

## Optimal Design of Photovoltaic Domestic Installations Considering Second-Purpose Batteries

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**Abstract.** About 11 million tons of retired batteries are expected to be produced globally by 2030, of which a huge percentage will proceed from individual owners who charge their vehicles at home. To overcome this issue, multiple studies focused on the viability of reusing mobility batteries for different applications. However, this kind of analysis in individual dwellings are still scarce. This paper aims at filling this gap by developing a novel optimization methodology for design of photovoltaic arrays in domestic installations considering second-purpose batteries from mobility. In particular, we aim at analyzing the effect of using batteries from vehicles when they are no longer valid for mobility. Thus, we consider the problem in which these batteries are used for stationary applications at home, observing their effects on the photovoltaic design as well as other aspects like total project cost and self-consumption rates. To this end, a planning strategy is developed including suitable models of photovoltaic units, flexible loads and electrical vehicle. The developed methodology is tested on a benchmark prosumer environment and different scenarios are profusely studied. The results obtained demonstrate that the use of second-purpose batteries seem profitable in smart homes, reducing the total cost by 15 % and increasing the self-consumption rate by 20 %. Moreover, other aspects like its effect on the final scheduling and the behavior under limited photovoltaic capacity are commented. Lastly, the importance of the developed methodology for future similar studies is highlighted.

**Keywords.** Electric vehicle; Photovoltaic; Second-purpose batteries; Smart home.

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## Nomenclature

### Parameters and variables

$\Delta_t$	Time interval [0.5 h – 30 min]
$\delta^i$	Operation time slots of the controllable appliance $i$
$\varepsilon_{bt}$	Self-discharge coefficient of the battery [%/hour]
$\eta_{ad}$	Efficiency of the AC/DC converter [%]
$\theta_{bt}$	Consumed life rate of the battery [p.u.]
$\kappa_i$	Ratio of operation and maintenance cost vs. initial investment cost for the $i$ th component of the PV domestic installation [%]
$\xi_{pv,k}$	Normalized PV power in p.u. at a time period $k$
$\rho_{P,k}$ ( $\rho_{S,k}$ )	Purchase (selling) price of the kWh at any time period $k$ [€/kWh]
$\rho_{Pc,k}$	Contracted power price at any time period $k$ [€/kW]
$\chi_{bt}^{rat}$	Rated depth-of-discharge of the battery [%]
$A_b^{cyc}, B_b^{cyc}$	Coefficients of degradation cycle aging function
$A_b^{cal}, B_b^{cal}, C_b^{cal}$	Coefficients of degradation calendar aging function
$C_d$	Daily electricity cost of the photovoltaic domestic installation ([€/day])
$C_{EE,d}$ ( $C_{EE,k}$ )	Cost from energy exchange of the photovoltaic domestic installation with the grid [€/day], (€/period)
$C_I^i$ $i \in \{ad, pv\}$	Investment cost of the $i$ th unit [€/unit]
$\{C_{I,d}\} (C_{O\&M,d})$	Total cost of {initial investment} (operation and maintenance) for the photovoltaic domestic installation (€/year)
$d$	Nominal discount rate [%]
$DOD$	Depth of discharge [%]
$g$	Expected inflation [%]
$J$	Objective function [€/day]
$LB^i$	Lower band of allowable operation time slot of the controllable appliance $i$
$Le_{bt}^b$	Beginning energy of the battery [kWh]
$Le_{bt}^{N_i}$	End energy of the battery [kWh]
$Le_{bt,y}^{max}$	Maximum energy of the battery in the year $y$ [kWh]
$Le_{bt,k}$	Battery energy at any time period $k$ [kWh]
$N_b$	Calendar lifetime
$N_m$	Number of sampling intervals in a month
$N_t$	Number of sampling intervals in a year
$N_i$ $i \in \{pv, bt, ad\}$	$i$ th minimum unit lifetime [year]
$N_{G_{br}}^{max}$	MBU lifetime according to maximum cumulated aging rate [year]
$N_p$	Photovoltaic lifetime [years]
$P_{ad}$	Power of an AC/DC converter unit [kW]
$P_{bt-}^{max}$ ( $P_{bt+}^{max}$ )	Maximum charge (discharge) power for the battery [kW]

$P_c$	Contracted power from the electric mains [kW]
$P_{ev, k}$	Electric vehicle load at any time period $k$ [kW]
$P_{g-, k}$ ( $P_{g+, k}$ )	Grid power output (input) at any time period $k$ [kW]
$P_{hl, k}$	Total load non-controllable at any time period $k$ [kW]
$p^i$	Power of the controllable appliance $i$ [kW]
$P_{pv}$	Power of a photovoltaic panel [kWp]
$P_{pv, k}$	Photovoltaic power produced by the photovoltaic system at any period $k$ [kW]
$r_{O\&M}$	Annual escalation rate of the operation and maintenance cost [%]
$r_{pv}$	photovoltaic degradation rate [%]
$T$	Set of time intervals
$P_{bt-, k}$ ( $P_{bt+, k}$ )	Optimal charge (discharge) power for the battery at any period $k$ [kW]
$u_k^i$	Commitment status of the controllable load $i$ for the time $k$ [OFF=0, ON=1]
$\bar{u}_k^i / u_{-k}^i$	Transition of the controllable load $i$ for the time $k$ [OFF-ON / ON-OFF=1]
$UB^i$	Upper band of allowable operation time slot of the controllable appliance $i$
$\Omega_{pv}$	Number of photovoltaic panels
$\Omega_{ad}$	Number of units of the AC/DC converter

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### Subscripts

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d	Daily
ad	AC/DC converter
b	Battery
bt- (bt+)	To(from) the battery
EE	Energy exchange with the grid
g- (g+)	To(from) the utility grid
I	Initial investment
$k$	Index of time period
max	Maximum
min	Minimum
O&M	Operation and maintenance
pv	Photovoltaic Generation

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### Superscripts

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$t_1$	At the beginning
$t_{N_i}$	At the end
$i$	Index of component of the photovoltaic household-prosumer
max	Maximum
min	Minimum

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### Acronyms

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DOD	Depth of discharge
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DW	Dishwasher
EV	Electric vehicle
PV	Photovoltaic
RES	Renewable energy source
SD	Spin dryer
SFC	Self-consumption
SOC	State of charge
TOU	Time-of-use
TLBO	Teaching-learning-based optimization
WM	Washing machine

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## 1 - Introduction

### 1.1 - Context & motivation

The role of energy storage in future decarbonization of the electricity sector is clear and indisputable [1]. It is expected that storage systems increase their penetration in the near future, with the aim of increasing the efficiency of the system and help to increment the penetration and participation of renewable energy sources (RESs) [2]. In this context, storage systems appear in stationary or mobility applications. In the latter case, the overall system can benefit from on-board battery packs in electric vehicles (EVs) through vehicle-to-grid or vehicle-to-home features [3].

Despite their clear advantages, energy storage systems are still costly and based on damaging materials [4]. In this regard, there is a growing interest on incrementing the useful life of storage units, especially batteries. However, in mobility applications, it results difficult and conflictive with the interest of drivers, who are keen on obtaining a high autonomy. This way, mobility batteries have a shorter lifecycle and need to be replaced after a predefined number of cycles [5]. Nevertheless, these batteries are useful yet for different applications in a practise known as second-life or second-purpose batteries [6]. Thereby, battery systems that are no longer useful for mobility applications can be still used with other aims such as renewable integration. This paper is focused on possible second-life application of mobility batteries in domestic installations.

