Assessing the potential of PV hybrid systems to cover HVAC loads in a grid-connected residential building through intelligent control

J.C. Solano, L. Olivieri, E. Caamaño-Martín

HIGHLIGHTS

- A grid connected PV-battery system model is proposed to supply HVAC loads.
- Two optimized control strategies for the battery energy storage system are proposed.
- Simulations are validated with actual data coming from the monitoring campaign.
- An economic assessment of the strategies, including sensitivity analysis are included.

ABSTRACT

This paper presents theoretical and experimental work that is being carried out in a grid-connected residential building demonstrator available at the Instituto de Energía Solar (IES) of the Universidad Politécnica de Madrid (UPM) in Madrid, Spain. The house is provided with a building-integrated photovoltaic (PV) system coupled to a battery energy storage system (BESS), and a heating, ventilation, and air-conditioning system (HVAC) based on two air-to-air direct expansion reversible heat pumps. Thermal loads, HVAC consumption, and PV generation are simulated using different dynamic models, and they are validated with actual data derived from monitoring the experimental campaign. A model of intelligent control of BESS is proposed, which aims to supply the selected application (HVAC load) with two control strategies: increasing PV self-consumption and grid-peak shaving. This model has been validated with experimental data (error < 10%). Furthermore, the study includes aging and degradation effects on the batteries to make allowance for realistic lifetime assessment. The results of the case study show that in a building without a BESS, the self-consumption rate is about 30%; however, with the implementation of the proposed control, it could achieve approximately 50%, depending on the BESS capacity and the PV generator nominal power. Likewise, by using a combination of both strategies, it is possible to reduce both contracted power and energy consumption (77% and 49% respectively for case study).

1. Introduction

Heating, Ventilations, and Air Conditioning systems (HVAC) represent between 40% and 60% of energy demand for buildings in Europe [1], and are also of increasing importance for buildings worldwide [2]. Despite the importance of thermal systems in the energy balance of buildings, existing research indicates that specific strategies for combining local photovoltaic (PV) generation with electricity-powered air conditioning equipment (especially reversible heat pumps) are still under examination [3-5].

In fact, the IEA Solar Heating and Cooling Programme has shown interest in these kinds of systems, particularly within its Task 53 [6]. Its main objective is to analyse the use of solar driven systems for cooling and heating, including PV driven systems, from both technical and economic points of view.

In a previous study by the authors [7], it was shown that annual billing for HVAC demand in commercial buildings could be reduced by up to 50% using PV solely without storage systems, primarily because thermal loads match reasonably well with PV energy production. In contrast, most of the HVAC consumption in the residential sector is time-shifted with respect to the PV generation. Therefore, the addition of a Battery Energy Storage System (BESS) is required in order to decouple generation and consumption, increasing the self-consumption rate.

Many studies simulating PV systems coupled to HVAC equipment have been published [8-12], demonstrating the interest of using PV
energy to condition the indoor climate in buildings, despite not having been validated experimentally. Other studies have presented experimental results, such as [13] where the operation and the energy behaviour of an air conditioner simultaneously connected to the grid and a PV system were analysed. However, this system does not use a storage system. In another research [5], the performance of a solar PV driven air conditioner was experimentally analysed in the hot-summer and cold-winter zone in China, but it did not present control strategies or a model in a dynamic regime that would allow the determination of the system's behaviour for other operating conditions.

In the field of grid-connected PV-battery systems, several simulation-based studies have been proposed [14-17] that show the benefit of using a BESS to reduce grid electricity consumption. However, these studies do not present experimental data or control strategies based on PV generation, load condition, and battery state of charge. As regards the economic viability of PV-battery systems, significant studies such as [3,18-20] have been carried out. However, these studies are not intended to cover a specific load such as HVAC for both cooling and heating throughout the year, and they do not present the economic savings of PV-battery systems compared to other grid-connection scenarios.

In this context, the main objective of this work is to assess the technical and economic benefits of using PV hybrid systems in combination with reversible heat pumps and optimised control strategies to supply HVAC loads in residential buildings. To meet this goal, a grid-connected PV-battery model is proposed. With the aim of increasing PV self-consumption and grid-peak shaving, two optimised control strategies for the BESS are proposed, simulated, and validated with actual data coming from the experimental campaign. Finally, an economic analysis is presented, which shows the billing savings that the PV hybrid system would produce in comparison with a conventional system. Likewise, the levelized cost of electricity (LCOE) and the payback time were calculated by taking into account the current costs of the hybrid system and the BESS as well as batteries’ lifetime, equipment changes, and current electricity pricing.

Remarkable contributions involving modelling and control strategies in grid-connected PV hybrid systems have been published and validated with experimental data [19,21-23]. Nevertheless, the present work proposes a dynamic model that differs from other similar models [19,21,22,24-27] in five main aspects: (1) The model is optimised to operate with two control strategies at the same time maximizing self-consumption and grid-peak shaving and giving the user the possibility of choosing one or the other, as presented in the case study. (2) The model can include C-rate data (C-rate is a measure of the rate at which a battery is discharged relative to its maximum capacity) to improve its accuracy. (3) The model includes a formulation to avoid over-charge and over-discharge of the battery by using adjustable values, and (4) the model includes calculation of losses in the battery inverter. The last two aspects are intrinsically related to the characteristics of the battery inverters where the control strategies can be ultimately implemented. Additionally, (5) the model presents a method to quantify the expected energy not supplied (RENS), which is also called ‘Loss of Load’ (LoL), terms used in research literature to show the amount of on-site generation that does not cover on-site demand [28-30]. This method is
valid only when the grid-peak shaving control strategy is used, and it occurs when there is not enough PV generation, the minimum state of charge level of storage is reached, and principally due to power restriction in which power imported from the grid is not higher than contracted power. Although, in terms of realistic operation, the load will never be unserved: A penalty fee by the utility grid could be imposed, or high electricity prices could be applied. Thus, the LoL rate can be used to design an optimal size for a PV-battery system to supply power and energy in terms of a particular application, in this case an HVAC load, as shown in the case study presented in Section 5.

This research has been developed in Spain at the premises of the Instituto de Energía Solar - Universidad Politécnica de Madrid (IES-UPM), where a prototype of a Zero-Energy Residential Building called 'Magic Box' has been installed since 2006 (Fig. 1). Magic Box was the first European entry in the Solar Decathlon international competition and has been recognized internationally as an outstanding urban-scale PV system integration project [31,32]. Several research initiatives have been carried out with the prototype [26,33,34], such as the project 'Residential electricity demand side management with PV technology 2008–2010'. Within this project, the first theoretical and experimental evidence of the possibilities of performing an Active Demand Side Management (ADSM) of domestic electricity consumption was demonstrated worldwide.

2. Methodology

This research is based on experimental measurements that have been used to develop a theoretical model of a PV hybrid system. With this model, annual simulations have been performed in a MATLAB® programming environment.

The experimental process consisted of measurements that were recorded every minute and managed remotely through a data acquisition system. The system measured the values through sensors and then stored them through automated tasks performed by Ubuntu-Linux. The measured variables were as follows: global horizontal irradiance, outdoor temperature, indoor temperature, indoor relative humidity, indoor concentration of CO₂, electricity consumption of the heat pumps, electricity generated by the PV system, grid power, battery power, and battery state of charge.

