Towards the Minimization of the Levelized Energy Costs of Microgrids using both Long-term and Short-term Storage Devices

Vincent François-Lavet, Quentin Gemine, Damien Ernst, Raphael Fonteneau

Abstract

This chapter falls within the context of the optimization of the levelized energy cost (LEC) of microgrids featuring photovoltaic panels (PV) associated with both long-term (hydrogen) and short-term (batteries) storage devices. First, we propose a novel formalization of the problem of building and operating microgrids interacting with their surrounding environment. Then we show how to optimally operate a microgrid using linear programming techniques in the context where the consumption and the production are known. It appears that this optimization technique can also be used to address the problem of optimal sizing of the microgrid, for which we propose a robust approach. These contributions are illustrated in two different settings corresponding to Belgian and Spanish data.

1 Introduction

Economies of scale of conventional power plants have progressively led to the development of the very large and complex electrical networks that we know today. These networks transmit and distribute the power generated by these power plants to the consumers. Over recent years, a new trend opposing this centralization of power facilities has been observed, resulting from the drop in price of distributed generation, mainly solar photovoltaic (PV) panels [1]. Due to this effect, it is expected that in the future, small scale industries and residential consumers of electricity will rely more and more on local renewable energy production capacities for covering, at least partially, their need for electrical power. This leads to the creation of the so-called microgrids that are electrical systems which include loads and distributed energy resources that can be operated in parallel with the broader utility grid or as an electrical island. State-of-the-art issues and feasible solutions associated with the deployment of microgrids are discussed in [2].

Due to the fluctuating nature of renewable energy sources (RES) (mainly solar and wind energy), small businesses and residential consumers of electricity may also be tempted to combine their local power plants with storage capacities. In principle, this would, at least partially, allow themselves freedom from using the network, enabling balancing their own electricity generation with their own consumption. This would result in paying less in transmission and distribution fees which typically make up around 50% of their electricity bill. Many different technologies are available for energy storage as discussed in the literature (see e.g. [3]). On the one hand, hydrogen is often considered as a storage solution to be combined with RES [4, 5], mainly due to its high capacity potential that makes it suitable for long-term storage [6, 7]. On the other hand, batteries are often used to ensure sufficient peak power storage and peak power generation [8]. In this chapter we focus on the specific case of microgrids that are powered by PV panels combined with both hydrogen-based storage technologies (electrolysis combined with fuel cells) and batteries (such as, for instance, $LiFePO_4$ batteries). These two types of storage aim at fulfilling, at best, the demand by addressing the seasonal and daily fluctuations of solar irradiance.

One of the main problems to be addressed in the field of microgrids is how to perform optimal sizing. The main challenge when sizing microgrids comes from the need to determine and simulate their operation, i.e. the dispatch strategy, using historical data of the loads and of the RES. Broadly speaking, the research presented in this paper relates to the research that has been done for solving planning and scheduling problems in the field of electrical power systems. In this context, various methods have been investigated, for instance model predictive control (MPC) [9] or learning-based approaches [10, 11]. One can also mention commercial solutions such as the well-known energy modeling software HOMER [12], dedicated to hybrid renewable energy systems.

In this chapter, we first propose a novel and detailed formalization of the problem of sizing and operating microgrids. Then, we show how to optimally operate a microgrid so that it minimizes a levelized energy cost (LEC) criterion in the context where the energy production and demand are known. We show that this optimization step can be achieved efficiently using linear programming. We then show that this optimization step can also be used to address the problem of optimal sizing of the microgrid, for which we propose a robust approach by considering several energy production and consumption scenarios. We run experiments using real data corresponding to the case of typical residential consumers of electricity located in Spain and in Belgium. Experimental results show that there is an important benefit in combining batteries and hydrogen-based storage, in particular when the cost for interruption (value of loss load) in the supply is high. Note that this chapter focuses on the production planning and optimal sizing of the microgrid, and that the real-time control aspects of the microgrid to maintain both angle stability and voltage quality are left out of the scope of the chapter (see e.g. [13] for more details on that subject).

Subsequently, the chapter is organized as follows. A detailed formalization of the microgrid framework is proposed in Section (2) and several optimization schemes for minimizing the LEC are introduced in Section (3). The simulation results for Belgium and Spain are finally reported in Section (4) while Section (5) provides the conclusion.

2 Formalization and problem statement

In this section we provide a generic model of a microgrid powered by PV panels combined with batteries and hydrogen-based storage technologies. We formalize its constitutive elements as well as its dynamics within the surrounding environment. For the sake of clarity, we first define the space of exogenous variables and then gradually build the state and action spaces of the system. The components of these two latter spaces will be related to either the notion of *infrastructure* or the notion of *operation* of the microgrid. We then characterize the problem of sizing and control that we want to address using an optimality criterion, which leads to the formalization of an optimal sequential decision-making problem. The evolution of the system is described as a discrete-time process over a finite time-horizon of length T. We denote by $\mathcal{T}$ the set $\{1, ..., T\}$ of time periods and by Δt the duration of a time step. We use subscript t to reference exogenous variables, state and actions at time step t. Finally we introduce the notion of LEC and discuss how it can be used as an optimality criterion.

2.1 Exogenous variables

We start with a definition of the microgrid's environment, i.e. the space of exogenous variables that affect the microgrid but on which the latter has no control. Assuming that there exists, respectively, J, L, and M different photovoltaic, battery, and hydrogen storage technologies, and denoting the environment space by $\mathcal{E}$, we can define the time-varying environment vector $\mathbf{E}_t$ as:

$$\mathbf{E}_t = (c_t, i_t, \mathbf{e}^{PV}_{1,t}, ..., \mathbf{e}^{PV}_{J,t}, \mathbf{e}^{B}_{1,t}, ..., \mathbf{e}^{B}_{L,t}, \mathbf{e}^{H_2}_{1,t}, ..., \mathbf{e}^{H_2}_{M,t}, \boldsymbol{\mu}_t) \in \mathcal{E},\ \forall t \in \mathcal{T} \tag{1}$$

$$\text{and with } \mathcal{E} = {\mathbb{R}^+}^2 \times \prod_{j=1}^{J} \mathcal{E}^{PV}_j \times \prod_{l=1}^{L} \mathcal{E}^{B}_l \times \prod_{m=1}^{M} \mathcal{E}^{H_2}_m \times \mathcal{I}\,, \tag{2}$$

where:

- c_t [W] $\in \mathbb{R}^+$ is the electricity demand within the microgrid;
- i_t [W/m^2 or W/W$_p$] $\in \mathbb{R}^+$ denotes the solar irradiance incident to the PV panels;
- $\mathbf{e}^{PV}_{j,t} \in \mathcal{E}^{PV}_j$, $\forall j \in \{1, ..., J\}$, models a photovoltaic technology in terms of cost $c^{PV}_{j,t}$ [€/m^2], lifetime $L^{PV}_{j,t}$ [s] and efficiency $\eta^{PV}_{j,t}$ to convert solar irradiance to electrical power:

$$\mathbf{e}^{PV}_{j,t} = (c^{PV}_{j,t}, L^{PV}_{j,t}, \eta^{PV}_{j,t}) \in \mathcal{E}^{PV}_j,\ \forall j \in \{1, ..., J\} \text{ and with } \mathcal{E}^{PV}_j = {\mathbb{R}^+}^2 \times\ ]0, 1]\,; \tag{3}$$

