RESEARCH ARTICLE

Reliable planning of isolated Building Integrated Photovoltaic systems

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Abstract

In this paper, two probabilistic reliability indices are presented to define the effect of clouds on different types of Building Integrated Photovoltaic (BIPV) systems. Existing indices do not match the main features of photovoltaic (PV) sources, such as variability, uncertainty and dependency on weather conditions. In addition, they are time indicators that describe the percentage of total failure time per year without any indication about power or energy mismatch. By using the available Geographic Information System solar-irradiation database, the proposed indices consider a similar pattern of expected daily solar irradiation as a model of PV systems. Two different models are studied for diverse building loads: an energy model for flexible loads and a constant-power model for critical loads. A comparative study is implemented for six different locations: Cairo, London, Berlin, Beijing, Madrid and Riyadh. Moreover, three types of BIPV systems are studied: fixed, double-axis-tracking and concentrated PV systems. The presented results show the effects of clouds, PV type and locations on the system performance.

Graphical Abstract

Keywords: stand-alone building; reliability analysis; capacity planning; solar power generation; BIPV
Building Integrated Photovoltaic (BIPV) systems refer to the inclusion of photovoltaic (PV) modules in the building envelope in the early construction phase, which reduces significantly the cost of a PV system. In addition, BIPV systems can improve the whole building’s thermal characteristics specifically in cold regions [1]. Therefore, many countries encourage building owners to install BIPV schemes in their utilities using subsidy programmes for small-scale residential PV systems as discussed in [2]. For instance, in Germany, the average cost of a typical 10- to 100-kWp PV rooftop system has reduced within last 28 years from 14 000 €/kWp to only 1070 €/kWp due to different PV-support programmes [3].

On the other hand, PV power depends mainly on climatic conditions. For instance, PV power generated 8.2% of Germany’s gross load in 2019, although it can supply about half of the same load in sunny days [4]. Accordingly, several studies concern climate impact on PV-system planning [5]. In [6], the impact of ambient temperature on both PV and load behaviour is studied for five different locations. To include the weather effect on PV energy, a weather-corrected PV-quality-estimation method is proposed in [7].

Communities in remote or rural off-grid areas suffer usually from lack of access to electrical utilities. Off-grid BIPV systems can be considered as an ideal solution for those isolated buildings. PV modules are modular in nature with a wide variety of configurations that suit different building structures. Besides their technical benefits, PV systems have zero sound pollution, low maintenance requirements and high economical profits, as discussed in [8].

Reliability is a main aspect in sizing any off-grid power systems to confirm the continuity of power supply. Nevertheless, PV power is unreliable itself. Therefore, adequate planning of both PV and storage systems is essential for isolated BIPV systems. Many considerations are proposed for the planning of isolated PV systems. In [9], a monthly sizing of the PV/battery is recommended for stand-alone PV systems to fit both variable monthly expected load and solar-radiation characteristics, whereas, in [10], maximum daily expected loads should be arranged in the worst possible order to examine the sufficiency of battery size. Moreover, batteries are proposed for nighttime loads, while other more reliable sources, such as fuel cells or even diesel generators, are recommended in the case of low sunshine on consecutive days in [11].

Recent experience of the initial sizing of PV systems is based on the average annual global solar radiation, system efficiency and a quality factor, such as the performance index [12]. Battery sizing depends on the PV size that differs according to the system-uncertainty degree [13]. For isolated buildings, discreet deterministic planning is recommended. Daily PV-system energy should cover two consecutive days’ loads according to the least expected daily solar radiation [14].

Unfortunately, such deterministic sizing methods cannot satisfy the sizing of BIPV systems in isolated buildings. Proper probabilistic reliability studies should confirm the relevance of BIPV systems to the stochastic behaviour of both the sources and the loads [15]. Therefore, many optimization techniques were proposed to define the optimal size of stand-alone PV systems with the aid of a probabilistic reliability index, such as the theory of stochastic processes [16], differential evolution multi-objective optimization [16], generalized regression neural networks [17] and artificial-bee-colony algorithms [18]. Moreover, maximizing the PV-system reliability was the main objective in some proposed sizing methods, as stated in [19, 20].

