Active network management for electrical distribution systems: problem formulation and benchmark

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Motivations

Environmental concerns are driving the growth of renewable electricity generation

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Installation of wind and solar power generation resources at the distribution level

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Current fit-and-forget doctrine for planning and operating of distribution network comes at continuously increasing network reinforcement costs

Active Network Management

ANM strategies rely on short-term policies that control the power injected by generators and/or taken off by loads so as to avoid congestions or voltage problems.

Simple strategy:

Curtail the production of generators.

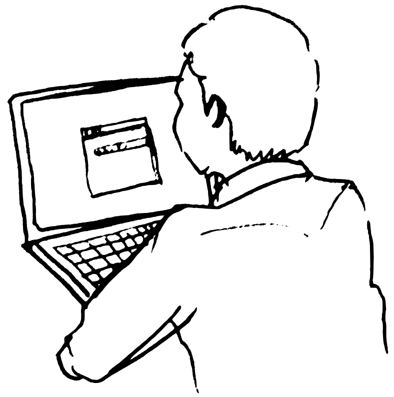
More advanced strategy:

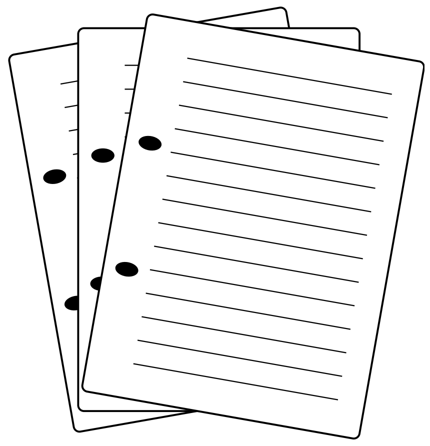
Move the consumption of loads to relevant time periods.

→ Such advanced strategies imply solving *large-scale optimal sequential decision-making problems under uncertainty*.

Observations

Several researchers tackled this operational planning problem.





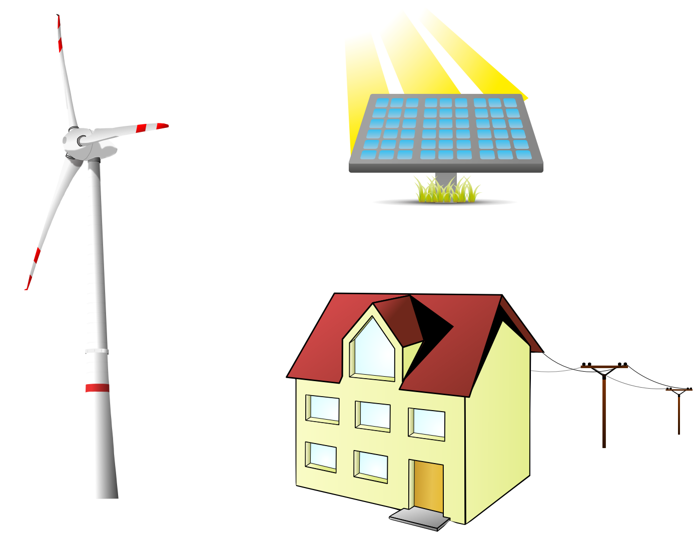
They rely on different formulations of the problem, making it harder for one researcher to build on top of another one's work.

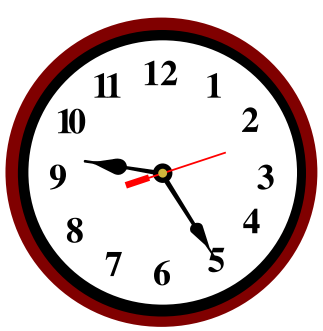
We are looking to provide a generic formulation of the problem and a testbed in order to promote the development of computational techniques.

Problem description

We consider the problem faced by a DSO willing to plan the operation of its network over time, while ensuring that operational constraints of its infrastructure are not violated.

This amounts to determine over time the optimal operation of a set $\mathcal{D}$ of electrical devices.