- $\mathbf{e}^{B}_{l,t} \in \mathcal{E}^{B}_l$, $\forall l \in \{1, ..., L\}$, represents a battery technology in terms of cost $c^{B}_{l,t}$ [€/Wh], lifetime L^{B}_l [s], cycle durability $D^{B}_{l,t}$, power limit for charge and discharge $P^{B}_{l,t}$ [W], discharge efficiency $\zeta^{B}_{l,t}$, and charge retention rate $r_{l,t}^B$ [s^{-1}]:

$$\mathbf{e}_{l,t}^B = (c_{l,t}^B, L_{l,t}^B, P_{l,t}^B, \eta_{l,t}^B, \zeta_{l,t}^B, r_{l,t}^B) \in \mathcal{E}_l^B,\ \forall l \in \{1, ..., L\} \tag{4}$$

$$\text{and with } \mathcal{E}_l^B = {\mathbb{R}^+}^3 \times\ ]0,1]^3 \ ; \tag{5}$$

- $\mathbf{e}_{m,t}^{H_2} \in \mathcal{E}_m^{H_2}$, $\forall m \in \{1, ..., M\}$, denotes a hydrogen storage technology in terms of cost $c_{m,t}^{H_2}$ [€/W$_p$], lifetime $L_{m,t}^{H_2}$ [s], maximum capacity $R_{m,t}^{H_2}$ [W], electrolysis efficiency $\eta_{m,t}^{H_2}$ (i.e. when storing energy), fuel cells efficiency $\zeta_{m,t}^{H_2}$ (i.e. when delivering energy), and charge retention rate $r_{m,t}^{H_2}$ [s^{-1}]:

$$\mathbf{e}_{m,t}^{H_2} = (c_{m,t}^{H_2}, L_{m,t}^{H_2}, R_{m,t}^{H_2}, \eta_{m,t}^{H_2}, \zeta_{m,t}^{H_2}, r_{m,t}^{H_2}) \in \mathcal{E}_m^{H_2},\ \forall m \in \{1, ..., M\} \tag{6}$$

$$\text{and with } \mathcal{E}_m^{H_2} = {\mathbb{R}^+}^3 \times\ ]0,1]^3 \ . \tag{7}$$

Finally, the components denoted by $\boldsymbol{\mu}_t \in \mathcal{I}$ represent the model of interaction. By model of interaction we mean all the information that is required to manage and evaluate the costs (or benefits) related to electricity exchanges between the microgrid and the rest of the system. We assume that $\boldsymbol{\mu}_t$ is composed of two components k and β:

$$\boldsymbol{\mu}_t = (k, \beta) \in \mathcal{I},\ \forall\ t\ \in\ \mathcal{T} \text{ and with } \mathcal{I} = {\mathbb{R}^+}^2 \ . \tag{8}$$

The variable β characterizes the price per kWh at which it is possible to sell energy to the grid (it is set to 0 in the case of an off-grid microgrid). The variable k refers to the cost endured per kWh that is not supplied within the microgrid. In a connected microgrid, k corresponds to the price at which electricity can be bought from outside the microgrid. In the case of an off-grid microgrid, the variable k characterizes the penalty associated with a failure of the microgrid to fulfill the demand. This penalty is known as the value of loss load and corresponds to the amount that consumers of electricity would be willing to pay to avoid a disruption to their electricity supply.

2.2 State space

Let $\mathbf{s}_t \in \mathcal{S}$ denote a time varying vector characterizing the microgrid's state at time $t \in \mathcal{T}$:

$$\mathbf{s}_t = (\mathbf{s}_t^{(s)}, \mathbf{s}_t^{(o)}) \in \mathcal{S},\ \forall t \in \mathcal{T} \text{ and with } \mathcal{S} = \mathcal{S}^{(s)} \times \mathcal{S}^{(o)} \ , \tag{9}$$

where $\mathbf{s}_t^{(s)} \in \mathcal{S}^{(s)}$ and $\mathbf{s}_t^{(o)} \in \mathcal{S}^{(o)}$ respectively represent the state information related to the infrastructure and to the operation of the microgrid.

2.2.1 Infrastructure state

The infrastructure state vector $\mathbf{s}_t^{(s)} \in \mathcal{S}^{(s)}$ gathers all the information about the physical and electrical properties of the devices that constitute the microgrid. Its components can only change because of investment decisions or due to aging of the devices. In particular, we define this vector as:

$$\mathbf{s}_t^{(s)} = (x_t^{PV}, x_t^B, x_t^{H_2}, L_t^{PV}, L_t^B, L_t^{H_2}, P_t^B, R_t^{H_2}, \eta_t^{PV}, \eta_t^B, \eta_t^{H_2}, \zeta_t^B, \zeta_t^{H_2}, r_t^B, r_t^{H_2}) \in \mathcal{S}^{(s)} \ , \tag{10}$$

$$\forall t \in \mathcal{T} \text{ and with } \mathcal{S}^{(s)} = {\mathbb{R}^+}^8 \times\ ]0,1]^7 \ , \tag{11}$$

where x_t^{PV} [m^2], x_t^B [Wh], and $x_t^{H_2}$ [W$_p$] denote, respectively, the sizing of the PV panels, battery and hydrogen storage. The other components have the same meaning than the exogenous variables using a similar symbol, with the difference here that they are specific to the devices that are present at time $t \in \mathcal{T}$ in the microgrid. Note that by using such a representation, we consider that, for each device type, a single device can operate in the microgrid. In other words, an investment decision for a device type substitutes any prior investment.

2.2.2 Operation state

For the devices with storage capacities, i.e. battery and hydrogen storage, the information provided by the environment vector $\mathbf{E}_t$ and by the infrastructure state vector $\mathbf{s}_t^{(s)}$ is not sufficient to determine the set of their feasible power injections or demands. Additional information that corresponds to the amount of energy stored in these devices for each time period is required. For this reason we introduce the operation state vector $\mathbf{s}_t^{(o)}$:

$$\mathbf{s}_t^{(o)} = (s_t^B, s_t^{H_2}) \in \mathcal{S}^{(o)},\ \forall t \in \mathcal{T} \text{ and with } \mathcal{S}^{(o)} = \mathbb{R}^{+2} \ , \tag{12}$$

where s_t^B [Wh] is the level of charge of the battery and with s_t^B [Wh] the level of charge of the hydrogen storage.

2.3 Action space

As for the state space, each component of the action vector $\mathbf{a}_t \in \mathcal{A}$ can be related to either sizing or control, the former affecting the infrastructure of the microgrid while the latter affects its operation. We define the action vector as:

$$\mathbf{a}_t = (\mathbf{a}_t^{(s)}, \mathbf{a}_t^{(o)}) \in \mathcal{A}_t,\ \forall t \in \mathcal{T} \text{ and with } \mathcal{A} = \mathcal{A}^{(s)} \times \mathcal{A}_t^{(o)} \ , \tag{13}$$

where $\mathbf{a}_t^{(s)} \in \mathcal{A}^{(s)}$ relates to sizing actions and $\mathbf{a}_t^{(o)} \in \mathcal{A}_t^{(o)}$ to control actions.

2.3.1 Sizing actions

The sizing actions correspond to investment decisions. For each device type, it defines the sizing of the device to install in the microgrid and its technology:

$$\mathbf{a}_t^{(s)} = (a_t^{PV}, a_t^B, a_t^{H_2}, j_t, l_t, m_t) \in \mathcal{A}^{(s)},\ \forall t \in \mathcal{T} \tag{14}$$

$$\text{and with } \mathcal{A}^{(s)} = \mathbb{R}^{+3} \times \{1, ..., J\} \times \{1, ..., L\} \times \{1, ..., M\} \ , \tag{15}$$

where a_t^{PV} [m^2], a_t^B [Wh], and $a_t^{H_2}$ [Wp] denote, respectively, the new sizing at time $t+1 \in \mathcal{T}$ of the PV panels, battery and hydrogen storage. Discrete variables j_t, l_t, and m_t correspond to indices that indicate the selected technology from the environment vector for PV panels, battery, and hydrogen storage, respectively. When a sizing variable (i.e. a_t^{PV}, a_t^B, or $a_t^{H_2}$) is equal to zero, it means that there is no new installation for the corresponding device type and that the present device, if it exists, remains in operation.