Most of the recently proposed sizing methods are based on PV-power simulation during the whole year to include the variability and uncertainty of the hourly PV power. However, all previous methods are based on an accumulated reliability time indicator such as loss-of-load probability (LOLP) or similar. These indices define the risk as the probable total time of supply power/energy deficiency per year. Such indices are suitable for fully controlled conventional sources that are affected only by their failure and repair rates. While PV systems have different features, they have variable uncontrolled power that is mainly affected by weather conditions.

Recently, the Geographic Information System (GIS) has provided much data related to PV power such as solar irradiation and ambient temperature all over the world. In this paper, two new probabilistic reliability indices are proposed. These indices are based on GIS solar-insolation data. They mainly concern the effect of a cloudy-day scenario on both PV daily power and energy. The main contributions are shown as follows:

- The Loss Of Solar Energy (LOSE) index estimates the expected daily reduction in PV energy during cloudy days. This index helps in choosing the best BIPV topology from the reliability point of view. It also can help in sizing PV/storage systems for flexible building loads.
- LOSE gives a good monthly indication for the energy-management-system requirements of buildings.
- The Cloud Effect On Load Loss (CEOLL) index predicts the expected PV-power-mismatch behaviour according to the effect of clouds. This index can help in sizing the proper reserve margin for isolated BIPV critical inflexible loads.
- Six locations in different regions are studied for three PV topologies, namely fixed PV, double-axis-tracking PV and concentrated PV (CPV), to define the effect of clouds on both the daily power and the energy of PV systems.

This paper is organized as follows. Section 1 discusses the necessary technical background about practical-reliability indices for both conventional and PV sources. Section 2 presents recent experiences in using the available solar-radiation databases, models and simulation programs. Section 3 describes the main features of the three studied...
PV types and their applications in BIPV systems. In Section 4, two new indices are proposed to quantify the effect of clouds on PV-system behaviour. Section 5 verifies the suggested indices in six locations on three continents. Section 6 addresses the main conclusions.

1 Reliability analysis

Reliability analysis is about how generation sources are satisfying the demand over long-term operation. Adequacy analysis defines the system reliability under scheduled and reasonably expected unscheduled system outages. Therefore, reliability and adequacy analyses confirm accurate capacity planning in any power system [21].

Generation reliability cannot be expressed by only one index. Several deterministic and probabilistic indices were proposed to evaluate the generation reliability. Probabilistic reliability indices consider the stochastic properties of all components in the studied system such as generator failure and load uncertainties.

1.1 Conventional indices

The most conventional reliability studies are based on the Forced Outage Rate (FOR) index. FOR can be defined as the probability of generating-unit unavailability due to forced outage based on historical data of each generating-unit type [22].

Generating reserve capacity is usually determined by using the LOLP index, as discussed in [23]. Although LOLP was introduced in 1947 [24], many studies on reserve planning have been based on this index until now, such as [25–27].

To calculate the LOLP index, a proper model for the peak hourly or daily power demand should be defined. In addition, the total power generation should be modelled by considering different failure and repair-time rates for each generating unit. LOLP can be calculated as the probability of generation deficiency in supplying the total power load [28].

Loss of load occurs when the system load exceeds the generating capacity in service. The overall probability of such events is called the LOLP. LOLP can be used to measure the loss-of-load risk by hour or just consider the expected peak load during the dispatch period.

For long-run and installed-capacity evaluation, a cumulative load curve is used. The LOLP calculation is illustrated in Fig. 1 with a daily-peak load curve. \( O_k \) is the magnitude of the k-th outage in the system, \( P_k \) is the probability of a capacity outage of magnitude \( O_k \) and \( t_k \) is the number of days over which an outage of magnitude \( O_k \) would cause a loss of load in the system.

Capacity outages of less than the reserve will not contribute to loss-of-load risk. At particular capacity-outage events, which are greater than the reserve, the overall risk is calculated as the product of the outage probability and the number of affected days.

Therefore, the system LOLP for the period is:

\[
\text{LOLP} = \sum_{k} P_k \times t_k
\]

where \( P_k \) is the probability of a capacity outage of magnitude and \( t_k \) is the time of outage in days.

