Subway stations energy and air quality management
by multistage stochastic optimization

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Optimization for subway stations

Paris urban railway transport system energy consumption $\equiv$ $\frac{1}{3}$ subway stations + $\frac{2}{3}$ traction system

Subway stations present a significantly high particulate matters concentration

We use optimization to harvest unexploited energy ressources and improve air quality.

Outline

1. Subway stations optimal management problem
   - Energy
   - Air quality
   - Energy/Air management system
   - Multistage stochastic optimization problem formulation
2. Two methods to solve the problem
   - We are looking for a policy
   - Dynamic programming in the non Markovian case
   - Model Predictive Control
3. Numerical results
   - Random variables modeling
   - Resolution methods
   - Results and conclusion

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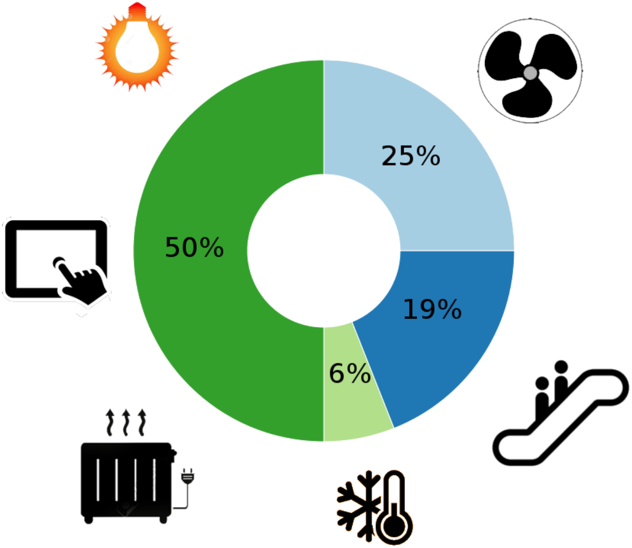
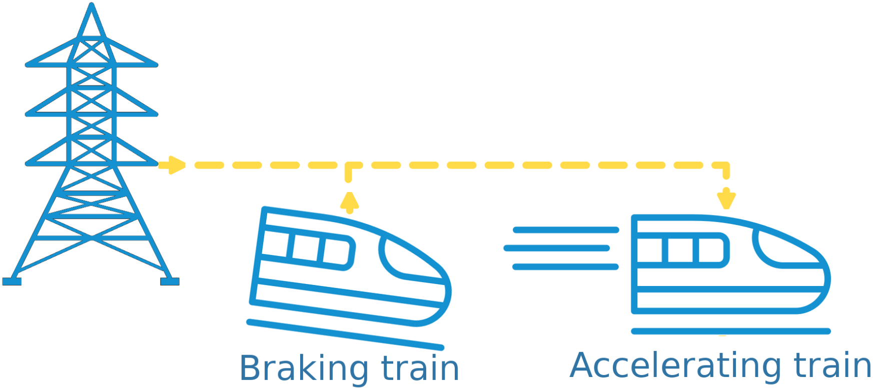
Energy

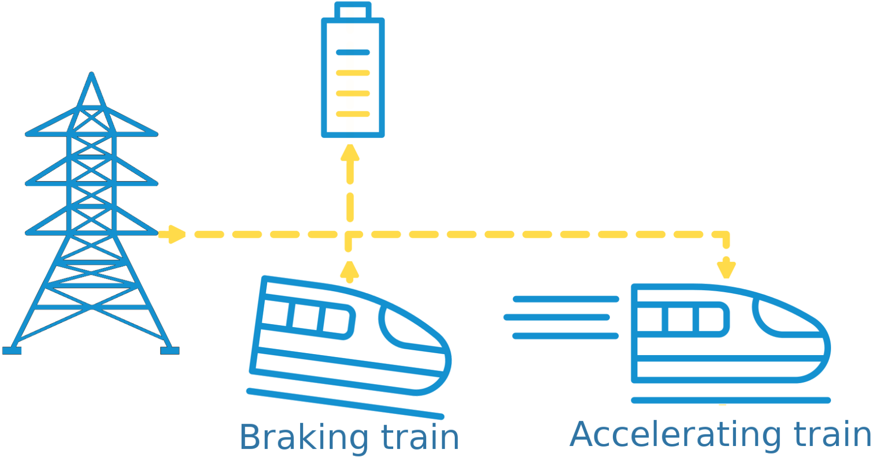
Subway stations typical energy consumption



