Energy management of microgrids: from a mixed-integer linear programming problem to a rule-based real-time algorithm

Anthony Roy, François Auger, Jean-Christophe Olivier, Bruno Auvity, Emmanuel Schaeffer, Salvy Bourguet

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Anthony Roy
IREENA
Université de Nantes
Saint Nazaire, France
anthony.roy1@univ-nantes.fr

François Auger
IREENA
Université de Nantes
Saint Nazaire, France
francois.auger@univ-nantes.fr

Jean-Christophe Olivier
IREENA
Université de Nantes
Saint Nazaire, France
jean-christophe.olivier@univ-nantes.fr

Bruno Auvity
LTEN
Université de Nantes
Nantes, France
bruno.auvity@univ-nantes.fr

Emmanuel Schaeffer
IREENA
Université de Nantes
Saint Nazaire, France
emmanuel.schaeffer@univ-nantes.fr

Salvy Bourguet
IREENA
Université de Nantes
Saint Nazaire, France
salvy.bourguet@univ-nantes.fr

***Abstract*— To ensure the economic viability and the reliability of microgrid operation, an adapted energy management system (EMS) has to be designed. Most of the studies have discussed optimization-based approaches, for example with a mixed-integer linear programming (MILP) problem, to get the best operating profiles for each microgrid device allowing economic, technical or environmental objectives to be met. However, this kind of EMS requires a forecasting ability of the power generation and of the demand, and the management of the uncertainties. In some microgrids, especially in industrial areas, the power generation and the load demand cannot be accurately forecasted. In such cases, only a rule-based algorithm can be considered for the real-time energy management. In this paper, a rule-based algorithm is proposed for the management of a seaport multi-energy microgrid, using electricity and hydrogen as energy vectors. The rules are designed on the basis of the results obtained with MILP problem solving with the aim being to maximize income and use the energy generated by the local energy sources as well as possible by taking dynamic pricing into account. Moreover, specific strategies are designed for the management of the electrolyzer and hydrogen tank to avoid premature ageing. The results show that the proposed real-time algorithm and rules enable the economic and energetic criteria to reach values close to those obtained with MILP problem solving, with an increase of the payback period less than 2%.**

Keywords—Microgrid, energy management, rule-based algorithm, storage management

I. INTRODUCTION

The development of multi-energy microgrids faces constraints related to reliability, emission of pollutants, economic viability, etc. [1]. Thus, specific energy management systems (EMS) have to be designed to take goals and constraints into account. Several kinds of approaches can be found in the literature for the design of EMS [2]. Some of them are based on optimization problems involving linear or non-linear programming, whereas others consider rule-based (RB) algorithms. Most of the time, the EMS based on optimization involves the ability to forecast the future (power generation, power demand, electricity purchasing and selling prices, etc.) to minimize an objective function. Such optimization problems ensure that an optimal solution can be found, but the uncertainties management and the computation time can be problematic [2], [3]. For real-time management and when data forecasting is not really possible, the RB algorithms are more suitable to take operating decisions according to the state of the system [4], [5]. Several studies have compared the results obtained by optimization and RB approaches [6]–[10]. Those based on optimization lead to better economic results but require greater computation time in comparison with RB approaches. To obtain results as close as possible to those obtained with optimization, some authors have proposed rules-based methods to control the microgrid devices, such as using binary variables in [4] or fuzzy rules in [11]. The management of storage solutions and dynamic pricing appear to be key points [12].

However, the literature survey shows that the design of RB algorithms for industrial multi-energy microgrids where multiple ways of valorisation exist has not been deeply investigated. Thus, the aim of this paper is to propose a RB algorithm for a multi-energy microgrid considering electricity and hydrogen energy vectors. The algorithm's design was based on results obtained through solving a MILP problem. The idea is to define the operating decisions solely on the basis of the current situation of the system, without taking the power generation and demand expected in the incoming hours into account. The case study used is related to a seaport area, in which generation and demand forecasting is difficult. The strategies are designed to get economic results as close as possible to those obtained with MILP problem solving. This paper is organized as follows: the modelling of the studied microgrid is presented in Section II. Then, the proposed RB algorithm is described in Section III. The obtained results and a comparison with MILP problem results are given in Section IV. Section V consists of a conclusion and some perspectives.