Limits of acceptable LOLP in the planning phase vary from 1 to 5 days in 10 years, as discussed in [29]. Many other indices are inspired by LOLP for multimachine systems, such as the effective load-carrying capability (ELCC) [30] and capacity credit [31].

1.2 PV indices

From the early 1980s, many analyses and recommendations were proposed to guarantee the reliability of PV systems [32]. For instance, Fault Tree Analysis was applied for PV-system reliability in [33, 34]. In addition, PV-system reliability was assessed by relatively more complicated methods such as the Markov process, Monte-Carlo simulation, etc., as discussed in [35]. All these techniques considered failure-rate and maintenance schedules to model and define the best configurations of PV systems.

In contrast to conventional power-generation sources, the failure rate is not the main factor of weakness in PV systems. PV systems do not have any rotating or thermal switches [37]. Therefore, many researchers are concerned with the reliability assessment of PV inverters, such as [38]. Furthermore, many classical indices were studied to express the adequacy of PV power. Both ELCC and capacity credit are used to define the equivalent load and generation capacities of PV power in many regions, respectively, as discussed in [39–41].

For a stand-alone PV system, an adequacy index has been proposed since 1983, which is called the Loss-of-Power-Supply Probability (LPSP) [42]. LPSP is defined as the probability of losing both PV and storage power for a
stand-alone PV system [43]. LPSP can be formulated mathematically, as follows [44]:

\[
LPSP = \sum_{t=0}^{T} \frac{Power\ Failure\ time}{T} = \frac{\sum_{t=0}^{T} Time\ (P_{available}(t) < P_{needed}(t))}{T}
\]

where \(T\) is the total study time, \(P_{available}\) is the available power from PV modules or storage and \(P_{needed}\) is the load power.

LPSP was a final reliability check with several optimization techniques for capacity-planning studies of stand-alone PV systems, such as Ant Colony Optimization in [45] and Genetic Algorithm [44]. LPSP gives only a time indication of PV/storage power loss as in the LOLP index. Therefore, the same limits of LOLP usually apply to LPSP and stand-alone PV-system planning.

LPSP cannot define generation deficiency in terms of power or even energy to modify PV/storage sizing accurately. It can be considered as the percentage of the accumulated yearly failure time. It does not provide any indication about how daily power behaviour changes seasonally. It also does not consider the effect of clouds on PV-generated power. In other words, LPSP neglects the main features of PV power, such as variability, uncertainty and changing daily weather effects.

2 Solar-irradiation database

Solar irradiation has three different components. The first is direct normal irradiance, or DNI, which is the direct incidence beam of sunlight. Scattered photons of the sunlight form another component of solar irradiance, known as diffuse radiation. A small part of sunlight is reflected from the ground to any inclined surfaces, which is known as the reflected component. The total incident-radiation flux to any surface is called the global normal irradiance, or GNI [46]. The generated power of PV and CPV modules depends mainly on GNI and DNI, respectively [47]. Meteorological satellite data were used for predicting the behaviour of solar radiation from about five decades [48]. Many pieces of research on different solar-energy technologies have been implemented based on GIS data, as discussed in [49]. For instance, models for the solar-energy potential of roofs and façades were proposed for different buildings in a Portuguese urban area by using GIS data [50].

Recently, several web-based solar-irradiation databases have become available for PV planners all over the world [51]. In [52], an interesting study was implemented to define the household-PV-system potential in Indonesia based on web-based GIS data. The potential of PV systems in Tibet was studied similarly from another web-based database [53].

On the other hand, there are many atmospheric attenuations for solar irradiance. Clouds are the strongest deteriorating factor for solar irradiance [54]. Therefore, different models for solar irradiation in cloudy-sky scenarios have been implemented, as discussed in [55]. In [56], another model based on GIS is proposed for both clear- and cloudy-sky scenarios for PV-planning assessment.

