Subway stations energy and air quality management

with stochastic optimization

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Optimization for subway stations

Paris urban railway transport system energy consumption = $\frac{1}{3}$ 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
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
   - Methods
   - Results

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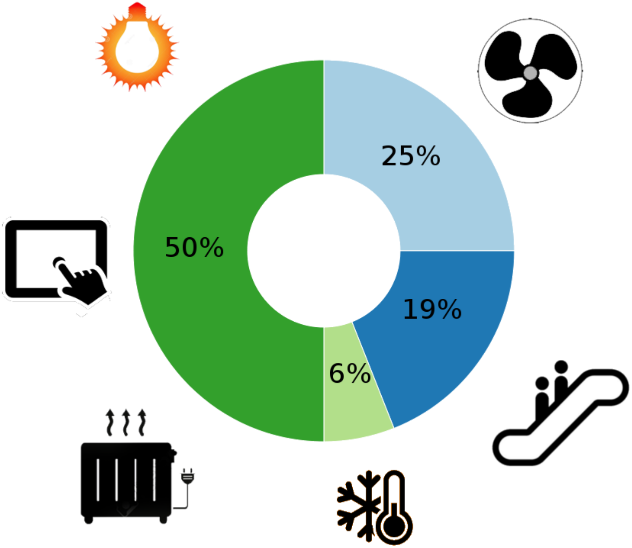
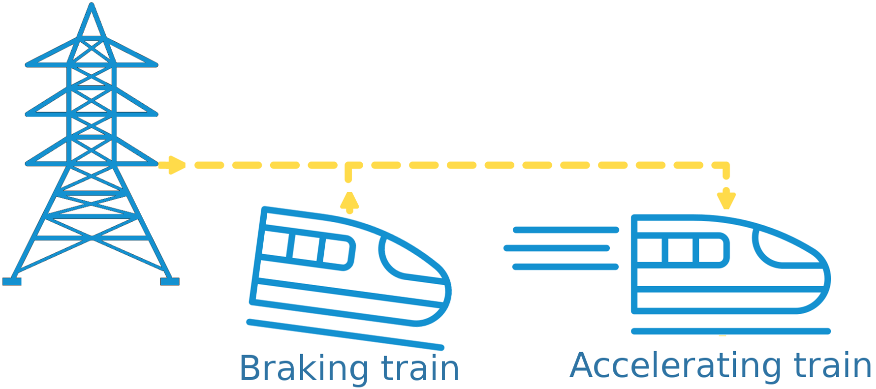
Energy

Subway stations typical energy consumption



Subway stations have unexploited energy ressources



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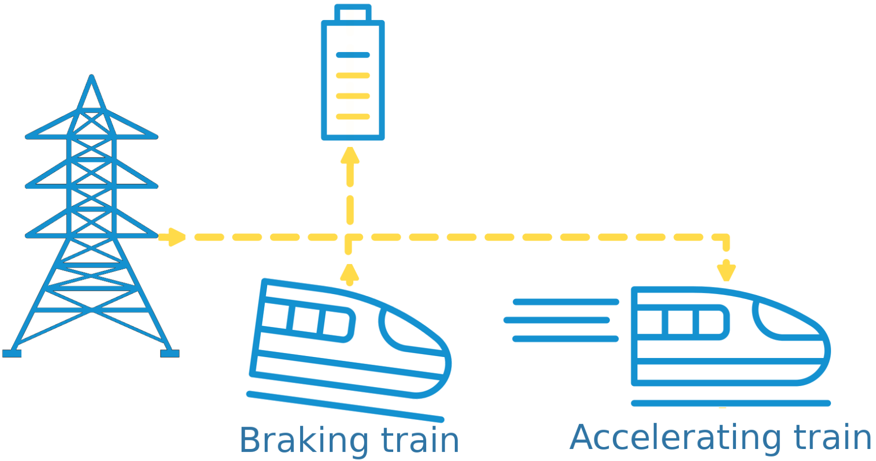
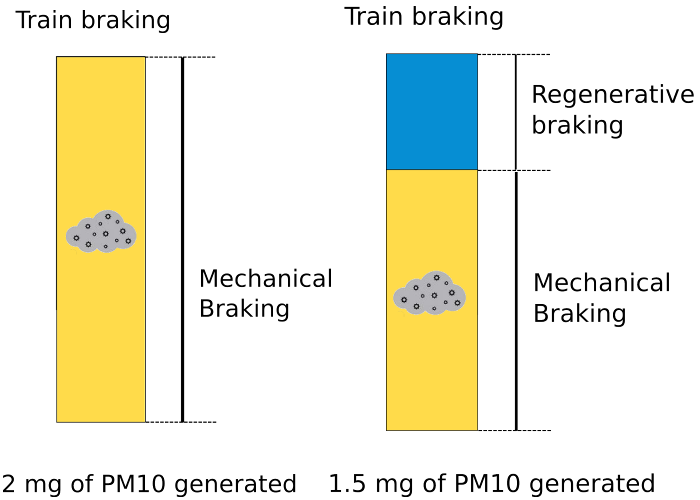
Energy recovery requires a buffer