Subway stations have unexploited energy ressources



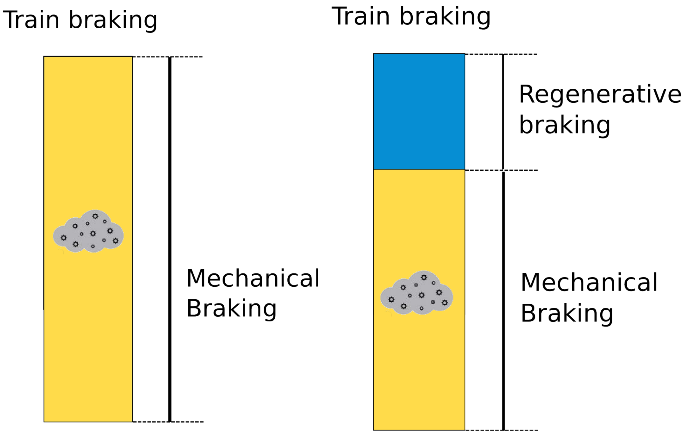
Energy recovery requires a buffer



Air quality

Subways arrivals generate particulate matters

Rails/brakes wear and resuspension increase PM10 concentration

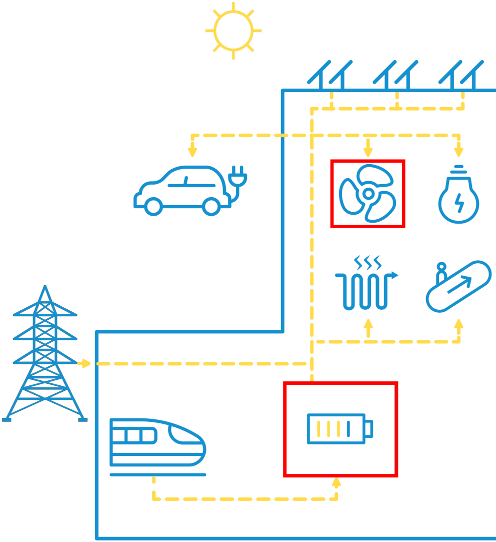


2 mg of PM10 generated   1.5 mg of PM10 generated

Recovering energy improves air quality

Energy/Air management system

Subway station microgrid concept



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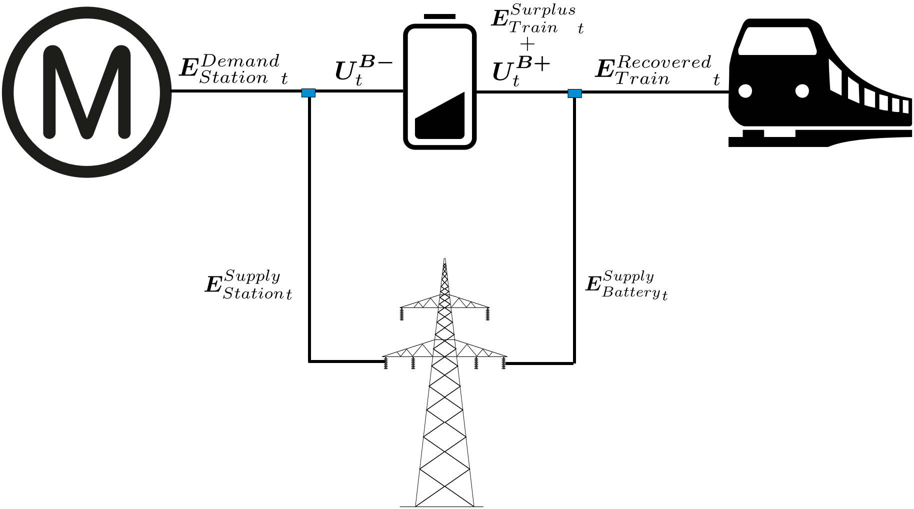
We control the battery every 5 seconds



