Two-scale stochastic dynamic optimization

Energy storage investment and operation in subway stations

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CERMICS, ENPC
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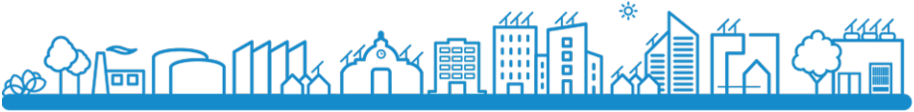
Optimization for subway stations

Paris subway stations consumption $\equiv$ 40.000 houses

Energy transition of cities requires significant investments

Is electrical storage affordable for subway stations?

We use stochastic optimization for short term control and long term management of batteries



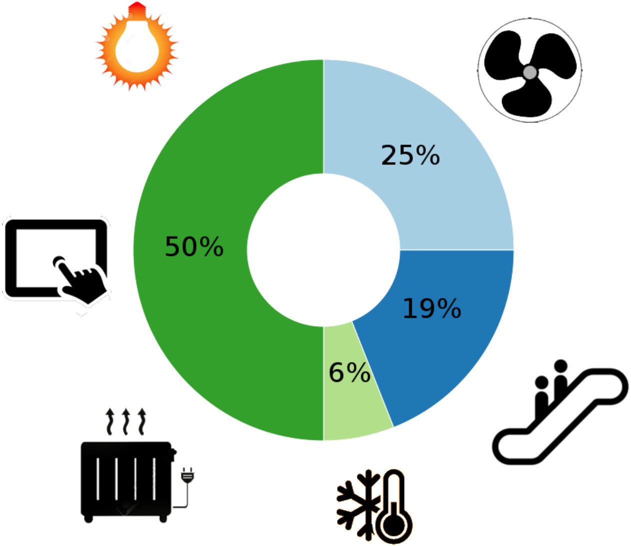
Outline

1. Electrical storage management issues
   - Why electrical storage in subway stations?
   - Managing storage short term operations
   - Battery operation impacts long term aging!
2. Long term management of batteries aging and renewal
   - Two scales management: investement/operation
   - Short term management problem formulation
   - Long term management problem formulation
   - We formulate a two-scale stochastic optimization problem
3. Resolution method and first results
   - Long term value functions and Bellman equation
   - Preliminary numerical results

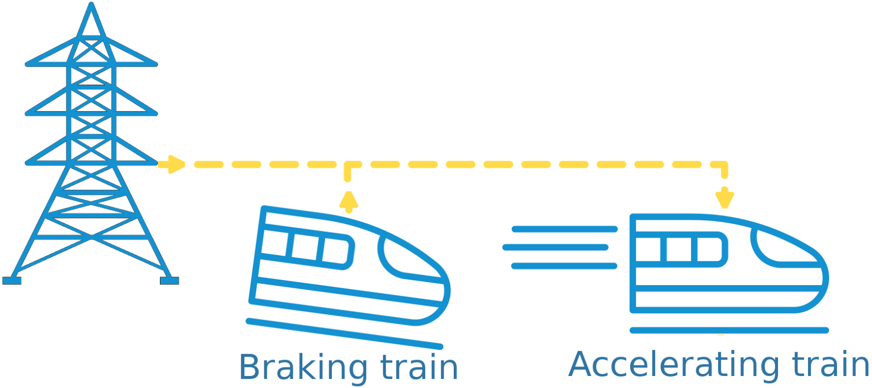
Outline

Why electrical storage in subway stations?

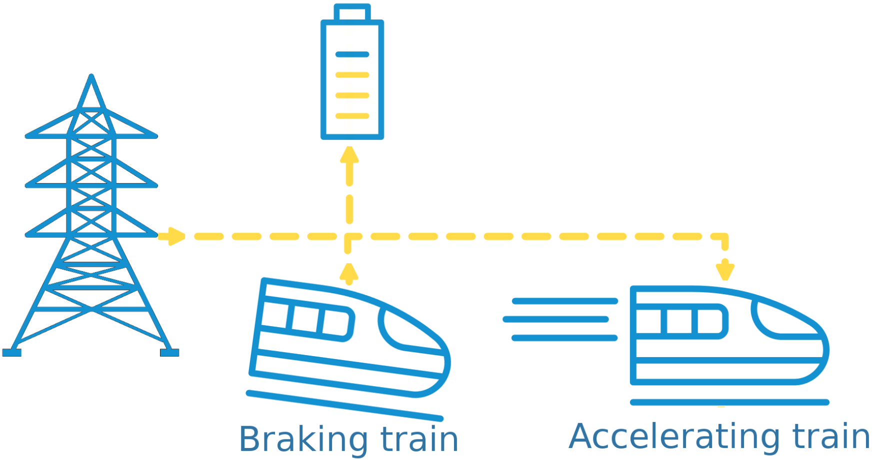
Subway stations typical energy consumption



