Optimization of an urban district microgrid

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(*presentation by F. Pacaud at the PGMO Days 2016*)

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École des Ponts
ParisTech

efficacity

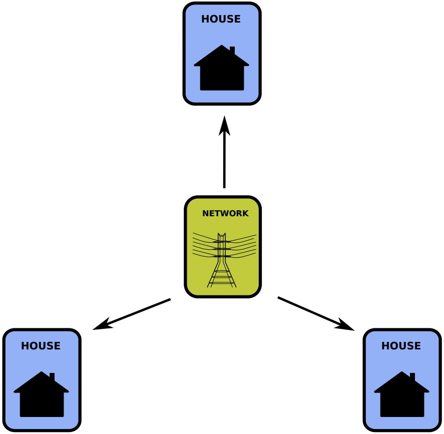
A partnership between mathematicians and thermicians

- Efficacity is a research institute for energy transition — an original mix of companies and academic researchers

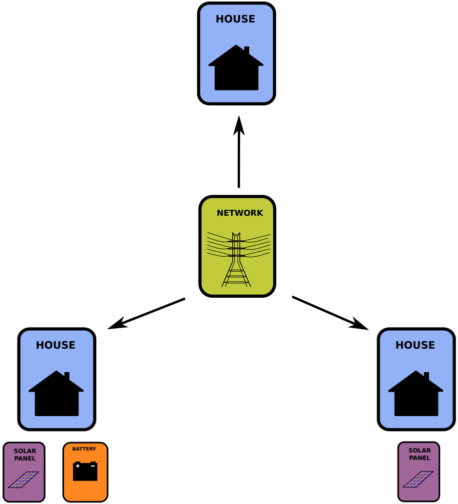
- This presentation sums up a common work between CERMICS and Efficacity

- This cooperation develops optimization algorithms for real problems concerning the energy transition

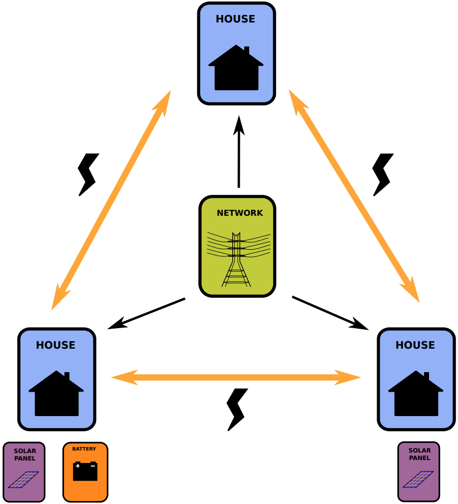
Usually houses import electricity from the grid



But more and more houses are equipped with solar panel



Is it worth to add a local grid to exchange electricity?



Is it worth to connect different houses together inside a district?

Challenges:

- Handle electrical exchanges between houses

We turn to mathematical optimization to answer the question

Outline of the presentation

A brief recall of the single house problem

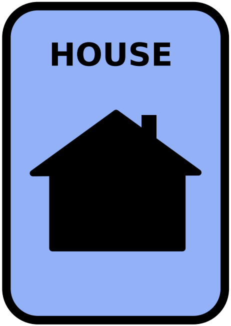
Optimization problem for a district

Numerical resolution

Conclusions and perspectives

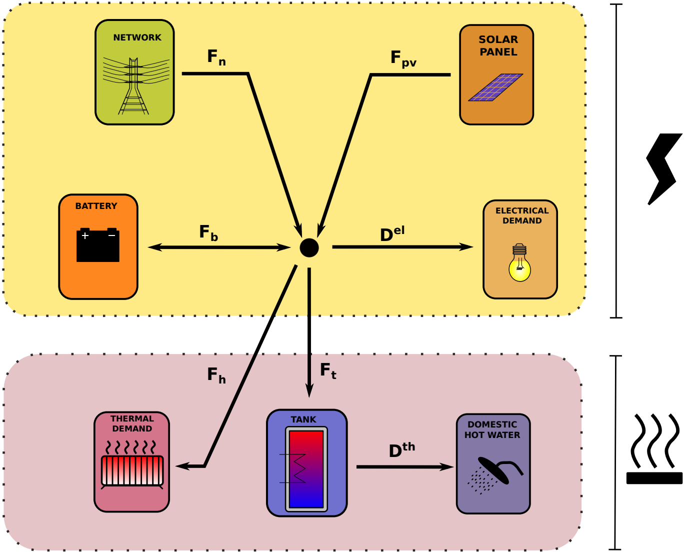
Outline of the presentation

Two goals for the control of a house

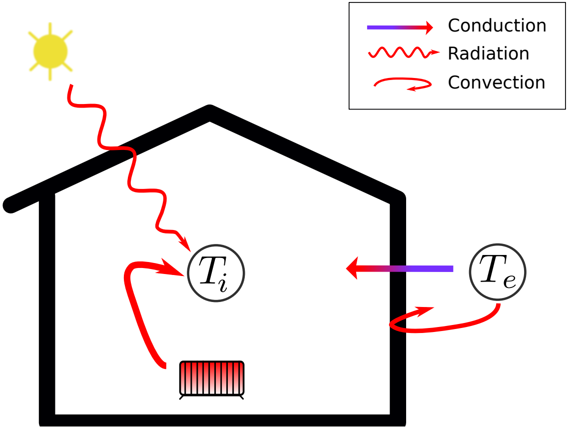


- Satisfy thermal comfort
- Optimize operational costs

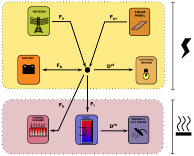
For each house, we consider the electrical system. . .

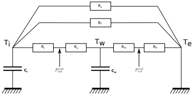


...and the thermal enveloppe



We introduce states, controls and noises

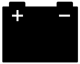




- **Stock variables** $X_t = \left(B_t, H_t, \theta_t^i, \theta_t^w\right)$
  - B_t, battery level (kWh)
  - H_t, hot water storage (kWh)
  - θ_t^i, inner temperature ($^\circ C$)
  - θ_t^w, wall's temperature ($^\circ C$)
- **Control variables** $U_t = \left(F_{B,t}^+, F_{B,t}^-, F_{T,t}, F_{H,t}\right)$
  - $F_{B,t}^+$, energy stored in the battery
  - $F_{B,t}^-$, energy taken from the battery
  - $F_{T,t}$, energy used to heat the hot water tank
  - $F_{H,t}$, thermal heating
- **Uncertainties** $W_t = \left(D_t^E, D_t^{DHW}, P_t^{ext}, \theta_t^e\right)$
  - D_t^E, electrical demand (kW)
  - D_t^{DHW}, domestic hot water demand (kW)
  - P_t^{ext}, external radiations (kW)
  - θ_t^e, external temperature ($^\circ C$)

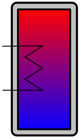
Discrete time state equations

So we have the four state equations (all linear):



$$B_{t+1} = \alpha_B B_t + \Delta T \Big(\rho_c F^{+}_{B,t} - \frac{1}{\rho_d} F^{-}_{B,t} \Big)$$

$$H_{t+1} = \alpha_H H_t + \Delta T \big[F_{T,t} - D^{DHW}_t \big]$$



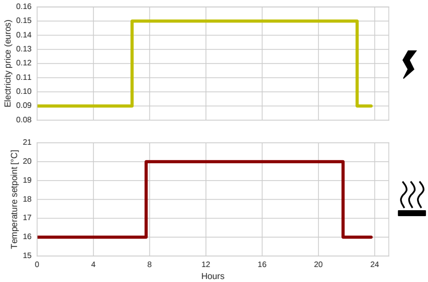
$$\theta^w_{t+1} = \theta^w_t + \frac{\Delta T}{c_m} \left[\frac{\theta^i_t - \theta^w_t}{R_i + R_s} + \frac{\theta^e_t - \theta^w_t}{R_m + R_e} + \gamma F_{H,t} + \frac{R_i}{R_i + R_s} P^{int}_t + \frac{R_e}{R_e + R_m} P^{ext}_t \right]$$

