# Optimization Project in Energy PGE 306

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2 Deterministic model

- Main goal: programming numerical methods (Energy Management System) for a very simple model of a microgrid.
- Microgrid: a set consisting of the following elements:
  - a small-size electrical load (a building, a few houses)
  - a source of **renewable energy** (solar panels, a wind turbine)
  - a storage device (Energy Storage System, a battery)
  - a macrogrid (an access to a large-scale energy network).

- Time scale: the decisions are taken every hour during the day.
- Optimization variables (at each time step) :
  - the amount of energy to be stored or withdrawn from the battery
  - the amount of energy bought or sold to the network.

#### Contraints:

- nonnegativity of variables
- evolution of the battery
- storage capacity of the battery.

## Cost function:

- Cost of the energy bought on the network...
- minus the cost of the energy sold on the network.

# Main challenge:

- The electrical load and the production of renewable energy are random.
- No available probabilistic model, instead the history of electrical load and solar production.

## Tools and mathematical concepts:

- Dynamic programming (temporal aspect for decision process).
- Autoregressive processes.

## Optimization is useful for...

- minimizing the management costs
- modelling random processes
- describing some functions, for which no analytical expression is available (interpolation).

## Philosophy:

- Compromise between the complexity of stochastic modelling and solvability of the problem.
- Emphasis on the mathematical approach. Maths concepts useful in other application contexts.
- We will work with models of **increasing** complexity.

## Warning:

- (Very) simplified models, with artificial data.
- The purpose is not to conclude on the relevance of the introduction of such or such technology.

## References :

- Le Franc, Carpentier, Chancelier, de Lara. EMSx: an Energy Management System numerical benchmark. Energy System, 2021.
- Hafiz, Awal, de Queiroz, Husain. Real-time Stochastic Optimization of Energy Storage Management using Rolling Horizon Forecasts for Residential PV Applications, 2019.
- Olivares et al. Trends in microgrid control. IEEE Transactions on smart grid, 2014.

## Organisation:

- 6 units: January 11, January 18, January 25, January 26, February 1, February 2.
- It is highly recommended to participate to all units.
- Work in pairs (please form the groups by next week).
- Programming with Matlab.
- Evaluation: programming exercises to solve + work in class.

2 Deterministic model

- Horizon: 24 hours, stepsize: 1 hour. Optimization over T = 24 intervals.
- Optimisation variable :
  - x(s): state of charge of the battery at time s, s=1,...,T+1
  - **a**(s): amount of electricity bought on the network (s = 1, ..., T).
  - $\mathbf{v}(s)$ : amount of energy sold on the network (s=1,...,T).

## Parameters:

- d(s): net demand of energy (load minus solar production) at time s, s = 1, ..., T.
- $Arr P_a(s)$ : unitary buying price of energy at time s
- $P_{\nu}(s)$ : unitary selling price of energy at time s
- $x_{\text{max}}$ : storage capacity of the battery.

Remark: the demand is supposed to be deterministic (that is to say, known in advance), for the moment.

Contraints:

$$x(s+1) = x(s) - d(s) + a(s) - v(s), \forall s = 1, ..., T$$

$$x(1) = 0$$

■ 
$$a(s) \ge 0, \forall s = 1, ..., T$$

$$v(s) \ge 0, \ \forall s = 1, ..., T$$

$$0 \le x(s) \le x_{\text{max}}, \forall s = 1, ... T + 1.$$

Cost function to be minimized:

$$J(x, a, v) = \sum_{s=1}^{T} (P_{a}(s)a(s) - P_{v}(s)v(s)).$$

The buying and selling prices  $P_a$  and  $P_v$  depend on time. It holds:  $P_a(s) > P_v(s)$ , so that it is useless to try to buy and sell electricity on the network at the same time!

## Exercise 1

- Write the optimization problem in a form that is compatible with the function linprog of Matlab.
- 2 Write a Matlab program that solves the optimization problem corresponding to the deterministic model.

## Main idea behind dynamic programming:

- We **parametrize** the problem to be solved  $\rightsquigarrow$  a sequence of problems of increasing complexity.
- We look for a relation ("dynamic programming principle") between the optimal values of the different problems.

## Parameters:

- Initial time  $t \in \{1, ..., T + 1\}$ .
- Initial state-of-charge of the battery  $y \in [0, x_{max}]$ .

We are interested in the problem with t = 1 and y = 0.

