Two time scales stochastic dynamic optimization

Managing energy storage investment, aging and operation in microgrids

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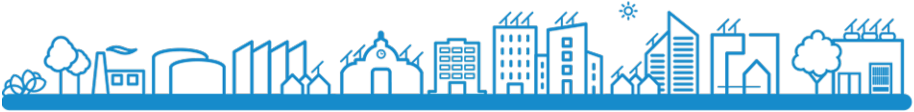
Optimization for microgrids with storage

Microgrids control architecture is often constituted of multiple levels handling multiple time scales

Energy storage management requires to deal with uncertainty and information dynamic

We use two time scales stochastic dynamic optimization to model two control levels and their interaction



Outline

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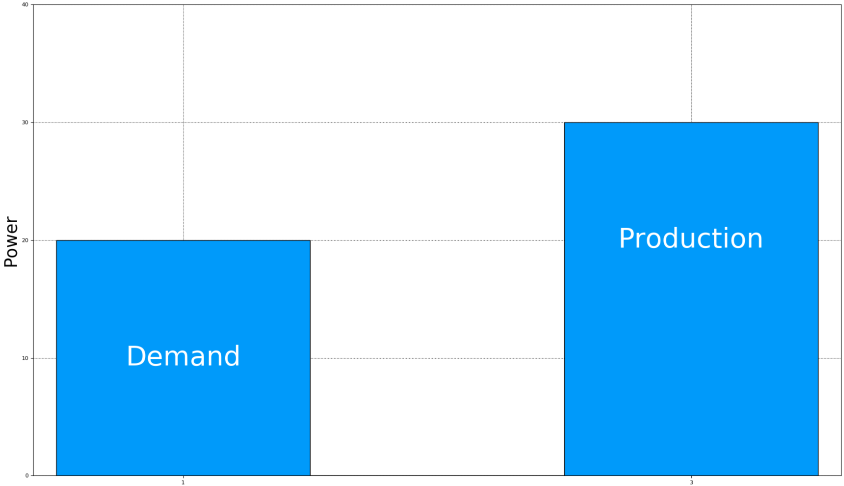
1. Introduction: Electrical storage management in microgrids
   - Storage control in a microgrid
   - Hierarchical control architecture of microgrids
2. Modeling: Managing intraday arbitrage, aging and renewal
   - Two time scales management of a battery in a subway station
   - Intraday arbitrage problem statement
   - Long term aging/investment problem statement
   - Two time scales stochastic optimization problem
3. Solving: Decomposition method and numerical results
   - Decomposition method
   - Numerical experiment

Storage control in a microgrid

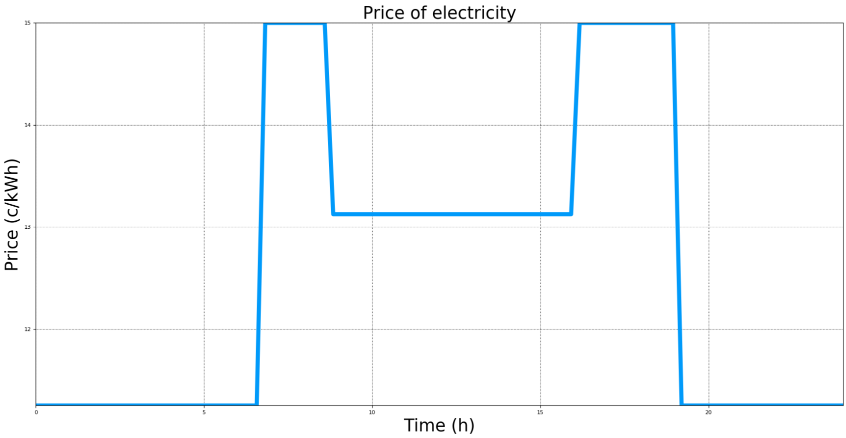
Why storage in a microgrid?