Subway stations have unexploited energy ressources

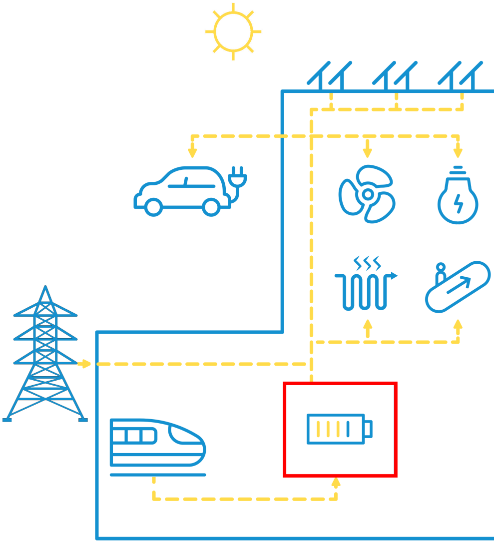


Energy recovery requires a buffer



Managing storage short term operations

Microgrid concept for subway stations



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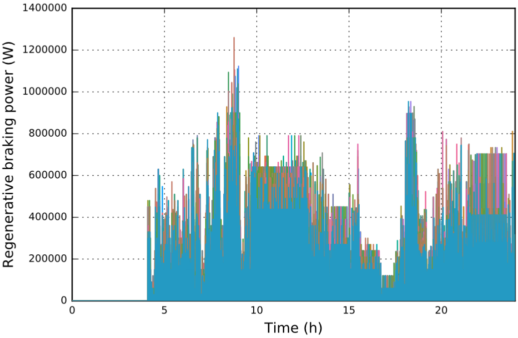
Stochastic optimization is relevant

Subways braking energy is unpredictible



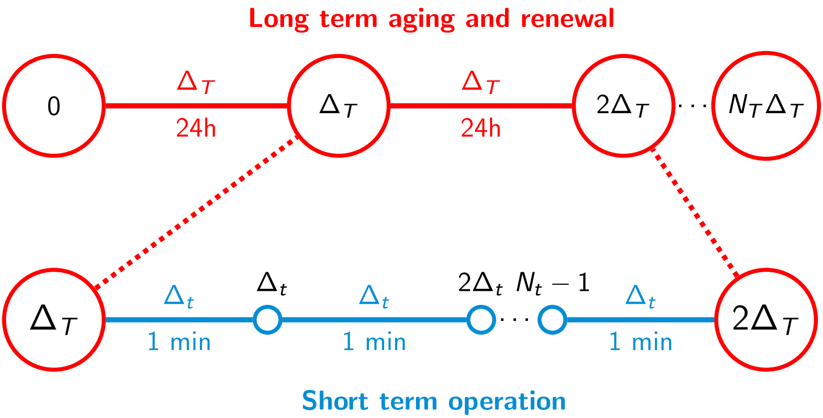
We can optimize battery operations using
Stochastic Dynamic Programming

Battery operation impacts long term aging!

Outline

Two scales management: investement/operation

Two time scales

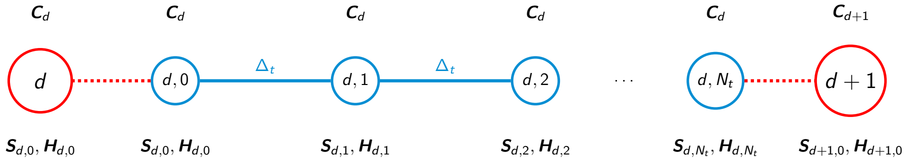


What happens every minute m of every day d?

