Optimal Control of a Microgrid with Combined Heat and Power Generator

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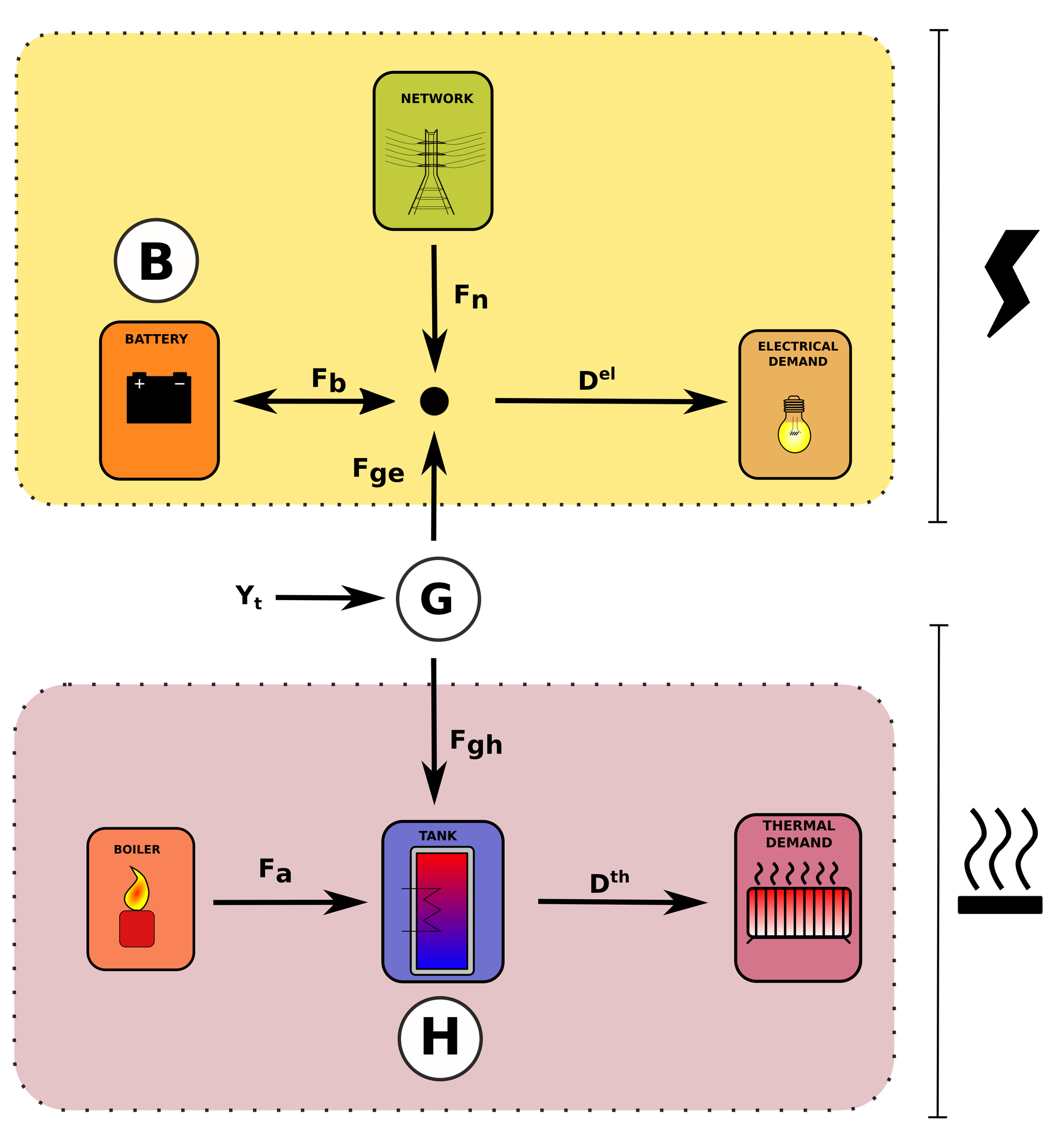
Introduction

Deterministic controls, such as Model Predictive Control (MPC), are the most used methods to manage a micro-grid. But consumptions and renewable energy productions are hardly foreseeable, and it is often difficult to satisfy the adequation between demand and production in deterministic framework. That is why we focus on stochastic optimal management to control a micro-grid.

