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Photovoltaic/battery system sizing for rural electrification in Bolivia: Considering the suppressed demand effect

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HIGHLIGHTS
● Battery state of charge profiles are affected by the suppressed demand effect.
● In small rural systems the suppressed demand effect impacts directly to reliability.
● Considering the suppressed demand effect lead to more sustainable systems design.

ARTICLE INFO

Keywords: Photovoltaic Energy storage State of charge Renewable energy Rural electrification Li ion batteries

ABSTRACT

Rural electrification programs usually do not consider the impact that the increment of demand has on the reliability of off-grid photovoltaic (PV)/battery systems. Based on meteorological data and electricity consumption profiles from the highlands of Bolivian Altiplano, this paper presents a modelling and simulation framework for analysing the performance and reliability of such systems. Reliability, as loss of power supply probability (LPSP), and cost were calculated using simulated PV power output and battery state of charge profiles. The effect of increasing the suppressed demand (SD) by 20% and 50% was studied to determine how reliable and resilient the system designs are. Simulations were performed for three rural application scenarios: a household, a school, and a health centre. Results for the household and school scenarios indicate that, to overcome the SD effect, it is more cost-effective to increase the PV power rather than to increase the battery capacity. However, with an increased PV-size, the battery ageing rate would be higher since the cycles are performed at high state of charge (SOC). For the health centre application, on the other hand, an increase in battery capacity prevents the risk of electricity blackouts while increasing the energy reliability of the system. These results provide important insights for the application design of off-grid PV-battery systems in rural electrification projects, enabling a more efficient and reliable source of electricity.

1. Introduction

During the last two decades, access to electricity has had deep impacts on the wellbeing of rural families through significant socio-economic development in Bolivia [1]. However, 34% of the total rural population in the country still have no access to electricity [2]. Developing countries have implemented rural electrification programs to reduce poverty and improve the socio-economic situations of the affected population [3,4]. The Bolivian government has set the goal to achieve 100% access to electricity by the year 2025 as a part of the strategy called “Agenda Patriótica 2025” [5]. Despite the continuous but slow expansion of the national electricity grid to rural areas, some are still inaccessible and disperse, requiring off-grid electrification solutions.

Off-grid renewable electrification systems such as micro hydro-power, small wind generators, and solar photovoltaic (PV) are widely...
used among rural electrification programs [6]. Off-grid PV systems rely on energy storage to supply power when the sun is not shining, and batteries are the most common energy storage devices used in rural electrification programs [7].

Particular operation characteristics have significant impacts on the battery performance, such as variable power charge rate, depth of discharge (DOD), partial cycling, and remaining at high state of charge (SOC) [8]. The battery performance and SOC profile behaviour in off-grid PV applications have been studied in [9–11]. In these studies, the solar PV charging effect on the battery lifetime is evaluated by presenting various SOC profiles as cycling procedures and reproducing conditions which are believed to increase the degradation rate of the battery. In the work presented by Krieger et al. [9], the effect of variable charging rate and incomplete charging was studied by comparing two different storage technologies (lead-acid and lithium ion batteries), finally concluding that lithium ion batteries perform better for off-grid applications due to less degradation and better voltage performance. Consequently, as the price is decreasing by the year [12], the trend is moving towards the use of lithium-ion batteries [7,13]. Further works on lithium-ion batteries have studied the impact of stress factors such as current, ΔSOC, SOC, and temperature on the cell capacity and impedance [14,15]. In [16], Käbitz et al. studied the effect of SOC and temperature on capacity fade and therefore the lifetime of NMC cells was studied, revealing that the cells stored at a 100% SOC show a higher rate of degradation as compared to those stored at lower SOCs.

Although the use of lead-acid batteries in off-grid PV systems is common among electrification programs, factors such as short life and challenging final disposal, have driven stakeholders to use lithium ion batteries. Moreover, technologies such as sodium-sulphur, redox flow and nickel-cadmium are widely applied as electricity storage [17]. However, due to their complexity and relatively high cost, they are not part of this study. In addition to this, Bolivia is developing the lithium ion battery industry and one of the main goals is to use those batteries in stationary applications [18]. Therefore, in the present study, the battery technology of choice is lithium ion.