### 1.2 - Related works

A growing interest in second-life applications for batteries has been observed in recent years, focusing on economic or environmental advantages/viability of such practise. In this regard, [7] develops an aggregator model for gridable vehicles and second-life batteries, in the way as they can be centralized managed for their participation on the distribution network. Likewise, [8] focuses on developing a proper energy management control for power converters interfacing second-life battery packs in stationary applications. Sáenz-de-Ibarra, et al [9] discussed an optimal sizing methodology for a second-life Li-ion battery bank with grid implications. In [10], second-life and fresh batteries are economically compared for wind farm applications. To this end, a model predictive control scheduler is developed for a wind farm owner, concluding that second-life batteries may outperform fresh packs if wind energy price decreases more rapidly than batteries cost in the future.

One of the most attractive application of batteries is frequency regulation due to their fast response. This is the main focus of [11], where the performance of second-life EV batteries in frequency regulation services is investigated. On the other hand, [12] studies the applicability of second-life batteries in reducing peak demand of charging stations for battery EVs, for which an optimal sizing method is proposed comparing the results

obtained using fresh or repurposed battery packs. In the same line, [13] develops an optimal sizing methodology for centralized charging stations considering second-life batteries. In [14] it is pointed out that the high peak power offered by discarded mobility batteries will find a promising application in ancillary services. Keeping this on mind, an economic analysis is performed determining that frequency containment reserve service is the most prominent application of second-life batteries from mobility applications.

Chai, et al [15] propose a holistic framework to evaluate the feasibility of second-life batteries in grid applications. To this end, a multi-stage methodology is developed which evaluates the battery lifetime modelling in detail its capacity degradation. An energy management model considering uncertainties is developed in [16], being especially suitable for fast charging stations with photovoltaics (PVs) and second-life batteries. Lacap, et al [17] discuss the design and construction of a 262-kWh storage microgrid encompassing PVs and second-life batteries. In particular, the authors considered a retired Nissan leaf battery pack after reaching 71% state-of-health, demonstrating that repurposed batteries may find application in commercial installations. Applicability of second-life batteries in residential communities is studied in [18], for which a hierarchical energy management structure is developed encompassing community and load reshaping decisions within a multi-level framework.

Yang, et al [19] propose an integrated planning framework for power networks including fresh and retired batteries. Within this paradigm, a lifespan model is proposed based on the state-of-health of battery packs, which can be integrated in the network together with fresh units. Likewise, different scenarios are compared in [20] for microgrid planning based on either fresh or repurposed batteries, concluding that the use of second-life batteries can reduce the levelized cost of energy by 1%. In [21], a techno-economic evaluation procedure is developed for evaluating the viability of second-life batteries in stationary applications. The proposed methodology was applied to a local energy community in Italy, showing that second-life batteries may be attractive in such schemes helping to reduce bills and increase self-consumption levels. Different indicators and price models were developed in [22], with the aim of evaluating sustainability factors of second-life batteries. Results concluded that higher initial state-of-health and slower degradation rate normally yield better sustainability performance.

### *1.3 - Contributions & paper organization*

According to [23], about 11 million tons of retired batteries are expected to be produced globally by 2030, of which a huge percentage will proceed from individual owners who charge their vehicles at home. However, most of the studies above analyse the viability of second-life batteries on power networks, microgrids or similar, while very few studies are focused on residential installations. Only [18, 21] are focused on communities but, to the best of our knowledge, no reference has studied the viability of second-life batteries in individual dwellings. Note that optimization frameworks for studying the viability of second-purpose batteries in communities may notably vary with the models considered for individual dwellings. Indeed, power consumption in communities is high as well as different kind of energy trading appear (e.g. peer-to-peer energy trading among prosumers). Due to these differences, we consider that the viability of second-purpose batteries in individual domestic installations needs to be studied and proper optimization models need to be developed and discussed. Moreover, important aspects such as controllable appliances or individual PV arrays gain importance in individual installations compared with collective communities.

After a vehicle battery pack results useless for mobility, vehicle owners can choose whether returning the batteries to the manufacturer or using them at home to increase the

energy efficiency and self-consumption rate. To evaluate this decision, we develop an optimal sizing methodology for PV domestic installations considering second-life batteries from individual EVs. In particular, the contributions of this paper are twofold:

- Developing and optimal planning methodology for rooftop domestic PV systems. The new proposal allows to consider second-life batteries from EV so that different scenarios can be evaluated.
- Evaluate and analyse different scenarios considering second-life batteries after completing their lifecycle for mobility or not, together with different tariffs and layouts. This contribution allows us to discern if the use of second-life batteries from mobility may be attractive for domestic applications and how their use affects to the optimal design of rooftop PV arrays.

In the rest of this paper, Section 2 describes the home installation under study together with the methodology adopted for evaluating the use of second-life mobility batteries in dwellings. Section 3 explains the mathematical foundations of the paper and the solution methodology adopted. Section 4 presents a case study with results under different scenarios, providing a discussion and an in-depth analysis of the results obtained. Finally, the main conclusions are duly drawn in Section 5.

## 2 - Preliminaries

### 2.1 - Description of the home system

This paper focuses on smart homes equipped with a series of controllable and non-controllable devices, as shown in Fig. 1. Thus, we assume that a set of appliances (e.g. washing machine or dishwasher) can be centrally managed by a home energy management (HEM) system, with the purpose of improving the overall efficiency and economy of the system. In contrast, other appliances (e.g. TV or computers) are scheduled on the basis of human behaviour and therefore are inhibited of the action of the HEM scheduler. The home installation can be either supplied from the distribution system (which is owned by a retailer) under a previously agreed tariff mechanism (e.g. a time-of-use (TOU) tariff), or from on-site assets such as PV panels or storage systems. In this case, the on-site batteries are assumed to be formed by second-life units from an inhabitant-owned EV, which is charged at home. Thereby, such storage system may not be exploited in the domestic installation if second-purposed for EV batteries is not considered, as explained in the following section.

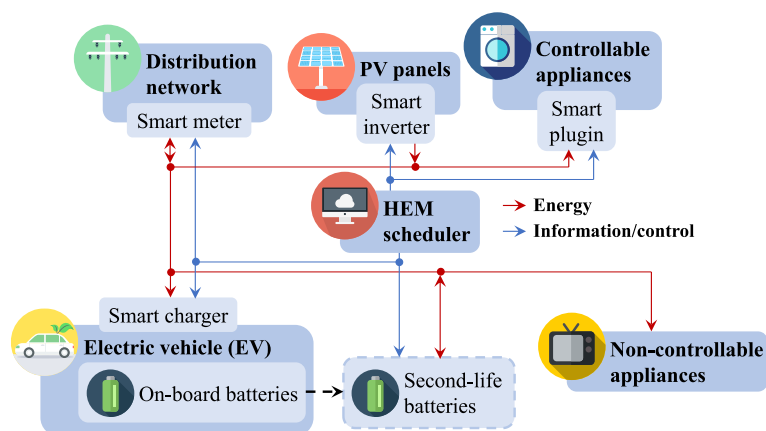


Fig. 1 - Pictorial representation of the home system under study

### 2.2 - Overview of the considered problem

This paper focuses on optimal PV planning for domestic installations considering second-life batteries from EV. In this regard, we suppose that the system is optimized over a predefined project lifetime, for which the size of the PV array is determined. At the beginning of the time horizon, it is assumed that the batteries are only used for mobility and therefore they cannot supply the home. As shown in Fig. 2, when the vehicle batteries are no longer useful for mobility (normally when their state-of-health is below 80 % [17]), the home inhabitants can decide whether the batteries are returned to the manufacturer (thus obtaining a compensatory payment) or used at home for supplying the domestic installation. Thus, this paper aims to evaluate both possibilities, determining the possible benefits obtained by EV owners from using second-life batteries, as well as their impact on determining the optimal sizing of PV panels.