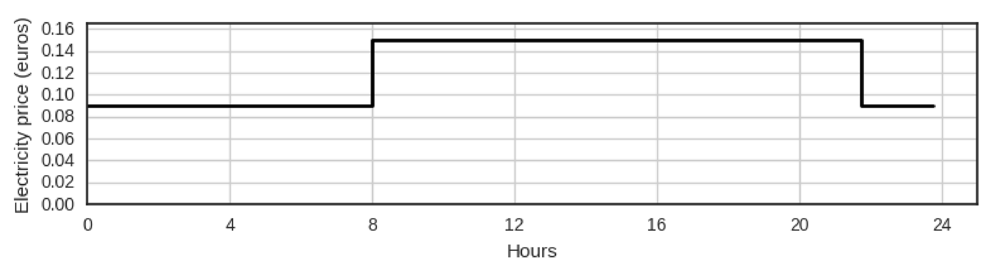
We consider here a domestic micro-grid, composed of a smart home equipped with smart devices (thermostat, controller) and whose most of thermal and electrical needs are provided thanks to a micro-cogeneration unit. An auxiliary boiler and external electricity network help to cover thermal and electrical peak demands. Stochastic optimal control is used to manage the energy in this system. We show that stochastic dynamic programming offers promising results to control such a system, as we gain 6.6 % cost reduction compared to MPC.

Microgrid



Costs

$$\mathcal{C}(Y_t, F_t, \widetilde{F}_{t+1}) = \underbrace{\pi_{chp} Y_t}_{CHP} + \underbrace{\theta \pi_{gas} F_{A,t}}_{Burner}$$
$$- \pi_{inj} \max\{0, -\widetilde{F}_{NE,t+1}\} + \pi_{elec} \max\{0, \widetilde{F}_{NE,t+1}\}$$
$$- \pi_{th} \max\{0, -\widetilde{F}_{H,t+1}\} + \pi_{th} \max\{0, \widetilde{F}_{H,t+1}\}$$



Electricity prices

Algorithms

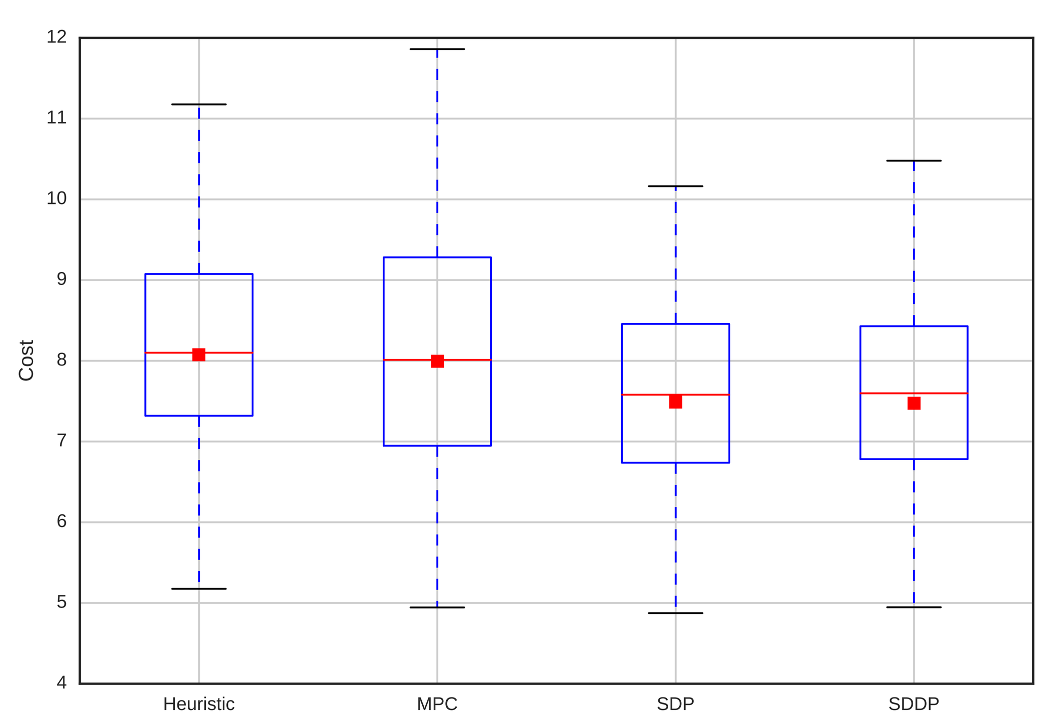
Rule-based heuristic: Manage CHP with (s,S) policy

