Renewable Energy 131 (2019) 1–11

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Accounting for low solar resource days to size 100% solar microgrids power systems in Africa

N. Plain [a, b, c, *], B. Hingray [a], S. Mathy [b]

[a] Univ. Grenoble Alpes, CNRS, IGE UMR 5001, Grenoble, F-38000, France
[b] Univ. Grenoble Alpes, CNRS, INRA, Grenoble INP, GAEL, UMR 5313, Grenoble, F-38000, France
[c] Schneider Electric Strategy and Innovation, F-38000, Grenoble, France

ARTICLE INFO

Article history:
Received 4 April 2018
Received in revised form
31 May 2018
Accepted 8 July 2018
Available online 11 July 2018

Keywords:
Low solar resource days
Service quality level
Solar isolated microgrids
Rural electrification
Sub-Saharan Africa

ABSTRACT

In many regions worldwide, the electrification of rural areas is expected to be partly achieved through micro power grids. Compliance with the COP21 conference requires that such systems mainly build on renewable energy sources. To deliver a high power and quality service may be difficult to be achieved, especially when micro-grids are based on variable renewable sources. We here explore the multiscale temporal variability of the local solar resource in Africa and its implication for the development of 100% solar systems. Using high resolution satellite data of global horizontal irradiance (GHI) for a 21-year period (1995–2015), we characterize the seasonality and temporal variability of the local resource. We focus on its low percentile values which give a first guess on the size of the solar panels surface required for the micro-grid to achieve a given quality service. We assess the characteristics and especially persistence of the low resource situations, for which the local demand would not be satisfied. We finally assess how the ability of electricity consumers for some day-to-day flexibility (e.g. via the postponement of part of one day as demand to the next), would help to achieve the design level of service quality with a smaller microgrid system.

1. Introduction

In 2016, 1.1 billion people lack access to electricity in the world [1]. Sustainable Development Goals number 7 has set a target for 2030 to extend access to “modern forms of affordable, reliable and sustainable energy” to the entire world population. Compliance with the COP21 objective signed in 2015 in Paris, to limit global warming below 2 °C requires that this electrification is based on carbon-free electricity generation [2]. In this context, variable renewable energies (VRE) have a decisive role to play.

However, an additional constraint to the achievement of these objectives is that globally 80% of people without access to electricity live in rural or even isolated areas where it can be difficult and too expensive to operate or consider a connection to the main power network.

The electrification in rural areas is expected to be partly achieved in the next decades through the deployment of off-grid systems and microgrids. According to the IEA [3], of the 315 million of African people expected to have access to electricity by 2040, 80 million are expected to access it through off-grid systems and 140 through microgrids (MG). The development of MG raises a large number of issues, which have been given even more attention in the recent years [4]. Among those, the technical and socioeconomic feasibility conditions are at the center of several works [5].

These works usually consider hybrid MG, where VRE production (solar, wind and/or hydraulic) is supplemented by biomass and/or diesel generator [6–11]. The possibility of developing MG with renewable energy alone is however a crucial issue whether to contribute to the deep decarbonization pathways required to limit climate change below 2 °C [12], or to be able to do without oil, an energy source for which it is difficult to ensure a regular supply in remote areas and which could become increasingly expensive in the medium term.

MG based on solar resource only are worth some specific attention. They may be especially relevant for several regions such as in Africa where the solar resource is abundant [6,13,14]. They also present many other advantages: a continuous increase in the efficiency [15] and a sharp decrease of the cost [16,17] of solar panels, a rapid installation, a low maintenance cost, a possible construction

* Corresponding author. Univ. Grenoble Alpes, CNRS, IGE UMR 5001, Grenoble, F-38000, France.
E-mail address: nicolas.plain@univ-grenoble-alpes.fr (N. Plain).

https://doi.org/10.1016/j.renene.2018.07.036
0960-1481/

Abbreviations

JJA	June, July, August
MAM	March, April,May
MG	Microgrid
MGS	Microgrid System
PQR	Power and Quality Requirement
PX	Percentile Xth
SON	September, October, December
SQL	Service Quality Level
SSA	Sub-Saharan Africa
TOA	Top-Of-Atmosphere
VRE	Variable Renewable Energy
DJF	December, January, February
DSL	Demand Satisfaction Level

next to places of consumption reducing the cost of distribution lines, a high degree of modularity to keep up with the possible increase in demand. 100% solar MG are likely to be the only relevant solution in several locations, for instance in regions with a very low and/or irregular wind and hydro resource or in sites far from water courses.

One of the criteria necessary for the deployment of MG is to deliver a high power and quality requirement (PQR) for users, i.e. to meet demand at an affordable price for all consumers and always outside a low and considered acceptable level of failure [18]. The multiscale variability and intermittency of the solar resource, its seasonality or periods of low levels can make this objective difficult to be achieved in several locations worldwide.

The technical-economic implications of the high frequency (e.g. sub-daily) variability of the resource and the day-to-day and low-frequency variability (between different days, seasons and years) are not the same.

In the first case, there is a question of satisfying at every moment a request potentially very variable in time while ensuring the stability of the MG. This requires managing the intermittency of the resource and its temporal mismatch with the demand. This is for example the passage of a cloud, causing a sudden decrease in solar production. Similarly, at lower frequency, the demand profile often has a peak in the morning and another in the evening when the solar resource is close to zero. The impact of this variability on the sizing of MGS has already been extensively explored in the literature, particularly about the sizing of batteries necessary for the temporary and very high frequency storage and release of excess energy produced during the day [19–21].

The day-to-day and seasonal variability of the solar resource will obviously impact the functioning of MG. Partly driven by weather conditions, the solar resource regularly presents low to very low extremes, which may moreover show some persistence and last several days or even weeks, leading to so-called solar production droughts [22]. In hybrid systems, the low photovoltaic (PV) production during low solar resource periods or seasons is compensated by a larger use of diesel generators [23] and there is no reason for the PQR of the MG to be affected by such low resource periods. The more frequent and the more intense the low resource, the more frequent and the higher the energy produced from diesel generators. The existence of low solar resource periods or seasons would conversely prevent 100% solar off-grid systems delivering the expected power service quality unless an over-investment in PV capacity or in large storage capacity. If the day-to-day and low frequency variability of the solar resource was systematically disregarded in hybrid MG projects, it can obviously not be ignored in diesel free MGs where solar is the main, if not the only, energy source. Early work on the study of solar resource variability for PV systems dates to the 1980s [24–28] focusing mainly on the seasonal and spatial variability of the resource. Recent works have roughly followed similar objectives, making use of the high-resolution and much longer database nowadays available worldwide [29–31]. As reported recently [32], there is, however, still a poor understanding of solar resource variability in regions such as Europe where a strong penetration of VRE is sought in a very short term (27% of renewables in energy consumption by 2030 [33]). Furthermore, all studies were produced in a context where solar production is integrated in national power system grids, ignoring thus variability issues potentially critical for autonomous and local scale power systems. The need to develop 100% solar systems in several locations worldwide definitively calls for comprehensive analyses dedicated to those multiscale variability issues.

In our work, we focus on Africa where very important expectations have been declared on solar PV development for the electrification of populations in rural areas [34]. In this context, we thus characterize some variability features of the local solar resource expected to be relevant for 100% solar MGs. We consider the variability of Global Horizontal Irradiation (GHI) that is the main driver of PV production. As mentioned above, a key issue with a 100% solar production is the sub-daily temporal mismatch between the resource and the demand. In our work, we disregard this issue and focus on the day-to-day and low-frequency variability of the resource. We assume that this mismatch issue can be solved with some appropriate sub-daily storage facility obtained from battery or whatever other storage technology [6,35].

Section 2 presents the study area and the solar radiation datasets. Section 3 describes some variability features of the local solar resource relevant for 100% solar MG and how they vary according to African regions. We especially characterize the low resource daily values, directly related to level of power service quality that can be achieved somewhere. We give then some insights on the characteristics of low solar resource periods, which correspond to periods when the supply-demand balance is likely to be difficult to be established. The results are discussed in Section 4 and Section 5 concludes the study.

2. Study area and data

We consider the whole African continent, from the latitude of $-34.5°$ in south Africa to $37.21°$ in Tunisia and from longitude $-17.32°$ in Senegal to $51.25°$ in Somalia. With more than 1.2 billion inhabitants, Africa is the second most populous continent after Asia and represents 16.4% of the world's population in 2016. Africa is crossed, almost in its middle, by the equator and presents several climates: hot and humid close to the equator, tropical in the regions between the equator and the tropics, hot and arid around the tropics, temperate in the highlands.