Reliability (based on energy supply interruption frequency) and cost analysis have been used as optimization criteria for designing off-grid PV-systems [19–22]. The reliability is estimated over a long period of time, typically one year, based on a simulation model using radiation and electricity consumption data as inputs. The comparison of different systems operating under the same conditions was found useful to choose an optimal design.

In order to design reliable systems, off-grid applications in remote and disperse areas with high solar irradiation need to be evaluated. This not only guarantees the sustainability of rural electrification projects but also has great significance on the adoption of renewable power technologies as reliable alternatives to traditional ones.

This study discusses and evaluates the effect of suppressed demand (SD) on the system reliability for three different remote and disperse rural scenarios: a household, a school and a health centre.

The SD effect arises when an installed system’s power is insufficient to meet the basic needs of the user. This can be due to low incomes, inadequate infrastructure, high cost of technologies, or a combination of these [23]. Moreover, the SD effect also represents the forecasted increase of user demand due to the expected improvement of economic situations, which is an inherent objective of electrification programs [24]. This effect is typically observed when the user is provided with a system which delivers enough electrical power supply for their basic needs such as lighting and communication. Hence, the electrical power demand is expected to increase due to the acquisition of more appliances such as TVs or refrigerators in the following operating years.

The PV-battery system power output was simulated based on climatic and geographical data from the Bolivian highlands. Moreover, annual SOC profiles data were obtained from simulations performed in Matlab® software, which are further used to evaluate the impact of SD on the system reliability using the open-source code OptiCE [25].

The paper is organized as follows: the methodology section starts by estimating the electrical load profile (consumption) for three scenarios; then, the power output from the PV was calculated using weather and geographical data from the Patacamaya region; finally, the procedure for calculating loss of power supply probability (LPSP) was presented. The results and discussion section compares the obtained PV/battery
system design for a household, a school and a health centre, to analyse their reliability when considering the SD effect. Moreover, a detailed analysis of the calculated SOC curves was performed at annual base. Finally, the conclusions are presented.

2. Methodology

This study used computer-aided simulation of mathematical models as the representation of a PV/battery system, generating synthetic load profiles to analyse the resulting SOC profiles through sensitivity analysis and optimization methods such as genetic algorithm (GA).

Sections 2.1–2.4 describe the component models that are employed in the system. Section 2.5 describes the methodology used for evaluation of parameters such as reliability and cost.

2.1. System configuration description

The system is designed for operating in the region of the Bolivian rural highlands, Colquencha’s municipality. In the case of the Bolivian remote highlands, off-grid PV-battery systems are often used since the grid is too expensive to expand. High solar radiation in the region, up to 6 kWh/m²/day, provides an practical and economic advantage of using PV technology [26]. As shown in Fig. 1, the system includes a PV module, an inverter, a battery charger and a battery pack. The PV module generates electricity which is used to charge the battery through a battery charger. Finally, the battery current goes through an inverter to meet the load requirements.

2.2. Electrical load profile modelling

As rural electrification aims to supply electricity to residents who currently do not have electricity connection, there is no historical record of electricity consumption. No detailed information of electrical load profiles is available in this region, and only monthly electrical bills were gathered and used as Ref. [27]. Consequently, a synthetic electrical load profile was generated for a household, a school and a health centre respectively using a bottom-up model. The bottom-up model is based on data from three main factors: (i) the types of appliances demanding electricity; (ii) the electricity demand of each appliance during usage; and (iii) the usage patterns of each appliance [28]. By employing the statistical energy usage data and time resolved user-behaviour, a representative profile can be developed [29]. A schematic flow-chart of the implemented methods is shown in Fig. 2.

