Economic and environmental benefits of PV-battery systems for residential consumers in different pricing scenarios

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Solar-PV has the potential to make an important contribution to global sustainability. However, the misalignment between solar production and residential demand imposes an operational limitation to widespread solar-PV adoption. Combining solar with storage is one way that this challenge can be overcome. Here we compare the economic and energy saving benefits of standalone-PV and coupled PV-storage systems for nearly 4,600 residential consumers under both feed-in-tariff and net-energy-metering policies. By grouping consumers according to their load profiles we are able to identify consumers most suitable for PV. While PV-storage is uneconomic with current tariff policies, we show that feed-in-tariffs that include a self-consumption bonus and reduced export prices can provide incentives for consumers whose generation is misaligned with their consumption to adopt storage. We also find that feed-in-tariffs are more favorable than net-energy-metering policies for coupled PV-storage systems in terms of energy conservation. Conversely, net-energy-metering policies offer faster investment recovery for most consumers with PV-only systems, but do not favor storage of surplus PV generation. Looking into the future, we project scenarios following a combination of the current international trends of increasing electricity prices, decreasing solar subsidies and decreasing battery prices. By 2020 in several regions worldwide this leads to a regime in which coupled PV-battery systems yield faster financial returns than standalone PV for the majority of residential consumers.

The electricity industry is the single biggest contributor to global greenhouse gas emissions worldwide [1] — in the US it accounts for 30% of the nation’s GHG emissions [2]. The residential sector represents 36% of the total electricity consumption [3] and is an important area where savings can be realized. Solar PV is a popular way of reducing emissions through clean solar-generated electricity, the uptake of which has been driven both by energy policy and consumers heightened awareness of environmental issues. As a result, many regions in both the US and Europe have or are currently experiencing a boom in the levels of installed PV in the local distribution grid. For example, at the end of 2015 California had over 10 GW of installed solar, of which 3GW was installed in 2015 [4], while in Germany the installed PV capacity has recently surpassed 40 GW (having been only 2GW in 2005) [5].

Although these PV generators reduce the electricity that must be provided by conventional power plants, there are still significant challenges associated with widespread solar deployment. These include increasing the required grid ramping rates and altering utilization factors for existing power plants [6], introducing voltage and frequency stability concerns [7, 8], as well as increasing wholesale electricity price fluctuations, particularly in balancing markets [9]. The result is a limit on the amount of PV generation that can be accommodated in many systems without additional flexibility [10]. A particular problem is that regional PV outputs are highly correlated, simultaneously peaking in the midday and falling in the early evening, requiring sustained high ramp-up and ramp-down rates from grid connected power plants to keep the electric system in balance. Importantly, the demand during the daytime may be reduced sufficiently such
Figure 1: The solar ‘duck’ and the effects of storage under different tariff policies. a The notorious ‘solar duck’ effect arises as solar generation is not well-aligned with peak loads. Over-generation can occur if enough consumers adopt PV — on a typical day in our simulations once the solar adoption rate reaches 40%, there is more PV generation than local demand in the middle of the day. b The effect of storage with the NEM policy. 40% PV-only adoption is compared with 40% PV+battery adoption. Consumers charge their batteries at night with cheap electricity and discharge at peak times, thus the batteries are not useful to attenuate the solar surplus and increase the consumption from the grid. c The effect of storage under the FIT policy. 40% PV-only adoption is again compared with 40% PV+battery adoption. Consumers charge their batteries with their solar generation and save their imports from the grid at night.

that over-generation occurs due to the minimum running requirements of other thermal power plants [11].

This situation is illustrated in Fig. 1a, and leads to the infamous solar ‘duck’ curve.

