Imitative Learning for Online Planning in Microgrids

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Abstract. This paper aims to design an algorithm dedicated to operational planning for microgrids in the challenging case where the scenarios of production and consumption are not known in advance. Using expert knowledge obtained from solving a family of linear programs, we build a learning set for training a decision-making agent. The empirical performances in terms of Levelized Energy Cost (LEC) of the obtained agent are compared to the expert performances obtained in the case where the scenarios are known in advance. Preliminary results are promising.

Keywords: Machine learning · Planning · Imitative learning · Microgrids

1 Introduction

Nowadays, electricity is distributed among consumers by complex and large electrical networks, supplied by conventional power plants. However, due to the drop in the price of photovoltaic panels (PV) over the last years, a business case has appeared for decentralized energy production. In such a context, microgrids that are small-scale localized station with electricity production and consumption have been developed. The extreme case of this decentralization process consists in being fully off-grid (i.e. being disconnected from conventional electrical networks). Such a case requires to be able to provide electricity when needed within the microgrid. Since PV production varies with daily and seasonal fluctuations, storage is required to balance production and consumption.

In this paper, we focus on the case of fully off-grid microgrids. Due to the cost of batteries, sizing a battery storage capacity so that it can deal with seasonal fluctuations would be too expensive in many parts of the world. To overcome this problem, we assume that the microgrid is provided with another storage

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technology, whose storage capacity is almost unlimited, such as for example as it is the case with hydrogen-based storage. However, this long-term storage capacity is limited by the power it can exchange.

Balancing the operation of both types of storage systems so as to avoid at best power cuts is challenging in the case where production and consumption are not known in advance. The contribution presented in this paper aims to build a decision making agent for planning the operation of both storage systems. To do so, we propose the following methodology. First, we consider a family of scenarios for which production and consumption are known in advance, which allows us to determine the optimal planning for each of them using the methodology proposed in [4] which is based on linear programming. This family of solutions is used as an expert knowledge database, from which optimal decisions can be extracted into a learning set. Such a set is used to train a decision making agent using supervised learning, in particular Extremely Randomized Trees [5]. Our supervised learning strategy provides the agent with some generalization capabilities, which allows the agent to take high performance decisions without knowing the scenarios in advance. It only uses recent observations made within the microgrid.

The outline of this paper is the following. Section 2 provides a formalization of the microgrid. Section 3 describes the related work. Section 4 introduces a linear programming formalization of microgrid planning with fully-known scenarios of production and consumption. Section 5 describes our imitative learning approach. Section 6 reports and discusses empirical simulations. Section 7 concludes this paper.

2 Microgrids

Microgrids are small structures providing energy available within the system to loads. The availability of the power strongly depends on the local weather with its own short-term and long-term fluctuations. We consider the case where microgrids have both generators and storage systems and also loads. This section formally defines such devices. It ends with a definition of Levelized Energy Cost within a fully off-grid microgrid.

2.1 Generators

Generators convert any source of energy into electricity. They are limited by the power they can provide to the system. More formally, let us define G as the set of generators, y^g as the supply power limit of $g \in G$ in Wp and η^g the efficiency, i.e. the percentage of energy available after generation, of $g \in G$ and p_t^g the available power from the source of energy. The following inequation describes the maximal power production:

$$p_t^g \eta^g \leqslant y^g. \tag{1}$$

In our work, we consider photovoltaic panels, for which the power limitation is linearly dependent of the surface size of the PV panel which is expressed in m^2.