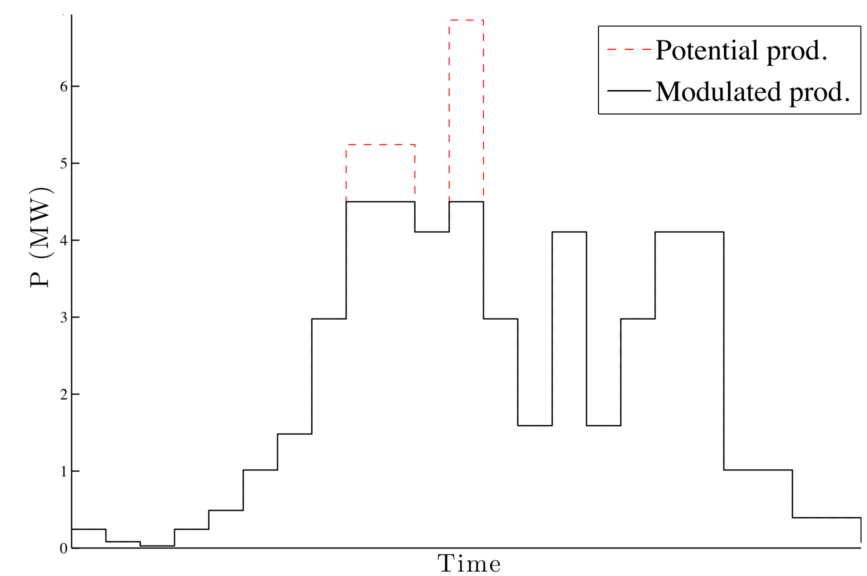




We describe the evolution of the system by a discrete-time process having a time horizon T (fast dynamics is neglected).

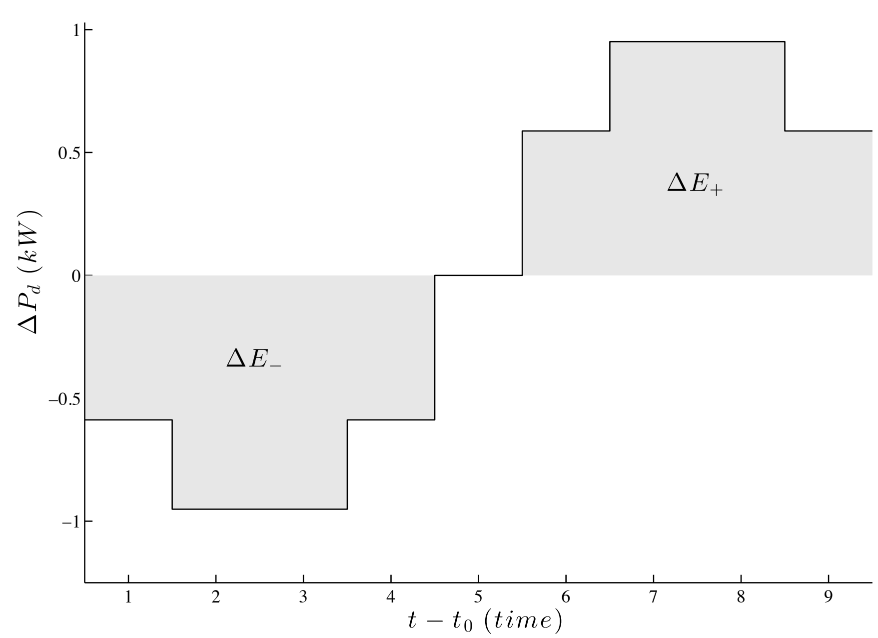
Control Actions

Control actions are aimed to directly impact the power levels of the devices $d \in \mathcal{D}$.



Curtailment instructions can be imposed to generators.

Cost: $\mathrm{En}_{\mathrm{curt}}\ [\mathrm{MWh}] \times \mathrm{Price}\left[\frac{€}{\mathrm{MWh}}\right]$



Flexibility service of loads can be activated.

Cost: activation fee

Time-coupling effect.

Problem Formulation

The problem of computing the right control actions is formalized as an optimal sequential decision-making problem.

We model this problem as a first-order Markov decision process with mixed integer and continuous sets of states and actions.

$$\mathbf{s}_{t+1} = f\big(\mathbf{s}_t, \mathbf{a}_t, \mathbf{w}_{t+1}\big)$$

$$\mathbf{s}_t, \mathbf{s}_{t+1} \in \mathcal{S}$$

$$\mathbf{a}_t \in \mathcal{A}_{\mathbf{s}_t}$$

$$\mathbf{w}_{t+1} \sim p\big(\cdot \big| \mathbf{s}_t\big)$$

System state s_t

The electrical quantities can be deduced from the power injections of the devices.

in s_t → Active power injections of loads and power level of the primary energy sources of DG (i.e. wind and sun).