These issues cause divergent opinions between pro-solar groups and incumbent electric utilities about rewarding PV generation, with pro-solar groups focusing on the positive environmental aspects of PV and incumbent utilities on the operational challenges posed. In the US, a controversial issue is whether or not to preserve Net Energy Metering (NEM) [12] — which is currently the favored policy approach regarding residential PV in most states. Under a NEM policy, consumers with PV are billed based on their net electrical usage, and surplus solar-generated electricity is rewarded at the same price per kWh as electricity from the grid would have cost the consumer at that time period. Alternatively Feed-In-Tariffs (FITs) are the preferred approach in much of Europe. FIT policies usually oblige the local utility to buy all of a consumer’s surplus solar-generated electricity at a fixed export rate, which is specified by the relevant authority. Both of these policies have been designed to promote investment in PV technologies, however FIT rates are designed to be reduced as target levels of capacity are achieved and surpassed. For example, in Germany the PV FIT rate has been reduced from 0.20 Euro/kWh in 2012 to 0.10 Euro/kWh in 2015, while in the UK the FIT rate has fallen from 0.17 GBP/kWh to 0.11 GBP/kWh in the same period.

Energy storage is one effective way of overcoming the technical challenges associated with intermittent solar generation [13]. Storage can absorb surplus solar generation, releasing it at times when it needs to be consumed. At the utility scale, compressed air energy storage and pumped hydro storage are currently best placed to add value to wind or solar [14], however at the residential scale lithium-ion batteries are the most promising storage option [15]. Several companies are already marketing batteries to residential PV consumers and recent studies have suggested that they may become an economical option for residential consumers in future scenarios, where surplus solar generation is largely unrewarded [16, 17, 18]. However, most of these studies have considered only one or a couple of consumer load profiles and have not linked tariff policies, actual energy use and consumer behavior. This work addresses these challenges, illustrating how different consumers have differing degrees of suitability for PV and storage under different tariff
policies. Taking into account the effects in consumers’ economics and energy requirements, our results inform about possible scenarios for utilities, policy makers and the technology market alike.

We use data-driven simulations to compare the time to recover the investment by the residential users. Namely, the payback periods of investments in PV-only and PV-battery systems for 4,574 residential consumers, and link the financial rewards to consumer behavior under both NEM and FIT policy scenarios. To identify separate behaviors we grouped the consumer-days into 9 distinct clusters, based on the times of peak consumption. Our results illustrate several points of importance. Current NEM policies result in narrow payback distributions, with the fastest payback (13.2 years) for consumers with PV-only systems. This time is independent of consumer behavior or overproduction. However, we find that NEM policies are unfavorable for widespread PV-battery deployment because they do not reduce consumers’ imports from the grid or promote the storage of surplus solar production. While battery discharging is favored at peak times, battery charging is favored during the late night when the prices are lowest (Figure 1b — this is compared with Figure 1c which shows the case for FIT), and accordingly the total imports from the grid increase 3% in the PV-battery scenario in comparison with PV-only.

In contrast, FIT policy can offer a number of potential advantages. Consumer payback under FIT policy is behavior dependent and offers the fastest rewards for PV-only systems to consumers whose demand peaks in the daytime. However for PV-battery systems under the baseline FIT policy (which only included an export tariff), consumers lack an economic incentive to use a battery. Therefore, we propose an scenario where the export tariff was reduced to the average wholesale electricity price, and a self-consumption bonus was added. We found that a self-consumption bonus of $0.15/kWh made the median payback for PV-batteries equal to PV-only systems. In particular, consumers with high levels of solar production significantly favored by the use of batteries. In terms of the identified consumer groups, the optimal production-to-consumption ratio increased for all consumer groups compared with the PV-only case, however the specific values differed for each group. Consumers with peak consumption in the late morning and lunch times benefit most by producing 50-75% of their required electricity, whereas for consumers whose peak consumption occurs in the early morning and evening this dropped to 25-50%. With PV-batteries, the FIT policies achieved significant reductions in the demand for imported grid-electricity, reducing the total imports of consumers by an extra 20% compared with the PV-only case. Therefore, motivated by the FIT advantages for batteries, we examined the sensitivity of consumer payback to electricity prices and FIT export tariffs (with no self-consumption bonus) in two battery price scenarios. We find that with 2020 battery cost estimates (a reduction of approximately 30% on current prices), coupled PV-battery systems offer better investments to the majority of consumers in some regions, including Spain and Italy. Additionally, the general trends of increasing retail electricity prices and decreasing solar subsidies reinforce this result, and other regions (for example, Germany) are close to this regime.

