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► **To cite this version:**

Sarah Ouédraogo, Ghjuvan Antone Faggianelli, Guillaume Pigelet, Gilles Notton, Jean Laurent Duchaud. Performances of energy management strategies for a Photovoltaic/Battery microgrid considering battery degradation. *Solar Energy*, 2021, 230, pp.654-665. 10.1016/j.solener.2021.10.067. hal-04643151

**HAL Id: hal-04643151**

**<https://hal.science/hal-04643151v1>**

Submitted on 22 Jul 2024

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# 1 Performances of energy management strategies for a Photovoltaic/Battery 2 microgrid considering battery degradation

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8 **Abstract:** Several energy management strategies, of increasing complexity, are compared in term of cost  
9 benefit for a Photovoltaic /battery system providing electricity to an accommodation building with an electric  
10 vehicle. Rule based control methods with or without production forecasting are implemented and compared  
11 to a linear programming strategy used as a reference. The improvement in term of gain between simplest and  
12 reference methods is about 27%. It appears that the battery cycles number differs greatly (up to 55%), leading  
13 to a more or less rapid ageing. Battery degradation models are thus added and a corresponding cost is  
14 introduced in the strategy benefit. The results, depending on the initial battery cost, are significantly  
15 impacted, changing the relevance of the control strategies.

16 **Keywords:** solar microgrid; energy management system; rule based control; battery ageing model.  
17

## 18 1. Introduction

19 The growing use of microgrids to integrate distributed energy resources (DERs) involves the use of  
20 specific controllers with integrated Energy Management Systems (EMS) for proper management and  
21 efficient system operation [1]. Such EMS can be used to schedule the operation of distributed  
22 generators (DGs), loads and storage within a microgrid, allowing the reduction of operating costs and  
23 CO<sub>2</sub> emissions. They are particularly useful when variable pricing and generation are involved [2]. We  
24 can differentiate two main types : EMS relying on mathematical optimization, using prevision of the  
25 future system behavior [3] [4], or rule based EMS consisting in a combination of rules. Rule based  
26 control (RBC) presents the advantage of being simple and easy-to-use but the rules may be hard to  
27 tune [5]. Unlike mathematical optimization such as linear or dynamic programming, they can rely or  
28 not on load and production prevision depending on their availability.

29 In a previous paper [6], several EMS were applied to an existing microgrid located in Ajaccio,  
30 Corsica (FRANCE). In this study, we focused on a part of the modular microgrid PAGLIA ORBA  
31 including energy production: PV modules, storage: lead acid batteries and loads: accommodation  
32 building and electric vehicle. One of the main results was to highlight the performance of a well-  
33 designed RBC in terms of cost optimization, even with multiple constraints: limitation of the power  
34 exchanged with the main grid and price fluctuation of energy (peak and off-peak hours). However,  
35 such work had a few drawbacks. At that time, only two weeks of data had been assessed. As PV  
36 production and load consumptions are affected by climate and seasonal effect, this is not enough to  
37 draw a definitive conclusion. Indeed, it seems easier to calibrate an RBC to work on a short specific  
38 period rather than on a whole year, which could be compared to the “overfitting” problem in  
39 optimization. We also observed that the different strategies had different uses of the battery  
40 reflected by various levels of SoC, DoD and cycles numbers. In these circumstances, it may be unfair  
41 not to consider the battery cost affecting the real cost of the system. This paper thus aims to  
42 overcome these two main drawbacks. For the first point, we can now provide such study with a  
43 whole year of data, allowing to test the previous RBCs on a longer period and improve them to take

44 seasonal effects into account. For the second point, the choice of a method to calculate battery  
45 ageing is far from trivial.

46 In a PV microgrid, the storage can complement variable renewable generation to improve the  
47 matching of solar PV production with electricity demand. If the PV module price decreased  
48 exponentially, the price of the energy storage also decreased importantly; between all the energy  
49 storage means, it appears clearly that for small or medium PV installations, as studied in this paper,  
50 electrochemical storage is the most appropriate. Between all the electrochemical storages, the  
51 market share of Li-ion batteries for electric vehicles (EVs) and stationary storage climbed from 5% in  
52 2010 to more than 60 % in 2017 [7]. The Lead acid battery technology represented in 2016 about 6%  
53 of the storage market (without hydro pumping system) [8]. Even if this battery technology is today  
54 less used than Li-ion technology, it is the type of battery integrated in the PV microgrid studied in this  
55 paper. In this context, storage systems have been the subject of several researches because they  
56 represent an important part of the microgrid. Storage systems are used to stock excess energy  
57 produced by the PV plant and to supply electricity to the load when necessary; it helps balancing the  
58 grid by reducing the intermittent and random nature of renewable energy, but also supplying  
59 demand in the event of power shortage.

60 The utilization of battery in a PV system implies to develop methods to take a decision on its  
61 management. A storage, particularly a battery, is neither treated as production nor as load. The  
62 decision to be taken for its use depends, obviously, on the energy availability but it can also be  
63 scheduled for a future dispatch moment as per the dynamic behavior of electricity tariff, load, and  
64 production. Numerous researchers focused on optimal operating strategies of battery for increasing  
65 its performance, efficiency, and life-time [9] keeping in mind that battery is a very costly part of the  
66 microgrid. Such a strategy was developed by Tran and Khambadkone [10] with a Peukert life-time  
67 model to predict the battery life-time and a stochastic dynamic programming for optimization. They  
68 showed, in this case-study, that it is possible to improve energy efficiency of ESS from 74.1% to  
69 85.5% (+15%) and the lifetime of two battery packs from 3.6 years to 5 years (+39%) and from 2.4  
70 years to 5.7 years (+140 %) showing the importance of such battery management. The same Peukert  
71 model was also used to determine the loss of health for the battery which is minimized in the  
72 operation of a PV system [11]. However, Azuatalam *et al.* [12] shows that using a sophisticated EMS  
73 may not necessarily improve the performance and economic viability of the system as the battery  
74 degradation adversely affects its lifetime.

75 A battery life estimator with, as main variables, the varying depths and rate of discharge was  
76 considered in a power management framework for a commercial hybrid renewable microgrid with  
77 battery storage [13]. Studies on the integration of battery degradation issues within battery control  
78 are available in the literature, in which the battery defines an upper bound on the maximum number  
79 of cycles [14], or defines upper bounds and lower bounds on the state of charge of the battery  
80 without formal optimization [15].

81 In a multi-carrier energy hub, a cost-effective strategy based on a mixed-integer non-linear  
82 optimization and considering the degradation cost of battery were applied [16] and proved its  
83 positive impact on the economic operation of this energy hub while meeting the system's  
84 constraints. In view to extend the lifetime of the battery, the variation of the wind turbine output is  
85 reduced using an optimal dispatch strategy [17].

86 The degradation, life-time, operation and maintenance costs of the battery can be incorporated in  
87 the optimization process to increase the profit of a microgrid system using model predictive control  
88 (MPC) [18]. Cai *et al.* [19] also developed a MPC applied to a sustainable building in view to decrease

89 the utility costs while minimizing battery degradation. Bordin *et al.* [20] developed a methodology  
90 including battery degradation processes via a degradation cost inside the optimization model.

91 Although not exhaustive, this bibliographical study on the inclusion of battery degradation and  
92 lifetime in optimization processes for energy management highlights the importance of this topic in  
93 the development of microgrids with storage and using mainly an intermittent production from  
94 renewable sources. A literature survey on the influence of battery degradation model will be  
95 presented later.

96 The aim of this paper is thus to complete and improve the previous study [6] allowing to assess  
97 the relevance of using an RBC as an EMS for microgrid while taking into account the battery cost. The  
98 paper is structured as follows:

- 99 • a brief overview of the facilities (PAGLIA ORBA microgrid) and data used in this study;
- 100 • a description of the different EMS tested and their improvements;
- 101 • a presentation of the methods to consider batteries ageing cost;
- 102 • the main results considering energy and cost savings;
- 103 • the conclusion and perspectives for following works.

## 104 2. R&D PAGLIA ORBA microgrid

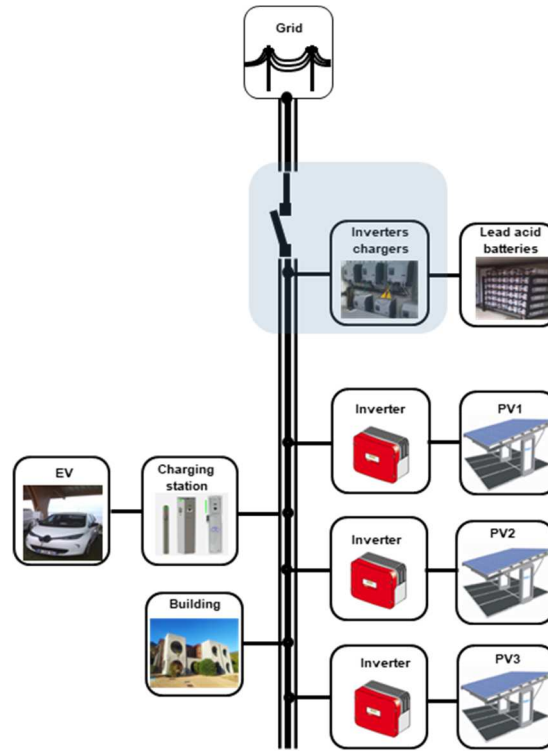
105 An R&D solar microgrid called PAGLIA ORBA (Figure 1) is operating in the SPE laboratory  
106 (University of Corsica, Ajaccio, FRANCE). In this study we focus on a part of this microgrid including  
107 three Distributed Generation systems (DG: 3 PV arrays of 17 kW AC), an Energy Storage System (ESS:  
108 electrochemical batteries with a total capacity of 70 kWh DC) and 2 loads (one accommodation  
109 building and one electric vehicle). This three-phase microgrid uses a common AC bus and can operate  
110 both in grid-connected or islanded mode. A general schematic is also presented in Figure 2.



