

Subway stations energy and air quality management

using discrete time stochastic optimal control

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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 resources 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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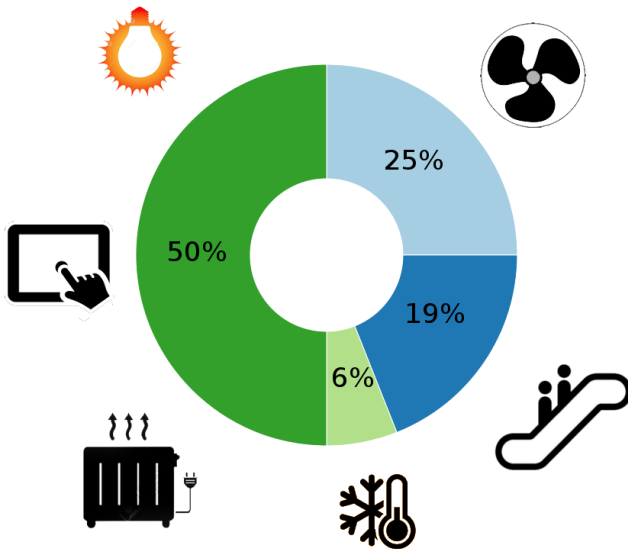
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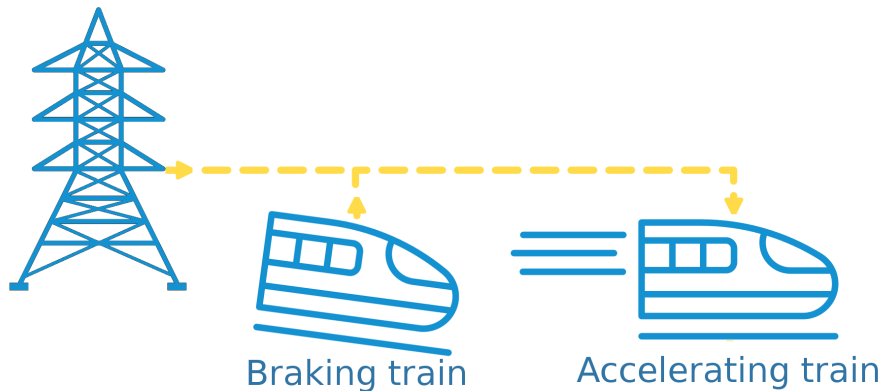
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Energy

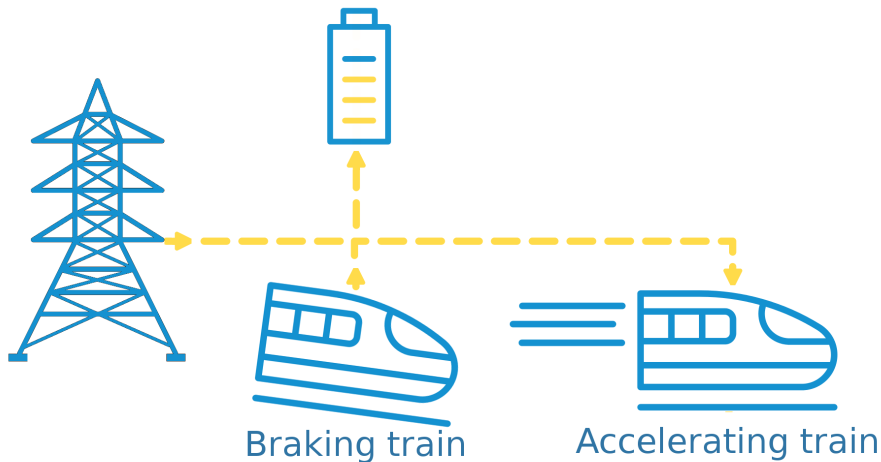
Subway stations typical energy consumption