We use GHI data from: Surface Solar Radiation Data Set - Heliosat (SARAH) - Edition 2 produced by the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) [36]. Data are available from January 1, 1983 to December 31, 2015 and cover the area $\pm 65°$ longitude and $\pm 65°$ latitude. Instantaneous radiation data are available every 30 min with a spatial resolution of $0.05° \times 0.05°$. This database is obtained by satellite observations of the visible channels of the MVIRI and SEVIRI instruments aboard several Meteosat geostationary satellites that have succeeded one another.

[41] found some horizontal stripes artifacts in the Meteosat GHI data over the period 1983–1994. We, therefore, select the 1995–2015 period for our analysis. In the following, we

characterize the variability of the resource based on 21-year time series of mean daily GHI values derived from local 30-min GHI data.

3. Results

3.1. Mean solar resource and its variability

The mean annual and seasonal values of GHI obtained for the 1995–2015 period are presented in Fig. 1. The Earth's revolution around the sun and the weather variability are the two main drivers of the temporal variations of GHI. As described in many publications, the mean annual GHI is on average globally higher for areas of medium latitude compared to the ones near equator. The high nebulosity in central and west Africa near equator can explain this relatively lower resource level [42]. Conversely, the mean annual GHI presents high value in desert areas: the Sahara in the north and the Kalahari in the South West. It tends then to decrease for high latitudes (e.g. Maghreb and south of South Africa).

In most African regions, the seasonality of GHI follows globally that of the Top-Of-Atmosphere (TOA) radiation (see supplementary material). The seasonality is low to very low close to the equator and, compared to other periods of the year, GHI is much higher in North Africa from March to August and in the southern part of Africa from September to February. The seasonality of GHI is conversely in phase opposition with that of TOA radiation for a wide horizontal band to the north of the equator (latitude between $0°$ and $+15°$). In here, GHI is higher in DJF than in JJA. This results from the cycle of nebulosity in this area, which is much more important in the JJA season, as a result of the west African monsoon onset in that period [43]. A similar but less pronounced phase opposition signature is found in the south-eastern part of Africa with a rather low GHI resource in DJF (southern hemisphere's summer) compared to JJA (southern hemisphere's winter). This results here also from the monsoonal circulation which takes place over the southern part of the continent during the southern hemisphere's summer leading to high nebulosity and precipitation amounts from Angola on the west coast of southern Africa all the way to Madagascar [44].

Fig. 2 maps the coefficient of variation of daily GHI values, for the whole period and for each season S in turn, estimated as $CV_S = \sigma_S/\mu_S$ where μ_S is the mean daily GHI for season S (or for the whole period if $S = 0$) and where $\sigma_S^2 = 1/(n\text{-}1)\ \Sigma_{j\in S}\ (\mathrm{GHI}(j) - \mu_S)^2$ is the standard deviation of daily values GHI(j) for season S (or for whole period).

At an annual scale, the variability mainly depends on latitude. It roughly increases northward and southward with basically two main exceptions: near the equator where the variability is relatively high (e.g. Gabon, Congo Democratic Republic) and in the southern part of the Sahara region where the variability is much lower than elsewhere.

Depending on the location, the daily variability can also vary a lot from one season to the other. This is for instance the case for the north part of Namibia and northern Africa which presents a much lower variability in summer compared to the other seasons. This is also illustrated in Fig. 3 which presents for a set of 15 grid points (for 1995–2005) the mean interannual cycle of daily GHI and for each calendar day the values of the 10th and 90$^{\mathrm{th}}$ percentiles of daily GHI (P10 and P90 resp.). The day-to-day variability, expressed by the inter-percentile distance, depends a lot on the grid point and the season considered. For instance, for the extreme south-west grid point near Namibia, it is very low in the JJA season where the P10 and P90 curves are almost confused and it is conversely very large in the other seasons.

The variability within each season is obviously related to the day-to-day weather variability. The variability of GHI obtained for the whole year additionally depends on the seasonality of TOA radiation resulting from the Earth's revolution around the sun. The percentage of the annual variability explained by the seasonal and rather predictable component of the resource is presented in Fig. 4. As already suggested from previous graphs, the annual variability is almost fully explained by the mean seasonal cycle of the resource in the North and in the South of Africa whereas it is almost fully

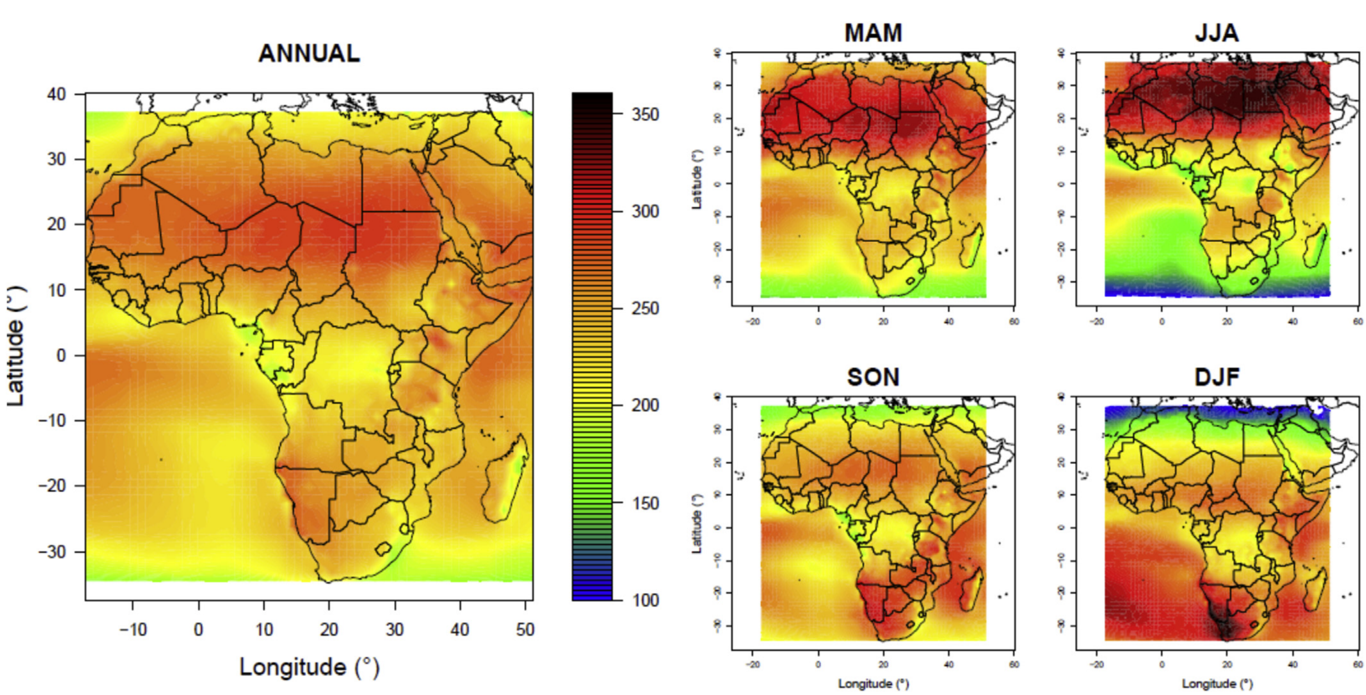

Fig. 1. Mean daily GHI in W/m^2 (annual mean (left) and seasonal means for 4 seasons (on the right) (MAM: March, April, May; JJA: June, July, August; SON: September, October, December; DJF: December, January, February) for the period 1995–2015.