II. System Description

A scheme of the studied industrial microgrid is proposed in Fig. 1. Power flow modelling was considered for this study. The electrical power generation (P_{gen}, in W) is carried out thanks to solar photovoltaic panels and energy harvesting from engines testing. This generated power can be either fed into an electrolyzer (P_{elz}) to be converted into hydrogen, used for the supply of electrical loads (the total load power is denoted by P_{dem}), fed into the main grid ($P_{gr\text{-}s}$), used for the charge of the batteries ($P_{bat\text{-}c}$) or fed into a dump load (P_{dp}). In the case of low generated power, the electrical load demand can be supplied by the batteries discharge ($P_{bat\text{-}d}$), the fuel cell (P_{fc}) or thanks to electricity purchased to the main grid ($P_{gr\text{-}p}$). It should be noted that the power $P_{gr\text{-}p}$ can be separated in two variables, one for the supply of electrical loads ($P_{gr\text{-}p/el}$) and the other one for the hydrogen production ($P_{gr\text{-}p/H2}$). The hydrogen produced can be used for the supply of local needs ($L_{H2\text{-}dem}$, in Nm^3/h, normal cubic meter per hour) including hydrogen mobility and industrial requirements and can also be fed into the urban gas network ($L_{H2\text{-}g}$). Moreover, the hydrogen produced can be stored in hydrogen tank for a later use. Each of these powers is constrained by a maximum value related to the sizing and/or the operation of each subsystem. This limit is denoted with the subscript *max*, such as for example the power limit $P_{elz\ max}$ for the electrolyzer. The minimum value of these powers is zero, except for the batteries discharge power ($P_{bat\text{-}d\ min}$) considered negative.

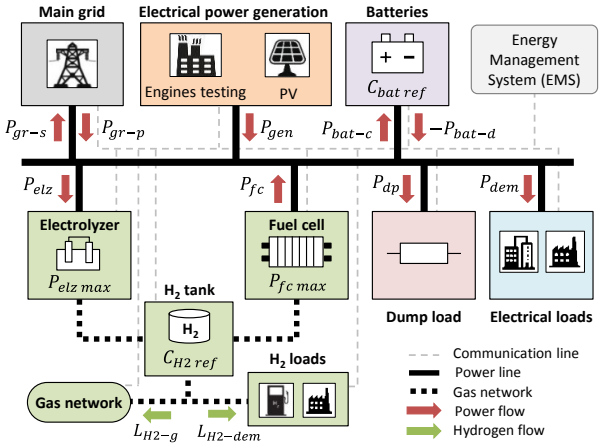

Fig. 1. Overview of the considered microgrid

The power balance of this system must be achieved at each time sample t_k to ensure the whole demand can be supplied:

$$P_{gen}(t_k) + P_{gr\text{-}p}(t_k) + P_{fc}(t_k) - P_{bat\text{-}d}(t_k) = P_{dem}(t_k) + P_{gr\text{-}s}(t_k) + P_{elz}(t_k) + P_{bat\text{-}c}(t_k) + P_{dp}(t_k) \quad (1)$$

The modelling of the storage solutions and a summary of the management considered in the MILP optimization problem are described in the following subsections.

A. Batteries modelling

The model considered for the batteries is based on the state of charge (*SoC*) calculation, defined at each time sample t_k by:

$$SoC(t_k) = \alpha_{bat}\, SoC(t_{k-1}) + (\eta_{bat\text{-}c}\, P_{bat\text{-}c}(t_{k-1}) + P_{bat\text{-}d}(t_{k-1})/\eta_{bat\text{-}d})\, \Delta t / C_{bat\text{-}ref} \quad (2)$$

where $C_{bat\text{-}ref}$ is the nominal capacity of the batteries [Wh], $\eta_{bat\text{-}c}$ and $\eta_{bat\text{-}d}$ the efficiencies in charge and discharge, α_{bat} the coefficient related to the batteries self-discharge rate between two consecutive time samples and Δt the time step. It should be noted that the charging power $P_{bat\text{-}c}$ is considered positive and the discharging power $P_{bat\text{-}d}$ negative. The *SoC* is constrained by a lower limit SoC_{min} and an upper limit SoC_{max}, so that at each time sample the inequalities $SoC_{min} \leq SoC(t_k) \leq SoC_{max}$ are met.