Subway stations have unexploited energy resources



Energy recovery requires a buffer

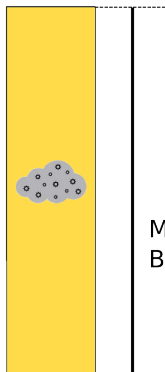


Air quality

Subways arrivals generate particulate matters

Rails/brakes wear and resuspension increase PM10 concentration

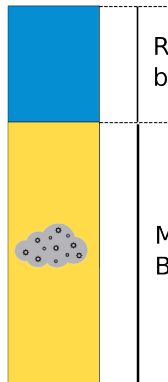
Train braking



Mechanical
Braking

2 mg of PM10 generated

Train braking



Regenerative
braking

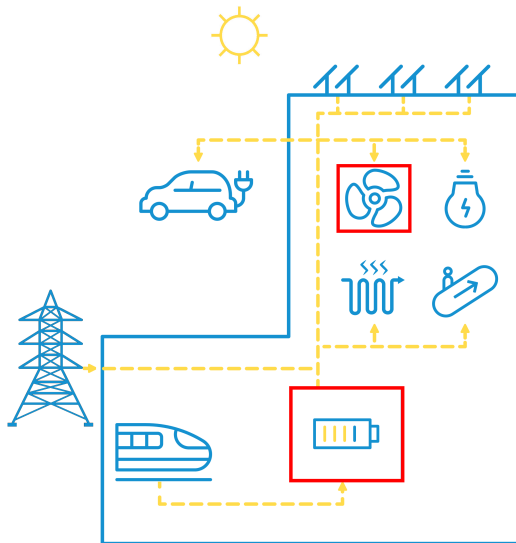
Mechanical
Braking

1.5 mg of PM10 generated

Recovering energy improves air quality

Energy/Air management system

Subway station microgrid concept

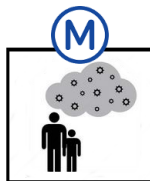
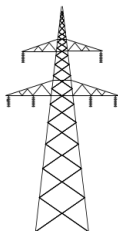


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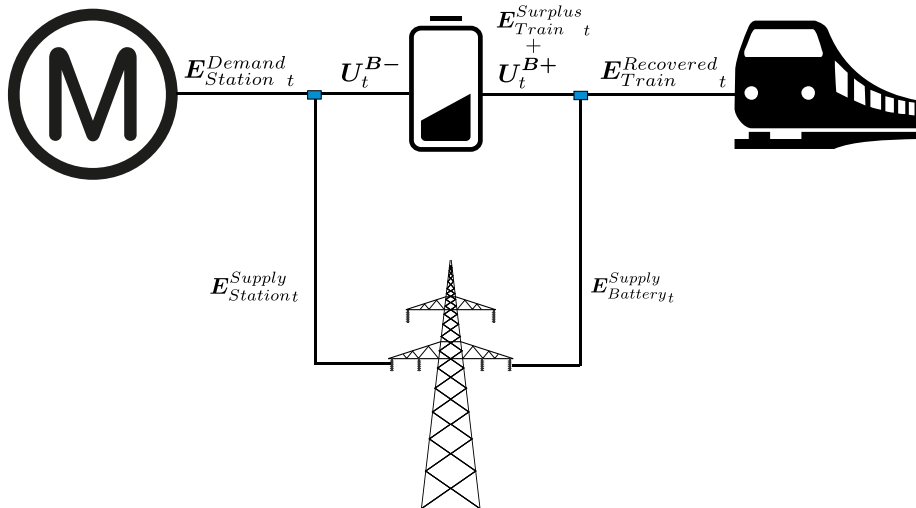
Objective: We want to minimize energy consumption and particles concentration

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

$$\sum_{t=0}^T \text{Cost}_t \underbrace{(E_{\text{Station } t}^{\text{Supply}} + E_{\text{Battery } t}^{\text{Supply}})}_{\text{Grid supply}} + \lambda \underbrace{C_{P_t}^{\text{In}}}_{\text{PM10}}$$



We control the battery



We have many uncertainties

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

- 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 : ρ^R_t
- Deposition rate : ρ^D_t

We set a stochastic optimal control problem

$$\min_{\mathbf{U} \in \mathcal{U}} \mathbb{E} \left(\sum_{t=0}^T \text{Cost}_t (\mathbf{E}_{\text{Station } t}^{\text{Supply}} + \mathbf{E}_{\text{Battery } t}^{\text{Supply}}) + \lambda \mathbf{C}_{P t}^{\text{In}} \right) \quad \left. \vphantom{\min_{\mathbf{U} \in \mathcal{U}}} \right\} \text{Objective}$$