The first stage is the selection of appliances and aggregation of their respective hourly loads. The load is defined according to the hourly user behaviour along the day in a stochastic manner. Therefore, to add the stochastic component, these limits are defined as the maximum expected peak and the frequency at which the appliance is used, for the daily variation and the time-to-time variation respectively. The second stage combines daily load profiles into a yearly load profile while including the SD and seasonal effect (SD, i.e. 0%, 20%, 50% increased demand), thus obtaining three yearly electrical load profiles for each SD value. Moreover, as technology costs go down and energy efficiencies go up, households may start using more services.

Electricity consumption in rural households is restricted to basic needs such as lighting, communication (radio and TV) and phone charging. Meier et al. [30] describes the most commonly used appliances by rural users and their hourly usage profiles in the Altiplano region. Furthermore, for the case of school and health centre, the type and number of appliances were determined from reports of rural electrification projects previously executed in Bolivia [31]. The power consumption and usage time for a household, a school and a health centre are shown in Table 1.

2.3. Climatic data and photovoltaic module simulation

Climatic data for the south-west highlands region in Bolivia was obtained from a global climatic database, Meteonorm [32], which includes global horizontal radiation (W/m²), diffuse horizontal radiation (W/m²) and ambient temperature (°C).

The PV module power output was simulated by assuming a surface facing north, and the tilt angle correction was performed according to [33]. The yearly total radiation flux profile used is shown in Fig. 3. Simulation of the solar module power output was performed using

![Fig. 2. Schematic flow-chart for generating the load profile using the bottom-up model.](image-url)
the single diode model described in [33]. The I-V curve for the PV module was obtained using Eq. (1):

\[ I_{PV} = I_{ph} - I_0 \left( \frac{V_{PV} + I_{PV} \cdot R_{sh}}{R_{in}} - 1 \right) - \frac{V_{PV} + I_{PV} \cdot R_{sh}}{R_{in}} \]  

(1)

where, \( I_{ph} \) is the photocurrent (A), \( I_0 \) is the diode reverse saturation current (A), \( a \) is the ideality factor (V), \( R_{sh} \) is the shunt resistance (\( \Omega \)), and \( R_{in} \) is the series resistance (\( \Omega \)). The calculation methodology is described with more details in a previous work [34].

Maximum power point tracking (MPPT) procedure was used to ensure maximum power output from the PV module. Eq. (2) was used to calculate MPPT, which was extracted from [35].

\[ P_{PV, mpp} = \max(I_{PV} \cdot V_{PV}) \]  

(2)

The PV module characteristics used in the model were from BlueSolar® polycrystalline panels [36], which are described in Table 2.

### 2.4. Battery state of charge calculation

The battery SOC profile was calculated for an entire year with an hourly interval, following the scheme given in Fig. 4. Eqs. (3) and (4) were used in the energy balance procedure for discharge and charge respectively:

\[ P_d(t) = P_b(t-1)(1 - \sigma) - \left( \frac{P_{PV}(t)}{\eta_d} - P_i(t) \right) \]  

(3)

\[ P_c(t) = P_b(t-1)(1 - \sigma) + \left( \frac{P_{PV}(t) - P_i(t)}{\eta_c} \right) \eta_c \]  

(4)

where \( P_b(t-1) \), \( P(t) \) represent the battery energy at the beginning and the end of the interval \( t \), respectively, \( P_i(t) \) is the load demand at the time \( t \), \( P_{PV}(t) \) is the energy generated by the PV module at the time \( t \), \( \sigma \) is the self-discharge factor and \( \eta_d, \eta_c \) represent the battery charging and inverter efficiency, respectively, as presented in [37]. Battery operation values are presented in Table 3.

### 2.5. Reliability indicator

Off-grid PV systems are intermittent sources of power, and therefore the reliability is considered as an important design factor. The system’s reliability is expressed in terms of loss of power supply probability (LPSP), which is the ratio of the loss of power supply (LPS) to that required by the load during a defined time period [38]. LPSP is obtained from Eq. (5).

\[ \text{LPSP} = \frac{\sum_{t=0}^{t=\text{Lisp}} \text{LPS}(t)}{\sum_{t=0}^{t=\text{Lisp}} \text{Load}(t)} \]  

(5)
Three scenarios for each application were proposed for LPSP analysis. The first scenario represents the obtained synthetic base-case load profile. The second and third scenarios represent 20% and 50% increment on load demand respectively, which is the suppressed demand (SD) effect.

