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1 **The least cost design of 100% solar power microgrids in Africa: sensitivity to meteorological**
2 **and economic drivers and possibility for simple pre-sizing rules**

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11

12 **Abstract**

13 Autonomous micro-grids based on solar photovoltaic (PV) are one of the most promising solutions to
14 provide electricity access in many regions worldwide. Different storage/PV capacities can produce the
15 same level of quality service, but an optimal design is typically identified to minimize the levelized cost
16 of electricity. This cost optimization however relies on technical and economic hypothesis that come
17 with large uncertainties and/or spatial disparities.

18 This article explores the sensitivity of the optimal sizing to variations and uncertainties of such
19 parameters. Using data from Heliosat and ERA5, we simulate the solar PV production and identify the
20 least cost configurations for 200 locations in Africa.

21 Our results show that the optimal configuration is highly dependent on the characteristics of the
22 resource, and especially on its co-variability structure with the electric demand on different timescales.
23 It is conversely rather insensitive to cost hypotheses, which allow us to propose simple pre-sizing rules
24 based on the only characteristics of the solar resource and electricity demand.

25 The optimal storage capacity can be estimated from the 75th percentile of the daily nocturnal demand
26 and the optimal PV capacity from the mean demand and the standard deviation of the daily power
27 difference between solar production and demand.

28 **Keywords:** PV microgrids, microgrid sizing, Rural electrification, Levelized Cost of Electricity
29 (LCOE), Africa

30

31 1 Introduction

32 The seventh Sustainable Development Goal of the United Nations is to "ensure access to affordable,
33 reliable, sustainable and modern energy for all" [1]. Almost 550 million inhabitants do not have access
34 to electricity in Sub-Saharan Africa and this number will increase with the fast demographic growth in
35 this area [2]. Most of them are located in rural areas and in many cases, an affordable and sustainable
36 electricity supply could help improving living conditions and developing local economies [1]. Fostering
37 electricity access there requires large electrification programs, such as SE4all (Sustainable energy for
38 all), the International Solar Alliance, the Terawatt Initiative or the Power Africa plan [3]–[6].

39 Such programs require governments and stakeholders (investors, researchers, manufacturers, ...) to
40 be guided toward the most interesting electrification strategy – which is expected to be region
41 dependant [7]. In the recent years, a number of works have then estimated the cost-optimal options
42 for different regions worldwide [8]–[12]. The choice, typically to be made between grid extension and
43 micro-grid (MG) installation, is often based on the levelized cost of electricity (*LCOE*) [8], [13]–[16].

44 The *LCOE* of a MG depends on many different features. It relies first on the technical configuration,
45 e.g. the type of energy source or mix (e.g. diesel, photovoltaic, wind, hydroelectricity) and the required
46 storage capacity of battery if any. Different MG configurations with different energy mix are then
47 typically compared to identify the least-cost one. The cost-optimal configuration is expected to vary
48 from one site to the other. When the MG is based on renewable sources, this configuration depends
49 on the available resource and its variability (seasonality, day-to-day variability and low resource
50 periods). This has been illustrated for 100% photovoltaic solar MG by Huld et al. [10] and Plain et al.
51 [17].

52 The cost-optimal configuration for a site also depends on the socio-economical features of the system,
53 for instance, the temporal profile expected for the electricity load, mainly determined by the different
54 types of uses expected for the system. In a photovoltaic (PV) MG with batteries, less storage capacity
55 is needed if the nocturnal load decreases, which is typically found when productive uses increase
56 compared to domestic ones [9]. For a given PV installed capacity, a lower storage capacity results in a
57 lower *LCOE*. The cost-optimal configuration also depends on the relative costs of the different
58 technical components of the MG, e.g. costs of PV panels, converters, batteries.

59 A potentially critical problem for the identification of the cost-optimal configuration is that many
60 features come with large variabilities, uncertainties or spatial disparities. The cost-optimal MG
61 configurations, which have been estimated in a number of previous works, especially regarding
62 electrification planning, are obtained using mean values for PV and battery costs. However, large costs
63 variations are observed from one region to the other resulting from different country regulations,
64 distribution circuits or local terrain constraints [18], [19]. Looking at a specific location, part of the unit
65 costs can be well estimated but some other can come with large uncertainties: this is for instance
66 expected to be the case for installation costs related to civil engineering, transportation or for
67 maintenance costs related to the lifetime of the components, especially batteries as highlighted by
68 [20], [21].

69 On the other hand, the costs of the different MG components can also significantly evolve with time,
70 because of changes in country-specific costs due to regulations and taxes [22] and/or because of
71 learning by doing: the large deployment and maturation of photovoltaic panels for instance led its
72 price to be divided by almost 4 in 5 years [23]–[25]. These costs evolutions are expected to depend on
73 the component of the MG. Learning rates for instance, defined as the relative unit cost reduction when
74 doubling the installed capacity, were estimated around 23% for PV panels, 12% for on-shore wind

75 turbines and between 6% and 9% for lithium batteries [26], [27]. These evolutions are in turn expected
76 to change the cost ratio between the components.

77 To our knowledge, the sensitivity of the cost-optimal configurations to cost hypothesis has not been
78 characterized so far. Our first objective is to evaluate, for a generic 100% solar MG project in rural sub-
79 Saharan Africa, the sensitivity of the cost-optimal MG configuration to the costs of the main MG
80 technical components, namely the battery and the PV panels. In particular, this will allow to assess
81 how the lowest cost MG configurations targeted for electrification or obtained in existing studies are
82 modified with alternative component cost assumptions.

83 On the other hand, determining cost-optimal configurations is not straightforward. This is typically
84 achieved with computation demanding simulations of the MG behaviour under a rather large number
85 of different MG configuration scenarios requiring ad-hoc weather data, namely long time series of local
86 weather and ad-hoc simulation models [28]. Such a simulation-based design process is not accessible
87 to all operators especially in the context of a government or rural electrification agency tender where
88 the profitability of MG over large areas needs to be estimated quickly. Simple pre-sizing rules,
89 bypassing the need for simulations, are thus of high interest, for instance to discriminate between
90 different solutions (MG, national grid, Solar Home Systems) or to assess a large portfolio of sites in
91 rural electrification planning [8]. ECOWAS Centre for Renewable Energy and Energy Efficiency
92 (ECREEE), International Energy Agency (IEA) and the Institute of Electrical and Electronics Engineers
93 (IEEE) propose such rules for West Africa based on simple estimates of the demand and of the mean
94 solar resource. These rules do however only target solar / diesel hybrid MGs [29], [30] or stand-alone
95 PV systems [31].

96 The second objective of this paper is to test the possibility for simple rules for the pre-sizing of 100%
97 PV MG systems. In Africa, the solar resource is indeed abundant and the large reduction in PV costs
98 observed in the last decades makes such systems potentially highly competitive. 100% PV MGs
99 produce moreover low greenhouse gases and air pollutant emissions compared to diesel generator
100 and are not subject to fuel price volatility and supply difficulties [32]–[34]. This makes 100% PV MGs
101 also very attractive as they will help countries to achieve the Nationally Determined Contributions
102 (NDCs) they committed to fulfil during the 2015 Paris' Agreement [35]. However, contrary to solar /
103 diesel hybrid MGs, where the electricity production can be adjusted at any time with less or more
104 genset production, the quality service level that can be achieved with a 100% solar system, i.e. its
105 ability to satisfy the demand at any time, fully depends on its design. To ensure reliable energy with
106 such systems, the development of robust sizing rules is thus obviously key.

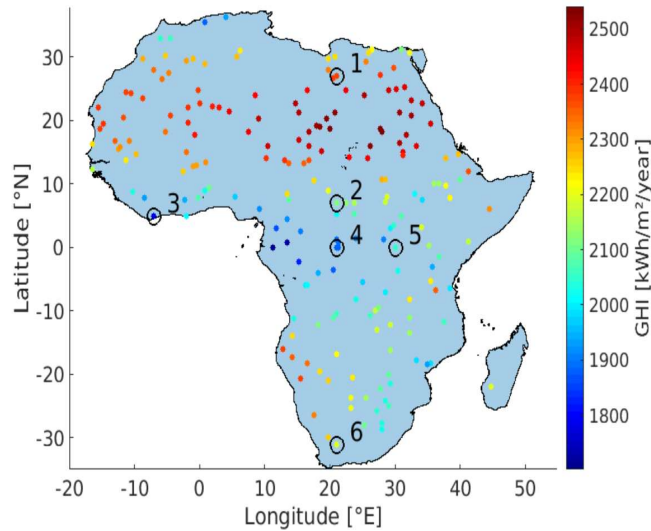
107 Section 2 details the data and hypothesis considered for the study as well as the methodology used to
108 estimate the least cost MG configuration. The robustness of the least cost configuration to cost
109 variations and their effects on the *LCOE* is presented for different shapes of load profiles in section 3.
110 This section also presents and evaluates simple rules to design the storage capacity and the size of the
111 PV field of 100% PV micro-grids. Results are discussed in section 4 and the main conclusions are
112 summarized in section 5.

113 2 Methodology

114 In the following, we consider a fictitious MG system, where the power production, obtained from PV
115 panel only, can be temporarily stored in batteries. The analysis is carried out for 200 different locations
116 randomly selected in Africa (Figure 1). Some of them will be used for illustrative purpose when
117 relevant.

118 For each location, the MG configuration is optimized to achieve a prescribed level of quality service
 119 with the lowest possible *LCOE*. The optimization is obtained thanks to simulations of the system
 120 behavior over a multiple year period. For any PV capacity/ storage capacity configuration, we simulate
 121 the PV production from local weather data and the storage cycles required to best meet a given
 122 demand profile, prescribed for the whole simulation period. The different steps of the
 123 simulations/optimization process are described in the following.