111  
112 *Figure 1. PAGLIA ORBA microgrid*

113 The PV system is composed of 3 × 56 monocrystalline silicon 327 Wp modules (SUNPOWER E20)  
114 connected to 3 × 17 kW inverters (SMA SUNNY TRIPOWER 17000TL-10). The ESS consists in 24 × 2V  
115 lead acid batteries (OPzV) in series and is operated by six inverters/chargers (STUDER INNOTECH  
116 XTENDER). For the loads, the consumption of the accommodation building varies depending on the  
117 period and the capacity of the EV is 22 kWh. The EV is used every day from 9:00 to 16:00 and is

118 considered as fully discharged at 16:00. From 16:00 to 18:00, the EV is charging in the microgrid with  
119 a maximum power of 22 kW and a mean power of 11 kW. If we consider the total consumption, this  
120 leads to a maximum power of 34.2 kW and a mean power of 3.5 kW.

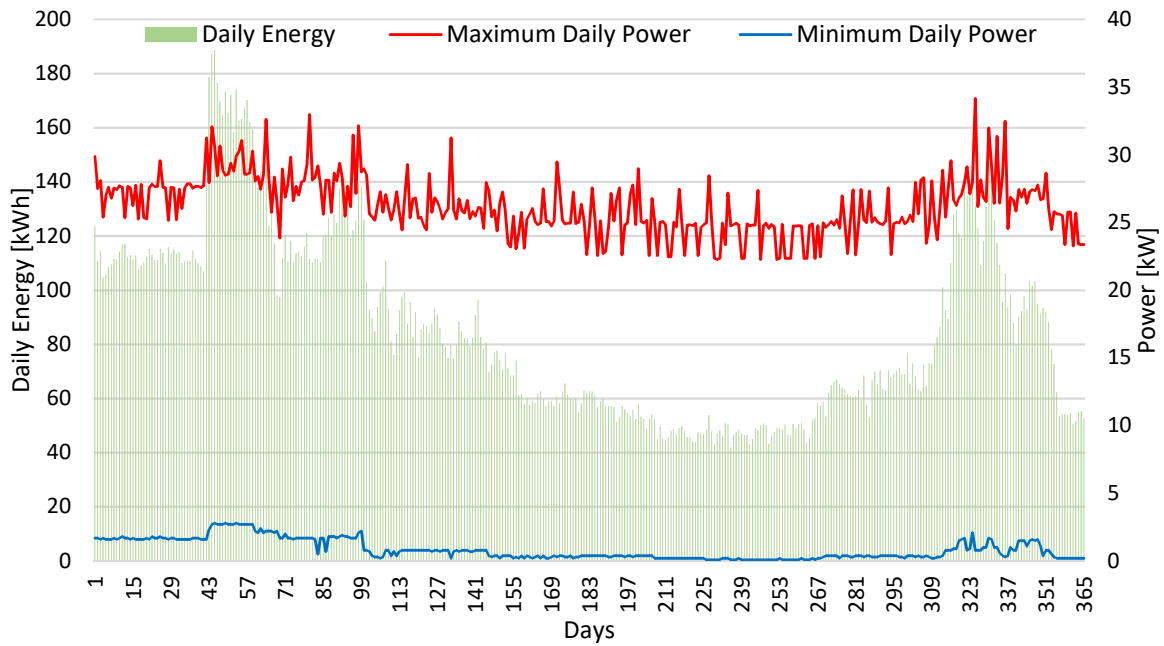


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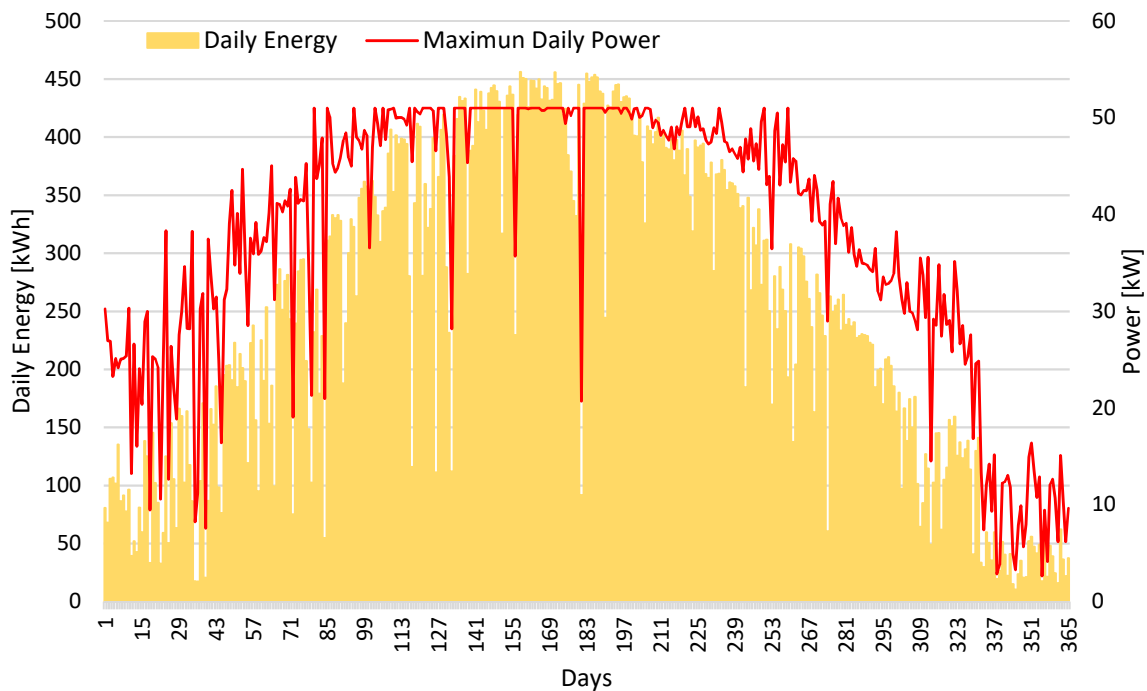
Figure 2. General Schematic of the microgrid

123 This study focuses on one year of data, from 2017 January 1<sup>st</sup> to December 31<sup>th</sup>. The daily profiles  
124 for loads and PV production for the whole period are shown in Figure 3 and Figure 4. These figures  
125 highlight the seasonal effect of PV and the variation of load consumption. Lowest values of energy  
126 consumption in summer are due to the fact that the accommodation building does not have air-  
127 conditioning. For PV profile, the threshold at 51 kW corresponds to the maximum power of the PV  
128 inverters in AC.



129  
130

Figure 3. Load profile



131  
132

Figure 4. PV profile (AC)

133 At last, we consider that the microgrid is buying and selling energy from and to the main grid with  
134 different prices, corresponding to a real electricity contract available in this region:

- 135
- Energy bought from the main grid,  $Cost_{buy}$ : 122.4 €/MWh during “off-peak hours”, from 22:00 to 04:00 and 163.1 €/MWh during “peak hours”, from 04:00 to 22:00.
  - Energy sold to the main grid,  $Cost_{sell}$ : constant price of 137.7 €/MWh.
- 136  
137  
138