MPC: Optimization w.r.t a forecast of demands (shrinking horizon)

SDDP: Stochastic Dual Dynamic Programming

DP: Stochastic Dynamic Programming

Costs distribution



Optimization problem

We denote $\mathcal{A}_t$ the σ-algebra: $\mathcal{A}_t = \sigma(D_1^E, D_1^T, \dots, D_t^E, D_t^T)$, where $\left(D_t^E, D_t^T\right)$ are electrical and thermal stochastic demands at time t

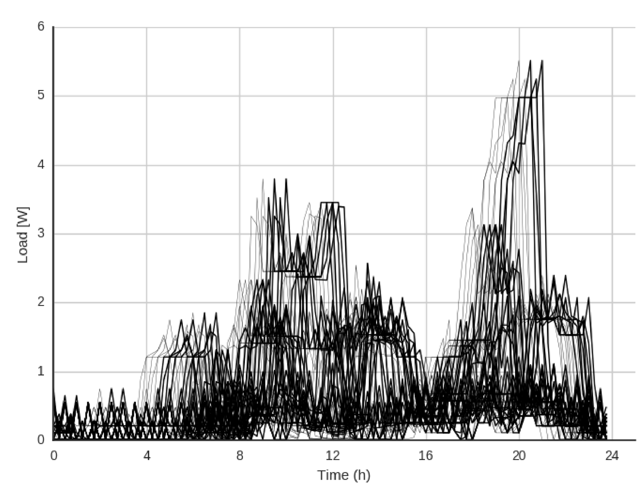
$$J = \min_{Y_\cdot \in \{0,1\}, F_\cdot \geq 0} \mathbb{E}\left[\sum_{t=0}^{T_f - 1} \mathcal{C}(Y_t, F_t, \widetilde{F}_{t+1}) - \pi_H H_{T_f} - \pi_B B_{T_f}\right]$$

$$
\begin{aligned}
s.t. \quad & B^\flat \leq B_t \leq B^\sharp \\
& H^\flat \leq H_t \leq H^\sharp \\
& B_{t+1} = \alpha_B B_t - \beta_B F_{B,t} \\
& \widetilde{F}_{NE,t+1} = D_{t+1}^E - F_{GE,t} - F_{B,t} \\
& \Delta B^\flat \leq B_{t+1} - B_t \leq \Delta B^\sharp \\
& H_{t+1} = \min\left[\max\left(\alpha_H H_t + \beta_H \left(F_{GH,t} + F_{A,t} - D_{t+1}^T\right), H^\flat\right), H^\sharp\right] \\
& F_{H,t+1} = \min\left[D_{t+1}^H, \left(\alpha_H H_t - H^\flat\right)/\beta_H + F_{A,t} + F_{GH,t}\right] \\
& \widetilde{F}_{H,t+1} = D_{t+1}^T - F_{H,t+1} \\
& F_{GH,t} = Y_t \times power^T \\
& F_{GE,t} = Y_t \times power^E \\
& 0 \leq F_{A,t} \leq F_A^\sharp \;, \quad -F_B^\sharp \leq F_{B,t} \leq F_B^\sharp \\
& F_{A,t} \preceq \mathcal{A}_t \;, \quad F_{B,t} \preceq \mathcal{A}_t \\
& Y_t \preceq \mathcal{A}_t \\
& \widetilde{F}_{t+1} \preceq \mathcal{A}_{t+1}
\end{aligned}
$$