2.3.2 Operational planning

A microgrid featuring PV, battery and storage using H_2 has two control variables that correspond to the power exchanges between the battery, the hydrogen storage, and the rest of the system:

$$\mathbf{a}_t^{(o)} = (p_t^B, p_t^{H_2}) \in \mathcal{A}_t^{(o)} \ , \forall t \in \mathcal{T} \ , \tag{16}$$

where p_t^B [W] is the power provided to the battery and where $p_t^{H_2}$ [W] is the power provided to the hydrogen storage device. These variables are positive when the power flows from the system to the devices and negative if it flows in the other direction. Note that the set $\mathcal{A}_t^{(o)}$ of control actions is time dependent. This comes from the fact that the feasible power exchanges with these devices depend on their capacity and level of charge. We have, $\forall t \in \mathcal{T}$:

$$\mathcal{A}_t^{(o)} = \left([-\zeta_t^B s_t^B, \frac{x_t^B - s_t^B}{\eta_t^B}] \cap [-P_t^B, P_t^B] \right) \times \left([-\zeta_t^{H_2} s_t^{H_2}, \frac{R_t^{H_2} - s_t^{H_2}}{\eta_t^{H_2}}] \cap [-x_t^{H_2}, x_t^{H_2}] \right) \ , \tag{17}$$

which expresses that the bounds on the power flows of the storing devices are, at each time step $t \in \mathcal{T}$, the most constraining among the ones induced by the charge levels and the power limits.

2.4 Dynamics

Using the formalism proposed above, the dynamics of the microgrid follows the following discrete-time equation:

$$\mathbf{s}_{t+1} = f(\mathbf{s}_t, \mathbf{a}_t), \forall t \in \mathcal{T} \text{ and with } (\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{t+1}) \in \mathcal{S} \times \mathcal{A}_t \times \mathcal{S} \ . \tag{18}$$

The dynamics specific to the infrastructure state $\mathbf{s}_t^{(s)} \in \mathcal{S}^{(s)}$ are straightforward and can be written, $\forall t \in \mathcal{T}$:

$$(x_{t+1}^{PV}, L_{t+1}^{PV}, \eta_{t+1}^{PV}) = \begin{cases} (a_t^{PV}, L_{j_t,t}^{PV}, \eta_{j_t,t}^{PV}) & \text{if } a_t^{PV} > 0, \\ (0, 0, \eta_t^{PV}) & \text{if } L_t^{PV} \leq 1, \\ (x_t^{PV}, L_t^{PV} - 1, \eta_t^{PV}) & \text{otherwise,} \end{cases} \tag{19}$$

$$(x_{t+1}^{B}, L_{t+1}^{B}, P_{t+1}^{B}, \eta_{t+1}^{B}, \zeta_{t+1}^{B}, r_{t+1}^{B}) = \begin{cases} (a_t^{B}, L_{l_t,t}^{B}, P_{l_t,t}^{B}, \eta_{l_t,t}^{B}, \zeta_{l_t,t}^{B}, r_{l_t,t}^{B}) & \text{if } a_t^{B} > 0, \\ (0, 0, 0, \eta_t^{B}, \zeta_t^{B}, r_t^{B}) & \text{if } L_t^{B} \leq 1, \\ (x_t^{B}, L_t^{B} - 1, P_t^{B}, \eta_t^{B}, \zeta_t^{B}, r_t^{B}) & \text{otherwise,} \end{cases} \tag{20}$$

$$(x_{t+1}^{H_2}, L_{t+1}^{H_2}, R_{t+1}^{H_2}, \eta_{t+1}^{H_2}, \zeta_{t+1}^{H_2}, r_{t+1}^{H_2}) = \begin{cases} (a_t^{H_2}, L_{m_t,t}^{H_2}, R_{m_t,t}^{H_2}, \eta_{m_t,t}^{H_2}, \zeta_{m_t,t}^{H_2}, r_{m_t,t}^{H_2}) & \text{if } a_t^{H_2} > 0, \\ (0, 0, 0, \eta_t^{H_2}, \zeta_t^{H_2}, r_t^{H_2}) & \text{if } L_t^{H_2} \leq 1, \\ (x_t^{H_2}, L_t^{H_2} - 1, R_t^{H_2}, \eta_t^{H_2}, \zeta_t^{H_2}, r_t^{H_2}) & \text{otherwise,} \end{cases} \tag{21}$$

which describes that a device is either replaced because of a new investment or because of aging. At the end of the device's lifetime, it is discarded from the microgrid. Note that a more advanced model could include aging rules for the other physical properties of the devices (i.e. efficiency, energy retention, capacity and power limit) but this is outside the scope of the present work.

Concerning the dynamics of the operation state $\mathbf{s}_t^{(o)} \in \mathcal{S}^{(o)}$, we have to ensure that the charge level of a storage device is reset to zero when it is replaced by a new investment. In addition, the correct efficiency factor differs depending on the direction of the power flow:

$$s_{t+1}^{B} = \begin{cases} 0 & \text{if } a_t^{B} > 0, \\ r_t^B s_t^B + \eta_t^B p_t^B \Delta t & \text{if } p_t^B \geq 0, \\ r_t^B s_t^B + \frac{p_t^B \Delta t}{\zeta_t^B} & \text{otherwise,} \end{cases} \tag{22}$$

$$s_{t+1}^{H_2} = \begin{cases} 0 & \text{if } a_t^{H_2} > 0, \\ r_t^{H_2} s_t^{H_2} + \eta_t^{H_2} p_t^{H_2} \Delta t & \text{if } p_t^{H_2} \geq 0, \\ r_t^{H_2} s_t^{H_2} + \frac{p_t^{H_2} \Delta t}{\zeta_t^{H_2}} & \text{otherwise.} \end{cases} \tag{23}$$

2.5 Problem statement formalization

We now rely on the introduced formalism to define three optimization problems of increasing complexity. The first one focuses on the optimal operation of a microgrid, while the two others respectively include the optimal and robust sizing of the microgrid.

2.5.1 Optimal operation

Let $\mathcal{G}_T$ be the set of all positive scalar functions defined over the set of T-uplets of (state, action, environment) triplets:

$$\mathcal{G}_T = \left\{ G_T : (\mathcal{S} \times \mathcal{A}_t \times \mathcal{E})^T \to \mathbb{R}^+ \right\} . \tag{24}$$

Problem 1 *Given a function $G_T \in \mathcal{G}_T$ and a trajectory $(E_1, \ldots, E_T)$ of T environment vectors, we formalize the problem of optimal operation of a microgrid in the following way:*

$$\begin{aligned} \min_{\substack{a_t \in \mathcal{A}_t, \forall t \in \mathcal{T} \\ s_t \in \mathcal{S}, \forall t \in \mathcal{T} \setminus \{1\}}} \quad & G_T((s_1, a_1, E_1), \ldots, (s_T, a_T, E_T)) \\ s.t. \quad & \mathbf{s}_t = f(\mathbf{s}_{t-1}, \mathbf{a}_{t-1}), \quad \forall t \in \mathcal{T} \setminus \{1\} , \\ & (a_t^{PV}, a_t^B, a_t^{H_2}) = (0, 0, 0), \quad \forall t \in \mathcal{T} . \end{aligned}$$

This problem determines the sequence of control variables that leads to the minimization of G_T when the sizing decisions are made once for all at a prior stage $t = 0$. The initial state $\mathbf{s}_1$ of the system contains the sizing information of the microgrid and stands as a parameter of this problem.