Ensure supply demand balance without wastes or curtailment:



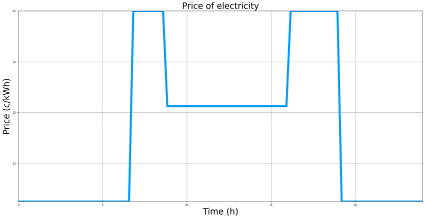
Why storage in a microgrid?

Energy tariff arbitrage and ancillary services

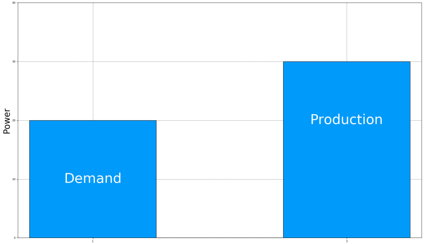


Why stochastic dynamic optimization?

Price of electricity might be uncertain



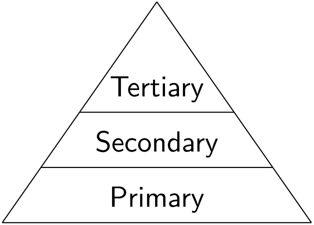
Demand and production are uncertain



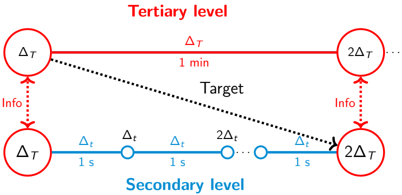
Hierarchical control architecture of microgrids

A way to deal with multiple time scales

Multiple control levels

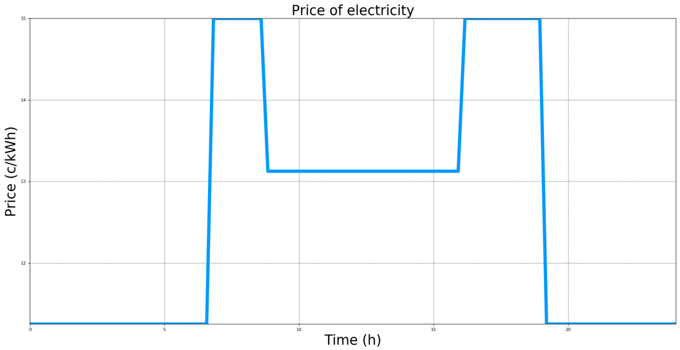


To handle multiple time scales



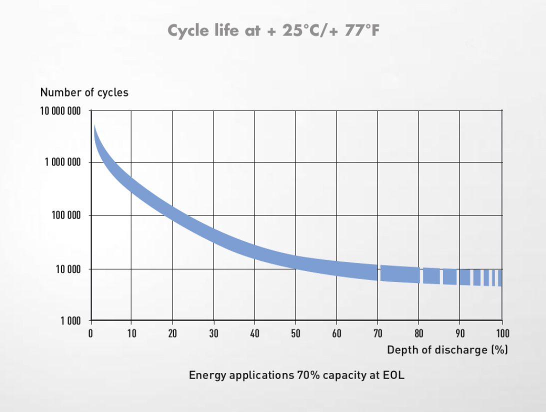
Medium time scale: intraday energy tariff arbitrage

- Objective: energy intraday arbitrage
- Time step: 1 min
- Horizon: 24h
- Input from superior level: storage aging target everyday
- Output to inferior level: storage input/output energy target every minute



Large time scale: long term aging and investments strategy

- Objective: storage long term economic profitability
- Time step: 1 day
- Horizon: 10 years
- Output to inferior level: storage aging target every day