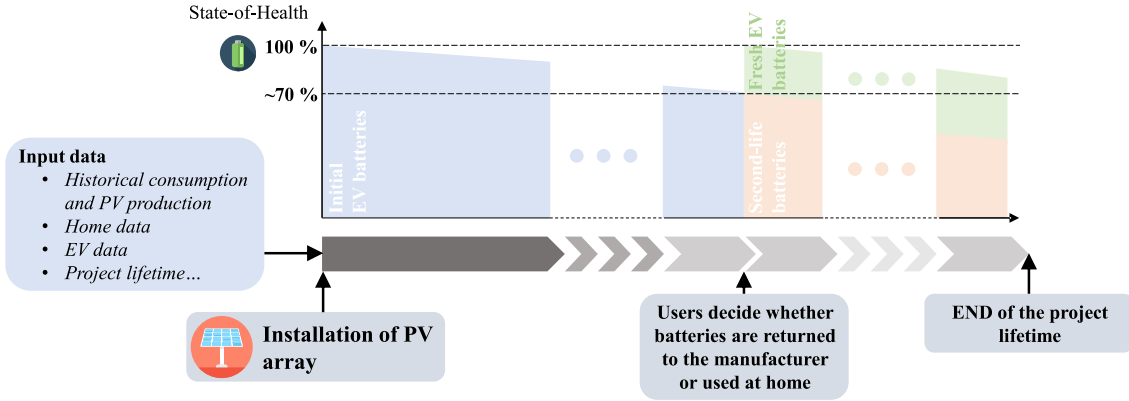


Fig. 2 - Overview of the project timeline for optimal PV sizing

### 3 - Mathematical modelling

#### 3.1 - Utility grid modelling

The power exchanges with the utility grid are upper bounded by either physical or contractual limits, as said (1) and (2). On the other hand, simultaneous exports and imports are avoided by declared these two variables complementary in (3).

$$p_{g+,k} \leq P_c, \quad \forall k \quad (1)$$

$$p_{g-,k} \leq P_c, \quad \forall k \quad (2)$$

$$p_{g-,k} \cdot p_{g+,k} \leq P_c, \quad \forall k \quad (3)$$

#### 3.2 - PV modelling

The normalized PV power of a panel or unit,  $\xi_{pv,k}$ , depends on ambient temperature, solar irradiance and efficiency of the PV panels [24]. Thus, considering the power of a panel or unit,  $P_{pv}$ , and the number of units,  $\Omega_{pv}$ , the total PV potential can be defined in any time period  $k$  as:

$$P_{pv,k} = \Omega_{pv} \cdot \xi_{pv,k} \cdot P_{pv}, \quad \forall k \quad (4)$$

On the other hand, the total PV installed capacity may be upper bounded due to multiple factors (e.g. available surface), which is modelled by the following constraint:

$$0 \leq \Omega_{pv} \leq \Omega_{pv}^{\max} \quad (5)$$

### 3.3 - Battery modelling

The stored energy is modelled as the SOC at the previous time interval and the power exchanged with the home installation, as follows:

$$Le_{bt,k} = Le_{bt,k-1} - \varepsilon_{bt} \cdot Le_{bt,k-1} + \Delta_t \cdot \left( \eta_{ad} \cdot \eta_{bt} \cdot p_{bt-,k} - \frac{p_{bt+,k}}{\eta_{ad} \cdot \eta_{bt}} \right), \quad \forall k > 1 \quad (6)$$

The battery model is completed by adding additional constraints. Thus, the energy stored in batteries is upper and lower limited by their nominal capacity and depth-of-discharge settings, as said (7). On the other hand, (8) and (9) impose limits on the power exchanged with the home. As customary, (6) is completed by (10), which establishes that the initial and final SOC are equal. Finally, (11) and (12) impose positivity and complementarity in the related variables, thus avoiding simultaneous charging and discharging of storage devices.

$$Le_{bt,y}^{\max} \left( 1 - \frac{\chi_{bt}^{rat}}{100} \right) \leq Le_{bt,k} \leq Le_{bt,y}^{\max}, \quad \forall k \quad \forall y \quad (7)$$

$$p_{bt-,k} \leq P_{bt-}^{\max}, \quad \forall k \quad (8)$$

$$p_{bt+,k} \leq P_{bt+}^{\max}, \quad \forall k \quad (9)$$

$$Le_{bt}^{t_1} = Le_{bt}^{t_{N_t}} \quad (10)$$

$$p_{bt-,k}, p_{bt+,k}, Le_{bt,k} \geq 0, \quad \forall k \quad (11)$$

$$p_{bt-,k} \cdot p_{bt+,k} = 0, \quad \forall k \quad (12)$$

In addition to (8) and (9), charging/discharging power of batteries is limited by the installed capacity of AC/DC converters, as said (13) and (14). Note that these two constraints are valid in the case of the batteries are used for mobility or at home in stationary applications. In such a case, the power is actually limited by the rated power of the bidirectional charger.

$$p_{bt-,k} \leq \Omega_{ad} \cdot P_{ad}, \quad \forall k \quad (13)$$

$$p_{bt+,k} \leq \Omega_{ad} \cdot P_{ad}, \quad \forall k \quad (14)$$

We consider that on-board batteries are replaced after seven years, as customary. After this period, the degradation of batteries typically reaches 20 %, being thus useless for mobility applications. Therefore, after the seventh year, the batteries can be used for stationary application at home, but its maximum SOC is a 20 % lower compared with their nominal capacity, being needed to be replaced after 15 years according to the data and results collected in [25].

Once the batteries are used in stationary applications, their degradation strongly depends on the imposed charging-discharging plan. In such a case, a more elaborated degradation model is considered, which is described in the following section.

### 3.4 – Battery and PV degradation

Battery degradation is categorized into two main types: battery cycle aging and battery calendar aging. Cycle aging is influenced by several factors, including the number of charge-discharge cycles, the depth of discharge, temperature, the average of SOC during each cycle, and the C-rate. However, the stress function caused by the average of SOC has little impact on cycle aging. Furthermore, calendar aging depends on the temperature, time and average of SOC. Nevertheless, temperature impacts marginally on degradation. Consequently, the cycle aging function can be approximated by considering

the number of cycles and the depth of discharge, while the calendar aging can be approximated by the average of SOC and time. These approximations are estimated using equations (15) and (16) [26]:

$$B_{degyc} = A_b^{cyc} \cdot DOD_b^2 + B_b^{cyc} \cdot DOD_b \quad (15)$$

$$B_{degal} = A_b^{cal} \cdot (SOC_b^{ave})^2 + B_b^{cal} \cdot SOC_b^{ave} + C_b^{cal} \quad (16)$$

Therefore, the capacity of the battery in the year  $y$  is given by:

$$Le_{bt,y+1}^{\max} = Le_{bt,y}^{\max} - B_{degyc,y} - B_{degal,y} \quad \forall y \quad (17)$$

On the other hand, over time, solar panels experience degradation at an average rate of 1% per year [27]. Like any other technology, PV panels gradually produce less energy as they age. This degradation rate leads to a reduction in power production over the panel's lifespan.

