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# Two time scales stochastic dynamic optimization for microgrids control

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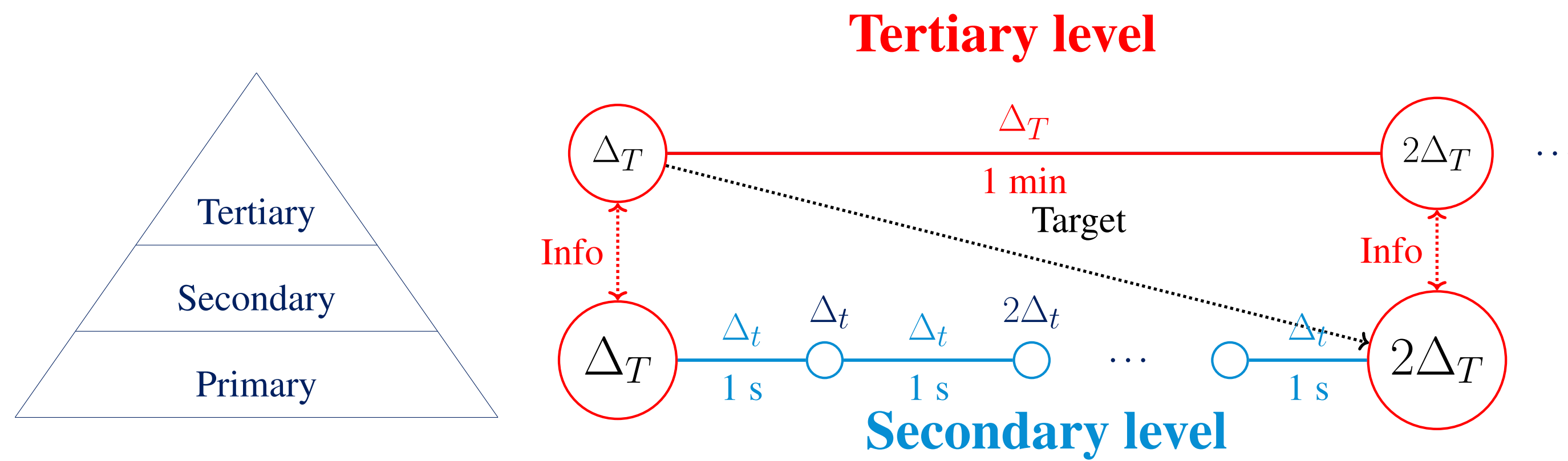
ENSTA, ENPC, Efficacity

## Stochastic optimization for storage management in microgrids

Energy storage is often used to mitigate the uncertainty related to energy demand and production. Renewable energies are especially intermittent and some electrical demands particularly uncertain. Stochastic optimization is a tool to ensure supply demand balance without wasting energy or curtailing demand.