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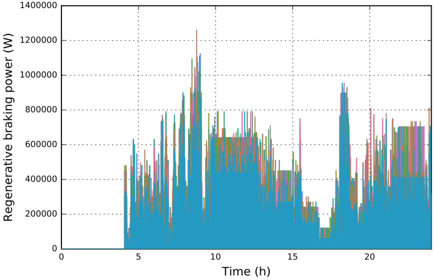
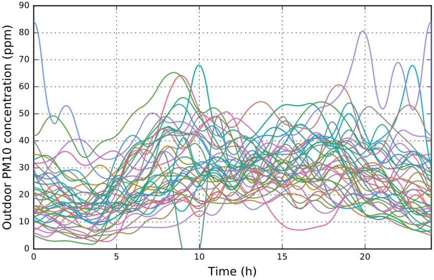
Some input variables display stochasticity

Braking energy and outside PM10 concentration every 5s





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We have many uncertainties

Let $\boldsymbol{W}_t$ the random variables vector of uncertainties at time t:

- Outdoor particles concentration : ${\boldsymbol{C}_P^{Out}}_t$
- Regenerative braking : ${\boldsymbol{E}_{Train}^{Available}}_t$
- Station consumption : ${\boldsymbol{E}_{Station}^{Demand}}_t$
- Cost of electricity : $\boldsymbol{C}ost_t$
- Particles generation : ${\boldsymbol{Q}_P}_t$
- Resuspension rate : ${\boldsymbol{\rho}^R}_t$
- Deposition rate : ${\boldsymbol{\rho}^D}_t$

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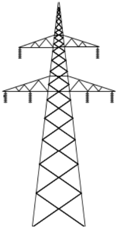
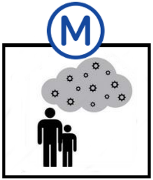
Objective: We want to minimize energy consumption and particles concentration

A parameter λ measures the relative weights of the 2 objectives:

$$\sum_{t=0}^{T} Cost_t \underbrace{(E^{Supply}_{Station\,t} + E^{Supply}_{Battery\,t})}_{Grid\ \ supply} + \lambda \underbrace{C^{In}_{P\,t}}_{PM10}$$





We formulate a multistage stochastic optimization problem

We set a stochastic optimal control problem

$$\min_{\boldsymbol{U} \in \mathbb{U}} \mathbb{E}\Big(\sum_{t=0}^{T} Cost_t(\boldsymbol{E}^{Supply}_{Station\,t} + \boldsymbol{E}^{Supply}_{Battery\,t}) + \lambda \boldsymbol{C}^{In}_{P\;t} \Big) \quad \Big\} \text{ Objective}$$

$s.t$

$$\boldsymbol{S}oc_{t+1} = \boldsymbol{S}oc_t - \frac{1}{\rho_{dc}} \boldsymbol{U}^{B-}_t + \rho_c(\boldsymbol{U}^{B+}_t + \boldsymbol{E}^{Surplus}_{Train\quad t}) \quad \Big\} \text{ Battery dynamics}$$

$$\left.\begin{aligned}
\boldsymbol{C}^{In}_{P\;t+1} &= \boldsymbol{C}^{In}_{P\;t} + \frac{\boldsymbol{d}^{Ventil}_t}{V}(\boldsymbol{C}^{Out}_{P\quad t} - \boldsymbol{C}^{In}_{P\;t}) \\
&+ \frac{\boldsymbol{\rho}^R_t}{S} \boldsymbol{C}^{Floor}_{P\qquad t} - \frac{\boldsymbol{\rho}^D_t}{V} \boldsymbol{C}^{In}_{P\;t} + \frac{\boldsymbol{Q}_{P\,t}}{V} \\
\boldsymbol{C}^{Floor}_{P\qquad t+1} &= \boldsymbol{C}^{Floor}_{P\qquad t} + \frac{\boldsymbol{\rho}^D_t}{S} \boldsymbol{C}^{In}_{P\;t} - \frac{\boldsymbol{\rho}^R_t}{V} \boldsymbol{C}^{Floor}_{P\qquad t}
\end{aligned}\right\} \text{ Particles dynamics}$$

$$\left.\begin{aligned}
\boldsymbol{U}^{B+}_t + \boldsymbol{E}^{Surplus}_{Train\quad t} &= \boldsymbol{E}^{Supply}_{Battery\,t} + \boldsymbol{E}^{Recovered}_{Train\qquad t} \\
\boldsymbol{E}^{Demand}_{Station\quad t} &= \boldsymbol{E}^{Supply}_{Station\,t} + \boldsymbol{U}^{B-}_t
\end{aligned}\right\} \text{ Supply/demand balance}$$

$$\left.\begin{aligned}
Soc_{Min} \leq \boldsymbol{S}oc_t \leq Soc_{Max} \\
\boldsymbol{C}^{In}_{P\;t} \geq 0
\end{aligned}\right\} \text{ Constraints}$$