$$\theta^i_{t+1} = \theta^i_t + \frac{\Delta T}{c_i} \left[\frac{\theta^w_t - \theta^i_t}{R_i + R_s} + \frac{\theta^e_t - \theta^i_t}{R_v} + \frac{\theta^e_t - \theta^i_t}{R_f} + (1 - \gamma) F_{H,t} + \frac{R_s}{R_i + R_s} P^{int}_t \right]$$

which will be denoted:

$$\boxed{X_{t+1} = f_t(X_t, U_t, W_{t+1})}$$

Prices and temperature setpoints vary along time



- $T_f = 24\text{h}$, $\Delta T = 15\text{mn}$
- Electricity peak and off-peak hours
- $\pi_t^E = 0.09$ or 0.15 euros/kWh
- Temperature set-point $\bar{\theta}_t^i = 16^\circ C$ or $20^\circ C$

The costs we have to pay

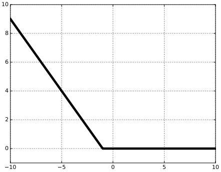
- Cost to import electricity from the network

$$-\underbrace{b_t^E \max\{0, -F_{NE,t+1}\}}_{\text{selling}} + \underbrace{\pi_t^E \max\{0, F_{NE,t+1}\}}_{\text{buying}}$$

where we define the recourse variable (electricity balance):

$$\underbrace{F_{NE,t+1}}_{Network} = \underbrace{D_{t+1}^E}_{Demand} + \underbrace{F_{B,t}^+ - F_{B,t}^-}_{Battery} + \underbrace{F_{H,t}}_{Heating} + \underbrace{F_{T,t}}_{Tank} - \underbrace{F_{pv,t}}_{Solar\ \ panel}$$

- Virtual Cost of thermal discomfort: $\kappa_{th}(\underbrace{\theta_t^i - \bar{\theta}_t^i}_{\text{deviation from setpoint}})$



κ_{th}
Piecewise linear cost
Penalize temperature if
below given setpoint

Instantaneous and final costs for a single house

- The instantaneous convex costs are

$$L_t(X_t, U_t, W_{t+1}) = \underbrace{-b_t^E \max\{0, -F_{NE,t+1}\}}_{buying} + \underbrace{\pi_t^E \max\{0, F_{NE,t+1}\}}_{selling} + \underbrace{\kappa_{th}(\theta_t^i - \bar{\theta}_t^i)}_{discomfort}$$

- We add a final linear cost

$$K(X_{T_f}) = -\pi^H H_{T_f} - \pi^B B_{T_f}$$

to avoid empty stocks at the final horizon T_f

That gives the following stochastic optimization problem

$$\min_{X,U} \quad J(X,U) = \mathbb{E}\left[\sum_{t=0}^{T_f-1} \underbrace{L_t(X_t, U_t, W_{t+1})}_{instantaneous\ \ cost} + \underbrace{K(X_{T_f})}_{final\ \ cost}\right]$$

$$\begin{aligned}
s.t \quad X_{t+1} = f_t(X_t, U_t, W_{t+1}) & \quad \text{Dynamic} \\
X^\flat \leq X_t \leq X^\sharp & \\
U^\flat \leq U_t \leq U^\sharp & \\
X_0 = X_{ini} & \\
\sigma(U_t) \subset \sigma(W_1, \dots, W_t) & \quad \text{Non-anticipativity}
\end{aligned}$$

