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Effects of time resolution on finances and self-consumption when modeling domestic PV-battery systems

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Abstract

When modeling a renewable energy system, the timestep to use is an important consideration. Timestep, or time resolution, can have an impact on results, influencing the sizing of the system and whether or not to invest at all. In this work, real measured data for an entire year at 15-s resolution from a rooftop PV array and 8 household loads in the UK are used. The PV and load time series are averaged to lower resolution: 1-min, 5-min, 30-min and 1-h, and the results from using them as input to a 25-year simulation of PV-only and PV-battery systems are compared to the 15-s resolution results. Load resolution is confirmed to be more important than PV resolution for improving accuracy of self-sufficiency and cost metrics; the presence of a battery is confirmed to reduce the errors of using low resolution compared to PV-only. However, these findings only apply to the commonly tested Greedy algorithm but not the newly developed Emissions Arbitrage algorithm. A wider range of metrics are calculated here than in previous work, finding consistency in that low resolution overstates the benefits of PV-battery, but variation in percentage difference across the metrics used. Further aspects not studied before include: the diminishing returns in computation speed when time resolution is lowered, and the effect of time resolution on the tipping point when certain configurations become more attractive propositions than others. Time resolution of input data and modeling are issues not only for researchers in academia and industry, but from a consumer protection perspective too.

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Keywords: Solar PV; Battery; Techno-economic; Time resolution; Modeling

1. Introduction

Computer modeling is an indispensable tool for designing and developing business models for renewable energy systems. Decisions made on the basis of modeled results include the sizing of system components, such as solar PV and battery capacities, and whether to invest in the system at all based on projected payback time, net present value (NPV), internal rate of return (IRR), or reduction of greenhouse gas emissions.

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Nomenclature

CO_2-eq.	Carbon dioxide equivalent
FiT	Feed-in Tariff
GBP	Great British Pounds
IRR	Internal Rate of Return
kW_p	Kilowatts-peak (unit of PV (DC) capacity)
LCoE	Levelized Cost of Energy
PV	Photovoltaic
Q	Battery charge capacity (Ah)
R	Battery internal resistance (Ω)
SSR	Self-sufficiency ratio (%)
V_0	Battery voltage (V)

Sometimes input data, specifically time series of PV generation and electricity consumption, are not available at very high resolution. For example, balancing market data in the UK is recorded at half hourly intervals. This is appropriate for national level electricity analysis but is not viable for domestic demand and solar generation modeling where there are much higher variances in supply and consumption. Furthermore, computer run time and data storage requirements increase when the system is modeled at higher resolution. Decisions must be made in trading off accuracy for computation speed, and whether or not to simulate super-resolved versions of the inputs, as that can introduce further inaccuracies.

Regarding previous literature on the topic, Wright and Firth [1] used 1-min resolution data measured at 8 houses in England. They studied the effect on electrical import and export of averaging the data to lower resolutions. However, they assumed constant generation power and no storage, and only studied 2 houses in detail for week-long periods. Wyrsch et al. [2] used 6-s load data and 1-min PV data measured in Switzerland to model and calculate the self-consumption with different battery capacities. They found less error from low time resolution when a battery is present. Beck et al. [3] found similarly, using 2-s load data and 10-s PV data measured in Germany. The error in self-consumption could be kept below 5% in PV-only cases with PV resolution 15-min and load resolution 1-min, but this is achievable at load resolution 5-min if there is a battery too. In addition, they studied the effects of time resolution on optimal sizing of the system (to minimize costs), recommending 5-min resolution or better for sizing the battery power (kW), but finding negligible effects of time resolution on sizing the PV capacity (kW) nor battery capacity (kWh). In contrast, Hittinger et al. [4] had found optimal battery size 236% higher at 1-min modeling resolution compared to hourly. This could be due to the different context: a standalone microgrid on a Southeast Asian island, whereas others have studied grid-connected houses. Hittinger et al. [4] also studied the effects on levelized cost of electricity (LCoE), finding a 25% under-estimation for a PV-diesel microgrid modeled at hourly resolution compared to 1-min, and 3% under-estimation when a lead–acid battery is added to the system. Quoilin et al. [5] modeled domestic PV-battery systems in many EU countries, finding an unusually low error of 1.5% in the self-sufficiency values at 1-min compared to hourly resolution. This was for PV-only systems, and decreased further as the battery capacity is increased.

