EMSx: an Numerical Benchmark for Energy Management Systems

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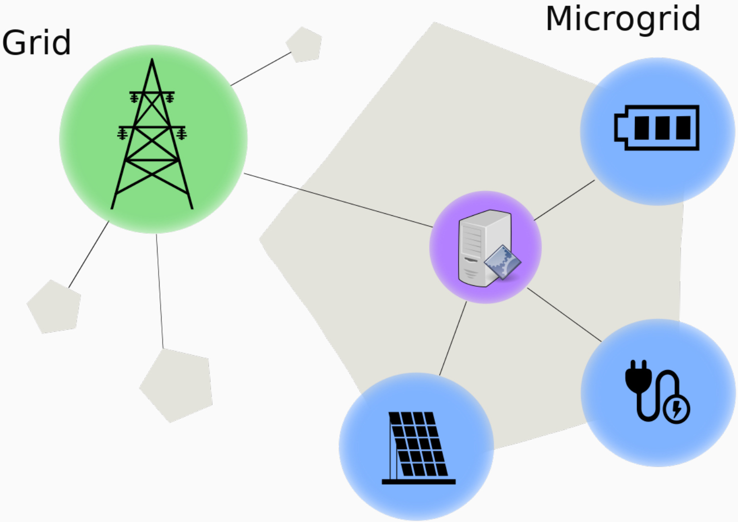
Grid
Microgrid

Problem context

- **Question**

  How to evaluate an **Energy Management System** (EMS) designed for operating a microgrid with **uncertain load and production** at **least expected cost** ?

- **Our contribution**

  We introduce EMSx, a **microgrid controller benchmark** to compare (deterministic and stochastic) EMS techniques on an **open** and **diversified** testbed

Outline of the presentation

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1. The EMSx benchmark
2. Numerical examples
3. Conclusion

Outline of the section

1. **The EMSx benchmark**

   The EMSx dataset

   The EMSx mathematical framework

   The EMSx software

Examples of daily scenarios from EMSx

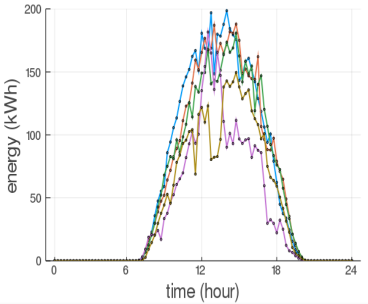

Figure 1: Examples of daily photovoltaic profiles

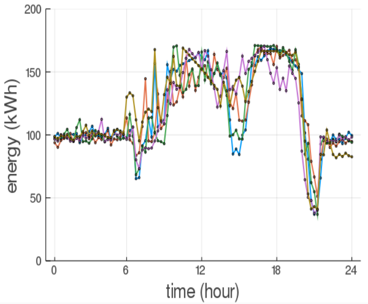

Figure 2: Examples of daily load profiles

(data collected by Schneider Electric on real industrial sites)

Detailed description of the dataset

- Over 1 year of historical data for **70 industrial sites**
- 15 minutes sampled **historical observations**
- 15 minutes actualized 24h ahead **historical forecasts**
- Publicly available