### 3.5 - Controllable appliances

As commented in subsection 2.1, in this work a smart home is equipped with a series of controllable and non-controllable devices. The controllable appliances (electric vehicle, dishwasher, spin drier and washing machine) are centrally managed by a HEM in order to improve the efficiency and economy of the system. Each controllable appliance must complete its duty cycle within established time windows, as said (18). Furthermore, these loads have to be operated continuously and can only be activated once in their time horizon, as expressed in (19) and (20), respectively.

$$\sum_{k=LB^i}^{UB^i} u_k^i = \delta^i; \quad \forall i \in \{EV, WM, DW, SD\} \quad (18)$$

$$\bar{u}_t^i - u_{-k}^i = u_k^i - u_{k-1}^i; \quad \forall k \in T \setminus k > 1, \quad \forall i \in \{EV, WM, DW, SD\} \quad (19)$$

$$\sum_{k=LB^i}^{UB^i} \bar{u}_k^i = 1; \quad \forall i \in \{EV, WM, DW, SD\} \quad (20)$$

According to other related references (e.g. [28]), the EV has been modelled as a controllable appliance. Note that this is a plausible assumption as smart chargers do not usually allow charging before 0:00 h its scheduling routine can be predefined.

### 3.6 - Power balance

During any time, the power balance in the home installation is ensured by imposing (21).

$$p_{pv,k} - p_{hl,k} - \sum_i u_k^i \cdot p^i + p_{g+,k} - p_{g-,k} + p_{bt+,k} - p_{bt-,k} = 0 \quad \forall k \wedge i \in \{EV, WM, DW, SD\} \quad (21)$$

### 3.7 - Economic model

In this study, the daily cost of energy is considered as the main indicator that determines the profitability of a domestic PV installation. This parameter encompasses various costs that account for capital, O&M and energy expenditures, as well as possible

incomes from selling energy to the grid. Firstly, the investment cost  $C_{I,d}$  is divided among the whole project lifetime, as follows:

$$C_{I,d} = \sum_i C_{I,d}^i, \quad i \in \{ad, pv, bt\} \quad (22)$$

At the same time, the investment cost of each component depends on the installed power, capital costs and number of components, as said (23).

$$C_{I,d}^i = \frac{\Omega_i \cdot C_I^i}{365 \cdot N_i}, \quad i \in \{pv, ad\} \quad (23)$$

As stated in section 2, when the state-of-health of the vehicle batteries is below 80 %, the home inhabitants can decide whether the batteries are returned to the manufacturer or used at home for supplying the domestic installation. It is assumed that the vehicle manufacturer establishes some compensatory payment ( $C_{cp}^{bt}$ ) if the batteries are returned to her. In case of deciding for using the batteries for home supplying, auxiliary equipment is necessary, resulting in an additional investment cost, namely  $C_{I,d}^{bt}$ , which is calculated in a similar way to (24), as follows.

$$C_{I,d}^{bt} = \frac{C_{cp}^{bt}}{365 \cdot N_{bt}} \quad (24)$$

In addition to investment costs described above, the home installation incurs in daily expenditures due to O&M, as follows

$$C_{O\&M,d}^i = \frac{1}{N_p \cdot 365} \cdot C_{O\&M}^i \cdot \frac{K_p^i \left(1 - (K_p^i)^{N_p}\right)}{1 - K_p^i}, \quad i \in \{pv, ad, bt\} \quad (25)$$

where:

$$K_p^i = \frac{1+g}{1+d} \left(1 + r_{O\&M}^i\right) \quad (26)$$

$$C_{O\&M}^i = \kappa_i \cdot C_I^i, \quad i \in \{pv, ad\} \quad (27)$$

This way, considering the O&M costs of each equipment, the total daily maintenance costs can be calculated, as follows:

$$C_{O\&M,d} = \sum_i C_{O\&M,d}^i, \quad i \in \{pv, ad, bt\} \quad (28)$$

The energy cost results from the balance between purchases and sales. In this work, we consider TOU and fixed tariffs. In this regard, energy price can be considered fixed or variable. Thereby, the cost of exchanging energy with the grid is calculated by (29), whereas (30) extends this value for the whole lifetime considering inflation rates.

$$C_{EE,k} = \begin{cases} \rho_{P,k} \cdot \Delta_t \cdot P_{g+,k} & P_{g+,k} \geq 0 \\ -\rho_{S,k} \cdot \Delta_t \cdot P_{g-,k} & P_{g-,k} \geq 0 \end{cases} \quad (29)$$

$$C_{EE,d} = \frac{1}{365 \cdot N_p} \cdot \sum_{n=1}^{n=N_p} \frac{(1+g)^n}{(1+d)^n} \cdot \sum_{k=1}^{k=N_p} C_{EE,k} = \frac{q \cdot (1 - q^{N_p})}{N_p \cdot (1 - q)} \cdot \sum_{k=1}^{k=N_p} C_{EE,k} \quad (30)$$

where:

$$q = \frac{1+g}{1+d} \quad (31)$$

In some countries like Spain, it is not realistic to assume that the total incomes from selling energy exceeds the total purchasing cost [29]. This restriction is ensured by imposing the constraint (32).

$$\sum_{k=1}^{k=N_p} C_{EE,k} \geq 0 \quad (32)$$

## 4 - Optimization methodology

### 4.1 - Problem statement

This paper aims at developing a methodology for optimal design of domestic PV installations considering second-purpose batteries from mobility. In this regard, we develop an optimization model which seeks for the optimal sizing of PV units while optimizing power flows among the different home assets and the utility grid. The objective function of the proposed problem is to minimize the project cost, as follows:

$$\sum_{k=1}^{N_i} F(L_{e_{bt,k}}, p_{bt-,k}, p_{bt+,k}, \Omega_{pv}, k) = C_{I,d} + C_{O\&M,d} + C_{I,d}^{bt} + \frac{q \cdot (1 - q^{N_p})}{N_p \cdot (1 - q)} \cdot \sum_{k=1}^{N_i} C_{EE,k} \quad (33)$$

Indeed, the objective function (33) encompasses investment expenditures, O&M costs, battery replacement and energy costs. On the other hand, the search space contains all the possible configurations and power exchanges, as follows:

$$\Omega_{pv} \in [0, \Omega_{pv}^{\max}] \text{ and } p_{bt,k} \in [p_{bt}^{\min}, p_{bt}^{\max}] \quad (34)$$

### 4.2 - Proposed optimization algorithm

In the previous sections, a large number of restrictions have been seen that must be considered in the optimization of this research. Furthermore, the dimension of the problem must contemplate the number of days, number of intervals and years in which the maximum capacity of the battery varies. All of this leads to an extensive number of variables that the optimization problem must consider.

The non-linearity and complexity of the problem along with its high number of constraints proposes the resolution of a problem with high computational cost and a search space with multiple local optima. For this reason, this study has to use a robust optimization algorithm appropriate for a complex search with many input and output variables.

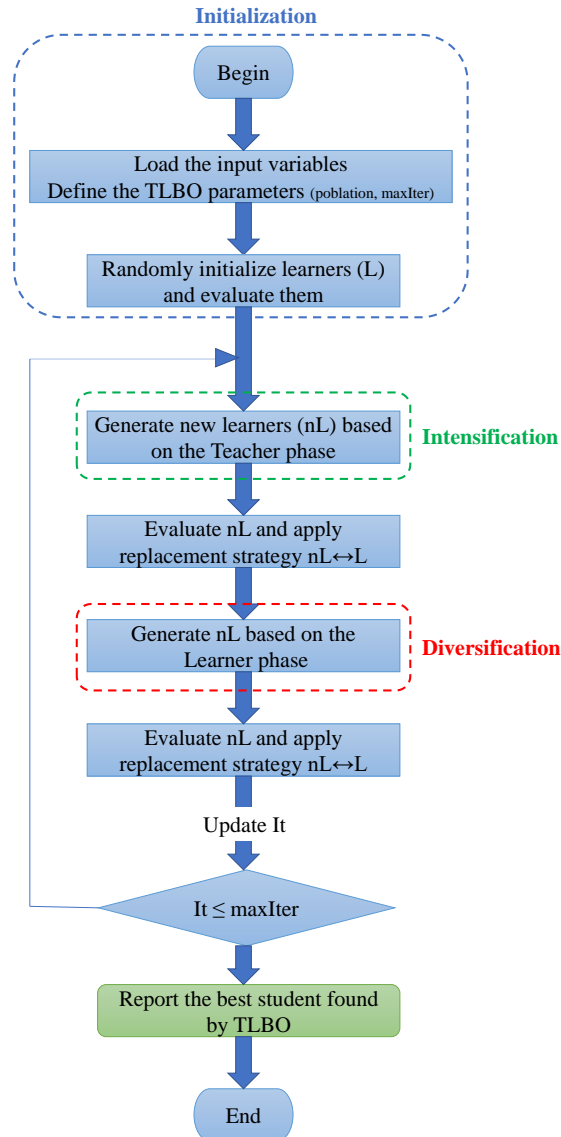


Fig. 3 - Flowchart proposed optimization algorithm.