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Summary of the equations

- State of the system: $\boldsymbol{X}_t = \begin{pmatrix} \boldsymbol{Soc}_t \\ \boldsymbol{C^{In}_P}_t \\ \boldsymbol{C^{Floor}_P}_t \end{pmatrix}$
- Controls: $\boldsymbol{U}_t = \begin{pmatrix} \boldsymbol{U}^{B-}_t \\ \boldsymbol{U}^{B+}_t \\ \boldsymbol{d}^{Ventil}_t \end{pmatrix}$,
- Dynamics:

$$\boldsymbol{X}_{t+1} = f_t(\boldsymbol{X}_t, \boldsymbol{U}_t, \boldsymbol{W}_{t+1})$$

- We add the non-anticipativity constraints:

$$\sigma(\boldsymbol{U}_t) \subset \sigma(\boldsymbol{W}_1, ..., \boldsymbol{W}_t)$$

Compact formulation of a stochastic optimal control problem

We obtain a stochastic optimization problem consistent with the general form of a time additive cost stochastic optimal control problem:

$$\min_{\boldsymbol{X},\boldsymbol{U}} \mathbb{E}\left(\sum_{t=0}^{T-1} L_t(\boldsymbol{X}_t, \boldsymbol{U}_t, \boldsymbol{W}_{t+1}) + K(\boldsymbol{X}_T)\right)$$

$$\begin{aligned} s.t. \quad \boldsymbol{X}_{t+1} &= f_t(\boldsymbol{X}_t, \boldsymbol{U}_t, \boldsymbol{W}_{t+1}) \\ \sigma(\boldsymbol{U}_t) &\subset \sigma(\boldsymbol{X}_0, \boldsymbol{W}_1, ..., \boldsymbol{W}_t) \\ \boldsymbol{U}_t &\in \mathbb{U}_t \end{aligned}$$

Outline

We are looking for a policy

What is a solution?

In the general case an optimal solution is a function of past uncertainties:

$$\boldsymbol{U}_t \preceq \sigma(\boldsymbol{X}_0, \boldsymbol{W}_1, ..., \boldsymbol{W}_t) \Rightarrow \boldsymbol{U}_t = \pi_t(\boldsymbol{X}_0, \boldsymbol{W}_1, ..., \boldsymbol{W}_t)$$

This is an history-dependent policy

In the Markovian case (noises time independence) it is enough to restrict the search to state feedbacks:

$$\boldsymbol{U}_t = \pi_t(\boldsymbol{X}_t)$$

In the Markovian case we can introduce value functions:

$$\forall x \in \mathbb{X}_t,\ \ V_t(x) = \min_{\pi} \mathbb{E}\Big(\sum_{t'=t}^{T-1} L_{t'}(\boldsymbol{X}_{t'}, \pi_{t'}(\boldsymbol{X}_{t'}), \boldsymbol{W}_{t'+1}) + K(\boldsymbol{X}_T) \Big)$$
$$\text{s.t} \qquad \boldsymbol{X}_t = x \text{ and dynamics}$$

and use Bellman equation

Dynamic programming in the non Markovian case

Dynamic programming in the general case

Bellman equation does not hold in the non Markovian case.
Let $\tilde{\mathbb{P}}$ be the probability s.t $(\boldsymbol{W}_t)_{t \in [|1,T|]}$ are time independent but keep the same marginal laws.