The simulation stage was divided into two distinct parts. For the first part, the grid power, the battery power, and the state of charge were simulated based on a model of PV hybrid system and control strategies developed within this research and presented in Section 4. The results obtained were compared and validated with experimental measurements presented in Section 4.7. For the second part, the electricity consumption of the heat pumps and the electricity generated by the PV system were simulated using validated tools presented in Sections 5.1 and 5.2 respectively, and the results were validated with experimental data.

2.1. Relevant parameters

(a) $P_{pv}$: Power produced by the PV system
(b) $P_{load}$: HVAC loads and corresponding electricity consumption of the heat pumps
(c) $P_{grid}$: Exported/imported grid power
(d) $P_{bat}$: Charge/discharge battery power
(e) $\varepsilon_{ss}$: Self-sufficiency, and $\varepsilon_{sc}$: Self-consumption
(f) Economic analysis: LCOE, payback-time, and billing saving.

In Fig. 2a diagram of the input and output variables of the entire process is shown, and Fig. 3 shows the electrical scheme of the system.

2.2. Experimental measurements

2.2.1. Heating, ventilation and air-conditioning system (HVAC)

To determine the electricity consumption of HVAC thermal loads, two air-to-air electrical reversible heat pumps from Daikin (model FTX25KV1B) are used. This kind of heat pumps is experiencing a significant market penetration due to two main characteristics. First, using the same installation for both heating and cooling requirements can be met by simply inverting the operating cycle with a reversing valve. The second relevant advantage of these systems in comparison with other HVAC solutions is that both processes are developed with high efficiencies, which contribute to improving the overall energy efficiency of

Fig. 2. Flowchart of relevant parameters.
2.2.2. PV system

The PV systems of Magic Box consists of six independent mono-crystalline silicon PV arrays (Fig. 5a) with 7 kWp of total nominal power. This system was designed to exploit the different tilts of the sun along the year. To achieve this goal, the PV system is distributed in different south-oriented surfaces, which allow one or more PV arrays to be used, depending on electrical consumption as discussed in Section 5.2 below. Each PV array has an associated string-type inverter, and therefore the PV AC power is supplied to a common AC bus (see Fig. 3).

The PV system also has a meteorological station with the following sensors: an Eppley pyranometer (first class pyranometer, according to ISO 9060) for measuring global horizontal solar radiation, and a platinum thermoresistance (PT-100) for the measurement of ambient temperature.

In Table 1, the main features for each PV array have been shown: tilt angle, nominal power (\(P_{G}\)), inverter maximum power (\(P_{inv}\)), and the annual expected PV energy production (\(E_{pv}\)) according to Madrid’s typical meteorological year \([35,36]\). The PV generators have been illustrated in Fig. 5b.

2.2.3. Battery energy storage system

The house is equipped with a stationary lead-acid battery bank (Sonnenschein A602/625) with dryfit gel – VRLA (valve-regulated lead-acid battery) technology. Lead-acid batteries are still widely used in both off-grid and grid-connected PV systems \([18,37]\). Lead-acid batteries are reliable, globally manufactured, and therefore, a widely understood technology. Furthermore, it has lower prices compared to other storage technologies for PV systems, such as Lithium batteries \([37,38]\). The VRLA technology also provides some advantages compared to other types of lead-acid batteries, such as no maintenance, high current capability, deep-discharge conditions, good power density, and wide operating temperature \([39,40]\).

The battery bank is divided into 24 cells, with each cell having a capacity (\(C_{10}\)) of 455 Ah and a nominal voltage of 2 V. Therefore, the total battery bank voltage is 48 V, with a capacity of around 22 kWh. The storage system has a bidirectional battery inverter (SMA – Sunny Heat pumps

In addition, to monitor the comfort conditions inside the house, STR100 thermistors from Schneider Electric with an accuracy of \(\pm 0.35^\circ C\) are used to measure the indoor temperature. Likewise, relative humidity (0–100%) and concentration of \(CO_2\) (0–2000 ppm) are measured by the SCR110 sensor from Schneider Electric with an accuracy of \(\pm 2\%\). The positions of these devices and sensors are shown in Fig. 4.

Fig. 3. Electrical scheme of the entire system.

Fig. 4. Location scheme of heat pumps and indoor sensors.
3. Description of control strategies

The general aim of implementing control strategies is to profit from the use of local PV production to provide an efficient supply to HVAC demand. Thus, the two proposed strategies have been implemented to control the BESS.

3.1. Control strategy 1: maximize the use of PV energy (increasing PV self-consumption)

In this strategy, the power generated by PV system supplies the HVAC demand; excess of PV charges the battery, and if the battery is full, PV surplus is exported to the grid. Likewise, from a demand-side point of view, HVAC demand is supplied first by PV. If more power is required, it is obtained from the battery, and finally, it is imported from the grid. It is noteworthy that a direct power exchange between the grid and the battery is not allowed in any circumstance.

3.2. Control strategy 2: reduction of grid power (grid-peak shaving)

In this strategy, as in strategy 1, the power generated by the PV system supplies the HVAC demand, the excess of PV charges the battery, and if the battery is full, PV surplus is exported to the grid. From a demand-side point of view, strategy 2 is similar to strategy 1; the difference is that the battery is discharged only to supply power peaks. In fact, HVAC demand is supplied firstly by PV and then by the grid. However, in this case, the power supplied from the grid is limited to an established value \( P_{\text{max}} \). If demand exceeds this limit, the battery is discharged so that the grid demand is curtailed. Also, in this case, power exchanges between grid and battery are not allowed.

The different operations of the control strategies are shown in Fig. 6. Fig. 6a shows the operation of strategy 1 and Fig. 6b shows the operation of strategy 2 with an illustrative value of \( P_{\text{max}} = 805 \) W. Both strategies are illustrated for the same day, where \( P_{\text{in}}, P_{\text{grid}} \) and \( \text{SoC} \) are simulated based on experimental data of \( P_{\text{in}} \) and \( P_{\text{load}} \).

As shown in Fig. 6a, the battery supplies (positive \( P_{\text{in}} \)) the HVAC demand until it reaches the minimum state of charge allowed (in this case \( \text{SoC}_{\text{min}} = 20\% \)). Then, the required power is imported from the grid (positive \( P_{\text{grid}} \)). PV generation is used first to supply the local demand; the surplus of PV charges the battery (negative \( P_{\text{in}} \)) up to 100%, and the PV excess is exported to the grid (negative \( P_{\text{grid}} \)).

In strategy 2 (Fig. 6b), the battery reduces grid power demand over \( P_{\text{max}} \), which represents a reduction of the assumed initial contracted power required to supply the HVAC loads. However, in terms of grid energy savings, the outcome is minimal. The potential benefit of this control strategy can be explained by considering the impact that the contracted peak power has on the electricity bill, which strongly depends on the regulatory framework and/or billing contract conditions.

In Spain, for instance, the power term has an impact on the electricity bill, increasing by nearly 100% since 2007 to the present day [41,42]. Therefore, a BESS control strategy focused on reducing power peaks supplied by the grid is worthy of study.