124

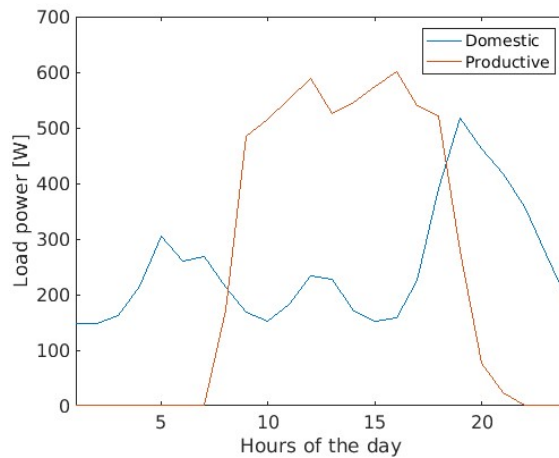


125

126 *Figure 1 : Mean annual Global Horizontal Irradiance (GHI) for the 200 randomly selected locations. The six numbered*
 127 *locations will be used as examples to illustrate some results in the following. They have been chosen for their different*
 128 *resource characteristics (seasonality, day-to-day variability).*

129 2.1 Load profile

130 Load profiles for microgrid projects are difficult to estimate, even with surveys [36]. We consider two
 131 hypothetical daily load profiles, representing domestic and productive uses (Figure 2). These profiles are
 132 derived from generic profiles considered in previous publications [37]. The domestic use profile is
 133 characterized by two peaks (morning + evening) and a quite low demand during the day. Conversely,
 134 the electricity demand only occurs during working hours during the day for the productive profile.



135

136

Figure 2 : Domestic and productive daily load profile

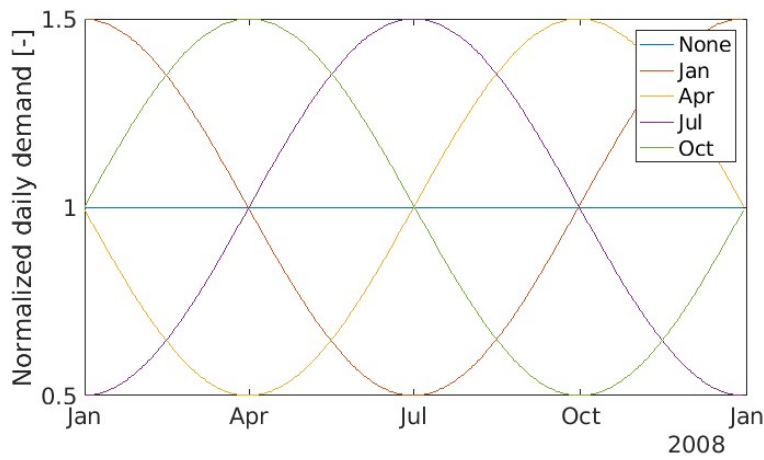
137 Seasonal variations in demand may occur especially for agricultural activities like irrigation or post-
 138 harvest processing which are common in many rural areas of Africa [38]. For the sake of simplicity, we
 139 model the seasonal profile of the energy demand as a sinusoidal function of time.

$$\bar{D}_d = \bar{D} \left(1 + A \cos \left(2\pi \frac{d - d_{max}}{365} \right) \right) \quad (1)$$

140

141 Where \bar{D}_d [Wh] is the daily energy demand of calendar day d , \bar{D} [Wh] is the annual mean daily energy
 142 demand, A is the half amplitude of seasonality and d_{max} is the calendar day for the maximum. In the
 143 following A is set to 0.5 and four seasonal profiles are in turn considered with a maximum daily demand
 144 occurring in January, April, July or October respectively. In addition, we also consider a non-seasonal
 145 profile, i.e. a profile where the daily electricity demand is the same throughout the year (cf. Figure 3).

146



147

Figure 3 : The five seasonal patterns considered for the electricity demand

148

149

150 2.2 PV power production

151 The solar PV production in the MG is simulated at 15-min resolution for the 2008-2015 period using
 152 satellite derived solar irradiance from Heliosat SARA2 [39] and temperatures from ERA5
 153 meteorological reanalyses [40]. Irradiance data are available with a 0.05°x0.05° spatial resolution and
 154 ERA5 data with a 0.5° grid.

155 The electrical power delivered by the system (P_{AC} [W]) at a given time (t) is estimated from Global Tilted
 156 Irradiance (GTI [W/m^2] : global irradiance over an inclined panel) and module temperature T_m [°C]
 157 with the model of Lorenz et al. [41]. The model is described in equations (2) to (4):

$$P_{AC} = \eta \cdot (1 + \alpha (T_m - 25^\circ C)) \cdot C_{PV} \cdot \frac{GTI}{1000 W/m^2} \quad (2)$$

158

159 Where C_{PV} [W_p] is the peak power of installed PV panels, $1000W/m^2$ corresponds to the irradiance
 160 at standard conditions, α is the sensitivity of panel efficiency to the module temperature T_m . The panel
 161 efficiency (η) accounts for inverter efficiency and for losses of the PV production system. Global tilted
 162 irradiance, the irradiance received by PV panels, is calculated as:

$$GTI = DNI \cdot \cos(\theta) + DHI \quad (3)$$

163

164 Where Direct Normal Irradiance (DNI: solar energy that reaches the surface in a straight line from the
165 sun) and Diffuse Horizontal Irradiance (DHI: solar energy that has been scattered by particles in the
166 atmosphere before reaching the surface) are derived from GHI based on the empirical method from
167 Sandia National Laboratory [42] and where θ is the “effectiveness” angle, a function of solar angles
168 (azimuth and zenith) and solar panel inclination and orientation. In the present work, PV panels are
169 assumed facing south in the northern hemisphere and facing north in the southern hemisphere. As a
170 rule of thumb, the tilt angle (inclination) is set equal to the latitude of the location [43].

171 The panel efficiency is typically considered to be a decreasing function of the module temperature.
172 The sensitivity of the panel efficiency to temperature is here set to that of crystalline silicon cells
173 ($\alpha = -0.0035 / ^\circ C$). The temperature of the module (T_m) is estimated as a function of the ambient
174 temperature (T_{amb}) and GHI , expressed as:

$$T_m = T_{amb} + \gamma \cdot GHI \quad (4)$$

175 Where γ is a parameter related to the mounted type of the system (roof integrated, free standing...).
176 We consider a mean value: $\gamma = 0.04 \text{ } ^\circ C \cdot m^2 / W$.

177 2.3 Storage simulation

178 The storage/discharge cycles in the batteries of the MG are simulated as follows: the battery is charged
179 when (1) the power production from PV panels is higher than the demand and when (2) the state of
180 charge is below 100%. The battery is discharged when (1) production is lower than demand and when
181 (2) the state of charge is higher than a minimum value set to 20% of the storage capacity. The same
182 efficiency ($\eta_{storage} = 0.95$ [44]) is applied for charge and discharge sequences.

183 2.4 The sizing curve for a given quality service level

184 In our MG configuration, the demand is only supplied by the PV panels production and/or the batteries
185 discharge. The multiscale variability of the solar resource makes it difficult to satisfy the demand at
186 any time, one main challenge being to deliver electricity during periods with no solar resource (night)
187 and with low solar resource (e.g. winter) (cf. [10], [17]). Satisfying the demand at any time would
188 require provisioning significant storage and /or significant extra PV production capacity. This may in
189 turn lead to costly and unaffordable systems. Following [10], [17], the design thus typically requires a
190 compromise between the costs of the system and its reliability. In other words, a not fully reliable
191 system, i.e. a system where the demand is not always fully satisfied, is targeted which allows reducing
192 its size and thus its costs [17]. In this work, the systems are designed to achieve a prescribed reliability
193 level; namely the hourly demand must be met 95% of the time. In other words, production may be
194 lower than demand for 5% of the hours over the simulation period. This reliability level is based on the
195 criteria of the Tier 5 in the multi-tier framework developed by ESMAP [45].

196 Different storage / PV panel configurations can produce the same level of quality service. The optimal
197 design is identified to minimize the *LCOE*.

198 If a configuration is found suitable for a prescribed quality service level, configurations obtained by
199 either increasing the PV capacity (the surface area of the PV panel array) or the storage capacity are
200 also suitable. A minimal storage capacity is needed for each possible PV capacity. Conversely, a minimal
201 PV capacity is needed for each possible storage capacity. The set of the least equipment configurations
202 allowing for a prescribed level of quality service defines what we will refer to as the “sizing curve” for
203 this level.

204 In the following, to ease the comparison between sites, the sizing curve is normalized using the annual
 205 mean power demand D_0 . The sizing curve will next describe the relationship between the (normalized)
 206 storage capacity S and the (normalized) PV production capacity C_{PV} required to satisfy a demand D_0
 207 with the prescribed level of quality service. Thus, the storage capacity S [hrs_{eq}] is expressed in hours
 208 of equivalent demand (1 hrs_{eq} corresponds to the energy amount to supply one hour of electricity at
 209 the annual mean demand power D_0).

210 Due to the multiscale variability of the solar resource, PV panels do not always produce power at their
 211 rated power. The PV capacity C_{PV}^0 [W_p], that would be required to produce over the whole period, an
 212 energy amount exactly equal to the total energy of a constant demand D_0 is thus greater than D_0 . It is
 213 actually proportional to the inverse value of the so-called capacity factor CF of the PV panels for the
 214 considered site: $C_{PV}^0 = D_0 / CF$. Note also that the PV capacity C_{PV} [W_p] required to achieve the desired
 215 level of quality service for a constant demand equal to D_0 is expected to be even larger than the
 216 "reference" capacity C_{PV}^0 discussed above. This needed PV "oversizing" is actually required to allow for
 217 enough production during the periods of low solar resource. In the following, the ratio $x = C_{PV} / C_{PV}^0$
 218 is named the oversizing ratio of the PV system. It is dimensionless. For the seek of normalisation and
 219 comparison between locations, the sizing curve will finally relate the normalized storage capacity S and
 220 the oversizing ratio x . This normalized sizing curve obtained for a configuration where a level of quality
 221 service Q is further referred to as the $S_Q(x)$ function.

