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Quantifying self-consumption linked to solar home battery systems: Statistical analysis and economic assessment ☆

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HIGHLIGHTS

- PV self-consumption with or without battery is evaluated for many households in EU.
- Self-sufficiency cannot exceed 80% without excessively oversizing the system.
- A simple equation is proposed to compute self-consumption from PV and battery sizes.
- Economic optimizations indicate that further decreases in battery costs are required.

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ABSTRACT

The recent development of new and innovative home battery systems has been seen by many as a catalyst for a solar energy revolution, and has created high expectations in the sector. Many observers have predicted an uptake of combined PV/battery units which could ultimately disconnect from the grid and lead to autonomous homes or micro-grids. However, most of the comments in social media, blogs or press articles lack proper cost evaluation and realistic simulations. We aim to bridge this gap by simulating self-consumption in various EU countries, for various household profiles, with or without battery. Results indicate that (1) self-consumption is a non-linear, almost asymptotic function of PV and battery sizes. Achieving 100% self-consumption (i.e. allowing for full off-grid operation) is not realistic for the studied countries without excessively oversizing the PV system and/or the battery; (2) although falling fast, the cost of domestic Li-Ion storage is most likely still too high for a large-scale market uptake in Europe; (3) home battery profitability and future uptake depend mainly on the indirect subsidies for self-consumption provided by the structure of retail prices; (4) the self-sufficiency rate varies widely between households. For a given household, the volume of self-consumption cannot be predicted in a deterministic way. Along with these results, this study also provides a database of synthetic household profiles, a simulation tool for the prediction of self-consumption and a method for the optimal sizing of such systems.

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1. Introduction

The recent development and marketing of new home battery systems, combined with significant price reductions, have been seen by many as a catalyst for a solar energy revolution and have created high expectations in the sector. Significant uptake of combined photovoltaic (PV)/battery units is now seen as a possible future, which would lead to increased decentralised generation and higher self-consumption levels. In addition, if current cost reduction trends persist, it is predicted that these systems could ultimately disconnect from the grid and lead to autonomous homes or micro-grids.

At present, however, solar home battery systems are not in themselves economically viable in most EU countries: rooftop PV panels still require subsidies in the form of feed-in-tariffs, green certificates or favourable net metering schemes [1,2]. The benefits of battery systems are closely linked to higher levels of self-consumption and thus to exemptions from taxes and grid fees on the self-consumed part [2]. Increased self-consumption also raises concerns as regards the sharing of grid costs, taxes and levies: it

☆ The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

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tends to reallocate costs from some prosumers who can afford the necessary investment to consumers who depend fully on the grid. The fact that the latter bear a higher proportion of non-energy-related costs is unfair and unsustainable [3].

The typical installation considered in this paper is depicted in Fig. 1: it consists of a DC-coupled PV and battery system, covering part of the household consumption and feeding excess electricity to the grid. Although the scope of the study is limited to single households, the proposed approach could easily be extended to public or commercial buildings, or to micro-grids comprising several households.

In order to provide reliable profitability indicators, we have to assess the volume of self-consumption made possible by a standalone PV system or the combination of a PV system with a home battery. A common simplification consists in assuming a fixed number of charging cycles over the lifetime of the battery. This is a convenient hypothesis, since it makes it easy to calculate the levelised cost of stored energy: if the lifetime is 10 years, a total of 3650 full daily cycles is assumed, which, once multiplied by the battery capacity and divided by the annualised investment, gives the levelised cost of stored kWh. As we demonstrate, however, this approach is erroneous, because the number of full equivalent cycles is usually less than one per day, and is highly dependent on battery capacity: a small battery tends to perform almost one full cycle every day, while a large battery presents much more limited average charge/discharge cycles.

The economic viability of PV combined with battery storage was evaluated in 2014 in the German context [5]. The authors concluded that, for an economically rational household, investments in battery storage are already profitable for small residential PV systems. However, the cost assumption for the battery system was very low (EUR 171/kWh + EUR 172/kW); a Bloomberg market survey from January 2016 indicates that the 2015 cost for batteries should be taken as being around USD 1250/kWh [6]. Other studies, such as [7], find that PV is profitable under current German regulations, but that batteries still need to become significantly cheaper if they are to be economically viable.

Truong et al. [8] analyses the profitability of a particular home battery brand in the case of Germany. They conclude that these

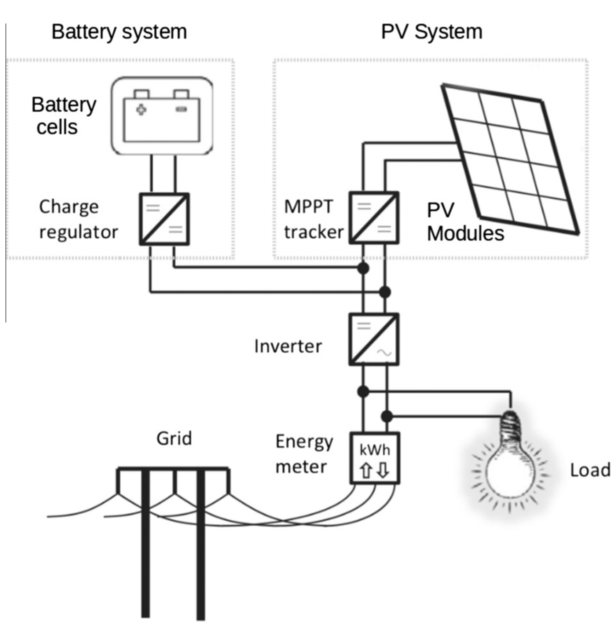

Fig. 1. Conceptual scheme of the considered DC-coupled system. Adapted from [4].

systems require subsidies and increasing retails price of electricity to be economically viable. In [9], the economics of PV/battery systems is evaluated for the case of a supermarket. The results indicate that PV alone is profitable, with an optimum installed capacity around 200% of the peak load. However, the only scenario in which a battery is profitable is the one in which it costs decreases down to 200/kWh.

Studies on solar home batteries focus, *inter alia*, on systems' peak-shaving capabilities: if the maximum power that can be exchanged with the grid is limited, power curtailment can be significantly reduced by using a battery and an appropriate charging strategy. However, this also decreases the self-consumption rate (SCR) [10,11].