### Hierarchical control architecture

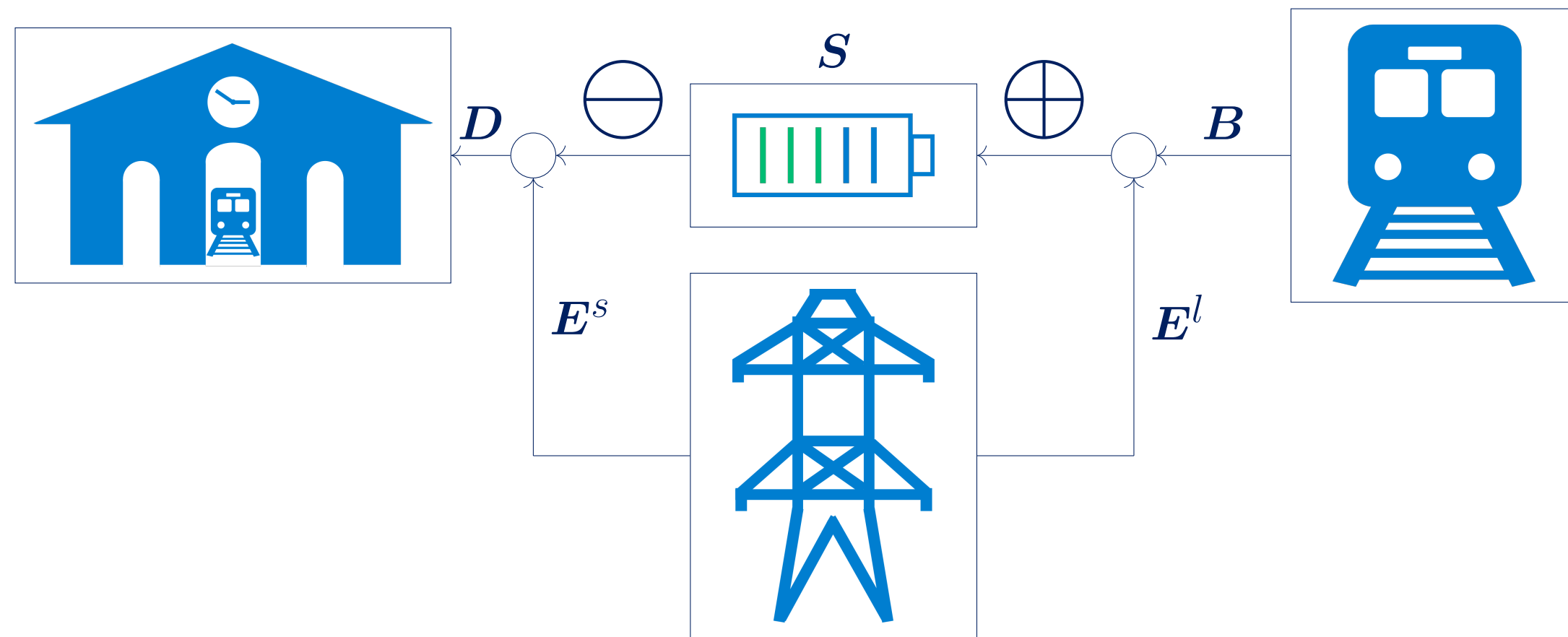
Microgrids control architecture is divided into multiple layers to handle multiple time steps. Primary level is devoted to ensure the microgrid voltage stability, secondary level is devoted to the energy management while the tertiary level is devoted to economic reliability.



A superior level purpose is to provide a target that the next inferior level has to reach at the end of its horizon while reaching its own objective.

### Example: intraday energy arbitrage and battery long term aging management

We study hereby a two time scales problem to manage a battery ageing over the long term while using it everyday for intraday energy arbitrage. The example we use is a battery in a subway station able to recover subways braking energy and to provide power to the station.



#### Station node

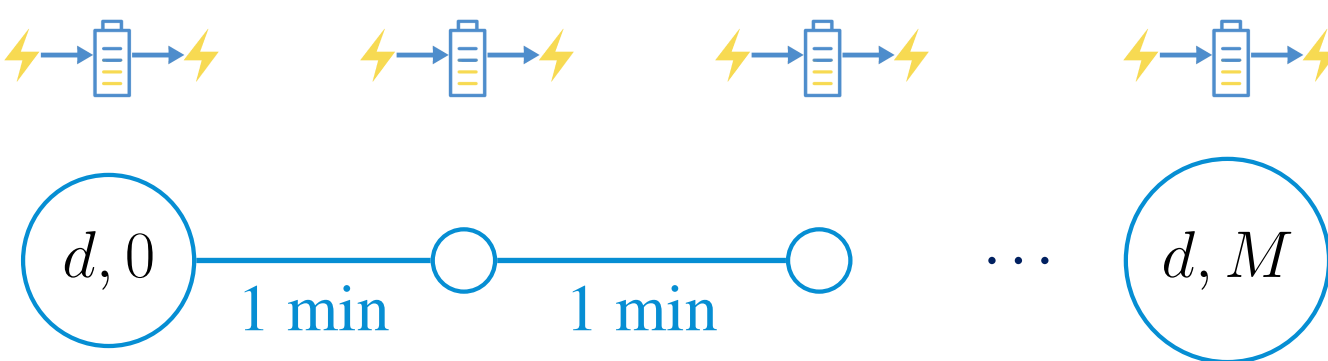
- $D$ : Demand station
- $E^s$ : From grid to station
- $\ominus$ : Discharge battery