222 For any given location considered in the following, the sizing curve is identified from simulations. For
 223 a given normalized (PV capacity (oversizing ratio), storage capacity) configuration, a simulation consists
 224 of simulating 1) PV production, 2) storage operations (charge, discharge) over the whole period, and
 225 of 3) estimating the corresponding quality service level of the system. For different PV capacities in
 226 turn, simulations are used to identify the storage capacity value required to achieve the target quality
 227 service level (dichotomic identification).

228 2.5 *LCOE* calculation and cost optimal mini-grid configuration

229 The least *LCOE* MG configuration is finally identified from the $S_Q(x)$ curve as follows. For each (PV
 230 capacity, storage capacity) configuration, we use a simple economic modelling to estimate the total
 231 costs over the whole project lifetime and then the *LCOE* of the system. The total costs of the project,
 232 TC in [€], have the following expression:

$$TC = C_S \alpha_S + C_{PV} \alpha_{PV} \quad (5)$$

233 where C_S and C_{PV} are the installed storage [Wh] and PV capacity [W_p] respectively and where α_S
 234 [$€/Wh$] and α_{PV} [$€/W_p$], the full unit costs of storage and PV respectively, simply read:

$$\alpha_S = Cost_S \cdot \left(\sum_{k=0}^{int(\frac{L-1}{L_S})} \frac{1}{(1+d)^{kL_S}} + \sum_{k=1}^L \frac{P_{O\&M,S}}{(1+d)^k} \right) \quad (6)$$

$$\alpha_{PV} = Cost_{PV} \cdot \left(\sum_{k=0}^{int(\frac{L-1}{L_{PV}})} \frac{1}{(1+d)^{kL_{PV}}} + \sum_{k=1}^L \frac{P_{O\&M,PV}}{(1+d)^k} \right) \quad (7)$$

235

236 where $Cost_S$ [€/Wh] and $Cost_{PV}$ [€/W_p] are the unit investment cost associated to storage and PV
 237 panels respectively, where L, L_S, L_{PV} are the project, storage and PV panel lifetime respectively [yrs]
 238 and where d is the discount rate [-]. The second term of each equation is related to the full cost
 239 contribution to cover maintenance and operation of the system where $P_{O\&M}$ is a proportionality
 240 coefficient between investment and cover maintenance costs [-] (maintenance and operation costs
 241 are assumed to be time invariant and proportional to investment costs of each components).

242 Note that the total costs of the project can be also expressed as:

$$TC = C_S \cdot \alpha_S + x \cdot C_{PV}^0 \cdot \alpha_{PV} = \left(S_Q \cdot \alpha_S + \frac{x}{CF} \cdot \alpha_{PV} \right) \cdot D_0 \quad (8)$$

243 Where D_0 [W] is the mean demand power, where x [-] is the oversizing ratio, where S_Q [Wh/W] and
 244 C_0 [W_p/W] are the normalized storage and reference PV capacities and where CF is the capacity factor
 245 introduced previously.

246 The $LCOE$ [€] for the considered MG has next the following expression:

$$LCOE = \frac{TC}{\sum_{k=1}^L \frac{D_{supply}}{(1+d)^k}} \quad (9)$$

247 where D_{supply} [Wh] is the mean demand energy supplied each year by the system. It reads:
 248 $D_{supply} = Q \cdot D_0 \cdot 8760$ where Q is the quality service factor achieved with the system ($Q = 0.95$ in the
 249 following). Merging equation 7 and 8, the $LCOE$ then simplifies to

$$LCOE = \frac{\left(S_Q \cdot \alpha_S + \frac{x}{CF} \cdot \alpha_{PV} \right)}{Q \sum_{k=1}^L \frac{8760}{(1+d)^k}} \quad (10)$$

250 The $LCOE$ depends thus on 2 technical design variables, the normalized storage capacity S_Q and the PV
 251 oversizing factor x . For any given value of x , the sizing curve $S_Q(x)$ gives the normalized storage
 252 capacity required to achieve the target quality service level. The $LCOE$ can also thus be expressed as
 253 a function of x only.

254 Two limiting configurations from the sizing curve are to be noticed. When x tends to infinity, i.e. when
 255 the PV production capacity tends to infinity, the storage capacity tends to a minimum strictly positive
 256 value. Whatever the production capacity, a non-zero storage is indeed needed to move part of the
 257 diurnal production to the nocturnal electricity demand. As a result also, when x tends to infinity, $LCOE$
 258 thus tends to be a linear increasing function of x .

259 If the battery system was perfect (with no energy losses in storage/discharge cycles), the other limiting
 260 configuration would roughly correspond to $x = 0.95$. This would correspond to the configuration where
 261 all the production could be used to satisfy 95% of the demand. This configuration would obviously
 262 require that a huge (and unrealistic) storage capacity is available (e.g. seasonal storage) to allow for
 263 the temporal redistribution of the production from resource rich periods to resource poor ones. In
 264 practice, the minimum value of the oversizing ratio x is greater than 0.95 because of storage losses
 265 that result from smaller than 1 storage efficiency. As mentioned above, for this minimum x value, the
 266 storage gets a typically very large value.

267 In practice, the minimum value for $LCOE$ is therefore reached for $x = x^* > 0.95$ where:

$$\frac{\partial LCOE}{\partial x}(x^*) = \frac{\left(\frac{\partial S_Q}{\partial x}(x^*)\alpha_S + \frac{\alpha_{PV}}{CF}\right)}{Q \sum_{k=1}^L \frac{8760}{(1+d)^k}} = 0 \quad (11)$$

268 The optimal x^* value follows the equation:

$$\frac{\partial S_Q}{\partial x}(x^*) = -\frac{\alpha_{PV}}{\alpha_S \cdot CF} = -\frac{r}{CF} \text{ with } r = \frac{\alpha_{PV}}{\alpha_S} \quad (12)$$

269 The optimal oversizing value x^* and the optimal storage value $S^* = S_Q(x^*)$ depend only on CF and
 270 on the full cost ratio r .

271 It is not possible to derive an analytical expression for $S_Q(x)$. $S_Q(x)$ depends on the storage efficiency,
 272 the shape of the load profile, the temporal variability structure of the local solar resource and the
 273 chosen quality service level. As mentioned previously, $S_{95}(x)$ was here estimated for each location by
 274 simulations.

275 2.6 Statistical distributions of costs for PV and batteries

276 The full costs of batteries and photovoltaic panels vary from one country to another due to different
 277 political, regulatory or institutional contexts, from one region to another due to local constraints and
 278 specific transport costs depending on access facilities. In addition, each type of investor has its own
 279 profitability objectives and its own perceptions of the risks inherent in each project. This leads to the
 280 use of specific discount rates that strongly impact the LCOE [18], [19], [46], [47]. The costs of batteries
 281 and photovoltaic panels are also expected to decrease over time as a result of learning by doing [23],
 282 [26], [48]. Cyclical effects may also occur, e.g. pressures on equipment production capacity or on
 283 materials that may drive prices up more or less temporarily.

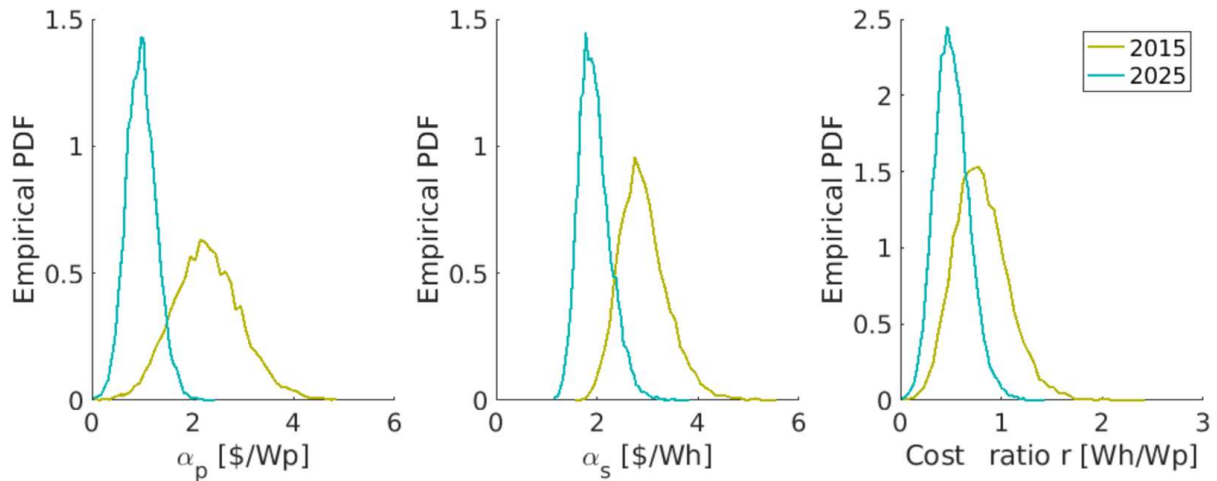
284 In the following, we explore how robust the optimal design is to economic hypotheses. To do this, we
 285 rely on a statistical distribution of full costs estimated via Monte-Carlo simulations. For storage, the
 286 values of the different variables in Eq. (6) (storage costs, battery lifetime, project lifetime, discount
 287 rate, proportionality coefficient for O&M costs) are randomly sorted from their respective statistical
 288 distributions allowing in turn to give one estimate of the storage full costs. This simulation process is
 289 repeated 10'000 times to produce a probability density function (PDF) of the full costs for storage. The
 290 same process is applied for calculating PV full costs. Due to the lack of information and for the sake of
 291 simplicity, the different variables in Eq. 6 (resp. Eq. 7) are assumed independent and the PDF of each
 292 variable is modelled with a normal distribution. The mean and variance of each PDF (cf. Table 1) have
 293 been estimated so that the 10th and 90th of the PDF correspond to the range of values given by the
 294 IRENA (International Renewable Energy Agency) for 2015 and 2025 [19], [25], [44]. These estimations
 295 are based on a bottom-up analysis of the different technologies implied in PV and storage systems and
 296 an estimation of the learning cost curve for these technologies. Due to the lack of information, the
 297 PDFs for the O&M costs proportionality coefficient and the discount rate are assumed to be the same
 298 for both periods.