The chosen algorithm is the TLBO meta-heuristic which was based on [30]. A flowchart optimization algorithm is shown in Fig. 3. A difficult requirement that a good metaheuristic technique has to satisfy is to keep a strong compromise between exploration (diversification or global search) and exploitation (intensification or local search) [31]. In this sense, the TLBO algorithm has two phases, teacher phase and learner phase. The first guarantees intensification and the second diversification. Therefore, TLBO is consistent with both the exploration and exploitation, this is its main advantage over other metaheuristic techniques. In addition, TLBO is a very robust and efficient algorithm for solving complex high-dimensional optimization problems. On the other hand, TLBO eliminates the need for fine-tuning specific parameters as it exclusively relies on general parameters like the number of iterations and population size.

Nevertheless, it used a variant for improving its performance. Thus, in teaching phase, a perturbed scheme was applied to prevent that current best solution from being trapped in local minima. The perturbed scheme encourages students to venture beyond the teacher's neighbourhood and explore a new search space, promoting a diversification

process where each solution moves away from the current best solution. No additional special parameters are introduced during the modified teacher phase [32].

Whereas a global crossover strategy was incorporated into the learning phase, which aimed at balancing local and global searching effectively. This global crossover utilizes global information to enhance learning efficiency and expand the perspective of the learning process [32]. The proposed variant does not introduce any additional parameters.

In this study, the learners are composed of the following state variables that influence the value of the objective function:

$$\Omega_{pv}, \Omega_{ad}, Le_{bt,k}, P_{bt,k}, P_{bt+,k}, P_{g+,k}, P_{g-,k}, u_k^{DW}, u_k^{EV}, u_k^{SD}, u_k^{WM}, k \quad \forall k$$

## 5 - Case study

### 5.1 – Scenario description

Throughout this section, we present several results obtained using the developed optimization algorithm on a benchmark smart prosumer environment such as that showed in Fig. 1. The developed optimization problem was coded under Matlab R2019b. The project lifetime was taken equal to 15 years, which is considered an acceptable lifetime for Li-ion batteries [33]. In order to check the viability of the proposed PV domestic installations with second-purpose batteries, four scenarios are tested, whose conditions are summarized in Table 1.

Table 1 – *Scenarios considered in simulations*

Scenario	Description
S1	Photovoltaic system without batteries and fixed market price
S2	Photovoltaic system without batteries and variable market price
S3	Photovoltaic system with second-life batteries and fixed market price
S4	Photovoltaic system with second-life batteries and variable market price
S5	Photovoltaic system with second-life batteries, variable market price and freely controllable appliances. In this sense, time windows are ignored and appliances can be scheduled any time instant

### 5.2 – Input data

As in other related papers, we only consider some representative profiles instead of the entire year. In this regard, we used clustering techniques [33] to determine which days can be considered the most representative of the whole input data. In particular, the k-medoids method was employed. This technique clusters the original set of data into clusters, which are represented by a unique member called medoid, which can be considered an accurate representation of all the members within the cluster. One major inconvenient of the k-medoids method is that the number of clusters must be selected a priori. Note that this point results critical for obtaining good results. Indeed, if the number of clusters is reduced, the accuracy of results may be questionable. In contrast, the computational burden of the optimization problem increases dramatically if the number of clusters is very high. To properly select the number of clusters and therefore representative days, we use the elbow method [34], which is a heuristic methodology based on the total sum of distances. To determine the optimum number of clusters, we combine the elbow method with triangle threshold as in [35]. As result, Fig. 3 plots the 12 representative profiles used in simulations for PV potential and non-controllable demand. These input data were taken from [36] and correspond to real measurements for a household installation in Jaén, Spain.

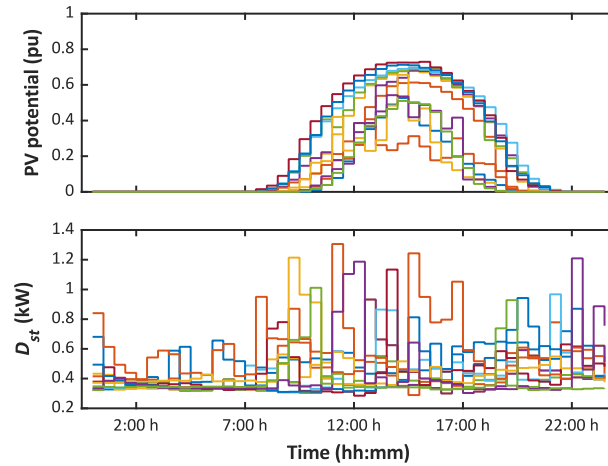


Fig. 3 – The 12 representative profiles used in simulations

In this paper, the Spanish retail market has been considered. Normally, the retail companies offer two types of tariffs, fixed tariffs and time-variable tariffs. Regarding the fixed tariff, a purchasing and selling price of 0.25 and 0.11 €/kWh, respectively, have been considered. On the other hand, Fig. 4 plots the profiles of a time-variable tariff corresponding to the 12 representative days considered in simulations, each one corresponds to a month of the year.

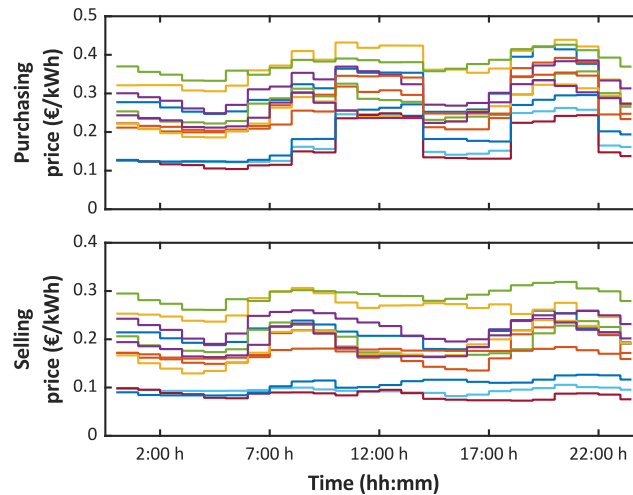


Fig. 4 – Time variable tariff considered in simulations

The different economic and technical parameters are summarized in Table 2 and have been adapted from [26, 37, 38]. In order to run TLBO, a population size of 500 and a number of iterations of 500 have been considered [38]. On the other hand, Table 3 collects the data referred to the controllable appliances. As in other papers [39], we considered a washing machine, dishwasher and spin dryer. Lastly, Table 4 summarizes the data regarded the EV. We consider a battery capacity degradation according to the model described in Section 3, taking in account that their state-of-health falls to 80 % in 7 years.