Day: d, Minute: m

- Battery capacity: $\boldsymbol{C}_d = \boldsymbol{C}(d\Delta_T)$
- Battery state of charge: $\boldsymbol{S}_{d,m} = \boldsymbol{S}(d\Delta_T + m\Delta_t)$
- Battery state of health: $\boldsymbol{H}_{d,m} = \boldsymbol{H}(d\Delta_T + m\Delta_t)$

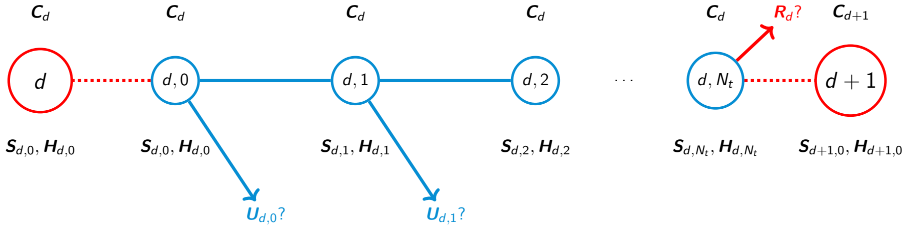
$\boldsymbol{S}_{d,m}$ and $\boldsymbol{H}_{d,m}$ change every minute m



Battery capacity $\boldsymbol{C}_d$ changes with health state at end of day d

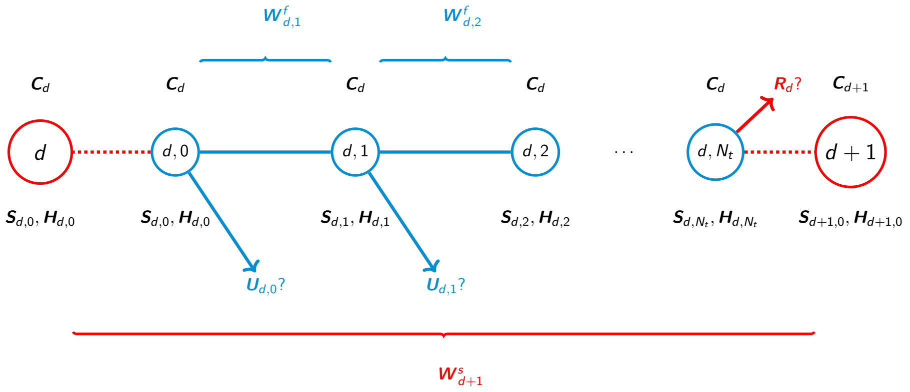
Battery $\boldsymbol{C}_d$ can be replaced every day d

We make both short and long term decisions



Uncertain events occur

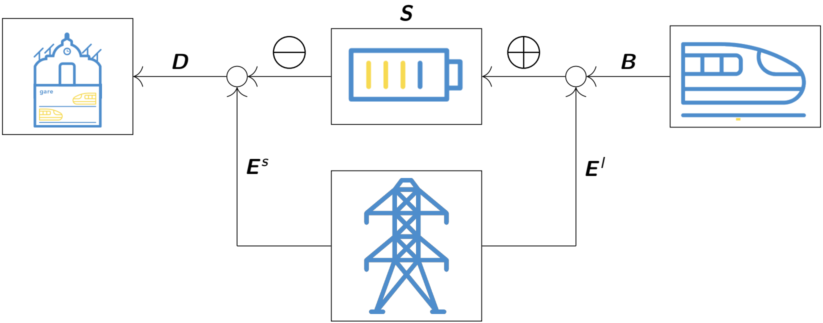
$W^f_{d,2}$: electricity demand every minute



W^s_{d+1}: battery prices every day

Short term management problem formulation

Electrical network representation



Station node

- D: Demand station
- E^s: From grid to station
- ⊖: Discharge battery

Subways node

- B: Braking
- E^l: From grid to battery
- ⊕: Charge battery

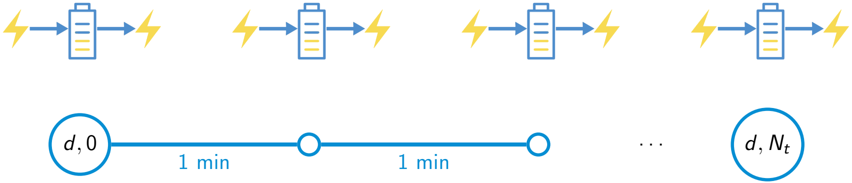
Battery state of charge dynamics

For a given charge/discharge strategy $\boldsymbol{U}$ over a day d:

$$\boldsymbol{S}_{d,m+1} = \boldsymbol{S}_{d,m} - \underbrace{\frac{1}{\rho_d}\boldsymbol{U}^{-}_{d,m}}_{\ominus} + \underbrace{\rho_c sat(\boldsymbol{S}_{d,m}, \boldsymbol{U}^{+}_{d,m}, \boldsymbol{B}_{d,m+1})}_{\oplus}$$

with

$$sat(x, u, b) = \min(\frac{S_{max} - x}{\rho_c}, \max(u, b))$$



Battery aging dynamics

For a given charge/discharge strategy $\boldsymbol{U}$ over a day d

$$\boldsymbol{H}_{d,m+1} = \boldsymbol{H}_{d,m} - \frac{1}{\rho_d}\boldsymbol{U}^{-}_{d,m} - \rho_c sat(\boldsymbol{S}_{d,m}, \boldsymbol{U}^{+}_{d,m}, \boldsymbol{B}_{d,m+1})$$

Every minute we save energy and money

If we have a battery on day d and minute m we save:

$$p^e_{d,m}\Big(\underbrace{\boldsymbol{E}^s_{d,m+1} + \boldsymbol{E}^l_{d,m+1} - \boldsymbol{D}_{d,m+1}}_{\text{Saved energy}}\Big)$$

$p^e_{d,m}$ is the cost of electricity on day d at minute m

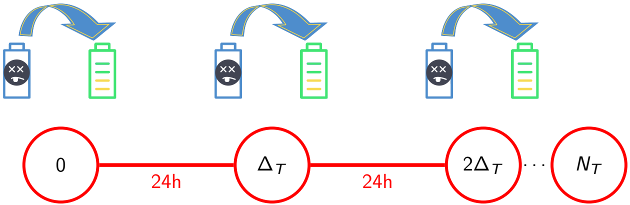
Summary of short term/Fast variables model

We call, at day d and minute m,

- fast state variables: $\boldsymbol{X}^f_{d,m} = \begin{pmatrix} \boldsymbol{S}_{d,m} \\ \boldsymbol{H}_{d,m} \end{pmatrix}$
- fast decision variables: $\boldsymbol{U}^f_{d,m} = \begin{pmatrix} \boldsymbol{U}^-_{d,m} \\ \boldsymbol{U}^+_{d,m} \end{pmatrix}$
- fast random variables: $\boldsymbol{W}^f_{d,m} = \begin{pmatrix} \boldsymbol{B}_{d,m} \\ \boldsymbol{D}_{d,m} \end{pmatrix}$
- fast cost function: $L^f_{d,m}(\boldsymbol{X}^f_{d,m}, \boldsymbol{U}^f_{d,m}, \boldsymbol{W}^f_{d,m+1})$
- fast dynamics: $\boldsymbol{X}^f_{d,m+1} = F^f_{d,m}(\boldsymbol{X}^f_{d,m}, \boldsymbol{U}^f_{d,m}, \boldsymbol{W}^f_{d,m+1})$

Long term problem formulation

We decide our battery purchases at the end of each day



Should we replace our battery $\boldsymbol{C_d}$ by buying a new one $\boldsymbol{R_d}$ or not?

$$\boldsymbol{C_{d+1}} = \begin{cases} \boldsymbol{R_d}, \text{ if } \boldsymbol{R_d} > 0 \\ f(\boldsymbol{C_d}, \boldsymbol{H_{d,N_t}}), \text{ otherwise} \end{cases}$$

paying renewal cost $\boldsymbol{P_d^b R_d}$ at uncertain market prices $\boldsymbol{P_d^b}$

Summary of long term/Slow variables model

We call, at day d,

- slow state variables: $\boldsymbol{X}_d^s = (\boldsymbol{C}_d)$
- slow decision variables: $\boldsymbol{U}_d^s = (\boldsymbol{R}_d)$
- slow random variables: $\boldsymbol{W}_d^s = (\boldsymbol{P}_d^b)$
- slow cost function: $L_d^s(\boldsymbol{X}_d^s, \boldsymbol{U}_d^s, \boldsymbol{W}_{d+1}^s) = \boldsymbol{P}_d^b \boldsymbol{R}_d$
- slow dynamics: $\boldsymbol{X}_{d+1}^s = F_d^s(\boldsymbol{X}_d^s, \boldsymbol{U}_d^s, \boldsymbol{W}_{d+1}^s)$