Variable	2015		2025	
	Mean	Standard deviation	Mean	Standard deviation
Storage investment costs $Cost_S$ [\$/Wh]	1.1	0.1	0.9	0.1
PV investment costs $Cost_{PV}$ [\$/W _p]	1.8	0.5	0.8	0.2
Storage lifetime L_S [yrs]	5	0.7	6.7	0.9
PV lifetime L_{PV} [yrs]	20	1.7	20	1.7
Proportionality coefficient for O&M costs $P_{O\&M}$ [-]	0.02	0.003	0.02	0.003
Discount rate d [-]	0.08	0.01	0.08	0.01

299 *Table 1 : Economic parameters and component lifetimes distribution. The PV related parameters (investment cost and lifetime)*
300 *are obtained from [25] and the storage ones from [44]. Discount rate and Proportionality coefficient for operation and*
301 *maintenance are obtained from [19].*

302 The PDFs of the full costs for each unit of storage or PV (α_S and α_{PV}) and the PDFs of the cost ratio r
303 resulting from the Monte Carlo simulations are presented in Figure 4. As highlighted in the figure, the
304 full costs for both PV and storage are expected to decrease with time. The full costs for PV is however
305 expected to decrease faster leading to a shift of the cost ratio distribution to lower ratio values.

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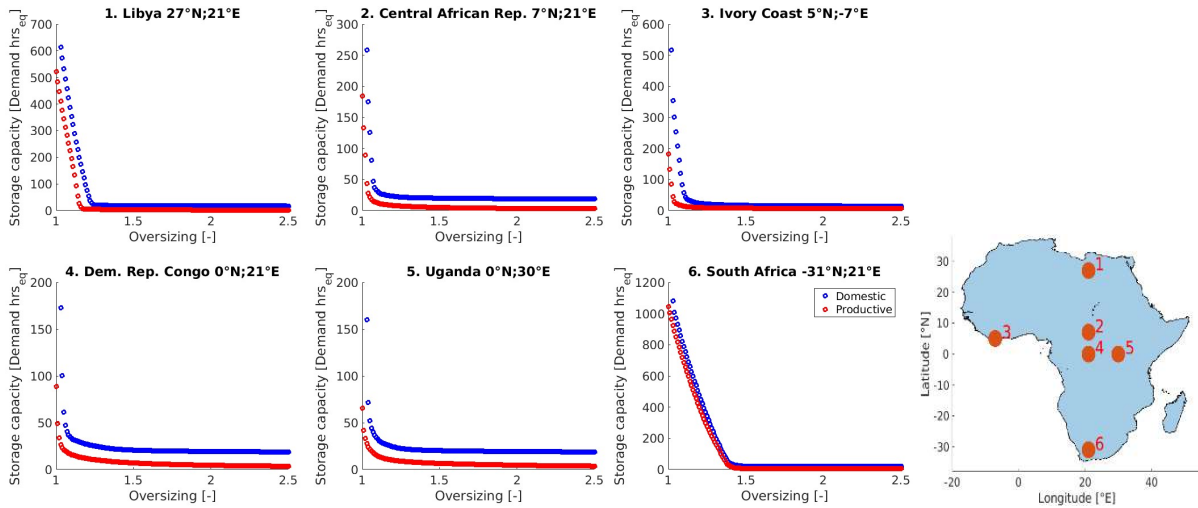
308 *Figure 4 : Probability Density Functions of full PV costs (left), full storage costs (middle) and for the cost ratio r (PV/Storage)*
309 *(right) as obtained from Monte Carlo simulations for two periods of time (2015 and 2025)*

310 3 Results

311 3.1 Sizing curves for a 95% quality service level

312 For the sake of concision, the following sections (3.1, 3.2 and 3.3) only present results obtained for the
313 non-seasonal demand profiles. Results for the seasonal demand profiles are presented in the
314 Supplementary Material (Figures SM 1-10).

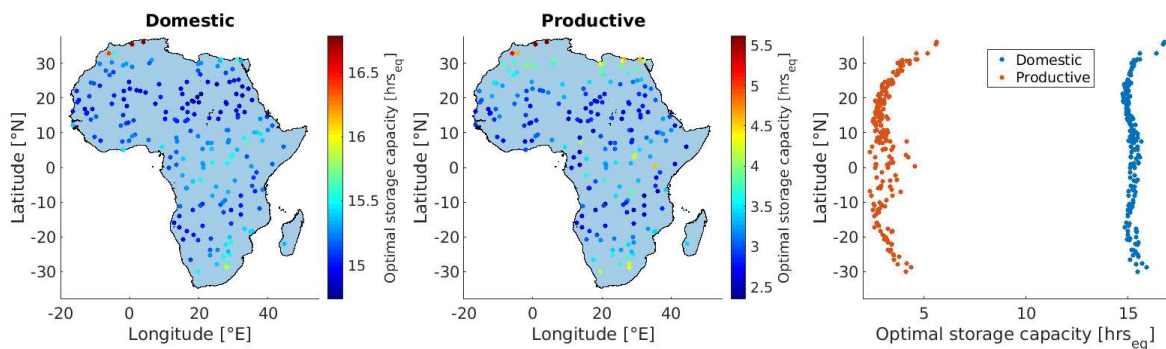
315 Figure 5 shows the $S_{95}(x)$ sizing curves obtained with the two daily load profiles of Figure 2, for 6
316 locations in contrasted climates (see Supplementary Material SM1 and SM2 for other locations).



317

318 *Figure 5 : Sizing curves $S_{95}(x)$ (normalized storage capacity S as a function of oversizing factor x) for six locations and for two*
 319 *demand profiles: domestic (blue) and productive (red) without seasonal variations. All MG configurations allow for a 95th*
 320 *quality service level.*

321 Whatever the location and the load profile, the storage need is very sensitive to the oversizing value
 322 when the latter tends to 1. The large to very large storage needs obtained for an oversizing value close
 323 to one depend on the location and on the demand profile. When the size of PV panels is just enough
 324 to produce the yearly energy demand (i.e. $x = 1$) in average over the year, large to very large storage
 325 capacity is needed where the seasonality of the solar resource or of the demand is significant (cf.
 326 Supplementary Material SM1 and SM2). This allows to balance the energy from summer to winter or
 327 vice-versa (cf. Libya or South Africa). Much smaller storage values are needed for locations where the
 328 resource seasonality is small, as this is typically the case near the equator (cf. Central African Republic
 329 or Ivory Coast) (cf. Figure 5). This seasonal footprint is largely due to the latitude of the location, but
 330 this is not always the case. A significant resource seasonality is also observed in a number of equatorial
 331 locations because of significant seasonal variations of the nebulosity (cf. Uganda or Republic of Congo).



332

333 *Figure 6 : Normalized storage capacities $[hrs_{eq}]$ for the 200 locations obtained with a large oversizing ratio ($x = 2.5$). (The*
 334 *normalized required storage capacity is the storage capacity $[Wh]$ required per unit of mean power demand (i.e. 250 W)*
 335 *to satisfy the demand 95% of hours in a year. It is expressed in $[Wh/W]$ or in $[hrs_{eq}]$. Left and middle maps: results for a domestic*
 336 *and a productive daily profile. Right: normalized storage capacities as a function of latitude (blue dots: domestic and red dots:*
 337 *productive, only a part of the abscissa (from 5 to 13) is not shown).*

338 As mentioned previously, the storage capacity is expected to tend to a minimum value for large
 339 oversizing values (cf. illustration in Figure 6). The limiting value per unit of energy demand highly
 340 depends on the type of use. Whatever the location, it is larger for domestic uses than for productive
 341 ones (cf. Figure 6). It is actually always smaller than 16 hours in the first case and smaller than a few
 342 hours in the other. The storage is thus almost only required to deal with the sub-daily resource /
 343 demand mismatch, e.g. to move the energy produced during the day to the evening/night-time in the

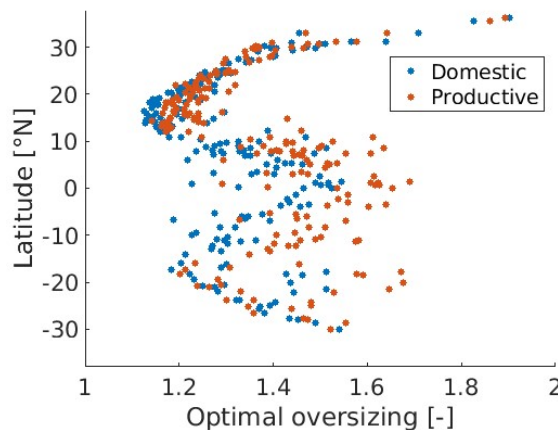
344 domestic case. Another interesting point is that this minimum required storage value is almost always
345 already reached for rather small PV oversizing values (values below 2.5) (cf. results for the 6 locations
346 of Figure 5). For larger oversizing values, the required storage capacity decreases but the decrease is
347 small and almost always less than one hour at mean demand power. For many locations, the storage
348 is thus used for long temporal scale redistributions only when the oversizing value is small to very
349 small.

350 For small oversizing values (below 1.5), the storage requirements are modified in a case of a seasonal
351 demand. A larger seasonal resource / demand mismatch leads to a larger storage requirement (cf.
352 Supplementary Material SM1 and SM2). For large oversizing values (above 2.5), the storage
353 requirement almost no more depends on the demand seasonality.

354 3.2 Least-cost configurations

355 This section presents the least cost configurations obtained for the 200 locations with different
356 demand profiles, a 20 years project lifetime and a cost ratio $r = 1$. The case of $r = 1$ is close to the
357 most unfavourable cost configuration for PV for 2025 ($r = 1$ actually corresponds to the 99th percentile
358 of the cost ratios distribution for this period). Estimating the oversizing values for $r = 1$ gives thus
359 almost the minimum possible value of the optimal oversizing. In other words, the oversizing of a given
360 project is very unlikely to be smaller than this value, whatever the cost-ratio configuration for the 2025
361 cost conditions.