Parameterized problem:

$$V(t,y) = \inf_{\substack{x(t),x(t+1),...,x(T+1)\\ a(t),a(t+1),...,a(T)\\ v(t),v(t+1),...,v(T)}} \sum_{s=t}^{t} P_{a}(s)a(s) - P_{v}(s)v(s)$$

$$(P(t,y))$$

under the constraints:

$$x(s+1) = x(s) - d(s) + a(s) - v(s), \forall s = t, ..., T$$

$$\mathbf{x}(t) = y$$

■ 
$$a(s) \ge 0, \forall s = t, ..., T$$

■ 
$$v(s) \ge 0$$
,  $\forall s = t, ..., T$ 

■ 
$$0 \le x(s) \le x_{\text{max}}, \forall s = t, ... T + 1.$$

The function V is called **value function**; it plays a crucial role, in particular in the treatment of the stochastic version of the problem.

## Theorem [Dynamic programming principle]

The following holds true:

$$V(t,y) = \inf_{(z,a,v) \in \mathbb{R}^3} \quad P_a(t)a - P_v(t)v + V(t+1,z),$$
 s.t.: 
$$\begin{cases} a \ge 0 \\ v \ge 0 \\ z = y - d(t) + a - v \\ 0 \le z \le x_{\max} \end{cases}$$
  $(DP(t,y))$ 

for all  $t \in \{1, ... T\}$  and  $y \in [0, x_{max}]$  and

$$V(T+1,y)=0.$$

## Computation of the value function

- Let us suppose that the function  $y \mapsto V(t+1,y)$  is known, with  $t \in \{1,...,T\}$ . By solving DP(t,y) for all possible values of y, we can compute  $y \mapsto V(t,y)$ .
- In practice, we can only solve DP(t,y) for a sample of values of  $y \in [0, x_{\text{max}}]$ . We evaluate V(t,y) for those values of y; then we interpolate.
- In that way, we can compute (an approximation of) the value function, in a recursive and backward fashion (from  $\mathcal{T}+1$  to 1).

## Solving the initial problem.

- Let (z, a, v) denote a solution of DP(1, 0). Let us set:  $\bar{x}(2) = z$ ,  $\bar{a}(1) = a$ ,  $\bar{v}(1) = v$ .
- Let (z, a, v) be a solution of  $DP(2, \bar{x}(2))$ . Let us set:  $\bar{x}(3) = z$ ,  $\bar{a}(2) = a$ ,  $\bar{v}(2) = v$ .
- Let (z, a, v) be a solution of  $DP(3, \bar{x}(3))$ . Let us set:  $\bar{x}(4) = z$ ,  $\bar{a}(3) = a$ ,  $\bar{v}(3) = v$ .
- ... and so on, until the resolution of  $DP(T, \bar{x}(T))$ .

- Let  $y \in \mathbb{R}^J$  and let  $z \in \mathbb{R}^J$ . We consider a function f such that  $z_j = f(y_j)$ , for all j = 1, ..., J.
- $\blacksquare$  We interpolate f with a second-order polynomial, by solving

$$\inf_{\alpha \in \mathbb{R}^3} \sum_{j=1}^J \left( \alpha_1 + \alpha_2 y_j + \alpha_3 y_j^2 - z_j \right)^2.$$

■ Let  $\bar{\alpha}$  be the solution. We get the approximation:

$$f(y) \approx \bar{\alpha}_1 + \bar{\alpha}_2 y + \bar{\alpha}_3 y^2$$
.

## Exercise 2

Write a function interpolate implementing the interpolation with a second-order polynomial.

Inputs:  $J, y \in \mathbb{R}^J, z \in \mathbb{R}^J$ . Outputs:  $\alpha \in \mathbb{R}^3$ .

## Exercise 3

Write a function DP\_solve with output the solution (z, a, v) of problem DP(t, y).

We assume that the function  $V(t+1,\cdot)$  is approximated by a second-order polynomial, described by a coefficient  $\alpha \in \mathbb{R}^3$ .

Input:  $t \in \{1, ..., T\}$ ,  $y \in [0, x_{\text{max}}]$ ,  $\alpha \in \mathbb{R}^3$ .

## Exercise 4

Write a function DP\_backward which compute a polynomial approximation of V, in the form of a matrix  $\alpha \in \mathbb{R}^{(T+1)\times 3}$ , that is to say:

$$V(t,y) \approx \alpha_{t,1} + \alpha_{t,2}y + \alpha_{t,3}y^2$$
.

We will proceed in a recursive fashion:

- Given  $\alpha_{t+1,1}$ ,  $\alpha_{t+1,2}$ ,  $\alpha_{t+1,3}$ , evaluate  $V(t,y_j)$  for all j=1,...,J, where  $y_j=(j-1)/(J-1)x_{\text{max}}$ .
- Calculate  $\alpha_{t,1}$ ,  $\alpha_{t,2}$ , and  $\alpha_{t_3}$  by interpolating the values of  $V(t,\cdot)$ .

## Exercise 5

Write a function DP\_forward computing the solution to the original problem. We will first make use of DP\_backward to get an approximation of the value function.