The work presented here uses 15-s resolution measured data across one full year for a PV time series and 8 household load profiles in the UK, putting it amongst the best in terms of quantity and resolution of input data used. A wider range of metrics is analyzed: LCoE and self-sufficiency like in previous literature mentioned above, but also total import/export of electricity, battery cycling, annual bill savings, IRR, and CO_2-eq. intensity. The range of error at low resolution can be seen to vary across the metrics, and from house to house. The effect of low resolution is found to depend on the battery operating strategy used, an aspect which has not been studied before. Furthermore, little work has been done previously into how the optimal decision for which system configuration to invest in changes over time. This too is found to be affected by time resolution of modeling.

2. Method

Using high-resolution measured time series of PV generation and electricity consumption at 8 houses in the UK, a domestic PV-battery system was simulated across 25 years starting from 2019, at 15-s resolution, and also with input data averaged to lower resolution: 1-min, 5-min, 30-min, 1-h. That is, the value at each lower-resolution timestep is the mean of the 15-s values within the corresponding period. The acquisition of PV and household load data is described next, followed by a description of the PV-battery system and how it is modeled, and definitions of the key metrics calculated from the modeling results. The code was developed and run in Matlab R2018a.

2.1. PV data

Generation power (instantaneous values) were logged for a 3.6 kW_p rooftop PV array with 3.6 kW inverter. The system is located in Reading, UK, and is SE-facing, inclined roughly 45° from horizontal. Data were logged at intervals between 1–4 s for the period 2nd December 2015 to 30th November 2016. The system is owned by Dickon Hood, who implemented the data logging and made the data available upon request [6].

As the timesteps were irregular, data were averaged to 15-s timesteps (in keeping with load data, see Section 2.2). If no data were logged for more than 6 continuous hours, zeros are written, as the data logger switches off when power is zero such as at night. Gaps of 5 min or less are filled with the previous value. Gaps of between 5 min to 6 h are filled with data from the day ahead (in the first half of the year) or the day behind (in the second half). Any gaps remaining are linearly interpolated over. Any days for which more than 95% of the values are zero, are replaced entirely by the previous day's data.

The same year's data is used for all houses, scaled to the required (kW_p) capacity, and repeated for all years of the simulation, but reduced by 0.7% each year to account for PV degradation [7]. The effects of year-to-year and regional PV output variation are outside the scope of this work.

2.2. Load data

The REFIT electrical load dataset contains measured load time series for 20 houses in the UK logged at an intended rate of every 8 s, between September 2013 to July 2015 [8]. The aggregate active power (over all appliances) consumed at each house was the basis of the input load data used in this work. As the timesteps were in practice irregular, data for the whole of 2014 were averaged to 15-s timesteps, excluding missing values. Gaps of 5 min or less had missing values replaced by the previous value. Gaps of more than half a day had the entire day's values replaced by the corresponding day (weekday or weekend) in 2013, and if still missing, by the corresponding day in 2015. Remaining gaps had missing values replaced by data from 7 days ahead (first half of the year) or 7 days behind (second half). This is repeated once more.

This left 8 houses with fewer than 100 out of 8760 h containing missing data, which were then linearly interpolated over. These 8 covered an adequate range of annual total consumption values: in descending order, 6451, 5818, 4714, 4116, 4069, 3982, 3258, 2572 kWh, for respectively houses 5, 8, 7, 6, 2, 1, 12, 19. They had no PV, except for 1, 6 and 7, for which Murray et al. [8] had made the load measurements to exclude effects of PV generation.

The same year's data is repeated for all 25 years of the simulation, as there is insufficient reliable data to adjust the load profiles to future years: whether there will be load growth due to more appliances consuming more energy in each house; whether the appliances will be more energy-efficient.