362



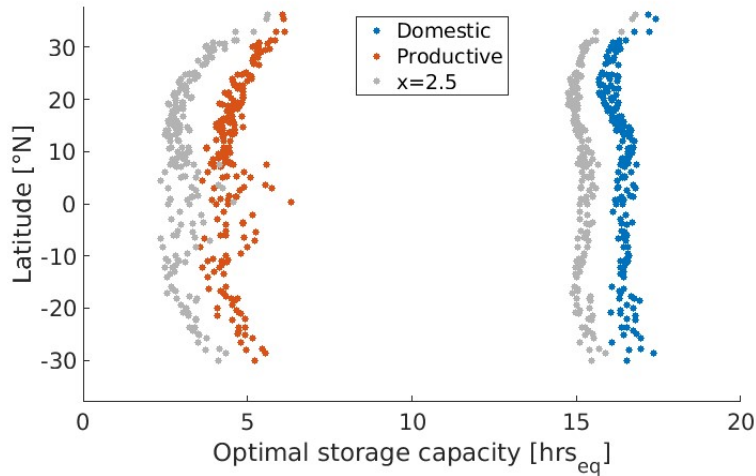
363

364 *Figure 7 : Optimum oversizing x^* obtained by simulation with a cost ratio $r=1$ and without seasonality as a function of the*
365 *latitude for a domestic (blue dots) and a productive (red dots) demand profile.*

366 The PV optimal oversizing values as a function of latitude varies between 1.1 and 2 without major
367 differences between the two daily load profiles. The optimal oversizing values are higher for regions
368 with a high nebulosity (near the equator) or a high seasonality (north and south of Africa). The lowest
369 values for optimal oversizing are obtained in the Sahelian part (around 15°N). Adding seasonality to
370 the demand profile increases the optimal oversizing values but most of them stay below 2.1 (cf.
371 Supplementary Material SM3 and SM4). This increase is larger when the peak demand occurs during
372 the low resource period, which modify the shape obtained in Figure 7. When the peak demand occurs
373 in the northern summer, the optimal oversizing values are lower in the north and higher in the south.

374 The required (normalized) storage capacities for the domestic profile are around 15 to 18 hours
375 depending on the location (Figure 7). They are around 4 to 7 hours for the productive profile. Even
376 with a cost ratio that favours large storage capacities ($r = 1$), these values are relatively close to the

377 minimal storage requirements from Figure 6. As for the optimal PV oversizing values, the optimal
 378 storage capacities are increased when adding seasonality to the demand, especially for the domestic
 379 load profile (cf. Supplementary Material SM5 and SM6). The demand / resource seasonal mismatch
 380 has a similar effect: when the peak demand occurs in northern summer, the optimal storage values
 381 are lower in the north and higher in the south. Note that whatever the type of use and seasonality, the
 382 required storage is smaller than 24 hours. The storage capacities for the domestic load profile could
 383 be perceived high for electrochemical storage, however these storage levels can be found in existing
 384 solar MG and they are much lower than what is proposed by the IEEE rule [31].

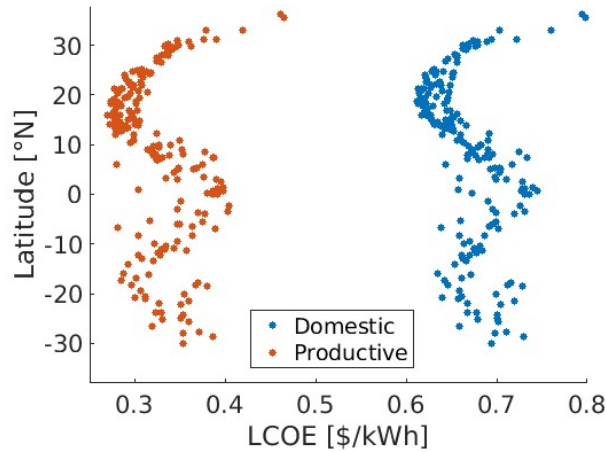


385

386 *Figure 8 : Optimal normalized storage capacity S^* obtained by simulation with a cost ratio $r=1$ and without seasonality as a*
 387 *function of the latitude for a domestic (blue dots) and a productive (red dots) demand profile. Grey dots correspond to the*
 388 *limiting storage capacity requirement presented in figure 6 for $x = 2.5$.*

389 The *LCOE* values found here are in the same order of magnitude as the ones calculated by Nerini et
 390 al. [8] or by Szabo et al. in [13]. They are also logically higher than the *LCOE* for electricity delivered
 391 by national grids with values below 0.1\$/kWh for Zambia to 0.6\$/kWh for Liberia but below 0.35\$/kWh
 392 for most of the countries in Sub-Saharan Africa [49]. The *LCOE* values we obtain are very sensitive to
 393 the sub-daily demand profile (cf. Figure 9). The *LCOE* for a productive profile can be two to three times
 394 lower than the one for a domestic profile. This logically follows the much lower storage requirements
 395 that are two to three times lower in the productive case whereas PV capacities are similar in both
 396 demand configurations. The *LCOE* evolution with the latitude is similar to the one found for the
 397 optimal oversizing values.

398 If the *LCOE* is much less sensitive to the seasonality of the demand than to the sub-daily profile, a
 399 seasonal demand leads, for most locations, to larger oversizing values and storage capacities and, in
 400 turn to larger *LCOE* values (cf. Supplementary Material SM7 and SM8).



401

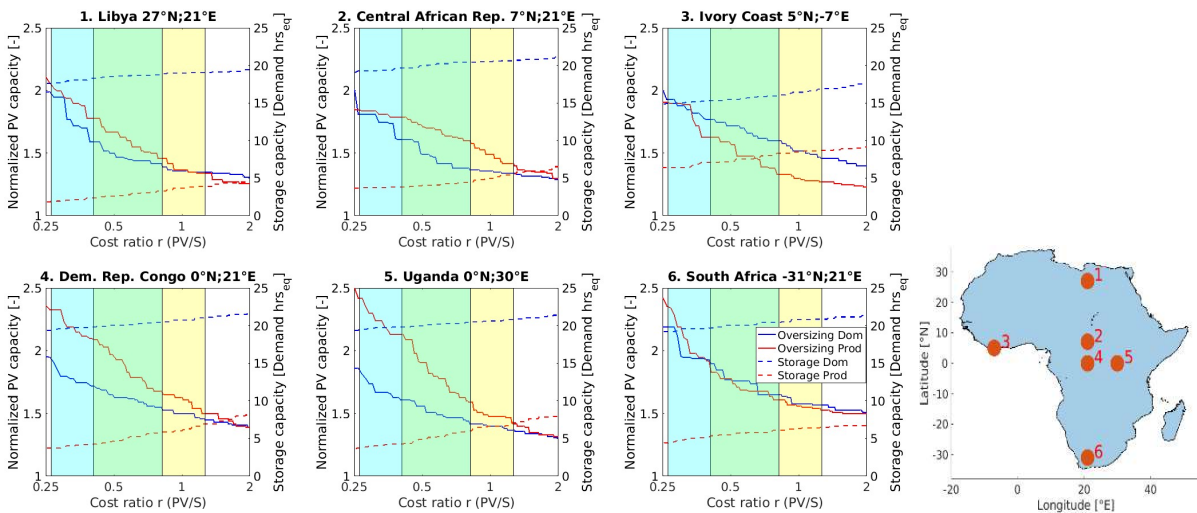
402 *Figure 9 : Optimal LCOE obtained by simulation with a cost ratio $r=1$ and without seasonality as a function of the latitude*

403

404 3.3 Sensitivity of the optimal configurations to cost ratio

405 As mentioned previously, the least-cost configuration depends on the cost ratio r . The PV oversizing
 406 level and the storage capacity of the least cost configuration is presented as a function of r for the six
 407 locations in Figure 10. Note that the variation range of cost ratios explored in the figure is larger than
 408 the variation ranges of the 2015 and 2025 distributions. For the sake of clarity, the 90% range of the
 409 2015 and 2025 distributions is highlighted by the yellow and cyan vertical bands.

410



411

412 *Figure 10 : Least LCOE configurations (normalized PV capacity (continuous lines; left scales); normalized storage capacity*
 413 *(dotted lines, right scales)) as a function of cost ratio (PV full costs / storage full costs, log scale) for six locations and for the*
 414 *domestic (blue lines) and the productive (red lines) load profiles. The 90% confidence interval of the cost ratio distribution is*
 415 *presented for 2015 (yellow vertical band) and 2025 (cyan vertical band). The green band corresponds to the overlap of cyan*
 416 *and yellow bands. All configurations allow for a 95th quality service level.*

417 Larger r values (i.e. larger PV/S cost ratios) logically lead to smaller PV oversizing values and larger
 418 storage capacities.

419 For both variables, the range of the optimal design values is rather small. Considering the 200 locations,
 420 while the cost ratio varies by a factor of 8 (from 0.25 to 2), the optimal oversizing coefficient only varies

421 by a factor 1.5 for the domestic profile and of 1.7 for the productive one, for 90% of the locations. The
422 ratio between the largest and the smallest possible PV oversizing value is always smaller than 2.

423 The robustness of the sizing of the storage capacity is even larger. Whatever the type of use, its
424 variation range is often less than 10%. For both variables, the variation range is even smaller when the
425 cost ratio is kept in the 90% variation range of the 2025 distribution (cyan vertical band). The optimal
426 configuration is actually much more sensitive to the daily load profile than to the cost hypothesis. Even
427 if optimal storage capacities and oversizing values are higher when adding seasonality to the demand,
428 the robustness of the optimal configuration is similar to the one described here (cf. Supplementary
429 Material and SM10).