Various studies also focus on quantifying self-consumption with respect to system design. For example [12], shows that, depending on the battery size (0–32 kWh), the self-sufficiency rate (SSR) varies from 30% to 66% in winter and 48–99% in summer. Truong et al. [8] obtains similar results for a German houshold, in which a 7 kWh battery increases SSR from 38% to 65%. However, this effect decreases in time due to battery degradation. Weniger et al. [7] shows that self sufficiency of roughly 54% is achievable with a battery system of 1 kWh per MWh of yearly consumption and a PV system of 1 kWp/MWh. For SSRs above 70%, the PV and battery systems become prohibitively large.

To increase self-consumption, an alternative to battery storage is demand side management (DSM) through load shifting. This option has also been considered in previous studies, with very variable results. In [13], DSM only increases self-consumption by 7% and the system does not seem economically viable. Constrastingly, in [14], DSM increases SSR from 30.9% to 56.9%, and this figure goes up to 76% if a battery is added to the system.

Because consumption and production profiles directly affect SSR, the quality of the input data is key when evaluating self-consumption. Household consumption profiles are often available as aggregates, obtained by averaging the profiles of different households or daily profiles over a given time period (e.g. one month) [15]. This approach neglects the fast and wide variations in consumption. It can therefore bias the analysis: Kastel and Gilory-Scott [16] shows that the error between aggregated and original curves varies between 10% and 15% for the computation of self-consumption. To overcome this, we considered only high time-resolution, disaggregated household consumption profiles. Contrary to most previous studies, we also aim to simulate a high number of profiles so as to provide statistically-significant self-consumption indicators.

The final goal is to develop a simple tool (in the form of an equation) to quantify self consumption as a function of the installed PV and battery sizes. This kind of information is key for researchers or policy makers willing to evaluate the impacts (e.g. financial) of the deployment of such technologies. Because of its computational efficiency, it can also be used for the optimal sizing of such systems in a large number of possible configurations and cost assumptions.

We propose the following general approach:

1. A database of household 15-min electricity consumption profiles is gathered for the following countries: Belgium, Spain, Germany, Denmark, Hungary, Italy, Romania, France and the United Kingdom. These are simulated in conjunction with a PV generation model and a simple battery model. Irradiation and temperature profiles are obtained from typical meteorological year datasets;
2. The volume of self-consumption is derived as a function of the relative sizes of the yearly demand, PV generation and battery capacity. This analysis is carried out for all household profiles, the number of which is deemed sufficient to derive statistically significant SCR and SSR values; and

3. We evaluate the economic profitability of the systems as a function of the PV system and battery sizes in a particular regulatory framework. An optimisation model is set up to maximise system profitability from a user perspective and sensitivity analyses are carried out to determine the influence of the battery cost.

2. Data sources

Realistic time series of domestic electricity demand and PV production throughout the year should be used to evaluate the potential for self-consumption and the levelised cost of a home battery storage system. This is necessary to account for the (mis) match between solar generation and household consumption at each moment of the day. The analysis should also cover several distinct geographical areas, since the variations in the load patterns across countries impact the volume of self-consumption: warmer climates are associated with higher cooling loads and therefore present a better match between solar irradiation and electricity consumption. This effect will be detailed in the following sections.

There are several ways of obtaining these time series. Current best-practice load profile generation techniques work bottom-up: appliances and home activity are modelled and used to create load profiles (see for example [17] or [18]). The disadvantages of this approach are the data requirements and the modelling intensity. Other studies [19,20] model the consumption in a top-down fashion using Markovian models. In this work, we avoid consumption modelling by relying on historical monitoring data available from various sources, for various countries.

Given the stochasticity of electricity consumption and generation, reliable values of the self-consumption indicators must be computed from a statistical of a large number of consumption/production profiles. The main challenge is the scarcity of easily accessible data for household consumption profiles in different EU countries. Most of the published data is aggregated over a large number of households (standard load profiles) and therefore smoothens out the variability of the individual profiles. Nevertheless, we have gathered a significant number of monitored consumption profiles from various sources, and, where only aggregated data was available, stochastic variations were added to the profiles.

2.1. Historical monitoring data

We built up a database of historical household electrical consumption profiles from available sources, with the following requirements:

- monitoring over at least a year to account for seasonal variability;
- time steps of 15 min or less;
- monitoring campaign in a European country; and
- disaggregated (i.e. non-averaged) data.

We have a useful data source complying with these requirements in the field of machine learning and nonintrusive load monitoring: open datasets are released to test and train the models, and provide household consumption profiles with a high time-resolution. A good example is described in [21], with a monitoring campaign comprising 2,075,259 measurements gathered in a French household between December 2006 and November 2010 (47 months). The time step is one minute and the monitored value is the active power. In that case, the one-minute data is aggregated over 15 min and four monitoring years are added to the database. Since there is no data for December 2010, the December 2009 values are duplicated to give us a complete four-year series.

Other datasets focus on the monitoring of multiple households, such as in [18]: electricity data was measured with a one-minute resolution in 22 UK dwellings over two complete years (2008 and 2009). Each dwelling was fitted with a single meter covering electricity use of the whole dwelling.

Table 1 summarises the historical datasets used in this work.

2.2. Synthetic individual load profiles

Thanks to the EUs REMODECE project, household consumption profiles are available for various Member States [24]. This dataset is particularly valuable because of the large number of monitored households (>850). Its main drawback is that the load profiles are hourly profiles for one typical day in the month. As a result of the aggregation into average days, the high frequency-stochastic variability is lost, which might impact the evaluation of self-consumption. More specifically, having smooth average load usually overestimates the system's performance and consequently the SSR, for two reasons: (1) the load duration curve is smoother and shallower, implying a higher load factor of the installation; and (2) the system's response to fast load variations are neglected.

We therefore add stochastic noise on top of each individual REMODECE profile.

2.2.1. Stochastic noise model

The historical monitoring data [18] is used to calibrate a stochastic model of the load variations around its averaged daily profile, in order to generate realistic time series from the aggregated data. We used the following methodology is applied:

1. average the historical data into average daily profiles for each month and for each household;
2. compute the logarithmic error between the data and the averaged values;
3. generate stochastic time series calibrated with the characteristic of the log-normal noise; and
4. apply this stochastic noise to the REMODECE averages historical profiles to generate realistic yearly time series.

A log-normal distribution of the noise is selected, because its skewness matches that of the error between the load and the average curve in the data. The logarithmic error is computed by:

$$LE = \log\left(\frac{Load_{hist}}{Load_{mean}}\right) \tag{1}$$

Fig. 2 displays the logarithmic noise value for the monitored data of a UK household, together with its duration curve. The purpose is to generate stochastic times series with characteristics close to those of this monitored noise. One of the main characteristics is the maximum load throughout the year, which conditions the battery's capacity to offset it and therefore affects self-consumption. To ensure that this value is conserved, the stochastic model should conserve the duration curve in Fig. 2.

