Stochastic Optimization Problems for Domestic and Reserve Microgrid Management

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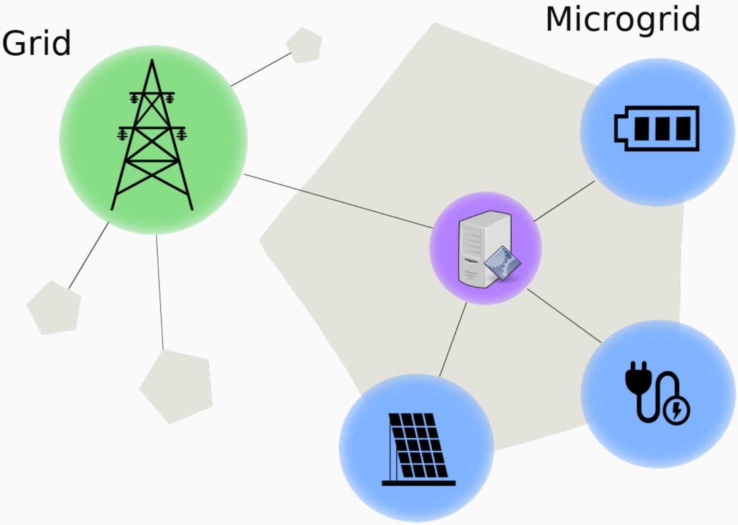
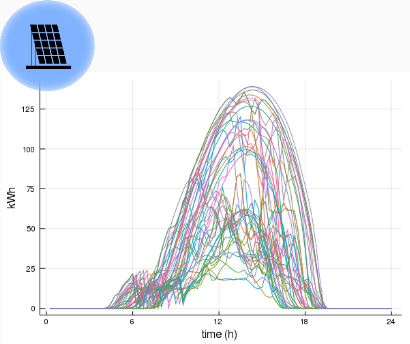
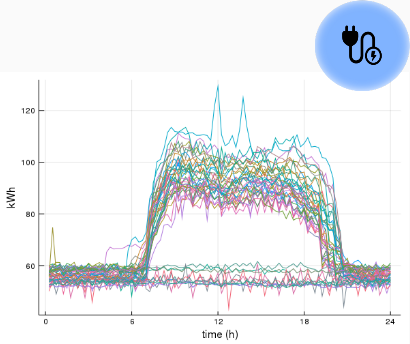
Basic components of a microgrid



Stochasticity arises from PV production and electrical demand



50 daily PV scenarios
observed on the same site



50 daily demand scenarios
observed on the same site

PhD thesis context

Schneider Electric and Efficacity institute are interested in

- Testing stochastic methods against Model Predictive Control on a benchmark of real microgrid data for a basic **domestic power management problem**
- Designing control algorithms to manage microgrids enrolled in **reserve services** resulting in additional **controls**, **costs** and **time scales**

Outline of the presentation

1. **Optimal domestic power management in microgrids**
2. **Co-management of domestic power usage and reserve services**
3. **Perspectives**

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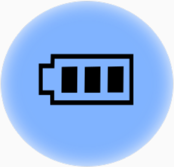
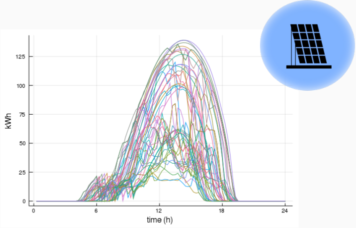
Outline of the section

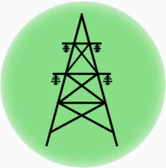
We model the microgrid as a dynamical system



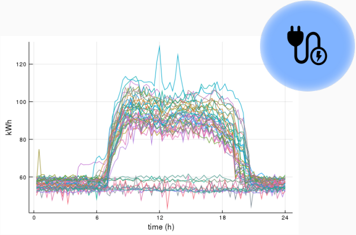
State of charge of the battery SoC_t



uncertain production $\mathbf{PV}_t$ (kWh)



Imported energy E_t (kWh)



uncertain demand $\mathbf{D}_t$ (kWh)