Air quality

Subways arrivals generate particulate matters

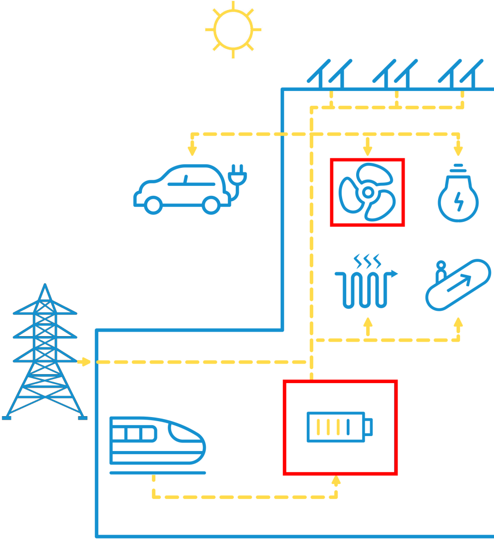
Rails/brakes wear and resuspension increase PM10 concentration



Recovering energy improves air quality

Energy/Air management system

Subway station microgrid concept



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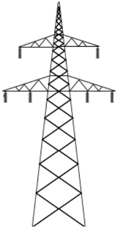
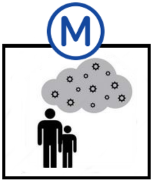
Objective: We want to minimize energy consumption and particles concentration

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

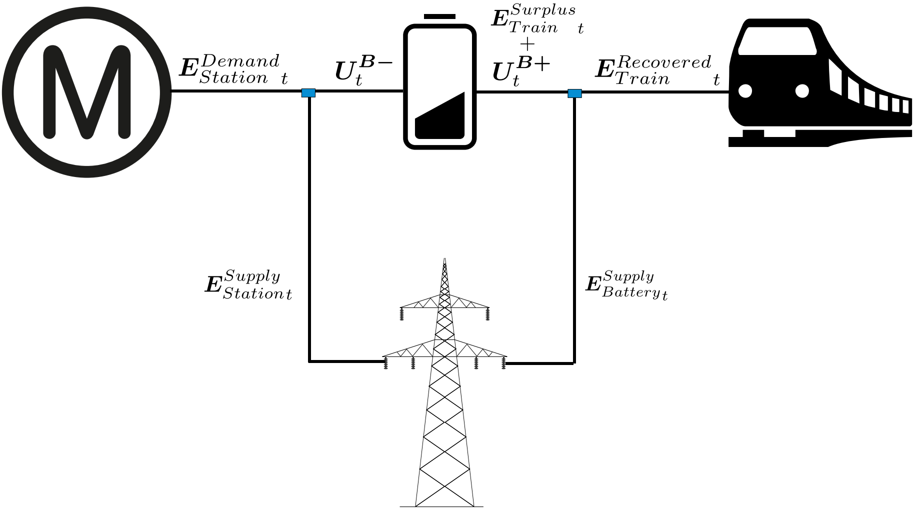
$$\sum_{t=0}^{T} Cost_t \underbrace{\left(E^{Supply}_{Station\,t} + E^{Supply}_{Battery\,t}\right)}_{Grid\ \ supply} + \lambda \underbrace{C^{In}_{P\ t}}_{PM10}$$





We should control the system every 5 seconds

We control the battery



Energy system equations

State of charge dynamics:

$$\boldsymbol{Soc}_{t+1} = \boldsymbol{Soc}_t - \underbrace{\frac{1}{\rho_{dc}} \boldsymbol{U}_t^{B-}}_{Discharge} + \underbrace{\rho_c(\boldsymbol{U}_t^{B+} + \boldsymbol{E}^{Surplus}_{Train\ \ t})}_{Charge}$$

We have constraints on the battery level to ensure good ageing:

$$Soc_{Min} \leq \boldsymbol{Soc}_t \leq Soc_{Max}$$

We ensure the supply/demand balance at station and battery nodes:

$$\underbrace{\boldsymbol{U}_t^{B+} + \boldsymbol{E}^{Surplus}_{Train\ \ t}}_{Charge} = \underbrace{\boldsymbol{E}^{Supply}_{Battery\ t}}_{Grid\ \ supply} + \underbrace{\boldsymbol{E}^{Recovered}_{Train\ \ t}}_{E^{Available}_{Train} - \boldsymbol{E}^{Excess}_{Train}}$$

$$\underbrace{E^{Demand}_{Station\ \ t}}_{Station\ \ consumption} = \underbrace{\boldsymbol{E}^{Supply}_{Station\ t}}_{Grid\ \ supply} + \underbrace{\boldsymbol{U}_t^{B-}}_{Discharge}$$