Our data reflect a large diversity of microgrids

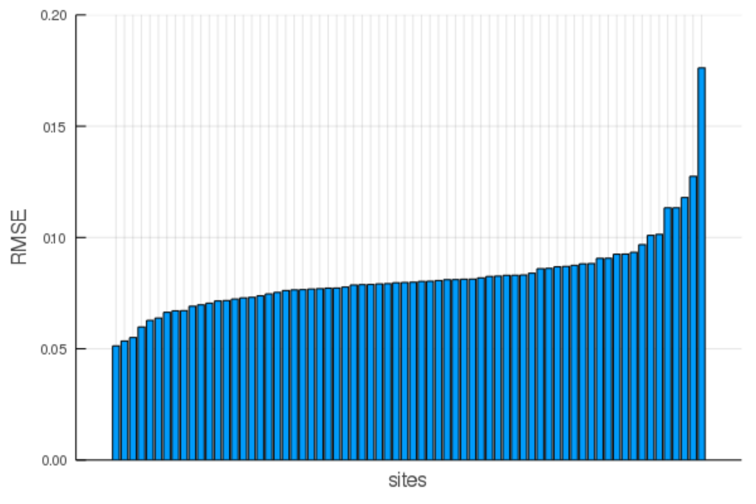

Figure 3: RMSE of the net demand forecasts for each of the 70 sites

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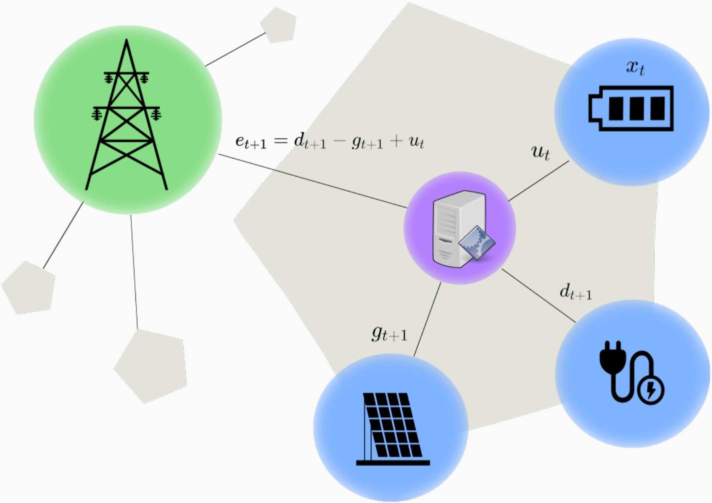
Time scale and variables

We manage a microgrid over time steps $t \in \{0, 1, \dots, T\}$, $\Delta_t = 15$ min

- $x_t \in [0, 1]$ state of charge of the battery
- $u_t \in [\underline{u}, \overline{u}]$ energy charged ($u_t \geq 0$) or discharged ($u_t \leq 0$) over $[t, t+1]$
- $w_{t+1} = (g_{t+1}, d_{t+1})$ generation and demand historical data over $[t, t+1]$
- $\hat{w}_{t,t+k} = (\hat{g}_{t,t+k}, \hat{d}_{t,t+k})$, $k \in \{1, \dots, 96\}$ generation and demand historical forecast at time t over $[t+k-1, t+k]$


x_t
$e_{t+1} = d_{t+1} - g_{t+1} + u_t$
u_t
d_{t+1}
g_{t+1}

Our microgrid management model

- state of charge ruled by the **dynamics**

$$x_{t+1} = f(x_t, u_t) = x_t + \frac{\rho_\mathrm{c}}{c} u_t^+ - \frac{1}{\rho_\mathrm{d} c} u_t^-$$

- controls restricted to the **admissibility set**

$$\mathcal{U}(x_t) = \{u_t \in \mathbb{R} \mid \underline{u} \leq u_t \leq \overline{u} \text{ and } 0 \leq f(x_t, u_t) \leq 1\}$$

- energy exchanges induce a **cost**

$$L_t(u_t, w_{t+1}) = p_t^{\mathrm{buy}} \cdot (d_{t+1} - g_{t+1} + u_t)^+ - p_t^{\mathrm{sell}} \cdot (d_{t+1} - g_{t+1} + u_t)^-$$

Online information for the management problem

- The **online information** contains
  - 24h of historical observation
  - 24h of historical forecasts

- At time $t \in \{0, \dots, T-1\}$, we have access to

$$h_t = \begin{pmatrix} w_t, w_{t-1}, \dots, w_{t-95} \\ \hat{w}_{t,t+1}, \dots, \hat{w}_{t,t+96} \end{pmatrix} \in \mathbb{H} = \mathbb{R}^{2\times 96} \times \mathbb{R}^{2\times 96}$$

- The sequence $\{0, \dots, T-1\}$ is characterized by the **partial chronicle**

$$h = (h_0, \dots, h_{T-1}) \in \mathbb{H}^T$$

A generic controller definition

A **controller** is a sequence of mappings $\phi = (\phi_0, \dots, \phi_{T-1})$ such that

$$\begin{aligned} \phi_t \ : \ & [0,1] \times \mathbb{H} \to \mathbb{R} \\ & (x_t, h_t) \mapsto \phi_t(x_t, h_t) \in \mathcal{U}(x_t) \end{aligned} , \ \ \forall t \in \{0, \dots, T-1\}$$

- decisions are **non anticipative**
- this **generic** definition covers a large class of controllers

Management cost of a controller

For a site i in the total pool of sites $I = \{1, \ldots, 70\}$,
the application of a controller ϕ^i along a partial chronicle $h \in \mathbb{H}^T$
yields a **management cost**

$$J^i(\phi^i, h) = \sum_{t=0}^{T-1} L_t^i(u_t, w_{t+1})$$

$$x_0 = 0$$

$$x_{t+1} = f^i(x_t, u_t)$$

$$u_t = \phi_t^i(x_t, h_t)$$

Gain of a controller ϕ^i on site $i \in I$

We have a pool of **simulation chronicles** $\mathscr{S}^i$

- We define the (relative) **gain** of ϕ^i as the management cost $J^i(\phi^i, h)$ centered by the management cost of a **dummy controller** ϕ^{d} (which does not use the battery)

$$G^i(\phi^i) = \frac{1}{|\mathscr{S}^i|} \sum_{h \in \mathscr{S}^i} J^i(\phi^{\mathrm{d}}, h) - J^i(\phi^i, h)$$