Table 2 - Economical and technical parameters considered in simulations

Parameter	Value	Parameter	Value
$\Delta_i$	30 min	$C_{cp}^{bt}$	1000 €
$N_p$	15 years	$N_{bt}$	8 years
$N_{pv}$	20 years	$P_{bt+}^{\max} (= -P_{bt-}^{\max})$	C-rate =1
$C_{pv}$	1500 €/kWp	$\chi_{bt}^{rat}$	80%
$P_{pv}$	0.25 kW/unit	$d$	3 %
$\Omega_{pv}^{\max}$	50 units	$g$	3 %
$P_c$	4 kW	$Le_{bt}^{\max}$	20 kWh
$C_{O\&M}^{bt}$	400 € (50 €/year)	$r_{pv}$	0.5%
$r_{O\&M}^{pv}$	1.4 %	$r_{O\&M}^{bt}$	2 %
$A_b^{cyc}$	$4.83 \cdot 10^{-4}$	$B_b^{cyc}$	$2.38 \cdot 10^{-5}$
$A_b^{cal}$	$4.34 \cdot 10^{-6}$	$B_b^{cal}$	$2.73 \cdot 10^{-5}$
$C_b^{cal}$	$1.45 \cdot 10^{-5}$		

Table 3 – Data of controllable appliances

Appliance (i)	$p^i$ (kW)	$\delta^i$	$LB^i$	$UB^i$
WM	1.50	3	1	29
DW	1.25	2	1	48
SD	1.00	2	31	48

Table 4 – EV data

Parameter	Value
Initial capacity (kWh)	25
$LB^i$	1
$UB^i$	14
$\delta^i$	6
$p^i$ (kW)	3.5

### 5.3 – Results

Table 5 reports the main results obtained with the developed algorithm in the four considered scenarios. As seen, the most profitable results were obtained in the scenarios 3 and 4, i.e. when considering second-purpose batteries, reducing the total project cost by ~15 %. It strengthens the idea that using second purpose batteries is a viable option and may result profitable in a variety of installations, as pointed out in [40]. From Table 5 it is also observed that PV size does not directly depend on the installation of second-purpose batteries rather than the tariff considered, resulting in a bigger PV array when fixed tariffs are contemplated. It is observed as the percentage of self-consumption with batteries is remarkably higher than without them, there is a difference of more than 20%.

Table 5 - Results obtained for the five scenarios.

Scenario	$C_d$ (€)	Optimal PV (kWp)	SCR
S1	4.8837	7.25	45.27 %
S2	4.7012	5.75	42.24 %
S3	4.2994	9.00	69.86 %
S4	4.2328	7.50	62.75 %
S5	3.3439	9.25	89.93 %

From Table 5 is also deduced that the self-consumption rate (SCR) is notably higher in the scenarios 3 and 4 (>20%). This result was expected as stationary batteries allows a more efficient management of renewable energy. In this regard, when surplus PV generation is available, it can be stored in batteries in contrast to the scenarios 1 and 2, when stationary batteries are not considered. These results evidence that storage systems are beneficial in installations with high renewable penetration, enabling a more efficient use of renewable sources and thus improving economic and environmental indexes. In scenario 5, the PV array is oversized. This is due to in this case controllable appliances are scheduled mostly at midday, leveraging high PV potential, as explained later. In this sense, the algorithm tends to increase the PV size to maximize the self-consumption.

Table 6 summarizes the total energy exchanged with the grid as well as the total PV generation over the project lifetime. As expected, results obtained in scenarios 1 and 2 were similar for all the years considered, since in this case second-purpose batteries are not considered and therefore the system does not change at seventh year, when batteries are no longer valid for mobility. For these scenarios, the main differences were observed on the energy sold and PV generation, observing that both indicators were higher in the scenario 1 due to the higher PV size. In particular, the total energy sold and PV generation were a 20 % and 15 % higher, respectively, in the first scenario with respect to S2. As expected, the best results were observed in scenario 5, as previously mentioned.

Table 6 - Energy flows for the five scenarios.

Result	Year	S1	S2	S3	S4	S5
Purchasing energy (kWh/year)	Year 1-7	6,029.60	6,117.92	5,985.74	6,060.04	2,452.06
	Year 8	6,044.61	6,137.25	3,047.12	3,474.68	1,653.67
	Year 10	6,052.05	6,146.46	3,333.78	3,972.57	2,077.36
	Year 12	6,059.74	6,155.77	3,551.52	4,231.13	2,126.85
	Year 15	6,068.35	6,166.43	3,920.42	4,483.30	2,278.09
	Total	90,656.69	92,037.28	69,605.87	74,743.63	33,436.38
Selling energy (kWh/year)	Year 1-7	6,563.99	4,601.80	8,912.39	6,936.18	5,720.46
	Year 8	6,119.21	4,256.47	5,422.55	4,133.28	4,643.28
	Year 10	5,922.31	4,103.62	5,359.10	4,087.15	4,459.27
	Year 12	5,725.65	3,950.86	5,258.69	3,998.23	4,249.22
	Year 15	5,529.92	3,799.45	5,204.53	3,951.96	4,149.31
	Total	92,542.11	64,433.43	104,876.46	80,894.46	75,045.37
PV gen (kWh)	Year 1-7	9,910.79	7,860.28	12,303.05	10,252.55	12,644.81
	Year 8	9,451.01	7,495.63	11,732.29	9,776.91	12,058.19
	Year 10	9,246.67	7,333.56	11,478.62	9,565.52	11,797.47
	Year 12	9,042.32	7,171.50	11,224.95	9,354.13	11,536.76
	Year 15	8,837.98	7,009.43	10,971.28	9,142.73	11,276.04
	Total	142,531.52	113,042.24	176,935.68	147,446.40	181,850.56

For scenarios S3 and S4, the energy generated by the photovoltaic system increases proportionally to the installed power of the PV array. In these scenarios, both imports and exports are significantly reduced in comparison with scenarios 1 and 2 (up to 28 %). This

fact is more evident when second-purpose batteries are installed. Indeed, it can be seen that beyond the eighth year, the purchasing and selling energies drop significantly.

From Table 6 it can be also observed that energy exchanged with the grid increases with the years, due to the battery degradations affects to its capacity, which forces to recur to the grid for both, importing energy for covering the home demand but also to sell energy when surplus renewable generation is observed. In this sense, when the battery is able to absorb the surplus renewable, the scheduling algorithm prioritizes storing energy for self-consumption. However, when the capacity of the battery is limited, surplus energy must be exported to the grid.

For the sake of example, Figs. 5 and 6 plot the scheduling results on day 4 in the scenarios 1 and 2. It can be seen that, in both cases, controllable appliances were mainly scheduled during midday, when PV generation is high. This way, these appliances can be partially supplied from renewable sources at low cost. Regarding the EV, it is charged at night. When considering a fixed tariff, it is scheduled almost at the beginning of its time window. However, when a variable tariff is assumed, its charging is delayed to coincide with the lowest energy price.