B. Hydrogen production and storage modelling

The modelling of the hydrogen system is based on the calculation of the level of hydrogen *LoH* stored in the hydrogen tank [13]. At each time sample t_k, *LoH* is calculated thanks to:

$$LoH(t_k) = \alpha_{H2}\, LoH(t_{k-1}) + (P_{elz}(t_{k-1})\eta_{elz} - P_{fc}(t_{k-1})/\eta_{fc} - (L_{H2\text{-}g}(t_{k-1}) + L_{H2\text{-}dem}(t_{k-1}))\gamma_{H2})\, \Delta t / C_{H2\text{-}ref} \quad (3)$$

where $C_{H2\text{-}ref}$ is the nominal capacity of the hydrogen tank [Wh], η_{elz} and η_{fc} the efficiencies of the electrolyzer and the fuel cell, α_{H2} the coefficient representing the self-discharge rate of the hydrogen tank between two consecutive time samples and γ_{H2} the conversion factor between hydrogen volume and hydrogen energy.

C. Energy management based on the MILP problem

The energy generated can be valorised in different ways using this multi-energy microgrid. To obtain the operating decisions allowing the profits to be maximized over a given period of several hours, an optimization problem was formulated according to a MILP approach, as described in [14]. The main ideas underpinning this optimization problem are as follows:

- Decision variables: operating powers of the microgrid devices (P_{elz}, P_{fc}, $P_{bat\text{-}c}$, $P_{bat\text{-}d}$, P_{dp}), power exchanged with the main grid ($P_{gr\text{-}s}$ and $P_{gr\text{-}p}$) and hydrogen fed into gas network ($L_{H2\text{-}g}$).
- Objective function: to maximize income including:
  - the sale of electricity, remunerated according to $c'_{s\text{-}el}$ dynamic price depending on the hour of the day;
  - the sale of hydrogen fed into the gas network, remunerated according to $c'_{s\text{-}H2g}$ constant price;
  - the sale of hydrogen used for mobility, remunerated according to $c'_{s\text{-}H2dem}$ constant price;

  and minimize expenses including:
  - the operating costs of batteries ($c'_{op\text{-}bat}$), electrolyzer ($c'_{op\text{-}elz}$) and fuel cell ($c'_{op\text{-}fc}$);
  - the purchase of electricity based on a dynamic tariff $c'_{p\text{-}el}$ depending on the hour (night/day) and the season (winter/summer).
- Constraints: power balance (electrical and hydrogen demand have to be met, thus no load shaving), power limits, hydrogen flow limits, *SoC* and *LoH* limits, hydrogen tank filled at the beginning of each day.

This optimization problem was solved for a period of *K* time samples. Moreover, a rolling horizon simulation was considered to limit the number of decision variables, related to the period length, thus the computation time. In our case, the optimization problem was solved for a data period of two days

and the update time step was one day, while the simulation time step was set to 15 min.

Several trends can be highlighted by observing the results obtained through solving this optimization problem (see Fig. 5):

- The power dispatch shows that at each moment in time the generated energy was fed into the most profitable solutions in a hierarchical way: hydrogen production for the supply of hydrogen loads in priority, then supply of electrical loads (electricity purchase savings), then hydrogen production for injection into urban gas network, and finally injection into the main grid. This of course depends on the price assumptions.
- As the self-discharge was taken into account, the storage solutions were charged as late as possible and discharged as soon as possible to limit the energy losses. Moreover, the batteries were charged after the hydrogen tank, as the batteries self-discharge rate is higher than for hydrogen tank. The batteries were discharged before the hydrogen tank because of the self-discharge and bearing in mind using this discharged energy for the most profitable solution.
- The fuel cell was never used, as it is not profitable to convert hydrogen into electricity, in comparison to the sale of hydrogen both for hydrogen demand supply and injection into the gas network. Moreover, the efficiency of the fuel cell ($\eta_{fc} = 0.5$) also explains this trend.
- If the energy generated by the local energy sources is not sufficient to fill the hydrogen tank during the day, the charge can be ensured thanks to electricity purchase during the nightly low-price period (from 10 p.m. to 6 a.m.), to obtain a fully charged hydrogen tank each morning.