2.3. System model

A DC-coupled grid-connected PV-battery system is modeled in accordance with Fig. 1. In practice, different homeowners would likely choose different system sizes, but it was decided to make the simplification of fixed PV and battery sizes after some preliminary testing. Greater PV capacity was found to improve both financial returns and CO_2 savings. Therefore PV capacity was capped at 4 kW_p for all 8 houses, as few UK roofs can support more than this. The measured PV data were scaled accordingly. Greater battery capacity always worsened the finances compared to PV only (but in some cases improved them compared to having no PV), and similarly for CO_2 savings. Therefore each house was modeled for a case with PV only, and with 7 kWh battery as well, this being a commonly available size of batteries for UK households.

The battery is modeled as a constant voltage source $V_0 = 230$ V with internal resistance $R = 0.37\ \Omega$ and charge capacity $Q = 30.6$ Ah. Domestic batteries are typically $LiFePO_4$, Li-NMC, or similar lithium-ion batteries, which

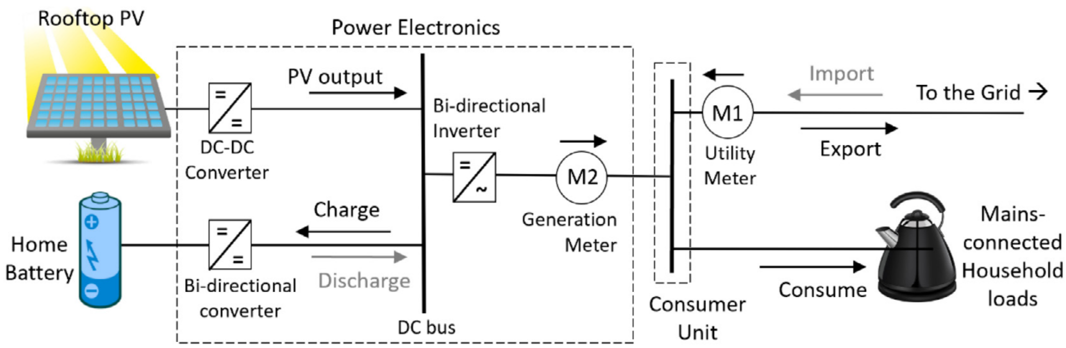

Fig. 1. Schematic of DC-coupled domestic PV-battery system, feeding household loads and the grid.

have almost constant voltage except at very low and very high state of charge, and close to 100% coulombic efficiency. Therefore energy losses are modeled as occurring only due to ohmic losses in the battery internal resistance, losses in the inverters, and self-discharge (at rate 0.001 C).

Battery degradation is modeled by resetting R and Q for each simulated year according to how many full equivalent cycles (energy throughput divided by battery capacity 7 kWh) have occurred in the previous year. R increases and Q decreases with cycling in a square-root fashion such that R has doubled and Q decreased to 75% of its original value by the time the battery has undergone 3000 equivalent cycles, following the method of Sathre et al. [9]. The battery is replaced after 15 years of operation, regardless of degradation.

The battery power electronics (both the bi-directional converter and inverter) are each modeled as being 96% efficient at maximum throughput, decreasing to 0% at zero throughput, with a knee point around 80% efficiency at throughput 14% of maximum, following Truong et al. [10]. Power electronics ancillary load is assumed negligible. No degradation is modeled for the power electronics, and they are replaced once in year 13.

In the PV-only cases, PV generation first serves the household loads and any excess is exported to the grid. If PV generation is insufficient, the remainder of the load is met by importing from the grid. Two different battery operating algorithms are run for the cases with battery: the Greedy algorithm, and the Emissions Arbitrage algorithm.

The Greedy algorithm is similar to PV-only, except excess PV generation goes into charging the battery before being exported, and any load exceeding PV generation is served by discharging the battery before importing from the grid. This is guaranteed to maximize the system's self-sufficiency (see Section 2.4) and is common amongst commercial battery products. It is popular for its simplicity, not requiring any forecasting, and its ability to reduce electricity bills [10].