According to the regulation for electrification programs in Bolivia, rural stand-alone storage systems should store enough energy to supply the user electricity consumption for at least two continuous days without charging [39]. Moreover, a sensitivity analysis was performed as the criterion to achieve the optimal design under restrictions of minimum LPSP and minimum cost.

2.6. System cost

The cost of the PV system hardware was set at 2.5 USD/Wp, which includes PV module, inverter, structural and electrical components, but excludes the battery. The considered cost is an averaged value and does not include installation labour and indirect cost such as business overhead, profits, supply-chain cost and regulatory cost, all of which vary by location and market [40].

There is no standard accepted benchmark cost for lithium ion batteries. The price we show here is a part of the breakdown for residential PV systems performed by [41]. The battery cost (battery charger included) is set at 0.90 USD/Wh.

2.7. Genetic algorithm

Genetic Algorithm (GA), as a well-suited meta-heuristic tool, is employed in this study to carry out multi-objective optimization. The objective functions are LPSP and system investment cost. The decision variables are the PV size and battery capacity. The optimization results are presented in the form of near-optimal Pareto-front and “tournament” selection function which chooses the better-fitted individual out of that set to be a parent [34]. The optimization procedure was conducted using Matlab® software, and the set of options used are listed in Table 4.

### Table 3

<table>
<thead>
<tr>
<th>Parameters used for the battery.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma$ (% per month)</td>
</tr>
<tr>
<td>$\eta_b$ (%)</td>
</tr>
<tr>
<td>$\eta_i$ (%)</td>
</tr>
</tbody>
</table>

### Table 4

<table>
<thead>
<tr>
<th>Options</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generations</td>
<td>300</td>
</tr>
<tr>
<td>Population size</td>
<td>700</td>
</tr>
<tr>
<td>Fraction tolerance</td>
<td>$1E-3$</td>
</tr>
<tr>
<td>Pareto fraction</td>
<td>0.5</td>
</tr>
<tr>
<td>Selection function</td>
<td>Tournament</td>
</tr>
</tbody>
</table>

3. Results and discussion

The system’s reliability and cost for a household, a school and a health centre were evaluated by considering the effect of suppressed demand (SD). Reliability limits were set at 2% for the household and the school and 1% for the health centre.

3.1. Electrical load profile modelling

In order to estimate the electrical load profile used to perform the system’s energy balance, an hourly profile of one year is required. The included randomness factor helps to obtain a more realistic profile, which also includes a seasonal variation observed in the real monthly profiles obtained through surveys of the region. The profiles obtained after the simulation are shown in Fig. 5. The household profile is the only application which includes the seasonal variation, whereas the school and health centre profiles only include the daily and time-to-time variation. The load profile of the school considers weekends as periods with no academic activities, and therefore no electricity usage. The health centre presents a more cyclic and predictable profile with a high background consumption, which is caused mainly by the usage of the refrigerator to store vaccines and other medications.

After television, radio and mobile phone charger, lighting is the most used appliance among remote and disperse rural populations. Moreover, for household and school load profiles, the power peaks observed during the morning corresponds to the usage of TV and radio principally, and during the evening to TV/DVD player and computer usage, while lighting is the background load in both cases.

3.1.1. Household

Fig. 6 shows the dependency of LPSP on PV size. A minimum LPSP value of 2% was set as the reliability limit (equivalent to 7.3 days of blackout per year) [39]. In both cases, the battery capacity is fixed at 1.2 kWh and 1.8 kWh for (a) and (b) respectively. These values were
obtained after evaluation of the daily household consumption considering the battery delivering energy for two days autonomously, and then rounding off the calculated capacity to commercially available sizes. Each point in Fig. 6 corresponds to a common commercial PV module size and the corresponding LPSP value calculated from the simulation. The PV module and battery sizes used here are the commonly employed in electrification projects in Bolivia [42]. Under these conditions, few PV module sizes can be considered as optimally reliable.