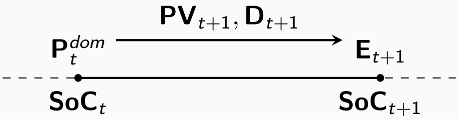
Information structure and decision chronology

- Uncertainties are modeled as random processes

$$\mathbf{D} : \omega \in \Omega \mapsto (\mathbf{D}_1(\omega), ..., \mathbf{D}_T(\omega)) \in \mathbb{R}^T$$
$$\mathbf{PV} : \omega \in \Omega \mapsto (\mathbf{PV}_1(\omega), ..., \mathbf{PV}_T(\omega)) \in \mathbb{R}^T$$

- $\mathbf{P}_t^{dom}$ is the power exchanged to (dis)charge the battery
- Controls $\mathbf{P}_t^{dom}$ are taken observing the history process $\mathbf{H}_t = (\mathbf{D}_1, \mathbf{PV}_1, ..., \mathbf{D}_t, \mathbf{PV}_t)$

$$\sigma(\mathbf{P}_t^{dom}) \subset \sigma(\mathbf{H}_t) \qquad \rightarrow \mathbf{P}_t^{dom} \text{ is } \textbf{non anticipative}$$



$\Delta t = 15$ min

Stochastic domestic microgrid management problem

$$\min_{\mathbf{P}_0^{dom}, \mathbf{P}_1^{dom} \ldots \mathbf{P}_{T-1}^{dom}} \quad \mathbb{E}\Big[\underbrace{\sum_{t=0}^{T-1} p_{buy,t}\mathbf{E}_{t+1}^{+} - p_{sell,t}\mathbf{E}_{t+1}^{-}}_{\text{management cost}} \Big]$$

$$\underbrace{\mathbf{E}_{t+1} = \mathbf{D}_{t+1} - \mathbf{PV}_{t+1} + \mathbf{P}_t^{dom} \cdot \Delta t}_{\text{national grid recourse}}$$

$$\underbrace{\mathbf{SoC}_{t+1} = \mathbf{SoC}_t + \{\rho_c \mathbf{P}_t^{dom,+} - \frac{1}{\rho_d}\mathbf{P}_t^{dom,-}\} \cdot \frac{\Delta t}{c}}_{\text{battery dynamics}}$$

$$\mathbf{SoC}_0 = soc_0$$

$$0 \leq \mathbf{SoC}_t \leq 1$$

$$-p\Delta_t \leq \mathbf{P}_t^{dom} \leq p\Delta_t$$

$$\underbrace{\sigma(\mathbf{P}_t^{dom}) \subset \sigma(\mathbf{H}_t)}_{\text{non anticipativity}}$$

Compact notations

- **State**

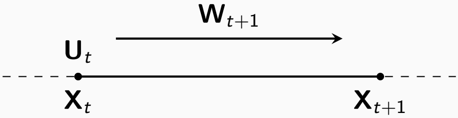
$$\mathbf{X}_t = \mathbf{SoC}_t$$

- **Noise**

$$\mathbf{W}_t = \mathbf{D}_t - \mathbf{PV}_t$$

- **Control**

$$\mathbf{U}_t = \mathbf{P}_t^{dom} \cdot \Delta t$$



Stochastic optimization problem in generic form

$$
\begin{aligned}
\min_{\mathbf{U}_0,\mathbf{U_1}\dots\mathbf{U}_{T-1}} \quad & \mathbb{E}\Big[\sum_{t=0}^{T-1} L_t(\mathbf{X}_t, \mathbf{U}_t, \mathbf{W}_{t+1})\Big] \\
& \mathbf{X}_0 = x_0 \\
& \mathbf{X}_{t+1} = f_t(\mathbf{X}_t, \mathbf{U}_t, \mathbf{W}_{t+1}) \\
& \mathbf{U}_t \in \mathcal{U}_t^{\mathrm{ad}}(\mathbf{X}_t) \\
& \sigma(\mathbf{U}_t) \subset \sigma(x_0, \mathbf{W_1}, \dots, \mathbf{W_t})
\end{aligned}
$$

$$\dim \mathbb{X} = 1 \qquad \dim \mathbb{U} = 1 \qquad \dim \mathbb{W} = 1$$

Outline of the section

Numerical methods

We compute controls u_t for the domestic microgrid management problem with three methods