This stochastic multistage optimization problem, corresponding to a single house, is solvable using standard Stochastic Dynamic Programming (SDP)

Outline of the presentation

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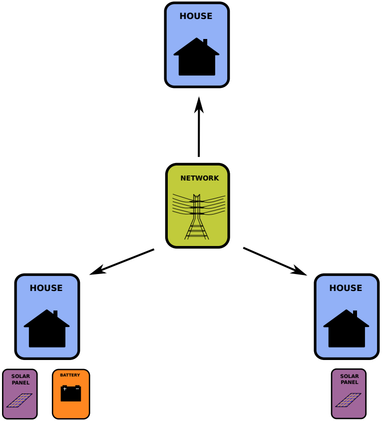
We have three different houses



Our (small) district:

- House 1: solar panel + battery
- House 2: solar panel
- House 3: nothing

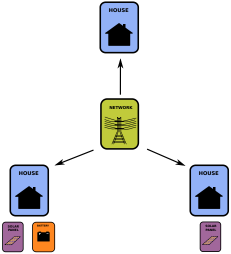
For the three houses:

- 10 stocks (= 4 + 3 + 3)
- 8 controls (= 4 + 2 + 2)
- 8 uncertainties
  (2 uncertainties in common)

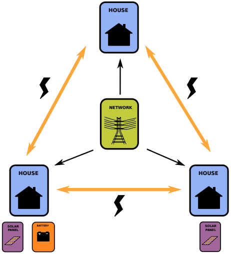
The total demand to the network is bounded:

$$\sum_{k=1}^{3} F^{k}_{NE,t+1} \leq F^{\sharp}_{NE}$$

We want to compare two configurations



No exchange between houses



Exchange in a local grid

How much costs decrease
while allowing houses to exchange energy
through a local grid?

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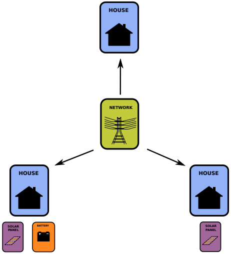
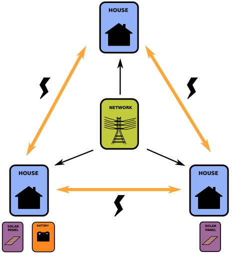


No exchange between houses



Exchange in a local grid

How much costs decrease
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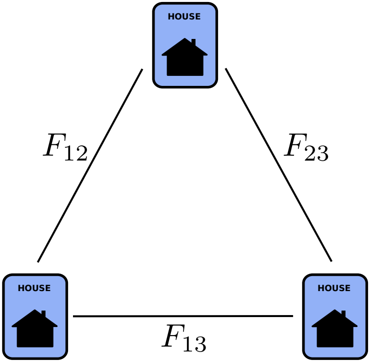
through a local grid?

We show that adding a grid decreases costs by 23 % during summer!

The grid adds three controls to the problem



How to solve this stochastic optimal control problem?

We recall the different parameters of our multistage stochastic problem:

- 96 timesteps (= 4 x 24)
- 10 stocks
- 11 controls
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We will compare two methods that overcome this curse:

1. **Model Predictive Control** (MPC)
2. **Stochastic Dual Dynamic Programming** (SDDP)

Outline of the presentation

A brief recall on Dynamic Programming

Dynamic Programming

μ_t is the probability law of W_t and is being used to estimate expectation and compute **offline** value functions with the backward equation:

$$V_T(x) = K(x)$$

$$V_t(x_t) = \min_{U_t} \mathbb{E}_{\mu_t}\Big[\underbrace{L_t(x_t, U_t, W_{t+1})}_{\text{current cost}} + \underbrace{V_{t+1}\Big(f(x_t, U_t, W_{t+1})\Big)}_{\text{future costs}}\Big]$$