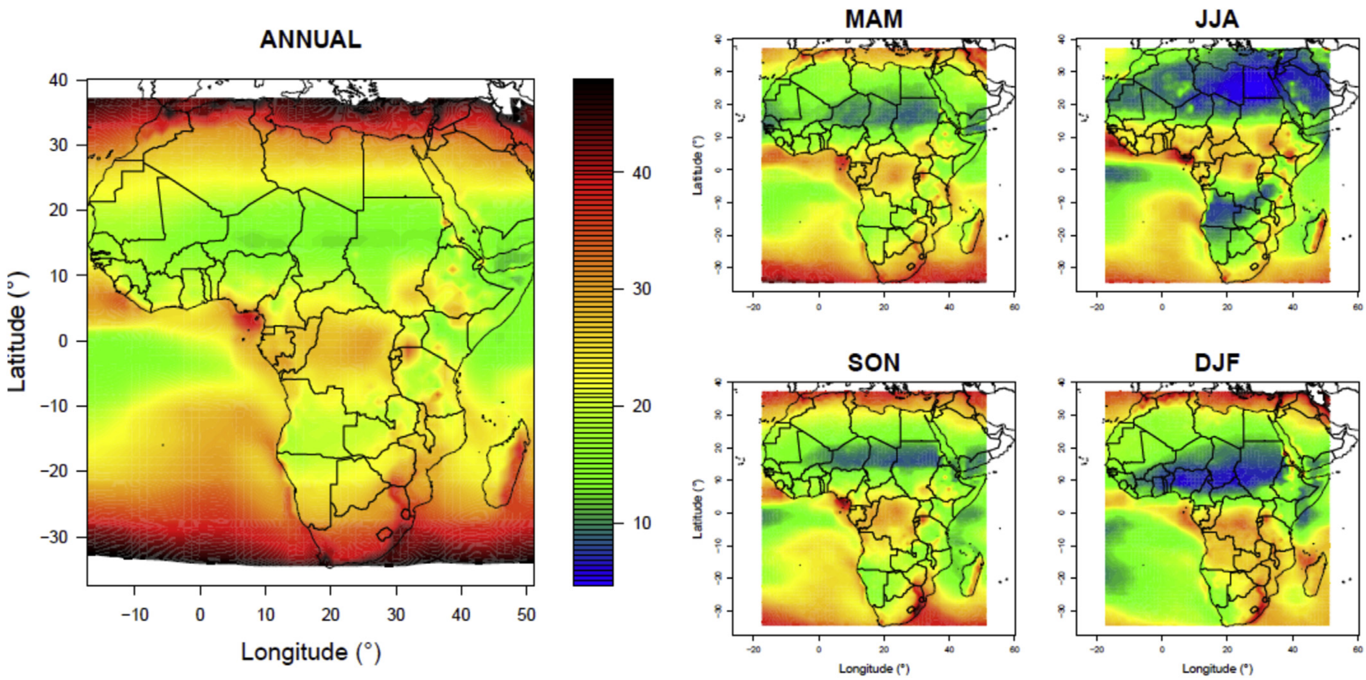

Fig. 2. Temporal variation coefficient of the daily GHI in percentage (total (on the left) and for the 4 seasons (on the right)) for the period 1995–2015.

explained by the day-to-day variability of weather around the equator.

3.2. Low resource percentiles

In a 100% solar MG configuration, days with low solar radiation are expected to be rather critical. They will likely lead to configurations where not enough electricity can be produced to satisfy all the potential loads, unless overinvestments in PV panels or in energy storage or unless demand side management shifts some energy uses to a period without solar resource problems. The quality level of the power service will be then partly determined by the occurrence probability of the low resource days.

The use of some day-to-day storage facility could allow to supply the required energy for low resource days, using the energy in excess from previous days. Here, we assume that the available storage only allows to cope with the sub-daily production/demand mismatch and that it is too small to allow the storage of excess energy produced during high resource days for a further use to low resource ones (see discussion Section).

In this configuration, the service quality level (SQL) obtained with a given MG will mainly depend on the amount of energy produced for the low resource days. For a given location, the amount of available energy increases with the size of the PV fleet. The more the surface of PV panels, the larger the production, the easier it will be to satisfy the demand each day, especially for days where the GHI is low or very low. In a 100% solar MG, a way to increase the SQL is thus to oversize the PV fleet [45,46].

SARAH GHI data allow to extract for each location the statistical distribution of daily GHI values. The low percentiles of daily GHI values give, in this context, a rough estimate of the equipment level that would be required to obtain a given SQL. Let for instance assume that the MG is designed so that the mean daily demand D kWh is satisfied more than 95% of the days. Let then consider Q_5, the daily production that can be obtained for 1 m^2 of PV panel from the 5th percentile of daily GHI amounts. The daily production for 1 m^2 of PV will be then equal or greater than this Q_5 value for 95% of the days. Consequently, the daily production from a PV panel fleet of D/Q_5 m^2 will be equal or greater than the requested demand D for 95% of the days. D/Q_5 m^2 of PV panels is thus enough to insure a Demand Satisfaction Level (DSL) of 95% (as long as we do not consider demand side management). A significant part of the energy production will be wasted but in counterpart, the demand will be satisfied 95% of the days.

As a result of the sub-daily variability of the demand, the resource, and the storage/release operations of the sub-daily storage facilities, the link between a given GHI percentile and the percentage of days where the demand is satisfied is not fully direct. Assuming that the daily demand is roughly constant in time and there is no multiple day storage facility, this link is, however, significant and the X^{th} percentile of the daily GHI statistical distribution is a rough but rather robust indicator of the resource value to be considered for the design of a 100% solar MG with the objective to have (100-X)% of days where the electricity demand is satisfied (see supplementary material, Fig. A1–A3): the higher the percentile value, the smaller the area of solar panels required to satisfy a given power demand amount.

Fig. 5 presents the percentile 1 (P1) and the percentile 5 (P5) of daily GHI values obtained from the period 1995–2015. In both cases, the spatial pattern of the percentile is very similar to the one obtained for the CV of daily GHI values (Fig. 3). In the northern part of Africa, except in the extreme north, P5 is relatively high especially in the southern part of Sahara. High values are also observed in the southwest region. Near the equator and in the southeast area, low value of P5 are observed especially because of the high cloudiness in these areas.

This is informative to compare for each location those percentile values to the mean GHI value. If the ratio is close to 1, this means that even during low resource periods, the solar resource is not too small and remains close to the average value Qmoy. On the contrary, if the ratio is much higher during these periods, the resource is very low.

In a number of places, P5 is very close to the mean GHI value. This means that the oversizing required to achieve a 95% DSL is