The control instructions of the DSO that affect the current period and/or future periods are also stored in the state vector.

in s_t → Upper limits on production levels and the number of active periods left for flexibility services

$$\boldsymbol{s}_t = (P_{1,t}, \ldots, P_{|\mathcal{C}|,t}, ir_t, v_t, \overline{P}_{1,t}, \ldots, \overline{P}_{|\mathcal{G}|,t}, s^{(f)}_{1,t}, \ldots, s^{(f)}_{|\mathcal{F}|,t}, q_t)$$

Transition Function

$$f : \mathcal{S} \times \mathcal{A}_{\boldsymbol{s}} \times \mathcal{W} \mapsto \mathcal{S}$$

Curtailment instructions for next period and activation of flexible loads.

Set of possible realizations of a random process, with $w_t \in \mathcal{W}$ that follows a conditional probability law $p_{\mathcal{W}}(\cdot | \boldsymbol{s}_t)$.

$$\begin{cases} P_{d,t+1} = f_d(P_{d,t}, q_t, w_{d,t}) \,, \\ v_{t+1} = f_v(v_t, q_t, w_t^{(v)}) \,, \\ P_{g,t+1} = \eta_g(v_{t+1}), \forall g \in \text{wind generators} \subset \mathcal{G} \,, \\ ir_{t+1} = f_{ir}(ir_t, q_t, w_t^{(ir)}) \,, \\ P_{g,t+1} = \eta_g \cdot \text{surf}_g \cdot ir_{t+1}, \forall g \in \text{solar generators} \subset \mathcal{G} \,, \end{cases}$$

Reward Function

The reward function $r : \mathcal{S} \times \mathcal{A}_{\boldsymbol{s}} \times \mathcal{S} \mapsto \mathbb{R}$ associates an instantaneous rewards for each transition of the system from a period *t* to a period *t+1*:

$$r(\boldsymbol{s}_t, \boldsymbol{a}_t, \boldsymbol{s}_{t+1}) = -\underbrace{\sum_{g \in \mathcal{G}} \max\{0, \frac{P_{g,t+1} - \overline{P}_{g,t+1}}{4}\} C_g^{curt}(q_{t+1})}_{\text{curtailment cost of DG}} - \underbrace{\sum_{d \in \mathcal{F}} a_{d,t}^{(f)} C_d^{flex}}_{\substack{\text{activation cost} \\ \text{of flexible loads}}} - \underbrace{\Phi(\boldsymbol{s}_{t+1})}_{\text{barrier function}}$$

Because the operation of a DN must be always be ensured, we consider the return *R* over an infinite trajectory of the system:

$$R = R_\infty = \lim_{T \to \infty} \sum_{t=0}^{T-1} \gamma^t r(\boldsymbol{s}_t, \boldsymbol{a}_t, \boldsymbol{s}_{t+1})$$

Optimal Policy

Let $\pi : \mathcal{S} \mapsto \mathcal{A}_{\boldsymbol{s}}$ be a policy that associates a control action to each state of the system, the expected return of this policy can be written as:

$$J^{\pi}(\boldsymbol{s}) = \lim_{T\to\infty} \mathop{\mathbb{E}}_{\boldsymbol{w}_t \sim p_{\mathcal{W}}(\cdot|\boldsymbol{s}_t)} \{\sum_{t=0}^{T-1} \gamma^t \underbrace{\rho(\boldsymbol{s}_t, \pi(\boldsymbol{s}_t), \boldsymbol{w}_t)}_{= r(\boldsymbol{s}_t, \boldsymbol{a}_t, f(\boldsymbol{s}_t, \boldsymbol{a}_t, \boldsymbol{w}_t))} | \boldsymbol{s}_0 = \boldsymbol{s}\}$$

Let Π be the space of all stationary policies. Addressing the operational planning problem of a DSO consists in finding an optimal policy $\pi^* \in \Pi$:

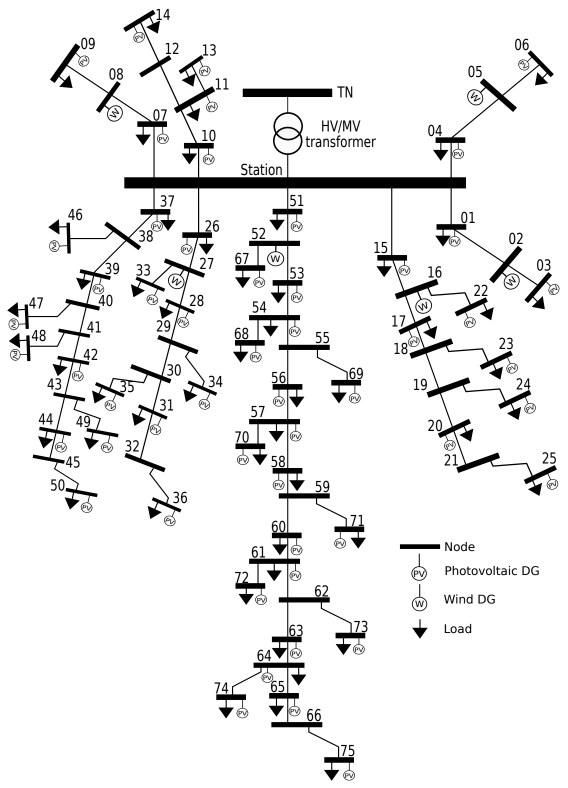
$$J^{\pi^*}(\boldsymbol{s}) \geq J^{\pi}(\boldsymbol{s}), \forall \boldsymbol{s} \in \mathcal{S}, \forall \pi \in \Pi\,.$$

Solution Techniques

We identified three classes of solution techniques that could be applied to the operational planning problem:

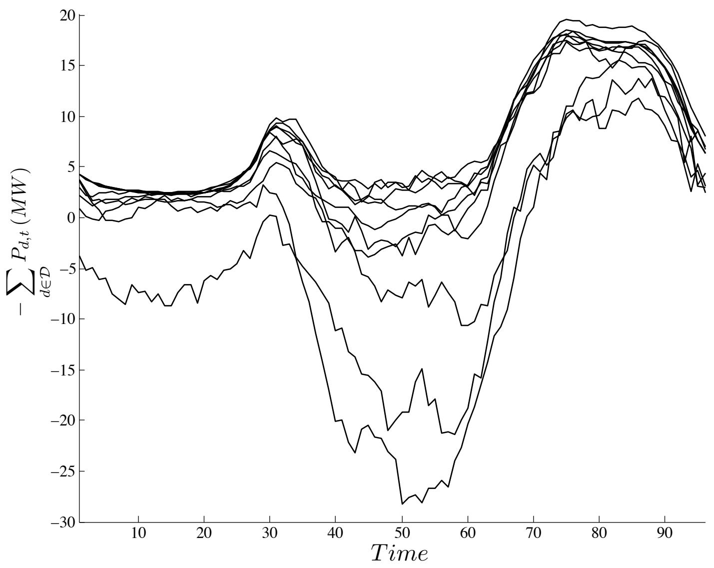
- mathematical programming and, in particular, multistage stochastic programming;
- approximate dynamic programming;
- simulation-based methods, such as direct policy search or MCTS.