Let x^g be the surface size of $g \in G$. The total power production by the surface size is expressed as the following equation, for which the constraint expressed above still holds:

$$\phi_t^g = x^g p_t^g \eta^g. \tag{2}$$

2.2 Storage Systems

Storage systems exchange the energy within the system to meet loads demand and possibly to fill other storage systems. They are limited either by capacity or power exchange. We denote these limits by x^{σ_c} and x^{σ_p} respectively, where $\sigma_c \in \Sigma_C$, $\sigma_c \in \Sigma_P$. We denote $\Sigma = \Sigma_P + \Sigma_C$ as the set of both kind of storage systems and η^σ the efficiency of $\sigma \in \Sigma$. We consider also, $\forall \sigma \in \Sigma$, the variables s_t^σ for the storage content, $a_t^{+,\sigma}$ and $a_t^{-,\sigma}$ for the decision variables corresponding discharge and the recharge amount of the storage system at each time t. Dynamics of storage systems are defined by the following equations:

$$s_{s,0}^\sigma = 0, \forall \sigma \in \Sigma, \tag{3}$$

$$s_t^\sigma = s_{(t-1)}^\sigma + a_{t-1}^{-,\sigma} + a_{(t-1)}^{+,\sigma}, 1 \leqslant t \leqslant T-1, \forall \sigma \in \Sigma. \tag{4}$$

2.3 Loads

Loads are expressed in kWh for each time step t. Power cuts occur when the demand is not met, and the lack is associated with a penalty cost. Formally, we define the net demand d_t as the difference between the consumption, defined by c_t and the available energy from the generators. The following equation holds:

$$d_t = c_t - \sum_{g \in G} \phi_t^g, \forall 0 \leqslant t \leqslant T-1. \tag{5}$$

Finally, F_t is defined as the energy not supplied to loads, expressed in kWh, by the following equation:

$$F_t = d_t - \sum_{\sigma \in \Sigma} \eta^\sigma (a_t^{+,\sigma} + a_t^{-,\sigma}), \forall 0 \leqslant t \leqslant T-1. \tag{6}$$

We now introduce in the model the possibility to have several levels of priority demand, defined by the cost associated to power cuts. Let Ψ be the set of priority demands, and F_t^ψ the number of kWh not supplied for the demand priority group $\psi \in \Psi$. Hence, Eqs. (5) and (6) become:

$$d_t = \sum_{\psi \in \Psi} c_t^\psi - \sum_{g \in G} \phi_t^g, \forall 0 \leqslant t \leqslant T-1, \tag{7}$$

$$\sum_{\psi \in \Psi} F_t^\psi = d_t - \sum_{\sigma \in \Sigma} \eta^\sigma (a_t^{+,\sigma} + a_t^{-,\sigma}), \forall 0 \leqslant t \leqslant T-1. \tag{8}$$

2.4 Levelized Energy Cost

Any planning of a microgrid given any scenario of production and consumption leads to a cost based on power cuts and initial investment. It also takes into account economical aspects (e.g. deflation). This cost, called the Levelized Energy Cost (LEC) for a fully off-grid microgrid is formally defined below:

$$LEC = \frac{\sum_{y=1}^{n} \frac{I_y - M_y}{(1+r)^y} + I_0}{\sum_{y=1}^{n} \frac{\epsilon_y}{(1+r)^y}}, \tag{9}$$

where

- n = Considered horizon of the system in years;
- I_y = Investments expenditures in the year y;
- M_y = Operational revenues performed on the microgrid in the year y (take into account the cost of power cuts during the year y);
- ϵ_y = Electricity consumption in year y;
- r = Discount rate which may refer to the interest rate or discounted cash flow.

3 Related Work

Different steps of our contribution have already been considered in various applications. We used linear programming for computing expert strategies. This kind of approach have already been discussed in [7–9] with different microgrid formulations. We used supervised learning techniques with solutions provided by linear programming. Cornélusse et al. [2] have considered this approach in the unit commitment problem. Our prediction model needs an additional step to ensure compliance of the policy learned by supervised learning algorithms with constraints related to the system. This step consists to use quadratic programming to post-process the solution. Cornélusse et al. [1] have considered a similar approach.