To that end, we used an algorithm adapted from the iterated amplitude adjusted Fourier transform (IAAFT) [25,26], which generates samples of a random process conforming to a given autocovariance and probability density function. The advantages of this approach are that it gives more insight into the underlying process,

Table 1
Historical household consumption profiles.

Dataset	Location	$N_{profiles}$	Period	Ref.
UKDA	UK	22	2008–2009	[18,22]
FR	France	1	2006–2010	[21]
SustData	Portugal	13	2010–2011	[23]

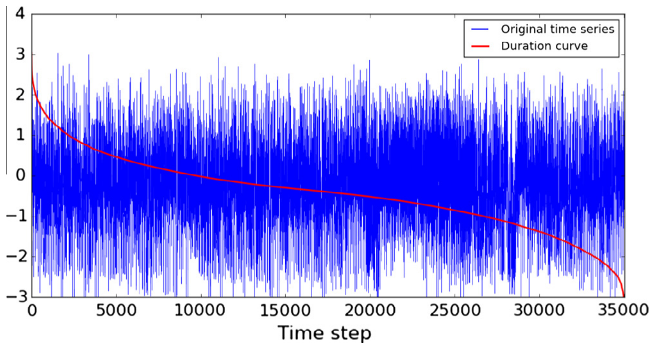

Fig. 2. Historical logarithmic noise for a UK household.

it can take as input only the marginals and autocorrelations, and it can generate time series of any length [27]. As a first step, a random realisation of a given probability distribution function (PDF) is created at the desired temporal sampling interval x_0. Then an iterative process starts, in which the realization is shuffled in order to match the given (two-sided) power spectral density (PSD) (S_{xx}). The PDF is not affected by the temporal reordering. In every iteration, the Fourier amplitudes of S_{xx} are compared with those of x_0. This procedure is summarised below (for more information, see [25]):

1. the phases of x_0 are calculated;
2. a new signal x is created with the same phases but with the amplitudes of S_{xx} via the IFFT transformation;
3. x lost its marginal information (became Gaussian), so a zero-mean non-linear transformation is applied. In this procedure, the values of the signal with the correct distribution, xo, are shuffled to match the rank of x;
4. the act of shuffling x alters the Fourier amplitudes and hence the PSD.

The above steps are iterated until the final step matches the rank from the previous iteration.

During this process, the PDF remains exactly the same, but there can be some small error in the PSD. According to [27] the error decreases with the length of the time series. For this paper, the length of the time series is large enough to give almost zero error on the PSD generated by the above procedure.

A total of 894 synthetic, yearly, 15-min time-step (i.e. 35,040 time steps) household profiles are generated using the above methodology. The conservation of the load duration curve and of the PDF ensures that these profiles present similar characteristics to the historical ones. Besides the stochasticity of the noise model, additional variability originates from the diversity of the historical, aggregated REMODECE basis profiles. The synthetic profiles generated in this manner comply with the historical monthly energy consumptions and properly represent the variability of household consumption patterns. They are therefore deemed realistic enough for the computation of self-consumption. The database of synthetic profiles is provided as an electronic annex to this paper, https://github.com/squoilin/Self-Consumption/releases.

2.3. PV generation

Each household generation profile is simulated using the typical meteorological year (TMY3 files) for the capital of the country in question [28]. A simple PV model is used, assuming a south orientation and a tilt angle of 35°. It should be noted that in practice, the orientation of the PV collectors vary from one household to the other: the azimuth angles can vary e.g. depending on the roof orientation and the tilt angle can vary depending on the shading (e.g. in mountainous areas) or on the latitude (for the considered countries, the optimum tilt angle varies from 32° to 38° [29]). Due to the lack of information and to simplify the analysis, we consider fixed azimuth and tilt angles for all households. In order to ensure realistic yearly PV generation, the computed profiles are however scaled to match the average capacity factor specific to each country, as provided in the JRC PVGIS information system [30].

3. Model description

3.1. PV and battery dispatch models

The storage capacity is dispatched in such a way as to maximise self-consumption; if the PV power is higher than the load, the battery is charged until full. As soon as the PV power is lower than the load, the battery is discharged until empty. The losses taken into account are battery round-trip efficiency and inverter efficiency. It is assumed that demand is not responsive.

At each time step, the following simple dispatch algorithm is executed: the maximum battery discharge power is calculated by:

$$P_{max,dis,i} = \min\left(P_{max,bat}, \frac{SOC_{i-1} \cdot \eta_{bat}}{\Delta t}\right) \tag{2}$$

and the maximum charging power by:

$$P_{max,ch,i} = \min\left(P_{max,bat}, \frac{CAP_{bat} - SOC_{i-1}}{\Delta t}\right) \tag{3}$$

The actual battery discharge is computed by comparing the PV generation with the load:

$$P_{dis,i} = \min\left[P_{max,dis,i}, \max\left(0, \frac{P_{load,i}}{\eta_{inv}} - P_{PV,DC,i}\right)\right] \tag{4}$$

The actual battery charging power is calculated in a similar manner:

$$P_{ch,i} = \min\left[P_{max,ch,i}, \max\left(0, P_{PV,DC,i} - \frac{P_{load,i}}{\eta_{inv}}\right)\right] \tag{5}$$

The energy balance is finally written:

$$SOC_i = SOC_{i-1} + P_{ch,i} \cdot \Delta t - \frac{P_{dis,i}}{\eta_{bat}} \cdot \Delta t \tag{6}$$

Fig. 3 illustrates the results of the dispatch algorithm for a French historical consumption profile in a typical week in July. Battery charging and feeding to the grid are indicated as negative values.

3.2. Yearly simulations

Combining the PV generation model, the demand profiles and the battery dispatch algorithm, it is straightforward to simulate a whole year of operation. This results in time vectors of the battery state of charge or of the power bought and sold to the grid. The various models and data processing are implemented in the Python language. The dispatch algorithm is compiled using Cython to improve the computational efficiency of the yearly simulation. The different scripts developed for this study are provided as electronic annexes.

3.3. Yearly energy flows

For a yearly simulation, the main variable of interest is the total volume of self-consumption, which is commonly expressed as a SSR or a SCR [7]. Other authors also refer to these variables as cover ratio, solar fraction or load fraction [16,31].