The Photovoltaic Geographical Information System, or PVGIS, is a web-based, interactive PV-estimation tool based on GIS data. PVGIS data are mostly from the European METEOSAT satellites that cover Europe, Africa and most of Asia. PVGIS provides assessments for stand-alone PV systems during clear- or cloudy-sky scenarios [56–58]. In this research, PVGIS3 provides daily solar-irradiation databases as an average equivalent day for each month. Three different PV types will be studied during both clear- and cloudy-sky scenarios. Fixed PV, double-axis-tracking PV and CPV systems will be studied for six different sites to define their reliability under various solar-region conditions.

3 PV types

Fixed PV, double-axis-tracking PV and CPV systems are analysed in this study. The features of each system will be described briefly in the following subsections.

3.1 Fixed PV

The fixed PV type is the simplest and the most mature type of BIPV system. In this type, electricity is generated by the PV-module semiconductors without any repositioning tracking system or any optical concentrators, as shown in Fig. 2a [47]. Many architectural requirements for BIPV have been satisfied in the fixed PV market, such as a variation in products, coloured cells, custom-made modules, etc. [59]. Many options are available for installing fixed PV cells that vary from rooftop modules to printed coloured glass-sticker modules [60].

Fixed PV systems are installed for many purposes besides generating electricity, such as building exteriors that reduce glare or heat gain [61]. In [62], a BIPV system is discussed to improve both the electrical and the thermal characteristics of buildings. Therefore, many software packages and simulators are implemented by a wide range of planners to facilitate such types of installations [63].

On the other hand, fixed PV has the least efficiency compared to other types. Commercial BIPV-module efficiencies vary from 4% to 16% [63]. The electrical power of PV modules depends on GNI. PV power is very sensitive to the position and slope of the modules.

Fig. 2 shows the variation in fixed horizontal PV global-radiation behaviour on a 1-m² area during an average day in two different months, namely May and November, at a site in London, England.

As shown in Fig. 2, the variation in GNI has steep behaviour over a variable-sunshine period that ranges from 14 to only 7.5 hours per day in May and November, respectively. The average daily solar power also varies in extreme behaviour seasonally. The maximum daily solar power is
reduced by 35% from summer to winter. Clouds also have an excessively bad effect on fixed PV. Clouds reduce the maximum available power by 40% and 54% in May and November, respectively.

3.2 Double-axis-tracking PV

In this type, the position of the PV modules is being changed to capture the most available solar radiation during the daylight period. Double-axis-tracking systems consist of two perpendicular axes of rotation to adjust the optimum angle of the PV-module inclination, as shown in Fig. 3a. In [65], two cases are discussed of building rooftop double-axis-tracking systems that improve the whole system efficiency by about 40% compared to fixed PV systems. In addition, an increase of ~30% in the total generated energy per year is recorded in a Turkish study due to a double-axis-tracking system [66]. A lightweight cheap double-axis-tracker prototype is proposed specifically for small-scale housing installations in [67] to maximize the benefits of installed PV modules.

On the other hand, Sun-tracking benefits are doubtful, especially during cloudy days. A double-axis-tracking PV system generates less power than a fixed one on cloudy days in many studies for different regions, such as Canada [68], the USA [69] and Algeria [70]. Tracking devices are always pointed towards the Sun. In other words, the tracking systems always follow the direct sunshine. Direct radiation is ~90% of solar irradiance on sunny days. But, on cloudy days, most of the solar radiation is diffused by the clouds. Therefore, horizontal fixed PV modules capture 1.5 times as much solar energy as compared to tracked modules during cloudy days, as discussed in [71].

Fig. 3 shows the variation in double-axis-tracked global-radiation behaviour on a 1-m² area during an average day in two different months, namely May and November, at a site in London, England. Global solar irradiance is flattened during most of the sunshine period due to the tracking system, as shown in Fig. 3. The effect of clouds reduces the tracked solar-irradiance energy by ~43% and 57% in the cloudy scenario compared with the clear-sky one in May and November, respectively.

3.3 CPV

CPV uses lenses or mirrors to concentrate sunlight onto the PV cell, as shown in Fig. 4a. Focusing solar insolation to relatively expensive solar cells by using optics reduces the whole cost of the PV system [47]. The reduced-size solar cell in CPV requires fewer semiconductors and facilitates the use of more efficient multiple semiconductor materials such as multijunction modules. According to [72], the measured CPV efficiency increases to 47.1%, while normal PV-cell efficiency ranges from 23.3% to 29.3%.