**Consumer demand and behavioral segmentation**

We model residential electricity consumption by integrating data from two sources. The first is 1-month of 15-minute resolution smart meter data provided by the Pecan Street project for 496 consumers [19]. The second is comprised of monthly electric bills for the City of Cambridge, MA, spanning a period of 3 years, obtained from Eversource (the local electric utility). The coordinates available in the Cambridge data-set allow us to select for single homes, which match the Pecan Street consumer-types that do not have coordinates. The Cambridge monthly usage distributions are similar throughout the year [20]. We, therefore, model a single month of hourly consumption in Cambridge, using the Pecan Street data from the month of April 2015. This month gives the best match with Cambridge monthly usage [20].
Figure 2: Groups of consumption profiles based in daily loads. a, Nine consumption clusters based on daily load shapes observed in smart meter data. The assigned names depend on the peak consumption time. The colors illustrate the density of observed measurements while the red line shows the average load. The percentage of consumer-days in each cluster is also shown. b, Distribution of individual consumer-days classified by the 9 load shapes. c, Fraction of consumers with that load shape as the most common day. d, The fraction of days in which a consumer is observed in the most common load profile (consumer’s Persistence). e, The distribution of the consumers entropy compared with their random entropy for the set of consumption profiles during one month.

For the smart-meter consumers each individual day of data is denoted a consumer-day. We divide their daily load-profiles into 9 groups (Fig. 2a-c). To that end, we first smooth each consumer-day via a moving average and then cluster using a K-means algorithm based on distance correlation [21] (see Supplementary note 1 and Supplementary Figs. 1-4). We opt to keep nine distinct groups, as we find that the marginal improvement in the variance explained by additional groups after the ninth cluster saturates at around 1% (see Supplementary Figure 2). In total 57% of the variance in the data is explained between the cluster centers. For other methods which produce similar consumer groups with more accounts and time of observation see Ref. [22]). The nine groups capture a diverse set of consumer load profiles and each group is characterized by one peak or two peaks in consumption at different times of day (Fig. 2a). We find that the proportion of consumer-days in each group is evenly distributed (around 10% each), except for the ‘no peak’ group which contains nearly 20% of the consumer-days (Fig. 2b). Each consumer is then assigned to a group depending on their most frequent load shape. We can see that while the proportion of ‘mid-morning’, ‘late-morning’ and ‘lunch’ load shapes is similar to the other groups, these shapes are
less likely to represent a consumer’s most frequent load profile (Fig. 2c). This is because, these load shapes occur more frequently at weekends (Supplementary Figs. 4). In order to see the variability of the consumption of each consumer, we calculate the persistence of their most common load shape and the entropy of their consumer-days. The persistence is defined as \( \frac{\text{no. of days in most common profile}}{\text{Total number of days}} \) and a consumer’s Shannon entropy is given by \( S = \sum_{i=1}^{N} \frac{1}{p_i} \log_2 \left( \frac{1}{p_i} \right) \), where \( p_i \) is the probability of the consumer being found in load shape \( i \) and \( N \) is the total number of load shapes for that consumer [22] (for that consumer the random selection is \( S^{\text{rand}} = \log_2 N \)). In general, very few consumers have high regularity in their daily consumption and most consumers switch load shapes frequently, presenting five of the nine possible load shapes (Figs 2d and 2e).

Finally, each Cambridge consumer’s hourly consumption for 1 month is modeled after a randomly selected Pecan Street consumer in the same monthly usage bracket, whose consumption is scaled to match the exact consumption of the Cambridge consumer (see Methods). The Cambridge consumer is also assigned the behavioral characteristics of the Pecan Street consumer (common load shape, persistence, entropy). This process allows us to expand the number of simulated users from 496 to 4,574.

**PV and battery modules**

We simulate the output of a consumer’s solar PV installation using the PV generation data available in the Pecan Street database. We compare the irradiance data from the National Solar Radiation Database (NSRDB) [23] for the stations at Austin Mueller Municipal Airport and Boston Logan International Airport, and find that the average yearly irradiance in Cambridge is most similar to the February irradiance in Austin (see Methods and Supplementary Figs. 5-6). We therefore model PV outputs for the Cambridge consumers using Pecan Street solar generation data for the month of February, applying a correction to exactly match the average February irradiance for Austin with the yearly average irradiance for Cambridge (see Methods). We assume that a residential PV system costs $5000/kWp of installed capacity.