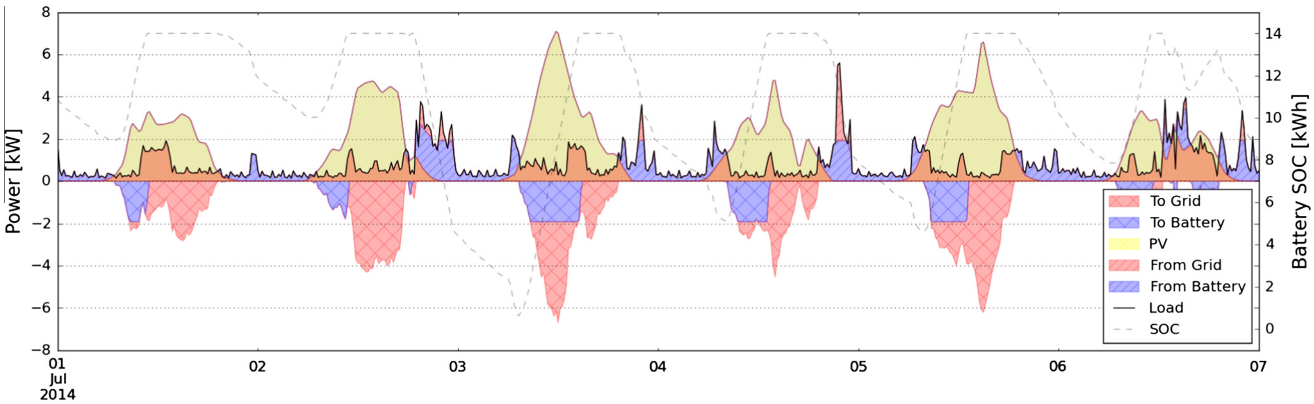

Fig. 3. Power dispatch for a typical week of July.

In this study, the SSR is defined as the ratio between the self-consumed energy and the total yearly energy demand:

$$SSR = \frac{E_{SC}}{E_{load}} = \frac{\sum_{i=1}^{N}(P_{dis,i} + P_{SC,DC,0,i}) \cdot \eta_{inv}}{\sum_{i=1}^{N} P_{load,i}} \tag{7}$$

where E refers to an annual energy flow and P to an instantaneous power. N is the number of time steps in one year and $P_{SC,DC,0,i}$ is the DC PV generation directly self-consumed (i.e. without passing through the battery).

The SCR is defined in a similar manner. Note that the reference is the annual energy produced by the PV array on the DC bus (i.e. before the inverter):

$$SCR = \frac{E_{SC}}{E_{PV,DC}} = \frac{\sum_{i=1}^{N}(P_{dis,i} + P_{SC,DC,0,i}) \cdot \eta_{inv}}{\sum_{i=1}^{N} P_{PV,DC,i}} \tag{8}$$

A summary of the relevant yearly energy flows within the considered system is shown in Fig. 4. Interestingly, each of these values can be derived from the yearly demand E_{load} and from the value of SSR computed with or without battery, as demonstrated below.

To compute all energy flows, we first need to determine the 'self-sufficiency without battery' value. We do this through the SSR_0 variable, defined as:

$$SSR_0 = \frac{E_{SC,0}}{E_{load}} = \frac{\sum_{i=1}^{N} P_{SC,DC,0,i} \cdot \eta_{inv}}{\sum_{i=1}^{N} P_{load,i}} \tag{9}$$

The relative PV system and battery sizes are defined as inputs of the simulation since they influence the different energy flows and the volume of self-consumption. They are normalised to the annual electricity demand:

$$R_{bat} = \frac{CAP_{bat}}{E_{load}} \left[\frac{\text{kWh}}{\text{MWh}}\right] \tag{10}$$

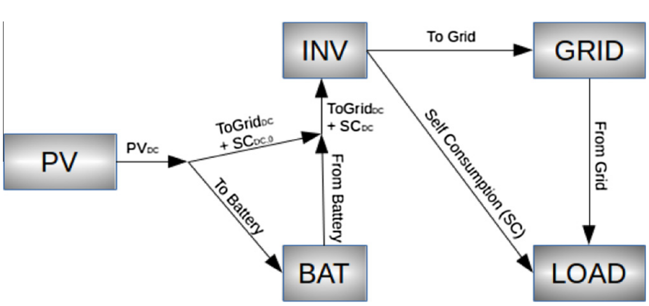

Fig. 4. Energy flows on a yearly basis.

where CAP_{bat} is the accessible battery capacity (i.e. the total battery capacity multiplied by the maximum depth of discharge).

The relative PV size is defined using the annual generation of the PV array on the DC bus (i.e. before inverter):

$$R_{PV} = \frac{E_{PV,DC}}{E_{load}} = \frac{P_{PV,peak} \cdot \eta_{inv} \cdot CF_{PV}}{E_{load}} \left[\frac{\text{kWh}}{\text{kWh}}\right] \tag{11}$$

where $P_{PV,peak}$ is the peak power (in kWp) of the PV system in the standard conditions and CP_{PV} is the capacity factor of the PV installation for the given location (in kWh/kWp). SCR can be deducted from SSR and the PV system capacity:

$$SCR = \frac{SSR}{R_{PV}} \tag{12}$$

The total amount of energy provided by the battery is self-consumption minus the self-consumption in the case without battery:

$$E_{FromBat} = E_{SC,DC} - E_{SC,DC,0} = \frac{E_{SC} - E_{SC,0}}{\eta_{inv}} \tag{13}$$

The amount of electricity sold to the grid is what remains from the PV production after removing the self-consumed energy flows:

$$E_{ToGrid} = \eta_{inv}\left(\cdot E_{PV,DC} - E_{SC,DC,0} - \frac{E_{FromBat}}{\eta_{bat}}\right) \tag{14}$$

From the above equations, it appears that the most important indicator is SSR, from which all others are deducted. Therefore, the following paragraphs focus on the influence of the operating parameters on the SSR value.

3.4. Direct self-consumption

This section focuses on the case of household self-consumption with a PV system but without battery. One of the goals of this analysis is to cross-check the very common hypothesis of a 30% SSR. To that end, the entire database of synthetic and historical profiles is simulated using the algorithm described in Section 3.2. For these simulations, it is assumed that $R_{PV} = 1$. The simulation time step is 15 min and the total number of simulated profiles is 929. The results of the simulations are shown in Fig. 5.