The Emissions Arbitrage algorithm increases CO_2 savings above the Greedy algorithm by only charging the battery at times when grid CO_2 intensity is lower than the mean of the previous 30 days, and only discharging when it is higher. Charging power comes first from PV and then from the grid if insufficient; discharged power first serves the load, and any excess is exported to the grid [11]. Note that the battery can charge from or discharge into the grid directly, which is never the case for the Greedy algorithm. The Emissions Arbitrage algorithm requires no forecasting and hence runs more quickly than ones which use linear or dynamic programming to optimize battery scheduling. It can be considered a conservative estimate of what is achievable with intelligent scheduling design.

2.4. Calculation of metrics

For all runs, the electricity imported from and exported to the grid is totaled across the 25-year system lifetime. The number of battery cycles during the first year is calculated as total energy throughput, divided by battery capacity.

For the financial metrics, the prices in Table 1 are used. Bills are calculated according to an Economy7 tariff, where consumption between 07:00 to 00:00 is charged 13.6 p/kWh and between 00:00 to 07:00, 7.6 p/kWh, with a daily standing charge of 18.6 p [12]. The Feed-in Tariff (FiT) scheme for PV in the UK ended in April 2019, so a generation tariff can no longer be collected. Regulations have not yet been put in place governing grid export

Table 1. Costs to homeowner of installation of PV-battery system components.

Component	Size	Cost (GBP)	Replacement cost (GBP)	Embodied CO_2 (kg)
Roof-mounted solar PV array	4 kW	5800[a]	–	4600[d]
Domestic lithium-ion battery	7 kWh	3200[b]	1500 (in y15)[c]	1490[e]
Power electronics	3.5 kW	800[b]	800 (no change)	440[f]

[a]Solar Guide [14].
[b]Naked Solar [15].
[c]Estimated based on findings of Goldie-Scot [16] for the EV battery market.
[d]Bekkelund [17]. Includes solar inverter and roof mounting.
[e]Hawkins et al. [18].
[f]Estimated from values for solar inverter [17].

payments, but in this work, export is metered and credited at 5.0 p/kWh, as some electricity suppliers are already offering. All elements of the bill and export payment are taken to increase 5% each year [13].

Bill savings in the first year are calculated as the difference between the bill in the given scenario, and the bill when there is no PV and no battery. In each case the bills are calculated as described above, with standing charge, day/night rates, and export payment, based on the import/export profiles yielded by the simulation.

Levelized Cost of Energy (LCoE) typically describes the cost per kWh of generating energy, including initial investment, fuel and running costs over the system lifetime. An analogous concept is defined here as the cost to the homeowner of consuming each kWh of electricity, including initial costs of PV and battery, replacement costs, and electricity bills over the 25-year lifetime. Operations and maintenance costs are assumed negligible. Future cash flows and electricity flows are both discounted, in accordance with the World Bank's definition of LCoE [19]. The discount rate used is 2%, a typical interest rate offered by UK high street banks on a savings account [20], as appropriate for a homeowner deciding between where to invest their savings.

Internal Rate of Return (IRR) is the discount rate that would make the system's Net Present Value (NPV) = 0. NPV is the system's lifetime profit, calculated by a discounted cash flow analysis. That is, capital expenditure and yearly costs (discounted) are subtracted from yearly revenues (discounted). Usually an investor sets a hurdle rate such that they only invest in a proposition whose IRR exceeds it. In this work, IRR is calculated relative to the case with no PV and no battery, that is, yearly savings are considered rather than profits.

Self-Sufficiency Ratio (SSR) is the percentage of electricity consumption that is met by sources other than the grid, that is, by PV and battery. It is calculated across the 25-year lifetime and thus accounts for degradation of system components. SSR is maximized by the Greedy algorithm.

CO_2 intensity is calculated similarly to LCoE but with embodied CO_2 of manufacture rather than monetary costs of each component, debiting CO_2 emissions of grid-imported electricity and crediting for export. Note that marginal rather than average grid CO_2 intensity is used here, as explained by Sun et al. [11]. The 'Community Renewables' scenario (rapid decarbonization using mostly decentralized sources such as wind and PV) is used here for future grid CO_2 intensity, interpolating between 2017 to 2030, and 2030 to 2050.