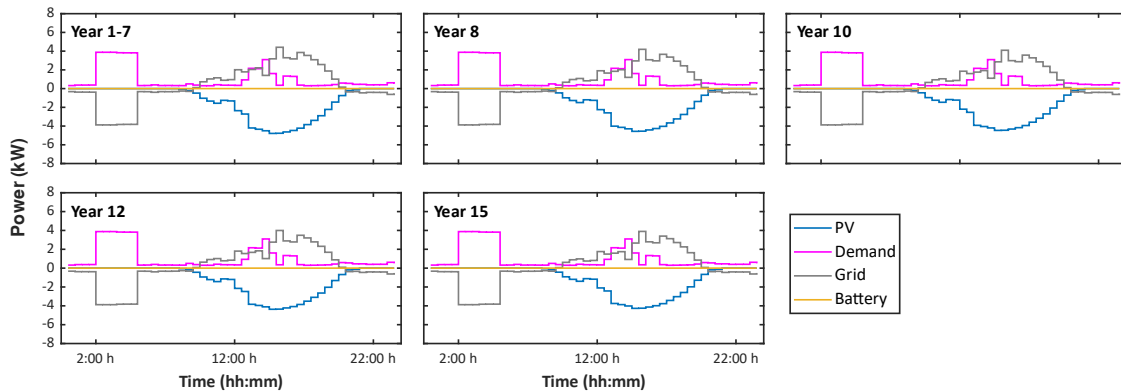


Fig. 5 – Scheduling result on day 4 (S1).

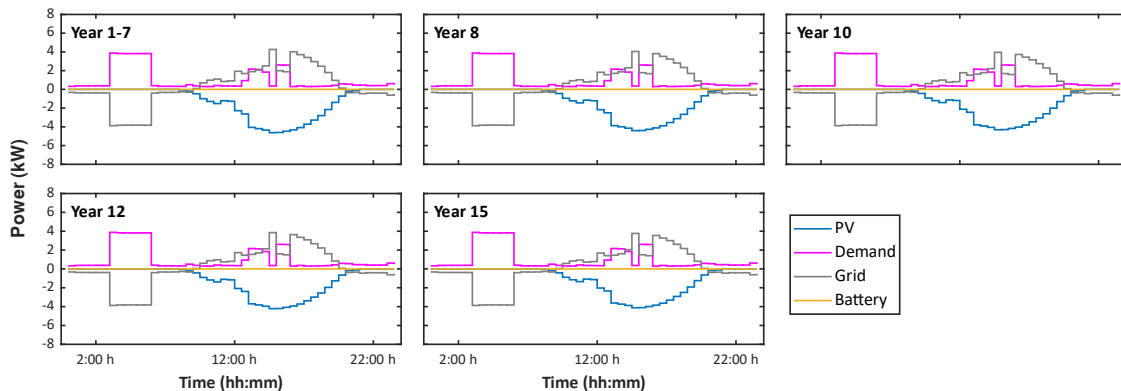
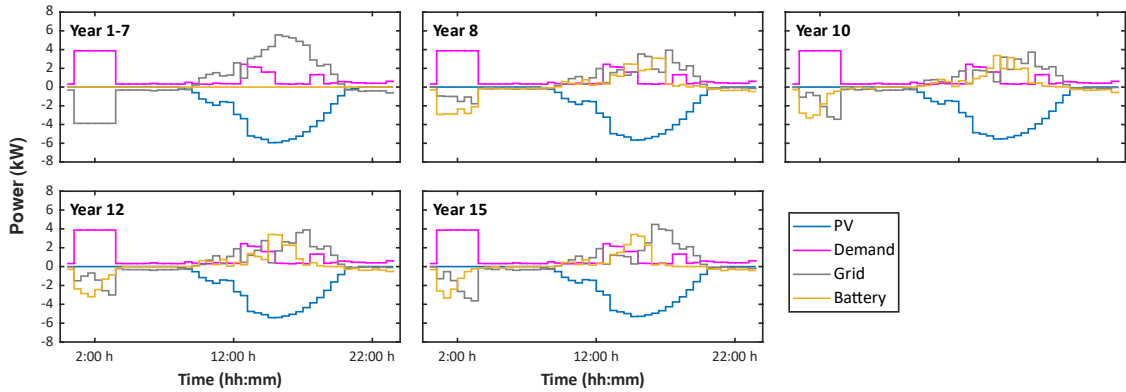


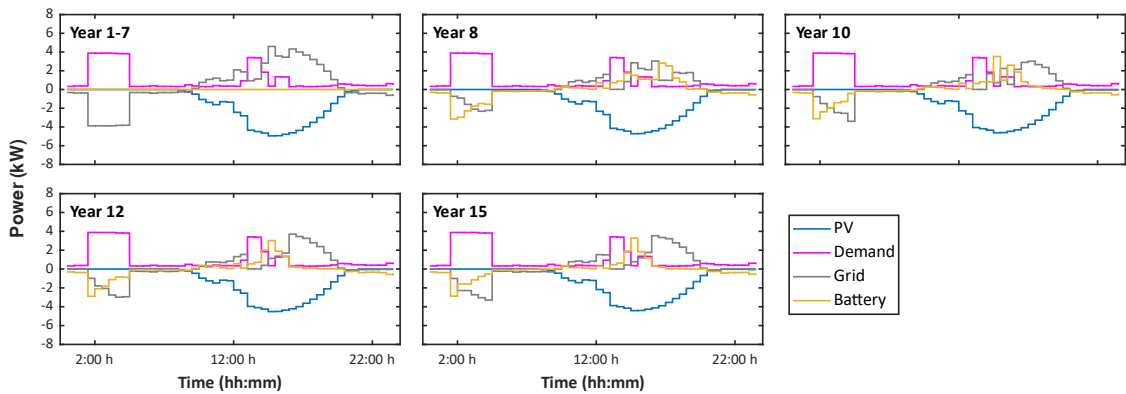
Fig. 6 - Scheduling result on day 4 (S2).

Figs. 7 and 8 are analogue to Figs. 5 and 6 but analysing the scenarios 3 and 4. In this case, different years are shown in order to analyse the effect of batteries in the scheduling result (from 0 to 7 years without batteries and beyond year 8 with second-purpose batteries installed at home). While the controllable appliances are scheduled during midday as in the scenarios 1 and 2, the behaviour of the vehicle is different and worth to be analysed. In year 8, the energy stored in the battery is almost enough to charge the EV but as the years progress, the capacity of the battery decreases due to its degradation and a certain amount of purchasing energy from the grid is required for the total EV charge. On the other hand, the behaviour is similar in S4, nevertheless, the difference lies largely

in that the EV charging is delayed to coincide with the lowest energy price and during the EV charging time second-purpose batteries are discharged combining with the energy input from the grid since its price is variable.

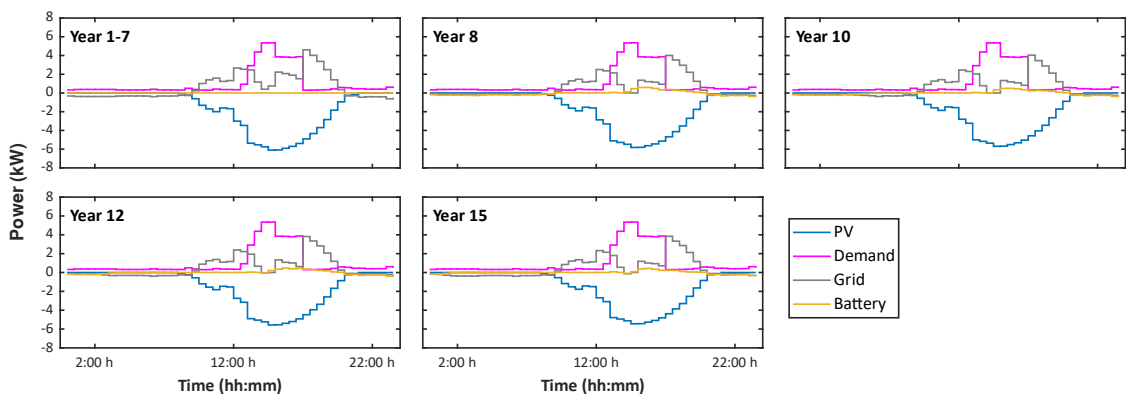


**Fig. 7.** Optimal power distribution on day 4 (S3).



**Fig. 8.** Optimal power distribution on day 4 (S4).

Regarding scenario S5, the results for day 4 are shown in Fig 9. As commented, controllable appliances are mostly scheduled at midday exploiting PV generation, which is oversized in this case. On the face of this situation, batteries play a secondary role as energy arbitrage is mostly provided by PV.