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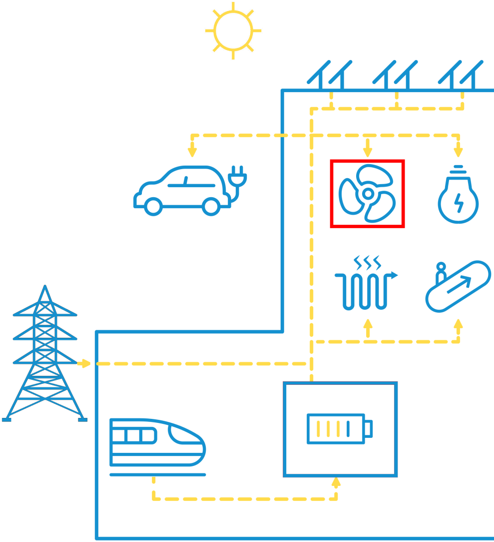
We control the station ventilations



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Particles concentration dynamics

In the indoor air

$$C^{In}_{P\,t+1} = C^{In}_{P\,t} + \underbrace{\frac{d^{Ventil}_t}{V}(C^{Out}_P - C^{In}_P)}_{In/Out\ \ exchange}$$

$$+ \underbrace{\frac{\rho^R_t}{S} * C^{Floor}_{P\,t}}_{Resuspension} - \underbrace{\frac{\rho^D_t}{V} * C^{In}_{P\,t}}_{Deposition} + \underbrace{\frac{Q_{P\,t}}{V}}_{Generation}$$

and on the floor

$$C^{Floor}_{P\,t+1} = C^{Floor}_{P\,t} + \underbrace{\frac{\rho^D_t}{S} * C^{In}_{P\,t}}_{Deposition} - \underbrace{\frac{\rho^R_t}{V} * C^{Floor}_{P\,t}}_{Resuspension}$$

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We have many uncertainties

Let $\boldsymbol{W}_t$ the random variables vector of uncertainties at time 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 : $\boldsymbol{\rho}^D{}_t$
- Outdoor particles concentration : $\boldsymbol{C}_P^{Out}{}_t$

Summary of the equations

State of the system: $\boldsymbol{X}_t = \begin{pmatrix} \boldsymbol{Soc}_t \\ \boldsymbol{C}_P^{In}{}_t \\ \boldsymbol{C}_P^{Floor}{}_t \end{pmatrix}$

Controls: $\boldsymbol{U}_t = \begin{pmatrix} \boldsymbol{U}_t^{B-} \\ \boldsymbol{U}_t^{B+} \\ \boldsymbol{d}_t^{Ventil} \end{pmatrix}$,

And the dynamics:

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

We add the non-anticipativity constraints:

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

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We set a stochastic optimal control problem

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

s.t

$$Soc_{t+1} = Soc_t - \frac{1}{\rho_{dc}} U^{B-}_t + \rho_c(U^{B+}_t + E^{Surplus}_{Train\;t})$$ Battery dynamics

$$C^{In}_{P\,t+1} = C^{In}_{P\,t} + \frac{d^{Ventil}_t}{V}(C^{Out}_{P\;t} - C^{In}_{P\,t})$$
$$+ \frac{\rho^R_t}{S} C^{Floor}_{P\;t} - \frac{\rho^D_t}{V} C^{In}_{P\,t} + \frac{Q_{P\,t}}{V}$$
$$C^{Floor}_{P\;t+1} = C^{Floor}_{P\;t} + \frac{\rho^D_t}{S} C^{In}_{P\,t} - \frac{\rho^R_t}{V} C^{Floor}_{P\;t}$$
Particles dynamics

$$U^{B+}_t + E^{Surplus}_{Train\;t} = E^{Supply}_{Battery\,t} + E^{Recovered}_{Train\;t}$$
$$E^{Demand}_{Station\;t} = E^{Supply}_{Station\,t} + U^{B-}_t$$
Supply/demand balance

$$Soc_{Min} \leq Soc_t \leq Soc_{Max}$$
$$C^{In}_{P\,t} \geq 0$$
Constraints

Compact stochastic optimal control problem

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

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

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

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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 limit the search to state feedbacks:

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

Backward induction: Stochastic Dynamic Programming

In the Markovian case we introduce the value functions:

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

$$\text{s.t} \quad \boldsymbol{X}_t = x \text{ and dynamics}$$

Algorithm

Offline: We compute the value functions by backward induction using Bellman equation, knowing the final cost:

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

Online: We compute the control at time t using the equation:

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

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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Remarks

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

It is a tool to produce history-dependent controls.