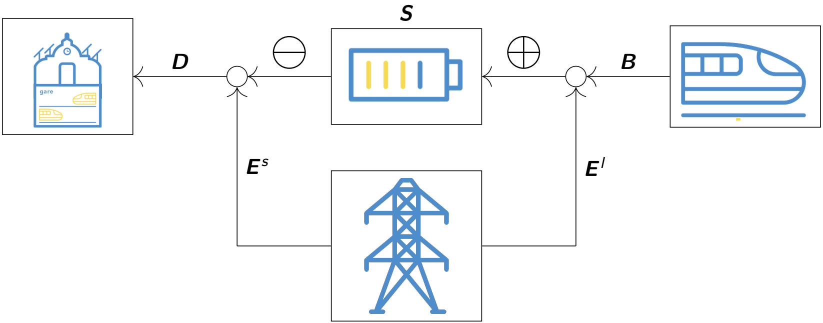


SAFT intensium max technical sheet

Outline

Two time scales management of a battery in a subway station

Representation of the subway station problem



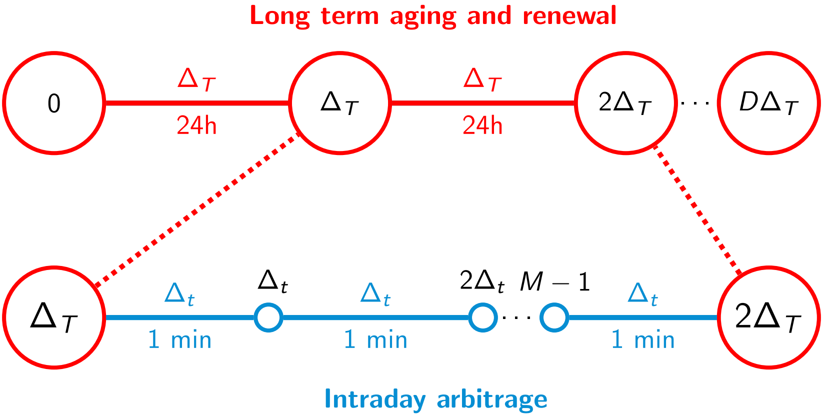
Station node

- 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

Two time scales



Intraday arbitrage problem statement

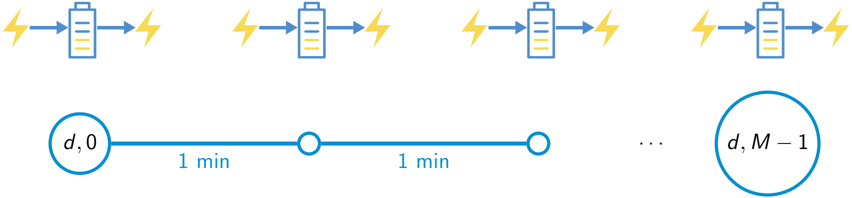
Battery state of charge dynamics

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

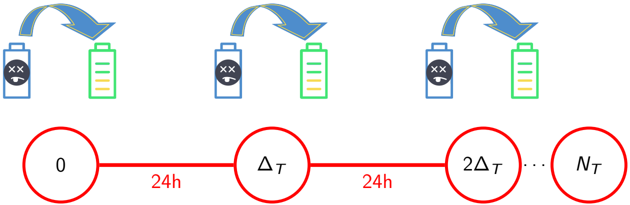
Summary of short term/Fast variables model

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 aging/investment problem statement

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?

$$\boldsymbol{C}_{d+1} = \begin{cases} \boldsymbol{R}_d, \text{ if } \boldsymbol{R}_d > 0 \\ f(\boldsymbol{C}_d, \boldsymbol{H}_{d,M}), \text{ otherwise} \end{cases}$$

paying renewal cost $\boldsymbol{P}_d^b \boldsymbol{R}_d$ at uncertain market prices $\boldsymbol{P}_d^b$

Summary of long term/Slow variables model

We call, at day d,

- slow state variables: $\boldsymbol{X}^s_d = (\boldsymbol{C}_d)$
- slow decision variables: $\boldsymbol{U}^s_d = (\boldsymbol{R}_d)$
- slow random variables: $\boldsymbol{W}^s_d = (\boldsymbol{P}^b_d)$
- slow cost function: $L^s_d(\boldsymbol{X}^s_d, \boldsymbol{U}^s_d, \boldsymbol{W}^s_{d+1}) = \boldsymbol{P}^b_d \boldsymbol{R}_d$
- slow dynamics: $\boldsymbol{X}^s_{d+1} = F^s_d(\boldsymbol{X}^s_d, \boldsymbol{U}^s_d, \boldsymbol{W}^s_{d+1})$