2.5.2 Optimal sizing under optimal operation

Let $\mathcal{G}_0$ be the set of all positive scalar functions defined over the set of (action, environment, T-long environment trajectory) triplets:

$$\mathcal{G}_0 = \left\{ G_0 : (\mathcal{A}_t \times \mathcal{E} \times \mathcal{E}^T) \to \mathbb{R}^+ \right\} . \tag{25}$$

Problem 2 *Given a function $G_0 \in \mathcal{G}_0$, a function $G_T \in \mathcal{G}_T$, a trajectory $(E_1, \ldots, E_T)$ of T environment vectors, and an initial environment E_0 that describes the available technologies at the sizing step, we formalize the problem of optimal sizing of a microgrid under optimal operation in the following way:*

$$\begin{aligned}
\min_{\substack{a_t \in \mathcal{A}_t, s_t \in \mathcal{S}, \\ \forall t \in \{0\} \cup \mathcal{T}}} \quad & G_0(a_0, E_0, E_1, \ldots, E_T) + G_T((s_1, a_1, E_1), \ldots, (s_T, a_T, E_T)) \\
\text{s.t.} \quad & \mathbf{s}_t = f(\mathbf{s}_{t-1}, \mathbf{a}_{t-1}), \quad \forall t \in \mathcal{T} , \\
& \mathbf{s}_0 = \mathbf{0} , \\
& (a_t^{PV}, a_t^B, a_t^{H_2}) = (0, 0, 0), \quad \forall t \in \mathcal{T} ,
\end{aligned}$$

with $\mathbf{s}_0$ being the null vector to model that we start from an empty microgrid.

This problem determines an initial sizing decision $\mathbf{a}_0$ such that, together with the sequence of control variables over $\{1, \ldots, T\}$, it leads to the minimization of $G_0 + G_T$.

2.5.3 Robust sizing under optimal operation

Let $\mathbf{E}$ be a set of environment trajectories:

$$\begin{aligned}
\mathbf{E} = \{ (E_t^1)_{t=1 \ldots T}, ..., (E_t^N)_{t=1 \ldots T} \} , \\
\text{with } E_t^i \in \mathcal{E}, \forall (t, i) \in \mathcal{T} \times \{1, \ldots, N\} .
\end{aligned} \tag{26}$$

Problem 3 *Given a function $G_0 \in \mathcal{G}_0$, a function $G_T \in \mathcal{G}_T$, an initial environment E_0, and a set* $\mathbf{E}$ *of trajectories of T environment vectors that describes the potential scenarios of operation that the microgrid could face, we formalize the problem of robust sizing of a microgrid under optimal operation in the following way:*

$$\begin{aligned}
\min_{a_0 \in \mathcal{A}_0} \max_{i \in \{1, \ldots, N\}} \min_{\substack{a_{i,t} \in \mathcal{A}_{i,t}, s_{i,t} \in \mathcal{S}, \\ \forall t \in \mathcal{T}}} \quad & G_0(a_0, E_0, E_1^i, \ldots, E_T^i) + G_T((s_{i,1}, a_{i,1}, E_1^i), \ldots, (s_{i,T}, a_{i,T}, E_T^i)) \\
\text{s.t.} \quad & \mathbf{s}_{i,t} = f(\mathbf{s}_{i,t-1}, \mathbf{a}_{i,t-1}) , \quad \forall t \in \mathcal{T} \backslash \{1\} , \\
& \mathbf{s}_{i,1} = f(\mathbf{s}_0, \mathbf{a}_0) , \\
& \mathbf{s}_0 = \mathbf{0} , \\
& (a_{i,t}^{PV}, a_{i,t}^B, a_{i,t}^{H_2}) = (0, 0, 0), \quad \forall t \in \mathcal{T} .
\end{aligned}$$

This robust optimization considers a microgrid under optimal operation and determines the sizing so that, in the worst case scenario, it minimizes the objective function. The innermost min is for the optimal operation, the max is for the worst environment trajectory and the outermost min is the minimization over the investment decisions. The outermost min-max succession is classic in robust optimizations (see e.g. [14]).

2.6 The specific case of the Levelized Energy Cost

In this section, we introduce the $r-$discounted levelized energy cost (LEC), denoted LEC_r, which is an economic assessment of the cost that covers all the expenses over the lifetime of the microgrid (i.e. initial investment, operation, maintenance and cost of capital). We then show how to choose functions $G_0 \in \mathcal{G}_0$ and $G_T \in \mathcal{G}_T$ such that Problems (1), (2), and (3) result in the optimization of this economic assessment. Focusing on the decision processes that consist only with an initial investment (i.e. a single sizing decision taking place at $t = 1$) for the microgrid, followed by the control of its operation, we can write the expression for LEC_r as

$$LEC_r = \frac{I_0 + \sum_{y=1}^{n} \frac{M_y}{(1+r)^y}}{\sum_{y=1}^{n} \frac{\epsilon_y}{(1+r)^y}}\,, \tag{27}$$

where

- n denotes the lifetime of the system in years;
- I_0 corresponds to the initial investment expenditures;
- M_y represents the operational expenses in the year y;
- ϵ_y is electricity consumption in the year y;
- r denotes the discount rate which may refer to the interest rate or to the discounted cash flow.

Note that, in the more common context of an electrical generation facility, the LEC_r can be interpreted as the price at which the electricity generated must be sold to break even over the lifetime of the project. For this reason, it is often used to compare the costs of different electrical generation technologies. When applied to the microgrid case, it can also be interpreted as the retail price at which the electricity from the grid must be bought in order to face the same costs when supplying a sequence $(\epsilon_1, \ldots, \epsilon_n)$ of yearly consumptions.

The initial investment expenditures I_0 and the yearly consumptions ϵ_y are simple to express as a function of the initial sizing decision $\mathbf{a}_0$ and environment vector $\mathbf{E}_0$ for the former, and of the environment trajectory $(E_1, \ldots, E_T)$ for the latter. Let $\tau_y \subset \mathcal{T}$ denotes, $\forall y \in \{1, \ldots, n\}$, the set of time steps t belonging to year y, we have:

$$I_0 = a_0^{PV} c_0^{PV} + a_0^{B} c_0^{B} + a_0^{H_2} c_0^{H_2} \tag{28}$$

$$\epsilon_y = \sum_{t \in \tau_y} c_t \ \Delta t,\ \forall y \in \{1, \ldots, n\}\,. \tag{29}$$

From these two quantities, we can define the function $G_0 \in \mathcal{G}_0$ that implements the LEC case as:

$$G_0(a_0, E_0, E_1, \ldots, E_T) = \frac{I_0}{\sum_{y=1}^{n} \frac{\epsilon_y}{(1+r)^y}} = \frac{a_0^{PV} c_0^{PV} + a_0^{B} c_0^{B} + a_0^{H_2} c_0^{H_2}}{\sum_{y=1}^{n} \frac{\sum_{t \in \tau_y} c_t \Delta t}{(1+r)^y}}\,, \tag{30}$$

while the remaining term of LEC_r defines $G_T \in \mathcal{G}_T$:

$$G_T((s_1, a_1, E_1), \ldots, (s_T, a_T, E_T)) = \frac{\sum_{y=1}^{n} \frac{M_y}{(1+r)^y}}{\sum_{y=1}^{n} \frac{\epsilon_y}{(1+r)^y}}\,. \tag{31}$$

The last quantities to specify are the yearly operational expenses M_y, which correspond to the opposite of the sum over the year $y \in \mathcal{Y}$ of the revenues ρ_t observed at each time step $t \in \tau_y$ when operating the microgrid:

$$M_y = -\sum_{t \in \tau_y} \rho_t\,. \tag{32}$$

These revenues are more complex to determine than the investment expenditures and depend, among other elements, on the model of interaction $\boldsymbol{\mu}_t$ at the time of the operation.