Online planning for microgrids has also been studied with others microgrid configurations. For example, Debjyoti and Ambarnath [3] focuses on the specific case of online planning using automatas, while Kuznetsova et al. [6] focuses on the online planning using a model-based reinforcement learning approach.

4 Optimal Sizing and Planning

4.1 Linear Program

Objective Function. Let $k_t^{\psi}, \forall 0 \leqslant t \leqslant T-1, \forall \psi \in \Psi$ be the value of loss load of the priority demand $\psi \in \Psi$. The LEC is instantiated in the following way:

$$LEC = \frac{\sum_{t=1}^{T} \frac{-\sum_{\psi \in \Psi} k_t^{\psi} F_t^{\psi}}{(1+r)^{y'}} + I_0}{\sum_{y=1}^{n} \frac{\epsilon_y}{(1+r)^y}}, \tag{10}$$

where $y' = t/(24 \times 365)$.

Constraints. Storage systems actions are limited by their sizes. The following constraints are added:

$$s_t^{\sigma_c} \leqslant x^{\sigma_c}, \forall \sigma_c \in \Sigma_C, 0 \leqslant t \leqslant T-1, \tag{11}$$

$$a_t^{+,\sigma_p} \leqslant x^{\sigma_p}, \forall \sigma_p \in \Sigma_P, 0 \leqslant t \leqslant T-1, \tag{12}$$

$$-a_t^{-,\sigma_p} \leqslant x^{\sigma_p}, \forall \sigma_p \in \Sigma_P, 0 \leqslant t \leqslant T-1. \tag{13}$$

Figure 1 shows the overall linear program.

$$\text{Min.} \ \frac{\sum_{t=1}^{T} \frac{-\sum_{\psi \in \Psi} k_t^\psi F_t^\psi}{(1+r)^y} + I_0}{\sum_{y=1}^{n} \frac{\epsilon_y}{(1+r)^y}}, y = t/(365 \times 24) \tag{14a}$$

$$\text{S.t.}, \forall t \in \{0 \ldots T-1\}: \tag{14b}$$

$$s_t^\sigma = s_{t-1}^\sigma + a_{t-1}^{-,\sigma} + a_{t-1}^{+,\sigma}, \forall \sigma \in \Sigma, \tag{14c}$$

$$s_t^{\sigma_c} \leqslant x^{\sigma_c}, \forall \sigma_c \in \Sigma_C, \tag{14d}$$

$$a_t^{+,\sigma_p} \leqslant x^{\sigma_p}, \forall \sigma_p \in \Sigma_P, \tag{14e}$$

$$a_t^{-,\sigma_p} \leqslant x^{\sigma_p}, \forall \sigma_p \in \Sigma_P, \tag{14f}$$

$$\sum_{\psi \in \Psi} F_t^\psi \leqslant -d_t - \sum_{\sigma \in \Sigma} \eta^\sigma (a_t^{-,\sigma} + a_t^{+,\sigma}), \tag{14g}$$

$$\sum_{\psi \in \Psi} F_t^\psi \leqslant 0, \tag{14h}$$

$$-F_t^\psi \leqslant c_t^\psi. \tag{14i}$$

Fig. 1. Overall linear program for optimization.

4.2 Microgrid Sequence

When planning is performed given sequences of production and consumption of length $T > 0$, a sequence of storage contents and a sequence of actions are generated. Such a group of four sequences is called a *microgrid sequence*. In the following, we abusively denote as an optimal microgrid sequence a set of sequences obtained by solving linear programs. Figure 2 shows an illustration of a sequence of decision, with the two kinds of storage systems. A microgrid sequence is formally defined below:

$$(c_0 \ldots c_{T-1}, \phi_0 \ldots \phi_{0 \ldots T-1}, s_0^\sigma \ldots s_{T-1}^\sigma, a_0^\sigma \ldots a_{T-1}^\sigma), \tag{15}$$

where $\forall t \in \{0 \ldots T-1\}, a_t^\sigma = a_t^{+,\sigma} + a_t^{-,\sigma}$.