From Fig. 6a, using a 1.2 kWh battery, the initial load curve (in blue) presents four points below the reliability limit, of which the one closest to the reliability limit is the one with the smallest allowable PV size (150 Wp), and thus the lowest cost. Using that point to design a PV/Battery system would present an acceptable LPSP value of 1.9% (7.3 days of blackout per year). However, once the SD effect is considered, the LPSP value for the same PV size will increase to 6.5% (27 days of blackout per year) and 12.8% (47 days of blackout per year) for 20% and 50% of SD effect, respectively. Therefore, to ensure a design within the reliability limit and resilient to the suppressed demand effect, a larger PV size is selected (250 Wp) with a LPSP value of 2.4% (8.7 days of blackout per year). Furthermore, Fig. 6b presents a case where a larger battery capacity is used. The incremental increase in battery capacity reduces the value of LPSP to 1.6% (5.8 days of blackout per year) when considering initial load and 150 Wp PV size. Moreover, for a 250 Wp PV size, the LPSP value considering 50% SD is reduced to 0.9% (3.2 days of blackout per year).

The results indicate that it is the PV size rather than the battery capacity that influences the system’s reliability for the household application, and therefore increasing the PV size is the lower investment option. As observed in Table 5, by increasing the PV size from 150 Wp to 250 Wp for a 1.2 kWh battery, the system’s cost is increased by 8.87% and the LPSP values are reduced by 1.9%, 6.3% and 10.4% for the initial case, 20% and 50% SD effect respectively. However, if we increase the capacity of the battery from 1.2 kWh to 1.8 kWh for a PV size of 150 Wp, we increase the system cost by 37% and reduce the LPSP values by 0.3%, 0.5%, and 1.2% for the initial case, 20% and 50% SD effect respectively.

The annual battery SOC profiles for the initial load, 20% SD and 50% SD cases are shown in Fig. 7a–c. During the rainy season from December to February, the battery is cycled in a wide SOC range because the generated power is considerably less. During winter from May to August, the battery is also cycled in a wide SOC range due to the higher consumption of electricity. It can clearly be seen how the increments in SD impact the SOC range over which the battery is cycled.

### 3.1.2. School

A small rural school in Bolivia works 5 days per week during the morning. In most of the cases, the teachers live in a room inside the school, contributing to a small consumption during the evening and weekends. However, the main peak is due to academic activities.

<table>
<thead>
<tr>
<th>Case</th>
<th>PV size, Wp</th>
<th>System cost, USD</th>
<th>LPSP (IL), %</th>
<th>LPSP (20% SD), %</th>
<th>LPSP (50% SD), %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.2 kWh Battery</td>
<td>150</td>
<td>1273</td>
<td>1.9</td>
<td>6.5</td>
<td>12.8</td>
</tr>
<tr>
<td></td>
<td>250</td>
<td>1386</td>
<td>0.0</td>
<td>0.2</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td>320</td>
<td>1465</td>
<td>0.0</td>
<td>0.0</td>
<td>1.3</td>
</tr>
<tr>
<td>1.8 kWh Battery</td>
<td>150</td>
<td>1743</td>
<td>1.6</td>
<td>6.0</td>
<td>11.6</td>
</tr>
<tr>
<td></td>
<td>250</td>
<td>1855</td>
<td>0.0</td>
<td>0.0</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>320</td>
<td>1934</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
</tr>
</tbody>
</table>
From Fig. 8a, using a 1.2 kWh battery, the initial load curve (blue line) presents four points below the reliability limit (dashed red), of which the one closest to the reliability limit is the one with the smallest acceptable PV size (500 Wp), and thus the least costly option. Using that point to design a PV/Battery system would present an acceptable LPSP value of 0.9% (3 days of blackout per year). However, the LPSP value for the same PV size (500 Wp) will increase to 3.0% (11 days of blackout per year) and 6.75% (24 days of blackout per year) for 20% and 50% of SD effect, respectively. Therefore, to ensure a design that is below the reliability limit and resilient to the SD effect, a larger PV size is selected (960 Wp) with an LPSP value of 1.4% (5 days of blackout per year) when considering 50% SD effect. Furthermore, Fig. 8b presents a case where a 1.8 kWh battery capacity is used. Considering the PV size of 500 Wp, this increment in battery capacity reduces the LPSP value to 1.0% (4 days of blackout per year), and 3.61% (13 days of blackout per year) for 20% and 50% SD effect, respectively. Moreover, by only increasing the PV size to 640 Wp, the LPSP value reduces to 1.75% (6 days of blackout per year) when 50% SD is considered.