Our storage model is based on currently available residential batteries from companies which provide lithium based batteries to residential consumers, specifically for use with PV, including Tesla *, Iron Edison † and Aquion Energy ‡. Typically these batteries have high efficiency (85-95%), capacities in the range 2-20kWh, guaranteed lifetimes between 2000-5000 cycles and capital costs in the range $400-700/kWh (recent costs estimates of Li-ion batteries in academic literature are around $500/kWh [24]).

In our simulations we assume batteries with an average round trip efficiency of 90% over the lifetime, a nominal capacity of 7 kWh, a charging rate of 2kW and a discharging rate of 3kW, a lifetime of 3000 cycles at 85% depth-of-discharge and capital costs of $500/kWh. The simulated consumers then use their batteries for energy time-shifting to minimize the cost of their electricity (see Methods, Supplementary note 3). It is important to note that in general the schedule of operation of any energy storage device is governed by its desired service, of which there are many that may offer rewards including energy management, peak shaving, voltage stability, providing ancillary services or deferring transmission/distribution infrastructure upgrades [25].

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*https://www.tesla.com/powerwall
†https://ironedison.com/
‡http://aquionenergy.com/
Comparing the benefits of residential PV and PV-battery systems

Figure 3: Electricity tariffs and distributions of payback times for residential consumers with PV and PV-battery systems. a, Illustration of a week of the different tariffs and price levels. b, Payback periods for the FIT policy. The top graph shows the cumulative distribution of the payback periods over the system lifetime for PV-only vs. PV-battery systems. The lower graphs show the payback period distributions for PV-only and PV-battery systems respectively c, Payback periods for the NEM-TOU policy. d, Payback periods for the NEM-DA policy e, Payback periods for FIT-SC policy. The areas under the curve are colored by the average production-to-consumption ratio of a consumer within the respective payback range, blue implying a smaller ratio and red a larger ratio. The NEM PV-only scenarios present fastest returns to consumers and under both NEM policies no consumer is better off with a battery. FIT presents variability that depends on strongly on production-to-consumption ratio and the differences in consumers’ load profiles. For combined PV-battery scenarios, NEM encourages over-production to recover the investment. Paradoxically, as we show later, this does not decrease the net imports from the grid in the NEM case.

Our goal is to study the economic and energy conservation effects when each of the 4,574 consumers first adopts PV-only and then a PV-battery system. We compare four policy scenarios: a basic FIT policy, a NEM policy with Time-Of-Use (TOU) prices, a NEM policy with wholesale-like prices and finally propose a FIT policy with an additional self-consumption reward. The standard FIT policy (denoted FIT-Ex) has a retail import electricity price of $0.24/kWh and an export tariff of $0.10/kWh, which is similar in structure to the majority of existing feed-in-tariff policies (FITs can also contain specific generation or self-consumption tariffs). The Net Energy Metering policy with Time-Of-Use prices, denoted as NEM-TOU, has rates of $0.19/kWh, $0.27/kWh and $0.38/kWh for super-off-peak, off-peak and peak times respectively.
This is based on 2015 Californian tariffs from the utility PG&E with an average price of $0.24/kWh. Thirdly, the other NEM policy (denoted as NEM-DA), is based on day-ahead electricity prices from ISO New England for the Boston region, scaled so that the average price is $0.24/kWh. Finally, the proposed FIT policy has a retail import price of $0.24/kWh, export rewarded at the average (actual) wholesale price ($0.03/kWh) and a self-consumption bonus of $0.15/kWh. It is denoted as FIT-SC.

A week of the different tariffs is shown in Figure 3a (see Supplementary note 4 for full details on the electricity pricing policies). To calculate the payback period and energy conservation for each of our simulated consumers we extrapolate the savings from the monthly simulations (see Methods).