Moreover, the operating profiles obtained with this approach show that the ability to forecast some data is necessary (power generation, demand and energy costs). The storage solutions were managed with a non-causal way, in the aim to maximize the net profit while taking the storage self-discharge and the dynamic tariffs (electricity purchasing and sale) into account.

III. Proposed rule-based algorithm

From the results obtained from solving the MILP optimization problem, a RB algorithm was designed. The aim of this algorithm is to define the operating rules (values of P_{elz}, P_{fc}, $P_{bat\text{-}c}$, $P_{bat\text{-}d}$, P_{dp}, $P_{gr\text{-}s}$, $P_{gr\text{-}p}$ and $L_{H2\text{-}g}$) at each time sample t_k in a causal way. Thus, the decisions must only be defined according to the state of the system and the costs at this time sample, characterized by the following input data: P_{gen}, P_{dem}, $L_{H2\text{-}dem}$, SoC, LoH, $c'_{s\text{-}el}$, $c'_{s\text{-}H2g}$, $c'_{s\text{-}H2dem}$ and $c'_{p\text{-}el}$. The constraints related to the power balance and the operating limits must also be dealt with.

The flowchart related to the main algorithm is shown in Fig. 2 which corresponds to the steps executed at a time sample t_k. The algorithm starts with an assessment of the storage systems (step 1). If hydrogen is already available, the discharge of the hydrogen tank is considered first for the supply of hydrogen loads (step 2), before considering the use of electrolyzer in the next steps. Step 3 aims to share the generated power among the devices thanks to the algorithm described in the section III-A. Once the power generated has been dispatched, the step 4 determines if and in which solution the batteries can be discharged, according to the algorithm presented in the section III-B. This 4th step aims also to determine if fuel cell has to be used. As the power generated and the discharge of storage solutions can be not sufficient to supply the electrical demand and hydrogen demand, the needed power drawn from the main grid is calculated in the step 5. Moreover, at this step, if the time t_k belongs to a low-price period for electricity purchase (from 10 p.m. to 6 a.m.), electricity is purchased to the main grid to fill as much as possible the hydrogen tank.

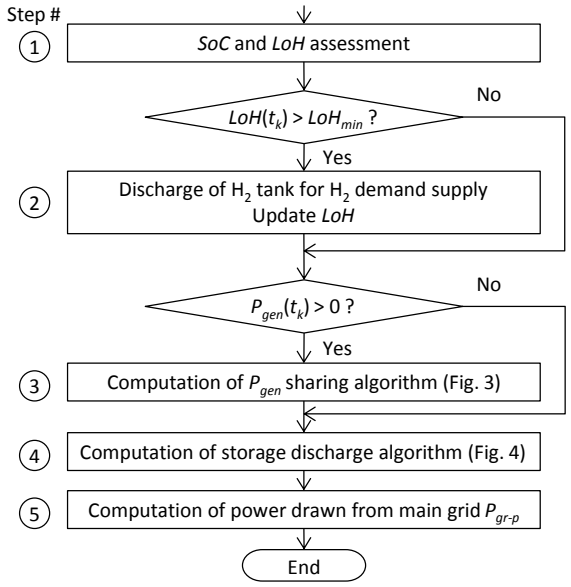

Fig. 2. Flowchart of the main algorithm applied at each time sample t_k

A. Algorithm considered for the energy valorisation

The algorithm designed for the dispatch of the power generated at a time sample t_k is presented in Fig. 3. As explained previously, the power generated is shared in a hierarchical way according to the valorisation costs, ranked from the most profitable to the less profitable (step 1). The costs are compared on the electrical bus side, thus the electrolyzer efficiency must be considered in the costs ranking to take the losses into account. If certain costs are identical, the order of priorities is as follows: use for electrical loads supply then hydrogen production and finally injection into the main grid. Then, the steps 2.a to 2.f are computed according to the *while loop* iteration, by defining at each step the power related to the considered device. The idea of these steps is to use the power generated as much as possible, taking into account the limits (device limits, available generated power and load power) and the powers which have been calculated in the previous steps. The power generated remaining to be used (P'_{gen}) is updated at each of these steps, according to the calculated use. It should be noted that a power threshold is considered for the filling of the hydrogen tank with the power