3. Results

3.1. Effects of load resolution and PV resolution

Fig. 2 shows how the 8 metrics (Section 2.4) vary when load resolution and PV resolution are each reduced while keeping the other at 15-s. This is for PV only, and PV-battery running the Greedy algorithm and Emissions Arbitrage, for House 2 (annual load 4069 kWh). This house was selected as an example because it illustrates the greatest difference at low resolution out of all the houses.

Load resolution is more crucial for accuracy than PV resolution, that is, errors increase more rapidly when load resolution is reduced than when PV resolution is reduced, from the highest resolution, 15-s. In nearly all cases, low resolution overstates how well the system performs: import, export, battery cycling, and LCoE are underestimated, while bill savings, IRR and SSR are overestimated. This is important from a consumer protection perspective. However, battery cycling and CO_2 intensity with Emissions Arbitrage are almost unaffected by time resolution. These findings are confirmed across all 8 houses in Section 3.2.

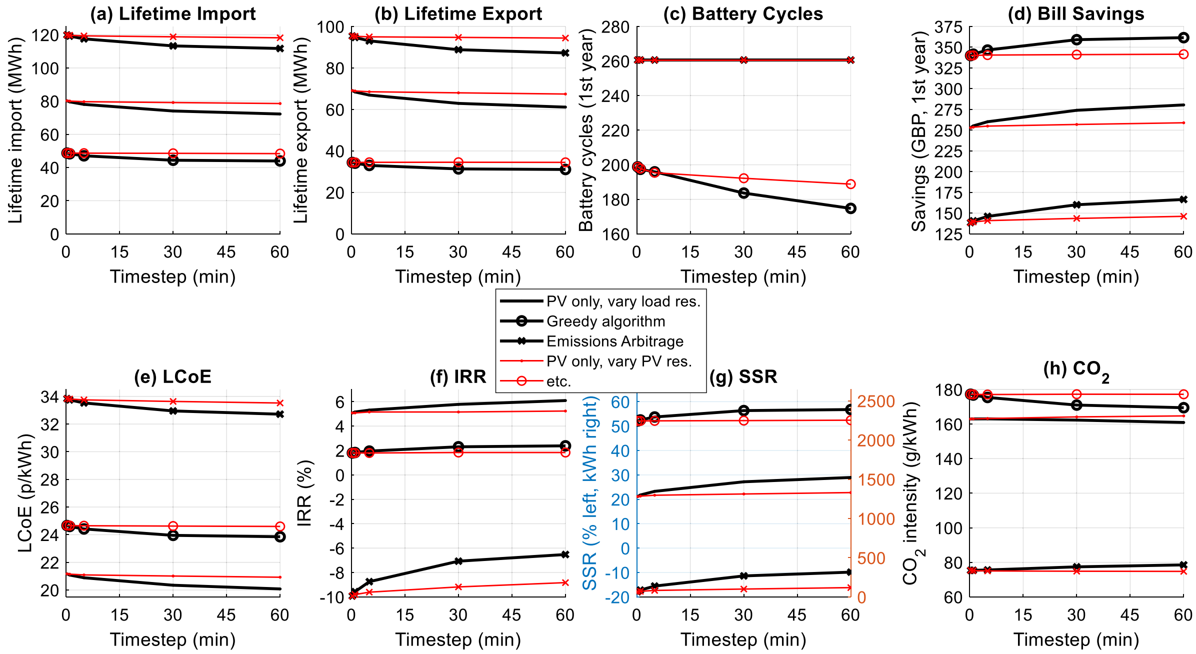

Fig. 2. The 8 metrics as a function of timestep, for House 2 with PV only, battery running Greedy algorithm, and running Emissions Arbitrage. Thick black lines: PV resolution 15-s while varying load resolution; thin red lines: load resolution 15-s while varying PV resolution.