Figures 3b-e show the payback period distributions for both PV-only and coupled PV-battery installations for residential consumers under the different pricing policies. Under the FIT-Ex policy, the payback periods for PV-only installations ranges from 14-30 years (30 years being the assumed system lifetime, therefore some consumers do not recover their cost). The dominant factor affecting a consumer’s payback period is their production-to-consumption ratio, with consumers whose production-to-consumption ratio is <25% receiving the fastest payback for all consumer groups. This is due to the typical degree of misalignment between PV generation and residential electricity consumption, implying that a larger solar installation required more investment and exported a larger fraction of its output. Under both the NEM policies the distribution of PV-only paybacks is relatively narrow (11-15 years for the modeled NEM-TOU tariff §) and is independent of a consumers’ production-to-consumption ratio. This is a result of consumers exporting their surplus generation at the retail price for electricity, and thus they are not penalized for excessive production. This is a clear disadvantage in regions where integrating additional PV generation causes operational stress. Since our modeled system costs scale with the installed capacity, the range of NEM paybacks is only due to differences between individual PV installations — for example those with higher efficiency or different shadings/orientations [26]. For the FIT-SC policy, the median payback of PV-only systems is 3.3 years shorter than the base FIT-Ex policy, and the spread is much larger, as consumers with

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1 2015 estimates for solar Payback in California are around 9 years, which include the solar Investment Tax Credit. This essentially allows 30% of capital costs to be claimed as tax deductible. Reducing the cost of solar panels by 30% in our simulation leads to a median payback of 9.3 years for the NEM-TOU tariff.
Figure 5: **Comparison of the economic and energy conservation benefits of pricing scenarios with PV-only and PV-battery systems.** The electricity import reduction and CO\(_2\) savings are representative for an average consumer (household). The average electricity use without PV is 23.5kWh per consumer and on average a consumer’s electricity consumption results in the emission of 13.1kg of CO\(_2\). The average solar value is the total reward plus saving per unit of solar electricity generated.

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**Figure 4** illustrates how the median payback for the FIT-SC policy changes with the self-consumption bonus.

With respect to coupled PV-battery systems, we find that the payback periods for all consumers are longer than with PV-only systems under all policies except the FIT-SC policy. For the FIT-Ex policy only 42% of consumers recover the PV-battery cost, while the median payback periods are 30% and 44% longer for the NEM-DA and NEM-TOU policies respectively. This is a clear indication that PV-battery systems have not yet reached the point of widespread economic viability. The addition of a self-consumption bonus offers a method of increasing the viability of PV-battery systems. Figure 4 illustrates that as the self-consumption bonus is increased, the median payback of PV-only and PV-storage systems for our consumers eventually intersect and 50% of consumers find PV-battery systems to have faster returns. As the inset shows, consumers with high production-to-consumption ratios have significantly faster payback periods with PV-
battery systems. We observe that the average value of solar electricity in the FIT-SC policy is increased above the NEM-TOU value when batteries are added (Figure 5a-d). Distributions of the consumers grid-imported electricity also illustrate that the FIT policies promote significant local energy conservation for PV-battery systems when compared to the NEM policies (Figure 5a-d and Supplementary Figure 9-10). The average daily imported electricity of our consumers is 23.5kWh without PV, and falls to 16.1kWh when PV is added, a reduction of 31%. With PV-battery systems the consumption falls an additional 14% to 12.9kWh with the FIT policies, however it rises 2% to 16.6kWh with the NEM policies. The rise in imported electricity with storage under the NEM tariffs is because it is more economically viable for consumers to export surplus PV generation, rather than storing it, as PV generation coincides with high prices. Hence NEM rewards consumers for charging their batteries with grid electricity during off-peak hours rather than with their surplus generation (see Figure 1), and accordingly the consumption of imported electricity increases when batteries are added due to the losses in the charge/storage/discharge processes of the battery. Therefore, NEM policies may increase problems associated with high PV penetration levels, specifically the solar-duck effect. We also estimate the CO$_2$ emission savings associated with each daily imported electricity distribution, assuming that natural gas is the marginal source of generation (shown in Figures 5a - d).