The following conclusions can be drawn from Fig. 5:

- The standard deviation is high. The self-consumption for a given household can therefore be evaluated only in a probabilistic way.
- The assumption $SSR_0 = 30\%$ seems to underestimate slightly the actual numbers obtained in this analysis. It can therefore be considered as a conservative hypothesis.

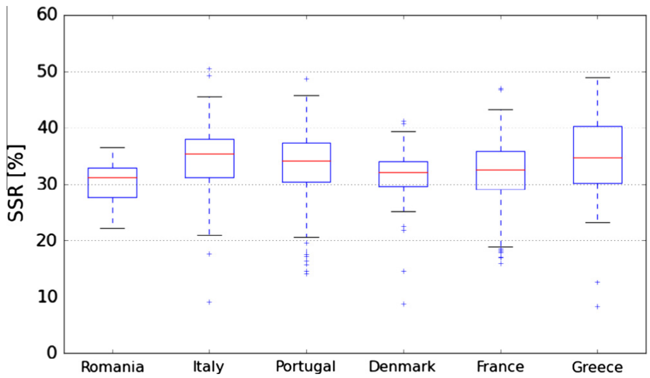

Fig. 5. Box plot of the self-sufficiency rate for each country (PV/demand ratio: 1).

- Southern countries tend to present a slightly higher SSR, probably due to the close correlation between cooling demand and solar irradiation.
- The average difference between countries is much smaller than the standard deviation within a country.

3.5. Economic performance of the system

From a user perspective, the levelised cost of a grid-connected solar home battery system can be calculated by considering the grid as a zero-investment generator producing at the retail price. Accordingly, the energy fed to the grid should also be taken into account as a negative cost.

The investment in the battery and PV systems is taken into account as a constant annuity:

$$A = \left(I_{PV} + I_{bat} * \left[1 + \frac{1}{(1+i)^{N_{bat}}} \right] \right) \cdot (CRF + OM) \quad (15)$$

where A is the annuity and I stands for investment. It is assumed that there is a second investment in the battery after N_{bat} years. OM is the fraction of annual operation and maintenance. CRF denotes the capital recovery factor calculated by:

$$CRF = \frac{i \cdot (1+i)^{N_{PV}}}{(1+i)^{N_{PV}} - 1} \quad (16)$$

where i is the weighted average cost of capital (WACC) and N_{PV} is the PV system lifetime in years.

The levelised cost of electricity from a prosumer perspective can be defined as:

$$LCOE = \frac{A + E_{FromGrid} \cdot P_{Retail} - E_{ToGrid} \cdot P_{ToGrid}}{E_{load}} \quad (17)$$

It is also useful to isolate the contribution of the battery by calculating the levelised cost of storage:

$$LCOS = \frac{A_{bat}}{E_{FromBat} \cdot \eta_{inv}} \quad (18)$$

where A_{bat} denotes the part of the annuities linked to the battery investment and re-investment (cfr. Eq. (15)).

4. Discussion

4.1. Influence of the battery capacity

Adding a battery to the system allows greater self-consumption, but each additional storage unit within the system has a utilisation rate lower than the previous one. This effect is illustrated by performing the same simulation as above and varying the battery size

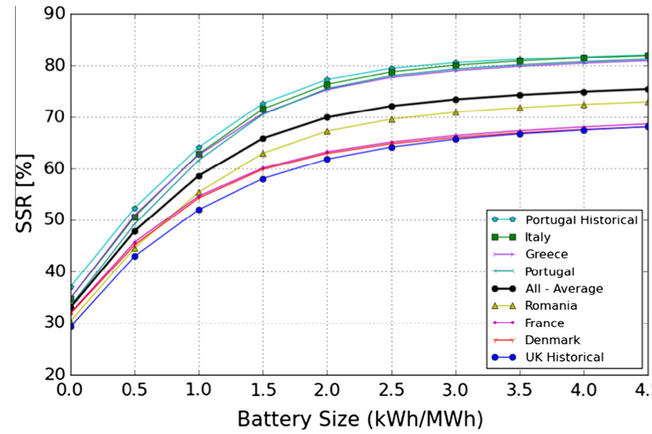

Fig. 6. Influence of the battery size on the self-sufficiency rate for each country (PV/demand ratio: 1).

(Fig. 6). As expected, the curve seems to present an horizontal asymptote: after a certain quantity, any additional kWh of battery storage increases the SSR only marginally. At higher capacity, the battery storage starts to balance longer variations (e.g. weekly or seasonal, rather than daily), which occur less frequently and therefore contribute less to the increase in SSR.

The following conclusions can be drawn from Fig. 6:

- the difference between countries is limited for $R_{bat} = 0$, but seems to increase with the battery capacity;
- interestingly, the only country for which both synthetic and historical profiles are available (Portugal) shows a close match between the two curves, which tends to confirm that the generated stochastic profiles are suitable for such simulation.

4.2. Influence of timestep and maximum battery power

In order to validate the proposed methodology with a 15-min time step, we should check the error linked to the simulation time-resolution. To that end, the French historical profile (one-minute time step) is simulated for 2012 with three different time steps: one minute, 15 min, and one hour. It is assumed that there is no constraint on the battery charging/discharging power. The simulations indicate that higher time-resolution leads to lower self-sufficiency since fast variations are smoothed out at low time-resolution (Fig. 7). However, the error is limited, with a maximum difference in the SSR value of 1.5% at $R_{bat} = 0$. It disappears almost entirely when a battery is added.

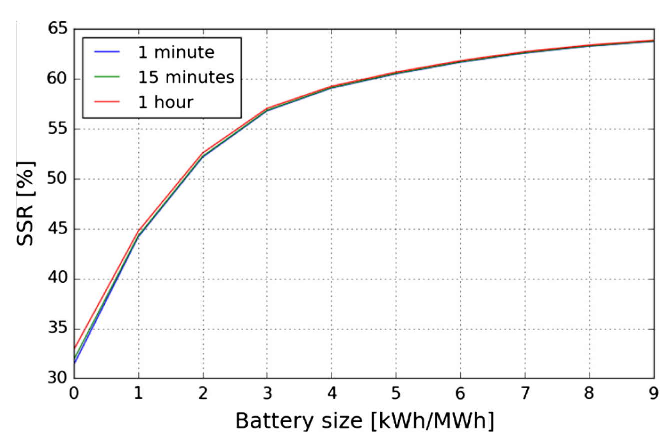

Fig. 7. Influence of the simulation time resolution.