The ratio between the concentrator optics area and the cells area is known as the concentration level and is
Fig. 3: Double-axis-tracking type (a) Simplified schematic, (b) tracked GNI in May, (c) tracked GNI in November (London site).

Fig. 4: CPV type (a) Simplified schematic, (b) DNI in May, (c) DNI in November (London site).
typically referred to as ‘x or suns’ [73]. CPV systems are classified according to their concentrators into high-, medium- and low-CPV systems. High-concentration systems need double-axis tracking with relatively large optics sizes, which are not suitable for all building types, whereas medium-concentration systems can be placed on flat roofs [74].

In [75], an low CPV (LCPV) system is designed for windows or glazing façades. Another LCPV system is optimized for transparent façades and skylights in [76]. In [77], a building-façade-integrated LCPV is designed specifically for vertical façades. Non-tracking LCPV increases the annual generated energy by 45% compared to traditional PV, as discussed in [78]. LCPV modules also have lower manufacturing costs than conventional PV modules [79]. Many studies are concerned with the thermal characteristics of the CPV. Thermo-photovoltaic (CPV/T) systems are analysed for heating and cooling purposes besides electricity generation, as in [80].

CPV electrical power depends mainly on solar DNI. Fig. 4 shows the variation in DNI behaviour in a 1-m² area during an average day in two different months, namely May and November, at a site in London, England. According to DNI behaviour, CPV output power changes in a dramatic way seasonally. The maximum DNI decreases from 850 w/m² during summer to only 620 w/m² in a clear-sky scenario. DNI also is affected badly by clouds. It decreases in the cloudy-sky scenario to one-third or less of the clear-sky scenario.

4 Proposed adequacy indices

By using GIS-based solar-irradiance data, PV power can be estimated under clear- or cloudy-sky conditions all through the year, considering variations during a day, a month or a season. Several assumptions are considered in this study, as follows:

• PV and CPV output powers are linearly proportional to GNI and DNI, respectively.
• The average efficiencies of PV and CPV systems are 20% and 40%, respectively, for all studied cases.
• The efficiencies of PV surfaces are constant, i.e. factors that may affect PV efficiency, such as dust, snow etc., are neglected.
• Clear- and cloudy-sky solar irradiations introduce BIPV-system models during healthy and failure operations, respectively.
• According to the IEEE recommendations in [9], the fixed-load energy is determined according to the worst-month solar radiation. Therefore, the month most affected by clouds will be studied.
• For simplification, only horizontal fixed PV panels are studied.

Building usually have many categories of electrical load. Some of them are critical, such as medical clinics requiring vaccine refrigeration, basic lighting, etc. These loads should not be interrupted, even on cloudy days. A constant-power model that depends mainly on storage to compensate for PV-power variability is assumed for critical loads. Other loads are flexible, i.e. they can be rescheduled, such as washing machines, televisions, etc. A constant-energy model that has minor dependency on storage to help only in rescheduling loads is assumed for flexible loads. Consequently, this study defines two indices of reliability: LOSE estimates the loss of PV energy, which is suitable for flexible loads; and CEOLL defines the possible power mismatch for constant-power critical loads.

4.1 LOSE

The LOSE index calculates the probability of the expected outage energy of a BIPV system. Clear- and cloudy-sky scenarios of different solar radiation are studied over the entire year. Next, the month most affected by cloudy weather is defined and analysed. The flexible-load model is represented as the same as the least-month clear-sky PV power. Consequently, the daily power shortage can be expressed as the difference percentage, Diff%, between clear-sky irradiation, i.e. the load energy model, and cloudy-sky irradiation. Diff% is normalized to its related clear-sky value to define the percentage of PV-power decay.

LOSE can be represented mathematically, as follows:

\[
LOSE = \frac{\sum t_k P_k \times Diff\%_k \times t_k}{t_i} \%
\]

where \(k\) is the number of studied time intervals per day, \(P_k\) is the probability for outage of solar generation, \(t_k\) is the time of solar-radiation outage in hours, \(t_i\) is the time of sunshine in hours and \(Diff\%_k\) is the percentage difference between the \(k\)th clear- and cloudy-sky values.