139 **3. EMS description**

140 In the previous study [6], several RBC strategies had been tested and compared on a fourteen  
 141 days period (March 16<sup>th</sup> to 29<sup>th</sup>). Each of them prioritizes the PV to supply the load and is based on  
 142 the difference between PV and load powers:

$$\Delta = Pp - Pl \quad (1)$$

143 They also respect a certain number of constraints, ensuring that the repartition of the power  
 144 flows is done in a realistic way. Such constraints mainly concern power limitation for PV, grid and  
 145 battery as well as the battery SoC:

$$SoC_{min} \leq SoC(t) \leq SoC_{max} \quad (2)$$

$$Pp, l(t) + Pb, l(t) + Pg, l(t) + Pm(t) = Pl(t) \quad (3)$$

$$Pp, g(t) + Pb, g(t) - Pg, l(t) = Pg(t) \quad (4)$$

$$Pp, g(t) + Pp, b(t) + Pp, l(t) + Pd(t) = Pp(t) \quad (5)$$

$$0 \leq Pp, l(t) \leq Pinv^{max} \quad (6)$$

$$0 \leq Pp, g(t) \leq \min(Pg_{out}^{max}, Pinv^{max}) \quad (7)$$

$$0 \leq Pp, b(t) \leq \min\left(\frac{Pb_{in}^{max}}{\eta_{in}}, Pinv^{max}\right) \quad (8)$$

$$0 \leq Pb, l(t) \leq Pb_{out}^{max} \eta_{out} \quad (9)$$

$$0 \leq Pb, g(t) \leq \min(Pb_{out}^{max} \eta_{out}, Pg_{out}^{max}) \quad (10)$$

$$0 \leq Pg, l(t) \leq Pg_{in}^{max} \quad (11)$$

$$0 \leq Pd(t) \quad (12)$$

$$0 \leq Pm(t) \quad (13)$$

146

147 Battery admissible powers during charge and discharge are also defined by:

$$Pb_{in}^{adm} = \min\left(Pb_{in}^{max}, \frac{(1 - SoC) Cap_{ESS}}{dt \eta_{in}}\right) \quad (14)$$

$$Pb_{out}^{adm} = \max\left(-Pb_{out}^{max}, \frac{-SoC Cap_{ESS} \eta_{out}}{dt}\right) \quad (15)$$

148

149 Main parameters values can be found in Table 1.

150

Table 1. Parameters information

Parameter	Value	Description
$Pp^{nom}$ [kW]	55	PV array nominal power (DC)
$Pinv^{max}$ [kW]	51	PV inverter maximum power (AC)
$Pg_{out}^{max}$ [kW]	24	Grid maximum power output (AC)
$Pg_{in}^{max}$ [kW]	24	Grid maximum power input (AC)
$Cap_{ESS}$ [kWh]	70	Battery useful capacity (DC)
$Pb_{in}^{max}$ [kW]	14	Battery maximum power input at 0.2 C (DC)
$Pb_{out}^{max}$ [kW]	35	Battery maximum power output at 0.5 C (DC)
$\eta_{in}$ [-]	0.9	Battery charge efficiency
$\eta_{out}$ [-]	0.9	Battery discharge efficiency



151

152 As the battery is controlled in order to prevent extreme conditions such as deep discharge and  
153 high charging/discharging current, its efficiency has been assumed to be constant and the same value  
154 is used both in charging and discharging mode [21].

155 At the start of the simulation, the SoC is set at 50%. At the end of the simulation it must end at  
156 0% (battery useful capacity). This way, we can easily compare the results of all strategies. At last, the  
157 grid cannot be used to charge the battery.

158 Based on this information, it is possible to calculate the energy balance cost on a given period by:

$$Cost_{tot} = \sum_{t=1}^N [Pg, l(t) Cost_{buy}(t) - (Pp, g(t) + Pb, g(t)) Cost_{sell}(t)] dt \quad (16)$$

159 This cost will be the main comparison criterion for the first part of this study.

160 Presentation of the RBCs as well as their flowcharts are given in [6]. Here, we only propose a brief  
161 summary of these RBCs before introducing their improvement, taking into account seasonal effects.

162 • RBC1 is a quite simple strategy which only maximizes self-consumption. While there is  
163 enough PV power, it supplies the load and the surplus is used to charge the battery or is sold  
164 to the grid when the battery is full. When PV power is not sufficient, the missing power is  
165 supplied by the battery by priority and then by the main grid.

166  
167 • In RBC2, the choice depends on the energy costs, the PV power and the battery SoC. This  
168 strategy favors the use of the grid during off-peak hours (from 22:00 to 4:00) when energy is  
169 less expensive. If a given PV level and SoC is reached, it also prevents the storage to be full  
170 too quickly by allowing the selling of PV power sooner. While reducing the self-consumption,  
171 this provides a more efficient management in terms of economy.

172  
173 • RBC3 is an improvement of RBC2 considering the forecasting of the mean PV production for  
174 the next six hours. This allows the controller to manage the battery more efficiently by  
175 avoiding events such as full battery due to high PV production all over the day. This is  
176 particularly important before the sunrise, to prepare for peak hours (4:00 to 22:00) and  
177 determine the SoC level that should be kept in the battery.

178 The forecasting used in this RBC is based on an Auto Regressive Mobile Average (ARMA)  
179 model [22] which has been tested in situ. By running the simulation with “perfect PV  
180 forecasting” (i.e. real data) it is also possible to calculate the maximum improvement this  
181 strategy could bring. In this case it will be referred to as RBC3r.

182 In order to assess the performance of the different strategies, we introduce an indicator called  
183 relative performance which indicates how close our solution is from the mathematical optimum. This  
184 optimum is obtained with a Linear Programming (LP) optimization, a mathematical optimization  
185 method for maximizing or minimizing a linear function of several variables.

186 The main results obtained from a 14 days’ period (from [6]) and from a whole year are presented  
187 in Table 2. An interesting result is that the seasonal effects have a limited impact on RBC  
188 performances. More advanced strategies have a loss of about 4 to 5 points on relative performance,  
189 despite important changes of inputs (Figure 3). It should be noted that missing energy (around 18  
190 kWh) now appears in all RBC and represents more than 130 shutdowns of the microgrid. Due to main



191 grid power limitation, the storage management has an important role for ensuring load supply. To  
 192 avoid this, non-critical loads could have been switched off. However, LP results show that it is  
 193 possible to manage the microgrid without any shutdown or load control. Moreover, this can even be  
 194 done with fewer battery cycles, increasing the lifetime of the batteries. As mentioned in introduction,  
 195 this is another important point which will be assessed later.

196

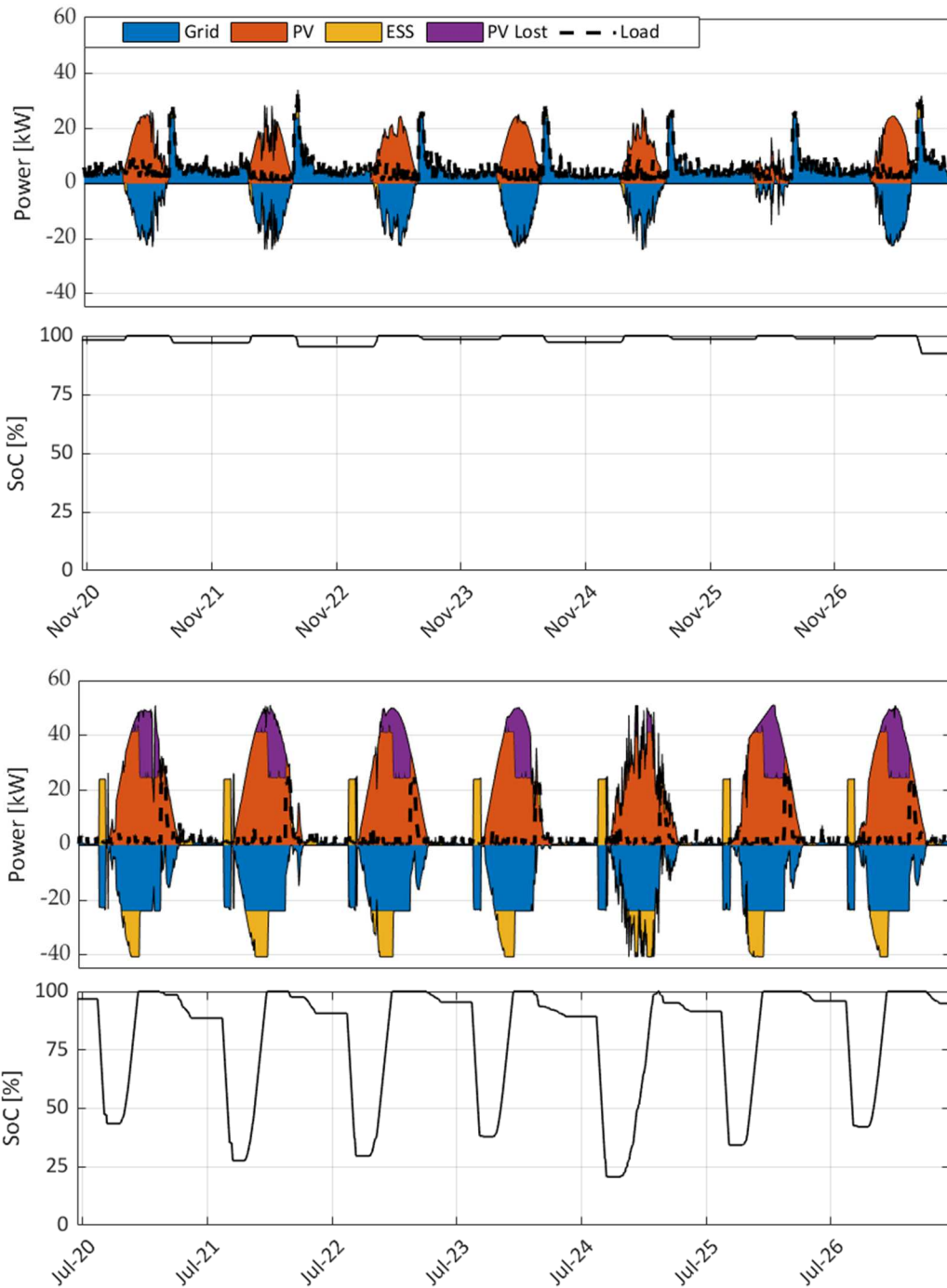
*Table 2. Main results comparison*

	14 days' period					One-year period				
	RBC1	RBC2	RBC3	RBC3r	LP	RBC1	RBC2	RBC3	RBC3r	LP
Total gain [€]	152.0	168.5	182.1	186.6	191.8	5170.3	5472.2	5896.9	6145.2	6592.7
Relative performance [%]	79.2%	87.8%	94.9%	97.3%	100%	78.4%	83.0%	89.4%	93.2%	100%
Battery cycles number [-]	13.3	11.5	11.4	11.5	6.7	192.7	218.6	213.3	208.2	164.1
Missing energy [kWh]	0	0	0	0	0	18.5	18.5	18.6	18.2	0