Different studies have proposed battery control strategies used with PV, related to strategy 1 [19,22,24,43] or strategy 2 [21,44-46] separately. This research proposes a unique model for both approaches, as shown in Sections 3.3 and 4, in order to perform annual simulations combining both control strategies for different approaches, such as seasonal periods, hourly electricity price, days of maximum solar irradiance, etc.

3.3. Control algorithm

The actual BESS is controlled by an algorithm developed in C++, whereby the battery inverter is used to provide relevant information (SoC, battery charging current, grid current, battery voltage, etc.) through a serial communication protocol. Similarly, the algorithm has real-time access to the data acquisition system, where the values of \( P_{\text{in}} \) and \( P_{\text{grid}} \) are obtained. Once the data has been registered, the controller will act on the grid contactor and set the inverter’s current limiters. The general scheme of the control algorithm implemented for both strategy

### Table 1

<table>
<thead>
<tr>
<th>Arrays</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tilt (°)</td>
<td>12°</td>
<td>12°</td>
<td>25°</td>
<td>25°</td>
<td>36°</td>
<td>90°</td>
</tr>
<tr>
<td>( P_{\text{in}} ) (kW)</td>
<td>1.45</td>
<td>1.44</td>
<td>1.34</td>
<td>1.34</td>
<td>0.80</td>
<td>0.61</td>
</tr>
<tr>
<td>( P_{\text{grid}} ) (kW)</td>
<td>1.50</td>
<td>1.50</td>
<td>1.50</td>
<td>1.50</td>
<td>1.00</td>
<td>0.60</td>
</tr>
<tr>
<td>( E_{\text{pv}} ) (kWh)</td>
<td>1745</td>
<td>1683</td>
<td>1774</td>
<td>1774</td>
<td>1026</td>
<td>572</td>
</tr>
</tbody>
</table>

Fig. 5. (a) Distributions of PV arrays at the Magic Box. (b) Detail of the technical room with inverters.

---

1 In Spain, customers can choose the power to be contracted, according to normalized current values [57].
Fig. 6. Daily power flow of: (a) strategy 1; (b) strategy 2. \( P_{pv} \): PV power; \( P_{load} \): HVAC load; \( P_{bat} \): battery power; \( P_{grid} \): grid power; \( SoC \): Battery state of charge.

\[ \begin{align*}
\text{if } P_{max} = 0, \text{ then } \text{strategy } 1 \text{ works} \\
\text{if } P_{max} > 0, \text{ then } \text{strategy } 2 \text{ works}
\end{align*} \]

Fig. 7. Algorithm diagram that controls the battery inverter.

1 \((P_{max} = 0)\) and strategy 2 \((P_{max} > 0)\) is presented in Fig. 7.

4. Grid-connected PV-battery modelling

The general formulation of the mathematical model presented here was designed to complement an existing control algorithm [26]. The improved model enables the choice between the two control strategies proposed, whereby the battery power, grid power exchange, battery state of charge, and self-consumption of the PV hybrid system are calculated.

4.1. Battery charge

When \( P_{pv}[n] > P_{load}[n] \), the battery inverter works in self-consumption mode, and the battery bank is charged only with \( P_{surplus} \). Then, the battery power \( P_{bat}[n] \) is calculated for each discrete time step \( n \):

\[
P_{bat}[n] = \begin{cases} 
\text{coef}[n]P_{surplus}[n], & \text{if } P_{required}[n] > P_{surplus}[n] \\
\text{coef}[n]P_{required}[n], & \text{if } P_{required}[n] < P_{surplus}[n]
\end{cases}
\]

(1)

where the PV surplus power, \( P_{surplus} \) is as follows:

(2)

\[
P_{surplus}[n] = |P_{load}[n] - P_{pv}[n]|
\]

Power required to complete battery’s charge \( (P_{required}) \) is as follows:

\[
P_{required}[n] = \begin{cases} 
0, & \text{if } SoC[n] \geq SoC_{max} \\
\frac{\text{SoC}[n] - \text{SoC}_{min}}{\Delta t} \text{ if } \text{SoC}_{min} < \text{SoC}[n] < \text{SoC}_{max} \\
\frac{\text{SoC}[n] - \text{SoC}_{up}}{\Delta t} \text{ if } \text{SoC}[n] < \text{SoC}_{up}
\end{cases}
\]

(3)

where the state of charge \( SoC \) must be among \( 0 \leq SoC[n] \leq 1 \).

The battery is charged up to \( SoC_{up} \) (upper limit of the state of charge), and it will continue charging from that point until the maximum state of charge \( SoC_{max} \) but with less power to avoid over-charging the battery. \( SoC_{up} \leq SoC_{max} \).

\( \Delta t \) is the time interval in which the data are analysed. For example, if \( n \) is recorded every minute, then \( \Delta t \) will be 1/60. \( \Delta t \) is expressed in hours, and it is between \( 0 < \Delta t < 1 \).

\( V_{dc} \) (V) is the nominal voltage of the battery bank, and \( C \) (Ah) is the nominal capacity. The battery capacity is governed by \( C\)-rate \((A\hspace{0.1cm}h)\). A \( C\)-rate is a measure of the rate at which a battery is discharged relative to its maximum capacity. When discharging, a battery is able to apply different capacities; a higher \( C\)-rate will produce a lower capacity and vice versa. \( C\)-rate depends on manufacturer specifications. For example, for Sonnenschein A602/625 battery (Table 2), capacities, service time, and \( C\)-rate are as follows:

For each step \( n \), the capacity \( C \) will be the result of the following condition:

\[
\begin{array}{cccccccc}
C_{(A\hspace{0.1cm}h)} & 275 & 369 & 410 & 455 & 523 & 565 & 604 & 666 & 623 \\
	ext{time},(h) & 1 & 3 & 5 & 10 & 24 & 48 & 72 & 100 & 120 \\
C\text{-rate},(A) & 275 & 123 & 82 & 45.5 & 21.8 & 11.8 & 8.4 & 6.1 & 5.2
\end{array}
\]

Table 2

C-rate when charging and discharging a Sonnenschein A602/625 battery. \( C_{1\text{-}C_{20}} \).
The charge coefficient, \( c_{of} \), represents the gradual reduction of \( P_{bat} \) to avoid over-charging. In this model, the \( P_{bat} \) in charge has a negative value, thus the \( c_{of} \) is between \(-1\) and \(0\).

\[
\text{coef} \left[ n \right] = \begin{cases} 
0 & \text{if } \left( \text{SoC}[n] < \text{SoC}_{\text{min}} - \Delta \text{SoC} \right) \\
0.5 & \text{if } \left( \text{SoC}_{\text{min}} - \Delta \text{SoC} \right) \leq \text{SoC}[n] \leq \text{SoC}_{\text{max}} \\
1 & \text{if } \left( \text{SoC}[n] > \text{SoC}_{\text{max}} \right)
\end{cases}
\]

(5)

4.2. Battery discharge

The battery is discharged when \( P_{load}[n] > P_{pv}[n] \). Then, the battery power \( P_{bat} \) is as follows:

\[
P_{bat}[n] = \begin{cases} 
P_{\text{surplus}}[n] & \text{if } P_{\text{remaining}}[n] < P_{\text{remaining}}[n] - P_{\text{max}} \\
P_{\text{remaining}}[n] & \text{if } P_{\text{remaining}}[n] > P_{\text{remaining}}[n] - P_{\text{max}}
\end{cases}
\]

(6)

Besides, the battery will never be discharged, \( P_{bat}[n] = 0 \), if at least one of the following conditions is met:

\( P_{\text{max}} > P_{\text{surplus}}[n] \), or \( \left( \text{SoC}_{\text{min}} \leq \text{SoC}[n] \leq \text{SoC}_{\text{max}} \right) \) & \( \Delta \text{SoC} \geq 0 \), or \( \text{SoC}[n] < \text{SoC}_{\text{min}} \).