3.2. Extent of low-resolution error across all houses

Fig. 3 shows the difference between 1-h resolution compared to 15-s (both PV and load resolution), for all 8 houses on each of the 8 metrics. The percentage difference is shown for all except IRR and SSR, for which the absolute percentage-point difference is shown, and CO_2 intensity, for which the absolute difference in g/kWh is shown. This is because these metrics' true (15-s resolution) values vary so much depending on the system configuration (PV-only, Greedy algorithm, or Emissions Arbitrage — see Fig. 2(f) and (g)) that percentage differences cannot be presented clearly on the same graph. Even with the variation between houses, three trends are apparent:

Firstly, the scenario with lowest errors is PV-battery running the Greedy algorithm, on all metrics except battery cycling and CO_2. As Wyrsch et al. [2] and Beck et al. [3] explained, the cause of the errors is that lowering the resolution blurs peaks in load and PV time series, overstating their overlap and hence the benefit of having PV; whereas a battery running the Greedy algorithm acts as a buffer between load and PV. In other words, the battery has a similar effect to simulating at low time resolution, but truly rather than erroneously.

Secondly, PV-battery running the Emissions Arbitrage algorithm has errors similar to those of PV-only. This should not be a surprise because the Emissions Arbitrage algorithm schedules charge/discharge according to grid CO_2 intensity, not load nor PV. This exposes it to the same peak-blurring overlap-overestimation error mechanism as the PV-only case, as the battery does not buffer between load and PV the way it does with the Greedy algorithm. It is for this reason too that battery cycling is almost independent of PV/load resolution under Emissions Arbitrage.

Thirdly, the order of magnitude of the percentage errors is not consistent across all metrics. LCoE, for example, has errors of 0.5%–5%, despite being calculated from import and export, which have errors in the range 1%–12%. The errors partly cancel because they go in the same direction: low time resolution underestimates both import and export, so expenditure on bills is underestimated but so too is income from export payments. The same cannot be said for other metrics: errors in battery cycling and bill savings exceed 15% in some cases, while IRR and SSR have very small or very large percentage errors depending on the system configuration.