430 As shown in Figure 3, the cost ratio r is expected to decrease in the coming years, which will further
431 favour cost-optimal configurations with higher PV oversizing [25], [44]. In a longer term however, the
432 cost ratio could increase again to values above 1 due to the learning-by-doing effects which are still
433 expected to be significant for storage technologies [47]. Considering the lower sensitivity of the
434 optimal configuration in the right-side of the oversizing curves in Figure 10, this would lead in turn to
435 an increased robustness of the optimal sizing.

436

437 3.4 The possibility for simple pre-sizing rules

438 As highlighted in previous sections, the optimal configuration reveals to be rather robust to cost
439 assumptions and to almost only depend on the characteristics of the solar resource, the demand and
440 their co-variability. This suggests that it might be possible to find simple sizing rules that would avoid
441 the computationally demanding simulations of any simulation-based optimization process.

442 We assess here the possibility for such a set of rules. These rules have been identified and tested from
443 all the optimal configurations obtained, with the simulation methodology presented in section 2, for
444 the 200 locations of Figure 1, the ten different load profiles presented in section 2.1 and four different
445 cost ratios (namely 0.3, 0.5, 0.8 and 1 corresponding respectively to the quantiles 5%, 50%, 95% and
446 99% of the cost ratio distribution for 2025). The rules have been first identified/calibrated from half of
447 the locations and their validity has then been assessed on the other half. The evaluation consists in
448 comparing, for each location and each demand profile/cost ratio, the estimated optimal configuration
449 and the reference one, i.e. the optimal configuration obtained with simulations. The detailed
450 procedure to apply these rules can be found in Supplementary Material.

451 Two indicators are used for this evaluation: the normalized mean bias error (eq. (13)) and the
452 normalized root mean square error (eq. (14)).

$$nMBE = \frac{1}{\bar{Y}} \sum_{i=1}^n \frac{Y - Y_{est}}{n} \quad (13)$$

$$nRMSE = \frac{1}{\bar{Y}} \sqrt{\frac{\sum_{i=1}^n (Y - Y_{est})^2}{n}} \quad (14)$$

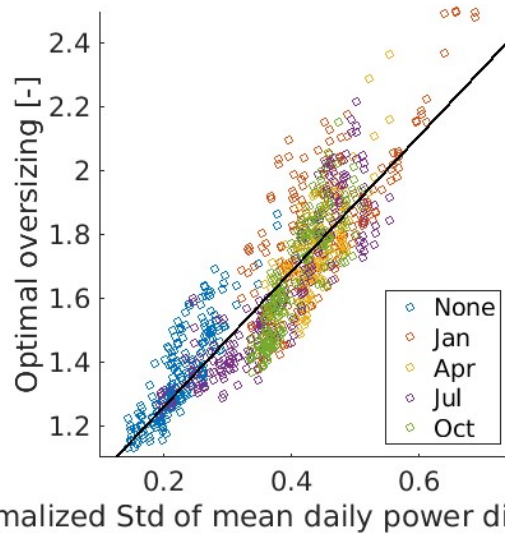
453 With Y and Y_{est} the design values obtained for the considered variable (e.g. storage capacity, PV
454 production capacity) for the reference configuration and with the simple rules respectively and \bar{Y} the
455 mean reference value obtained for the $n = 100$ evaluations stations.

456 The rules apply for the normalized PV oversizing factor and the normalized storage capacity. As
 457 mentioned in the “Method” section, the actual PV panel area and the storage capacity required for a
 458 given location can be simply obtained with those normalized variables from the mean daily demand
 459 and from the mean capacity factor of solar panels to be expected for the location. Whereas the mean
 460 capacity factor can be easily extracted from already published data sets (e.g. [50]), the mean daily
 461 demand has to be typically estimated from local surveys.

462 As mentioned previously, the required PV oversizing factor is related to the resource / demand
 463 temporal mismatch. An indicator of this mismatch is the standard deviation (σ_{Diff}) of the daily power
 464 differences that can be estimated each day between the mean electricity demand and the mean PV
 465 production. This standard deviation obviously depends on both the mean daily difference and on the
 466 temporal variations of the difference. For the sake of simplicity, σ_{Diff} is here estimated from the time
 467 series of differences between the normalized daily demand (normalized by the mean annual daily
 468 demand D_0), and the normalized daily PV production for this day (production achieved without any
 469 oversizing of the PV panel area ($x = 1$) and normalized by D_0).

470 As shown in Figure 11, the variation range of σ_{Diff} depends on the seasonal profile of the demand. In
 471 the case of a non-seasonal profile, σ_{Diff} simply refers to the coefficient of variation of the solar
 472 resource, which derives from the joint effects of the seasonality of the Top Of Atmosphere (TOA)
 473 radiation and of the day-to-day variations of the atmosphere characteristics (e.g. nebulosity, aerosols).
 474 In locations with both small TOA radiation seasonality and low day-to-day weather variability (e.g. in
 475 the Sahel and a part of Angola), low values of σ_{Diff} are obtained (< 0.25).

476 In the case of a seasonal demand profile, the power difference variability is modulated. When the peak
 477 demand occurs in the high solar resource season, the value of σ_{Diff} can significantly decrease. For
 478 instance, a high energy demand in July in the Maghreb area makes σ_{Diff} decrease from 0.35 to 0.2.
 479 When the peak demand occurs in the low resource period, σ_{Diff} is expected to increase. In Maghreb,
 480 it can be higher than 0.5 for a high winter demand.



481
 482 *Figure 11 : Optimum oversizing x^* as a function of σ_{Diff} , the normalized standard deviation of the daily production/demand*
 483 *differences (differences estimated each day between the mean production and the mean demand for this day (the production*
 484 *is estimated with an oversizing factor of 1) and normalized by D_0). Results are presented for 5 different seasonal profiles of*
 485 *the demand (None: No Seasonality; Jan, Apr, Jul, Oct: Seasonality with a maximum in January; April, July and October*
 486 *respectively). This graph presents the optimum oversizing value for $r = 1$ and for both the domestic and productive load*
 487 *profiles (no distinction is made here between the 2 profiles).*

488 As highlighted in Figure 11, regardless of the seasonality of the demand, the relationship between
 489 σ_{Diff} and the optimal oversizing x^* turns out to be strong, and a linear relation is expected to be a
 490 relevant first-order approximation.

$$x^*_{est,r=1} = 0.83 + 2.12\sigma_{Diff} \quad (15)$$

491 The nMBE and the nRMSE of this model stays respectively below 0.05 and 0.1 for each load profile (cf.
 492 Supplementary Material SM14). The global nRMSE for all categories is 0.07 which is quite good for such
 493 a simple rule.

494 The optimal normalized storage capacity was found to mainly depend on the sub-daily
 495 resource/demand mismatch (cf. Figure 12). It thus depends on the actual power production and in turn
 496 on the oversizing factor chosen for the system. For the storage capacity, the sizing rule is then based
 497 on the statistical distribution of the normalized nocturnal energy difference $E_{noct} [h]$ estimated each
 498 day between the load profile and the PV production profile of this day, where the PV production is
 499 obtained with the optimal oversizing x^*_{est} estimated by the previous rule (eq. (15)) and both
 500 production and demand are normalized by D_0 .

501 For any given day, this normalized nocturnal energy difference reflects the energy that must be
 502 delivered by the storage during night-time. The normalized nocturnal energy difference is calculated
 503 between mid-time and mid-time the day after using equations (16) to (18).

$$E_{noct}(d) = \sum_{h=-12}^{h=12} P_{noct}(t) \cdot 1hr \quad (16)$$

504

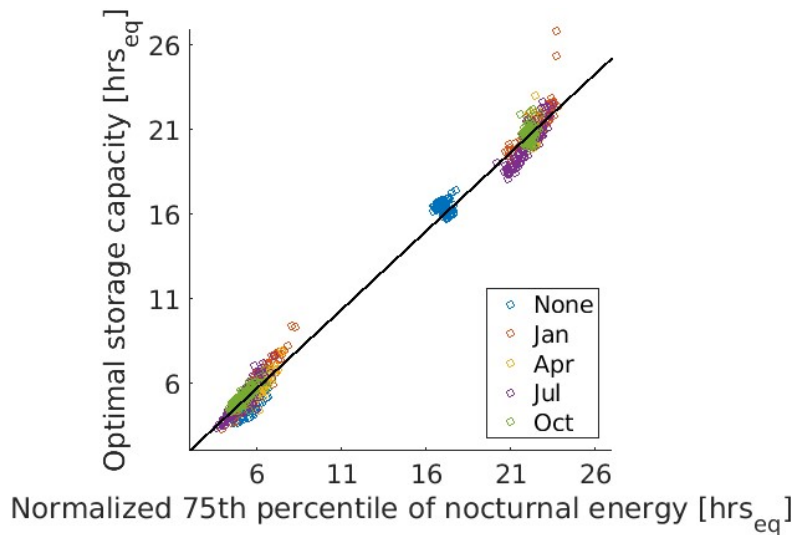
505 Where $P_{noct} [-]$ is the normalized nocturnal power difference for each day t defined as:

$$P_{noct}(t) = \begin{cases} (D(t) - P_{AC}^{x^*}(t))/D_0, & D(t) - P_{AC}^{x^*}(t) \geq 0 \\ 0, & D(t) - P_{AC}^{x^*}(t) < 0 \end{cases} \quad (17)$$

506 Where $P_{AC}^{x^*} [W]$ is the power produced by PV panels with the optimal oversizing x^*_{est} obtained from
 507 equation (15) and $D [W]$ is the power demand. The sizing rule for the optimal normalized storage
 508 capacity S_{95}^* is considered as:

$$S_{95est,r=1}^* = 0.93 \frac{p_{75}(E_{noct})}{\eta_{storage}} + 0.14 \quad (18)$$

509 Where $p_{75}(E_{noct}) [h]$ is the 75th percentile of the normalized nocturnal energy difference distribution
 510 and $\eta_{storage} [-]$ is the storage efficiency.