#### Subways node

- $B$ : Braking
- $E^l$ : From grid to battery
- $\oplus$ : Charge battery

#### Medium time scale: energy arbitrage

- Time step  $\Delta_t = 1$  min
- Horizon  $M = 24$ h
- Decision: battery charge/discharge
- Objective: energy cost minimization



For a given charge/discharge decision  $U_{d,m}$ : state of charge  $S$  changes

$$S_{d,m+1} = S_{d,m} - \frac{1}{\rho_d} U_{d,m} + \rho_c \text{sat}(S_{d,m}, U_{d,m}^+, B_{d,m+1})$$

state of health  $H$  decreases

$$H_{d,m+1} = H_{d,m} - \frac{1}{\rho_d} U_{d,m} - \rho_c \text{sat}(S_{d,m}, U_{d,m}^+, B_{d,m+1})$$

we save energy and money

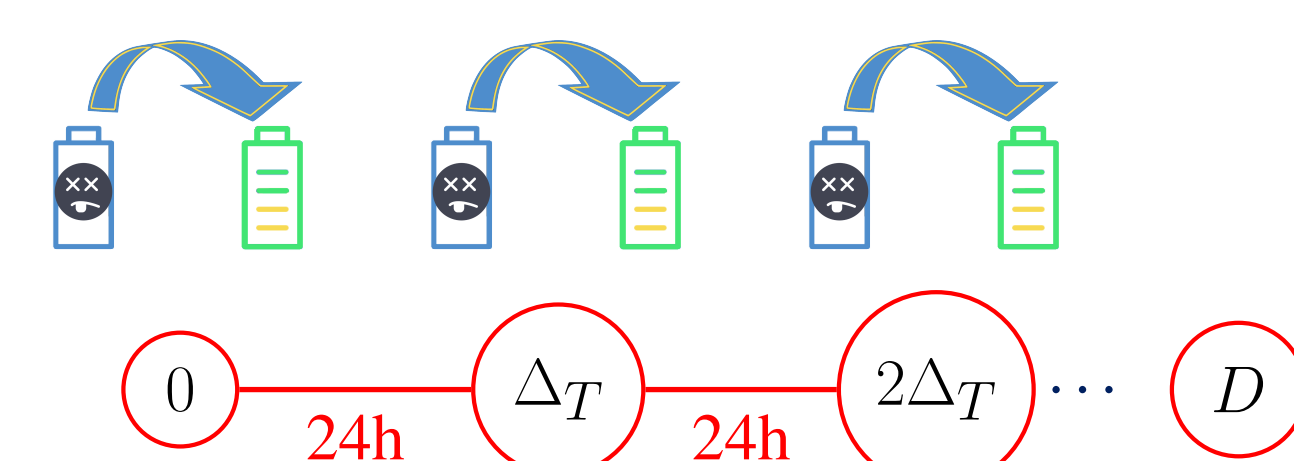
$$p_{d,m}^e (E_{d,m+1}^s + E_{d,m+1}^l - D_{d,m+1}) \text{ with } p_{d,m}^e \text{ the cost of electricity on day } d \text{ at minute } m$$

The link between the two scales is the global state at the beginning of each day:

$$(S_{d+1,0}, H_{d+1,0}, C_{d+1}) = \psi_d((S_{d,M}, H_{d,M}, C_d, R_d))$$

#### Large time scale: long term ageing

- Time step  $\Delta_T = 1$  day
- Horizon  $D = 10$  years
- Decision: battery replacement
- Objective: long term profitability



For a given replacement decision  $R_d$ : battery capacity changes

$$C_{d+1} = \begin{cases} R_d, & \text{if } R_d > 0 \\ C_d, & \text{otherwise} \end{cases}$$

we pay a replacement cost  $P_d^b R_d$  at uncertain market prices  $P_d^b$ .