197

198 As there is still room for improvement, RBC4 introduces new rules to consider seasonal effects  
 199 and compensate the missing power observed in other RBCs. Here, the operation of the microgrid  
 200 changes according to two periods, extended winter and summer; winter including months from  
 201 November to March, and summer months from April to October. During winter, we decide to save  
 202 the battery for the peak consumption because of lower PV production. To supply the load, the  
 203 system thus prioritizes the PV and then the grid, the battery being used as a security reserve in case  
 204 of power shortage. During summer, we prioritize the supplying of the load by the PV production,  
 205 then by the battery and finally by the grid. During this period, the PV production is high and the  
 206 battery can be often full. Since the battery is frequently used, we maintain a reserve, 10% of the  
 207 battery capacity, as a security to avoid missing energy. The complete flowchart of this strategy is  
 208 proposed in Appendix 1.

209 To illustrate, one week of data are plotted for each period. Figure 5 (top) presents the results in  
 210 winter where PV production is low. It can be seen that all the production is used to supply the load  
 211 and the remaining share is sold to the grid, while the battery is kept at a high SoC to prevent power  
 212 shortage. Figure 5 (bottom) shows the same results for a summer week. Here, we can observe the  
 213 apparition of PV lost due to the battery being full early in the day. However, this phenomenon is  
 214 limited by the PV forecasting, allowing the battery to be discharged in the morning.



215

216

217

Figure 5. RBC4r results for one week in winter (top) and summer (bottom)

218 As for RBC3, the results depend on the performance of the PV forecasting model, which is not the  
 219 main concern of the paper. Thus, we focus on RBC4r (perfect forecasting) showing best achievable  
 220 results with a simple and realistic control strategy. These results are presented in Table 3.

221

Table 3. Main results for RBC4r

Total gain [€]	Relative performance [%]	Battery cycles number [-]	Missing energy [kWh]
6365.8	96.6%	140.6	0

222

223 RBC4r reaches a relative performance of 96.6% for the whole year while addressing the problem  
 224 of missing energy. As well as being close to LP results, it also reduces the battery use. As already  
 225 shown for RBC3 and RBC3r, it should be noted that a realistic model such as ARMA will bring a loss of  
 226 about 5% of the total gain. At this point, it seems more interesting to work on the load forecasting to  
 227 improve these results rather than on the PV forecasting. For the next stage, we will focus on RBC4r  
 228 and LP which are the only strategies optimized for a yearly period and addressing the energy missing  
 229 issue, providing the same level of service.

230 As noted previously, according to the energy management strategy used, the number of battery  
 231 cycles varies in an important range, up to 79 cycles per year (+55%), from RBC2 to RBC4r. It is obvious  
 232 that the greater the cycles number is, more the battery life duration is reduced and this reduction  
 233 has a cost that must be taken into account. In the next section, a short bibliographic study on battery  
 234 ageing models is realized and two models will be retained to be implemented in the simulation.

#### 235 4. Batteries ageing models

##### 236 4.1 Bibliographic study

237 The behavior of a battery and the influence of various parameters (such as charge/discharge rate,  
 238 voltage, temperature...) on its operation, whatever type of battery it is, is complex to understand and  
 239 thus to model. Sometimes, the information found in the literature are even contradictory or at least  
 240 different concerning aging effect or cycle life time, due to the fact that it is not always defined in a  
 241 similar way and in the same operating conditions.

242 An overview of energy storage performances is given in [23] and particularly for battery storage as  
 243 reported in Table 4. This clearly shows the diversity in term of performance and cost data for the  
 244 same technology. These data were compiled from over 150 data sources, supplemented by expert  
 245 interviews and analysis by IRENA for the latest battery developments. For calendar life, cycle life and  
 246 installation cost, the reported data are worst, reference and best cases.

247  
 248

Table 4. Characteristics of battery storage in 2016 [23]

Type	Technology	Calendar life (years)	Cycle life (equivalent full-cycle)	Installation cost (€/kWh)	Roundtrip efficiency (%)
Lead Acid	Flooded	3-9-15	250-1500-2500	394-121-88	82
	VR	3-9-15	250-1500-2500	394-219-88	80
Li-Ion	LFP	5-12-20	1000-2500-10000	700-482-167	92
	LTO	10-15-20	5000-10000-20000	1051-875-394	96
	NCA	5-12-20	500-1000-2000	700-293-167	95
	NMC/LMO	5-12-20	500-2000-4000	700-350-167	95
Redox Flow	VRFB	5-12-20	12000-13000-14000	875-289-263	70
	ZBFB	5-10-20	300-1000-14000	1401-750-438	70
High Temp	NaNiCl <sub>2</sub>	8-15-22	1000-3000-7500	407-333-263	84
	NaS	10-17-25	1000-5000-10000	638-307-219	80

249 VR: valve-regulated; LFP: lithium iron phosphate; LTO: lithium titanate; NCA: nickel cobalt aluminium;  
 250 NCM/LMO= nickel manganese cobalt/ lithium manganese oxide; VRFB: vanadium redox flow battery;  
 251 ZBFB: zinc bromine flow battery.

252 As the battery has a limited lifetime, its aging can lead to significant replacement costs, so lifetime  
253 estimation is particularly important for the economic optimization of a system. As mentioned by  
254 Sauer and Wenzl [24], there are two types of aging in a battery, calendar aging and cyclic aging.  
255 Calendar aging is the degradation caused by the self-discharge of the battery. This degradation varies  
256 greatly depending on the storage conditions, which can accelerate or slow down the aging of the  
257 battery. Cyclic aging of the battery occurs when the battery is cycled (charged and discharged). In this  
258 paper, the focus is only on cyclic aging of the battery, because the batteries are considered as always  
259 used and continuously charged and discharged.

260 Over time, battery capacity depends on the following parameters [25]:

- 261 • the charging/discharging regime: the capacity often decreases as discharge rate increases  
262 since there is not enough time to “re-supply” the electrons through the standard chemical  
263 reaction; the Peukert’s law links the battery capacity to the discharge rate [26];
- 264 • the DoD of the battery cycles during its lifetime;
- 265 • its exposure to prolonged periods of low discharge;
- 266 • the average temperature of the battery over its lifetime: the chemistry reaction rate  
267 increases with temperature; thus, an increase of the temperature has a positive influence on  
268 the capacity but also reduces the battery lifetime.

269 As the battery storage used in our PV/storage microgrid is lead acid battery, we focused mainly on  
270 this technology. Although lead acid batteries are an old technology, it is also a mature one *i.e.* with a  
271 large operating experience; they are still used for energy storage [27] and the research continues to  
272 improve this technology. As an example, Meyers *et al.* [28] show in their study that the addition of  
273 discrete carbon nanotubes to the positive plate increases the longevity of lead acid batteries.  
274 Another advantage of lead acid batteries are their cost, which is favorable compared to other  
275 technologies as shown in a recent paper [29].

276 Several types of aging models can be found in the literature. Electrochemical aging models are  
277 based on physicochemical processes that describes phenomena that affect the components (anode,  
278 cathode, electrolyte) of batteries and they require knowledge of a lot of parameters. The  
279 implementation of such a model is difficult to tackle. We must first identify the phenomena that we  
280 will need to model and those that can be neglected. Such models are detailed by Sauer and Wenzl  
281 [24]. However, due to their complexity and the need of large amount of data, this type of models  
282 cannot be used for modeling the aging of the battery in our simulation.

283 Other methods estimate the aging using equivalent circuits. The methods based on these models  
284 usually identify the battery by an equivalent circuit model and use different methods to estimate the  
285 parameters of these models [30]. Among them, the SimSES battery model is detailed by Naumann *et al.*  
286 [31] which is based on full cell data features, accurate loss and temperature calculation. We will  
287 not focus on this type of models either because the requested data are difficult to measure.