The maximum power, \( P_{\text{max}} \), or curtailed power, is a specific variable of strategy 2, \( (P_{\text{max}} > 0) \), which determines the maximum power imported from the grid.

The battery will be allowed to discharge until the minimum state of charge \( \text{SoC}_{\text{min}} \), only when \( \text{SoC} \) overcomes the \( \text{SoC}_{\text{min}} \) level, it will be possible to discharge the battery again (thereby setting a level of hysteresis \( 0 \leq \text{SoC}_{\text{min}} \leq \text{SoC}_{\text{max}} \)).

\[ \Delta \text{SoC} = \text{SoC}[n] - \text{SoC}[n-1] \]

Finally, \( P_{\text{remaining}} \) is the power that can be extracted from the battery:

\[
P_{\text{remaining}}[n] = \frac{P_{\text{charge}}^\circ \text{SoC}[n] - \text{SoC}_{\text{min}}}{\Delta t}
\]

(8)

4.3. Losses in the battery inverter

In the previous sections \( P_{\text{bat}} \) is obtained in both charge (negative) and discharge (positive) regimes. In all cases, the absolute value of \( P_{\text{bat}} \) must not exceed the nominal power of the inverter, \( |P_{\text{bat}}[n]| \leq P_{\text{inverter}} \).

Considering the losses caused by the inverter, a new \( P_{\text{bat}} \) is calculated by the following polynomial expression based on the three characteristic efficiency coefficients of the inverter, in both charge \((k_{c0}, k_{c1}, k_{c2})\) and discharge \((k_{d0}, k_{d1}, k_{d2})\) [47].

\[
P_{\text{bat}}[n] = -P_{\text{inverter}} \left( \frac{(-1 + k_{c1}) + \sqrt{(-1 + k_{c1})^2 - 4k_{c2}(k_{c0} - \frac{|P_{\text{bat}}[n]|}{P_{\text{inverter}}})}}{2k_{c2}} \right), \quad \forall
\]

(9)

\[
\frac{|P_{\text{bat}}[n]|}{P_{\text{inverter}}} > k_{c0}
\]

\[
P_{\text{bat}}[n] = P_{\text{inverter}} \left( \frac{-(-1 + k_{d1}) + \sqrt{(-1 + k_{d1})^2 - 4k_{d2}(k_{d0} - \frac{|P_{\text{bat}}[n]|}{P_{\text{inverter}}})}}{2k_{d2}} \right), \quad \forall
\]

(10)

The losses in \( L \) the battery inverter, for both charge and discharge, are calculated as follows:

\[
L_{\text{charge}} = \sum_{n=1}^{m} \frac{P_{\text{bat}} - P_{\text{inverter}}}{P_{\text{inverter}}}, \quad \forall \quad P_{\text{bat}}[n] < 0
\]

(11)

\[
L_{\text{discharge}} = \sum_{n=1}^{m} \frac{P_{\text{bat}} - P_{\text{inverter}}}{P_{\text{inverter}}}, \quad \forall \quad P_{\text{bat}}[n] > 0
\]

(12)

4.4. Next state of charge

The next state of charge, \( \text{SoC}[n+1] \), is calculated as follows:

\[
\text{SoC}[n+1] = \frac{V_{\text{dC}} \text{SoC}[n] - \Delta \text{P}_{\text{bat}}[n]}{V_{\text{dC}}}
\]

(13)

4.5. Imported and exported grid power

The grid power, \( P_{\text{grid}} \) is calculated by the following expression:

\[
P_{\text{grid}}[n] = P_{\text{load}}[n] - P_{\text{pv}}[n] - P_{\text{bat}}[n]
\]

(14)

\( P_{\text{grid}} \) will automatically have a positive value when it is imported from the grid and will be negative when it is exported to the grid.

Finally, the accumulated power of \( P_{\text{pv}}, P_{\text{load}}, P_{\text{bat}} \) and \( P_{\text{grid}} \) can be expressed in terms of energy \( (E) \) in kWh for a certain period of time in the following way:

\[
P_{\text{pv}} = 0.001 \Delta t \sum_{n=1}^{m} P_{\text{pv}}[n]
\]

(15)

\[
P_{\text{load}} = 0.001 \Delta t \sum_{n=1}^{m} P_{\text{load}}[n]
\]

(16)

\[
P_{\text{charge}} = 0.001 \Delta t \sum_{n=1}^{m} P_{\text{bat}}[n], \quad \forall \quad P_{\text{bat}}[n] < 0
\]

(17)

\[
P_{\text{discharge}} = 0.001 \Delta t \sum_{n=1}^{m} P_{\text{bat}}[n], \quad \forall \quad P_{\text{bat}}[n] > 0
\]

(18)

\[
P_{\text{imported}} = 0.001 \Delta t \sum_{n=1}^{m} P_{\text{grid}}[n], \quad \forall \quad P_{\text{grid}}[n] > 0
\]

(19)

where \( m \) is the total number of data available. For example, for a value per minute \( (\Delta t = 1/60) \) over a period of 24 h, \( m = 24/\Delta t = 1440 \).

4.6. Self-sufficiency and self-consumption

The amount of PV energy locally consumed is called absolute self-consumption when it is instantaneously supplying the electrical demand consumption. However, this value can be expressed relative to the total consumption ‘self-sufficiency parameter’, or to the total generation ‘self-consumption parameter’ [48].

In the particular case of HVAC demand, the supply can come from two sources: PV (directly or indirectly through the battery) and the grid. The percentage of demand supplied from PV is the self-sufficiency \( (\varepsilon_{m}) \) of the system. Likewise, the energy produced by the PV system can have \( E_{\text{load}} \) three destinations: HVAC, the battery, and the grid. Of the total PV generation, the percentage of energy directed toward both battery and HVAC is the self-consumption \( (\varepsilon_{m}) \) of the system.

The expressions to calculate self-sufficiency and self-consumption for a PV hybrid system are as follows:

\[
\varepsilon_{m} = \frac{E_{\text{load}} + E_{\text{imported}}}{E_{\text{load}}} \times 100\%
\]

(21)
The system has been configured with the following parameters:

Strategy 1: SoC\[1\] = 0.78; SoC\[max\] = 1; SoC\[min\] = 0.85; SoC\[low\] = 0.45; SoC\[min\] = 0.40.

To validate strategy 2, results of February 15, 2017 are shown in Fig. 9. In this case, the system has been configured with the following parameters:

Strategy 2: SoC\[1\] = 0.92; SoC\[max\] = 1; SoC\[min\] = 0.85; SoC\[low\] = 0.45; SoC\[min\] = 0.40; P\[max\] = 805 W.