Test Instance



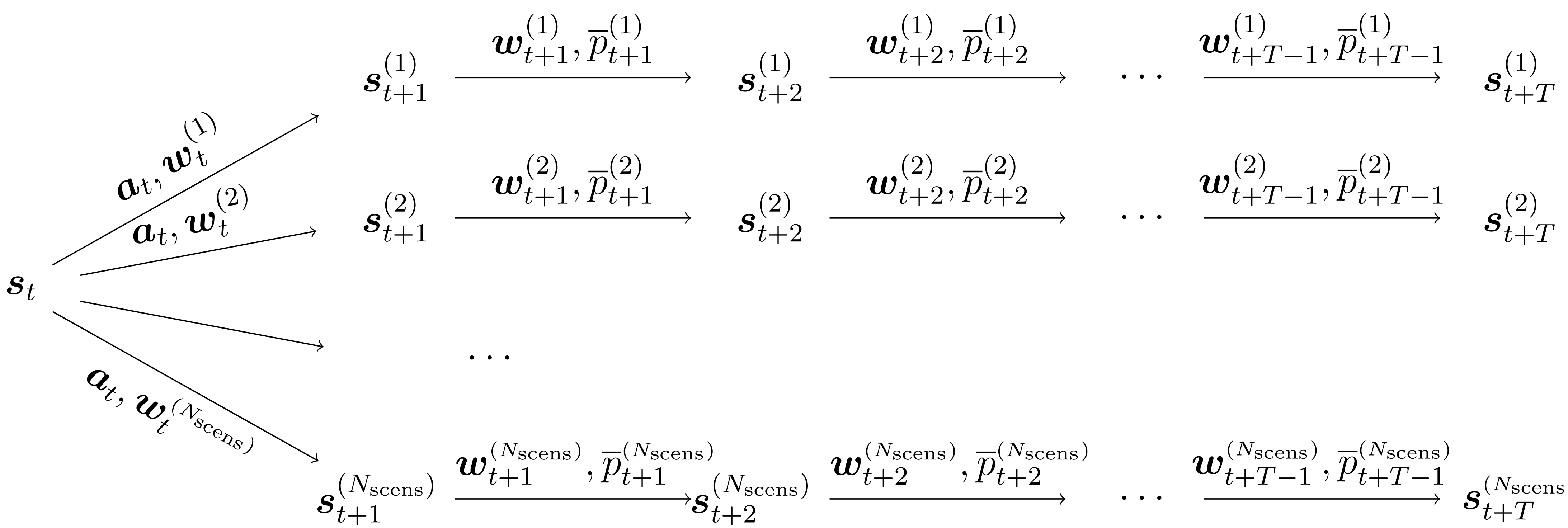
We designed a benchmark of the ANM problem with the goal of promoting computational research in this complex field.

The set of models and parameters that are specific to this instance as well as documentation for their usage are accessible as a Matlab class at www.montefiore.ulg.ac.be/~anm/ .



Example of Policy

In order to illustrate the operational planning problem and the test instance, let's consider a simple solution technique. It consists in a simplified version of a multi-stage stochastic program:



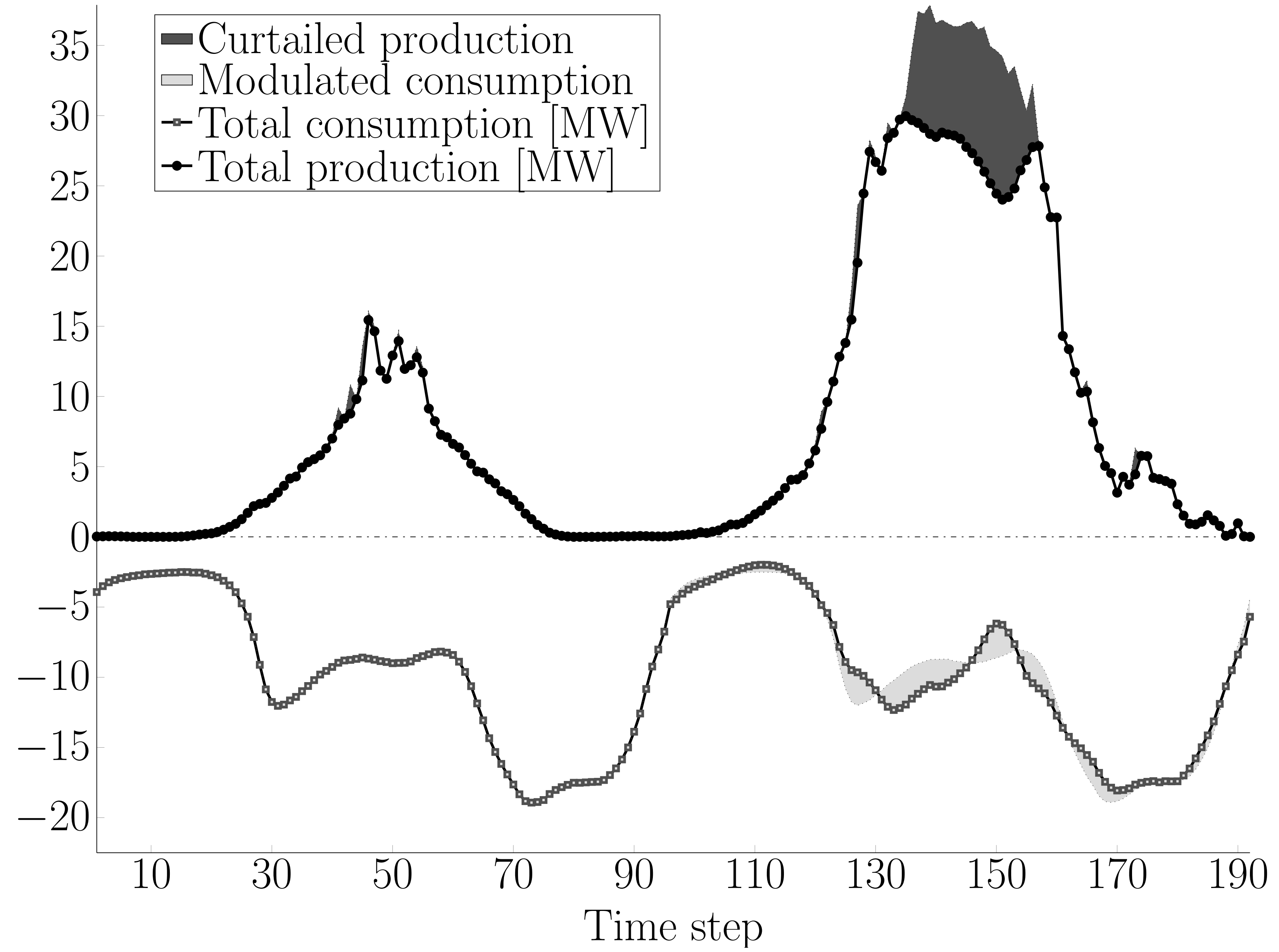
Example of Policy

In order to illustrate the operational planning problem and the test instance, let's consider a simple solution technique. It consists in a simplified version of a multi-stage stochastic program:

$$
\begin{aligned}
\hat{\pi}^*(\boldsymbol{s}) = \arg \min_{\boldsymbol{a} \in \mathcal{A}_s(\boldsymbol{s})} \quad & \min_{\substack{\forall k \in \mathcal{K}_t :\, \boldsymbol{s}_k\,, \\ \forall k \in \mathcal{K}_t \backslash \{0\} :\, \boldsymbol{a}_{\mathbb{A}_k}}} \sum_{k \in \mathcal{K}_t \backslash \{0\}} \Bigg[\mathbb{P}_k \gamma^{\mathbb{D}_k} \sum_{g \in \mathcal{G}} \Big(\frac{\Delta P_{g,k}}{4} C_g^{curt}(q_k) + \epsilon_2 \Delta P_{g,k}^2 \\
& \qquad - \epsilon_1 \Delta M_{g,k} + \epsilon_2 \Delta M_{g,k}^2 \Big) \Bigg] + \sum_{d \in \mathcal{F}} \Big[C_d^{flex} a_{d,0}^{(f)} \Big] \\
\text{s.t.} \quad & \boldsymbol{s}_0 = \boldsymbol{s} \\
& \boldsymbol{a}_0 = \boldsymbol{a} \\
& \boldsymbol{s}_k = f(\boldsymbol{s}_{\mathbb{A}_k}, \boldsymbol{a}_{\mathbb{A}_k}, \boldsymbol{w}_{\mathbb{A}_k})\,, \quad \forall k \in \mathcal{K}_t \backslash \{0\} \\
& \boldsymbol{a}_{\mathbb{A}_k} \in \mathcal{A}_{\boldsymbol{s}_{\mathbb{A}_k}}\,, \quad \forall k \in \mathcal{K}_t \backslash \{0\} \\
& \boldsymbol{a}_{\mathbb{A}_k}^{(f)} = \boldsymbol{0}\,, \quad \forall k \in \{ k \in \mathcal{K}_t \mid \mathbb{D}_k > 1 \} \\
& \boldsymbol{s}_k \in \hat{\mathcal{S}}^{(\mathrm{ok})}\,, \quad \forall k \in \mathcal{K}_t \backslash \{0\} \\
& \Delta P_{g,k} = \max(0, P_{g,k} - \overline{P}_{g,k}), \forall (g,k) \in \mathcal{G} \times \mathcal{K}_t \backslash \{0\} \\
& \Delta M_{g,k} = \max(0, \overline{P}_{g,k} - P_{g,k}), \forall (g,k) \in \mathcal{G} \times \mathcal{K}_t \backslash \{0\}
\end{aligned}
$$

$$
\text{with} \quad \hat{\mathcal{S}}^{(ok)} \equiv \Big\{ \boldsymbol{s} \in \mathcal{S} \Big| \sum_{g \in \mathcal{G}} \overline{P}_g + \sum_{d \in \mathcal{C}} (P_d + \Delta P_d) < \overline{C} \Big\}
$$