- We define the **anticipative gain** as the gain obtained by an **idealistic anticipative controller** (which has full knowledge of the future)

$$\overline{G}^i = \frac{1}{|\mathscr{S}^i|} \sum_{h \in \mathscr{S}^i} J^i(\phi^{\mathrm{d}}, h) - \underline{J}^i(h)$$

Normalized score of a control technique $(\phi^i)_{i \in I}$

- We define the **normalized gain** of a controller ϕ_i as

$$\mathcal{G}^i(\phi^i) = \frac{G^i(\phi^i)}{\overline{G}^i} = \frac{\text{average gain of } \phi^i \text{ vs } \phi^{\mathrm{d}}}{\text{average anticipative gain vs } \phi^{\mathrm{d}}}$$

- We define the **normalized score** of a control technique $(\phi^i)_{i \in I}$ as

$$\mathcal{G}\big(\left\{\phi^i\right\}_{i \in I}\big) = \frac{1}{|I|} \sum_{i \in I} \mathcal{G}^i(\phi^i)$$

Outline of the section

A Julia package: `EMSx.jl`

```julia
struct Information
    t::Int64
    soc::Float64
    pv::Array{Float64,1}
    forecast_pv::Array{Float64,1}
    load::Array{Float64,1}
    forecast_load::Array{Float64,1}
    price::Price
    battery::Battery
    site_id::String
end
```

The `EMSx.jl` built-in type `Information` gathers all the information available to the controller to make a decision

A Julia package: EMSx.jl

```julia
using EMSx

mutable struct DummyController <: EMSx.AbstractController end

EMSx.compute_control(controller::DummyController,
    information::EMSx.Information) = 0.

const controller = DummyController()

EMSx.simulate_sites(controller,
    "home/xxx/path_to_save_folder",
    "home/xxx/path_to_price",
    "home/xxx/path_to_metadata",
    "home/xxx/path_to_simulation_data")
```

Example of the implementation and simulation of a dummy controller with the EMSx.jl package

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Experimental setting

- We use EDF energy tariff
- For each site $i \in \{1, \ldots, 70\}$, we designed battery parameters $(c^i, \overline{u}^i, \rho_c^i, \rho_d^i)$ with Schneider Electric
- We split the data into **chronicles of 1 week**
  - 60% of **calibration** (training) data
  - 40% of **simulation** (testing) data (giving a total of 2474 simulation chronicles)

Normalized score per design technique

	Normalized score	Offline time (seconds)	Online time (seconds)
MPC	0.487	0.00	$9.82\ 10^{-4}$
OLFC-10	0.506	0.00	$1.14\ 10^{-2}$
OLFC-50	0.513	0.00	$8.62\ 10^{-2}$
OLFC-100	0.510	0.00	$1.87\ 10^{-1}$
SDP	0.691	2.67	$3.09\ 10^{-4}$
SDP-AR(1)	0.794	38.1	$4.44\ 10^{-4}$
SDP-AR(2)	0.795	468	$5.55\ 10^{-4}$
Upper bound	**1.0**	-	-

Model Predictive Control (MPC)

At time $t \in \{0, \dots, T-1\}$,

$$
\begin{cases}
u_t^\star \in \arg\min_{u_t} \min_{(u_{t+1}, \dots, u_{t+H-1})} & \sum_{s=t}^{t+H-1} L_s(u_s, \hat{w}_{t,s+1}) \\
& x_{s+1} = f(x_s, u_s) \ , \ \ \forall s \in \{t, \dots, t+H-1\} \\
& u_s \in \mathcal{U}(x_s) \ , \ \ \forall s \in \{t, \dots, t+H-1\} \\
\phi_t^{\mathrm{MPC}}(x_t, h_t) = u_t^\star &
\end{cases}
$$

Open Loop Feedback Control (OLFC)

At time $t \in \{0, \dots, T-1\}$,

$$\begin{cases} u_t^\star \in \arg\min_{u_t} \min_{(u_{t+1}, \dots, u_{t+H-1})} & \sum_{\sigma \in \mathbb{S}} \pi_t^\sigma \Big(\sum_{s=t}^{t+H-1} L_s(u_s, \hat{w}_{t,s+1}^\sigma) \Big) \\ & x_{s+1} = f(x_s, u_s) \ , \ \ \forall s \in \{t, \dots, t+H-1\} \\ & u_s \in \mathcal{U}(x_s) \ , \ \ \forall s \in \{t, \dots, t+H-1\} \\ \phi_t^{\mathrm{OLFC}}(x_t, h_t) = u_t^\star & \end{cases}$$

Stochastic Dynamic Programming (SDP)

- We compute value functions **offline**

$$
\begin{aligned}
V_T(x) &= 0 \\
V_t(x) &= \min_{u \in \mathcal{U}(x)} \sum_{\sigma \in \mathbb{S}^{\text{off}}} \pi_{t+1}^{\text{off},\sigma} \Big(L_t(u, w_{t+1}^{\text{off},\sigma}) + V_{t+1}\big(f(x,u)\big) \Big)
\end{aligned}
$$