In addition to the specific days presented in Fig. 8 and Fig. 9, 44-day experimental measurements (63,360 one-minute samples) between January and June 2017 have been carried out. In Fig. 10, the determination coefficients (R\(^2\)) that show the quality of the model in order to replicate the SoC, P\[grid\] and P\[bat\] are shown.

There are numerous formulas to determine the error between the measured values and the simulated values. However, in this study, Mean Absolute Error (MAE) and Symmetric Mean Absolute Percentage Error (SMAPE) have been considered to quantify the error of the proposed model (Table 3) in absolute and relative terms respectively.

MAE takes the absolute value of errors (measured value minus simulated value) and averages them over the entirety of the forecast time periods. Taking an absolute value of a number disregards whether the number is negative or positive and, in this case, avoids the positives and negatives cancelling each other out. SMAPE is an accuracy measure based on percentage (or relative) errors. The absolute difference between the measured value and the simulated value is divided by half the sum of measured value and the simulated value. The value of this
calculation is summed for every point and divided again by the total number of points.

5. Case study: technical analysis

In this section, the technical analysis of a specific case study is presented. The electrical consumption of HVAC is established using experimental data. Particular sizes of both PV system and BESS are used in order to simulate the behaviour of the grid-connected PV hybrid system, using the model presented in Section 4.

5.1. Annual HVAC load estimation

In order to estimate the annual thermal loads of the building and the associated electricity demand of the HVAC system, an extensive measuring campaign has been conducted to measure the HVAC electrical consumption and to monitor thermal comfort conditions inside the building to assess whether it meets internationally accepted standards. In this work, two thermal comfort methods described in [49] (see Fig. 11) have been analysed: Fanger’s PMV method and Adaptive Comfort method.
The Fanger’s PMV method is a heat balance model that views the human being as a passive recipient of thermal stimuli. The resulting Predicted Mean Vote Index (PMV) is calculated with the Fanger’s equation [50] and widely used with international standards ISO 7730 [51]. Thus, variables such as clothing, physical activity, CO₂ concentration, relative humidity, outdoor and indoor temperature among others are involved in this method.

The adaptive comfort model assumes that humans consciously or unconsciously modify their behaviour to adapt to thermal conditions. Therefore, the thermal balance equations cannot be strictly applied because the thermal adaptation is, by nature, a dynamic process [52]. The adaptive comfort formula does not directly take into account the classical comfort factors described above but simply establishes the indoor comfort temperature as a function of outdoor temperature [53,54].

Heat pumps have been configured to operate automatically at the following setpoint temperatures: 20 °C for months October to March, and 26 °C for months April to September. In total, 90,720 one-minute samples are within Category C; similarly, 98% of samples are within Category A. Furthermore, 58% are within Category A. 94% are within Category B limits; 58% are within Category A. 96% of the samples are within Category I; likewise, 82% of samples are within Category I limits.

Once comfort conditions have been guaranteed inside the house, the heat pump’s electrical consumption ($P_{\text{load}}$) is estimated —see Eq. (26)— depending on the main variables monitored: $T_{\text{indoor}}$: outdoor temperature (°C); $T_{\text{indoor}}$: indoor temperature (°C); $G_{\text{hrz}}$: global horizontal irradiation (W/m²); and $h$: hour (from 1 to 24).

Although the above variables have been monitored, in this first study a linear regression model was used to estimate $P_{\text{load}}$ because it presents better adjustments compared to other existing simulation tools. However, other methods can be used, such as Model Predictive Control (MPC) [55,56] in order to obtain $P_{\text{load}}$. Additionally, MPC, together with forecasting of PV generation [34] and the battery control strategy presented in this paper, could be carried out in future research.

$$P_{\text{load}} = a_0 + a_1 T_{\text{indoor}} + a_2 T_{\text{outdoor}} + a_3 C_{\text{hrz}} + a_4 h + a_5 T_{\text{outdoor}} T_{\text{indoor}} + a_6 T_{\text{indoor}} C_{\text{hrz}} + a_7 T_{\text{indoor}}^2 + a_8 T_{\text{outdoor}} + a_9 C_{\text{hrz}} + a_{10} h + a_{11} T_{\text{outdoor}}^2 + a_{12} T_{\text{indoor}} + a_{13} T_{\text{outdoor}} H + a_{14} C_{\text{hrz}} + a_{15} h^2$$  (26)

where coefficients $a_k$ vary depending on the season of the year. In Table 4(a), values of the coefficients and the associated $p$-values are reported for all seasons. As it can be noted, all the values are lower than the common statistical significance level of 0.05 with the exception of two values marked with an asterisk.

A low $p$-value ($<0.05$) in Table 4(a) indicates that the $a_k$ has a

---

**Table 3**

Error calculation (on a per-minute basis) of 44-day experimental measurements.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Error</th>
<th>MAR</th>
<th>SMAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>SoC</td>
<td>1.10%</td>
<td>0.34%</td>
<td></td>
</tr>
<tr>
<td>$P_{\text{out}}$</td>
<td>34.51 W</td>
<td>5.23%</td>
<td></td>
</tr>
<tr>
<td>$P_{\text{grid}}$</td>
<td>44.76 W</td>
<td>4.04%</td>
<td></td>
</tr>
<tr>
<td>$G_{\text{hrz}}$</td>
<td>13.90 kWh</td>
<td>2.40%</td>
<td></td>
</tr>
<tr>
<td>$T_{\text{indoor}}$</td>
<td>6.04 kWh</td>
<td>1.10%</td>
<td></td>
</tr>
<tr>
<td>$R_{\text{discharge}}$</td>
<td>6.39 kWh</td>
<td>0.27%</td>
<td></td>
</tr>
<tr>
<td>$R_{\text{charge}}$</td>
<td>14.61 kWh</td>
<td>2.62%</td>
<td></td>
</tr>
</tbody>
</table>

---

**Table 4**

(a) Coefficients $a_k$ of Eq. (26) and the corresponding $p$-value. (b) F-statistic parameter of regression model used.

<table>
<thead>
<tr>
<th>Season</th>
<th>Winter</th>
<th>Spring/Autumn</th>
<th>Summer</th>
<th>F-statistic vs. constant model</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_0$</td>
<td>-0.35</td>
<td>5.46E-05</td>
<td>1.11E-02</td>
<td>-108.80</td>
<td>1.79E-128</td>
</tr>
<tr>
<td>$a_1$</td>
<td>9.25E-03</td>
<td>3.08E-02</td>
<td>1.11E-02</td>
<td>6.04E-02</td>
<td>1.59E-128</td>
</tr>
<tr>
<td>$a_2$</td>
<td>-2.55E-03</td>
<td>3.43E-02</td>
<td>1.11E-02</td>
<td>4.46E-02</td>
<td>1.97E-128</td>
</tr>
<tr>
<td>$a_3$</td>
<td>-1.05E-03</td>
<td>3.89E-02</td>
<td>1.11E-02</td>
<td>4.79E-02</td>
<td>1.64E-128</td>
</tr>
<tr>
<td>$a_4$</td>
<td>4.04%</td>
<td>7.18E-2</td>
<td>1.05E-03</td>
<td>4.79E-02</td>
<td>1.30E-128</td>
</tr>
<tr>
<td>$a_5$</td>
<td>1.34</td>
<td>1.13E-11</td>
<td>3.32</td>
<td>0.73</td>
<td>1.90E-128</td>
</tr>
<tr>
<td>$a_{10}$</td>
<td>18.87</td>
<td>2.95E-08</td>
<td>1.24</td>
<td>1.87E-02</td>
<td>1.97E-108</td>
</tr>
<tr>
<td>$a_{11}$</td>
<td>-1.91E-04</td>
<td>4.58E-13</td>
<td>9.07E-05</td>
<td>-3.29E-05</td>
<td>1.79E-108</td>
</tr>
<tr>
<td>$a_{12}$</td>
<td>-0.28</td>
<td>6.24E-11</td>
<td>22.84E-02</td>
<td>0.78</td>
<td>1.35E-104</td>
</tr>
</tbody>
</table>

* Coefficients $a_k$ with $p$-value higher than 0.05 can be ignored because of poor correlation.