generated. To avoid frequent use of the electrolyzer which would lead to a fast ageing, the hydrogen tank is filled with the power generated only if the remaining generated power P'_{gen} is greater than a power threshold $P_{elz\ th}$ (steps 2.b and 2.d). This rule means the number of operating hours can be reduced by only turning on the electrolyzer for high power values. Then, if a surplus of generated power remains after the sharing between the four valuing solutions, the energy is stored as much as possible into the batteries. Finally, if a surplus still exists after considering batteries charging, the rest of generated power is fed into a dump load.

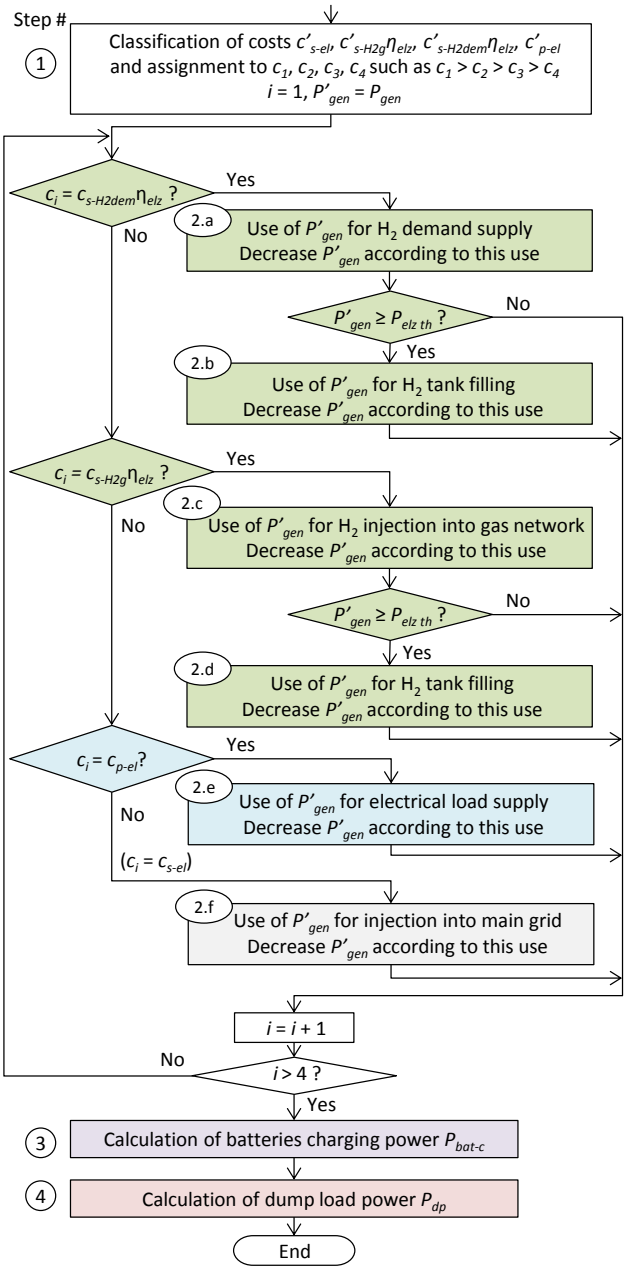

Fig. 3. Flowchart of the algorithm related to the power generated sharing

B. Algorithm considered for the use of the stored energy

The flowchart of the algorithm related to the storage discharge at each time t_k is presented in Fig. 3. The rule considered involves using the stored energy for the most profitable solution from the following: hydrogen production (for hydrogen load supply or injection into the urban gas network), electrical load supply and injection into the main grid. It should be noted that the batteries are discharged before considering using the hydrogen tank and the fuel cell, to minimize energy lost due to the self-discharge of the batteries. The maximum operating power of the chosen valorisation method and the possible uses calculated during the previous steps are taken into account to define the discharge of the batteries and the hydrogen tank.