2.6.1 Operational revenues

The instantaneous operational revenues ρ_t at time step $t \in \mathcal{T}$ correspond to the reward function of the system. This is a function of the electricity demand c_t, of the solar irradiance i_t, of the model of interaction $\boldsymbol{\mu}_t = (k, \beta)$, and of the control actions $\mathbf{a}_t^{(o)}$:

$$\rho_t : (c_t, i_t, \boldsymbol{\mu}_t, \mathbf{a}_t^{(o)}) \rightarrow \mathbb{R}\,.$$

We now introduce three quantities that are prerequisites to the definition of the reward function:

- ϕ_t [kW] $\in \mathbb{R}^+$ is the electricity generated locally by the photovoltaic installation, we have:

$$\phi_t = \eta_t^{PV} x_t^{PV} i_t\,; \tag{33}$$

- d_t [kW] $\in \mathbb{R}$ denotes the net electricity demand, which is the difference between the local consumption and the local production of electricity:

$$d_t = c_t - \phi_t\,; \tag{34}$$

- δ_t [kW] $\in \mathbb{R}$ represents the power balance within the microgrid, taking into account the contributions of the demand and of the storage devices:

$$\delta_t = -p_t^B - p_t^{H_2} - d_t\,. \tag{35}$$

These quantities are illustrated in a diagram of the system in Figure (1), which allows for a more intuitive understanding of the power flows within the microgrid.

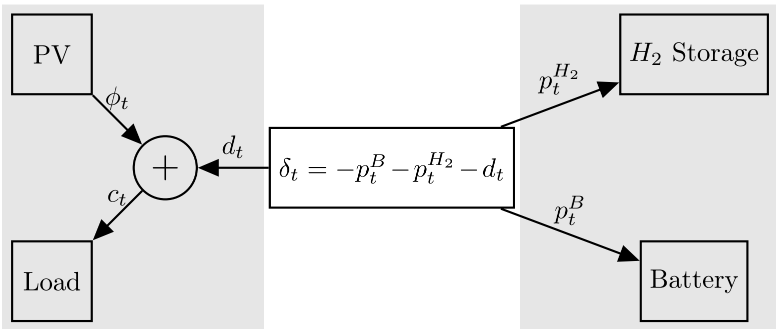


Figure 1: Schema of the microgrid featuring PV panels associated with a battery and a hydrogen storage device.

At each time step $t \in \mathcal{T}$, a positive power balance δ_t reflects a surplus of production within the microgrid, while it is negative when the power demand is not met. As the law of conservation of energy requires that the net power within the microgrid must be null, compensation measures are required when δ_t differs from zero. In the case of a connected microgrid, this corresponds to a power exchange with the grid. In the case of an off-grid system, a production curtailment or a load shedding is required. The instantaneous operational revenues we consider correspond to the financial impact of a surplus or lack of production. The reward function ρ_t is a linear function of the power balance δ_t and, because the price β at which the energy surplus can be sold to the grid usually differs from the retail price k to buy electricity from the grid, the definition of the reward function at time step $t \in \mathcal{T}$ depends of the sign of δ_t:

$$\rho_t = \begin{cases} \beta\ \delta_t \Delta t & \text{if } \delta_t \geq 0\,, \\ k\ \delta_t \Delta t & \text{otherwise.} \end{cases} \tag{36}$$

Using Equations (33), (34), and (35), the reward function can be expressed as a function of the system variables:

$$\rho_t = \begin{cases} \beta\ (-p_t^B - p_t^{H_2} - c_t + \eta_t^{PV} x_t^{PV} i_t)\ \Delta t & \text{if } -p_t^B - p_t^{H_2} - c_t + \eta_t^{PV} x_t^{PV} i_t \geq 0\,, \\ k\ (-p_t^B - p_t^{H_2} - c_t + \eta_t^{PV} x_t^{PV} i_t)\ \Delta t & \text{otherwise.} \end{cases} \tag{37}$$

3 Optimisation

In this section, we detail how to implement the LEC version of Problems (1), (2), and (3), to obtain an optimal solution using mathematical programming techniques. Even though the formalization of the problem includes non-linear relations (e.g. Equations (22), (23), and (37)), we show how to obtain a linear program by using auxiliary variables. The presented approach assumes that the following conditions are met:

- a single candidate technology is considered for each device type (i.e. $J = L = M = 1$);
- the lifetime of the devices is at least as long as the considered time-horizon (i.e. $L^{PV}, L^{B}, L^{H_2} \geq T$) and the aging of the devices can thus be ignored;
- the whole trajectory $E_1, \ldots, E_T$ of environment vectors is known at the time of operation (i.e. when minimizing G_T).

3.1 Optimal operation over a known trajectory of the exogenous variables

We first consider the implementation as a linear program of Problem (1) with G_T defined by Equation (31). The output of this program is the optimal sequence of control actions $\mathbf{a}_t^{(o)} = (p_t^{H_2}, p_t^{B})$ and the corresponding minimal value of G_T over the considered time-horizon T. Before writing the optimization model, we introduce, $\forall t \in \mathcal{T}$, the following auxiliary variables:

$$p_t^{B,+}, p_t^{B,-}, p_t^{H_2,+}, p_t^{H_2,-}, \delta_t^{+}, \delta_t^{-} \in \mathbb{R}^{+}, \text{ such that } \begin{cases} p_t^{B} = p_t^{B,+} - p_t^{B,-} \\ p_t^{H_2} = p_t^{B,+} - p_t^{B,-} \\ \delta_t = \delta_t^{+} - \delta_t^{-} \end{cases},$$

which allow the use of the adequate efficiency factor (i.e. η or ξ) and price (i.e. k or β) depending on the direction of the power flows. The overall linear program $\mathcal{M}_{\text{op}}$, having as parameters the time-horizon T, the time step Δt, the number of years n spanned by the time-horizon, the sets $\tau_1, \ldots, \tau_n$ mapping years to time steps, the discount rate r, a trajectory $\mathbf{E}_1, \ldots, \mathbf{E}_T$ of the exogenous variables, and the time-invariant sizing state $\mathbf{s}^{(s)} = \left(x^{PV}, x^{B}, x^{H_2}, P^{B}, R^{H_2}, \eta^{PV}, \eta^{B}, \eta^{H_2}, \zeta^{B}, \zeta^{H_2}, r^{B}, r^{H_2}\right)$ of the devices, can be written as:

$$\mathcal{M}_{\text{op}}\left(T,\Delta t,n,\tau_1,\ldots,\tau_n,r,\mathbf{E}_1,\ldots,\mathbf{E}_T,\mathbf{s}^{(s)}\right) = \min \quad \frac{\sum_{y=1}^{n} \frac{M_y}{(1+r)^y}}{\sum_{y=1}^{n} \frac{\sum_{t\in\tau_y} c_t \Delta t}{(1+r)^y}} \tag{38a}$$

$$\text{s.t.} \quad \forall y \in \{1, \ldots, n\}: \tag{38b}$$

$$M_y = \sum_{t\in\tau_y} \left(k\,\delta_t^{-} - \beta\,\delta_t^{+}\right) \Delta t\,, \tag{38c}$$