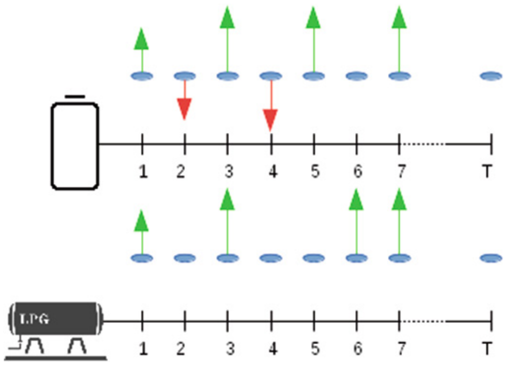

Fig. 2. Sequence scheme (discharging/recharging).

The cost associated to a microgrid sequence is defined below for any microgrid sequence s given any microgrid configuration M, any sequence of production $\phi_{0\ldots T-1}$ and any sequence of consumption $c_{0\ldots T-1}$:

$$LEC_M^{c_0\cdots c_{T-1},\phi_0\cdots\phi_{T-1}}(s) = \frac{\sum_{t=1}^{T} \frac{-\sum_{\psi\in\Psi} k_t^{\psi}((c_t - \sum_{g\in G}\phi_t^g) - \sum_{\sigma\in\Sigma}\eta^{\sigma}(a_t^{+,\sigma}+a_t^{-,\sigma}))}{(1+r)^{y'}} + I_0}{\sum_{y=1}^{n}\frac{\epsilon_y}{(1+r)^y}}. \tag{16}$$

5 Imitative Learning Approach

Optimal microgrid sequences are generated as an expert knowledge database. The decision-making agent is built using a subset of this database. Such an agent is evaluated on a distinct subset.

5.1 Data

Given production and consumption sequences, we can generate microgrid sequences by solving linear programs.

Formally, let $(\phi_t^{(k)}, c_t^{(k)})_{t\in\{0\ldots T-1\},k\in\{0\ldots K\}}$ be a set of production and consumption scenarios, with $K \in \mathbb{N}\backslash 0$. To this set corresponds a set of microgrid sequences:

$$(\phi_t^{(k)}, c_t^{(k)}, s_t^{(k,\sigma)}, a_t^{(k,\sigma)})_{k\in K,t\in\{0,\ldots,T-1\}}. \tag{17}$$

5.2 From Data to Feature Space

For each time $t \in \{0,\ldots,T-1\}$, production and consumption data are known from 0 to t. Let $\phi_{0\ldots t}^{(k)} = \left\langle \phi_0^{(k)} \ldots \phi_t^{(k)} \right\rangle$ and $c_{0\ldots t}^{(k)} = \left\langle c_0^{(k)} \ldots c_t^{(k)} \right\rangle$ be the sequences of production and consumption from 0 to t. We define a *microgrid vector* from the previous sequences:

$$(\phi_{0\ldots t}^{(k)}, c_{0\ldots t}^{(k)}, s_t^{(k,\sigma)}, a_t^{(k,\sigma)})_{k\in K, t\in\{0\ldots T-1\}, \forall\sigma\in\Sigma}. \tag{18}$$

We now introduce, $\forall t \in \{0\ldots T-1\}$, the function $e : \mathbb{R}^t \times \mathbb{R}^t \times \mathbb{R}^{bt} \to \mathbb{R}^{bt}$ where $b = \#\Sigma$. Such a function builds an information vector from sequences of production and consumption. Let $v = e(\phi_{0\ldots t}^{(k)}, c_{0\ldots t}^{(k)})$ be the information vector, v_l the l-th component of v and $L > 0$ the size of the vector. Finally we define, from the definition of microgrid vector, a feature space that will be used with supervised learning techniques as below:

$$(v_1 \ldots v_L, s_t^{(k,\sigma)}, a_t^{(k,\sigma)})_{k\in K, t\in\{0\ldots T-1\}, \forall\sigma\in\Sigma}. \tag{19}$$