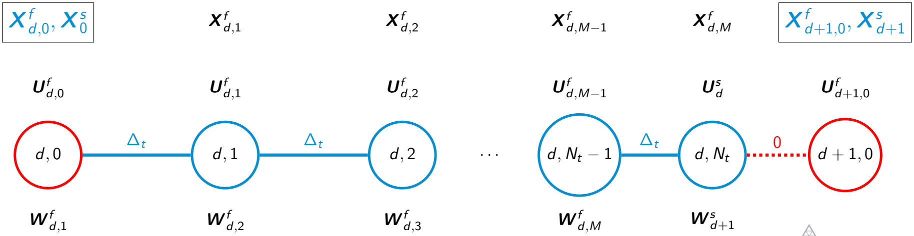
A link between days

The initial "fast state" at the begining of day d deduces from:

$$\boldsymbol{X}^f_{d,0} = F^i_d(\boldsymbol{X}^s_d, \boldsymbol{X}^f_{d-1,M})$$

The initial "slow state" at the begining of day $d+1$ deduces from all that happened the previous day:

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



We formulate a two time scales stochastic optimization problem

We minimize fast and slow costs over the long term

$$
\begin{aligned}
\min_{\boldsymbol{X}^f, \boldsymbol{X}^s, \boldsymbol{U}^f, \boldsymbol{U}^s} \quad & \mathbb{E}\Bigg[\sum_{d=0}^{D-1} \Bigg(\sum_{m=0}^{M-1} L^f_{d,m}(\boldsymbol{X}^f_{d,m}, \boldsymbol{U}^f_{d,m}, \boldsymbol{W}^f_{d,m+1}) \Bigg) \\
& \qquad + L^s_d(\boldsymbol{X}^s_d, \boldsymbol{U}^s_d, \boldsymbol{W}^s_{d+1}, \boldsymbol{X}^f_{d,0}, \boldsymbol{U}^f_{d,:}, \boldsymbol{W}^f_{d,:}) \Bigg] \\
& \boldsymbol{X}^f_{d,m+1} = F^f_{d,m}(\boldsymbol{X}^f_{d,m}, \boldsymbol{U}^f_{d,m}, \boldsymbol{W}^f_{d,m+1}) \\
& \boldsymbol{X}^f_{d,0} = F^i_d(\boldsymbol{X}^s_d, \boldsymbol{X}^f_{d-1,M}) \\
& \boldsymbol{X}^s_{d+1} = F^s_d(\boldsymbol{X}^s_d, \boldsymbol{U}^s_d, \boldsymbol{W}^s_{d+1}, \boldsymbol{X}^f_{d,0}, \boldsymbol{U}^f_{d,:}, \boldsymbol{W}^f_{d,:}) \\
& \sigma(\boldsymbol{U}^f_{d,m}) \subset \mathcal{F}_{d,m} \\
& \sigma(\boldsymbol{U}^s_d) \subset \mathcal{F}_{d,M}
\end{aligned}
$$

Stochastic optimal control reformulation

We call

$$\boldsymbol{X}_d = (\boldsymbol{X}^f_{d,0}, \boldsymbol{X}^s_d) \text{ storage state at the beginning of day d}$$
$$\boldsymbol{U}_d = (\boldsymbol{U}^f_{d,:}, \boldsymbol{U}^s_d) \text{ all decisions taken during day d}$$
$$\boldsymbol{W}_{d+1} = (\boldsymbol{W}^f_{d,:}, \boldsymbol{W}^s_{d+1}) \text{ all uncertainties realizing on day d}$$