Algorithm

Offline: We produce value functions with Bellman equation using this probability measure:

$$\tilde{V}_t(x) = \min_{u \in \mathbb{U}_t} \mathbb{E}_{\tilde{\mathbb{P}}_t} \Big(L_t(x, u, \boldsymbol{W}_{t+1}) + \tilde{V}_{t+1}(f_t(x, u, \boldsymbol{W}_{t+1})) \Big)$$

Online: We plug the computed value functions as future costs at time t:

$$u_t \in \arg\min_{u \in \mathbb{U}_t} \mathbb{E}_{\tilde{\tilde{\mathbb{P}}}_t} \Big(L_t(x_t, u, \boldsymbol{W}_{t+1}) + \tilde{V}_{t+1}(f_t(x_t, u, \boldsymbol{W}_{t+1})) \Big)$$

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We produce history-dependent controls

With $\tilde{\tilde{\mathbb{P}}}_t$ the probability updating $\boldsymbol{W}_{t+1}$ marginal law taking into account all the past informations: $\forall i \leq t,\ \boldsymbol{W}_i = w_i$.

If the $(\boldsymbol{W}_t)_{t \in 1..T+1}$ are independent the controls are optimal and $\tilde{\tilde{\mathbb{P}}}_t = \tilde{\mathbb{P}}_t$

Stochastic Dynamic Programming suffers the well known "curse of dimensionality".

Model Predictive Control

Rollout algorithms

To avoid value functions computation we can plug a lookahead future cost for a given policy:

$$u_t \in \arg\min_{u \in \mathbb{U}_t} \mathbb{E}_t \Big(L_t(x_t, u, \boldsymbol{W}_{t+1}) + J^{\pi^t}_{t+1}(f_t(x_t, u, \boldsymbol{W}_{t+1})) \Big)$$

It gives the cost of controlling the system in the future according to the given policy:

$$\forall x \in \mathbb{X}_{t+1},\ J^{\pi^t}_{t+1}(x) = \mathbb{E}_t \Big(\sum_{t'=t+1}^{T-1} L_{t'}(\boldsymbol{X}_{t'}, \pi_{t'}(\boldsymbol{X}_{t'}), \boldsymbol{W}_{t'+1}) + K(\boldsymbol{X}_T) \Big)$$

$$\text{s.t} \quad \boldsymbol{X}_{t+1} = x, \text{ and the dynamics}$$

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Model Predictive Control

Choosing π^t in the class of open loop policies minimizing the expected future cost:

$$\forall i \geq t+1,\ \exists \boldsymbol{u_i} \in \mathbb{R}^n,\ \forall x,\ \pi_i^t(x) = \boldsymbol{u_i}$$

$$u_t \in \arg\min_{u \in \mathbb{U}_t} \min_{(\boldsymbol{u_{t+1}},\dots,\boldsymbol{u_{T-1}})} \mathbb{E}_t\Big(L_t(x_t, u, \boldsymbol{W}_{t+1}) + \sum_{t'=t+1}^{T-1} L_{t'}(\boldsymbol{X}_{t'}, u_{t'}, \boldsymbol{W}_{t'+1})\Big)$$

With $\mathbb{E}_t$ replacing noises by forecasts, we obtain a deterministic problem.

Algorithm

Online: At every MPC step t, compute a forecast $(\bar{w}_{t+1}, \dots, \bar{w}_{T+1})$ using the observations $\forall i \leq t,\ \boldsymbol{W}_i = w_i$. Then compute control u_t:

$$u_t \in \arg\min_{u \in \mathbb{U}_t} \min_{(u_{t+1},\dots,u_{T-1})} L_t(x_t, u, \bar{w}_{t+1}) + \sum_{t'=t+1}^{T-1} L_{t'}(x_{t'}, u_{t'}, \bar{w}_{t'+1})$$

MPC is often defined with a rolling horizon.

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Random variables modeling

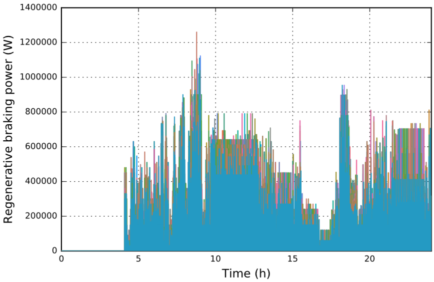
Some random variables are taken deterministic