s.t

$$\mathbf{Soc}_{t+1} = \mathbf{Soc}_t - \frac{1}{\rho_{dc}} \mathbf{U}_t^{B-} + \rho_c (\mathbf{U}_t^{B+} + \mathbf{E}_{\text{Train } t}^{\text{Surplus}}) \quad \left. \vphantom{\mathbf{Soc}_{t+1}} \right\} \text{Battery dynamics}$$

$$\begin{aligned} \mathbf{C}_{P t+1}^{\text{In}} &= \mathbf{C}_{P t}^{\text{In}} + \frac{\mathbf{d}_t^{\text{Ventil}}}{V} (\mathbf{C}_{P t}^{\text{Out}} - \mathbf{C}_{P t}^{\text{In}}) \\ &+ \frac{\rho_t^R}{S} \mathbf{C}_{P t}^{\text{Floor}} - \frac{\rho_t^D}{V} \mathbf{C}_{P t}^{\text{In}} + \frac{\mathbf{Q}_{P t}}{V} \\ \mathbf{C}_{P t+1}^{\text{Floor}} &= \mathbf{C}_{P t}^{\text{Floor}} + \frac{\rho_t^D}{S} \mathbf{C}_{P t}^{\text{In}} - \frac{\rho_t^R}{V} \mathbf{C}_{P t}^{\text{Floor}} \end{aligned} \quad \left. \vphantom{\mathbf{C}_{P t+1}^{\text{In}}} \right\} \text{Particles dynamics}$$

$$\mathbf{U}_t^{B+} + \mathbf{E}_{\text{Train } t}^{\text{Surplus}} = \mathbf{E}_{\text{Battery } t}^{\text{Supply}} + \mathbf{E}_{\text{Train } t}^{\text{Recovered}} \quad \left. \vphantom{\mathbf{U}_t^{B+}} \right\} \text{Supply/demand balance}$$

$$\mathbf{E}_{\text{Station } t}^{\text{Demand}} = \mathbf{E}_{\text{Station } t}^{\text{Supply}} + \mathbf{U}_t^{B-}$$

$$\mathbf{Soc}_{\text{Min}} \leq \mathbf{Soc}_t \leq \mathbf{Soc}_{\text{Max}}$$

$$\mathbf{C}_{P t}^{\text{In}} \geq 0$$

$\left. \vphantom{\mathbf{C}_{P t}^{\text{In}}} \right\} \text{Constraints}$

Summary of the equations

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

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

And the dynamics:

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

We add the non-anticipativity constraints:

$$\mathbf{U}_t \preceq \sigma(\mathbf{W}_1, \dots, \mathbf{W}_t)$$

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:

$$\min_{\mathbf{x}, \mathbf{u}} \mathbb{E} \left(\sum_{t=0}^{T-1} L_t(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_{t+1}) + K(\mathbf{x}_T) \right)$$

$$\begin{aligned} s.t. \quad & \mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_{t+1}) \\ & \mathbf{u}_t \preceq \sigma(\mathbf{x}_0, \mathbf{w}_1, \dots, \mathbf{w}_t) \\ & \mathbf{u}_t \in \mathbb{U}_t \end{aligned}$$

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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**:

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

This is an **history-dependent policy**

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

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

In the **Markovian case** we can introduce **value functions**:

$$\begin{aligned} \forall \mathbf{x} \in \mathbb{X}_t, \quad V_t(\mathbf{x}) = \min_{\pi} \mathbb{E} \left(\sum_{t'=t}^{T-1} L_{t'}(\mathbf{X}_{t'}, \pi_{t'}(\mathbf{X}_{t'}), \mathbf{W}_{t'+1}) + K(\mathbf{X}_T) \right) \\ \text{s.t.} \quad \mathbf{X}_t = \mathbf{x} \text{ and dynamics} \end{aligned}$$

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 $(\mathbf{W}_t)_{t \in [1, T]}$ are **time independent** but keep the **same marginal laws**.

Algorithm

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

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

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

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

We produce history-dependent controls

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

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

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**:

$$u_t \in \arg \min_{u \in \mathbb{U}_t} \mathbb{E}_t \left(L_t(x_t, u, \mathbf{w}_{t+1}) + J_{t+1}^{\pi^t}(f_t(x_t, u, \mathbf{w}_{t+1})) \right)$$

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

$$\forall x \in \mathbb{X}_{t+1}, J_{t+1}^{\pi^t}(x) = \mathbb{E}_t \left(\sum_{t'=t+1}^{T-1} L_{t'}(\mathbf{x}_{t'}, \pi_{t'}(\mathbf{x}_{t'}), \mathbf{w}_{t'+1}) + K(\mathbf{x}_T) \right)$$

s.t $\mathbf{x}_{t+1} = x$, and the dynamics

Model Predictive Control

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

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

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

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

Algorithm

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

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

MPC is often defined with a rolling horizon.