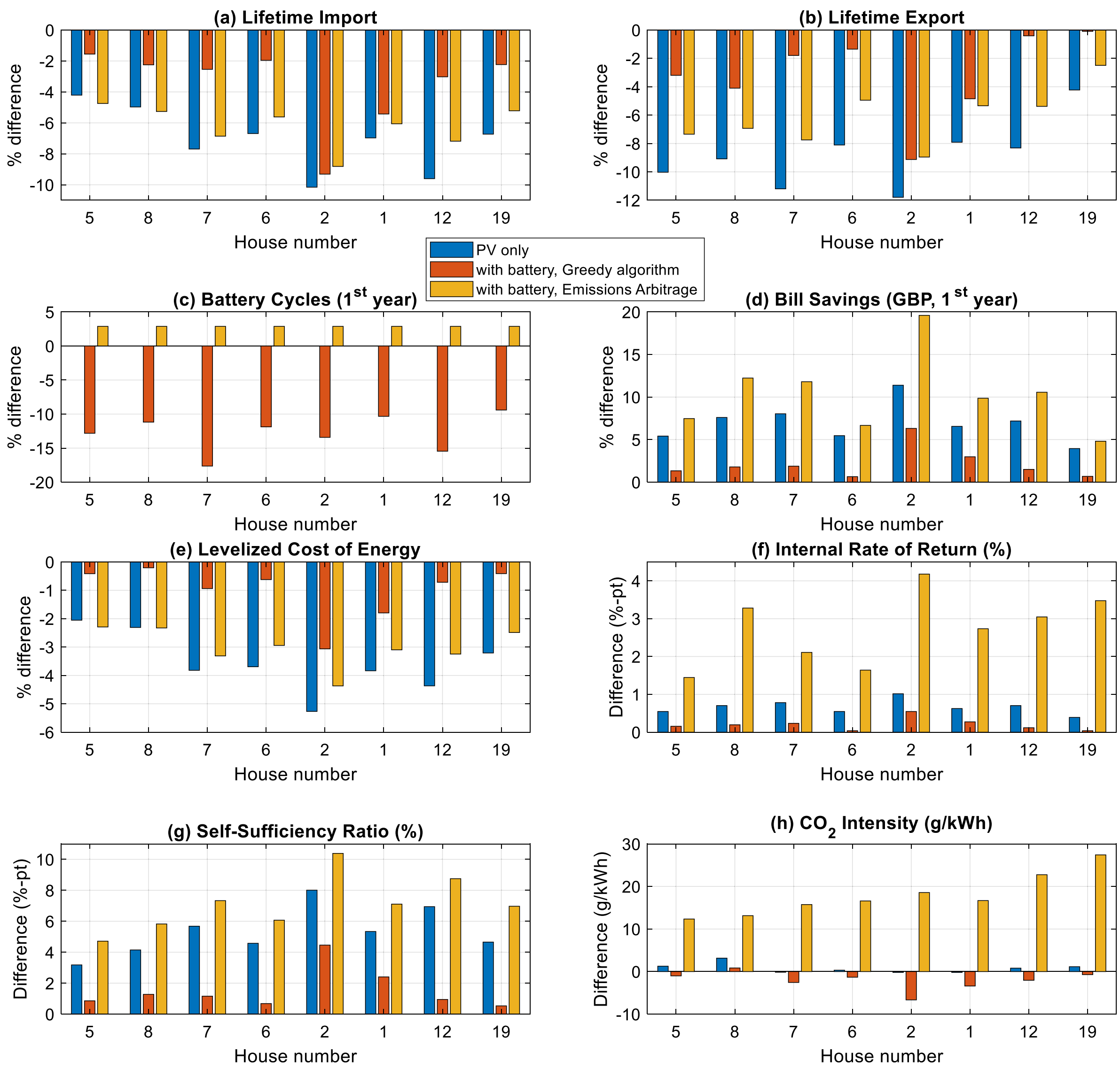

Fig. 3. For the 8 metrics, for each house and scenario, the difference between 1-h compared to 15-s resolution.

3.3. Relation between SSR error, timestep, and simulation run time

As an example of how a decision on time resolution may be made, Fig. 4 shows the error in SSR and the run time as a function of timestep. Run time includes both the simulation itself and calculation of metrics, the latter taking on the order of 1 s. The timestep is the minimum of the PV and load timesteps, as each simulation is run at the highest resolution of the two input series. This is why SSR error is not zero at 15-s resolution, because the average includes runs where only one (PV or load) is at 15-s but not the other. SSR error is shown both in percentage-points and kWh, found by multiplying SSR (%) by annual load (kWh).

Run time varies between machines and programming languages; it is not the values in Fig. 4(b) but the trends that are important. The improvement in accuracy by reducing timestep is more pronounced at shorter timestep, but incurs a greater penalty in run time. Increasing the timestep gives diminishing returns in computation speed. While a few hundred seconds may not be long to wait, run time can become an important consideration if one must simulate many scenarios, for example, to optimize a system over a wide parameter space.

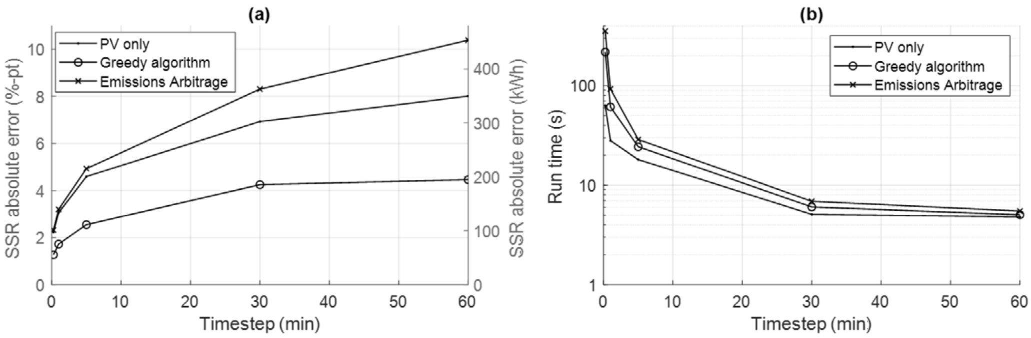

Fig. 4. (a) SSR error; (b) simulation run time, both averaged across all runs and houses, as a function of timestep.