288 Bindner *et al.* [32] tested three aging lead acid battery models with specific reference to their use  
289 in hybrid renewable energy systems with wind turbine and PV systems *i.e.* with very intermittent  
290 charge and discharge rates:

- 291 • the Ah Throughput model: considering there is a fixed amount of energy that can be cycled  
292 through a battery. This calculation is done regardless of the depth of the individual cycles of  
293 the battery;
- 294 • FhG/Risø model: combining a performance model and an aging lifetime model. It models the  
295 complete power system including its control.

- UMass model: also called Kinetic Battery model, including a capacity model, a voltage model and a lifetime model.

These three models have an increasing complexity and give results in term of tested lifetime close to the experimental measures. The first one has satisfying performances and has the advantage to be easily implemented. It is also available in the HOMER software developed by NREL (National Renewable Energy Laboratory) largely used in the energy community. Haessig *et al.* [33] used this model by introducing a formulation of cycling aging based on exchanged energy counting. It fits in the ESS control optimization and allows the control to set a maximum number of battery cycles over the lifetime.

Some other simple models were developed in the literature based on the Peukert's law. Loannou *et al.* [34] determined the actual capacity of the battery used as a function of discharge current. This law was originally developed for lead acid batteries and recently extended to lithium [35]. The PLET model [36] described a relationship between the Peukert constant and the depth of discharge in lead acid battery. In this model, the capacity that the battery delivers during its lifetime is function of its depth of discharge and total number of charge/discharge cycles.

#### 4.2 Description of selected models

As mentioned previously, the models must be easily implemented and must not require complex inputs to fit the need of the study. Two models were chosen: the Ah throughput model and its improvement considering the battery's depth of discharge (DoD).

- Ah Throughput Model:

As described above, this model assumes that the number of complete charge-discharge cycles that the battery can perform over its lifetime ( $C_{life}$ ) is constant regardless of the depth of the cycles ( $DoD_i$ ), *i.e.* two half cycles are counted as one full cycle. Here, we do not consider the SoC at the start of the cycle and at the end of the cycle, but only the cycle amplitude. The number of full cycles that the battery performs ( $C_{rea}$ ) is equal to the sum of the depth of each cycle ( $DoD_i$ ):

$$C_{rea} = \sum_{i=1}^N DoD_i \quad (17)$$

We used the number of cycles to quantify the degradation ratio  $A$  at the end of the simulation:

$$A = \frac{C_{rea}}{C_{life}} \quad (18)$$

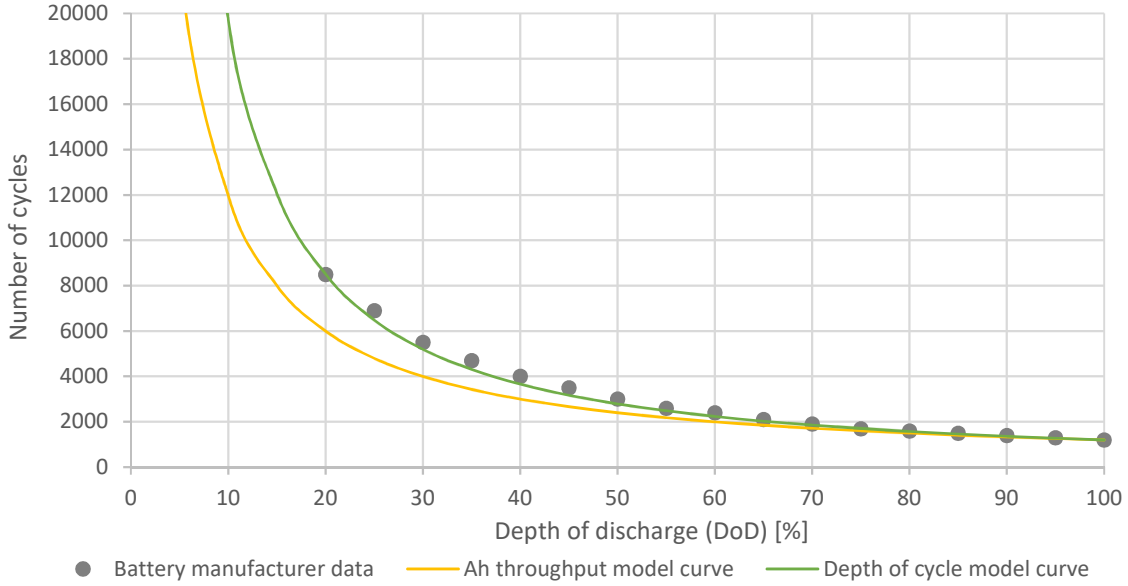
When  $A$  reaches 1, the battery is at the end of its life.

In this model we took  $C_{life} = 1200$  full cycles. This number has been obtained by interpolating the OPzV battery discharge curve described by the manufacturer [37]. It is close to the reference value presented in Table 4.

- Degradation model depending on the DoD:

This model is an improvement of the Ah Throughput model. In this model, the number of full cycles that the battery can perform over its lifetime varies with the depth of each cycle. Thus,

331 considering each cycle  $i$  of  $DoD_i$  we know the number of cycles achievable over the life of the  
 332 battery ( $C_{life,i}$ ). Here, we also use the data from the OPzV battery discharge curve given by the  
 333 manufacturer [37] (Figure 6).



334  
 335

Figure 6. Battery cycles curves

336 Compared with the first model, there is a higher increase in  $C_{life,i}$  when the DoD of the cycles  
 337 decreases. To model the number of cycles according to the DoD of each cycle  $i$ , a linear, exponential,  
 338 polynomial or power function can be used [38]. A power function, represented by green curve in  
 339 Figure 6, is used:

$$C_{life,i} = 325000 * (DoD_i * 100)^{-1.2162} \quad (19)$$

340

341 In this model, we have to recalculate the equivalent  $DoD_{i,eq}$  for each cycle  $i$ :

$$DoD_{eq,i} = \frac{C_{life}}{C_{life,i}} \quad (20)$$

342

343 And then  $C_{rea}$  is calculated as the sum of  $DoD_{eq,i}$ :

$$C_{rea} = \sum_{i=1}^N DoD_{eq,i} \quad (21)$$

344

### 345 5. Models implementation in simulation

346 Battery ageing models can be implemented both at the end of the simulation or at each time step  
 347 of the simulation. In this study, the two methods have been tested. The first one provides an  
 348 estimation of the real cost for the proposed strategies while the second one allows the use of this  
 349 information in the decision process.

350

351 5.1 At the end of the simulation

352 To use both models at the end of the simulation, the  $DoD_i$  of each cycle is calculated at the end  
 353 by the rainflow cycle counting algorithm [39]. This algorithm is used to study fatigue, to decompose  
 354 the cycles performed by the battery, using the extremums of the cycles. It takes as input the SoC of  
 355 the battery and identifies the amplitude of all the cycles contained in the series.

356 5.2 During the simulation

357 To optimize the energy management in the microgrid considering the aging of the battery in the  
 358 decision parameters, it is necessary to have a continuous cycle counting. Here, it is not possible to  
 359 use a rainflow algorithm for continuous cycle counting. Instead, a dynamic cycle counting is used.  
 360 This model also used by Haessig *et al.* [33] allows the knowledge of the instantaneous degradation of  
 361 the battery.

362 The degradation value  $A_i(t)$  at each time step is calculated using the battery requirement  
 363 represented by the DoD variation and the battery lifetime. At the beginning of a new cycle  $i$ , it is  
 364 calculated as:

$$A_i(t) = \frac{|DoD_i(t) - DoD_i(t - 1)|}{C_{life,i}(t)} \quad (22)$$

365 Then during a cycle  $i$ , the degradation increases according to:

$$A_i(t) = A_i(t - 1) + \frac{|DoD_i(t) - DoD_i(t - 1)|}{C_{life,i}(t)} \quad (23)$$

366 5.3 Degradation pricing

367 The degradation is priced by assuming that the batteries will have to be replaced when  $A$  reaches  
 368 1. The battery installation cost  $R$  must be adjusted according to the estimation of the batteries price.  
 369 In this study, we use the cost range proposed by IRENA in Table 4 [23] for lead acid technology (from  
 370 about 100 to 400 €/kWh).

371 The cost of the degradation ( $Cost_{bat}$ ) is then calculated at the end of the simulation:

$$Cost_{bat} = A * R \quad (24)$$

372 Or at each timestep:

$$Cost_{bat}(t) = A_i(t) * R \quad (25)$$

373 At last, to take into account the degradation cost in the battery management, it can be added to the  
 374 objective function:

$$Cost_{tot} = \sum_{t=1}^N [Pg, l(t)Cost_{buy}(t) + Pb * Cost_{bat}(t) - (Pp, g(t) + Pb, g(t))Cost_{sell}(t)] dt \quad (26)$$

375 For RBCs, a condition must be added in the decision process. The battery degradation cost has  
 376 thus been implemented in RBC4r.  $Cost_{bat}(t)$  is compared to the electricity purchase tariff  
 377  $Cost_{buy}(t)$  in case of load demand and when  $Cost_{bat}(t) < Cost_{buy}(t)$  battery can be used to  
 378 supply the load, otherwise the grid is used. In the situation where the grid cannot supply the whole  
 379 load, the battery is used without considering the cost of degradation in order to avoid missing  
 380 energy. To avoid any confusion, this strategy will be called RBC5r.