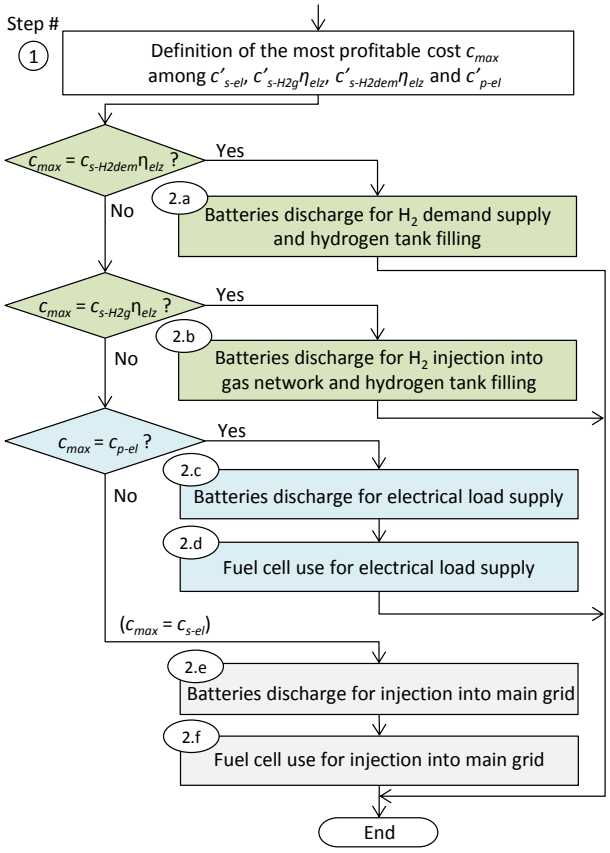

Fig. 4. Flowchart of the algorithm related to the discharge of the storage solutions

IV. SIMULATION RESULTS

The RB algorithm proposed in this article was validated with a simulation computed on MATLAB software. The case study was the industrial microgrid of the seaport of Saint-Nazaire (France). The considered theoretical sizing was: $C_{bat\ ref} = 1$ MWh, $C_{H2\ ref} = 12.5$ MWh, $P_{elz\ max} = 2.3$ MW, $P_{fc\ max} = 0.5$ MW. The electrical power was generated thanks to a 4 MW installed power of PV panels and an engine testing process with a maximum power of 26 MW. The electrical load demand considered is related to industrial buildings and seaport basin pumps, leading to a maximum demanded power of 3 MW. The hydrogen demand involves three kinds of mobility use (cars, bus and boats) with a total daily demand of 600 kgH_2. The following economic assumptions were made for electricity: the selling cost $c'_{s\text{-}el}$ varies during the day between 2.91 c€/kWh and 5.66 c€/kWh, while the purchasing cost $c'_{p\text{-}el}$ depends on the hour of the day and the season, with values

between 6.69 c€/kWh and 11.75 c€/kWh. The hydrogen selling prices were $c'_{s\text{-}H2g}$ = 10 c€/kWh and $c'_{s\text{-}H2dem}$ = 20 c€/kWh. The time step Δt was set at 15 min and the simulation was carried out for a one-year data period (real power demand and generated power data recorded in 2019). The power threshold $P_{elz\ th}$ was set at 1 MW (a sensitivity analysis is proposed at the end of this section).