---

**Fig. 11.** Evaluation of thermal comfort methods: (a) Fanger Method, and (b) adaptive model.
meaningful addition to the model since changes in the predictor's value are related to changes in the response variable. On the contrary, a p-value greater than the common level of 0.05 suggests that changes in the predictor are not associated with changes in the response. Moreover, the F-statistics of the regression model fit versus the constant model showed in Table 4(b) have a p-value lower than the statistical significance level of 0.05, which indicates that the regression model provides a better fit than the intercept-only model.

The output of the simulation was compared to the experimentally measured data (as mentioned above, minute samples over 9 months covering all seasons of the year) in order to obtain a feedback on the reliability and accuracy of the model. The R-squared value of 0.8612 means that the model explains about 86% of the variability in the response, showing a reasonably good agreement between the proposed linear-regression model and measured $P_{load}$, as it can be seen in Fig. 12.

Based on the regression model above, annual HVAC electricity demand with a minute-based resolution has been simulated, as shown in Fig. 13a. Annual accumulated energy for this demand is as follows: $E_{load} = 3807$ kWh.

In the specific case study, the simulation was performed with $P_{max} = 805$ W. Nevertheless, it is not the only possible value that can be used. In fact, in Spain, customers can choose different contracted power levels with the utility grid [57]. In this sense, any value higher than $P_{max}$ is considered as a peak-load. According to the values in Fig. 13a, in some cases, the demand exceeds 2300 W. Therefore, if a PV-battery system is not used, the contracted power by the user should be at least 3450 W (see Table 5). In the same Fig. 13a, seasonal periods with consumption peaks (winter and summer) can be identified. Consequently, it is reasonable to use strategy 2 (grid-peak shaving) in those periods. In order to determine the new contracted power, several simulations using Eq. (23) were performed with $P_{max}$ values lower than 3450 W. Table 5 shows that for $P_{max} = 805$ W, the $LoL$ rate is 1.70%, i.e. 65 kWh of the annual HVAC consumption would not be supplied by the PV hybrid system. This value has a low impact on the comfort conditions of the building, as previously indicated in Fig. 11. As $P_{max}$ decreases, it increases self-sufficiency as well. However, it will also drastically increase the $LoL$ rate, resulting in unsatisfying comfort conditions.

5.2. Annual PV generation

Annual simulation of the PV system's electrical production has been carried out according to the characteristics given in Section 2.2.2 using validated tools and procedures [35] for the determination of the solar potential, which includes the effects of shadows and consideration of losses (optical and thermal losses in the generator, voltage drops, conversion losses in the inverter, etc.).

Due to the fact that the HVAC consumption in buildings is, in general, just a part of the total load and the objective of this study is the assessment of the potential of PV hybrid systems to cover HVAC loads, specific PV arrays from the building demonstrator have been selected (arrays 3 & 4 from Table 1) so that annual expected PV generation (Fig. 13b) is $P_{pv} = 3548$ kWh, comparable to the annual HVAC consumption ($E_{load} = P_{load}$).

5.3. Battery capacity

The case study is simulated with a lead-acid battery bank coupled to the AC bus by means of a bidirectional inverter. According to [18], the optimal nominal storage size for residential buildings using PV systems was about 4.5 kWh in 2013, and it will be increasing significantly to 7 kWh in 2021 under different scenarios of electricity costs. In this work, the value of 6 kWh ($C_{opt} = 125$ Ah, $V_{dc} = 48$ V) widely used and tested [58] will be simulated along with variations between 0 and 10 kWh for further sensitivity analysis. In addition, 60% of depth of discharge ($SoC_{min} = 0.4$) has been established, which is the value recommended by the manufacturer to extend the lifetime of the batteries and to avoid over-discharge stress.

5.4. Annual power flows

Due to the considerable number of input variables, a specific case has been chosen to show the overall behaviour of PV hybrid system over one year based on the parameters of the following sections:

- Location: Madrid
- PV generator nominal power: 2.68 kWp
- Orientation and tilt angle: South, 25°
- BESS nominal capacity: 6 kWh ($V_{dc} = 48$ V; $C_{opt} = 125$ Ah)
- $SoC_{min} = 0.40$; $SoC_{max} = 0.95$; $SoC_{int} = 0.45$; $SoC_{cr} = 0.95$; $SoC_{max} = 1$
- Control strategies: strategy 2 in winter/summer; strategy 1 in spring/autumn.

The simulation of both $P_{grid}$ and $P_{be}$ are shown in Fig. 14a, and $SoC$ is shown in Fig. 14b. In winter and summer months (from day 1 to 90, 181 to 243 and 334 to 365), the battery is discharged to supply power values higher than $P_{max} = 805$ W (strategy 2). For the rest of the year, $P_{load}$ does not exceed the $P_{max}$. Therefore, the battery control strategy 1 is used to reduce energy consumption from the grid.

5.5. Grid demand duration curve

The grid load duration curves are shown in Fig. 15, which represent the grid electricity demand to supply the HVAC load in three different scenarios: the first one (blue\(^2\)) is without using PV or battery; the second curve (red) shows the case of using only PV (no BESS); the third curve (yellow) using PV and BESS.

Using the PV system alone to directly supply the HVAC demand only reaches 27%, i.e. 73% of energy comes from the grid. When the BESS is added, the energy from grid can be reduced to 54%, as observed in Fig. 15.

5.6. Self-sufficiency & self-consumption

The amount of PV energy locally consumed is called absolute self-consumption when it is instantaneously supplying the electrical demand consumption. However, this value (expressed as a percentage) can be relative to the total generation (self-consumption) or to the total consumption (self-sufficiency). Necessary energy to supply the HVAC demand comes from two sources: PV (directly or indirectly, through the

\(^2\) For interpretation of color in Figs. 15 and 16, the reader is referred to the web version of this article.
Table 5
Results of LoL and self-sufficiency parameters using combining of control strategies based on standard powers for single-phase distribution systems in Spain.