**Fig. 9.** Optimal power distribution on day 4 (S5).

#### 5.4 – Analysing the effect of limited PV size

So far, PV size was only limited by the available budget. However, the total PV installed capacity may be also bounded by other factors like the available surface. In this regard, we run different simulations limiting the PV size in the range 1-7 kWp, in order to analyse the effect of this parameter in final results. With these conditions, the most significant results (i.e. total project cost and SCR) are given in Fig. 10. As expected, the total project cost decreases while the SCR increases with the PV power limit (~33 % and 50 %, respectively). When comparing the different scenarios, it can be seen that the total project cost is lower when the system uses a second cycle battery (S3, S4 and S5). Likewise, the scenarios with fixed prices (S1, S3) showed worse results than those with variable prices. On the other hand, the percentage of self-consumption is always higher for scenarios with second cycle batteries and more specifically for scenarios with a fixed tariff.

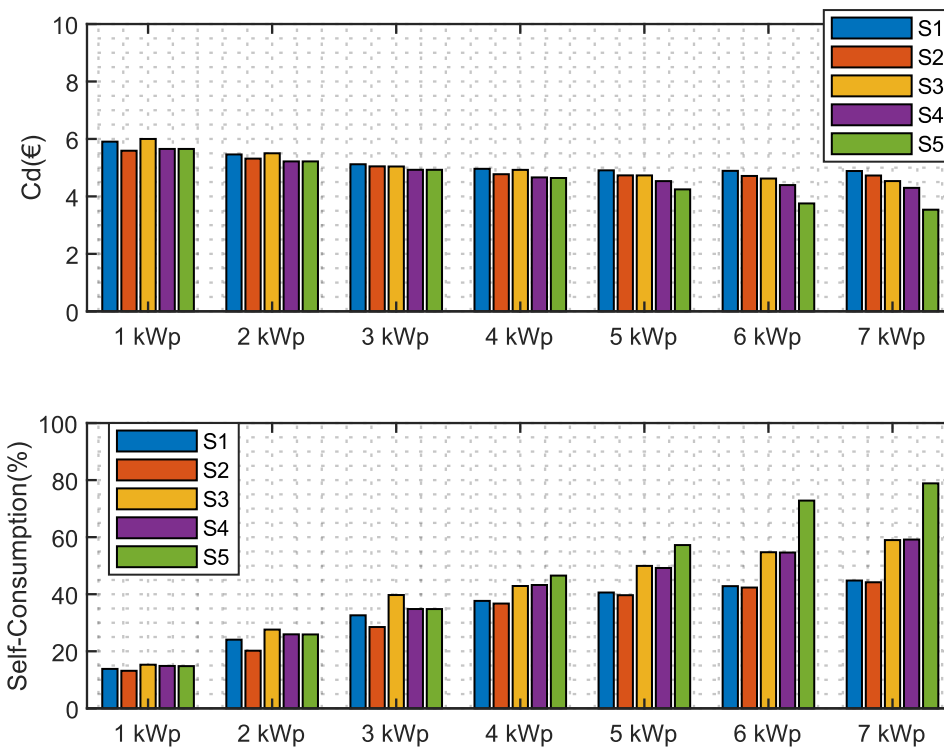


Fig. 10 - Daily cost (upper) and SCR (bottom) in systems with limited PV size

### 5.5 – Solver performance

Although this paper does not focus on developing any specific solver, we use a variant of the classical TLBO. For the sake of self-sufficiency, we provide here a brief comparison between the classical TLBO and its variant used in this paper. The convergence was proved in scenario S4, taking in account the same computational effort to both algorithms. In Fig. 11, it is shown the convergence of proposed TLBO is faster and more efficient. In order to achieve solutions of equal quality with classical TLBO, it was necessary to increase both the population size and the number of iterations (higher computational cost).

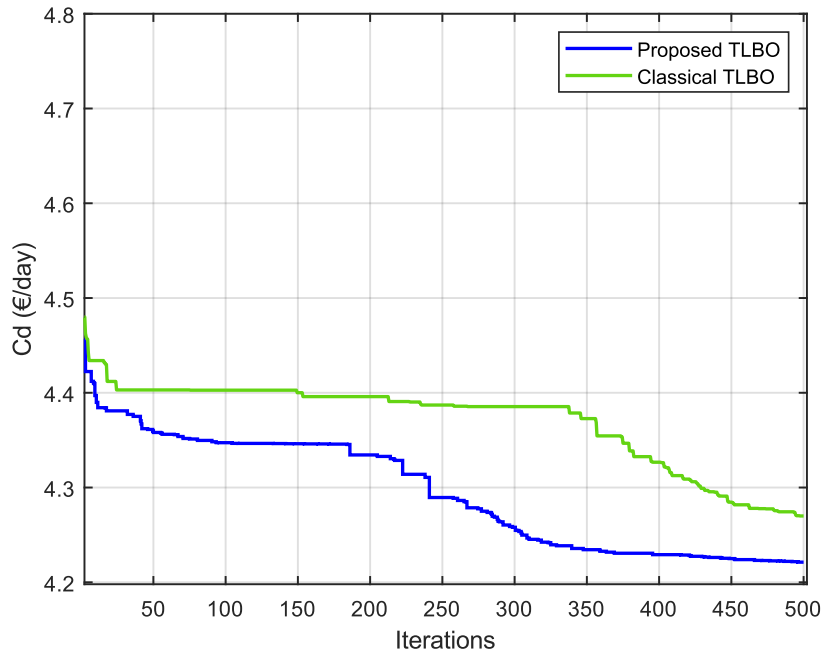


Fig. 11 – Comparison between classical and proposed TLBO

## 6 - Conclusions

The effect of considering second-purpose batteries in smart homes installation has been analysed. In particular, the effect of using batteries from mobility for stationary supplying on the optimal design of PV installations has been profusely studied. To this end, an optimal planning methodology for smart homes has been proposed, including models for controllable appliances, PV array and EV. The resulting optimization problem has been solved using metaheuristics and is applicable for planning purposes where the data encompass various years.

The developed methodology has been applied to a benchmark prosumer environment and various scenarios were analysed. The results obtained allows us to concluded that:

- The use of second-purpose batteries seems profitable in smart homes. Actually, the total project cost was reduced by 15 % when using second-purpose batteries in comparison with those scenarios when this asset is not considered. These results are in concordance with other conclusions extracted in related studies.
- However, the PV size does not depend on the use of second-purpose batteries rather on the tariff considered. In this regard, the lower project cost is more due to the reduced dependency of the grid. In fact, the SCR increased by 20 % when second-purpose batteries were considered.
- The degradation of batteries has a direct impact on the energy exchanged with the grid. Actually, it was observed that the dependency with the grid notably increases as the project evolves due to the limited capacity of batteries. In this regard, stationary batteries enable a more efficient use of surplus renewable generation.
- If controllable appliances can be scheduled any time instant, SCR increases notably as these devices are principally scheduled at midday exploiting high PV generation. Nevertheless, batteries play a secondary role in this case.

The developed methodology may serve as a benchmark to run similar studies in other smart homes or communities. In this sense, the promising results obtained in this study

will be further confirmed in future analysis, for which the developed methodology will be very valuable.

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