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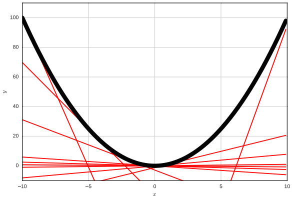
Stochastic Dual Dynamic Programming



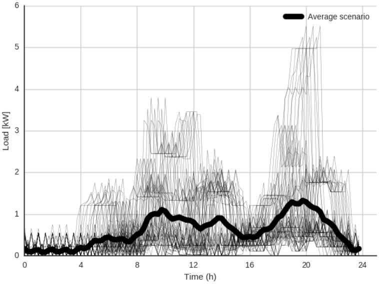
- Convex value functions V_t are approximated as a supremum of a finite set of affine functions
- Affine functions (=cuts) are computed during forward/backward passes, till convergence
- SDDP makes an extensive use of LP solver

$$\widetilde{V}_t(x) = \max_{1 \leq k \leq K} \{\lambda_t^k x + \beta_t^k\} \leq V_t(x)$$

MPC vs SDDP: uncertainties modelling

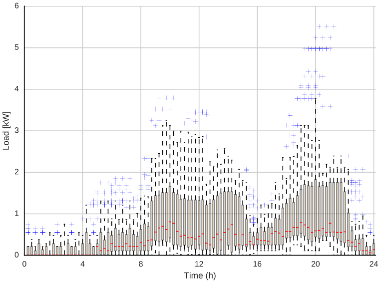
The two algorithms use optimization scenarios to model the uncertainties:

MPC



MPC considers the average...

SDDP



...and SDDP discrete laws

MPC vs SDDP: online resolution

At the beginning of time period $[\tau, \tau + 1]$, do

MPC

- Consider a **rolling horizon** $[\tau, \tau + H[$
- Consider a **deterministic scenario** of demands (forecast) $\left(\overline{W}_{\tau+1}, \dots, \overline{W}_{\tau+H}\right)$
- Solve the **deterministic optimization** problem

$$\min_{X,U} \left[\sum_{t=\tau}^{\tau+H} L_t(X_t, U_t, \overline{W}_{t+1}) + K(X_{\tau+H}) \right]$$

$$\begin{aligned} s.t. \quad X. &= (X_\tau, \dots, X_{\tau+H}) \\ U. &= (U_\tau, \dots, U_{\tau+H-1}) \\ X_{t+1} &= f(X_t, U_t, \overline{W}_{t+1}) \\ X^\flat &\leq X_t \leq X^\sharp \\ U^\flat &\leq U_t \leq U^\sharp \end{aligned}$$

- Get optimal solution $(U^\#_\tau, \dots, U^\#_{\tau+H})$ over horizon $H = 24h$
- Send only first control $U^\#_\tau$ to assessor, and iterate at time $\tau + 1$

SDDP

- We consider the approximated value functions $\left(\widetilde{V}_t\right)_0^{T_f}$

$$\underbrace{\widetilde{V}_t}_{\text{Piecewise affine functions}} \leq V_t$$

- Solve the **stochastic optimization problem**:

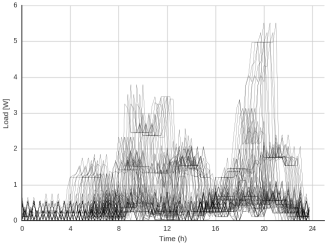
$$\min_{u_\tau} \mathbb{E}_{W_{\tau+1}} \Big[L_\tau(X_\tau, u_\tau, W_{\tau+1}) + \widetilde{V}_{\tau+1}\Big(f_\tau(X_\tau, u_\tau, W_{\tau+1})\Big)\Big]$$