5.3 Constraints Compliancy

An additional step is to ensure that the constraints related to the current information of the system are not violated with the actions performed by the decision making agent. A quadratic program is designed to search for closest feasible actions. This program is defined in Fig. 3. We use constraints from Fig. 1 with an extra one defined below which represents the limit of storage system recharging regarding the overall available energy in the system.

$$\sum_{\sigma\in\Sigma} a_t^{*+,\sigma} \leqslant -d'_t - \sum_{\sigma\in\Sigma} a_t^{*-,\sigma}, \tag{20}$$

where d'_t is defined below to take into account only the possible overproduction by the following equation:

$$d'_t = -max(0, d_t). \tag{21}$$

We are going to illustrate the postprocessing part (see also Fig. 4). We will consider three use cases below, with a battery limited in capacity by 11 kWh and a hydrogen tank with a power exchange limit of 7 kWp.

- Underproduction with both storage systems empty. Initial actions are both discharging but since this is not possible, the postprocessing part cancels the actions (Fig. 4 - top);
- Overproduction with hydrogen tank empty and battery containing 7 kWh. Initial actions are both charging. But the production itself does not entirely meet the consumption. Again, there is a projection where only the battery is discharging (Fig. 4 - middle);
- Underproduction with both storage systems are not empty. The actions are both charging but the energy requested does not meet entirely the consumption. As a consequence, the levels of charging of the battery and of the hydrogen tank are decreased by the projection (Fig. 4 - bottom).

$$\text{Min. } (a_t^{\prime+,\sigma} - a_t^{*+,\sigma})^2 + (a_t^{\prime-,\sigma} - a_t^{*-,\sigma})^2 - Ft \tag{22a}$$
$$\text{S.t :} \tag{22b}$$
$$s_t^{\sigma} + a_t^{*-,\sigma} + a_t^{*+,\sigma} \geqslant 0, \forall \sigma \in \Sigma \tag{22c}$$
$$s_t^{\sigma_c} \leqslant x^{\sigma_c}, \forall \sigma_c \in \Sigma_C \ , \tag{22d}$$
$$a_t^{*+,\sigma_p} \leqslant x^{\sigma_p}, \forall \sigma \in \Sigma_P \ , \tag{22e}$$
$$- a_t^{*-,\sigma_p} \leqslant x^{\sigma_p}, \forall \sigma \in \Sigma_P \ , \tag{22f}$$
$$\sum_{\psi \in \Psi} F_t^{\psi} \leqslant -d_t - \sum_{\sigma \in \Sigma} \eta^{\sigma} a_t^{*-,\sigma} + \frac{a_t^{*+,\sigma}}{\eta^{\sigma}} \ , \tag{22g}$$
$$\sum_{\psi \in \Psi} F_t^{\psi} \leqslant 0 \ , \tag{22h}$$
$$- F_t^{\psi} \leqslant c_t^{\psi} \ , \tag{22i}$$
$$- d_t^{\prime} \leqslant d_t \ , \tag{22j}$$
$$- d_t^{\prime} \leqslant 0 \ , \tag{22k}$$
$$\sum_{\sigma \in \Sigma} a_t^{*+,\sigma} \leqslant -d_t^{\prime} - \sum_{\sigma \in \Sigma} a_t^{*-,\sigma} \ . \tag{22l}$$

Fig. 3. Quadratic program defined for any time step $t \in \{0 \ldots T-1\}$ (postprocessing part).