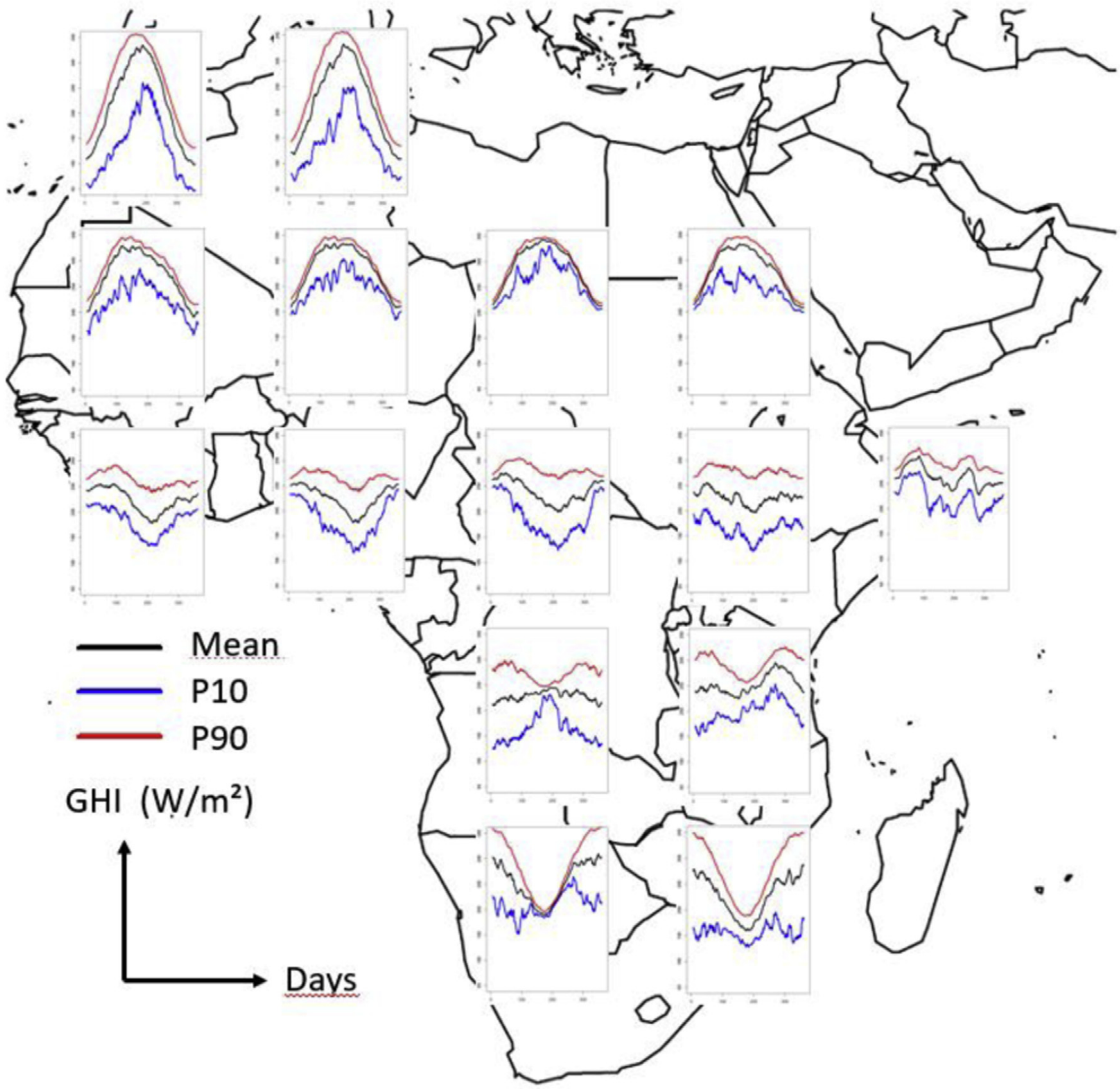

Fig. 3. Variability of daily GHI values [W/m^2] for 15 SARAH grid points in different African climates. Mean value (black), 10th (blue) and 90th (red) percentiles of daily GHI for each calendar day (1995–2015 period). See location of grid points in Fig. A1 of Supplementary Material. Scale for the y-axis: from 50 to 350 W/m^2. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

rather limited. This is the case in a large part of the Sahara region and of Namibia. Expected in the very northern parts of the Maghreb and some limited regions of South Africa, the P5 is never smaller than 2 to 2.5 times the mean resource. Oversizing solar farms by a factor 2.5 would allow to satisfy the demand with a 95% DSL roughly everywhere in Africa. To get a higher DSL, the oversizing requirement can be much higher. The P1 can be 4 to 5 times lower than the mean GHI, especially in central Africa and in the extreme south-east. Moving from a 95% DSL to a 99% DSL would imply an additional oversizing factor of 1.5–2 (Fig. 6, right).

These ratios provide us with orders of magnitude of the solar panel oversizing induced by the low percentile values to achieve a given SQL.

3.3. Required surface of PV panels for each kWh of demand

The percentiles estimated previously allow estimating the peak power of solar PV panels, further referred to as P_{Peak} , required to satisfy a given daily demand D_0 with a given SQL. P_{Peak} gives the amount of production that would be obtained with the considered PV installation for an idealistic solar radiation power of 1000 W. In the recent years, the efficiency of different technology for solar cell ranges from around 10%–30% leading to peak power ranges between 100 and 300 W per m2 of solar panel depending on the PV technology [15]. The peak power required to achieve a given electricity demand thus directly informs about the number of PV panels required in the PV farm, and about the cost of the PV farm depending on the cost of that technology.

For a given PV installation, the instantaneous PV production at a given time depends on GHI and temperature for that time. It is expressed as [8].

$$Prod_{PV} = P_{Peak} * \left(\frac{GHI}{1000}\right) * \eta_{MPPT}(T) \tag{1}$$

where $Prod_{PV}$ is the electricity production of solar panels (in Watt), P_{Peak} the electricity production considering a GHI equal to 1000 W/m^2, GHI is the global horizontal irradiance in W/m^2 and $\eta_{MPPT}(T)$ is the efficiency of the PV module depending on the ground temperature. As first approximation and for the sake of simplicity, we

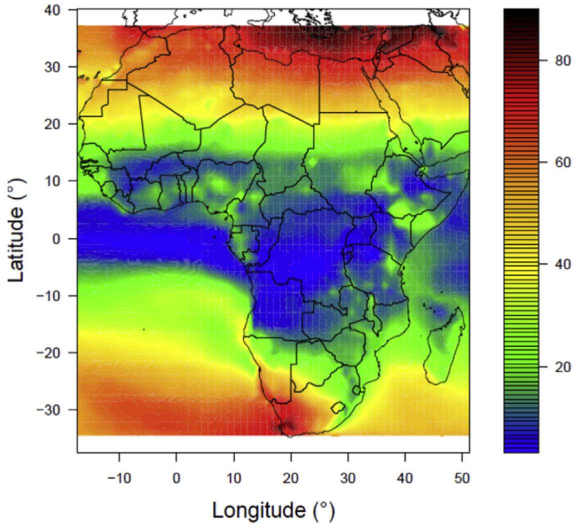

Fig. 4. Percentage of the day-to-day variability explained by the seasonal component of the GHI. The percentage is expressed as $\alpha = \sigma_1/\sigma_0$ where σ_0 is the standard deviation of daily GHI values calculated from all daily data in the 1995–2015 period ($\sigma_0^2 = 1/(n\text{-}1)\ \Sigma_{j=1.n}(\mathrm{GHI}(j) - \mu)^2$ where GHI(j) is the daily GHI value for day j, μ is the mean daily GHI for the period and n is the number of days in the period) and where σ_1 is the standard deviation of daily GHI values calculated from the 365 daily values of an average year ($\sigma_1^2 = 1/(365\text{-}1)\ \Sigma_{d=1.365}(\mathrm{GHI}(d)\text{-}\mu)^2$ where (GHI(d) is the inter-annual mean GHI (mean over 21 years) for the calendar day $d = 1.365$).

set this efficiency to one, considering that the temperature is all the time equal to the standard temperature.

The result for the electricity production for a specific day j is:

$$Prod_{PVj} = P_{Peak}{}^{*}\left(\frac{GHI_j}{1000}\right) \tag{2}$$

To have a mean daily production that equals in average to the mean daily demand D_0 in kWh, the required P_{Peak} has the following expression:

$$P_{Peak} = \frac{1000^{*}\ D_0}{24^{*}mean(GHI)} \tag{3}$$

Similarly, to have a mean daily production that equals in average to a given percentile value, the required P_{Peak} is:

- With a 95% DSL target:

$$P_{Peak\ P5} = \frac{1000^{*}\ D_0}{24^{*}P5(GHI)} \tag{4}$$

- With a 99% DSL target:

$$P_{Peak\ P1} = \frac{1000^{*}\ D_0}{24^{*}P1(GHI)} \tag{5}$$

In the following (Fig. 7), the peak power necessary to satisfy 1 kWh of demand is mapped for both DSL 95% and 99%.

P_{Peak} is proportional to the inverse of the percentile values used (Fig. 5). In areas where low percentile values are important, P_{Peak} is low, like in the Sahelian band. On the contrary, near the equator, in south-east and extreme north of Africa, P_{Peak} is really high compared to other areas. P_{Peak} required to achieve the 99% DSL is logically 1.5 to 2.5 times higher than the one for the 95% DSL (except in the Sahelian band where the P1 and P5 are similar).

4. Discussion

4.1. Low solar resource sequences

Beyond the level of the resource during the low resource periods, sizing a MG to achieve a given SQL should also consider the temporal organization of the low resource days and sequences during the year. The seasonality of the low solar resource days is presented in Fig. 8. Results obtained for the P1 percentile (not shown) are very similar to those obtained for the P5 percentile.