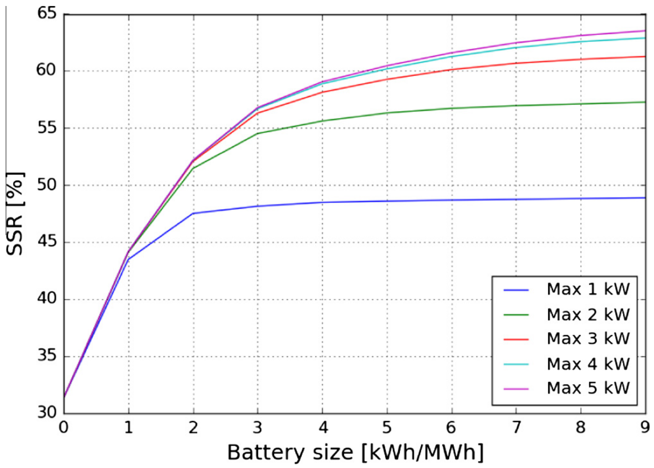

Fig. 8. Influence of the battery's maximum charging/discharging power on the self-sufficiency rate.

It is also useful to evaluate the impact of the battery's maximum charging/discharging power on self-consumption. In most cases, this limitation is not directly linked to the battery itself, but to the power electronics (i.e. the internal DC/DC converter). In this study, we assume that the maximum charging and discharging powers are equal and constant in time. This is a simplifying hypothesis since in a real application is might depend on the state of charge. At low power, the highest peaks in the load profile cannot be covered (see Fig. 3), which reduces the battery's power-offsetting capacity and thus the level self-consumption. Fig. 8 indicates that there are significant differences in the computed SSR values, but that these tend to disappear completely when maximum battery power reaches 4–5 kW.

5. Bivariate regression

The main aim of this section is to provide a tool for predicting SSR as a function of PV system and battery size. This kind of tool is particularly useful for evaluating the profitability of such systems, because it allows us to calculate the volumes of energy that are self-consumed, sold to the grid and bought from the grid. It should be simple to implement, accurate and computationally efficient.

As in the univariate analysis, the dispatch algorithm is first run for all the household profiles and for an array of R_{PV} and R_{bat} values. The SSR surfaces are then averaged for one geographical area or for the whole set of profiles. Fig. 9 shows the result of this procedure when all profiles are included. It is worthwhile to highlight that this SSR mapping is an average over all household profiles. Similarly to Fig. 5, it can vary significantly from one household to the other. As an example, for $R_{PV} = 1$ and $R_{bat} = 0$, the standard deviation is 5.9% and the coefficient of variation (i.e. the standard deviation divided by the SSR value) is 0.18. For $R_{PV} = 1$ and $R_{bat} = 4$, the standard deviation is 7.3% and the coefficient of variation is 0.10. This variation is significant and shows that the SSR map cannot be used deterministically when considering one household alone. It is only relevant to evaluate overall self-consumption levels for a large number of household in a given geographical area.

The challenge is to fit a two-dimensional function to this SSR surface, with the following desired characteristics:

- good overall accuracy between the model and the original values;
- exact number for SSR_0 with $R_{PV} = 1$, since this value is very commonly used;

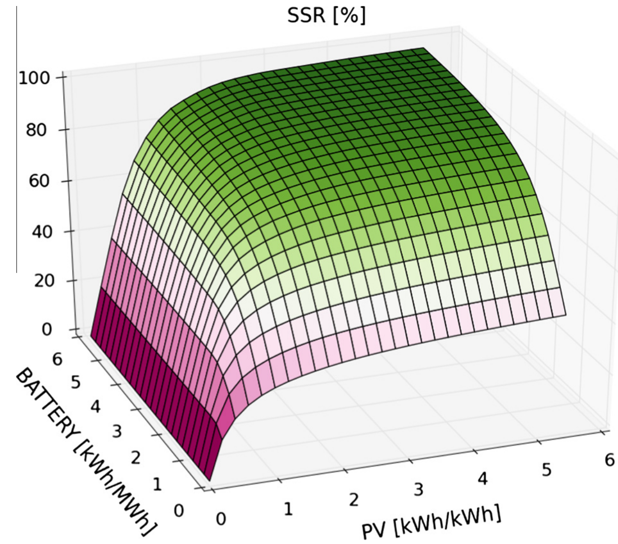

Fig. 9. Influence on SSR of PV system and battery size.

- excellent accuracy for the prediction of SSR vs R_{PV} with $R_{bat} = 0$ since it corresponds to the common case in which there is no battery;
- excellent accuracy for the prediction of SSR vs R_{bat} with $R_{PV} = 1$, since this is also a common case;
- $SSR \rightarrow 100\%$ for $R_{PV} \rightarrow \infty$ or $R_{bat} \rightarrow +\infty$;
- $SSR \rightarrow 0$ if $R_{PV} \rightarrow 0$.

Because the shape of the univariate curves SSR vs R_{PV} (Fig. 10) or SSR vs R_{bat} (Fig. 6) is nearly asymptotical at SSR = 100%, it can be fairly well approximated by a hyperbolic tangent function combined with a linear term.

Also, because some SSR values (Fig. 9) require a higher accuracy than others, a three-steps regression methodology is proposed.

First, a reference value of SSR is obtained directly from the data and imposed to the further steps:

$$SSR_{0,1} = SSR_{R_{bat}=0, R_{PV}=1} \tag{19}$$

Then, the univariate data at $R_{PV} = 1$ and $R_{bat} = 0$ is fitted using the following analytical expressions:

$$SSR_{R_{PV}=1} = SSR_{0,1} + a_1 \cdot tanh(a_2 \cdot R_{bat}) + a_3 \cdot R_{bat} \tag{20}$$

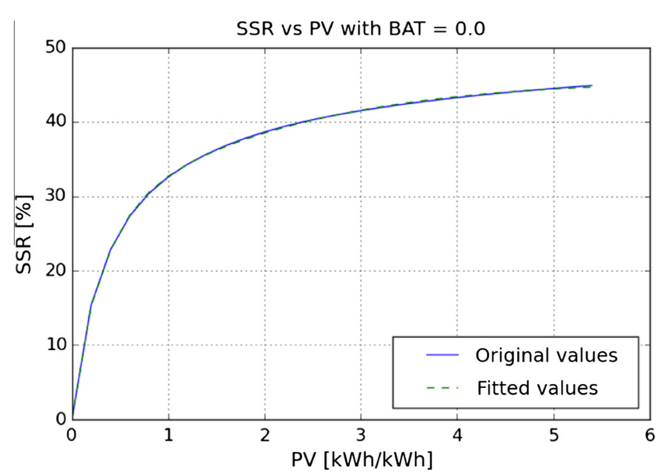

Fig. 10. SSR_0 as a function of PV size fitted with a hyperbolic function.

$$SSR_{R_{bat}=0} = b_4 \cdot \tanh(b_5 \cdot R_{PV}) + b_6 \cdot R_{PV} + b_7 \cdot \sqrt{R_{PV}} \quad (21)$$

where a_i and b_i are the coefficients determined by minimizing the root mean square error (RMSE) between the function and the data. These coefficients should remain positive to ensure that SSR grows monotonously with R_{bat} and R_{PV}.