5.4 Evaluation

An evaluation criterion consists to compute the difference of cost observed between control by the imitative agent and the optimally control microgrid, for a given context (i.e. profile of production/consumption and microgrid settings). More formally, let's consider s^* the optimal microgrid sequence and s' the microgrid sequence generated by the decision making agent. Then the cost difference is represented by the function below:

$$Err_M^{c_0 \ldots cT-1, \phi_0 \ldots \phi_{T-1}}(s') = LEC_M^{c_0 \ldots cT-1, \phi_0 \ldots \phi T-1}(s') - LEC_M^{c_0 \ldots cT-1, \phi_0 \ldots \phi_{T-1}}(s^*). \tag{23}$$

6 Simulations

6.1 Implementation Details

The programming language Python[1] was used for all the simulations, with the library Gurobi[2] for optimization tools and scikit-learn[3] for machine learning tools.

[1] www.python.org.
[2] http://www.gurobi.com/.
[3] www.scikit-learn.org.

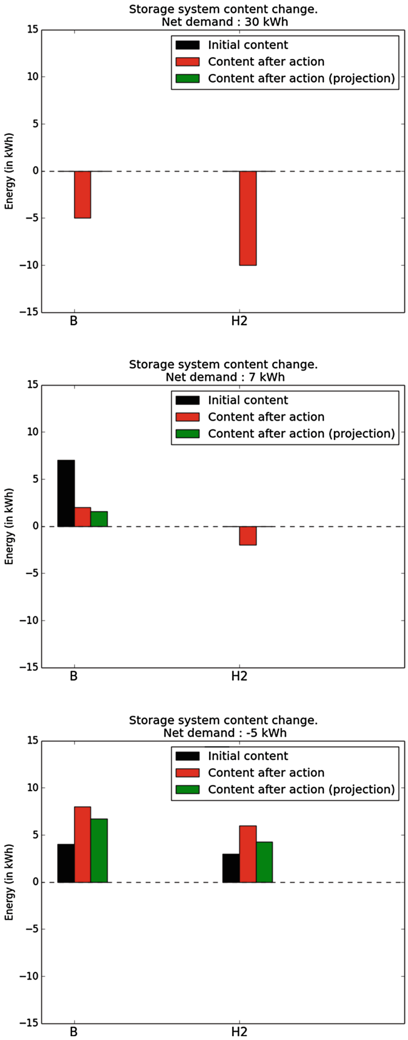

Fig. 4. Bar plots representing the projection from actions to feasible ones when needed.

6.2 Microgrid Components

Devices below are considered for the microgrid configuration.

- Photovoltaic panels accumulate energy from solar irradiance with a ratio of loss due to technology and atmospheric issues. According to Sect. 2, they are defined in terms of m^2 and of Wp per m^2. Table 1 gives the values of the elements describing the PV panels.
- Batteries are considered as short-term storage systems with no constraint on power exchange but with limited capacity. Table 2 gives the values of the elements describing the batteries.

– Hydrogen tanks, without capacity constraint, but limited in power exchange. They are long-term storage systems. Table 3 gives the values of the elements describing the hydrogen tanks.

Table 1. Photovoltaic panels settings.

Efficiency η^{PV}	20 %
Cost by m^2	200 €
Wp/m^2	200
Lifetime	20 years

Table 2. Batteries settings.

Efficiency charging/discharging η^{B}	90 %
Cost per usable kWh	500 €
Lifetime	20 years

Table 3. Hydrogen tank settings.

Efficiency charging/discharging η^{B}	65 %
Cost per kWp	14 €
Lifetime	20 years

6.3 Available Data

Consumption Profile. An arbitrarily pattern was designed as a representative model of a common residential daily consumption with two peaks of respectively 1200 and 1750 W. Figure 5 shows the daily graph of such a consumption profile.

Production Profile. The production scenarios are derived from the production data of a photovoltaic panel installation located in Belgium. These data have been processed in a straightforward way so as to have histories of production per m^2 of PV panels installed. These will be used later to define the production scenarios by simply multiplying them by the surface of the PV panels of the microgrid.

Figure 6 shows a typical production scenario for PV panels in Belgium.