Example of Policy



Thank you

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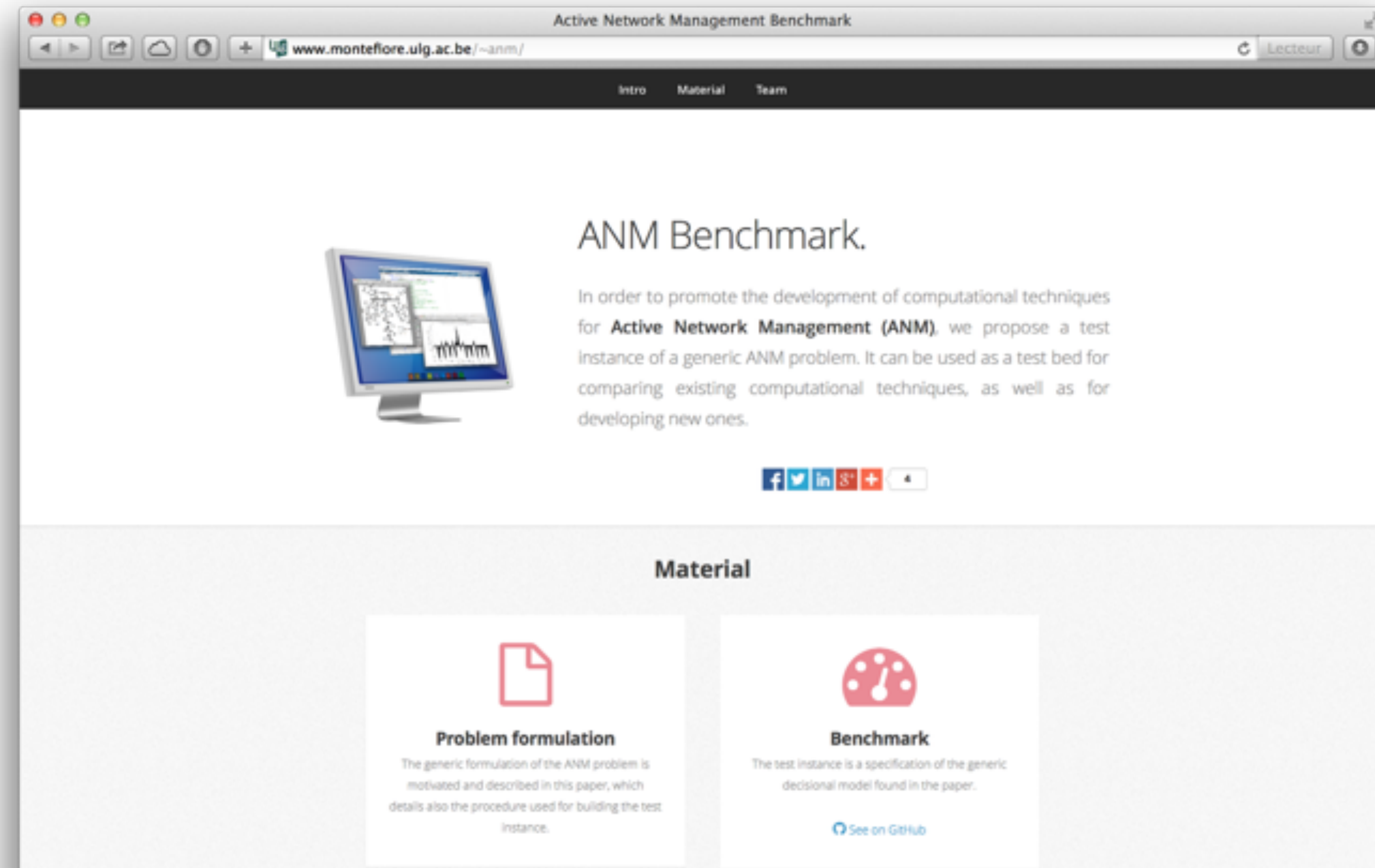

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