$$\forall t \in \{1, \ldots, T\}: \tag{38d}$$

$$0 \leq s_t^{B} \leq x^{B}\,, \tag{38e}$$

$$0 \leq s_t^{H_2} \leq R^{H_2}\,, \tag{38f}$$

$$-P^{B} \leq p_t^{B} \leq P^{B}\,, \tag{38g}$$

$$-x^{H_2} \leq p_t^{H_2} \leq x^{H_2}\,, \tag{38h}$$

$$\delta_t = -p_t^{B} - p_t^{H_2} - c_t + \eta^{PV} x^{PV} i_t\,, \tag{38i}$$

$$p_t^{B} = p_t^{B,+} - p_t^{B,-}\,, \tag{38j}$$

$$p_t^{H_2} = p_t^{B,+} - p_t^{B,-}\,, \tag{38k}$$

$$\delta_t = \delta_t^{+} - \delta_t^{-}\,, \tag{38l}$$

$$p_t^{B,+}, p_t^{B,-}, p_t^{H_2,+}, p_t^{H_2,-}, \delta_t^{+}, \delta_t^{-} \geq 0\,, \tag{38m}$$

$$\forall t \in \{2, \ldots, T\}: \tag{38n}$$

$$s_t^{B} = r^{B} s_{t-1}^{B} + \eta^{B} p_{t-1}^{B,+} - \frac{p_{t-1}^{B,-}}{\zeta^{B}}\,, \tag{38o}$$

$$s_t^{H_2} = r^{H_2} s_{t-1}^{H_2} + \eta^{B} p_{t-1}^{H_2,+} - \frac{p_{t-1}^{H_2,-}}{\zeta^{H_2}}\,, \tag{38p}$$

$$-\zeta^{B} s_T^{B} \leq p_T^{B} \leq \frac{x^{B} - s_T^{B}}{\eta^{B}}\,, \tag{38q}$$

$$-\zeta^{H_2} s_T^{H_2} \leq p_T^{H_2} \leq \frac{R^{H_2} - s_T^{H_2}}{\eta^{H_2}}\,. \tag{38r}$$

The physical limits of the storage devices are modeled by Constraints (38e)-(38h), while the transition laws of their state correspond to Constraints (38o) and (38p). Because of the absence of time step $T+1$, there is no guarantee that the charge levels that immediately follow the time-horizon are positive, which is why Constraints (38q) and (38r) ensure that the last action $\mathbf{a}_T^{(o)}$ is compatible with the last charge level of the devices. Finally, Constraints (38i) and (38c) respectively denote the power balance within the microgrid and the cost it induces on a yearly scale.

3.2 Optimal sizing under optimal operation

In Problem (2), the initial sizing of the microgrid becomes an output of the optimization model and the function G_0, here defined by Equation (30), integrates the objective function. We denote this new problem by $\mathcal{M}_{\text{size}}$, which is still a linear program:

$$\mathcal{M}_{\text{size}}(T,\Delta t,n,\tau_1,...,\tau_n,r,\mathbf{E}_0,\mathbf{E}_1,...,\mathbf{E}_T) = \min \quad \frac{I_0 + \sum_{y=1}^{n} \frac{M_y}{(1+r)^y}}{\sum_{y=1}^{n} \frac{\sum_{t\in\tau_y} c_t \Delta t}{(1+r)^y}} \tag{39a}$$

$$\text{s.t.} \quad I_0 = a_0^{PV} c_0^{PV} + a_0^B c_0^B + a_0^{H_2} c_0^{H_2}\,, \tag{39b}$$

$$(x^B, x^{H_2}, x^{PV}) = (a_0^B, a_0^{H_2}, a_0^{PV})\,, \tag{39c}$$

$$(38b) - (38r)\,. \tag{39d}$$

This new model includes all the constraints from $\mathcal{M}_{\text{op}}$, as well as the definition of the sizing of the devices from the initial sizing decisions, i.e. Constraint (39c), and the expression of the initial investment as a function of these sizing decisions, i.e. Constraint (39b). Note that the value of physical properties of the devices other then variables x^B, x^{H_2}, x^{PV} is provided by the initial environment vector $\mathbf{E}_0$, which also provides the cost of the available technology for every device type.

3.3 Robust optimization of the sizing under optimal operation

The extension of linear program $\mathcal{M}_{\text{size}}$ to an optimization model that integrates a set $\mathbf{E} = \{(E_t^1)_{t=1...T}, ..., (E_t^N)_{t=1...T}\}$ of candidate trajectories of the environment vectors, i.e. to the implementation of Problem (3), is straightforward and requires two additional levels of optimization:

$$\mathcal{M}_{\text{rob}}(T,\Delta t,n,\tau_1,...,\tau_n,r,\mathbf{E}_0,\mathbf{E}) = \min_{a_0^B, a_0^{H_2}, a_0^{PV}} \max_{i\in 1,...,N} \mathcal{M}_{\text{size}}(T,\Delta t,n,\tau_1,...,\tau_n,r,\mathbf{E}_0,\mathbf{E}_1^{(i)},...,\mathbf{E}_T^{(i)})\,. \tag{40}$$

This mathematical program cannot be solved using only linear programming techniques. In particular, the numerical results reported further in this chapter relied on an exhaustive search approach to address the outer min max, considering a discretized version of sizing variables.

4 Simulations

This section presents case studies of the proposed operation and sizing problems of a microgrid. We first detail the considered technologies, specify the corresponding parameter values, and showcase the optimal operation of a fixed-size microgrid. The optimal sizing approaches are then run using realistic price assumptions and using historical measures of residential demand and of solar irradiance with $\Delta t = 1h$. By comparing the solutions for irradiance data of both Belgium and Spain, we observe that they depend heavily on this exogenous variable. Finally, we compare the obtained LEC values with the current retail price of electricity and stress the precautions to be taken when interpreting the results.

4.1 Technologies

In this subsection, we describe the parameters that we consider for the PV panels, the battery and the hydrogen storage device. The physical parameters are selected to fit, at best, the state-of-the-art manufacturing technologies, and the costs that we specify are for self-sufficient devices, i.e. including the required converters or inverters to enable their correct operation.

PV panels. The electricity is generated by converting sunlight into direct current (DC) electricity using materials that exhibit the photovoltaic effect. Driven by advances in technology as well as economies of manufacturing scale, the cost of PV panels has steadily declined and is about to reach a price of 1€/W$_p$ with inverters and balance of systems included [15]. The parameters that are taken into account in the simulations can be found in Table (1).

Parameter	Value
c^{PV}	1€/W$_p$
η^{PV}	18%
L^{PV}	20 years

Table 1: Characteristics used for the PV panels.

Battery The purpose of the battery is to act as a short-term storage device; it must therefore have good charging and discharging efficiencies as well as enough specific power to handle all the short-term fluctuations. The charge retention rate and the energy density are not major concerns for this device. A battery's characteristics may vary due to many factors, including internal chemistry, current drain and temperature, resulting in a wide range of available performance characteristics. Compared to lead-acid batteries, $LiFePO_4$ batteries are more expensive but offer a better capacity, a longer lifetime and a better power density [16]. We consider this latter technology and Table (2) summarizes the parameters that we deem to be representative. $LiFePO_4$ batteries are assumed to have a power density that is sufficient to accommodate the instantaneous power supply of the microgrid. It is also assumed to have a charging efficiency (η^c) and discharging efficiency (ζ_0^B) of 90% for a round trip efficiency of 81%. Finally, we consider a cost of 500 €per usable kWh of storage capacity (c^B).

Parameter	Value
c^B	500 €/kWh
η_0^B	90%
ζ_0^B	90%
P^B	$>$ 10kW
r^B	99%/month
L^B	20 years

Table 2: Data used for the $LiFePO_4$battery.