- Based on Schneider's forecasts
  we apply Model Predictive Control **(MPC)**
- We apply Stochastic Dynamic Programming **(SDP)**
- We apply SDP modeling stagewise dependent uncertainties
  with an AR-1 process **(SDP-AR)**

Model Predictive Control (MPC)

- At each stage $t \in \{1, ..., T-1\}$ we receive a forecast $(\widetilde{w}_{t+1}, ..., \widetilde{w}_{t+H})$ of $\mathbf{W}$ over horizon $H = 24$h
- We solve a **deterministic** optimization problem (LP) to compute u_t

$$
\begin{aligned}
\min_{u_t, u_t \dots u_{t+H-1}} \quad & \sum_{h=t}^{t+H-1} p_{buy,h}(\widetilde{w}_{h+1} + u_h)^+ - p_{sell,h}(\widetilde{w}_{h+1} + u_h)^- \\
& x_t = soc_t \\
& x_{h+1} = x_h + \frac{\rho_c}{c} u_h^+ - \frac{1}{c\rho_d} u_h^- \\
& 0 \leq x_h \leq 1 \\
& -p\Delta_t \leq u_h \leq p\Delta_t
\end{aligned}
$$

Stochastic Dynamic Programming (SDP)

- We compute value functions **offline** using the Bellman equations

$$
\begin{aligned}
V_T(x) &= 0 \\
V_t(x) &= \min_{u \in \mathcal{U}_t^{\mathrm{ad}}(x)} \; \mathbb{E}_{\mathbf{W}_{t+1}} \Big[L_t(x, u, \mathbf{W}_{t+1}) + V_{t+1}\big(f_t(x, u, \mathbf{W}_{t+1})\big) \Big]
\end{aligned}
$$

- We compute optimal controls **online**

$$
u_t \in \operatorname*{arg\,min}_{u \in \mathcal{U}_t^{\mathrm{ad}}(x)} \; \mathbb{E}_{\mathbf{W}_{t+1}} \Big[L_t(x, u, \mathbf{W}_{t+1}) + V_{t+1}\big(f_t(x, u, \mathbf{W}_{t+1})\big) \Big]
$$

(When uncertainties $(\mathbf{W}_1, \ldots, \mathbf{W}_T)$ are stagewise independent,
this gives an optimal solution)

Modeling stagewise dependent uncertainties (SDP-AR)

We apply SDP to an extended-state version of the problem

$$
\begin{aligned}
V_t(x, w) \; = \min_{\mathbf{U}_t, \mathbf{U}_{t+1} \dots \mathbf{U}_{T-1}} \quad & \mathbb{E}_{\boldsymbol{\varepsilon}} \Big[\sum_{s=t}^{T-1} \; p_{buy,s} \big[\mathbf{U}_s + \mathbf{W}_{s+1} \big]^+ - p_{sell,s} \big[\mathbf{U}_s + \mathbf{W}_{s+1} \big]^- \Big] \\
& \mathbf{X}_t = x \\
& \mathbf{X}_{s+1} = \mathbf{X}_s + \frac{\rho_c}{c} \mathbf{U}_s^+ - \frac{1}{c \rho_d} \mathbf{U}_s^- \\
& \mathbf{W}_t = w \\
& \mathbf{W}_{s+1} = \alpha_s \mathbf{W}_s + \beta_s + \boldsymbol{\varepsilon}_{s+1} \\
& \mathbf{U}_s \in \mathcal{U}_s^{\mathrm{ad}}(\mathbf{X}_s) \\
& \sigma(\mathbf{U}_s) \subset \sigma(x, \boldsymbol{\varepsilon}_t, \dots, \boldsymbol{\varepsilon}_s)
\end{aligned}
$$

(When errors $(\varepsilon_1, \dots, \varepsilon_T)$ are stagewise independent,
this gives an optimal solution)