<table>
<thead>
<tr>
<th>$P_{\text{max}}$ (W)</th>
<th>Reduction (%)</th>
<th>LoL (%)</th>
<th>Self-sufficiency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3450</td>
<td>0.00</td>
<td>0</td>
<td>39.28</td>
</tr>
<tr>
<td>2300</td>
<td>33.34</td>
<td>$5 \times 10^{-4}$</td>
<td>39.28</td>
</tr>
<tr>
<td>1725</td>
<td>50.00</td>
<td>0.01</td>
<td>39.41</td>
</tr>
<tr>
<td>1150</td>
<td>66.67</td>
<td>0.13</td>
<td>40.35</td>
</tr>
<tr>
<td>805</td>
<td>76.67</td>
<td>1.70</td>
<td>44.04</td>
</tr>
<tr>
<td>690</td>
<td>80.00</td>
<td>4.19</td>
<td>45.48</td>
</tr>
<tr>
<td>345</td>
<td>90.00</td>
<td>21.26</td>
<td>48.56</td>
</tr>
</tbody>
</table>

Bold values indicate the $P_{\text{max}} = 805$ W is used in the case study because of both its high reduction of contracted power (almost 77%) and low impact of LoL (1.70%).

According to Eqs. (21) and (22), the annual values of self-sufficiency and self-consumption parameters have been calculated (see Fig. 16). Therefore, the HVAC consumption (Fig. 16a) is supplied directly by the PV (light green), the battery (dark green), or by the grid (orange).
6. Case study: economic analysis

In any investment on grid-connected PV system, in addition to solar potential, there are many parameters that must be considered in order to determine if it is worthwhile from a financial point of view [59]. In this section, an economic analysis of the case study is presented, using three important parameters: LCOE, payback time and billing saving.

6.1. Levelized cost of electricity (LCOE)

LCOE is one of the most important parameters in the field of PV systems economic analysis [60-62]. The LCOE is calculated by accounting for all the PV system’s expected lifetime costs (including construction, financing, maintenance, and taxes), which are then divided by the whole system’s lifetime expected PV energy (kWh). All cost and benefit estimates are adjusted for inflation and discount rate to account for the time-value of money. The importance of LCOE is to determine whether the system is technically and economically feasible. In addition, the actual lifetime of a specific battery bank depends on many factors, among the most important are: the state of charge, degradation, and cycling according to the specific application and BESS strategies. Thus, annual simulations have been carried out, and the battery aging models proposed in [63], widely used by the scientific community [64-67], have been implemented.

The full cycles method defines the end of the battery lifetime when a specified number of full complete cycles (charge-discharge) are reached. The method of Ah Throughput model is based on counting the cycles corresponding to each range of the depth of discharge (specific for a battery) over a year. Finally, the Kinetic Battery Model calculates the capacity loss by corrosion and degradation. The end of battery lifetime is reached when the remaining battery capacity is 80% of its initial capacity.

In Table 7, results of the three aging models can be compared for the same case study. In the sections below, the Kinetic Battery Model proposed by Schiffer [65] is considered because it provides the most realistic assessment of aging and degradation effects on battery performance. Therefore, assuming the hypothetical PV system’s lifespan expectancy is 30 years [62], it will be necessary to purchase the battery bank four times (4 × 7.3 = 30 years).

Considering that the price of the PV systems and the batteries are constantly reduced, many simulations have been carried out to calculate the LCOE (Fig. 17) with variations of the BESS between 100 €/kWh and 300 €/kWh, and with different PV system prices between 0.5 €/Wp, and 2 €/Wp, which represent the current market conditions [68].

According to [68], the installed PV system price in the residential sector for Spain is between 1.4 and 1.5 €/Wp including the price of modules, inverters, and the Balance of System (BoS). In this case study, 1.5 €/Wp is considered, assuming that the PV inverter also performs the BESS inverter function. Likewise, according to [17,20], the price of batteries ranges between 150 €/kWh and 300 €/kWh. For this case study, 243 €/kWh is considered because it is the actual purchase price of the installed batteries. Thus, the point (243 €/kWh, 1.5 €/Wp) can be located in Fig. 17, which results in 0.16 €/kWh.

6.2. Payback-time

One of the challenges of the PV systems is its cost effectiveness, and therefore, its ability to generate profits [69,70]. Payback-time is the time in years when the investment begins to generate economic benefits. It is a parameter derived from the Net Present Value (NPV) that is used to evaluate the ability to make a profit.

To calculate the payback-time (Fig. 18), the annual income of the economic savings coming from the PV hybrid system is considered. In addition, three scenarios of the PV surplus value are considered: Scenario A, where PV surplus is not valued and is exported to the grid without receiving any monetary compensation; Scenario B, where PV surplus is remunerated at the electric market price, and; Scenario C, where PV surplus is used to supply other loads into the house. Expenses correspond to the operation and maintenance and changing of equipment, where the PV inverter must be changed after 15 years, and the batteries must be replaced at the end of their lifetime.

The graphs presented in Fig. 18 are useful to evaluate any value of the payback time (expressed in years) for the established price ranges and for the mentioned scenarios of the PV surplus. For example, payback time at the point (243 €/kWh, 1.5 €/Wp) can be obtained in Fig. 18. Results are 26, 21, and 16 years for scenarios A, B, and C respectively.

6.3. Billing saving

In order to calculate the utility bill, the 2.0 DHA tariff period (residential tariff with two periods) was used, in accordance with the Spanish regulated prices currently in effect [42]. The cost in Euros that would be paid to the utility has been calculated over a year in the base
Table 6
Economic and technical input data used in Eq. (27).

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Unit</th>
<th>Meaning</th>
<th>Assumed value</th>
</tr>
</thead>
<tbody>
<tr>
<td>LCOE</td>
<td>€/kWh</td>
<td>Levelized Cost of Electricity</td>
<td>–</td>
</tr>
<tr>
<td>T</td>
<td>years</td>
<td>Economic lifetime of the PV system</td>
<td>30, according to [62].</td>
</tr>
<tr>
<td>t</td>
<td>year t</td>
<td>Operation &amp; Maintenance (O &amp; M) costs and equipment changes.</td>
<td>–</td>
</tr>
<tr>
<td>Q</td>
<td>€</td>
<td>Operation &amp; Maintenance (O &amp; M) costs and equipment changes.</td>
<td>65 €/kWh per year [62] + PV Inverter replacement at 15 years [18,62] + replacing batteries every 7.3 years (see Section 6.1.1).</td>
</tr>
<tr>
<td>E_t</td>
<td>kWh</td>
<td>PV electricity generated on year t</td>
<td>PV: ranging from 0.5€ to 2€ per Wh. + BESS: ranging from 100€ to 300€ per kWh.</td>
</tr>
<tr>
<td>I</td>
<td>%</td>
<td>Initial investment.</td>
<td>4.9% in Spain [62].</td>
</tr>
<tr>
<td>r</td>
<td>%</td>
<td>Discount rate</td>
<td>–</td>
</tr>
</tbody>
</table>

Table 7
Comparison of three different models of battery lifetime.

<table>
<thead>
<tr>
<th>Battery lifetime (years)</th>
<th>Equivalent full cycles</th>
<th>Ah throughput model</th>
<th>Kinetic Battery Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.2</td>
<td>11.1</td>
<td>7.3</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 17. Variation of LCOE depending on the cost of both PV and battery systems.

The case without PV-battery system and compared to two cases. In the first one, only the PV system is considered (no BESS), and in the second one, both PV and BESS systems are considered. The invoice is divided into three values: power, energy, and taxes, as shown in Fig. 19.