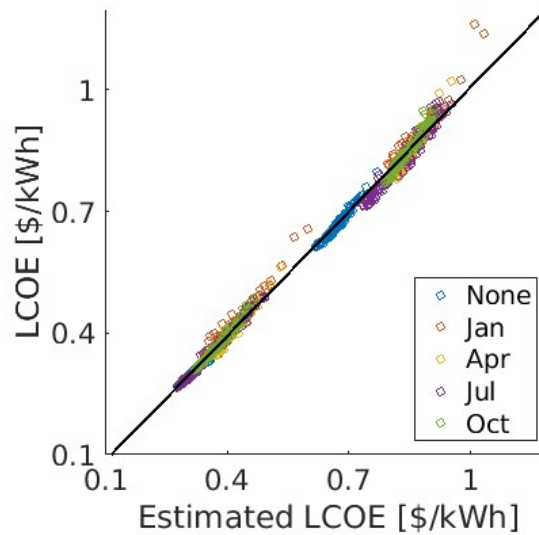
511

512 *Figure 12 : Optimum normalized storage capacity S^* as a function of the 75th percentile of the normalized nocturnal energy*
 513 *$p_{75}(E_{noct})$. Results are presented for 5 different seasonal profiles of the demand (None: No Seasonality; Jan, Apr, Jul, Oct:*
 514 *Seasonality with a maximum in January; April, July and October respectively). This graph presents the optimum storage*
 515 *capacity values for $r = 1$ and for both the domestic and productive load profiles (no distinction is made here between the 2*
 516 *profiles).*

517 As highlighted previously in the manuscript, the storage requirement depends mainly on the load sub-
 518 daily profile. If all hours would have to be satisfied ($Q = 100\%$), the storage requirement would be
 519 related to the maximum nocturnal energy difference. In this work, we set a quality service $Q = 95\%$,
 520 which means that 5% of the hours can be unsatisfied. In this configuration, the 75th quartile of the
 521 nocturnal energy difference distribution turns out to be a very good predictor of the storage
 522 requirement.

523 For the storage capacity, the good order of magnitude is reached with this simple rule whatever the
 524 load profiles. If relative errors are much higher for the productive profile than for the domestic one (as
 525 a result of smaller absolute values of the required storage), absolute errors are most of the time lower
 526 than 1 hour of storage. The estimations for the optimal storage are very satisfactory with a global
 527 nRMSE below 0.04.

528 The level of quality service obtained with the estimated design does not always fit the level initially
 529 targeted (between $QS = 92\%$ and $QS = 96\%$ for 90% of the locations, cf. Supplementary Material
 530 SM13). An overestimated (underestimated) optimal storage capacity leads to a higher (lower) level of
 531 quality service and the same applies for the optimal oversizing factor. As the storage capacity is
 532 estimated from the estimated oversizing factor, the storage/PV under- and overestimations often
 533 compensate themselves. All in all, these compensations allow to have a good estimation of the *LCOE*
 534 (cf. Figure 13).



535

536 *Figure 13 : Comparison between optimal LCOE obtained by simulation and configurations estimated by the sizing rule for all*
 537 *load profiles and $r = 1$*

538 3.5 Pre-sizing rules for over cost ratios

539 The above results refer to a cost ratio of $r = 1$. As highlighted previously, the storage optimal capacity
 540 was found to be almost independent on the cost ratio value (cf. Supplementary Material SM 12 and
 541 SM 15). Whatever the actual cost ratio value, the storage capacity estimated with equation (18),
 542 calibrated for $r = 1$, is very satisfactory. The global nRMSE of estimates remains below 0.06.

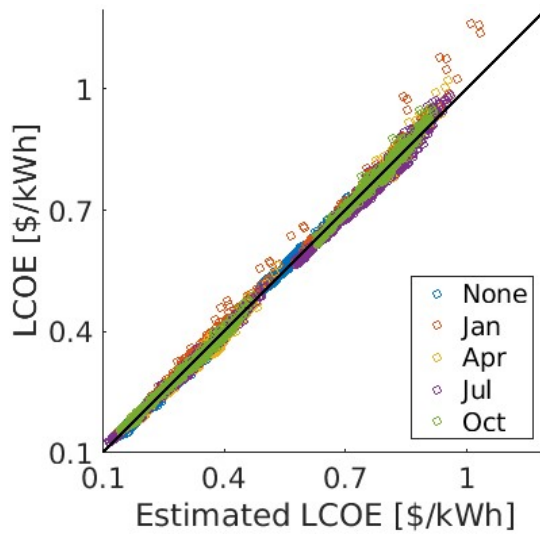
543 Results obtained for the PV optimal oversizing conversely significantly depend on the cost ratio value.
 544 Smaller cost ratios lead to more favourable configurations for PV and thus to higher oversizing values
 545 (cf. Supplementary Material SM 11 and SM 14). An efficient way to account for this in the pre-sizing
 546 rules is to multiply the optimal oversizing estimated for $r = 1$ by a constant factor $f(r)$. This factor
 547 was estimated to be equal to 1.5, 1.2 and 1.1 for cost ratios equal to 0.3, 0.5 and 0.8 respectively.

$$x^*_{est,r} = f(r) \cdot x^*_{est,r=1} \quad (19)$$

548 When no correction is considered, i.e. when the relation (15) is used for the pre-design of the PV
 549 optimal oversizing for any value of the cost ratio, the global nRMSE is 0.18. With the correction
 550 introduced in equation (19), it decreases to 0.08, which becomes also very satisfactory.

551 Using equations (18) and (19), the level of quality service stays between 93% and 97% for 90% of all
 552 configurations (cf. Supplementary Material SM13).

553 A detailed description of nMBE and nRMSE related to optimal oversizing factors, optimal storage
 554 capacities and LCOE estimation for each cost ratio and load profiles can be found in Supplementary
 555 Material SM16. Even if the deviations between the estimated and the reference optimal configurations
 556 for the storage, the PV oversizing and the level of quality service can be non-negligible, the errors
 557 obtained for the LCOEs are small whatever the cost ratios and the load profiles (global nRMSE around
 558 0.02, cf. Figure 14).

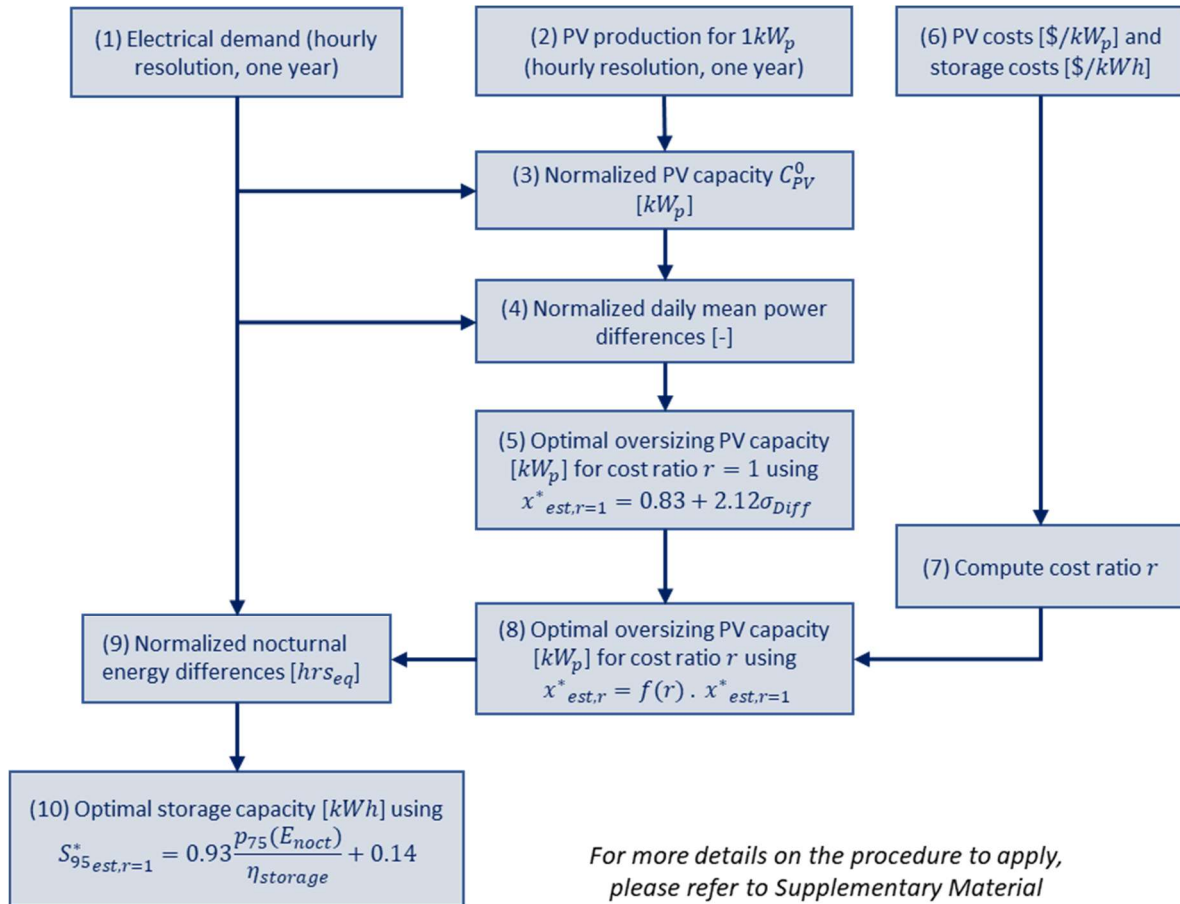


559

560 *Figure 14 : Comparison between optimal LCOE obtained by simulation and configurations estimated by the sizing rules for the*
 561 *four cost ratios (0.3, 0.5, 0.8, 1) and all load profiles.*

562 **3.6 Summary of pre-sizing rules**

563 The data, calculations and rules finally proposed in the present work for the pre-sizing of 100% solar
 564 MGs are summarized in the diagram of Figure 15. The details of each step are given in the
 565 Supplementary Material.