As expected, the percentage of days below the P5 values varies significantly from one season to the other. To the north of the 15° latitude North and especially in the east, most of the low resource days occur during the northern hemisphere's winter (DJF). As a result of the West African monsoon, this is not the case between 0° and ~+15° of north latitude, where most of the low resource days occur in the northern hemisphere's summer (JJA). A similar result is obtained for the band between 0° and 15° South. Most low resource days are during the southern summer (DJF) whereas the southern winter (JJA) presents the smallest number of such days. In

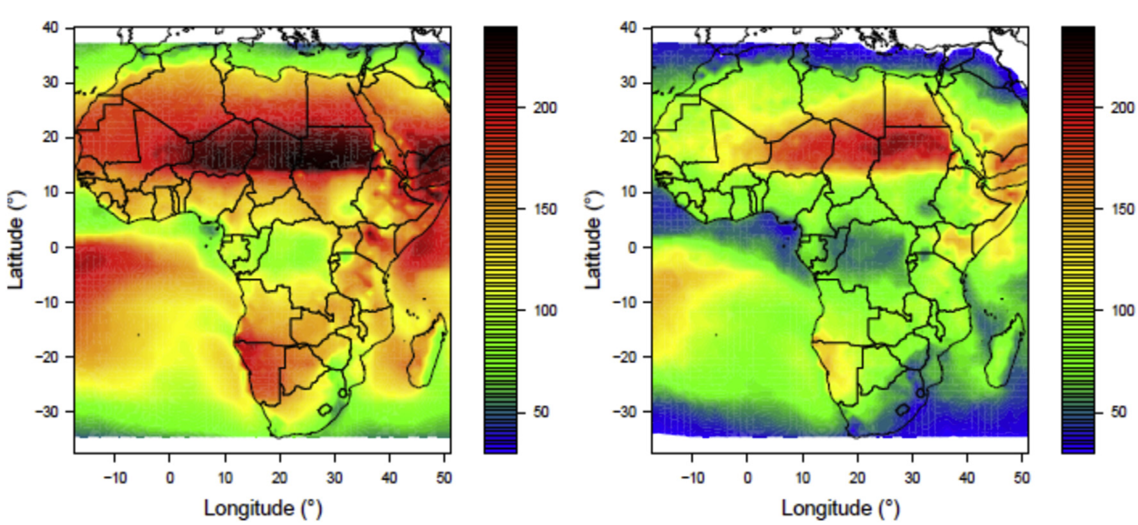

Fig. 5. Percentile 5 (left) and Percentile 1 (right) of the daily GHI for the period 1995–2015 in W/m^2.

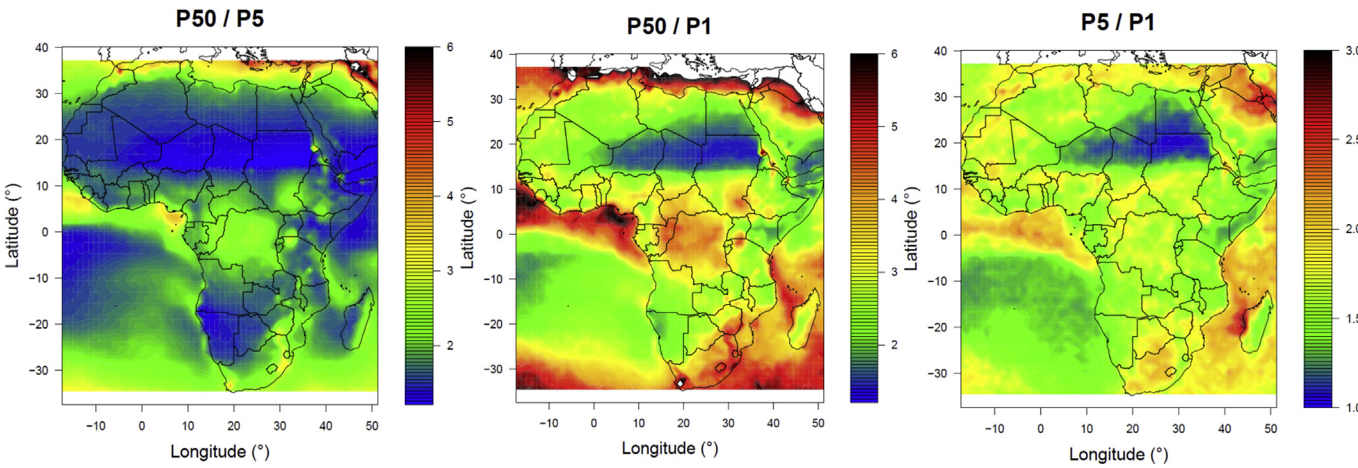

Fig. 6. Ratio of Percentile 50 on the Percentile 5 (left), Percentile 50 on the Percentile 1 (middle) and Percentile 5 on the Percentile 1 (right) of the daily GHI for the period 1995–2015.

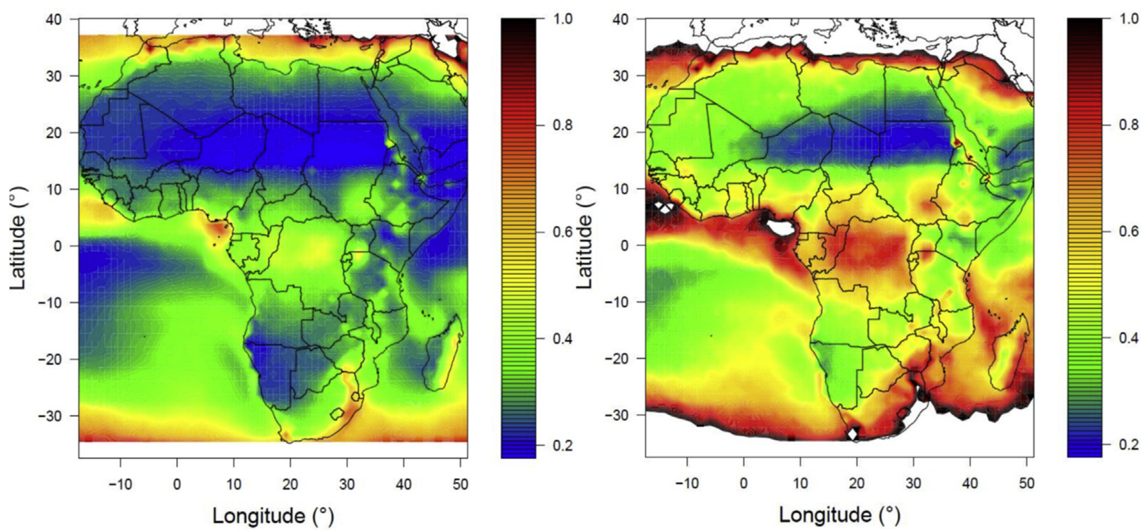

Fig. 7. Peak power of solar PV panels (in kWp) needed to satisfy 1 kWh of daily demand when calculated with the percentile 5 (left) and 1 (right) of the daily GHI for the period 1995–2015.

several African regions, the QSL in a 100% solar MG can thus significantly vary from one season to the other.

Another important feature to characterize the SQL for a 100% solar off-grid system is the temporal persistence of low resource situations. For a same number of low resource days, configurations where those days follow each other would likely have more negative impact than configurations where such days are never consecutive but conversely occur from time to time. The mean duration of time sequences of days with a GHI lower than the P5 is presented in Fig. 9. The maximum duration of such sequences is presented in the supplementary material (Fig. A5).

The average number of consecutive days inferior to P5 is close to 1 almost everywhere in Africa except in areas of higher latitude where we can have 1.5 up to more than 3 days in the north east part of Africa. These rather long low resource sequences are actually a direct consequence of the fact that, in this area, the variability of the daily GHI is mostly driven by the Earth's revolution, especially in the northern hemisphere's winter where most low GHI days occur (see the very low variability of the daily GHI for DJF in Fig. 3). Following that of the TOA irradiation, the persistence of GHI is thus very high, leading to long sequences of low GHI resources. Except in this area, the low resource sequences are on average restricted to one day.

The production during such periods is, however, not necessarily zero. It is “just” below the P5 level. Assessing the real impact of such events would require to estimate the amount of not-satisfied energy during this period. In all cases, the socio-economic impacts and the viability of the system to such extreme events should be analyzed carefully, checking for instance if the production would be at least enough to supply the electricity requirements for vital uses such as those needed for hospitals or some food related processes highly sensitive to lost-of-load events (continuous throughout a week or multiple weeks or months food transformation/conservation processes).