Linking the two scales

Long term (slow) decisions may impact short term (fast) initial state

$$\boldsymbol{X}^f_{d,0} = \phi_d(\boldsymbol{X}^s_d, \boldsymbol{X}^f_{d-1,N_t})$$

This is not the case here but, in general,
short term (fast) variables may impact long term (slow) dynamics

$$\boldsymbol{X}^s_{d+1} = F^s_d(\boldsymbol{X}^s_d, \boldsymbol{U}^s_d, \boldsymbol{W}^s_{d+1}, \boldsymbol{X}^f_{d,0}, \boldsymbol{U}^f_{d,:}, \boldsymbol{W}^f_{d,:})$$

as well as the long term (slow) cost

$$L^s_d(\boldsymbol{X}^s_d, \boldsymbol{U}^s_d, \boldsymbol{W}^s_{d+1}, \boldsymbol{X}^f_{d,0}, \boldsymbol{U}^f_{d,:}, \boldsymbol{W}^f_{d,:})$$

We formulate a two-scale stochastic optimization problem

Two-scale stochastic optimization problem

We minimize fast and slow costs over the long term

$$\min_{\boldsymbol{X}^f, \boldsymbol{X}^s, \boldsymbol{U}^f, \boldsymbol{U}^s} \mathbb{E}\Big[\sum_{d=0}^{N_T-1} \Big(\sum_{m=0}^{N_t-1} L^f_{d,m}(\boldsymbol{X}^f_{d,m}, \boldsymbol{U}^f_{d,m}, \boldsymbol{W}^f_{d,m+1})\Big) + L^s_d(\boldsymbol{X}^s_d, \boldsymbol{U}^s_d, \boldsymbol{W}^s_{d+1}, \boldsymbol{X}^f_{d,0}, \boldsymbol{U}^f_{d,:}, \boldsymbol{W}^f_{d,:})\Big]$$

$$\boldsymbol{X}^f_{d,m+1} = F^f_{d,m}(\boldsymbol{X}^f_{d,m}, \boldsymbol{U}^f_{d,m}, \boldsymbol{W}^f_{d,m+1})$$

$$\boldsymbol{X}^f_{d,0} = \phi_d(\boldsymbol{X}^s_d, \boldsymbol{X}^f_{d-1,N_t})$$

$$\boldsymbol{X}^s_{d+1} = F^s_d(\boldsymbol{X}^s_d, \boldsymbol{U}^s_d, \boldsymbol{W}^s_{d+1}, \boldsymbol{X}^f_{d,0}, \boldsymbol{U}^f_{d,:}, \boldsymbol{W}^f_{d,:})$$

$$\boldsymbol{U}^f_{d,m} \preceq \mathcal{F}_{d,m}$$

$$\boldsymbol{U}^s_d \preceq \mathcal{F}_{d,N_t}$$

Information model

$$\mathcal{F}_{d,m} = \sigma \begin{pmatrix} \boldsymbol{W}^f_{d',m'},\ d'<d,\ m' \leq N_t+1 \\ \boldsymbol{W}^s_{d'},\ d' \leq d \\ \boldsymbol{W}^f_{d,m'},\ m' \leq m \end{pmatrix} = \sigma \begin{pmatrix} \text{previous days fast noises} \\ \text{previous days slow noises} \\ \text{current day previous minutes fast noises} \end{pmatrix}$$

Fast information accumulation

$$\mathcal{F}_{d,m} = \mathcal{F}_{d,0} \vee \sigma(\boldsymbol{W}^f_{d,1:m})$$

Slow information implies a jump between d, N_t and $d+1, 0$

$$\mathcal{F}_{d+1,0} = \mathcal{F}_{d,N_t} \vee \sigma(\boldsymbol{W}^s_{d+1})$$