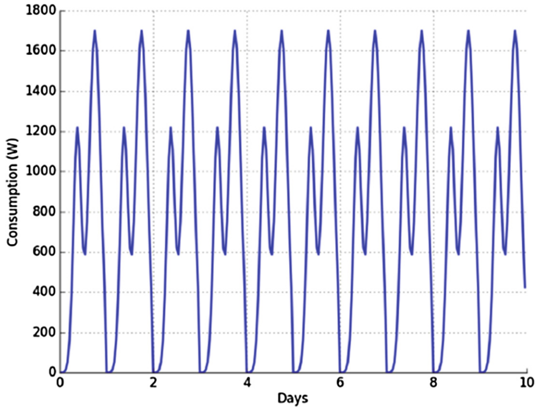

Fig. 5. Residential consumption profile.

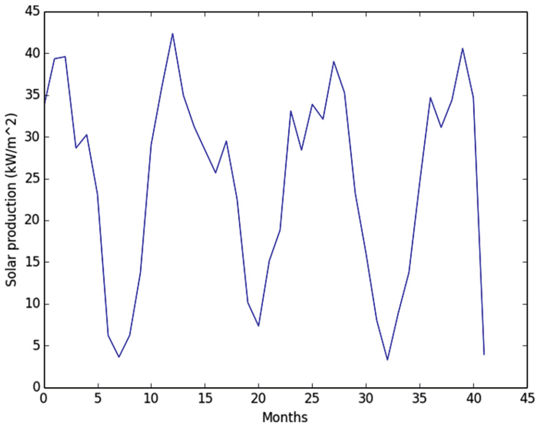

Fig. 6. Monthly production profile of PV panels in Belgium.

6.4 Test Protocol

We split the set of scenarios of production and consumption into two subsets, a learning set for training the agent and a test set to evaluate the performances. The learning set contains the two first years of production and the test set contains the last year of production. We also apply linear transformations as below to artificially create more scenarios for both learning and test sets.

$$\bigcup_{i\in\{0.9,1,1.1\}} \bigcup_{j\in\{0.9,1,1.1\}} \{(ic_t, j\phi_t)\}, t \in \{0 \dots T-1\}. \tag{24}$$

Table 4 details the configuration of our microgrid.

The following information vectors have been considered, $\forall t \in \{0 \dots T-1\}$:

Table 4. Microgrid configuration.

Photovoltaic panels area (in m^2)	42
Battery capacity (in kWh)	13
Hydrogen network available power (in kWp)	1

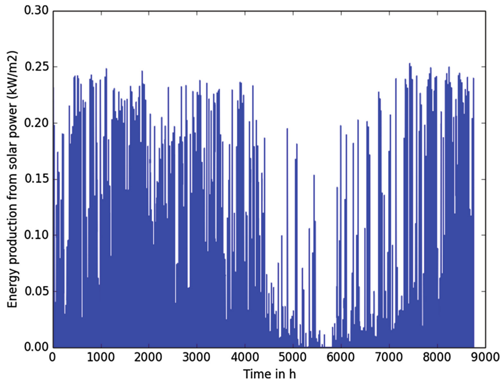

Fig. 7. Sample of typical Belgium production (1 year).

- 12 h of history, i.e. $e(\phi_0^{(k)} \dots \phi_t^{(k)}, c_0^{(k)} \dots c_t^{(k)}) = (\phi_{max(t-12,0)}^{(k)} \dots \phi_t^{(k)}, c_{max(t-12,0)}^{(k)} \dots c_t^{(k)})$;
- 3 months of history, i.e. $e(\phi_0^{(k)} \dots \phi_t^{(k)}, c_0^{(k)} \dots c_t^{(k)}) = (\phi_{max(t-24\times30\times3,0)}^{(k)} \dots \phi_t^{(k)}, c_{max(t-2160,0)}^{(k)} \dots c_t^{(k)})$;
- 12 h of history + summer equinox distance, i.e. $e(\phi_0^{(k)} \dots \phi_t^{(k)}, c_0^{(k)} \dots c_t^{(k)}) = (\phi_{max(t-12,0)}^{(k)} \dots \phi_t^{(k)}, c_{max(t-12,0)}^{(k)} \dots c_t^{(k)}, |t-t^*|)$, where t^* is the summer equinox datetime.