From Fig. 19, it can be seen that only using a PV system (2.68 kWp) would have 21% of billing reduction. However, the PV-battery system (2.68 kWp, 6 kWh) would enhance the savings in billing up to 56%.

6.4. Sensitivity analysis

The case study presented previously corresponds to a specific combination of PV-battery (2.68 kWp and 6 kWh). However, the variation of both PV and battery characteristics modifies the self-sufficiency (Fig. 20a), self-consumption, (Fig. 20b) and therefore, the billing savings (Fig. 20c). Thus, keeping the HVAC demand constant and using the same control strategies throughout the year (strategy 2 in winter/summer; strategy 1 in spring/autumn), multiple simulations were performed varying the battery size between 0 to 10 kWh (viable sizes for residential buildings), and the PV system size between 0.5 to 7 kWp (covering all fields of Magic Box).

The sensitivity analysis is useful to understand how the sizing of both PV and battery impacts the hybrid system. For example, setting a...
PV system of 2.68 kW, higher BESS sizes to 6 kWh does not significantly increase self-sufficiency (Fig. 20a). It is also worth noting that the combination of strategies affects the value of billing, even in cases where there is no battery (0 kWh in Fig. 20c), whereas small PV systems—less than 1 kW—allow billing savings around 40%.

The self-sufficiency, self-consumption, and billing savings rate increments are not linear with the BESS capacity, suggesting that the optimal size of the PV-battery system is a crucial factor to be established, based on different energy and economic approaches [16].

7. Discussion of results

The experimental measurements have confirmed that the comfort conditions are within the levels established by widely used standards. In the same way, these measurements allowed the elaboration of the HVAC electrical consumption for the entire year and to develop strategies of control in order to increase self-consumption and decrease power demand.

The BESS control strategies used here allow one to reduce...
consumption of both energy and power from the grid. Strategy 1 is useful in electricity markets whose value of energy (kWb) is high, while strategy 2 is useful in electrical markets, such as in Spain, where the contracted power (kW) has a high cost in billing (38.04 €/kW/year in 2016 for the residential sector, compared to 19.25 €/kW/year in 2007) [41,42]. For the case study, the contracted power required for the HVAC system (according to the different standardized levels) is 3.45 kW. However, using PV hybrid system, the contracted power is reduced to the smallest reasonable value: 0.805 kW (77% less). The combination of both strategies, as shown in Fig. 14, enables to limit the power from the grid in the months of peak demand (winter and summer) and to reduce grid electricity imports for the rest of the year.

In Fig. 18, scenario A (the least favourable), the consumer does not receive bonus for exporting PV surplus into the grid. In the second scenario, the consumer would be considered a prosumer, who is able to sell the PV surplus. However, this scenario depends on the political situation and regulations in each country. In contrast, this paper presents this scenario to provide evidence of the potential benefit that this type of system would have. The most realistic scenario is C, where PV surplus supplies other demands within the home (lights, appliances, machinery, electric vehicles, etc.). This scenario is the subject of further studies by the authors. Additionally, the authors are developing models for other types of batteries—specifically Lithium batteries—which have other characteristics, maximum and minimum states of charge, cost, etc. This will provide other studies and different results.

The model and battery control strategies presented in this paper are also applicable for other realistic situations, where HVAC power consumption is only a part of the total building load. In order to illustrate this situation, electrical consumption of two consecutive days is shown in Fig. 21a, where both HVAC (P\text{load}) and other load consumption (P\text{building}) such as electric vehicle, home appliances, and office equipment are plotted. Fig. 21a also shows PV generation of two days of experimental measurements (27 and 28 May 2017) where day 1 is a sunny day with cloudy intervals, and day 2 is a cloudy day. In this scenario, the strategy 1 operation is illustrated on the first day, where the battery can be charged with PV surplus. Day 2 uses strategy 2 (setting P\text{max} at 2300 W which is a value equivalent to the maximum expected power) allowing the battery to keep enough capacity longer. In Fig. 21b dynamic results of the grid-connected PV-battery system and the battery state of charge are shown.

Another important aspect to consider in a realistic situation is the quality of data. The input data can be obtained from simulations from software tools (typically hourly values) or from measured data. Time resolution is a very important factor in the accuracy of the model, as indicated in [21,22], where the results will be more reliable with sub-hourly data, especially to capture the high-peak powers. Once P_E and P_load are entered, the model works to obtain P_{bat}, P_{grid} and SoC in each time-step, depending on the control strategy used.

8. Conclusions

In this paper, theoretical and experimental works that are being carried out in a grid-connected residential building prototype available at the IES-UPM have been presented. In particular, the following conclusions have been drawn from the analysis done on the influence of the specific application and the BESS control strategy.

(a) The mathematical model presented here has been developed for grid-connected PV-battery systems; as long as the battery is only charged with the PV surplus, it will never be charged from the grid. Although the focus of this article is the HVAC demand, the model is valid for other types of load (P\text{load}) inside the house. According to the experimental data, the theoretical model has an error margin lower than 10%.

(b) It is important to know the annual distribution of electrical loads to determine which season or hourly periods with higher power demand justify the existence of some kind of strategy allowing consumption from the grid to be reduced. In this paper, two strategies have been proposed: the first helps to reduce energy consumption, and the second helps to reduce power peak demand from the grid. In the case study considered (Magic Box: 2.68 kWp coupled to a 6 kWh/48 V Lead-Acid battery with bidirectional inverter; annual PV generation comparable to HVAC demand), when using a combination of both strategies, it is possible to reduce both contracted power and energy consumption (77% and 49% respectively for case study).

(c) The implementation of local PV and electrical storage systems to power HVAC loads improves the self-sufficiency rate in varying degrees, depending not only on the PV power, but also on the HVAC load and storage control capacity. This behaviour implies that the optimal sizing of PV & BESS must be carried out in each case by considering both energy and economic aspects.

(d) It is clear that, at present, the billing saving by itself might not be enough to encourage the use of PV hybrid systems. It will also strongly depend on the electricity tariff structure and energy policy in each country, in addition to PV and storage systems costs. This will determine whether the investment will be profitable from the financial point of view.

Acknowledgements

This work has been partially financed by the Spanish Ministry of Economy and Competitiveness within the framework of the project 'DEM: Sistema distribuido de gestión de energía en redes eléctricas inteligentes' (TEC2013-66126-R).

The authors gratefully acknowledge the financial support by the National Secretary of Higher Education, Science, Technology and Innovation of Ecuador (SEINSECYT) for a PhD scholarship to the first author.

The authors also acknowledge support of the ‘Fundación Iberdrola España’ by means of the ‘2015 Ayudas a la Investigación en Energía y Medio Ambiente’ in the ‘Smart Grids para la eficiencia en redes eléctricas: caso práctico en la ETSIT-UPM’ project.

References

[11] Williams CJC, Binder JO, Kelm T. Demand side management through heat pumps,


Glossary

ADSM: Active Demand Side Management
BESS: battery energy storage system
HVAC: heating, ventilation and air-conditioning
IEA: International Energy Agency
IES: Instituto de Energía Solar, Solar Energy Institute
LCOE: levelized cost of electricity
MAE: Mean Absolute Error
MPC: Model Predictive Control
PMV: Predicted Mean Vote Index
PV: photovoltaic
SMAPE: symmetric mean absolute percent error