Each studied time interval has its unique power-decay percentage. Therefore, a suitable step change of 5% was chosen in ranking the Diff% values for probability calculations. Fig. 5 shows the proposed index flowchart. LOSE gives a good indication of the worst expected daily energy-outage scenario due to cloudy-sky effects.

LOSE can be defined as the daily average weighted energy loss due to the effect of clouds. The energy loss of each interval is weighted by its occurring probability during the day. LOSE can be used in the planning phase for choosing appropriate PV topology for any studied site. The PV type with the lowest value of LOSE will guarantee the minimum expected daily energy decay. Moreover, LOSE indicates the BIPV minimum energy-loading capacity.

4.2 CEOLL

Critical loads are usually supplied through special uninterruptable storage. The total covered demand power by a PV system only can be calculated as:

\[
\text{CEOLL} = \frac{\sum t_k P_k \times Diff\%_k \times t_k}{t_i} \%
\]
\[ PDemand = P_{load} - P_{Discharge} + P_{charge} \]  
where \( P_{load} \) is the constant critical load power, \( P_{Discharge} \) is the partial load power covered by storage discharge and \( P_{charge} \) is the PV extra power for storage charging during sunshine.

The reserve margin is usually calculated as a fixed ratio of the rated capacity of the traditional sources. PV systems have varying capacity according to the expected solar radiation. Therefore, a fixed loading level or constant reserve range cannot fit the varying behaviour of PV power. This study proposes a new reliability index that defines the appropriate monthly reserve/loading level. The loading level is calculated according to the related clear-sky solar radiation. By using the CEOLL index, reliable reserve levels can be checked and adapted in the case of cloudy weather.

CEOLL can be represented mathematically as follows:

\[ CEOLL = \sum_k P_k \cdot LOL_k \cdot t_k \]  
where \( k \) is the studied time interval per day, \( P_k \) is the probability for an outage of solar generation, \( LOL_k \) is the loss of load from clear solar-radiation outage (W/m²), \( t_k \) is the time of solar-radiation outage in hours and \( t_{tot} \) is the time of total sunshine radiation in hours.

The initial reserve percentage is usually calculated using the BIPV-planning technique. In this paper, the clear-sky maximum power is assumed to be 5%. Consequently, load curves can be defined from the clear-sky solar-radiation behaviour. By comparing the load with the cloudy-sky solar-radiation scenario, CEOLL can be calculated; 0.01 W/m² average loss of load per day is assumed as the maximum acceptable value in the reserve-level evaluation. The adapted reserve-level step is 5% from the clear-sky power. Fig. 6 shows a flowchart of the proposed CEOLL-index calculation.

5 Case studies
Six different locations are studied, which cover three regions of GNI levels. London and Berlin are in low-GNI regions, at <3 kWh/m² daily, whereas Madrid and Beijing have medium GNI levels, as their daily average value is ~4.5 kWh/m². Cairo and Riyadh are characterized by high GNI levels, with daily average values of >6 kWh/m². All data are provided in the Supplementary Data (see online Supplementary Data). After the solar radiation for
the studied configurations has been analysed, the worst month for each location can be estimated. The difference percentages, Diff%, between clear and cloudy radiation are calculated.

Table 1 shows the expected maximum Diff% percentage for each PV configuration. As shown in Table 1, the effect of clouds varies intensely according to the PV type and the studied site. CPV power decreases by >60% in four studied locations: London, Berlin, Madrid and Beijing. CPV systems cannot be reliable for isolated buildings without fuel-based sources, such as fuel cells or diesel generators, in all sites except for Cairo and Riyadh. Tracking systems also have a minor bad effect on PV power during cloudy weather for all studied sites compared to fixed PV systems. LOSE is calculated to define the impact of clouds on total daily energy, as shown in Table 2.