Under the FIT policies we also observe significant differences in payback periods between the different consumer groups for both PV-only and coupled PV-battery systems. Figures 5e-f show PV-only and PV-storage payback periods for the NEM-TOU and FIT-SC policies by consumer group. For the PV-only systems in the FIT-SC policy scenario, the late morning and lunch groups have the shortest paybacks (2.6 and 2.4 years shorter than the average respectively across all production-to-consumption ratios) while the mid and late evening groups have the longest (2.5 and 2.2 years longer than the average respectively across all production-to-consumption ratios). We also find that lower entropy consumers have shorter paybacks in the daytime load shapes, whereas higher entropy consumers have shorter paybacks for the early morning and evening load shapes (Supplementary Figure 11). For the FIT-SC policy and PV-battery systems, we find that the optimum production-to-consumption ratio is different between the consumer groups; the late-morning, lunch and no-peak consumer groups should produce 50-75% of their energy needs whereas the other groups should produce 25-50% to minimize their payback period (insets Figure 5f). Under the NEM policy we observe no significant differences between the consumer groups for the payback periods of PV-only systems. For PV-battery systems we find that consumers in the afternoon and early-evening load shapes have the fastest payback period as they are most likely to have peak-time consumption which can be reduced by the battery. Noticeably, for all consumer groups the payback period decreases with increasing production-to-consumption ratio. This is because all consumers minimize their payback time with coupled PV-battery systems by over-sizing their PV, as a result of minimizing the fraction of investment corresponding to the battery.

A future boom for PV-battery systems?

The results of the previous section illustrate that without explicit incentives for self-consumption, PV-battery systems do not yet represent a good economic choice for most consumers when compared with PV-only systems. However, we noted that FIT policies may offer several advantages for PV-battery systems, like promoting local self-sufficiency (by rewarding consumers who match their generation and demand) and a corresponding reduction in local surplus PV generation. Hence FITs are likely to be more desirable for grid operation and energy conservation in regions with high PV adoption. An important question then is, when do PV-storage systems offer better economics for the majority of consumers than PV-only installations for a FIT policy without extra incentives for self-consumption? To answer this, we
Figure 6: **When are PV-battery systems a better investment than PV-only systems?** Heat maps showing the difference between the median payback period of PV-only and PV-battery systems (i.e. PV-only minus PV-battery payback) for the median consumer in the FIT scenario (only export tariff) using: **a** Current battery costs. **b** A 2020 estimate. Red indicates that PV-battery systems offer faster payback periods for the median user while blue indicates PV-only systems offer faster paybacks. The gray region illustrates where there is no payback achieved within the lifetime of the system (30 years).

study the sensitivity of the median payback period of our consumers to the retail electricity price and FIT export tariff, with both current battery costs and a 2020 estimate. Estimates of 2020 for battery costs are shown in Supplementary Figure 12 — we use the mean estimate of $350/kWh [27]. Figure 6 shows that as electricity prices increase and the export tariff level decreases, PV-battery systems become comparatively better investments when compared with PV-only systems. The exact shape of the boundary between the PV-only and PV-storage regions is dependent on the limited lifetime of the battery, and changes abruptly between similar price points where the majority of consumers must either replace or not replace a battery before recovering the costs of the PV-battery system.

In Figure 6, we add points to illustrate the approximate position of real electricity prices and FIT export tariffs for the years 2012 and 2015 in different regions with high solar adoption (see Supplementary Table 3). We see that the shifts in FIT policy have been dramatic in Spain (ESP) and Italy (IT), where FITs have been suspended and are effectively zero. In Germany (DE) and the UK the decline of the FIT rate has been more gradual. All of the plotted regions have seen an increase in the average retail electricity price between 2012 and 2015, except for Hawaii (HI), whose primary energy supply is heavily dependent on petroleum. We observe that with 2020 battery prices, PV-battery systems are a more viable option for the majority of consumers in Spain and Italy at 2015 electricity price levels. Germany is also close to this region.