566

567 *Figure 15 : Summary diagram of the procedure to apply the pre-sizing rules*

568

569 4 Discussion

570 4.1 Influence of the load profile choice

571 As highlighted here and in some other publications, the load profile has an important influence on the
572 optimal MG configuration. On the other hand, the load profile to be expected for a rural community is
573 very uncertain *a priori* (cf. [36], [51], [52]). Having a good estimate of the load profile is thus obviously
574 a key challenge and an important design issue. This however not modifies the relevance and impact of
575 our analyses. On the one hand, an interesting finding of our work is indeed that the design is almost
576 not sensitive to cost hypothesis. Our results additionally suggest that this applies whatever the load
577 profile. Analyses with an intermediate daily profile (50% domestic/50% productive) give for instance
578 similar (intermediate) results (cf. Supplementary Material SM 17 and SM 19). On the other hand, the
579 simple design rules proposed here are expected to apply whatever the daily/yearly load profile. The
580 characteristics of the load profile are indeed considered both (1) in the mean power difference
581 between production and demand, that is used to estimate the optimal oversizing factor, and (2) in the
582 mean nocturnal energy difference, that is used to calculate the optimal storage capacity.

583

584 4.2 Influence of technical/economic hypothesis and choices

585 Our results were obtained under a set of technical choices and economic hypothesis. How they might
586 influence the optimal configuration, the LCOE and the robustness of the sizing rule would need to be
587 studied.

588 For instance, the targeted level of quality of service is expected to impact the optimal configuration. A
589 lower level would decrease the storage requirements and /or the PV installation size and would
590 decrease in turn the battery and/or PV costs [17], [53]. The way the quality of service is defined is also
591 expected to impact the design. This would probably be an issue for specific research.

592 Similarly, unit costs of PV and storage are expected to depend on PV panels and battery efficiency, on
593 the minimum state of charge of the battery below which the battery should not fall. The possible
594 effects of some of these features on the design are easily predictable. A higher value for the minimum
595 battery state of charge would logically increase the storage requirement and in turn the storage costs.
596 A smaller PV efficiency would similarly increase the required surface of PV panels and in turn PV costs.

597 A modification of unit costs and of their respective variation ranges would change the PV/battery cost
598 ratio and its variation range. If the influence of such modifications would be worth investigating, our
599 results are not expected to be significantly modified. Results obtained in Figure 10 are very similar
600 when the variation range of r is extended to the range $[0.1, 3]$: the robustness of the optimal
601 configuration to modifications of the cost ratio is slightly smaller on the range $[0.1, 0.25]$ but it is larger
602 on the range $[2, 3]$ (cf. Supplementary Material SM 19).

603 A more detailed modeling could be also considered to account for auxiliary costs such as costs of civil
604 engineering, cost of the distribution grid and costs of distribution losses, etc. (cf. [54]). Some of those
605 auxiliary costs are not expected to modify the optimal configuration of a 100% solar MG and are not
606 expected to modify the pre-sizing rules discussed above. They would just result in the introduction of
607 a fixed cost and increase in turn the *LCOE* by a constant value. Another issue could be the influence
608 of economies of scales, with lower unit costs for larger project sizes [55], or the influence of the

609 component lifetimes, which are very sensitive to maintenance quality, local weather conditions,
610 charge/discharge cycles for the battery, degradations,... [20], [21].

611 4.3 Comparison with other sizing rules

612 As stated in the introduction, some international organizations propose rules or guidelines to design
613 isolated MG in Africa.

614 In all cases, the load profile of the community has to be estimated based on the different appliances
615 (light bulb, TV, fridge, ...) to be used and on their respective consumption profiles. This allows in turn
616 estimating the mean daily demand and the nocturnal energy consumption of the whole system.

617 The Institute of Electrical and Electronics Engineers (IEEE) [31] proposes a rule to size 100% PV systems
618 that can be compared to our rule. The PV array is sized using the mean daily demand and solar resource
619 for the worst month (high monthly demand and low resource). For the storage capacity, the IEEE
620 recommends 5 to 7 days of autonomy to deal with sequences of low resource days. This leads to much
621 larger *LCOEs* (with storage capacities at least 5-8 times larger than the ones estimated in the present
622 work).

623 Contrary to the IEEE, the International Energy Agency (IEA) [30] and the ECOWAS Centre for Renewable
624 Energy and Energy Efficiency (ECREEE) [29] give rules to design hybrid PV/diesel MG. In such a
625 configuration, the level of service quality that can be achieved is no more an issue, as the genset can
626 supply the missing solar production at any time.

627 Similarly to the IEEE rule, the rule proposed by ECREEE [29] uses the mean daily demand and solar
628 resource for the worst month to size the PV array but they recommend a smaller storage capacity
629 corresponding to 2 times the value of the nocturnal energy consumption.

630 For the IEA [30], the design recommendations take the form of general guidelines: the installed PV
631 capacity should be able to supply more than 20% of the daily energy demand and the storage capacity
632 should be large enough to supply the nocturnal energy demand apart from the evening peak power
633 that should be supplied by the diesel genset. A large part of the demand is thus expected to be supplied
634 by the genset making the design of the PV / storage components rather simple.

635 The two previous rules apply to hybrid PV / diesel systems. They are not necessarily suited for remote
636 locations where fuel supply is not reliable enough or for MG operators who want to use only
637 decarbonized technologies. The rules we propose in the present work apply to 100% solar systems that
638 could fit with the above constraints/objectives. Our results show that a 95% level of quality service can
639 be reached with such systems, without any diesel generator and with smaller storage capacities than
640 those proposed by the ECREEE. Our work additionally shows that the least cost configurations for such
641 systems, very robust to a set of economic hypotheses, have to be adapted from one location to the
642 other depending on the local climate features and on the sub-daily demand profile.

643 Our rules do not replace a more accurate sizing of a MG that could be done with HOMER [56] or any
644 similar optimization software. It only aims at pre-assessing the regions where 100% PV MGs have a
645 potential by quickly estimating the cost of power generation and compare it with other energy sources
646 or other electrification solutions (national grid, solar home systems) for rural electrification planning.
647 The sites for which this comparison favours a 100% PV MG will need to be studied in more detail.

648 5 Conclusion

649 The optimal configuration and the *LCOE* of autonomous PV + battery systems is expected to depend
650 on cost hypotheses. The robustness of the least cost configuration to cost assumptions is investigated
651 for 200 African locations. The simulation-based design is carried out to achieve a prescribed level of
652 quality service, namely to supply energy for 95% of the hours.

653 Whatever the shape of the load profiles (domestic or productive), we show that different storage / PV
654 oversizing configurations are suited to achieve a prescribed level of quality service. The large storage
655 requirements usually recommended can be reduced by oversizing the PV production capacity. In most
656 of the cases, an oversizing coefficient of 2.5 is enough and the storage energy requirements are close
657 to the value that allows to deal with the sub-daily resource/demand mismatch.

658 The least-cost configuration that allows to achieve a given level of quality service depends, among
659 other drivers, on relative costs of PV and battery, but the sensitivity to the cost ratio is not large. The
660 robustness of the configuration is thus rather good. When the cost ratio varies with a factor 8, the
661 variations of the optimal oversizing factor are most of the time not larger than 70%, while the one for
662 the required storage capacity are often smaller than 10%. The required storage capacity is thus highly
663 robust to cost ratio variations.

664 The *LCOE* for a productive load profile is two to three times lower than the one for a domestic load
665 profile. This is an incentive for micro-grid designer to integrate as much productive uses as possible
666 when assessing the electricity demand of a community. This definitively also calls scientists and
667 practitioners to collect, share and publish demand data for a better knowledge of the temporal profile
668 of the demand and its possible evolution through years.

669 All in all, the optimal (PV capacity / storage) configuration almost only depends on the characteristics
670 of the solar resource, the electricity demand and their co-variability. This allows to propose simple
671 rules for a rapid but reliable design. The goal of these rules is not to find the accurate optimal
672 configuration for one specific site, it is rather to evaluate quickly the cost of electricity from solar MG
673 over a large area. Such estimation can then be used to compare solar MG to different electrification
674 solutions in a preliminary planning. The optimal oversizing factor can be estimated using the standard
675 deviation of the mean daily power difference between the solar power production and the power
676 demand. The required storage capacity can be calculated using the 75th percentile of the daily
677 nocturnal energy difference between the load profile and the solar power production. These rules give
678 a good estimate of the optimal configurations whatever the load profile (domestic or productive,
679 seasonal or not) and the cost ratio (between 0.3 and 1) considered.

680 The approach used in this work and the results offer further research perspectives. A least *LCOE*
681 criterion was used to determine the optimal configuration. It could be interesting to compare the
682 results for this criterion obtained with our rule and with the ones proposed by the IEEE, the IEA and
683 the ECREEE. This comparison should also consider the environmental impact of the MG (for instance,
684 the greenhouses gases emissions, the land use or the toxicity to human health and to ecosystems) and
685 modified rules could be derived by including these criteria in the optimization.

686 The methodology presented here was applied to identify the optimal (PV capacity/storage)
687 configuration of 100% PV MGs. It could also be used for MGs based on other variable energy sources
688 such as wind or hydroelectricity that are also promising renewable energy sources in many regions
689 worldwide (e.g. [57]). For wind power and hydroelectricity, the important civil engineering works to
690 be produced and the large variety of terrain configurations to be found would likely result in a large

691 variability of installation and in turn equipment costs. The robustness of the optimal design
692 configurations is expected to be in turn rather low.

693 The demand profiles considered in this article are constant from one year to the other, however the
694 evolution of the electricity demand during the lifetime of the MG could change the performance of the
695 system. A better knowledge of the processes involved in the evolution of the electricity demand are
696 necessary to choose the most suitable profile on which the sizing rules must be applied.

697

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699 writing - original draft preparation: T.C.; writing – review and editing T.C., B.H. and S.M.

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703

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