## General two time scales stochastic optimization problem

We minimize medium and large scale costs taking into account the medium and large scales dynamics,  $f$  index means fast (medium scale),  $s$  index means slow (large scale):

$$\begin{aligned} \min_{\mathbf{X}^f, \mathbf{X}^s, \mathbf{U}^f, \mathbf{U}^s} \mathbb{E} & \left[ \sum_{d=0}^{D-1} \left( \sum_{m=0}^{M-1} L_{d,m}^f(\mathbf{X}_{d,m}^f, \mathbf{U}_{d,m}^f, \mathbf{W}_{d,m+1}^f) \right) \right. \\ & \left. + L_d^s(\mathbf{X}_d^s, \mathbf{U}_d^s, \mathbf{W}_{d+1}^s, \mathbf{X}_{d,0}^f, \mathbf{U}_{d,0}^f, \mathbf{W}_{d,0}^f) \right] \\ \mathbf{X}_{d,m+1}^f &= F_{d,m}^f(\mathbf{X}_{d,m}^f, \mathbf{U}_{d,m}^f, \mathbf{W}_{d,m+1}^f) \\ \mathbf{X}_{d,0}^f &= \psi_d(\mathbf{X}_d^s, \mathbf{X}_{d-1,M}^f) \\ \mathbf{X}_{d+1}^s &= F_d^s(\mathbf{X}_d^s, \mathbf{U}_d^s, \mathbf{W}_{d+1}^s, \mathbf{X}_{d,0}^f, \mathbf{U}_{d,0}^f, \mathbf{W}_{d,0}^f) \\ \sigma(\mathbf{U}_{d,m}^f) &\subset \mathcal{F}_{d,m} \\ \sigma(\mathbf{U}_d^s) &\subset \mathcal{F}_{d,M} \end{aligned}$$

we can reformulate the problem with

$$\begin{aligned} \mathbf{X}_d &= (\mathbf{X}_{d,0}^f, \mathbf{X}_d^s), \mathbf{U}_d = (\mathbf{U}_{d,0}^f, \mathbf{U}_d^s), \mathbf{W}_d = (\mathbf{W}_{d-1}^f, \mathbf{W}_d^s) \\ \min_{\mathbf{X}, \mathbf{U}} \mathbb{E} & \left[ \sum_{d=0}^{D-1} L_d(\mathbf{X}_d, \mathbf{U}_d, \mathbf{W}_{d+1}) \right] \\ \mathbf{X}_{d+1} &= F_d(\mathbf{X}_d, \mathbf{U}_d, \mathbf{W}_{d+1}) \\ \sigma(\mathbf{U}_{d,m}^f) &\subset \mathcal{F}_{d,m} \\ \sigma(\mathbf{U}_d^s) &\subset \mathcal{F}_{d,M} \end{aligned}$$

The last two constraints, called non anticipativity constraints, states that we make our decisions knowing only the past realizations of the noises.

$$\mathcal{F}_{d,m} = \sigma \left( \begin{matrix} \mathbf{W}_{d',m'}^f, d' < d, m' \leq M+1 \\ \mathbf{W}_{d'}^s, d' \leq d \\ \mathbf{W}_{d,m'}^f, m' \leq m \end{matrix} \right) = \sigma \left( \begin{matrix} \text{previous days fast noises} \\ \text{previous days slow noises} \\ \text{current day previous minutes fast noises} \end{matrix} \right)$$