Results

We compare MPC with stochastic methods
for the domestic power management problem
on **real microgrid data from Schneider**

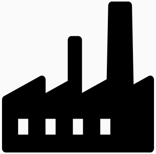
- We use **training data** for model calibration
- We use **testing data** for the simulation of microgrid management over 10 days periods
- We compute **scores** by averaging the gain of a method against a naive policy that applies $u_t = 0$ (i.e. no energy storage)

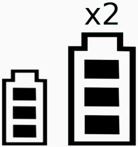
Testing data is organized in periods of 10 consecutive days

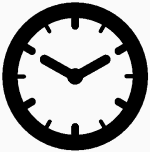
11 sites
to manage
separately

2 settings
of battery
per site

$\sim$ 10 periods
of 10 days
per site







Our results

Method	**SDP**	**SDP AR-1**	**MPC**
Score (%)	16.1	17.1	18.2

Average score on all testing periods. Higher is the better.

- Our first SDP-based attempts score lower than MPC
- Modeling stagewise dependence of uncertainties helps bridging the gap
- Forecasting was easy on these sites, Schneider provided new data that should be more challenging for MPC

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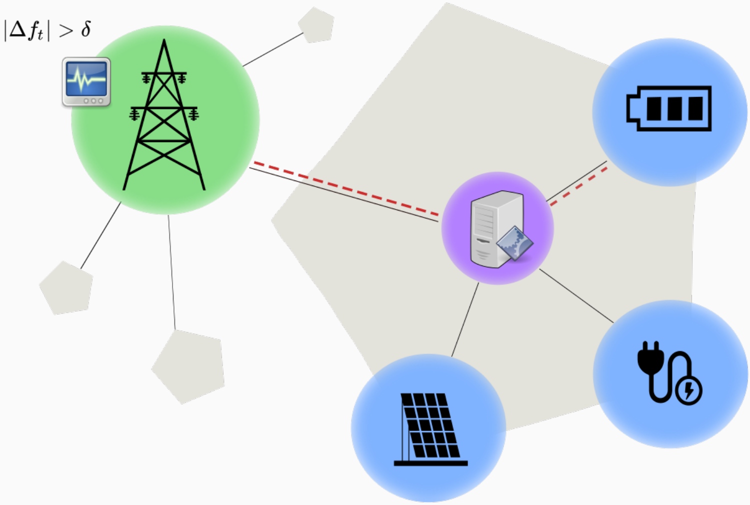
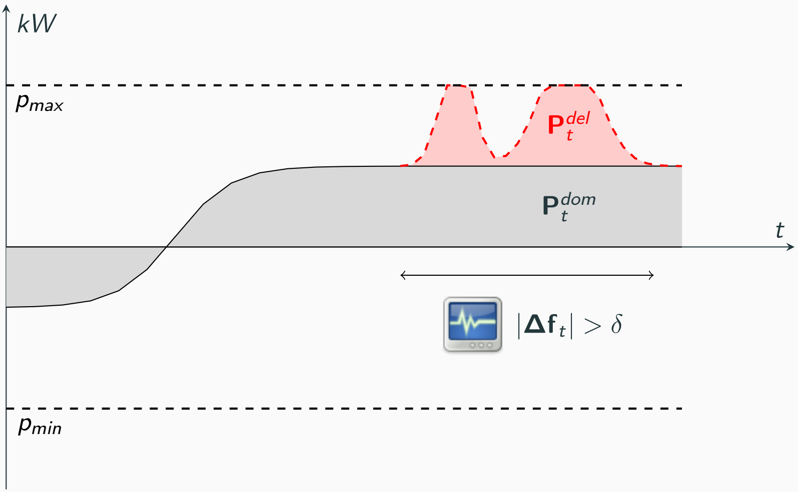
Activation of the reserve for frequency regulation



We deliver reserve power on top of domestic power usage



Outline of the section

The reserve mechanism

In order to **instantaneously** maintain the frequency balance, the operator relies on microgrids enrolled as **reserve providers**