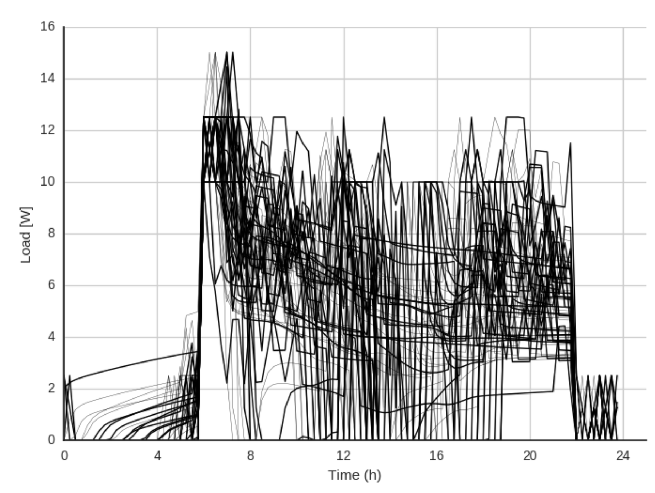
Trajectories obtained by Dynamic Programming

We take as input 60 scenarios of demands in winter:

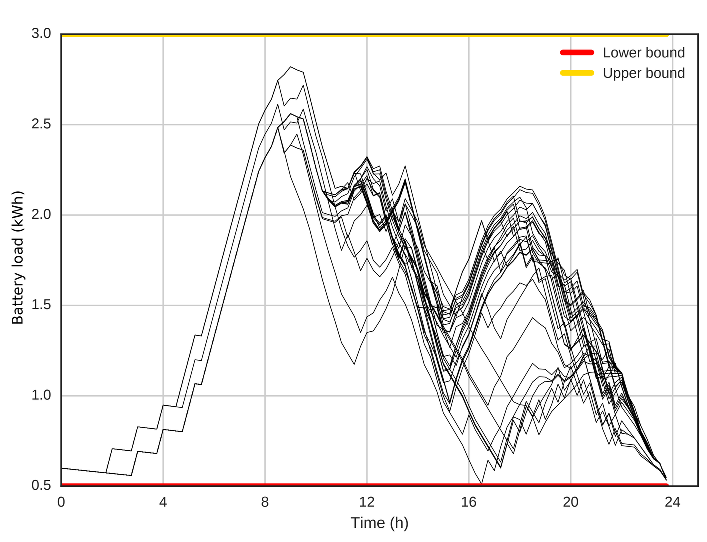
Electrical demand D^E



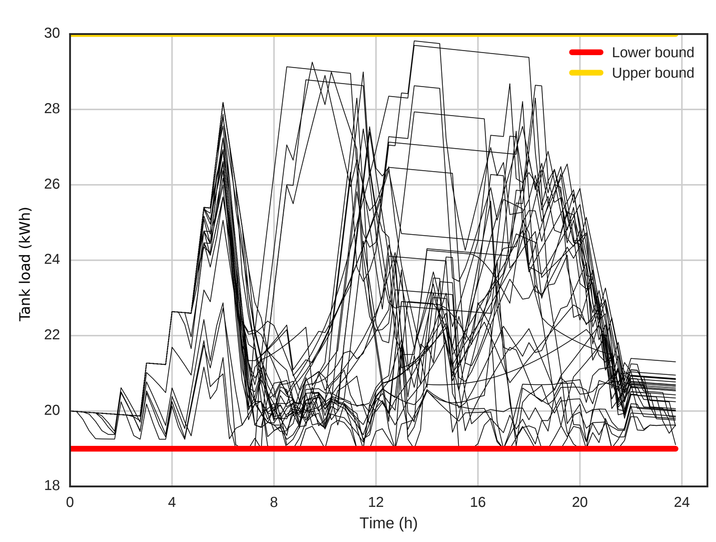
Thermal demand D^T



Battery level



Tank level



Conclusion & Perspectives

Conclusion

- DP is 6.6 % more efficient than MPC
- Once Bellman functions are calculated, it takes less than 1s to get optimal control at each timestep

Perspectives

- Connect different buildings together
- Use decomposition/coordination methods to optimize the system globally