**Discussion**

Combining residential PV installations with batteries offers a number of advantages in terms of energy conservation and power grid management, however, at current price levels PV-storage systems are less economic than standalone PV systems. We propose that formulating Feed-in-Tariff based policies with explicit bonuses for self-consumption offers one way to encourage PV-battery adoption, simultaneously exploiting the fact that FITs can offer a simple method of encouraging consumers to maximize their own
self-sufficiency and minimize PV exports back to the grid. Additionally, our results demonstrate that control over the exact FIT export tariff and a varying self-consumption bonus gives policy makers the flexibility to make PV-battery systems economic to consumers with differing degrees of PV overproduction. Taken together, this highlights the importance of flexible FIT policies which can adapt to changing technology costs. Conversely, we argue that Net Energy Metering policies are only suited to regions where additional solar energy can be easily accommodated into the local grid, as they provide a blanket incentive to encourage PV adoption for all consumers. Additionally, in their current inflexible format (i.e. having fixed-time pricing periods and without real-time responsive prices), for consumers who do choose batteries, NEM policies do not promote the storage of solar surplus. In consequence, this increases the duck’s effects associated with widespread solar generation, and increases consumers’ use of grid electricity, as opposed to self-consumption. A solution to this issue, would be to reformulate NEM policies to explicitly penalize reverse power flows at peak production times, as some recent works have suggested [28].

We also explored the different benefits for consumer types. To that end, we illustrated a method to identify consumer groups based on their load profiles, and calculated their differing suitability for residential PV. The different groups attained differing levels of self-sufficiency with the modeled PV-battery systems. As smart meters become more ubiquitous in future this type of approach will become more important for utilities or solar-companies seeking to intelligently target different types of consumers for PV adoption, or for companies developing storage to estimate the extent to which batteries can increase the self-sufficiency of different consumer groups. A direct extension to this work is to model different battery sizes, finding the optimum size for each consumer group.

While currently uneconomic for most consumers, we showed that projected declines in battery prices coupled with the current international trends of increasing retail electricity prices and decreasing FIT export rates will lead to a boom for PV-battery systems in high solar regions where FITs are the preferred policy option, even without explicit self-consumption bonuses. It is worth noting that second-life EV batteries and battery recycling also offer mechanisms for significantly reducing the costs of residential electricity storage [29]. In regions where NEM remains the relevant policy, we show that coupled PV-battery systems are unlikely to be consumers most economical option and as such battery adoption in these regions will remain limited compared to PV-only adoption rates, unless driven by other charges like those related to peak demand.

Given the potential for a residential storage boom, and the limited and expensive nature of the resources required for battery development [30], an important question is whether or not residential storage is the optimum solution. Other studies have suggested that microgrid storage or distribution-level storage are likely to be preferential over individual household storage [31]. We therefore suggest that both technical and energy policy studies addressing this question are be important and timely, and if storage at some other aggregation level is deemed preferential, then energy policy makers must act quickly to ensure that appropriate market mechanisms are put in place for new storage deployments. Novel electricity market structures should also be considered [32], in particular, decentralized micro-grid energy and ancillary service markets, wherein storage can be used as a controllable source of flexibility to keep the network in balance [33, 34]. In order to promote the best decisions in the energy industry, policy makers and academics must work together to establish the best course of action and we hope that the presented analysis helps us in that direction.
Methods

Generating demand profiles for Cambridge users

The Cambridge bills are geolocated by parcel using GIS data for the city of Cambridge (MA) and accounts which have a monthly consumption in the range 200-2000 kWh and occupy a single geographic parcel are selected (4,574 accounts). This data corresponds to residential monthly usage for single houses and matches the typical monthly usage range of the 496 Pecan Street users in April. Despite the different locations, there is sufficient agreement between the usage distributions to model the Cambridge users after the Pecan Street users in several months of the year [20] (the closest match being in April and July for the Pecan Street and Cambridge data sets respectively). Importantly, we find that the monthly electricity usage distribution for the Cambridge users is relatively uniform throughout the year [20], providing justification for extrapolating a month long simulation to obtain annualized results. To simulate hourly demands for the Cambridge users both data sets are binned into monthly usage ranges, and for each of the Cambridge users a Pecan Street demand profile in the same monthly usage bracket is randomly selected, scaling up or down by a constant factor to match the exact monthly usage of the Cambridge user. Random noise of the form $d_i(t) = d_0^i(t)(1 + \beta \epsilon_i)$ is added, where $d_0^i(t)$ is the initial demand of the user $i$ at time $t$, $d_i(t)$ is the demand after noise has been added, $\epsilon_i$ is a uniformly distributed random variable in the range $[-1, 1]$ and $\beta = 0.2$ in order to keep the demands within 20% of the Pecan Street profiles at all times.