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".

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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:

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

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

Model Predictive Control

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

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

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

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.

Outline

Random variables modeling

Some random variables are taken deterministic

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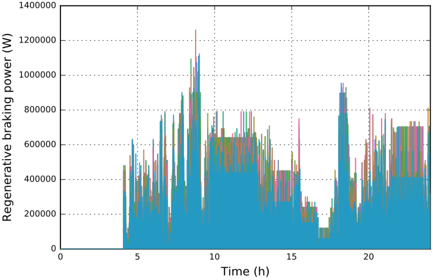
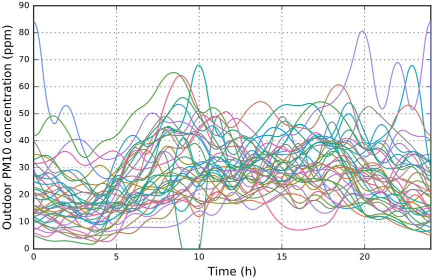
- Station consumption : $\mathbf{E}_{Station}^{Demand}{}_{t}$
- Cost of electricity : $\mathbf{C}ost_t$
- Particles generation : $\mathbf{Q}_{P\,t}$
- Resuspension rate : $\rho^{R}{}_{t}$
- Deposition rate : $\rho^{D}{}_{t}$
- Outdoor particles concentration : $\mathbf{C}_{P}^{Out}{}_{t}$

Stochastic models

We have multiple equiprobable scenarios:

Braking energy and outside PM10 concentration every 5s





We deduce the discrete marginal laws from these scenarios.

Details on the methods

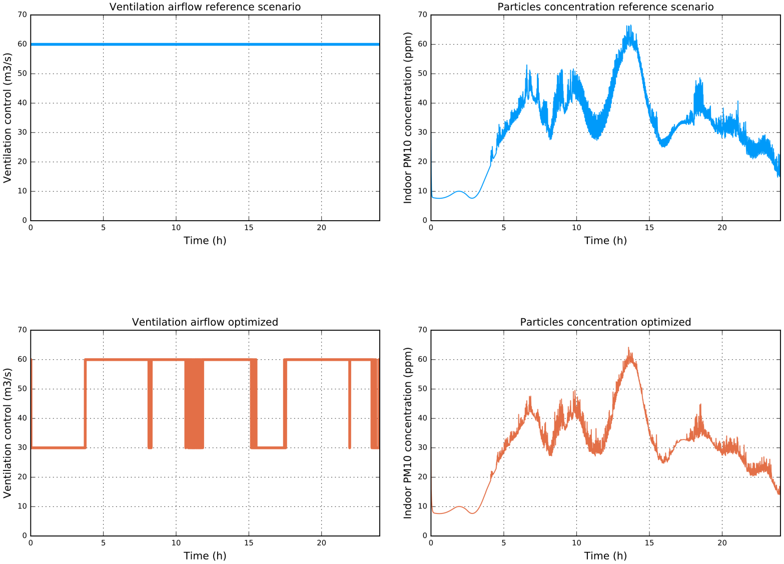
Stochastic Dynamic Programming:
We compute value functions every 5s. We can compute a control every 5s. The algorithm is coded in Julia.

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 forecasts strategies:

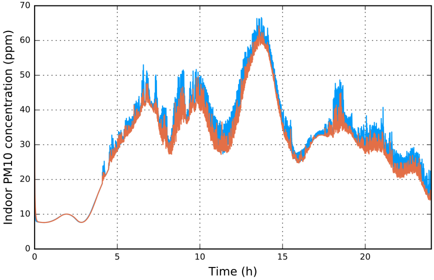
- **MPC1**: Expectation of each noise ignoring the noises dependence
- **MPC2**: Scenarios where the next outside PM10 concentration is not too far from the previous one

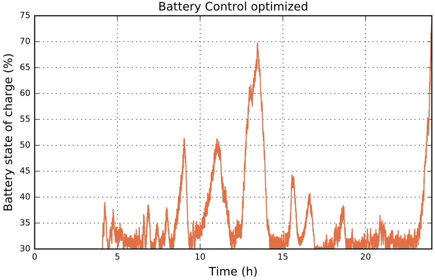
Results

Air quality simulation



Energy recovery lower peaks





Energetic results

Assessor: 50 scenarios of 24h with time step = 5 sec
Reference: Energy consumption cost over a day without battery and ventilation control

	MPC1	SDP
Offline comp. time	0	12h
Online comp. time	[10s,200s]	[0s,1s]
Economic savings	-26%	-31%

On just one assessment scenario for the moment:

- **MPC1**: -22.3%
- **MPC2**: -22.7%
- **SDP**: -26.8%

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Conclusion & 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 but requires more offline computation time

We are now focusing on:

- Using other methods that handle more state/control variables
- 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