3.4. *Effect of low time resolution on tipping point years*

For an investment in 2019, all financial metrics show that a battery is still a more costly option than PV only. While a battery running Emissions Arbitrage will save more CO_2 than having PV only, running the Greedy algorithm saves slightly less, albeit still rendering a CO_2 benefit above having no PV and no battery. Emissions Arbitrage costs the homeowner more overall than having no PV and no battery. However, batteries and PV are both falling in price, while electricity bills keep rising. The generation technologies on the grid are also changing. This means a homeowner may benefit from delaying the date of initial investment.

To explore the effect of time resolution, three tipping points were analyzed: when PV-battery with the Greedy algorithm is more cost-effective than PV only in terms of LCoE, when PV-battery with the Greedy algorithm is more eco-friendly than PV only in terms of CO_2, and when PV-battery with Emissions Arbitrage is more cost-effective than no PV and no battery in terms of LCoE. These were found by calculating LCoE and CO_2 intensity for the relevant configurations for all houses at 15-s and 1-h resolution, for investment starting in years 2019, 2025, 2031, 2037. The tipping-point year was found by linear regression in each case, and are shown in Fig. 5.

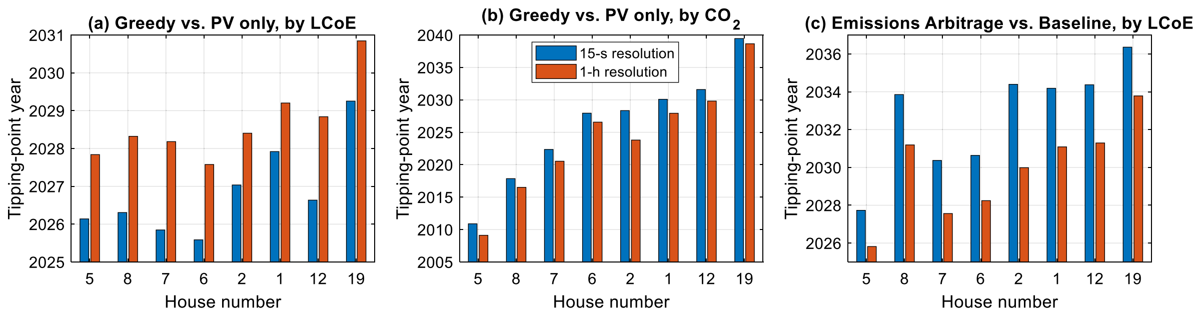

Fig. 5. Tipping-point year for each house at 15-s and 1-h resolution when (a) LCoE of PV-battery with Greedy algorithm becomes less than PV only; (b) CO_2 intensity of the same comparison; (c) LCoE of PV-battery with Emissions Arbitrage becomes less than no-PV-no-battery.

The tipping-point year for the Greedy algorithm becoming more cost-effective than PV only is 1–2 years later at 1-h resolution compared to 15-s. However, at 1-h resolution, the Greedy algorithm becomes more eco-friendly than PV only 1–4 years sooner, and Emissions Arbitrage becomes more cost-effective than no PV and no battery 2–3 years sooner. While these results depend on the assumptions made for PV, battery, electricity pricing and grid generation future trends, the effect of time resolution on tipping-point year is clearly consistent in direction.

4. Conclusions

The findings of Wyrsch et al. [2], Beck et al. [3], and Hittinger et al. [4] have been confirmed: load resolution is more important than PV resolution for improving accuracy of SSR and LCoE; errors are less for PV-battery with the Greedy algorithm than for PV only. However, these findings do not apply to all PV-battery systems: the errors for Emissions Arbitrage are of similar magnitude to the PV-only cases, showing the importance of testing the effects of time resolution when developing new operating algorithms. While the error growth in SSR (and indeed other metrics) decelerates with increasing timestep, there are diminishing returns in computation speed when doing so. The effect of time resolution on the tipping point when certain configurations become more attractive propositions than others has not been studied before. While small, the effect is consistent in direction. Prospective customers should be wary of being sold an investment whose projected returns are based on modeling at hourly resolution.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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