Finally, the 2D regression is performed by imposing the two univariate curves (coefficients $a_{1\to3}$ and $b_{4\to7}$) and fitting additional coefficients $c_{8\to15}$. In order to improve accuracy, the regression procedure is split in two ($R_{PV} \leqslant 1$ and $R_{PV} > 1$). The final expression of the regression is given by:

$$SSR = W \cdot \xi_1 + (1 - W) \cdot \max(R_{PV}, \xi_2) \quad (22)$$

where W is a weighting function between 0 and W_{max} given by:

$$W = \min\left[1, \max\left(0, \frac{R_{bat}}{W_{max}}\right)\right] \quad (23)$$

W_{max} is taken equal to 0.4.

ξ_1 provides the dependency of SSR with R_{bat} and R_{PV}. It is divided in two to ensure a good fit at $R_{PV} = 1$:

If $R_{PV} \geqslant 1$:

$$\xi_1 = (c_8 + c_9 \cdot R_{bat}) \cdot \tanh(c_{10} \cdot (R_{PV} - 1)) + c_{11} \cdot (R_{PV} - 1) + SSR_{R_{PV}=1} \quad (24)$$

If $R_{PV} < 1$:

$$\xi_1 = [c_{12} \cdot \tanh(c_{13} \cdot (1 - R_{PV})) + SSR_{R_{PV}=1}] \cdot R_{PV} \quad (25)$$

ξ_2 ensures that the regression remains accurate for low R_{bat} values:

$$\xi_2 = SSR_{R_{bat}=0} \cdot [1 + c_{14} \cdot \tanh(R_{bat})] + c_{15} \cdot \tanh(R_{bat}) \quad (26)$$

A total of 15 empirical coefficients is needed to ensure that the regression fulfils the requirements. These coefficients are provided in Table 2 for three different cases that are representative of the results obtained in this study: a southern European country (Portugal), the average for all countries and a northern European country (Denmark). The quality of the regression can be evaluated using the coefficient of determination, leading to $R^2 = 99.84\%$ for the overall average, $R^2 = 99.87\%$ for Portugal and $R^2 = 99.91\%$ for Denmark; this is deemed acceptable.

The implementation of the final function can be cross-checked with the following values (in the "average" case):

$$SSR_{R_{bat}=0.8, R_{PV}=0.8} = 52.67610\%$$

$$SSR_{R_{bat}=1.2, R_{PV}=1.2} = 66.55167\%$$

Table 2
Coefficients of the fSSR function.

	Average	Portugal	Denmark
$SSR_{0,1}$	32.603	33.438	32.184
a_1	38.220	47.093	30.685
a_2	0.854	0.715	0.844
a_3	1.019	0.081	0.968
b_4	13.268	15.802	11.238
b_5	2.092	2.496	2.120
b_6	−4.760	−4.463	−5.381
b_7	24.589	22.350	26.751
c_8	8.998	9.459	10.694
c_9	1.742	1.245	1.516
c_{10}	1.379	1.347	0.841
c_{11}	1.221	0.954	1.854
c_{12}	34.320	22.511	67.400
c_{13}	1.459	2.676	0.782
c_{14}	0.373	0.282	0.441
c_{15}	15.027	16.318	8.756

6. Example test case

This section illustrates how the analytical expression derived in Eq. (22) can be used to optimize and evaluate the profitability of the PV/battery home system, taking into account the benefits of self-consumption.

Fig. 11 describes the rationale whereby a prosumer maximises SSR. Germany is taken as an example because its tariff structure is favourable to solar home batteries: the large price difference between buying electricity (at the retail price) and selling it (at the feed-in-price) can justify investing in self-consumption.

In such a context, households optimise their solar home battery investment by comparing the levelised cost of storage and of the PV installation with the residential electricity tariff. The latter includes network tariffs, taxes, levies and other surcharges that can be avoided when consuming self-produced PV electricity instead of purchasing from the grid. The tariff structure can thus be seen as creating an indirect financial incentive to self-consumption.

It should be noted that this mechanism is unsustainable in a scenario in which such systems enjoy significant uptake, since it generates revenue shortfalls for government, municipalities and system operators. These losses of revenue need to be compensated, either by increasing the network tariffs or by changing the tariff structure, e.g. switching from a volume (per kWh) remuneration to a hybrid scheme involving fixed or capacity-dependent remuneration for the grid connection. Interestingly, tariff structures are already being adjusted in this way in several EU countries [1].

Fig. 12 shows the influence of the PV system and battery sizes on the LCOE for the conditions of Table 3. Note that the battery cost function is much lower than the current price levels. It is representative of a hypothetic future situation in which battery costs keep decreasing. In these conditions, an optimum clearly appears, in terms of both PV size and battery size: if the battery is oversized, its utilisation is low, which leads to excessive investment costs. On the other hand, for small batteries, the displaced load is low and the impact on the self-consumption is marginal. The same is true for the PV system, whose revenues are significantly higher

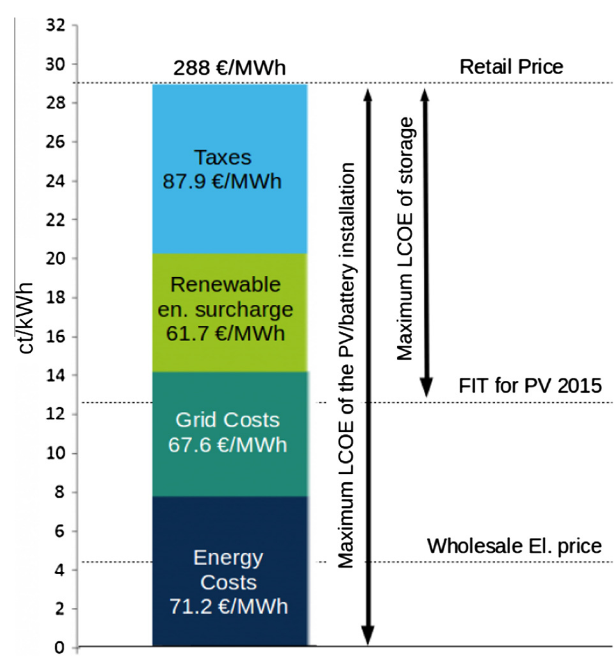

Fig. 11. Average retail tariff structure in Germany (2015) and impact on self-consumption.