The operating profiles obtained in the simulation are shown in Fig. 5, for a one-day time window (February 6th 2019). The results obtained by solving the MILP optimization problem are also presented to compare them with the results of the RB algorithm. Several trends can be highlighted from these results. With the RB algorithm, the batteries are charged as soon as an excess of generated energy exists rather than as late as possible as is the case with MILP. Moreover, the batteries are only discharged when the most profitable way of valorisation is available (hydrogen production) rather than as possible as with MILP. It can be seen that the hydrogen tank starts to fill a little earlier with the MILP approach to achieve a fully filled tank at 6:00 while with the RB algorithm the filling occurs at 22:00 only, when the low-price period starts. Moreover, the hydrogen tank was only allowed to be filled with the power generated when the available generated power overpasses the triggering power $P_{elz\ th}$ of 1 MW (for example at 10:15). This filling of the tank shows that less generated power is used for the supply of the electrical loads during the morning, thus more power has to be purchased from the main grid ($P_{gr\text{-}p/el}$) in comparison with the result obtained through solving the MILP problem. Also, the algorithm proposed for the sharing of the power generated involves a slight increase of the power fed into the main grid ($P_{gr\text{-}s}$) in comparison with MILP results. In fact, it has been considered that the generated energy should be used as much as possible when the generation occurs, following a hierarchical order based on the valorisation costs. It should also be noted that the fuel cell is never used in both simulations, as more profitable ways exists for the energy valorisation.

A comparison of the values of the technical and economic criteria obtained through solving the MILP problem and using the RB algorithm is presented in Table 1. These results show that slight differences in the results obtained by the two approaches. Using the RB algorithm was found to lead to a lower level of valorisation of the energy generated, which can be explained by a higher amount of energy converted into hydrogen meaning there were more losses due to the electrolyzer efficiency. Also, the electrolyzer is used more often and thus needs to be replaced earlier which means the related annualized replacement cost is higher. The differences observed for energy sharing and the broader use of devices was found to lead to a lower annual net profit with the RB approach and thus a five months longer payback period. The annual net profit is the difference between the incomes and the expenses, including electricity purchase, operation and maintenance costs and annualized replacement costs. However, the gap is small as the annual net profit is decreased by 2% only. It can be highlighted that the computation time is strongly diminished with the RB algorithm (3.3 s vs. 53.9 s for MILP). This can be an advantage in more complex studies in which the computation time has to be as low as possible, such as sizing optimization, sensitivity analysis and real-time management.