$\Rightarrow$ this problem resumes to solve a LP at each timestep

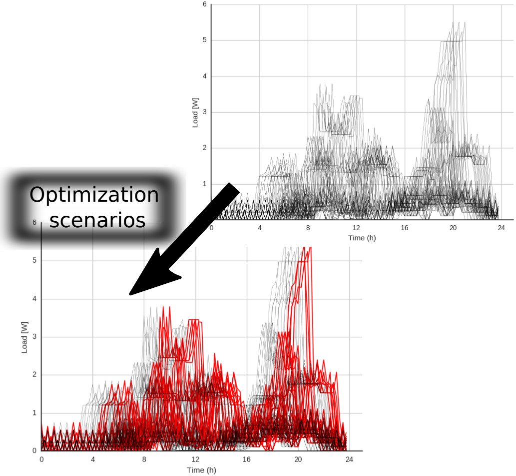
- Get optimal solution $U^\#_\tau$
- Send $U^\#_\tau$ to assessor

Outline of the presentation

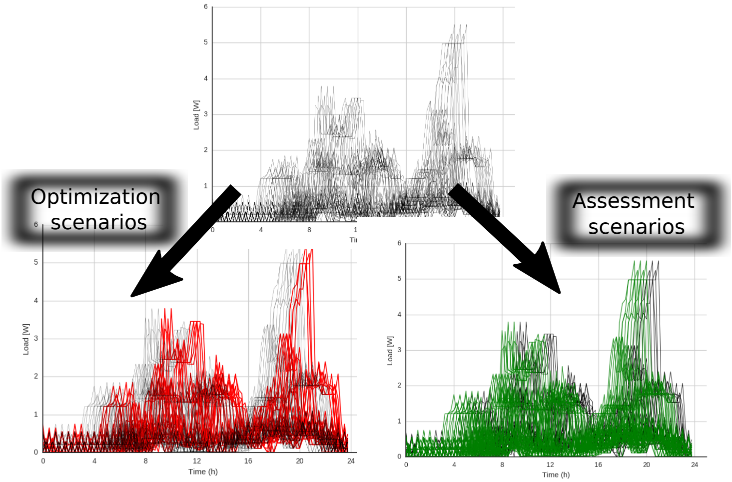
Out-of-sample comparison



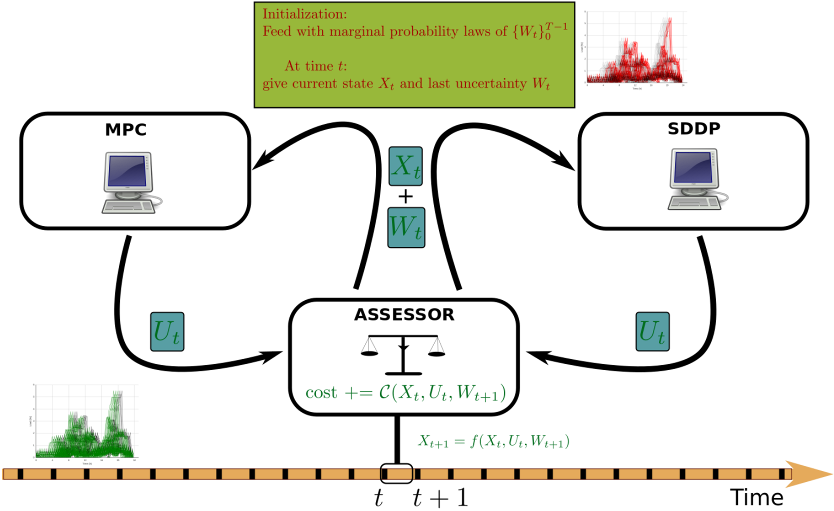
Out-of-sample comparison



Out-of-sample comparison



We compare SDDP and MPC with assessment scenarios



Outline of the presentation

Our stack is deeply rooted in Julia language

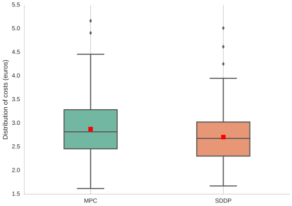
- Modeling Language: `JuMP`
- Open-source SDDP Solver: `StochDynamicProgramming.jl`
- LP Solver: `CPLEX 12.5`