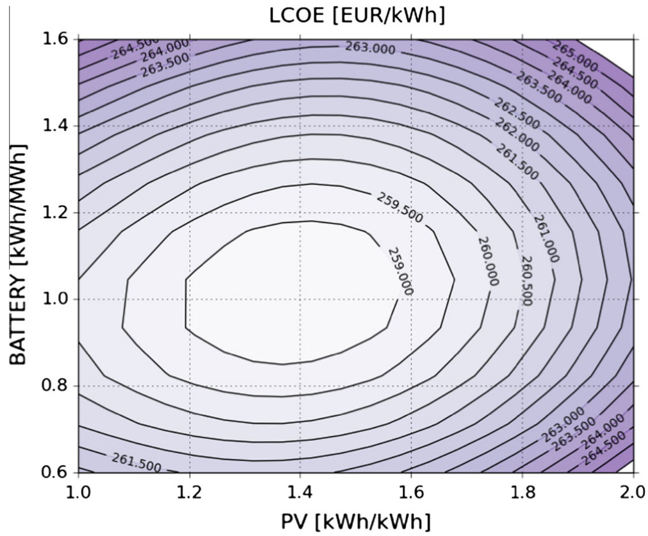

Fig. 12. LCOE as a function of the PV system and battery sizes.

Table 3
Cost parameters of the test case.

Variable	Unit	PV	Battery
Lifetime (N)	Years	20	10
Investment (I)	EUR	1500/kWp	300 + 200/kWh
O&M	EUR/year	$OM = 1.5\% \cdot I$	
Discount rate	%	$WACC = 4.16\%$	

for the self-consumed generation than for the energy fed to the grid. The optimal design of such a system can therefore be expressed as mixed-integer non linear programming optimisation (MINLP) problem. Since there are only two binary variables (presence of a battery system, presence of a PV system), the problem is solved with two optimisations performed in parallel (the third corresponds to the trivial case $R_{PV} = 0$ and $R_{bat} = 0$). The case in which a battery is installed without a PV system is irrelevant and not simulated. The global optimum is finally obtained by selecting the minimum of the objective functions.

To compute the break-even variable cost of the battery system, we conduct a parametric study by re-optimizing the system for a number of cost values. On the basis of the results in Fig. 13, we can draw the following conclusions:

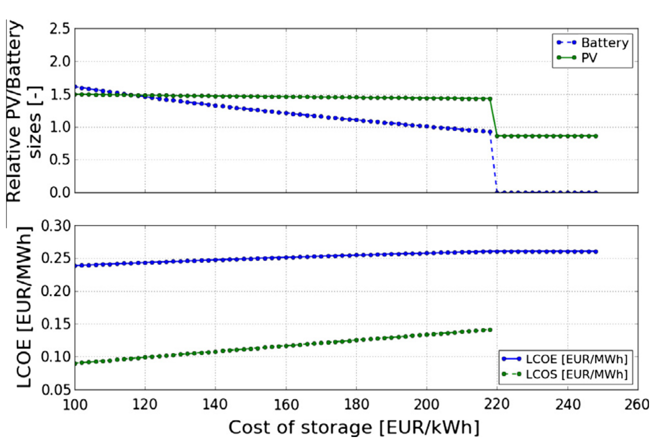

Fig. 13. Optimal values of R_{PV} and R_{bat} as a function of battery costs.

- the battery stops being profitable when its variable cost exceeds EUR 214/kWh; at this break-even point, the optimisation stops investing in the battery system, the cost of which becomes prohibitive;
- the optimal share of PV is lower in the absence of a battery. This is explained by the fact that the battery shifts a part of the PV generation to self-consumption, which is more profitable. This increases the profitability of the PV system, whose optimum size is thus increased.

7. Conclusions

The main objective of this study was to evaluate the level of self-consumption that can be expected for a household installing a PV system with or without battery. To be relevant, such analysis must be performed for a large number of different (stochastic) household consumption profiles. We therefore built up a database of profiles from monitoring data and generated a number of additional stochastic profiles.

The analysis has revealed the following:

- Self-consumption is a non-linear, almost horizontally asymptotic function of PV and battery size. Achieving 100% self-consumption (i.e. allowing for full off-grid operation) is not realistic without excessively oversizing the PV system and the battery;
- The SSR varies widely between households: for a given household, the volume of self-consumption can therefore not be predicted in a deterministic way;
- For an average European household, the SSR in the absence of battery varies between 30% and 37%. The value tends to be slightly higher in southern countries;
- The SSR can be significantly impacted by the maximum charging and discharging power of the battery, especially for high battery capacities;
- The benefits of self-consumption stem from the tariff structure and the difference between electricity buying and selling prices. They are therefore largely linked to the local regulation;
- A scenario of high penetration of self-consumption solutions might lead to an unfair distribution of network charges, taxes and levies, which self-consumers do no have to pay. This explains why the regulatory framework is currently changing in several EU countries;
- Depending on the financial inputs, there may be optimum PV and battery sizes: adding a battery to the system can result in a larger optimum PV array size;
- With the assumptions made for this study, a home battery system becomes profitable if its variable cost is below EUR 214/kWh (for a fixed cost of EUR 300). This is well below the current (January 2016) battery prices [6], which tends to indicate that further price reductions are required before there is a real uptake of these systems. These results are in line with those presented in [7]: PV systems are profitable in the current German context, but batteries become profitable only in longer-term scenarios with significantly lower prices.

To ensure that this work is easily reproducible, the database of household consumption profiles, the dispatch algorithm, the financial module and the optimisation procedure are provided as an electronic annex to this paper.[1]

Finally, it should be noted that the economic analysis presented here is mainly for illustrative purposes. It does not aim to cover the full spectrum of possible regulations and market tariffs. It can

1 https://github.com/squoilin/Self-Consumption/releases/tag/v1.0.

therefore not be considered a comprehensive evaluation of the profitability of home batteries. Future work will focus on using the self-consumption evaluation tool for policy support, in particular to evaluate the impact of the current developments in EU regulations on self-consumption and the future deployment of solar home battery systems.

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