A forest of 250 trees have been built with the method of Extremely Randomized Trees proposed in [5]. Our imitative learning agent and our optimal agent are also compared with a so-called greedy agent that behaves in the following way.

- If $d_t \geqslant 0$, i.e. if underproduction occurs, storage systems are discharged in decreasing order of efficiency;
- If $d_t \leqslant 0$, i.e. if overproduction occurs, storage systems are charged in decreasing order of efficiency.

The main idea of this greedy agent is to keep as most as possible energy into the system.

6.5 Results and Discussion

Optimal Sequence of Actions. Figure 8 shows the evolution of the storage systems contents given optimal sequences of actions, for a given scenario. The empirical mean LEC over the test set is 0.32€/kWh. The evolution is plotted over 1 year.

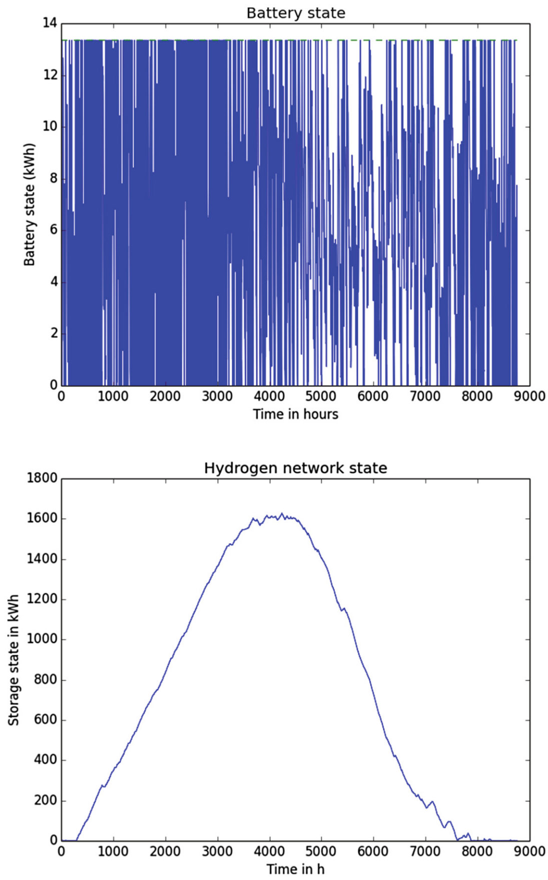

Fig. 8. Storage system state evolution (optimal).

As expected, the battery tries to handle short-term fluctuations. On the other hand, the hydrogen tank content gradually increases during summer before gradually decreasing during winter.

Greedy and Agent-Based Sequences of Actions. Table 5 shows the LEC for all the sequences generated by the greedy algorithm and the controller given several input spaces.

Considering a history of production and consumption of only 12 h is more expensive in terms of LEC, compared to a history of production and consumption

Table 5. Overall mean LECs.

Greedy controller	0.6
12 h	0.44
3 months	0.43
12 h + summer equinox distance	0.42

of 3 months. It shows that a decision making agent is more efficient with long-term information. Additionally, we also report experimental results for which the agent was also provided with the distance (in time) to summer equinox. This additional information improves the performances.

7 Conclusion

In this paper, we have proposed an imitative learning-based agent for operating both long-term and short-term storage systems in microgrids. The learning set was obtained by solving a family of linear programs, each of them being associated with a fixed production and consumption scenario.

As having access to real data is expensive, we plan to investigate how to transfer knowledge from one microgrid to another. In particular, we will focus on transfer learning strategies [10].

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