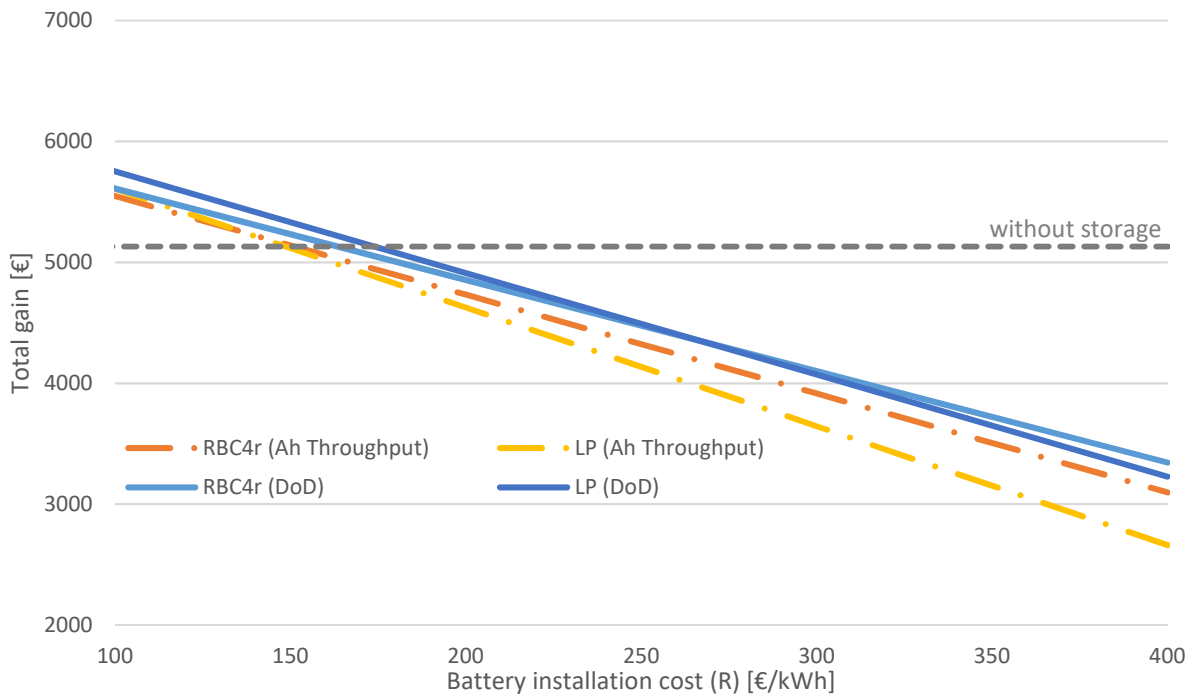
381 5.4 Simulation results

382 In this section, the two battery degradation models described previously are tested for the two  
 383 optimized strategies: RBC4r and LP. To begin, they are applied at the end of the simulation to  
 384 estimate the real cost of these strategies. Table 5 introduces the battery degradation ratio ( $A$ ) while  
 385 the Figure 7 presents the total gain including the battery cost.

386 *Table 5. Battery degradation results for the two models*

	RBC4r	LP
Battery degradation (Ah Throughput) [%]	11.68	14.04
Battery degradation (depending on DoD) [%]	10.79	12.02

387  
 388 As expected, the Ah Throughput model induces a higher degradation due to the linear counting  
 389 method. However, it is not so different from its improvement taking into account the battery DoD. It  
 390 seems still interesting to use it if we want to keep a safety margin in order to avoid overestimating  
 391 the gain. As the degradation is calculated as a percentage, this difference will greatly increase with  
 392 the battery cost. The greater the battery cost, the more impact the choice of the model will have.



393  
 394 *Figure 7. Total gain for different battery installation costs*

395 Figure 7 presents the total gain for different battery installation costs. It also includes the total  
 396 gain without storage to highlight the battery cost from which the battery improves the profitability of  
 397 the system. Depending on the battery degradation model and the strategy, this cost varies between  
 398 150 and 175 €/kWh which is close to the average value from IRENA estimation (Table 4). Below this  
 399 threshold, the battery is still important as it provides an efficient way to tackle missing energy and  
 400 allows the increase of PV share in the microgrid.

401 These results confirm the importance of considering the battery cost in the strategy used. To go  
 402 further, we compare the benefit with the consideration of battery degradation as a decision  
 403 parameter during simulation. For RBC5r, both degradation models can be used for continuous cycle  
 404 counting. However, the model depending on DoD introduces non-linearity and will not be tested with  
 405 the LP.

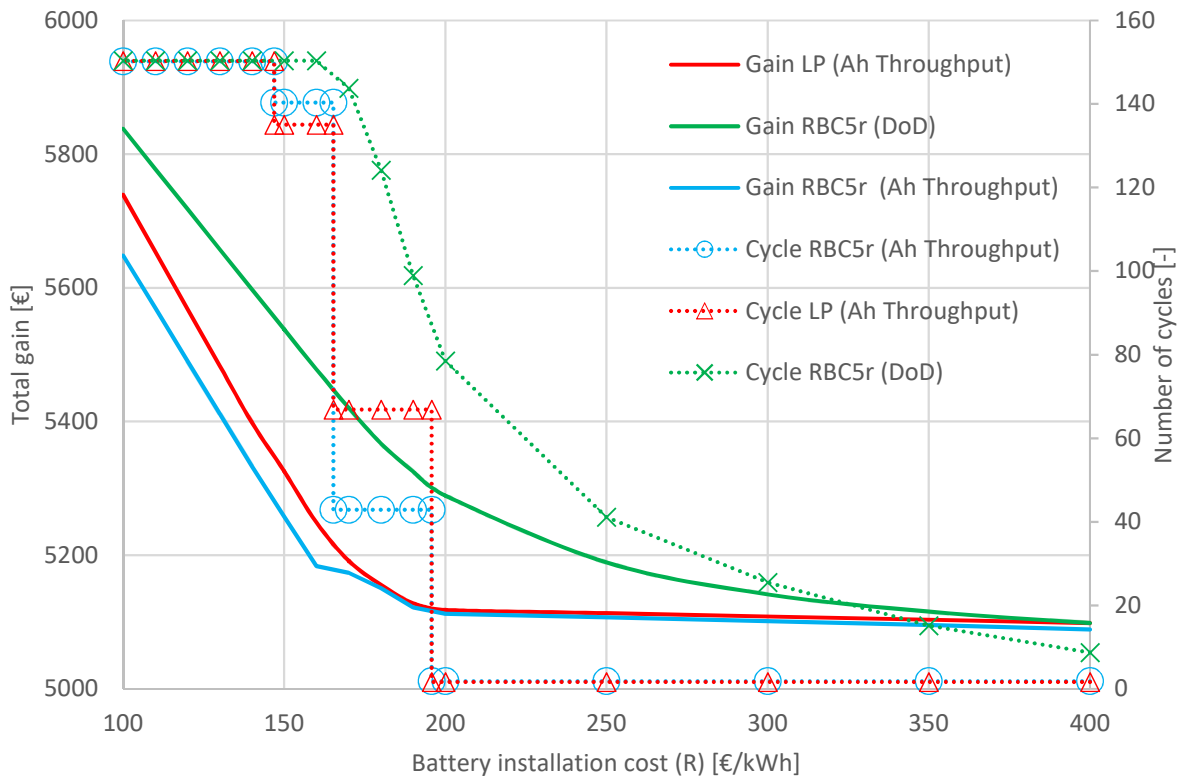


Figure 8. Total gain and number of cycles depending on battery cost and degradation model

406  
407

408 The total gain as well as number of cycles depending on battery costs and degradation models are  
 409 presented in Figure 8. With the Ah Throughput model, we observe that from 200 to 100 €/kWh  
 410 the battery usage increases significantly. In this range, the number of cycles presents three plateaux  
 411 corresponding to threshold values where battery costs became profitable compared respectively  
 412 with peak hours electricity tariff, grid electricity selling price and off-peak hours electricity tariff.  
 413 From 200 €/kWh, the battery is only used to avoid missing energy, which represent about two cycles.  
 414 In this case, it should be noted that the storage sizing may be no more reliable as a smaller battery  
 415 capacity would be less expensive and sufficient to compensate missing energy. Comparing RBC5r to  
 416 LP, it can be seen that both methods give similar results with a battery cost of more than 170 €/kWh.  
 417 The difference below this value is not so significant and shows that a well-designed RBC can be  
 418 suitable to manage the system. With the model depending on DoD, which is more realistic, we  
 419 observe that the battery is still used even at higher costs. For low battery costs (less than 150  
 420 €/kWh), the number of cycles converged and the only difference concerns the total gain.