- We use value functions to compute **online** controls at time $t \in \{0, \dots, T-1\}$

$$
\begin{cases}
u_t^\star \in \arg\min_u \sum_{\sigma \in \mathbb{S}^{\text{on}}} \pi_{t+1}^{\text{on},\sigma} \Big(L_t(u, w_{t+1}^{\text{on},\sigma}) + V_{t+1}\big(f(x,u)\big) \Big) \\
\phi_t^{\text{SDP}}(x_t, h_t) = u_t^\star \ .
\end{cases}
$$

(If uncertainties $\mathbf{W}_1, \dots, \mathbf{W}_T$ are stagewise independent SDP gives an optimal solution)

Modeling uncertainties with an AR(k) process

- We model the net demand $z_t = d_t - g_t$ with an AR(k) process

$$\mathbf{Z}_{t+1} = \sum_{j=0,\dots,k-1} \alpha_t^j \mathbf{Z}_{t-j} + \beta_t + \boldsymbol{\epsilon}_{t+1} \; , \;\; \forall t \in \{0, \dots, T-1\}$$

- We **extend the state** to $\widetilde{x}_t = (x_t, z_t, \dots, z_{t-k+1}) \in [0,1] \times \mathbb{R}^k$ with a new dynamics

$$\widetilde{f}_t(\widetilde{x}_t, u_t, \epsilon_{t+1}) = \begin{pmatrix} f(x_t, u_t) \\ \sum_{j=0,\dots,k-1} \alpha_t^j z_{t-j} + \beta_t + \epsilon_{t+1} \\ z_t, \dots, z_{t-k+2} \end{pmatrix}$$

SDP-AR(k)

Similarly, we compute value functions $\widetilde{V}_t$ **offline** and use them for computing **online** controls at time $t \in \{0, \dots, T-1\}$

$$\begin{cases} u_t^\star \in \arg\min_u \sum_{\sigma \in \mathbb{S}^{\mathsf{on}}} \pi_{t+1}^{\mathsf{on},\sigma} \Big(\widetilde{L}_t(\widetilde{x}_t, u, \epsilon_{t+1}^{\mathsf{on},\sigma}) + \widetilde{V}_{t+1}\big(\widetilde{f}_t(\widetilde{x}_t, u, \epsilon_{t+1}^{\mathsf{on},\sigma})\big)\Big) \\ \phi_t^{\text{SDP-AR}}(x_t, h_t) = u_t^\star \ . \end{cases}$$

(If uncertainties $\boldsymbol{\epsilon}_1, \dots, \boldsymbol{\epsilon}_T$ are stagewise independent SDP-AR(k) gives an optimal solution)

Detailed gain over the 70 sites

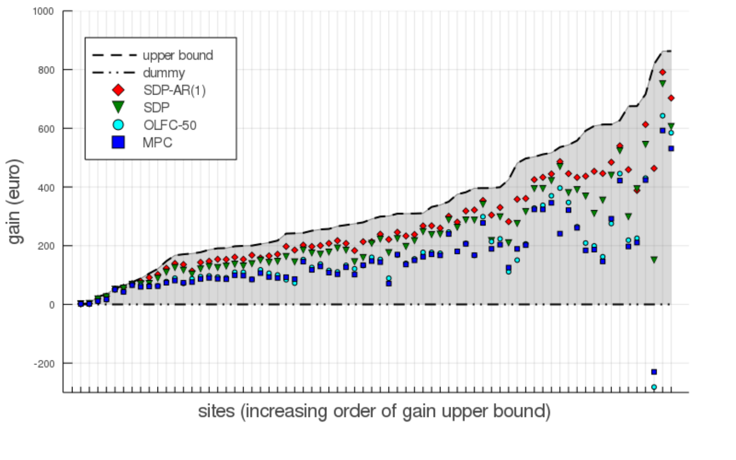

Figure 4: Gain $G^i(\phi^i)$ per sites $i \in I$ of controller design techniques MPC, OLFC-50, SDP and SDPAR(1), with anticipative gain $\underline{G}^i$ (dashed line) and gain of a dummy controller (dashed and dotted line)

Outline of the presentation

Conclusion

- EMSx provides a **dataset**, a **mathematical framework** and a **software** to compare microgrid controller techniques on a **publicly available**[1] benchmark
- EMSx makes it easy to implement and evaluate a **large class** of microgrid control techniques (closed loop stochastic ones stand out as the best technique tested so far)
- Further details are available in our submitted paper[2]

[1] https://github.com/adrien-le-franc/EMSx.jl
[2] https://hal.archives-ouvertes.fr/hal-02425913/document