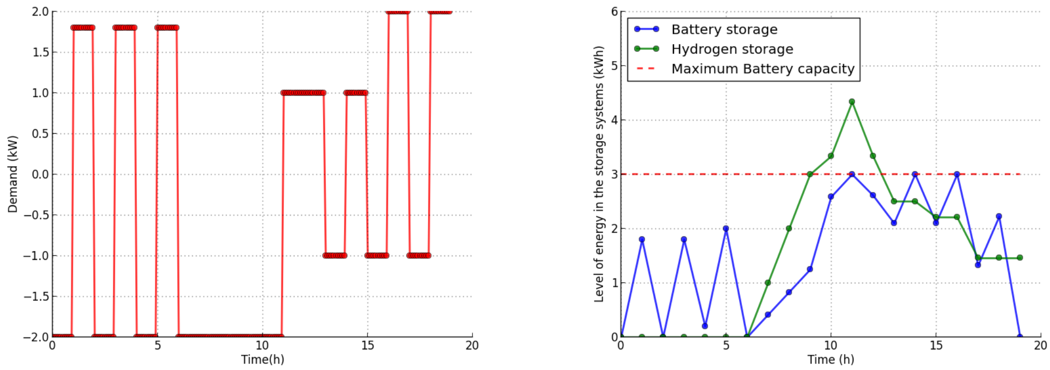
Hydrogen storage device The long-term storage device must store a large quantity of energy at a low cost while its specific power is less critical than that for the battery. In this chapter we will consider a hydrogen-based storage technology composed of three main parts: (i) an electrolyzer that transforms water into hydrogen using electricity (ii) a tank where the hydrogen is stored (iii) a fuel cell where the hydrogen is transformed into electricity (note that a (combined heat and) power engine could be used instead). This hydrogen storage device is such that the maximum input power of the fuel cell before losses is equal to the maximum output power of the electrolyzer after losses. The considered parameters are presented in Table (3).

Parameter	Value
c^{H_2}	14 €/W$_p$
$\eta_0^{H_2}$	65%
$\zeta_0^{H_2}$	65%
r^{H_2}	99%/month
L^{H_2}	20 years
R^{H_2}	∞

Table 3: Data used for the Hydrogen storage device.

4.2 Optimal operation

An example of output of the optimal operation program $\mathcal{M}_{\text{op}}$ in Figure (2(b)) illustrates well the role of each storage device. The figure sketches the evolution of the charge levels of the battery and of the hydrogen storage device when facing the net demand defined in Figure (2(a)). In this example, the battery has a capacity of 3kWh and the hydrogen storage device has a power limit of 1kW. The role of each storage device is clear as we observe that the battery handles the short fluctuations, while the hydrogen device accumulates the excesses of production on a longer time-scale. Overall, since the production is higher than the consumption by a significant margin, the optimization problem is not constrained and hydrogen is left in the tank at the end of the simulation.



(a) Net demand (negative demand represents a production higher than the consumption)

(b) Optimal operation of the storage devices

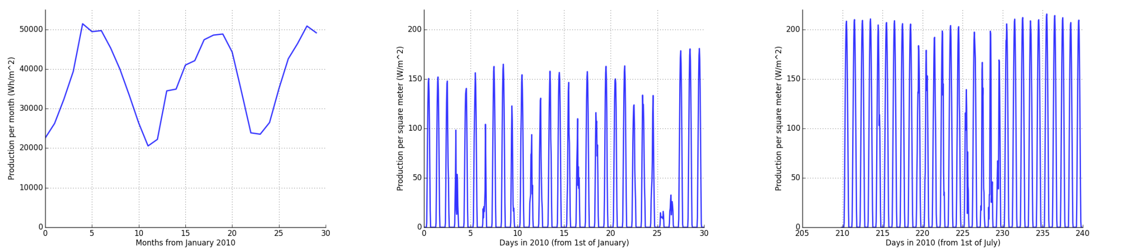
Figure 2: Left graphic shows the evolution of the charge levels within a microgrid that faces the given net demand of right graphic.

4.3 Production and consumption profiles

In this subsection, we describe the PV production profiles and the consumption profiles that will be used in the remaining simulations.

4.3.1 PV production

Solar irradiance varies throughout the year depending on the seasons, and it also varies throughout the day depending on the weather and the position of the sun in the sky relative to the PV panels. Therefore, the production profile varies strongly as a function of the geographical area, mainly as a function of the latitude of the location. The two cases considered in this chapter are a residential consumer of electricity in the south of Spain and in Belgium. The main distinction between these profiles is the difference between summer and winter PV production. In particular, production in the south of Spain varies with a factor 1:2 between winter and summer (see Figure (3)) and changes to a factor of about 1:5 in Belgium or in the Netherlands (see Figure (4)).

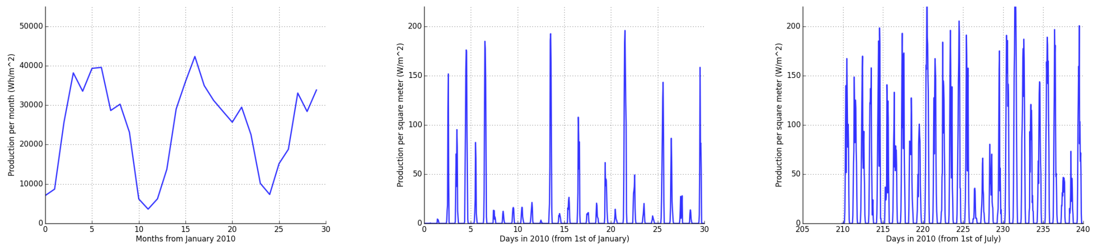


(a) Total energy produced per month (b) Example of production in winter (c) Example of production in summer

Figure 3: Simulated production of PV panels in the South of Spain (Data from Solargis [17] for the solar platform of Almeria in Spain).

4.3.2 Consumption

A simple residential consumption profile is considered with a daily consumption of 18kWh. The profile can be seen on Figure (5). This profile is a good substitute of any residential consumption profile with the same average consumption per day. Additional precautions should be taken in the case of high



(a) Total energy produced per month (b) Example of production in winter (c) Example of production in summer

Figure 4: Measurements of PV panels production for a residential customer located in Belgium.

consumption peaks to ensure that the battery will be able to handle large power outputs. Note that in a more realistic case, we may have higher consumption during winter, which may substantially affect the sizing and operation solutions.

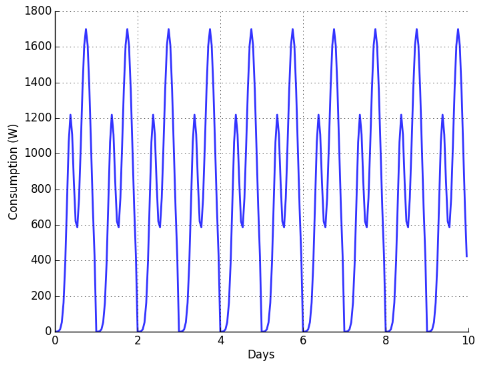


Figure 5: Representative residential consumption profile.

4.4 Optimal sizing and robust sizing

For the optimal sizing under optimal operation of the microgrid, as defined by Problem (2), we use a unique scenario built from the data described in Section (4.3) for the consumption and production profiles. Since the available data are shorter than the time-horizon, we repeat them so as to obtain a twenty-year-long time-horizon. In the following we make the hypothesis that $\beta = 0$ €/kWh.