From an optimal design point of view, to achieve an LPSP value below the reliability limit at the lowest cost, we have two possible options. As observed in Table 6, from the first scenario, for a 960 Wp PV size and 1.2 kWh battery capacity, we obtain a cost of USD 2185. From the second scenario, for a 640 Wp PV size and 1.8 kWh battery capacity, the cost of the system is USD 2294. Although the price of the second option is 5% higher, the surface area used by the panels, usually rooftop, is smaller than the first option.

The school battery SOC profiles (Fig. 9) show a weekly dependence on the annual irradiation profile and the system can almost fully recharge during the weekends. Although this helps to keep the reliability indicator within limits, SD will affect the LPSP values, especially during winter from May to August, when we can observe a higher concentration of blackout hours.

The battery behaviour of Fig. 9 shows frequent cycling between 80% and 100% SOC. By cycling between high SOC values and resting at high SOC values, the battery is subject to accelerated deterioration, reducing its lifetime and available capacity [13,16,43].

3.1.3. Health centre

The health centre is a small building that offers basic health services and stores essential medicine. The reason why no major equipment is used in this type of facility is that for more complex medical interventions, the patient is transferred to a first level hospital which usually is connected to the grid. Usually two persons are in service the whole week, including weekends. Due to the large size of the system, a genetic algorithm (GA) was used to optimize the LPSP and cost values of the system.

The generated Pareto frontier curves are presented in Fig. 10. Three scenarios were evaluated: initial load, 20% SD and 50% SD. A reliability limit was set at 1% LPSP (up to 3.6 days of blackout per year) as a tolerable limit for the operation of a health centre. As observed, the points marked with crosses indicate the optimal points within the reliability limit. These points show an LPSP value below 1% and the corresponding cost of the PV–battery system. The red cross indicates a reliable system size for the initial load case only. The yellow ones indicate optimal size for initial load and 20% SD case. Finally, the green cross indicates optimal system size in which the three scenarios are within the desired reliability limit.

The optimal values are correlated to the corresponding PV size and...
battery capacity. Therefore, for the optimal point (the top green cross) with 0.99% LPSP and a cost of 6703 USD, the corresponding PV and battery sizes are 2.4 kWp and 4.9 kWh, respectively. By rounding off to available commercial sizes, a system with 2.5 kWp PV module and a battery with 4.8 kWh capacity would be sufficient.

Table 7 presents selected values from the Pareto front. This results indicates that GA results vary with PV power instead of battery capacity, which was also observed as a way to achieve reliability for the household application.

The health centre does not consider seasonal effect in the electricity consumption, and therefore the load profile is symmetrical along the year. This is represented in the battery SOC profiles shown in Fig. 11. Several consecutive cloudy days can cause blackout periods since the battery reaches 20% SOC. As mentioned at the beginning of this section, the reliability limit was set at 1%. This value can be easily reduced to 0% if a demand management strategy is implemented, thereby guaranteeing electrical power supply 365 days per year.

3.2. Battery ageing

Ageing of the battery components is an inevitable phenomenon. Although it is impossible to avoid, it is possible to reduce. Two types of ageing are most commonly found (i) due to the cycling processes, full and partial cycling; and (ii) due to calendar ageing. Ageing due to cycling processes depends on the current rate at which the battery is operated, temperature and the depth of discharge (DOD) of the cycles. Moreover, the active components will also impact the lifetime of the battery. Higher DOD leads to shorter life. Capacity fade due to calendar ageing is caused by parasitic reactions in the electrodes and is dependent on SOC, temperature and active components of the battery. Higher SOC leads to shorter life. Although keeping the battery operating at high SOC will guarantee the system reliability, the low anode potential accelerates the loss of cyclable lithium [44], resulting in early capacity fade. By quantifying the time at which the battery remains at 100% SOC, it is possible to predict the capacity fade rate.