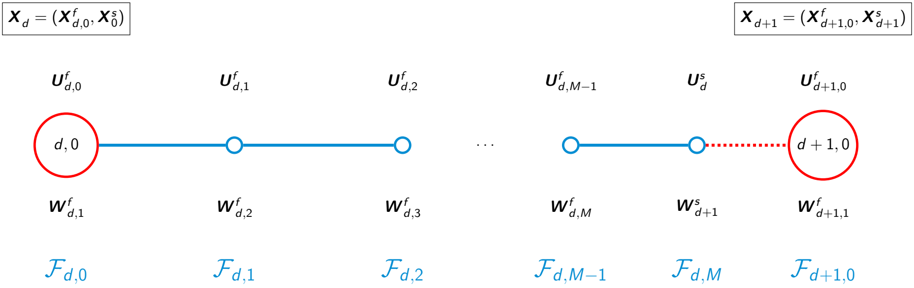
we reformulate the problem as

$$\min_{\boldsymbol{X},\boldsymbol{U}} \mathbb{E}\Big[\sum_{d=0}^{D-1} L_d(\boldsymbol{X}_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1})\Big]$$
$$\boldsymbol{X}_{d+1} = F_d(\boldsymbol{X}_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1})$$
$$\sigma(\boldsymbol{U}^f_{d,m}) \subset \mathcal{F}_{d,m}$$
$$\sigma(\boldsymbol{U}^s_d) \subset \mathcal{F}_{d,M}$$

where the non-anticipativity constraints are not standard

Information flow model

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

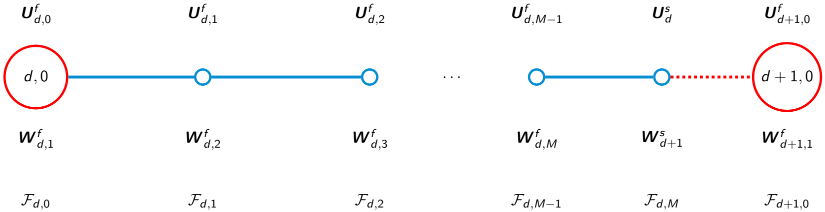


Value of storage every day

When braking energy yesterday doesn't impact braking energy today

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

$\boxed{V_d(x_d)}$ $\boxed{V_{d+1}(\boldsymbol{X}_{d+1})}$



Dynamic programming: a recursion between the value of storage each day

We define daily value functions that factorizes as function of the storage state $\boldsymbol{X}_d$ if the $\boldsymbol{W}_d$ are day-wise independent.

$$
\begin{aligned}
V_d(x_d) = \min_{\boldsymbol{X}_{d+1}, \boldsymbol{U}_d} \ & \mathbb{E}\left[L_d(x_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1}) + V_{d+1}(\boldsymbol{X}_{d+1}) \right] \\
\text{s.t } & \boldsymbol{X}_{d+1} = F_d(\boldsymbol{X}_d, \boldsymbol{U}_d, \boldsymbol{W}_{d+1}) \\
& \boldsymbol{U}^f_{d,m} \preceq \sigma(\boldsymbol{X}_d, \boldsymbol{W}^f_{d,1:m}) \\
& \boldsymbol{U}^s_d \preceq \sigma(\boldsymbol{X}_d, \boldsymbol{W}^f_{d,1:M}) \\
& \boldsymbol{U}_d = (\boldsymbol{U}^f_{d,:}, \boldsymbol{U}^s_d) \\
& \boldsymbol{X}_d = x_d
\end{aligned}
$$

$V_0(x_0)$ is the value of storage today $\Rightarrow$ Initial investment decision

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Decomposing the problem
into

a daily optimization problem
and

an intraday optimization problem.