- Providers submit day-ahead hourly power reserve proposals $(R_h)_{h=0,\dots,H-1}$
- During the day, reserve power controls $\mathbf{P}_t^{del}$ are activated if the frequency violates the dead band of 50.00 ± 0.05 Hz

Optimal daily reserve sizing

We must decide **day ahead** on a reserve proposal $(R_h)_{h=0,\dots,H-1}$ which minimizes the daily cost

$$\min_{R} \quad \underbrace{-c^T R}_{\text{reserve reward}} + \underbrace{\Phi(R)}_{\text{co-management cost}}$$

- R is an **open loop** control
- $\Phi(R)$ is the value of a stochastic optimization problem

Outline of the section

Compact notations for hourly decomposition

- **State**

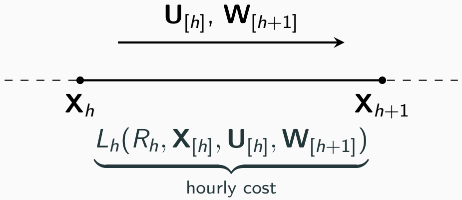
$$\mathbf{X}_h = \mathbf{SoC}_h \ ; \ \mathbf{X}_{[h]} = \mathbf{SoC}_{[h:h+1]}$$

- **Noise**

$$\mathbf{W}_{[h]} = (\mathbf{D}_{[h:h+1]}, \mathbf{PV}_{[h:h+1]}, \mathbf{\Delta f}_{[h:h+1]})$$

- **Control**

$$\mathbf{U}_{[h]} = (\mathbf{P}^{dom}_{[h:h+1]}, \mathbf{P}^{del}_{[h:h+1]})$$



Two-stages structure of the optimal reserve sizing problem

$$\min_{R} \quad \underbrace{-c^T R}_{\text{reserve reward}} + \overbrace{\min_{\mathbf{U}} \mathbb{E}_{\mathbf{W}}\Big[\sum_{h=0}^{H-1} L_h(R_h, \mathbf{X}_{[h]}, \mathbf{U}_{[h]}, \mathbf{W}_{[h+1]})\Big]}^{\Phi(R) \text{ daily co-management cost}}$$

$$\mathbf{X}_0 = x_0$$

$$\mathbf{X}_{h+1} = f_h(R_h, \mathbf{X}_{[h]}, \mathbf{U}_{[h]}, \mathbf{W}_{[h+1]})$$

$$\mathbf{U} \quad \text{is non anticipative}$$

$\Phi(R)$ is the value of a **multistage** stochastic problem

Outline of the section

Recall of the domestic microgrid management problem

$$\min_{\mathbf{P}_0^{dom},\mathbf{P}_1^{dom}\ldots\mathbf{P}_{T-1}^{dom}} \quad \mathbb{E}\Big[\underbrace{\sum_{t=0}^{T-1} p_{buy,t}\mathbf{E}_{t+1}^{+} - p_{sell,t}\mathbf{E}_{t+1}^{-}}_{\text{management cost}}\Big]$$

$$\underbrace{\mathbf{E}_{t+1} = \mathbf{D}_{t+1} - \mathbf{PV}_{t+1} + \mathbf{P}_t^{dom}\cdot\Delta t}_{\text{national grid recourse}}$$

$$\underbrace{\mathbf{SoC}_{t+1} = \mathbf{SoC}_t + \{\rho_c\mathbf{P}_t^{dom,+} - \frac{1}{\rho_d}\mathbf{P}_t^{dom,-}\}\cdot\frac{\Delta t}{c}}_{\text{battery dynamics}}$$

$$\underbrace{\sigma(\mathbf{P}_t^{dom}) \subset \sigma(\mathbf{H}_t)}_{\text{non anticipativity}}$$

(We omit some constraints for readability)

Hourly co-management problem (1/2)