The household battery SOC profiles, presented in Fig. 7a–c, show us that the battery will spend most of the time cycling between an upper limit of 100% and lower limits of 60%, 50% and 40%, respectively. Therefore, the SD will impact the battery ageing. When the battery cycles at a wider SOC range, there will be less time to remain at high potentials and therefore the degradation rate will be decreased [45]. However, when the battery cycles within shorter SOC ranges at higher SOC, the impedance increases and capacity fade will diminish the battery lifetime [46].

An even narrower cycling range is observed in the school battery SOC profiles. In Fig. 8a–c, we observe the battery is cycling around...
100% and 90% SOC in all cases. Although this helps to achieve high reliability of the system, cycling and resting the battery at high SOC could lead to accelerated capacity fade and impedance increase [14].

Finally, the health centre SOC profiles present a uniform cycling pattern throughout the year. As observed in Fig. 11a–c, the system’s battery SOC cycles between an upper limit of 100% and a lower limit of 60%, 55% and 45% for initial load, 20% SD and 50% SD respectively. If cycling around middle voltages could be accomplished, the battery would experience the lowest increase of internal resistance and decrease of capacity, as concluded in [46]. This could be achieved by introducing forecasting and setting the upper SOC limit at a lower level, except when a rainy period is forecasted.

4. Conclusions

The application of computational methods to design off-grid PV/battery systems resilient to the suppressed demand (SD) effect was analysed. The reliability of systems was improved using simulation tools for three applications: a household, a school and a health centre.

Synthetic load profiles were utilized based on monthly data of energy consumption of the region; however, real-life profiles can be uploaded to the computational model once a diagnosis of the energy situation is performed. Moreover, a qualitative battery ageing analysis shows the impact of SD effect on the battery SOC profile and thus the degradation due to cycling in certain SOC ranges. These findings indicate the importance of considering SD in the design of PV/battery systems and also provide a great opportunity to help policy makers and project managers develop better electrification programs.

Although the reliability of the systems was achieved by increasing the PV size rather than the battery size in the case of a household, we also observed that the increase in battery size could result in less ageing and therefore higher operation time due to cycling at middle SOC ranges.

The school system analysis considers the weekends as a break in academic activities, which has an impact in the reliability of the design. In this case, by increasing the peak power of the PV modules, acceptable reliability is achieved. However, increasing PV power means also increasing physical space requirements, which could present a problem in small rural schools. Furthermore, battery SOC profiles show that most of the partial cycles are performed at high SOC ranges, between 80% and 100%, which can be detrimental to the battery capacity due to ageing processes.

The health centre system was analysed using genetic algorithm (GA) to obtain the PV and battery sizes with the minimized LPSP values and initial cost. GA results show variation in PV sizes while maintaining the battery size constant at a certain value. Although this results in optimal PV and battery sizes, when considering space availability, a battery size increment would be a better option. Furthermore, battery SOC profiles present wider cycles than previous applications due to a uniform load profile distribution, which consequently results in less calendar ageing for the battery as a consequence of high SOC cycles.

As a result, the implementation of stand-alone PV systems in rural areas should include a reliability assessment based on its SOC profile. In other words, the lifetime of the battery under such operational conditions needs to be evaluated through extensive laboratory and field work.

Finally, it is important to point out that the use of efficient and smart appliances, software and hardware for distributed systems in rural electrification shows long-term benefits due to the rapid price drop in hardware and advanced software. This enables greater control and integration across the system components. Such components can be used to store energy. For instance, during energy conversion surplus periods, solar direct-drive vaccine refrigerators could cool down to lower temperatures for longer periods. The energy saved allows the battery to recharge more quickly, therefore avoiding blackouts.

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