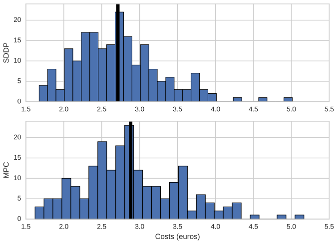
`https://github.com/JuliaOpt/StochDynamicProgramming.jl`

Outline of the presentation

Comparison of MPC and SDDP

We compare MPC and SDDP during one day in summer over 200 assessment scenarios:





	euros/day
MPC	2.882
SDDP	2.713

SDDP is in average *6.9 %* better than MPC!

Operational costs obtained in simulation

We compare different configurations, during summer and winter:

Summer

Local Grid	Elec. bill euros/day	Self cons. %
No	3.53	48.1 %
Yes	2.71	55.2 %

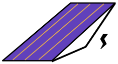
Winter

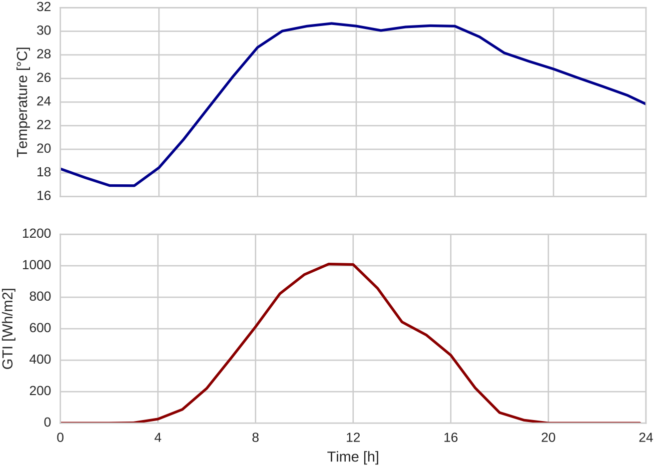
Local Grid	Elec. bill euros/day	Self cons. %
No	54.2	1.7 %
Yes	id.	id.

Outline of the presentation

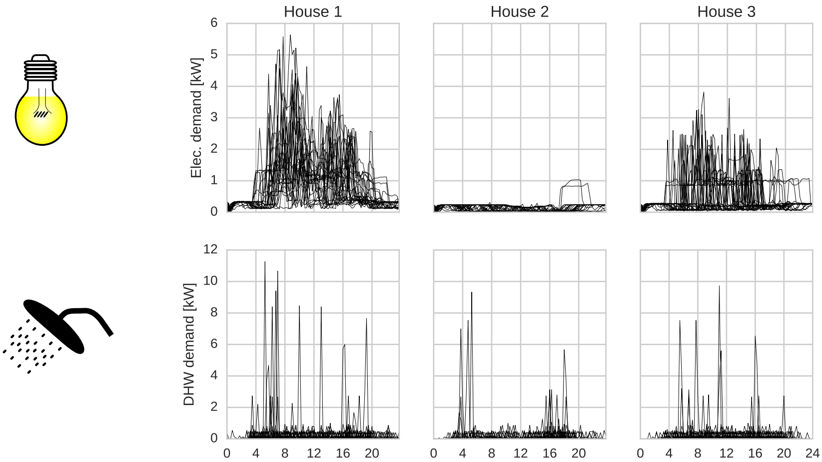
We work with real data

We consider one day during summer 2015 (data from Meteo France):