Setting short term goals to reach lifetime purposes

A "long term Planner" sets end of the day targets

$$V_d(x_d) = \min_{\boldsymbol{X}_{d+1}} \Big[\overbrace{\phi_d(x_d, [\boldsymbol{X}_{d+1}])}^{\text{intraday problem with target}} + \overbrace{\mathbb{E} V_{d+1}(\boldsymbol{X}_{d+1})}^{\text{expected cost to go}} \Big]$$

$$\text{s.t } \boldsymbol{X}_{d+1} \preceq \sigma(\boldsymbol{X}_d, \boldsymbol{W}_{d+1})$$

Planner takes a decision once a day

The "intraday Controller" has to reach end of the day state target

For a stochastic state target $\boldsymbol{X}_{d+1} \in L^0(\Omega, \mathcal{F}, \mathbb{P})$[1], the Controller solves[2]

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

Controller takes a decision every minute

[1] $\phi_d(x_d, [\boldsymbol{X}_{d+1}]) = +\infty$ if $\boldsymbol{X}_{d+1}$ is an unreachable target
[2] $f([\boldsymbol{W}])$ to emphasizes that f's domain is $L^0(\Omega, \mathcal{F}, \mathbb{P})$

Planner sends contingent targets

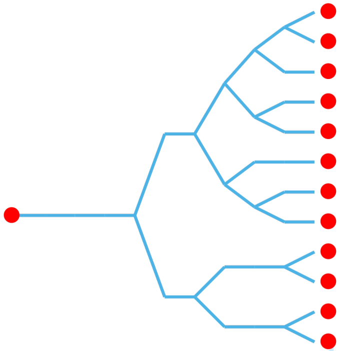
Planner sends a braking energy contingent target to Controller:

- If trains produce 900kWh over the day 900kWh have to flow through the battery
- If trains produce 1000kWh over the day 950kWh have to flow through the battery

Controller solves many multistage stochastic problems

One multistage stochastic optimization problem to solve for each
initial state, final target combination

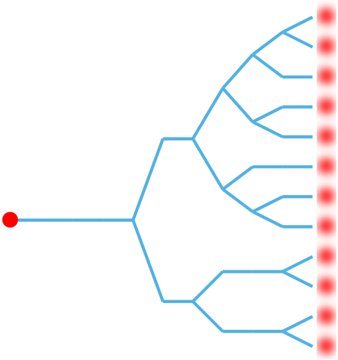
$(\phi_d)_{d=0,\ldots,D}$ computation:
$O(D \times N_X \times N_X^{N_S} \times \text{ControllerProblemComplexity})$



Simplifying trick 1: Relaxing the target

Value functions monotonicity allows Controller to aim anywhere above the target

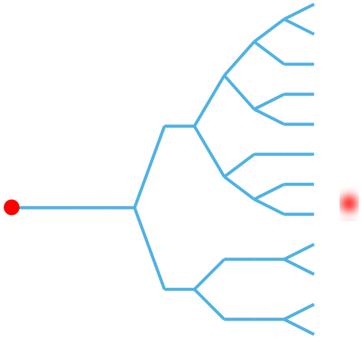
$$O(D \times N_X \times N_X^{N_S} \times \text{SimplerControllerProblemComplexity})$$



Simplifying trick 2: Choosing the target at the beginning of the day

We restrict to deterministic final state targets

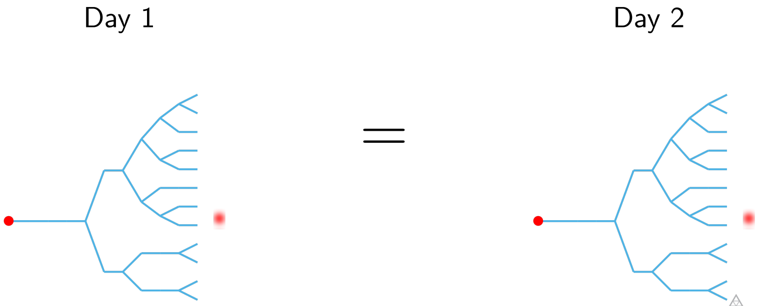
$$O(D \times N_X \times N_X \times \text{SimplerControllerProblemComplexity})$$