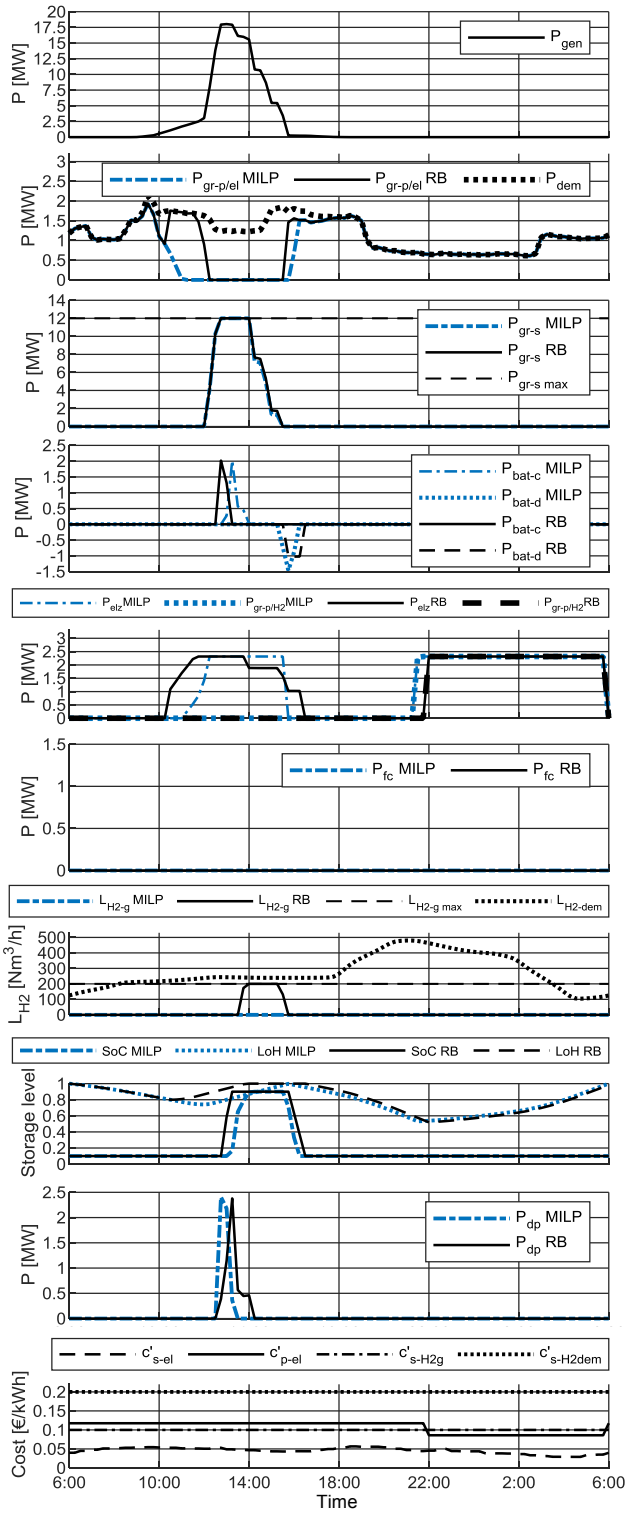

Fig. 5. Operating profiles for a one-day time window, obtained for MILP problem solving (blue curves) and rule-based algorithm (black curves)

The designed RB algorithm involves the parameter $P_{elz\ th}$ for the filling of the hydrogen tank with the power generated by the local sources, to avoid frequent turn on for small power values. The influence of $P_{elz\ th}$ value on the annual net profit and the valorised energy rate is shown in Fig 6. These results show that the value of 1 MW allows the annual net profit to be

maximized. If this threshold is decreased, the incomes obtained by the hydrogen production will increase but the number of operating hours of the electrolyser will also increase, leading to an annualized replacement cost higher than profits obtained by hydrogen selling. If the threshold value is set at a higher value, the electrolyzer will be used less which lowers replacement cost but the energy will be valorised in a less profitable way (electricity fed into the main grid or used for electrical load supply). However, less energy will be lost in comparison to using the electrolyzer. Thus, the rules must be designed with the right parameters to obtain a compromise between energy valorisation (from energetic and economic points of view) and operating costs related to the use of devices.

TABLE I. COMPARISON OF OBTAINED RESULTS FOR ONE YEAR

Criterion	Results	
	MILP problem	***RB algorithm***
Valorised energy (% of E_{gen})	7.13 GWh (83.7%)	6,83 GWh (80.1%)
Generated energy used for electrical loads supply [GWh]	2.59	1.535
Generated energy used for hydrogen production [GWh]	2.146	2.828
Generated energy used for injection into main grid [GWh]	2.395	2.465
Annual net profit [k€/y]	632.3	620.4
Payback period [years]	20.86	21.26

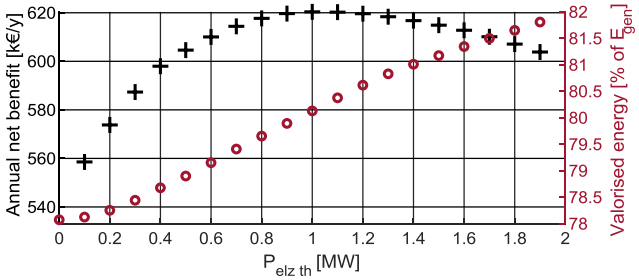

Fig. 6. Impact of electrolyzer power threshold $P_{elz\ th}$ on the annual net profit (+ marker) and the valorised energy rate (o marker)

V. CONCLUSION

In this article, a RB algorithm was designed to manage a multi-energy microgrid based on the results obtained through solving a MILP problem. The proposed approach was based on a prioritization of profits and on the choice of a power threshold to limit the electrolyzer ageing. The results presented in this article show that the economic benefits and the energy valorisation rate are close to those obtained with MILP problem solving. Thus, economic viability can be ensured for this microgrid without complex forecasting assumptions. However, the RB strategies must be designed carefully according to the sizing of the system devices and the considered input data (generated power, electrical and hydrogen load demand, energy costs, etc.). The storage devices must be managed to avoid too frequent use, which would lead to a premature ageing and thus high replacement costs. Several other potentially interesting avenues could be studied in the future, such as the integration of market mechanisms into the RB algorithm and a comparison with machine learning algorithms.

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