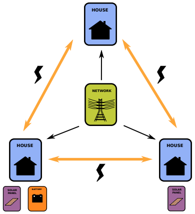


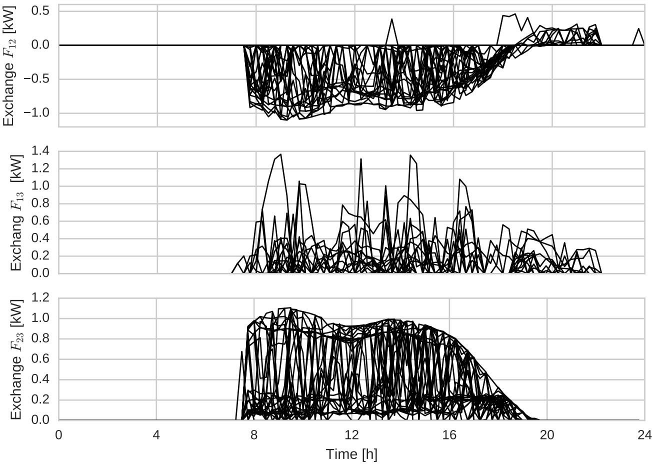
We have 200 scenarios of demands during this day



These scenarios are generated with `StRoBE`, a generator open-sourced by KU-Leuven

As we gain solar energy, surplus is traded in local grid



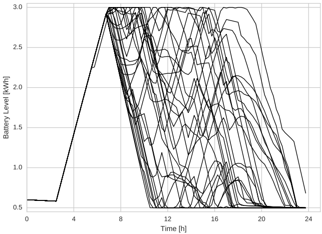


The battery is used as a global storage inside the local grid

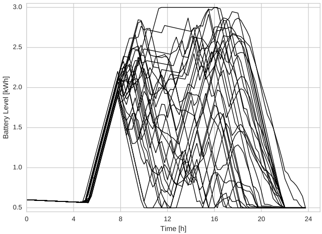
We observe that, in presence of the local grid,

- the battery is more widely used
- the saturation level is reached more often (need a bigger battery?)

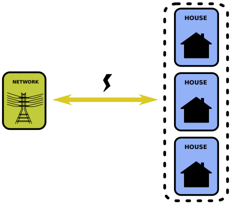
No local grid



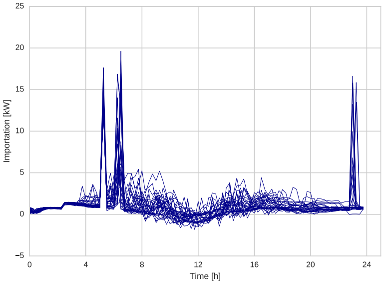
Local grid



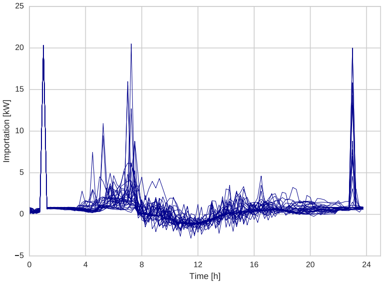
We minimize our average importation from the network



No local grid = 25.8 kWh



Local grid = 19.4 kWh



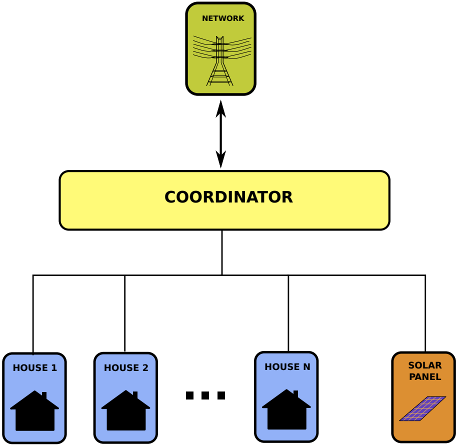
Outline of the presentation

Conclusions

- We extend the results obtained with a single house to a small district
- This study can help to perform an economic analysis
- It pays to use stochastic optimization: SDDP is better than MPC
- We want to scale for optimizing large microgrids

Perspectives

Mix dynamic programming techniques like SDP or SDDP with spatial decomposition like Dual Approximate Dynamic Programming (DADP) to control large urban neighbourhood



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