We consider a fixed hour $h \in \{0, \dots, 23\}$

$$\min_{\mathbf{P}^{dom}_{h,m},\ \mathbf{P}^{del}_{h,m,s}} \quad \mathbb{E}\Big[\sum_{m=0}^{M-1} p^{buy}_{h,m}\mathbf{E}^{+}_{h,m+1} - p^{sell}_{h,m}\mathbf{E}^{-}_{h,m+1} \underbrace{+ \sum_{s=0}^{S-1} \Pi_{h,m,s}(R_h, \mathbf{\Delta f}_{h,m+1,s+1}, \mathbf{P}^{del}_{h,m,s})}_{\text{new cost}}\Big]$$

$$\mathbf{E}_{h,m+1} = \mathbf{D}_{h,m+1} - \mathbf{PV}_{h,m+1} + \mathbf{P}^{dom}_{h,m} \cdot \Delta m \underbrace{+ \sum_{s=0}^{S-1} \mathbf{P}^{del}_{h,m,s} \cdot \Delta s}_{\text{new time scale}}$$

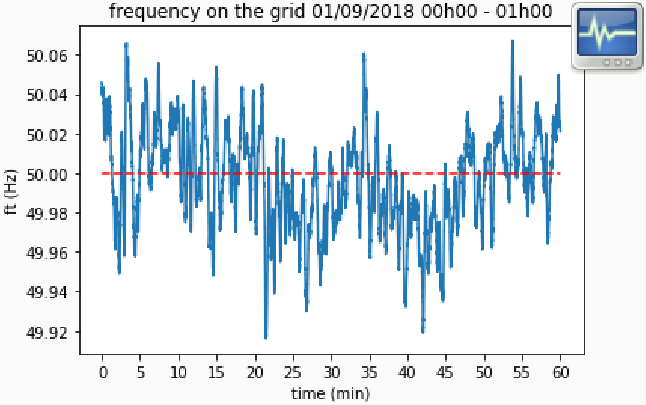
$$\mathbf{SoC}_{h,m,s+1} = \mathbf{SoC}_{h,m,s} + \{\rho_c(\mathbf{P}^{dom}_{h,m} + \mathbf{P}^{del}_{h,m,s})^{+} - \frac{1}{\rho_d}(\mathbf{P}^{dom}_{h,m} + \mathbf{P}^{del}_{h,m,s})^{-}\} \cdot \frac{\Delta s}{c}$$

$$\sigma(\mathbf{P}^{dom}_{h,m}) \subset \sigma(soc_0, \dots, \underbrace{\mathbf{\Delta f}_{h,m,1:S}}_{\text{new uncertainty}}, \mathbf{D}_{h,m}, \mathbf{PV}_{h,m})$$

$$\underbrace{\sigma(\mathbf{P}^{del}_{h,m,s}) \subset \sigma(soc_0, \dots, \mathbf{\Delta f}_{h,m,1:S}, \mathbf{D}_{h,m}, \mathbf{PV}_{h,m}, \mathbf{\Delta f}_{h,m+1,1:s})}_{\text{new non anticipative control}}$$

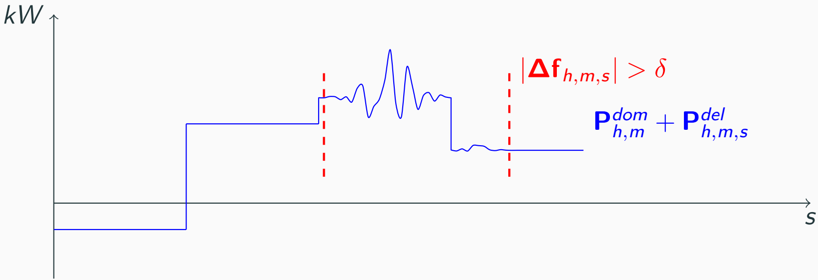
What is new ?

- We have a **new uncertainty** $\mathbf{\Delta f}_{h,m,s}$ for frequency deviation



What is new ?