## Resolution method: two time scales stochastic dynamic programming

The resolution method is based on primal decomposition and dynamic programming. We show that when the  $(\mathbf{W}_d)_{d=0,\dots,D}$  are stage(day)wise independent we can define inductively value functions:

Daily value function

$$\begin{aligned} V_d(x_d) &= \min_{\mathbf{X}_{d+1}} \left[ \begin{matrix} \text{intraday problem} \\ \phi_d(x_d, [\mathbf{X}_{d+1}]) \\ \text{expected next day value} \\ + \mathbb{E} V_{d+1}(\mathbf{X}_{d+1}) \end{matrix} \right] \\ \text{s.t } \mathbf{X}_{d+1} &\preceq \sigma(\mathbf{X}_d, \mathbf{W}_{d+1}) \end{aligned}$$

Intraday arbitrage problem with **almost sure stochastic target**

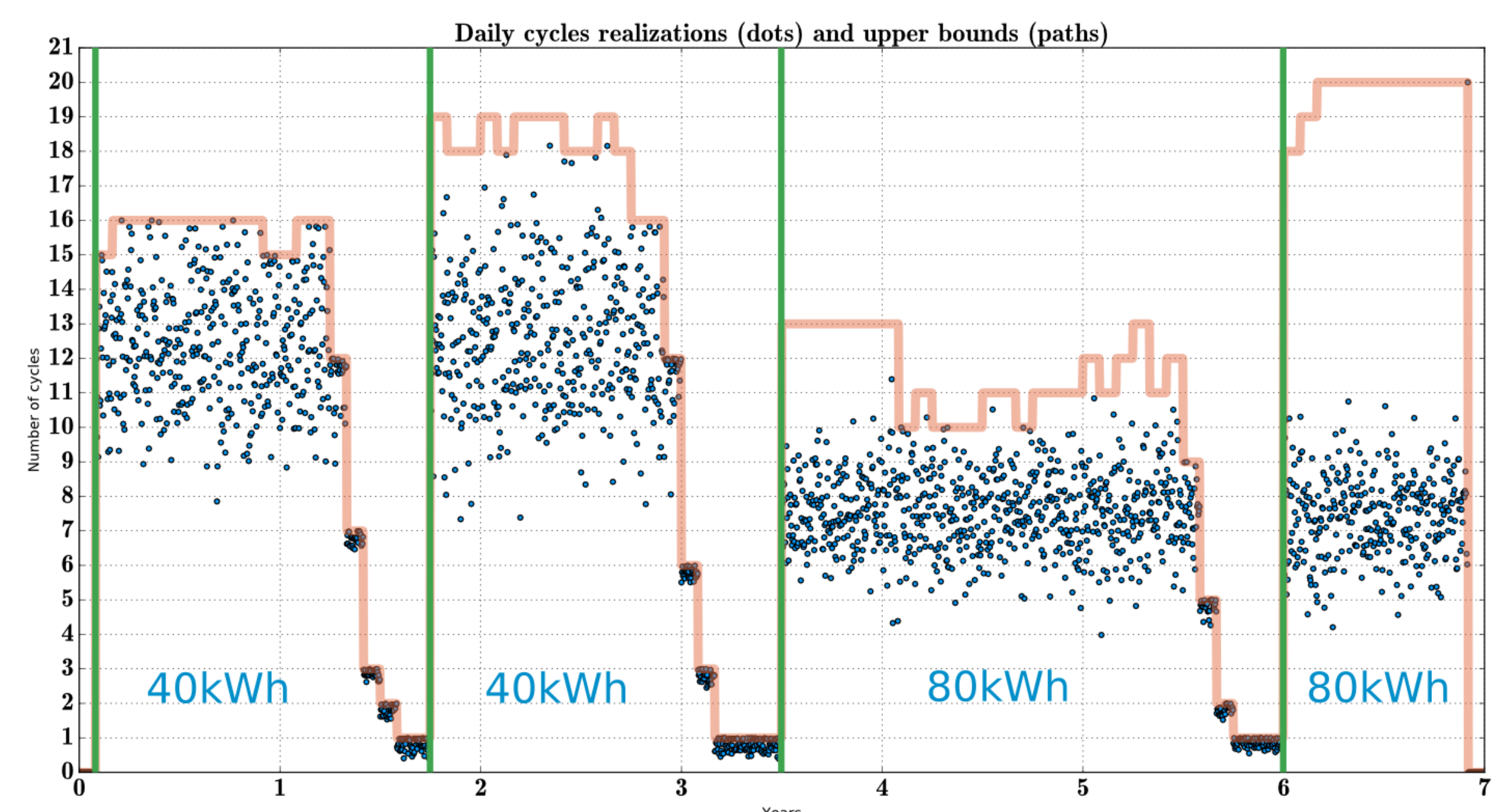
$$\begin{aligned} \phi_d(x_d, [\mathbf{X}_{d+1}]) &= \min_{\mathbf{U}_d} \mathbb{E} L_d(x_d, \mathbf{U}_d, \mathbf{W}_{d+1}) \\ \text{s.t } F_d(\mathbf{X}_d, \mathbf{U}_d, \mathbf{W}_{d+1}) &= \mathbf{X}_{d+1} \\ \mathbf{U}_{d,m}^f &\preceq \sigma(\mathbf{X}_d, \mathbf{W}_{d,1:M}^f) \\ \mathbf{U}_d^s &\preceq \sigma(\mathbf{X}_d, \mathbf{W}_{d,1:M}^f) \\ \mathbf{U}_d &= (\mathbf{U}_{d,0}^f, \mathbf{U}_d^s) \\ \mathbf{X}_d &= x_d \end{aligned}$$