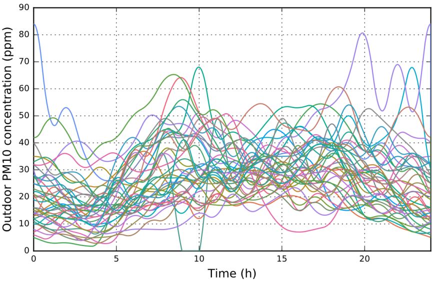
- Outdoor particles concentration : ${C_P^{Out}}_t$
- Regenerative braking : ${E_{Train}^{Available}}_t$
- Station consumption : ${E_{Station}^{Demand}}_t$
- Cost of electricity : $Cost_t$
- Particles generation : ${Q_P}_t$
- Resuspension rate : ${\rho^R}_t$
- Deposition rate : ${\rho^D}_t$

Stochastic models

We consider multiple equiprobable scenarios

Braking energy and outside PM10 concentration every 5s





We deduce discrete marginal laws from these scenarios

Details on the resolution methods

Stochastic Dynamic Programming

We compute value functions every 5s.
We compute a control every 5s.
The algorithm is coded in Julia.

Model Predictive Control

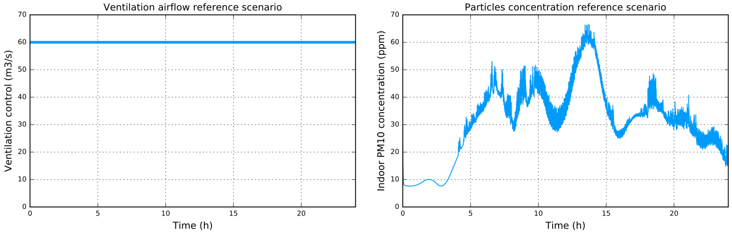
The deterministic problem is linearized, leading to a MILP.
It is solved every 15 min with a 2 hours horizon.
We use two forecast strategies:

- **MPC1**: Expectation of each noise ignoring the noises dependence
- **MPC2**: Scenarios where the next outside PM10 concentration is not too far from the previous one

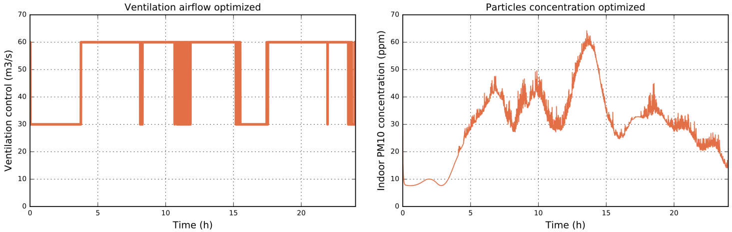
Results

Air quality comparaison

Reference case:

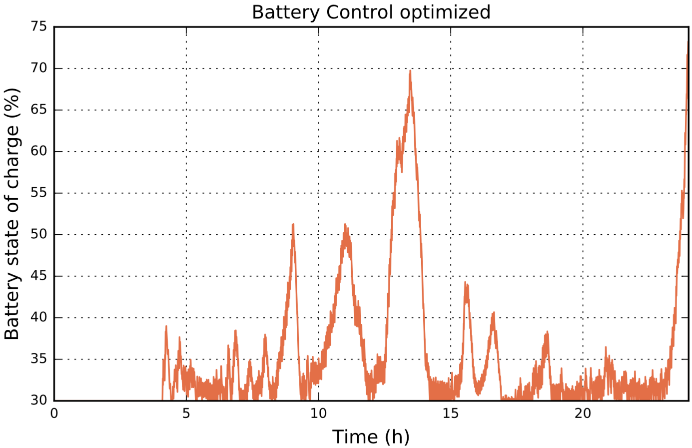


Optimized with SDP:



Battery control over a scenario

Result produced using SDP with a regular day



We achieve energy costs savings of 30%

Assessor: 50 scenarios of 24h with time step = 5 sec

Reference: Energy consumption cost over a day,
without battery and ventilation control

	MPC1	MPC2	SDP
Offline computation time	0	0	12h
Online computation time	[10s,200s]	[10s,200s]	[0s,1s]
Average economic savings	-26.2%	-27.4%	-30.7%

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Conclusion and ongoing work

Our study leads to the following conclusions:

- A battery and a proper ventilation control provide significant economic savings
- SDP provides slightly better results than MPC
- SDP requires more offline computation time, but is quite fast online

We are now focusing on:

- Using other methods to handle more state/control variables (SDDP)
- Taking into account more uncertainty sources
- Calibrating air quality models for a more realistic concentration dynamics behavior

Ultimate goal: apply our methods to laboratory and real size demonstrators