynamic Programming:

- Strategy 2: Buy now, replace when battery is dead, control aging
- Strategy 3: Start investment and buy batteries anytime, control aging

Preliminary results

- Cost 1 = -7000 euros $\Rightarrow$ do not invest!
- Cost 2 = +12000 euros $\Rightarrow$ do not strain your first batteries!
- Cost 3 = +33000 euros $\Rightarrow$ start investment in 2020 and do not strain your first batteries!

	SDP	**BSDP**
Offline comp. time	∞ (out of memory)	16min
Online comp. time	?	[0s,1s]
Simulation comp. time	?	[20s,30s]
Lower bound	?	+38k

In Julia with a Core I7, 2.6 Ghz, 8Go ram + 12Go swap SSD

Conclusion

Our study leads to the following conclusions:

- Controlling aging matters
- BSDP provides encouraging results
- BSDP can be used for aging aware intraday control

Ongoing work

We are now focusing on:

- Confirming, developing and improving BSDP results
- Improving risk modelling
- Improving batteries cost stochastic model
- Improving aging model
- Include environmental incentives (particulate matters)
- Apply the method to more complex energy efficiency investments

References

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Benjamin Heymann, Pierre Martinon, and Frédéric Bonnans.
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