## 421 6. Conclusion

422 Several strategies of energy management were developed and compared: the complexity of the  
 423 management algorithm is increased from a simple self-consumption strategy to a linear  
 424 programming optimization used as a reference. These strategies are rule based control algorithms  
 425 considering the sold and purchased kWh tariff and a forecasting of the photovoltaic production.

426 The simulations are applied to a PV/battery system integrated into a smart microgrid supplying a  
 427 small accommodation building and an electric vehicle on a yearly basis. For each strategy, several  
 428 variables were computed: energy produced by the PV system or lost when the storage is full, non-  
 429 satisfied load energy, electrical grid energy, number of battery cycles...

430 The sold and purchased electricity cost is calculated leading to a total gain, the best strategy being  
431 considered as the most “profitable”. The cost of the production system, which is the same for all  
432 cases, is not taken into account because only the influence of the energy management is studied.

433 The variation of the load and the PV production over the year conducted us to develop a seasonal  
434 strategy with two periods (RBC4) with different rules for both seasons; this strategy showed an  
435 interesting improvement. It appeared that according to the strategy used, the total gain varies  
436 greatly, between 5170 € per year for RBC1 to 6366 € (+ 23%) and 6593 € (+ 27%) for RBC4r and LP.  
437 However, it was noted that the number of battery cycles is different, varying from 141 cycles to 219  
438 cycles per year (+ 55%). This variation induces a more or less fast ageing and a more or less frequent  
439 replacement that needs to be considered in the cost balance.

440 A bibliographical study showed that several ageing battery models exist in the literature with  
441 different degrees of complexity and various input parameters often difficult to obtain and to  
442 implement. Two models were retained, the Ah throughput model and its improvement considering  
443 the battery DoD. Both have been implemented to calculate the cost at the end of the simulation as  
444 well as at each timestep, in the decision process.

445 With the inclusion of the battery degradation cost, the results are very different to the previous  
446 ones confirming the necessity to introduce this factor in the simulation. It appears immediately that  
447 considering the battery ageing has for consequences to make its utilization less frequent, depending  
448 on the battery installation cost. The use of a battery storage in such a system integrated in a smart  
449 microgrid is economically cost-effective only if the battery installation cost does not exceed a certain  
450 threshold (about 150 €/kWh) which is today an average value for lead acid battery in the market.  
451 However, whatever the price of the battery is, its presence allows the removal of the non-satisfied  
452 load energy and the increase of the green energy share in the system energy balance.

453 In this work, the optimization has been done on the balance cost of electricity but other ones can  
454 be added such as the environmental quality of the electricity, favouring the electricity supplied by  
455 the PV system instead of the one provided by the main grid, often with higher carbon footprint.

456 Various perspectives are open:

- 457 • The study of the PV and battery size influence on the strategy performances.
- 458 • A more developed cost study considering the total investment cost of the system, O&M and  
459 replacement cost on the system life duration.
- 460 • A study on the impact of the sold and purchased electricity tariff with a variation over the  
461 time, more adapted to a smart management of renewable energy production.
- 462 • The coupling of these strategies with a power management system to test them in real-time  
463 on PAGLIA ORBA microgrid.

464

Symbol	Description	Unit
ARMA	Auto Regressive Mobile Average	
DG	Distributed Generation	
DoD	Depth of Discharge	
ESS	Energy Storage System	
EMS	Energy Management System	
EV	Electric Vehicle	
LP	Linear Programming	
MPC	Model Predictive Control	
PV	Photovoltaic	
RBC	Rule Based Control	
SoC	State of Charge	
$A$	Degradation ratio	[-]
$C_{life}$	Maximum number of full battery cycles	[-]
$C_{rea}$	Effective number of full battery cycles	[-]
$Cap_{ESS}$	Battery useful capacity	[kWh]
$Cost_{buy}$	Energy buying price	[€/kWh]
$Cost_{sell}$	Energy selling price	[€/kWh]
$Cost_{tot}$	Energy balance cost	[€]
$dt$	Time step	[min]
$P_p$	PV power	[kW]
$P_l$	Load power	[kW]
$P_g$	Grid power	[kW]
$P_d$	Degraded PV power	[kW]
$P_m$	Missing power	[kW]
$P_{p,l}$	PV power to load	[kW]
$P_{p,b}$	PV power to battery	[kW]
$P_{p,g}$	PV power to grid	[kW]
$P_{b,l}$	Battery power to load	[kW]
$P_{b,g}$	Battery power to grid	[kW]
$P_{g,l}$	Grid power to load	[kW]
$P_p^{nom}$	PV array nominal power	[kW]
$P_{inv}^{max}$	Inverter maximum power	[kW]
$P_{g,out}^{max}$	Grid maximum power output	[kW]
$P_{g,in}^{max}$	Grid maximum power input	[kW]
$P_{b,in}^{max}$	Battery maximum power input	[kW]
$P_{b,out}^{max}$	Battery maximum power output	[kW]
$P_{b,in}^{adm}$	Battery admissible power input	[kW]
$P_{b,out}^{adm}$	Battery admissible power output	[kW]
$R$	Battery installation cost	[€]
$\Delta$	Difference between PV power and Load power	[kW]
$\eta_{in}$	Battery charge efficiency	[-]
$\eta_{out}$	Battery discharge efficiency	[-]

- 468 [1] M. Restrepo, C. A. Cañizares, J. W. Simpson-Porco, P. Su, and J. Taruc, 'Optimization- and Rule-  
469 based Energy Management Systems at the Canadian Renewable Energy Laboratory microgrid  
470 facility', *Applied Energy*, vol. 290, p. 116760, May 2021, doi: 10.1016/j.apenergy.2021.116760.
- 471 [2] Y. Ozturk, D. Senthilkumar, S. Kumar, and G. Lee, 'An Intelligent Home Energy Management  
472 System to Improve Demand Response', *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 694–  
473 701, Jun. 2013, doi: 10.1109/TSG.2012.2235088.
- 474 [3] D. E. Olivares, C. A. Cañizares, and M. Kazerani, 'A Centralized Energy Management System for  
475 Isolated Microgrids', *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1864–1875, Jul. 2014,  
476 doi: 10.1109/TSG.2013.2294187.
- 477 [4] W. C. Clarke, M. J. Brear, and C. Manzie, 'Control of an isolated microgrid using hierarchical  
478 economic model predictive control', *Applied Energy*, vol. 280, p. 115960, Dec. 2020, doi:  
479 10.1016/j.apenergy.2020.115960.
- 480 [5] Y. Zhu, Y. Chen, G. Tian, H. Wu, and Q. Chen, 'A four-step method to design an energy  
481 management strategy for hybrid vehicles', in *Proceedings of the 2004 American control  
482 conference*, 2004, vol. 1, pp. 156–161.
- 483 [6] S. Ouédraogo, G. A. Faggianelli, G. Pigelet, J. L. Duchaud, and G. Notton, 'Application of Optimal  
484 Energy Management Strategies for a Building Powered by PV/Battery System in Corsica Island',  
485 *Energies*, vol. 13, no. 17, p. 4510, Jan. 2020, doi: 10.3390/en13174510.
- 486 [7] N. Kittner, O. Schmidt, I. Staffell, and D. M. Kammen, 'Chapter 8 - Grid-scale energy storage', in  
487 *Technological Learning in the Transition to a Low-Carbon Energy System*, M. Junginger and A.  
488 Louwen, Eds. Academic Press, 2020, pp. 119–143. doi: 10.1016/B978-0-12-818762-3.00008-X.
- 489 [8] IEA, 'Tracking Clean Energy Progress 2017 – Analysis', IEA, Paris, May 2017. Accessed: Jun. 10,  
490 2021. [Online]. Available: <https://www.iea.org/reports/tracking-clean-energy-progress-2017>
- 491 [9] N. K. Paliwal, 'A day-ahead Optimal Scheduling Operation of Battery Energy Storage with  
492 Constraints in Hybrid Power System', *Procedia Computer Science*, vol. 167, pp. 2140–2152,  
493 2020, doi: 10.1016/j.procs.2020.03.263.
- 494 [10] D. Tran and A. M. Khambadkone, 'Energy Management for Lifetime Extension of Energy Storage  
495 System in Micro-Grid Applications', *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp. 1289–  
496 1296, Sep. 2013, doi: 10.1109/TSG.2013.2272835.
- 497 [11] Y. Qin, H. Hua, and J. Cao, 'Stochastic Optimal Control Scheme for Battery Lifetime Extension in  
498 Islanded Microgrid via a Novel Modeling Approach', *IEEE Transactions on Smart Grid*, vol. 10,  
499 no. 4, pp. 4467–4475, Jul. 2019, doi: 10.1109/TSG.2018.2861221.
- 500 [12] D. Azuatalam, K. Paridari, Y. Ma, M. Förstl, A. C. Chapman, and G. Verbič, 'Energy management  
501 of small-scale PV-battery systems: A systematic review considering practical implementation,  
502 computational requirements, quality of input data and battery degradation', *Renewable and  
503 Sustainable Energy Reviews*, vol. 112, pp. 555–570, Sep. 2019, doi: 10.1016/j.rser.2019.06.007.
- 504 [13] S. A. Pourmousavi, R. K. Sharma, and B. Asghari, 'A framework for real-time power  
505 management of a grid-tied microgrid to extend battery lifetime and reduce cost of energy', in  
506 *2012 IEEE PES Innovative Smart Grid Technologies (ISGT)*, Washington, DC, Jan. 2012, pp. 1–8.  
507 doi: 10.1109/ISGT.2012.6175707.
- 508 [14] S. Kato, H. Nishihara, I. Taniguchi, M. Fukui, and K. Sakakibara, 'Analysis on battery storage  
509 utilization in decentralized solar energy networks based on a mathematical programming  
510 model', in *The 6th International Conference on Soft Computing and Intelligent Systems, and The  
511 13th International Symposium on Advanced Intelligence Systems*, Nov. 2012, pp. 651–656. doi:  
512 10.1109/SCIS-ISIS.2012.6505251.
- 513 [15] R. Patil and R. Sharma, 'Quantifying the impact of battery constraints on microgrid operation  
514 using optimal control', in *ISGT 2014*, Feb. 2014, pp. 1–5. doi: 10.1109/ISGT.2014.6816419.
- 515 [16] M. S. Javadi, A. Anvari-Moghaddam, and J. M. Guerrero, 'Optimal scheduling of a multi-carrier  
516 energy hub supplemented by battery energy storage systems', in *2017 IEEE International  
517 Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial*