All in all, the seasonality of the low-resource occurrence and their persistence characteristics should be also additional variability features to account for in the design of 100% solar MGs. The requirement for a rather constant year-round SQL and for short duration low resource sequences would likely imply to further oversize the production system or could even make such systems

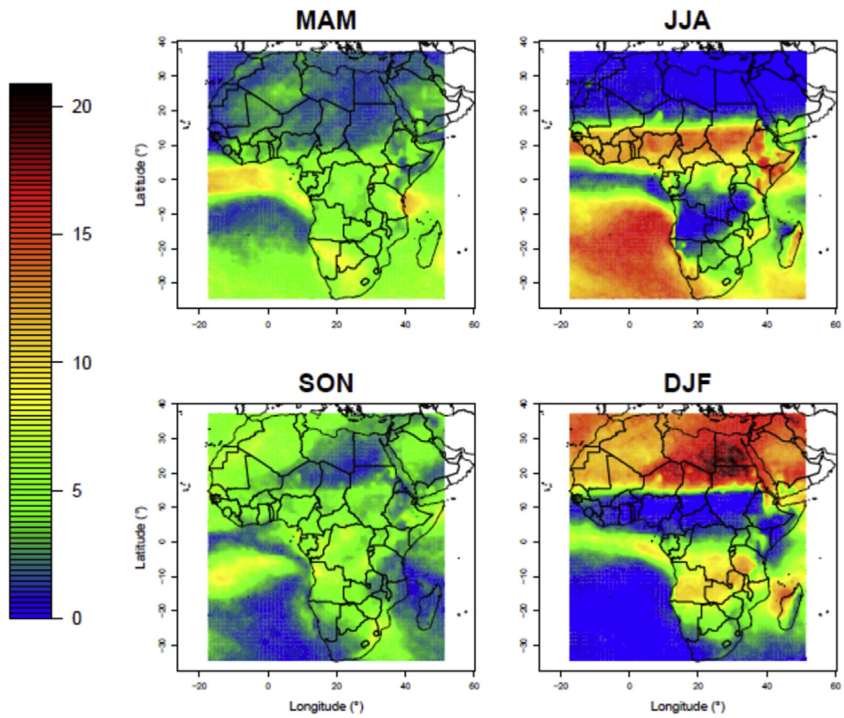

Fig. 8. Percentage of days inferior to the percentile 5 of the daily GHI for the period 1995–2015.

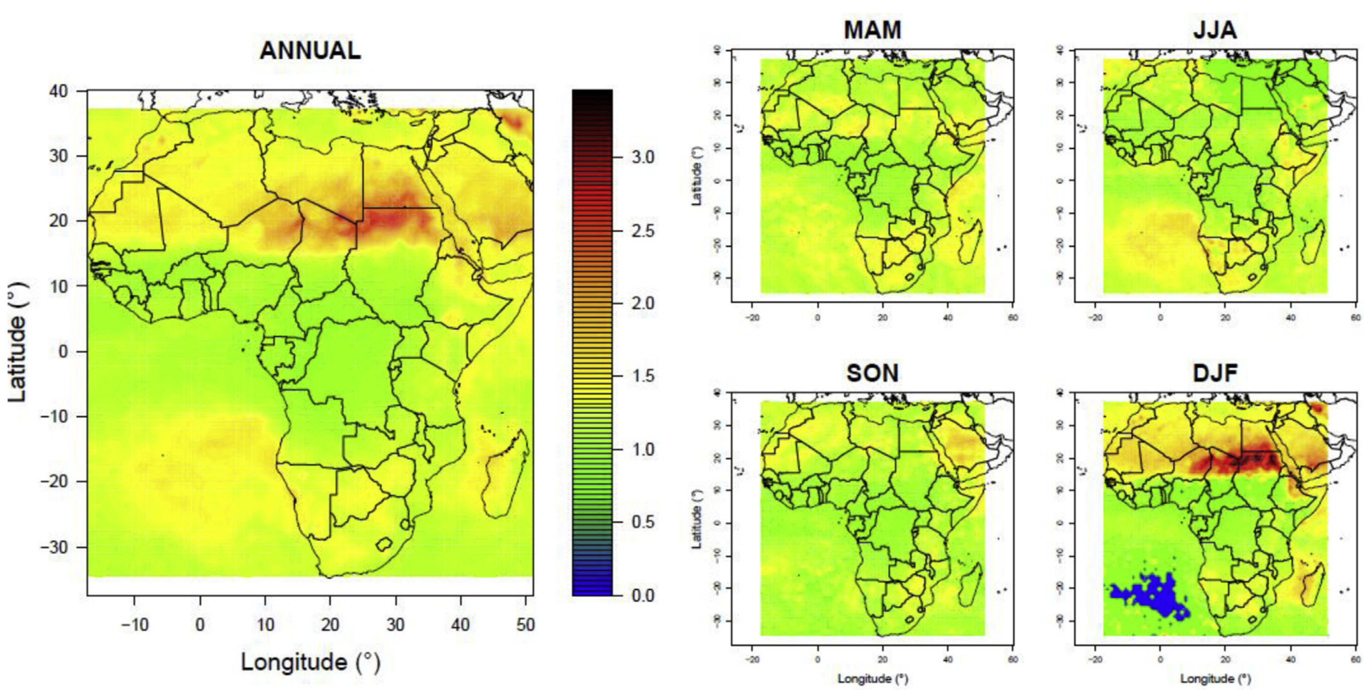

Fig. 9. Average duration period (in days) of consecutive days inferior to the percentile 5 of the total daily GHI (left) and for the 4 seasons (right) for the period 1995–2015.

not relevant.

4.2. *Demand flexibility and effects on MG design*

The percentage of days for which the electricity demand is not fully met has been taken in the article as a proxy for the service quality. Implicitly, we have also considered the daily demand as an exogenous and determined quantity. However, in a number of cases, some consumers could have the possibility to adapt to the day-to-day availability of the resource, postponing for instance part of their electricity demand from one day to another. This could be achieved with dedicated power resource forecasts that would inform and allow volunteer consumers to anticipate some postponement requirement. This could be also achieved with specific pricing systems for consumers ready to adapt their electricity demand. The possibility for such flexibility could impact significantly downward the sizing of the MGs, and thus the electricity price. As an illustration, we can consider that, for a given number of days in the year, and for consumers who subscribe a “flexibility” service contract, part of electricity uses planned during these days can be carried over to the next day if the solar resource is available.

The implementation of such demand-side solutions would be effective if for each 2 consecutive days sequence, the mean energy production is larger than the mean energy demand over that 2-day sequence. For a rough assessment of the size of the MG required for a given quality level, we could thus consider the low percentile values of the mean GHI value over 2 consecutive days. The P1 and P5 percentiles of this 2-day mean GHI variable is presented in Fig. 10. Compared to ones calculated with the daily GHI, these 2-day low percentiles are 1.5–2 higher, especially in areas where the 1-day P1 and P5 percentiles have low value (near the equator, in central Africa). This “flexibility” service contract can, therefore, have important cost reduction effects on the electricity produce with the MG and may be considered by the operator when sizing the project.

In other words, a one- or few-days flexibility of part of the demand could lead to much smaller MG requirement for a same SQL.

5. Conclusions

In this article, we performed a rough assessment of the level of PV equipment needed for a 100% solar MG to achieve a given SQL. The SQL is evaluated from the percentage of days for which the demand for electricity is satisfied. We used for this evaluation high-resolution radiation satellite data for a 21-year period, which are supposed to give a good picture of the local resource variability.

For a given location, the targeted SQL can be achieved by oversizing the surface of the PV panel fleet. We here provided an estimate of this oversizing requirement from the low percentile values of the daily GHI. In our context, sizing on the 5% percentile (resp. 1%) of the daily resource roughly allows to achieve that the demand is satisfied for 95% (resp. 99%) of the days. The surface of PV panels required when the MGS is sized with this 5% percentile is 2–3 times compared to the surface estimated from the mean annual GHI resource. The oversizing required to achieve a 95% DSL is thus “rather” limited. Conversely, targeting the 99% DSL would additionally require increasing the surface by a factor of 2.

In a first approximation, the SQL that can be achieved for a given MG depends on the value of the chosen daily GHI percentile (the sizing percentile). The SQL is also obviously expected to depend on the regularity in time and on the persistence or not of the days below the sizing percentile.

On the one hand, in a number of regions, days where the resource is lower than the sizing percentile are clustered in a given season. This would thus make the SQL variable in time. This may be not acceptable for a number of configurations, calling for a more restrictive SQL criterion and likely next, an increased size of the MG.

On the other hand, in most regions, the low resource days mostly occur individually, a rather convenient configuration, as soon as a part of the not-satisfied demand can be postponed to some days later when some extra solar resource is available. In a few areas, mainly located in the Sahara where the resource is not a lot influenced by the weather, the low resource days can be clustered within some temporal multiple days sequences. Such areas would obviously require a deep analysis of the potential socio-economic effects of such long solar drought events and a throughout assessment of the resulting system viability.