Two-scale stochastic optimal control reformulation

With the notations

$$\begin{aligned} \boldsymbol{X}_d &= (\boldsymbol{X}^f_{d-1,N_t}, \boldsymbol{X}^s_d) \\ \boldsymbol{U}_d &= (\boldsymbol{U}^f_{d,:}, \boldsymbol{U}^s_d) \\ \boldsymbol{W}_d &= (\boldsymbol{W}^f_{d-1,:}, \boldsymbol{W}^s_d) \end{aligned}$$

we can reformulate the problem as

$$\begin{aligned} \min_{\boldsymbol{X},\boldsymbol{U}} \mathbb{E} \Big[\sum_{d=0}^{N_T-1} & L_d(\boldsymbol{X}_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1}) \Big] \\ \boldsymbol{X}_{d+1} &= F_d(\boldsymbol{X}_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1}) \\ \boldsymbol{U}^f_{d,m} &\preceq \mathcal{F}_{d,m} \\ \boldsymbol{U}^s_d &\preceq \mathcal{F}_{d,N_t} \end{aligned}$$

where the non-anticipativity constraints are not standard

How to decompose
a two-scale stochastic optimization problem
into
a short term optimization problem
and
a long term optimization problem?

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Long term value functions and Bellman equation

We can define long term (slow) value functions

Every day d_0, we can define a long term (slow) value function

$$\begin{aligned} V_{d_0}(x_{d_0}) = \min_{\boldsymbol{X},\boldsymbol{U}} \mathbb{E} \Big[\sum_{d=d_0}^{N_T-1} L_d(\boldsymbol{X}_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1}) \Big] \\ \boldsymbol{X}_{d+1} = F_d(\boldsymbol{X}_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1}) \\ \boldsymbol{U}^f_{d,m} \preceq \mathcal{F}_{d,m} \\ \boldsymbol{U}^s_d \preceq \mathcal{F}_{d,N_t} \\ \boldsymbol{X}_{d_0} = x_{d_0} \end{aligned}$$

Long term (slow) value functions satisfy a Bellman equation

Assuming independence of the noises $\boldsymbol{W}_d$

$$V_d(x_d) = \min_{\boldsymbol{U}_d} \mathbb{E}\left[L_d(x_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1}) + V_{d+1}\Big(F_d(\boldsymbol{X}_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1})\Big)\right]$$

$$\text{s.t } \boldsymbol{U}_d = (\boldsymbol{U}^s_d, \boldsymbol{U}^f_{d,:})$$

$$\boldsymbol{U}^f_{d,m} \preceq \boldsymbol{W}^f_{d,1:m}$$

$$\boldsymbol{U}^s_d \preceq \boldsymbol{W}^f_{d,1:N_t}$$

with non standard non-anticipativity constraints as well

How we can decompose the two scales by Two Scale Stochastic Dynamic Programming

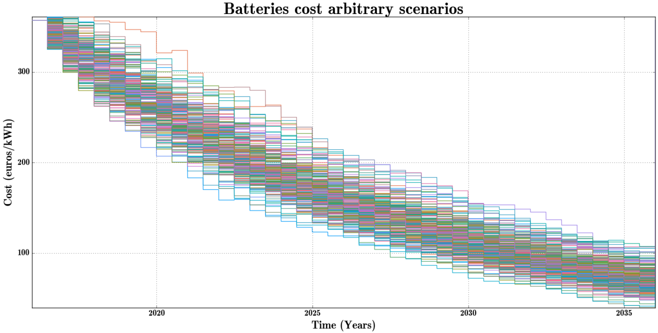
The long term (slow) value function
is the final cost of a daily stochastic optimization problem
which can be solved by different methods (SP, DP, SDDP)

Two Scale Stochastic Dynamic Programming (TSSDP)

Preliminary numerical results

Synthetic data

- Maximum exangeable energy: model proposed in Haessig et al. [1]
- Discount rate: 4.5%
- Batteries cost stochastic model: synthetic scenarios that approximately coincide with market forecasts



Comparison of 3 investement strategies over 20 years

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

- Strategy NPV : Buy now, replace battery when dead, no aging control
- Strategy NPVA: Buy now, replace battery when dead, control aging
- Strategy FNPVA: Buy anytime, replace battery anytime, control aging

Objective: maximize discounted revenues over 20 years

Preliminary results

- NPV = -7000 euros ⇒ do not invest!
- NPVA = +12000 euros ⇒ do not strain your first batteries!
- FNPVA = +33000 euros ⇒ start investment in 2020 and do not strain your first batteries!

	SDP	**TSSDP**
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 is relevant
- TSSDP provides encouraging results
- TSSDP can be used for aging aware intraday control
- Classical Net Present Value and Free Net Present Value strategies lead to different conclusions
- Free Net Present Value strategy correspond to a more accurate model of the investment management

Ongoing work

We are now focusing on

- Confirming, developing and improving TSSDP 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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