We use the notation  $f([\mathbf{W}])$  to emphasize that  $f$ 's domain is  $L^0(\Omega, \mathcal{F}, \mathbb{P})$ . Solving these two problems directly is computationally very expensive as the target to reach at the end of the day is measurable w.r.t all the intraday noises. We use 3 tricks to simplify the computation:

- We exploit the problem periodicity ( $\forall d, \phi_d = \phi_0$ )
- We exploit value functions monotonicity to relax the target  $F_d(\mathbf{X}_d, \mathbf{U}_d, \mathbf{W}_{d+1}) \geq \mathbf{X}_{d+1}$
- We simplify measurability ( $\mathbf{X}_{d+1} \preceq \sigma(\mathbf{X}_d)$ ) meaning that we choose the final state target at the beginning of the day! We loose optimality with this trick.

## Numerical application

We manage batteries in a subway station over 7 years and want to maximize the Net Present Value (NPV). We have to choose every month a maximum number of daily cycles for the current battery (orange horizontal line). We can decide to buy a new battery every month (green vertical lines are replacements). We use synthetic scenarios for the price of batteries on the market. We manage charge/discharge of the battery every 15 minutes, giving an effective number of cycles for each day (blue dots).



The algorithm is implemented in Julia with a Core I7, 1.7 Ghz, 8Go ram + 12Go swap SSD. It requires 16 min to compute daily value functions and intraday problem value offline. It then takes 20 ms to make a charge/discharge decision online every 15 minutes and to make an ageing daily target decision at the beginning of every month. We obtain a +128k euros upper bound for the NPV.

## Conclusion

This method allows to model two time scales stochastic optimization problems with a proper modelization of the information for the decision maker. The resolution method we present decouples the two time scales and could be applied to microgrid hierarchical management, sizing of storage or energy storage investment and long term ageing strategies.

## Stating a two time scales optimization problem

The previous example displays 2 state variables that changes every minutes and 1 state variable that changes every day. We make 1 charge/discharge decision every minute and 1 capacity replacement decision everyday. We can formulate a two-time scales stochastic optimization problem.