Our work was based on a number of assumptions, data and modelling choices, which potentially led to some uncertainty in the results. Our results were obtained with the high resolution SARAH radiation data. Satellite derived radiation data are frequently used to characterize the solar resource potential on large area since ground measurement have limited spatial coverage (e.g. Refs. [29–31,39]). SARAH data have been found to present good estimates of GHI when compared against high-quality ground measurements from stations of the Baseline Surface Radiation Network (BSRN) [37]: the bias and the mean absolute bias present for instance remarkably low values (1.12 and 12.1 W/m^2 respectively [38]). BSRN stations are however mainly located in Europe and Northern America and unfortunately, the number of stations in the African continent is very limited (5 stations). The quality of radiation data for this continent is thus roughly unknown. A recent comparison with radiation data from six ground stations of the Kenyan national measurement network suggests that the quality of SARAH data is reasonable in this region (correlation of roughly 0.5 on average between observed and SARAH monthly means) [31]. To our knowledge, no such evaluation was published for other regions of Africa. The lack of ground measurement data for a throughout

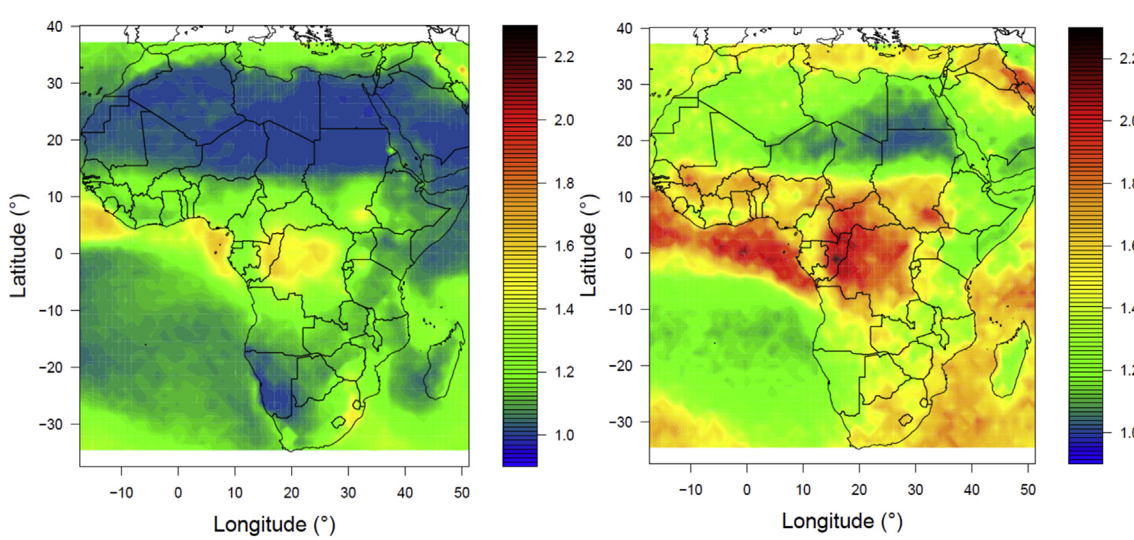

Fig. 10. Increase in low percentile values of daily GHI when estimated over a 2 days moving average window. Left: ratio between P5 values calculated respectively from 2 days mean GHI data and from raw daily data. Right: the same with P1 (percentiles obtained for period 1995–2015).

evaluation of the data across the continent is obviously a critical limitation and our results should be considered with care; they can especially not be used *stricto sensu* for the design of real projects.

The unknown quality of radiation data is obviously also a critical limitation for all projects that aim to develop solar systems in this continent. In this context, a major international effort for the deployment of a solar radiation measurement network, even if not that dense is definitively required. When one considers the very large societal demand for solar PV MG in the region, this effort could obviously imply governmental institutions (meteorological services, research laboratories) but also local communities and private companies. Numerous ground measurements are actually carried out at the present time in Africa for the development and management of numerous new solar power projects. Those data, when made available for all, would definitively give a great contribution to a better assessment of the quality of satellite radiation data and in turn to a better knowledge of the solar resource in Africa.

All in all, conversely to ground measurements, satellite data are available at high space-time resolution and classically cover rather long periods of time, even in ungauged regions. They produce definitively a valuable information and our analysis is expected to give a reasonable picture of some important features of the solar resource variability and low percentiles in this region. It allowed also to identify regions where the development of 100% solar MGS could be less costly than elsewhere. Further work would be worth to assess the sensitivity of such analyses to other satellite products. In all cases, such satellite data should be complemented and bias-corrected with ground measurements to be collected in places where projects are envisioned.

In our analysis, which ignores intraday supply-demand adequacy problems, we considered that the low percentile value of the daily resource determines the size of the PV fleet to be used in the MGS. This approach is to be related to the approach frequently used in a configuration where the production is obtained from hydropower. In such a case, the available resource that has to be considered for the MGS development is usually evaluated from a low flow characteristic variable extracted from the so-called flow-duration-curve. The 95% or 90% percentile of this curve is often used as design available discharge. Of course our approach lacks an overall consideration of the economic dimension. The cost of oversizing the PV fleet could be prohibitive. On the other hand, one could consider the possibility of multiday storage. We here assumed that the available storage only allows to cope with the sub-daily production/demand mis-match. The use of some multiday storage facility could allow to supply the required energy for low resource days, using the energy in excess from previous days. It would thus in turn reduce the need for oversizing. Disregarding the potentially critical issues relative to storage (e.g., environmental and technical constraints, life duration of batteries), one should consider the socio-economic interest of adding such multiday storage facility in the system. Considering the full cost of the storage/PV panel fleet system would allow to identify the best compromising storage/oversizing configuration; the latter may be rather different from that estimated here. Such an analysis will be carried out in a future work. It will require simulating the functioning of the MGS considering the temporal evolution structure of the demand. The sub-daily variations of the resource and of the demand will be of first importance as they fully determine the storage required to deal with the sub-daily production/demand temporal mismatch. The seasonality of energy uses and more particularly of energy demand for productive activities will have also to be considered (like agricultural activities which require specific and different electricity demand for long periods over the year with water pumping if needed when the cultures grow and then post-harvest processing methods). A location where the demand would share a similar seasonal pattern than the production would definitively lead to a smaller MG than a location where a seasonality mismatch between both is found. The development of productive activities whose electricity demand profile would be in line with the seasonal variability of the solar resource would undoubtedly limit the oversizing of the mini-grid and thus reduce the price per kWh supplied. The level of adaptability or flexibility to the energy demand is another issue to be considered for the optimization of the MG design. This issue will be obviously also worth some focused analysis.

Further work should also consider the interest of hybridizing solar resource with other renewables such as wind and run-of-the river hydro. The temporal complementarity between those different resources has been highlighted in a number of recent works (e.g. Refs. [45,47,48]). The complementarity of the sources for these low solar resource days would be worth a dedicated investigation as suggested by the recent work on energy droughts in different European regions by Raynaud et al. [22].

Acknowledgements

This work is part of a PhD thesis funded by the French Ministry of High Education, Research and Innovation and by Schneider Electric.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.renene.2018.07.036.

References

[1] IEA, World Energy Outlook, Organisation for Economic Co-operation and Development, OECD, 2017, 2017.
[2] M. Fay, S. Hallegatte, A. Vogt-Schilb, J. Rozenberg, U. Narloch, T. Kerr, Decarbonizing Development: Three Steps to a Zero-carbon Future, World Bank Publications, 2015.
[3] A. E. O. IEA, A focus on the energy prospects in sub-saharan africa, world energy outlook special report, International Energy Agency Publication (2014) 1–237.
[4] N. Lidula, A. Rajapakse, Microgrids research: a review of experimental microgrids and test systems, Renew. Sustain. Energy Rev. 15 (1) (2011) 186–202.
[5] P. Basak, S. Chowdhury, S.H. Nee Dey, S. Chowdhury, A literature review on integration of distributed energy resources in the perspective of control, protection and stability of microgrid, Renew. Sustain. Energy Rev. 16 (8) (2012) 5545–5556.
[6] M.D. Al-Falahi, S. Jayasinghe, H. Enshaei, A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system, Energy Convers. Manag. 143 (2017) 252–274.
[7] C. Cader, P. Bertheau, P. Blechinger, H. Huyskens, C. Breyer, Global cost advantages of autonomous solar–battery–diesel systems compared to diesel-only systems, Energy Sustain. Dev. 31 (2016) 14–23.
[8] N. Ghorbani, A. Kasaeian, A. Toopshekan, L. Bahrami, A. Maghami, Optimizing a hybrid wind-pv-battery system using ga-pso and mopso for reducing cost and increasing reliability, Energy (2017).
[9] R. Hosseinalizadeh, H. Shakouri, M.S. Amalnick, P. Taghipour, Economic sizing of a hybrid (pv–wt–fc) renewable energy system (hres) for stand-alone usages by an optimization-simulation model: case study of Iran, Renew. Sustain. Energy Rev. 54 (2016) 139–150.
[10] C. Wang, Y. Liu, X. Li, L. Guo, L. Qiao, H. Lu, Energy management system for stand-alone diesel-wind-biomass microgrid with energy storage system, Energy 97 (2016) 90–104.
[11] L. Wang, D.-J. Lee, L.-Y. Chen, J.-Y. Yu, S.-R. Jan, S.-J. Chen, W.-J. Lee, M.-H. Tsai, W.-T. Lin, Y.-C. Li, et al., A micro hydro power generation system for sustainable microgrid development in rural electrification of africa, in: Power & Energy Society General Meeting, 2009. PES'09. IEEE, IEEE, 2009, pp. 1–8.
[12] A.G. Dagnachew, P.L. Lucas, A.F. Hof, D.P. van Vuuren, Trade-offs and synergies between universal electricity access and climate change mitigation in sub-saharan africa, Energy Pol. 114 (2018) 355–366.
[13] H. Broesamle, H. Mannstein, C. Schillings, F. Trieb, Assessment of solar electricity potentials in north africa based on satellite data and a geographic information system, Sol. Energy 70 (1) (2001) 1–12.
[14] D.A. Quansah, M.S. Adaramola, L.D. Mensah, Solar photovoltaics in sub-