Horizontal fixed PV energy is very reliable in Cairo, Riyadh and Beijing, as the probable energy is reduced by <6% due to the cloudy-sky scenario. While all studied PV topologies are affected, Berlin showed the worst effect, as the energy is reduced by >70% during clouds. Tracking systems increase the probable reduced energy significantly in all studied cases compared to fixed PV systems. For instance, in Riyadh, the most reliable studied site, the probable daily energy reduction of the tracking PV system is 11.5% compared to only 3.5% for the fixed PV system. The Beijing site reliability varies considerably according to PV type, as LOSE varies from only 5.6% for a fixed type to 56.1% for a CPV type.

CEOLL is also calculated to investigate the uninterruptable base load fed by PV/storage only. The reserve level is calculated as a percentage of the daily maximum power of clear-sky behaviour. The reserve level is limited due to equalizing the daily battery charge/discharge energy according to clear-sky behaviour. As shown in Table 3, most of the studied cases, highlighted in grey cells, cannot satisfy the restricted limit of probable interrupted load power: 0.01 W/m². Only three cases of fixed PV types are reliable for critical constant-power load according to the proposed acceptable limit.

A low reserve margin is needed for many studied cases due to the flatness of solar radiation in the clear-sky scenario, while the negative impact of clouds in most cases increases the need for fuel-based sources for such isolated buildings. For example, London’s tracking type needs only 5% reserve from clear-sky power but has 0.33 W/m² probable load loss during cloudy days. On the other hand, fixed PV systems have steep power behaviours that require relatively high reserve margins. Clouds have a relatively insignificant effect on fixed systems, which increases the reliability of feeding constant base loads by fixed systems.

6 Conclusion

Weather predictions improve significantly during short-term or a few hours of operation. Therefore, reliability during the operation phase, i.e. short-term reliability,
can cope efficiently on an annual basis with the effect of clouds on solar power. On the other hand, long-term reliability for the planning phase cannot deal with this important factor. Therefore, this study proposes reliability indices for planning purposes to confirm a satisfactory operation for PV systems over long-term operation. By using GIS-based insolation data, the probability of PV energy or power loss during cloudy scenarios can be estimated.

The LOSE and CEOLL indices are proposed to estimate both PV probable energy and load-power loss due to clouds, respectively. LOSE evaluates the reliability degree for different PV topologies. LOSE can be used in choosing the most reliable PV system according to the solar-radiation behaviour of the site. The CEOLL index is suggested, which defines the appropriate reserve loading level every month. The loading level is calculated according to the related clear-sky solar radiation. By using the CEOLL index, a reliable reserve level can be checked and adapted in the case of cloudy weather with an acceptable limit of 0.01 W/m².

Three different behaviours of solar irradiation are studied related to fixed PV, double-axis-tracking PV and CPV types, respectively. In addition, six different sites are investigated: Cairo, London, Berlin, Beijing, Madrid and Riyadh. In contrast to other existing studies, constant-energy and power-load models are studied for flexible and critical loads, respectively. In addition, PV behaviour is modelled by both daily clear- and cloudy-sky radiation.

Results show high diversity in the effect of clouds according to the studied site and PV topology. The probable daily energy loss varies from only 3.7% to 83.4% for Cairo/fixed type and Berlin/CPV, respectively. CPV and dual-axis-tracking PV systems operate to follow the apparent motion of the Sun and maximize the direct radiation. Most solar radiation is diffused by clouds to different degrees. Therefore, these types are affected severely by clouds compared to fixed-plane PV systems. Although, the fixed PV type has the least efficiency with the steepest power behaviour, it is the most reliable topology for a constant base load with a minor effect of clouds.

LOSE and CEOLL summarize many features of the expected PV daily energy and power behaviour in a simple numerical way for a wide range of building planners. They facilitate the best selection and management of BIPV systems for isolated buildings. Simple and cheap hourly load scheduling can be implemented with the aid of these indices as a basis for reliable demand-side management on cloudy days for isolated buildings, especially in developing countries. These indices also can be adapted to include dust, temperature, fog and snow to have a comprehensive vision of PV output according to climate variations. The proposed indices can be also applied for isolated PV microgrids or large-scale PV plants to evaluate reliable loading capacities and the proper required spinning reserves.

Supplementary data
Supplementary data is available at Clean Energy online.

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Conflict of Interest
None declared.

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