- 518 *Power Systems Europe (EEEIC / I CPS Europe)*, Jun. 2017, pp. 1–6. doi:  
519 10.1109/EEEIC.2017.7977520.
- 520 [17] F. Luo, K. Meng, Z. Y. Dong, Y. Zheng, Y. Chen, and K. P. Wong, ‘Coordinated Operational  
521 Planning for Wind Farm With Battery Energy Storage System’, *IEEE Transactions on Sustainable  
522 Energy*, vol. 6, no. 1, pp. 253–262, Jan. 2015, doi: 10.1109/TSTE.2014.2367550.
- 523 [18] F. García and C. Bordons, ‘Optimal economic dispatch for renewable energy microgrids with  
524 hybrid storage using Model Predictive Control’, in *IECON 2013 - 39th Annual Conference of the  
525 IEEE Industrial Electronics Society*, Nov. 2013, pp. 7932–7937. doi:  
526 10.1109/IECON.2013.6700458.
- 527 [19] J. Cai, H. Zhang, and X. Jin, ‘Aging-aware predictive control of PV-battery assets in buildings’,  
528 *Applied Energy*, vol. 236, pp. 478–488, Feb. 2019, doi: 10.1016/j.apenergy.2018.12.003.
- 529 [20] C. Bordin, H. O. Anuta, A. Crossland, I. L. Gutierrez, C. J. Dent, and D. Vigo, ‘A linear  
530 programming approach for battery degradation analysis and optimization in offgrid power  
531 systems with solar energy integration’, *Renewable Energy*, vol. 101, pp. 417–430, Feb. 2017,  
532 doi: 10.1016/j.renene.2016.08.066.
- 533 [21] A. Parisio, E. Rikos, G. Tzamalís, and L. Glielmo, ‘Use of model predictive control for  
534 experimental microgrid optimization’, *Applied Energy*, vol. 115, pp. 37–46, Feb. 2014, doi:  
535 10.1016/j.apenergy.2013.10.027.
- 536 [22] J. G. De Gooijer and R. J. Hyndman, ‘25 years of time series forecasting’, *International Journal of  
537 Forecasting*, vol. 22, no. 3, pp. 443–473, Jan. 2006, doi: 10.1016/j.ijforecast.2006.01.001.
- 538 [23] IRENA, ‘Electricity Storage and Renewables: Costs and Markets to 2030’, International  
539 Renewable Energy Agency, Abu Dhabi, 2017.
- 540 [24] D. U. Sauer and H. Wenzl, ‘Comparison of different approaches for lifetime prediction of  
541 electrochemical systems—Using lead-acid batteries as example’, *Journal of Power Sources*, vol.  
542 176, no. 2, pp. 534–546, Feb. 2008, doi: 10.1016/j.jpowsour.2007.08.057.
- 543 [25] A. J. Ruddell *et al.*, ‘Analysis of battery current microcycles in autonomous renewable energy  
544 systems’, *Journal of Power Sources*, vol. 112, no. 2, pp. 531–546, Nov. 2002, doi:  
545 10.1016/S0378-7753(02)00457-3.
- 546 [26] D. Doerffel and S. A. Sharkh, ‘A critical review of using the Peukert equation for determining the  
547 remaining capacity of lead-acid and lithium-ion batteries’, *Journal of Power Sources*, vol. 155,  
548 no. 2, pp. 395–400, Apr. 2006, doi: 10.1016/j.jpowsour.2005.04.030.
- 549 [27] ‘ITRI-Report-Tin-in-Lead-Acid-Batteries-260318.pdf’. Accessed: Jun. 10, 2021. [Online].  
550 Available: [https://www.internationaltin.org/wp-content/uploads/2018/03/ITRI-Report-Tin-in-  
551 Lead-Acid-Batteries-260318.pdf](https://www.internationaltin.org/wp-content/uploads/2018/03/ITRI-Report-Tin-in-Lead-Acid-Batteries-260318.pdf)
- 552 [28] J. P. Meyers *et al.*, ‘Discrete carbon nanotubes promote resistance to corrosion in lead-acid  
553 batteries by altering the grid-active material interface’, *Journal of Energy Storage*, vol. 32, p.  
554 101983, Dec. 2020, doi: 10.1016/j.est.2020.101983.
- 555 [29] G. J. May, A. Davidson, and B. Monahov, ‘Lead batteries for utility energy storage: A review’,  
556 *Journal of Energy Storage*, vol. 15, pp. 145–157, Feb. 2018, doi: 10.1016/j.est.2017.11.008.
- 557 [30] M. Einhorn, F. V. Conte, C. Kral, J. Fleig, and R. Permann, *Parameterization of an electrical  
558 battery model for dynamic system simulation in electric vehicles*. 2010, p. 7. doi:  
559 10.1109/VPPC.2010.5729127.
- 560 [31] M. Naumann, C. N. Truong, M. Schimpe, D. Kucevic, A. Jossen, and H. C. Hesse, ‘SimSES:  
561 Software for techno-economic Simulation of Stationary Energy Storage Systems’, in  
562 *International ETG Congress 2017*, Nov. 2017, pp. 1–6.
- 563 [32] H. Bindner, T. Cronin, P. Lundsager, J. Manwell, U. Abdulwahid, and I. Baring-Gould, ‘Lifetime  
564 Modelling of Lead Acid Batteries’, Jan. 2005.
- 565 [33] P. Haessig, H. BEN AHMED, and B. Multon, ‘Energy Storage Control with Aging Limitation’,  
566 Eindhoven, Netherlands, Jun. 2015. doi: 10.1109/PTC.2015.7232683.
- 567 [34] D. Doerffel and S. A. Sharkh, ‘A critical review of using the Peukert equation for determining the  
568 remaining capacity of lead-acid and lithium-ion batteries’, *Journal of Power Sources*, vol. 155,  
569 no. 2, pp. 395–400, Apr. 2006, doi: 10.1016/j.jpowsour.2005.04.030.

- 570 [35] N. Omar, P. V. den Bossche, T. Coosemans, and J. V. Mierlo, 'Peukert Revisited—Critical  
571 Appraisal and Need for Modification for Lithium-Ion Batteries', *Energies*, vol. 6, no. 11, pp.  
572 5625–5641, Nov. 2013, doi: 10.3390/en6115625.
- 573 [36] D. Tran and A. M. Khambadkone, 'Energy Management for Lifetime Extension of Energy Storage  
574 System in Micro-Grid Applications', *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp. 1289–  
575 1296, Sep. 2013, doi: 10.1109/TSG.2013.2272835.
- 576 [37] HOPPECKE, 'Installation, commissioning and operating instructions for valve-regulated  
577 stationary lead-acid batteries', 7140203153 V1.4 (, 2021. [Online]. Available:  
578 [https://www.hoppecke.com/fileadmin/Redakteur/Hoppecke-Main/Products-](https://www.hoppecke.com/fileadmin/Redakteur/Hoppecke-Main/Products-Import/vrl_manual_en.pdf)  
579 [Import/vrl\\_manual\\_en.pdf](https://www.hoppecke.com/fileadmin/Redakteur/Hoppecke-Main/Products-Import/vrl_manual_en.pdf)
- 580 [38] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, and D. S. Kirschen, 'Modeling of Lithium-Ion Battery  
581 Degradation for Cell Life Assessment', *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 1131–  
582 1140, Mar. 2018, doi: 10.1109/TSG.2016.2578950.
- 583 [39] S. D. Downing and D. F. Socie, 'Simple rainflow counting algorithms', *International Journal of*  
584 *Fatigue*, vol. 4, no. 1, pp. 31–40, Jan. 1982, doi: 10.1016/0142-1123(82)90018-4.
- 585