Simplifying trick 3: Daily periodicity

The tree is the same everyday? We solve one problem instead of one for each day

$$O(1 \times N_X \times N_X \times \text{SimplerControllerProblemComplexity})$$



Summing up the offline computation of daily values of storage

1. Solve one intraday problem $\phi(x_d, x_{d+1})$ for every initial state x_d and deterministic target x_{d+1}
2. Compute daily value functions by backward induction

$$V_d(x_d) = \min_{x_{d+1}} \phi(x_d, x_{d+1}) + V_{d+1}(x_{d+1})$$

Two ways to take a decision online

Target approach

1. Beginning of day d: Compute an optimal target

$$x^\sharp_{d+1} \in \operatorname*{arg\,min}_{x_{d+1}} \phi(x_d, x_{d+1}) + V_{d+1}(x_{d+1})$$

2. Day d minute m: Use value functions of $\phi(x_d, x^\sharp_{d+1})$

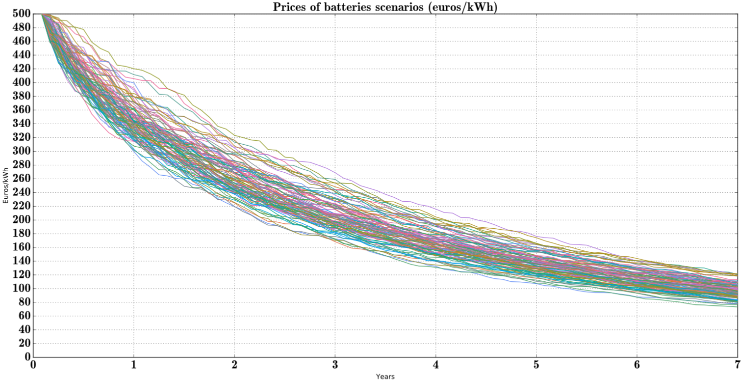
Final cost approach

1. Beginning of day d: Solve a new intraday problem $\phi^o_d(x_d)$ without target but V_{d+1} as final cost
2. Day d minute m: Use value functions of $\phi^o_d(x_d)$

Numerical experiment

Synthetic price of batteries data

- Batteries cost stochastic model: synthetic scenarios that approximately coincide with market forecasts



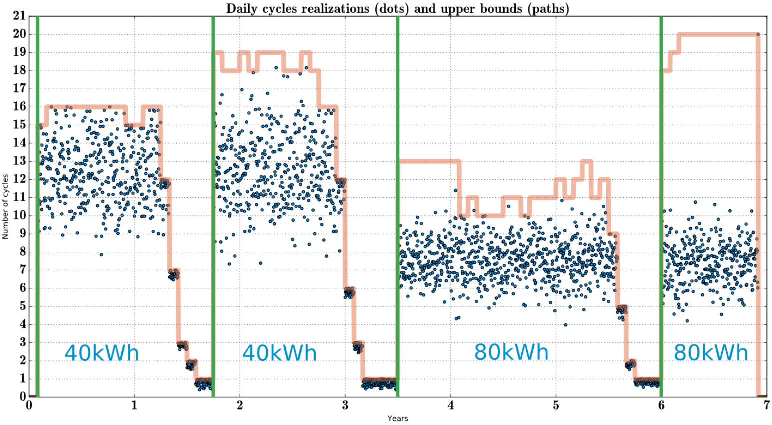
Maximize Net Present Value

Objective: maximize expected discounted revenues over 7 years
s.t

- Yearly discount factor $= \; 0.95$
- $10,000$ $\boldsymbol{C}^b$ scenarios to model randomness
- 1 buying/aging decision per month
- 1 charge/discharge decision every 15 min
- Constraint: having a battery everytime with at least one cycle a day

Simulation of battery cycles/renewals over 7 years

NPV = 80,000 euros



Conclusion and ongoing work

Our study leads to the following conclusions:

- Aging aware intraday control as well as investment management and assessment are made possible
- Modeling framework provides mathematically backed methods to solve multi time scales problems

We are now focusing on

- Relevant applications: real battery investments, microgrids management
- Aging model: with capacity degradation
- Other methods: dual decomposition, stochastic programming
- Risk modeling: risk averse battery control, contingent claim valuation

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