saharan africa—addressing barriers, unlocking potential, Energy Procedia 106 (2016) 97–110.
[15] M.A. Green, K. Emery, Y. Hishikawa, W. Warta, E.D. Dunlop, Solar cell efficiency tables (version 45), Prog. Photovoltaics Res. Appl. 23 (1) (2015) 1–9.
[16] K. Branker, M. Pathak, J.M. Pearce, A review of solar photovoltaic levelized cost of electricity, Renew. Sustain. Energy Rev. 15 (9) (2011) 4470–4482.
[17] M. Moner-Girona, R. Ghanadan, A. Jacobson, D.M. Kammen, Decreasing pv costs in africa: opportunities for rural electrification using solar pv in sub-saharan africa, Refocus 7 (1) (2006) 40–45.
[18] C. Marnay, G. Venkataramanan, Microgrids in the evolving electricity generation and delivery infrastructure, in: Power Engineering Society General Meeting, 2006. IEEE, IEEE, 2006, p. 5.
[19] S. Adhikari, F. Li, Coordinated vf and pq control of solar photovoltaic generators with mppt and battery storage in microgrids, IEEE Trans. Smart Grid 5 (3) (2014) 1270–1281.
[20] S. Chen, H.B. Gooi, M. Wang, Sizing of energy storage for microgrids, IEEE Trans. Smart Grid 3 (1) (2012) 142–151.
[21] M. Datta, T. Senjyu, A. Yona, T. Funabashi, C.-H. Kim, Photovoltaic output power fluctuations smoothing methods for single and multiple pv generators, Curr. Appl. Phys. 10 (2) (2010) S265–S270.
[22] D. Raynaud, B. Hingray, B. François, J.D. Creutin, Energy droughts from variable renewable sources in European climates, Renew. Energy 125 (2018) 578–589. https://doi.org/10.1016/j.renene.2018.02.130.
[23] B. Zhao, X. Zhang, J. Chen, C. Wang, L. Guo, Operation optimization of standalone microgrids considering lifetime characteristics of battery energy storage system, IEEE Trans. Sustain. Energy 4 (4) (2013) 934–943.
[24] H. Asano, K. Yajima, Y. Kaya, Influence of photovoltaic power generation on required capacity for load frequency control, IEEE Trans. Energy Convers. 11 (1) (1996) 188–193.
[25] M. Bouzguenda, S. Rahman, Value analysis of intermittent generation sources from the system operations perspective, IEEE Trans. Energy Convers. 8 (3) (1993) 484–490.
[26] W.T. Jewell, T.D. Unruh, Limits on cloud-induced fluctuation in photovoltaic generation, IEEE Trans. Energy Convers. 5 (1) (1990) 8–14.
[27] H.A. Lauffenburger, R.T. Anderson, Reliability terminology and formulae for photovoltaic power systems, IEEE Trans. Reliab. 31 (3) (1982) 289–295.
[28] R.C. Willson, S. Gulkis, M. Janssen, H. Hudson, G. Chapman, Observations of solar irradiance variability, Science 211 (4483) (1981) 700–702.
[29] C.A. Gueymard, S.M. Wilcox, Assessment of spatial and temporal variability in the us solar resource from radiometric measurements and predictions from models using ground-based or satellite data, Sol. Energy 85 (5) (2011) 1068–1084.
[30] M. Journée, R. Müller, C. Bertrand, Solar resource assessment in the benelux by merging meteosat-derived climate data and ground measurements, Sol. Energy 86 (12) (2012) 3561–3574.
[31] B.W. Kariuki, T. Sato, Interannual and spatial variability of solar radiation energy potential in Kenya using meteosat satellite, Renew. Energy 116 (2018) 88–96.
[32] I. Graabak, M. Korpås, Variability characteristics of european wind and solar power resources, a review, Energies 9 (6) (2016) 449.
[33] D.C. Action, 2030 framework for Climate and Energy Policies, 2015.
[34] S. Karekezi, W. Kithyoma, Renewable energy strategies for rural africa: is a pv-led renewable energy strategy the right approach for providing modern energy to the rural poor of sub-saharan africa? Energy Pol. 30 (11–12) (2002) 1071–1086.
[35] X. Tan, Q. Li, H. Wang, Advances and trends of energy storage technology in microgrid, Int. J. Electr. Power Energy Syst. 44 (1) (2013) 179–191.
[36] U. Pfeifroth, S. Kothe, R. Müller, J. Trentmann, R. Hollmann, P. Fuchs, M. Werscheck, Surface Radiation Data Set - Heliosat (Sarah), second ed., 2017, version 2.0. .
[37] Cm Saf Validation Report, Meteosat Solar Surface Radiation and Effective Cloud Albedo Climate Data Record, 2017 retrieved march 24, 2018 from, http://www.cmsaf.eu/en/documentation/documentation/validationrep/validationreports_node.html.
[38] R. Müller, U. Pfeifroth, C. Träger-Chatterjee, J. Trentmann, R. Cremer, Digging the meteosat treasureâ€”3 decades of solar surface radiation, Rem. Sens. 7 (6) (2015) 8067–8101.
[39] S. Pfenninger, I. Staffell, Long-term patterns of european pv output using 30 years of validated hourly reanalysis and satellite data, Energy 114 (2016) 1251–1265.
[41] M. Journée, C. Bertrand, Quality control of solar radiation data within the rmib solar measurements network, Sol. Energy 85 (1) (2011) 72–86.
[42] E. Harrison, P. Minnis, B. Barkstrom, V. Ramanathan, R. Cess, G. Gibson, Seasonal variation of cloud radiative forcing derived from the earth radiation budget experiment, J. Geophys. Res.: Atmosphere 95 (D11) (1990) 18687–18703.
[43] J.-L. Redelsperger, C.D. Thorncroft, A. Diedhiou, T. Lebel, D.J. Parker, J. Polcher, African monsoon multidisciplinary analysis: an international research project and field campaign, Bull. Am. Meteorol. Soc. 87 (12) (2006) 1739–1746.
[44] M. Rossignol-Strick, Mediterranean quaternary sapropels, an immediate response of the african monsoon to variation of insolation, Palaeogeogr. Palaeoclimatol. Palaeoecol. 49 (3–4) (1985) 237–263.
[45] B. François, B. Hingray, D. Raynaud, M. Borga, J. Creutin, Increasing climate-related-energy penetration by integrating run-of-the river hydropower to wind/solar mix, Renew. Energy 87 (2016) 686–696.
[46] A.L. Schmid, C.A.A. Hoffmann, Replacing diesel by solar in the amazon: short-term economic feasibility of pv-diesel hybrid systems, Energy Pol. 32 (7) (2004) 881–898.
[47] B. François, M. Borga, J.D. Creutin, B. Hingray, D. Raynaud, J.F. Sauterleute, Complementarity between solar and water power: sensitivity study to climate characteristics in Northern-Italy, Renew. Energy 86 (2015) 543–553, https://doi.org/10.1016/j.renene.2015.08.044.
[48] D. Heide, L. von Bremen, M. Greiner, C. Hoffmann, M. Speckmann, S. Bofinger, Seasonal optimal mix of wind and solar power in a future, highly renewable Europe, Renew. Energy 35 (11) (2010) 2483–2489. https://doi.org/10.1016/j.renene.2010.03.012.