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Random variables modeling

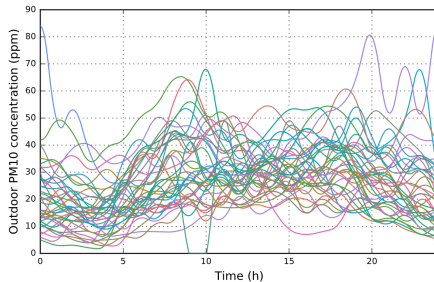
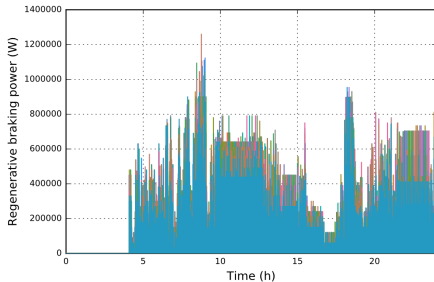
Some random variables are taken deterministic

- Outdoor particles concentration : $C_P^{Out}_t$
- Regenerative braking : $E_{Train}^{Available}_t$
- Station consumption : $E_{Station}^{Demand}_t$
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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:

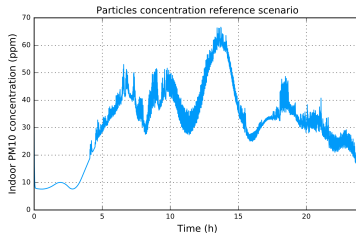
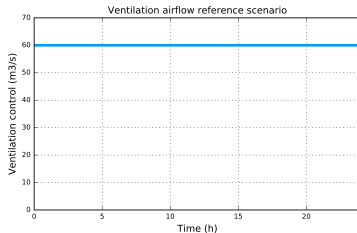
The deterministic problem is linearized leading to a MILP. It is solved every 15 min with a 2 hours horizon. We use two forecasts strategies:

- **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

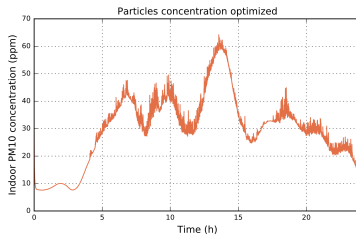
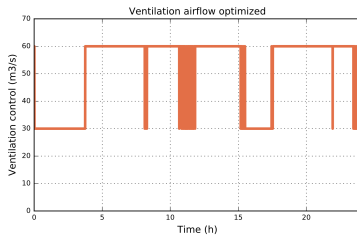
Results

Air quality comparison

Reference case:

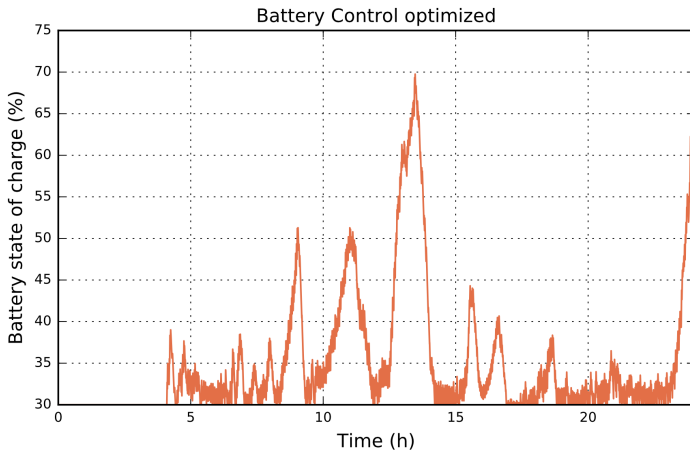


Optimized with SDP:



Battery control over a scenario

Result produced using SDP with a regular day



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	MPC2	SDP
Offline comp. time	0	0	12h
Online comp. time	[10s,200s]	[10s,200s]	[0s,1s]
Av. economic savings	-26.2%	-27.4%	-30.7%

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 (SDDP, RL...)
- 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