- We have a **new control** $\mathbf{P}^{del}_{h,m,s}$ for reserve power delivery
- We have a **new time scale** for controlling $\mathbf{P}^{del}_{h,m,s}$ every $\Delta s = 10$ seconds to follow the fluctuations of $\mathbf{\Delta f}_{h,m,s}$
- We have a **new cost** since $\mathbf{P}^{del}_{h,m,s}$ might induce a penalty $\Pi_{h,m,s}(R_h, \mathbf{\Delta f}_{h,m+1,s+1}, \mathbf{P}^{del}_{h,m,s})$



Hourly co-management problem (2/2)

We merge domestic time scale with reserve time scale: $(h, m, s) \to (h, s)$

$$\min_{\mathbf{P}^{dom}_{h,s},\ \mathbf{P}^{del}_{h,s}} \quad \mathbb{E}\Big[\sum_{s=0}^{S-1} p^{buy}_{h,s}\mathbf{E}^{+}_{h,s+1} - p^{sell}_{h,s}\mathbf{E}^{-}_{h,s+1} + \Pi_{h,s}(R_h, \mathbf{\Delta f}_{h,s+1}, \mathbf{P}^{del}_{h,s})\Big]$$

$$\mathbf{E}_{h,s+1} = \mathbf{D}_{h,s+1} - \mathbf{PV}_{h,s+1} + (\mathbf{P}^{dom}_{h,s} \underbrace{+\ \mathbf{P}^{del}_{h,s}}_{\text{single time scale}}) \cdot \Delta s$$

$$\mathbf{SoC}_{h,s+1} = \mathbf{SoC}_{h,s} + \{\rho_c(\mathbf{P}^{dom}_{h,s} + \mathbf{P}^{del}_{h,s})^{+} - \frac{1}{\rho_d}(\mathbf{P}^{dom}_{h,s} + \mathbf{P}^{del}_{h,s})^{-}\} \cdot \frac{\Delta s}{c}$$

$$\sigma(\mathbf{P}^{dom}_{h,s}) \subset \sigma(x_0, \ldots, \mathbf{\Delta f}_{h,s}, \mathbf{D}_{h,s}, \mathbf{PV}_{h,s})$$

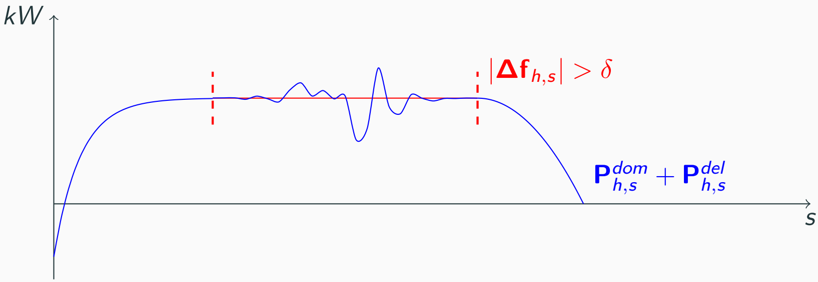
$$\sigma(\mathbf{P}^{del}_{h,s}) \subset \sigma(x_0, \ldots, \mathbf{\Delta f}_{h,s}, \mathbf{D}_{h,s}, \mathbf{PV}_{h,s})$$

$$\underbrace{|\mathbf{\Delta f}_{h,s}| > \delta \Rightarrow \mathbf{P}^{dom}_{h,s} = \mathbf{P}^{dom}_{h,s-1}}_{\text{new constraint}}$$

What did we change?

- We reduced the time scale of $\mathbf{P}_h^{dom}$ to $\Delta s = 10$ seconds to **avoid mixing two time scales** within 1 hour
- We must guarantee the observability of $\mathbf{P}_{h,s}^{del}$ so the grid operator imposes a **new constraint**

$$|\mathbf{\Delta f}_{h,s}| > \delta \Rightarrow \mathbf{P}_{h,s}^{dom} = \mathbf{P}_{h,s-1}^{dom}$$



Outline of the presentation

Conclusion - what we did

- We wrote a stochastic optimization problem for domestic microgrid management
- We showcased numerical results on Schneider's data for a benchmark of methods
- We proposed decompositions for the optimal sizing of reserve power
- Optimal reserve sizing introduces a mix of open loop and closed loop controls
- We identified the main challenges of the daily co-management problem
  - We have to deal with several time scales
  - The process $\boldsymbol{\Delta f}$ is very difficult to model

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