For the robust optimization of the sizing, we refer to the Problem (3). This approach requires the selection of a set of different environment trajectories and, for computational purposes, to discretize the sizing states. The three different scenarios considered are the following:

- The production is 10% lower and the consumption is 10% higher than the representative residential production/consumption profile.
- The production and the consumption are conform to the representative residential production/consumption profile (scenario used in the non-robust optimisation)
- The production is 10% higher and the consumption is 10% lower than the representative residential production/consumption profile.

To build the discretized sizing states we start by solving Problem (2) on the mean scenario. For our simulations we then select all possible variations compared to the sizing of each variable x^B, x^{H_2} and x^{PV} by $+0\%$, $+10\%$ and $+20\%$. This leaves us with 27 possible sizings that are used to build the discretized sizing space. Equation (40) is solved by performing an exhaustive search over this set of potential sizings so as to obtain the robust LEC.

4.4.1 The Spanish case

We first considered a residential consumer of electricity located in Spain. For different values of costs k endured per kWh not supplied within the microgrid, we performed the optimal sizing and the robust-type optimization schemes described above. We reported the obtained LEC in Figure (6). We observed the following : (i) for a retail price of 0.2€/kWh, the residential consumer of electricity benefits from a LEC of slightly more than 0.10€/kWh; (ii) in the fully off-grid case, the microgrid is still more profitable than buying electricity at all times from the utility grid for all configurations as long as k is lower than approximately 3€/kWh (i.e. with a value of loss load smaller than 3 €/kWh, it is always preferable to go fully off-grid than buying all the electricity from the grid); (iii) due to the relatively low inter-seasonal fluctuations (compared to Belgium for instance (see later)) investing in a hydrogen storage system is not actually profitable for low values of k.

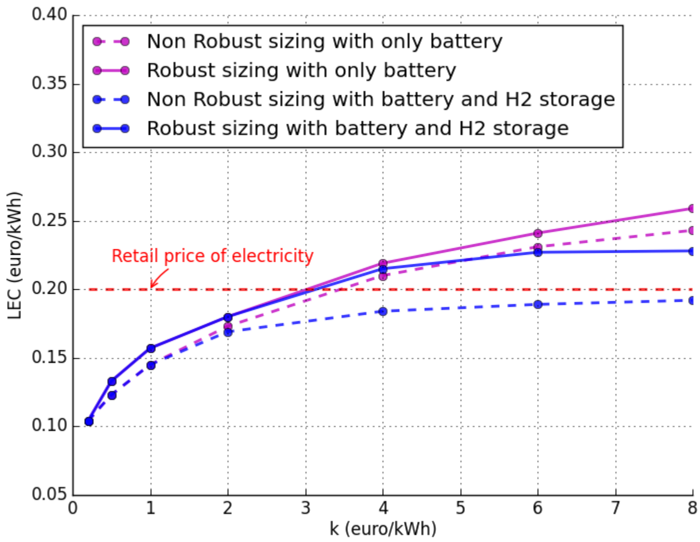


Figure 6: LEC ($r = 2\%$) in Spain over 20 years for different investment strategy as a function of the cost endured per kWh not supplied within the microgrid.

4.4.2 The Belgian case

We then considered a residential consumer of electricity located in Belgium and we reported the obtained LEC for different values of k. As can be seen from Figure (7), a residential consumer of electricity in Belgium has incentives to invest in his own microgrid system (at least PV panels) since the obtained LEC while operating in parallel with the main utility grid at a retail price of 0.2€/kWh gives the residential consumer of electricity a lower electricity price than buying it from the grid at all times. With the current state of the technology however, it is not yet profitable for a residential consumer of electricity in Belgium to go fully off-grid since they would then suffer from a higher overall cost. Contrary to the results observed for Spain, in Belgium there is an important potential gain in combining both short-term and long-term energy storage devices. This is due to the critical inter-seasonal fluctuations of PV electrical production in Belgium.

We also investigate how the LEC evolves as a function of the price decrease of the elements in the microgrid. Figure (8) shows the reported LEC as a function of a uniform price decrease of the elements of the microgrid while assuming a value of loss load of 0.2€/kWh and a robust sizing. It is shown that when the prices of constitutive elements of the microgrid are less than half of those given in Tables 1 to 3, the business case for a fully off-grid microgrid in Belgium may actually become cost-effective.

5 Conclusion

This chapter has proposed a novel formulation of electrical microgrids featuring PV, long-term (hydrogen) and short-term (batteries) storage devices. Using linear programming we managed to set up an

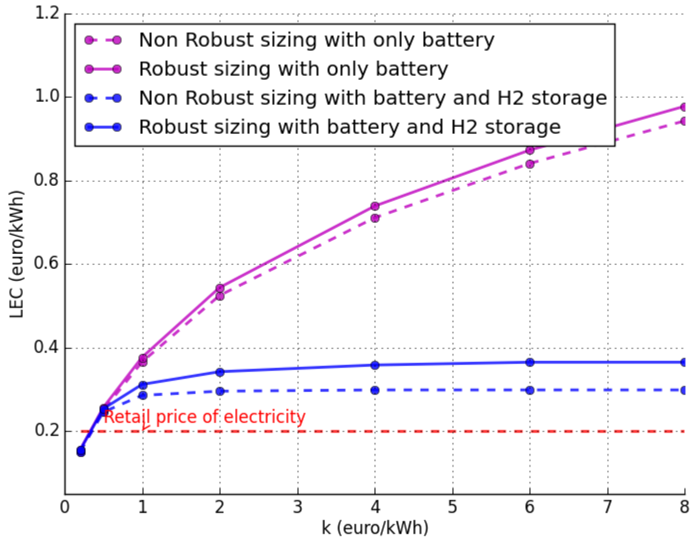


Figure 7: LEC (r=2%) in Belgium over 20 years for different investment strategy as a function of the cost endured per kWh not supplied within the microgrid.

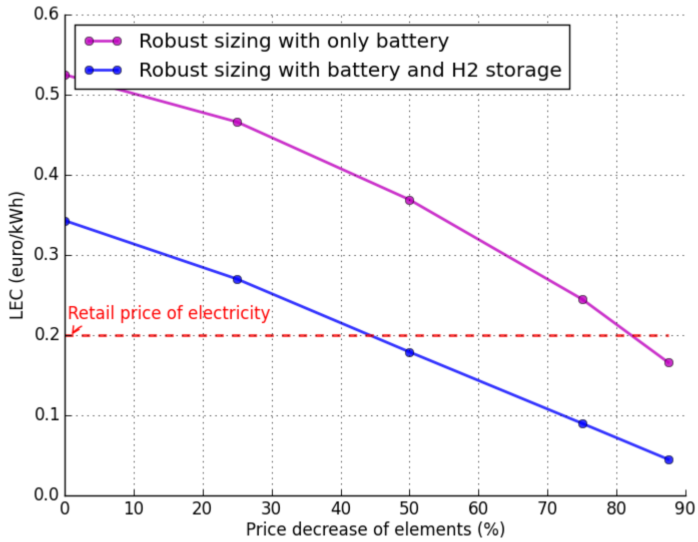


Figure 8: LEC (r=2%) in Belgium over 20 years for a value of loss load of 2€/kWh as a function of a uniform price decrease for all the constitutive elements of the microgrid.

algorithm for optimally sizing and operating microgrids under some (potentially robust) hypotheses on the surrounding environment. The approach has been illustrated in the context of Belgium and Spain, for which we evaluate the values of the LEC and compare it with the cost of electricity from traditional electricity networks.

Future works will include relaxing the assumption that the future is deterministically known when computing the optimal operation. In particular, we plan to investigate how to incorporate stochastic weather forecasts in the optimization of the microgrid operation.

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