Solar PV model

We model hourly solar PV production for the Cambridge users using the Pecan Street data (Supplementary Fig. 5). Generation profiles from faulty or under-performing installations are filtered out. We note by comparing average monthly solar irradiation data from the National Solar Radiation Database (NSRDB) [23] for the stations at Austin Mueller Municipal Airport and Boston Logan International Airport that the February profile for Austin is closest in magnitude to the yearly average irradiation profile of Cambridge (Supplementary Fig. 6). To match Austin’s February solar irradiation with Cambridge’s yearly average we offset the data by 1 hour and apply a relative correction $\frac{I_{Boston}(t) - I_{Austin}(t+1)}{\max(I_{Boston})}$ to each hour in terms of the maximum irradiance level, where $I(t)$ is the irradiance at a particular hour. We also find that there is very little correlation between users’ monthly PV generation (or peak power production) and their monthly usage. For each of the simulated Cambridge users adopting solar PV we then pick a random generation profile and a ratio of generation-to-consumption, scaling the generation profile accordingly and preserving the Pecan street distribution for generation-to-consumption ratio. Finally, to estimate the capital cost of the installation we assume the installed capacity is equal to the maximum peak 15 minute power output of the scaled profile.

Distributed energy storage model and scheduling algorithm

To model the residential batteries, this work follows a similar approach to much of the work which has previously optimized energy storage operational schedules [35, 36]. We assume that our consumers utilize their storage to minimize the total cost of their electrical units, without selling electricity from the storage device back to the grid. The model accounts for the physical capacity of the battery, charging and discharging limits, cycle life and losses during the charging and discharging processes. To schedule the operation of each consumer’s battery we use a modified version of the algorithm first used to optimally
schedule Pumped Storage plants [35]. Once the battery has been optimally scheduled the cost of electricity for the consumer is calculated.

The equation which governs the battery’s State Of Charge (SOC) is described as follows:

\[
\text{Charging/discharging: } \text{SOC}(t) = \text{SOC}(t-1) + \Delta t P(t)
\]

Here \( t \) is the time, \( P \) is the charging or discharging power of the storage (where \( P > 0 \) implies charging and \( P < 0 \) implies discharging) and \( \Delta t \) is the time between \( t \) and \( t + 1 \). The physical constraints on the battery imply that:

\[
\text{SOC}_{\text{min}} \leq \text{SOC}(t) \leq \text{SOC}_{\text{max}}
\]  

\[
\frac{P_{\text{rated}}}{\eta_{\text{dischg}}} \leq P(t) \leq \frac{P_{\text{rated}}}{\eta_{\text{chg}}}
\]  

These equations ensure that energy contained in the storage must always be between the minimum and maximum states of charge \([\text{SOC}_{\text{min}}, \text{SOC}_{\text{max}}]\) and the maximum charging or discharging power of the battery must always be between the specified rated charging and discharging power limits \([P_{\text{rated}}^{\text{dischg}}, P_{\text{rated}}^{\text{chg}}]\). \( \eta_{\text{chg}} \) and \( \eta_{\text{dischg}} \) are the charging and discharging efficiency of the battery, respectively. The energy input or output from the battery in a time period \( t \) is given by:

\[
\text{ES}(t) = (\Delta t \times P(t))/\eta_{\text{chg}} = \Delta \text{SOC}(t)/\eta_{\text{chg}} \text{ for } P(t) \geq 0
\]

\[
\text{ES}(t) = \Delta t \times P(t) \times \eta_{\text{dischg}} = \Delta \text{SOC}(t)\eta_{\text{dischg}} \text{ for } P(t) < 0
\]

For continuity, we add in a constraint which stipulates that the energy stored in the battery, SOC, must be consistent between the beginning and the end of the simulation period, i.e. \( \text{SOC}(t = 0) = \text{SOC}(t = t_{\text{max}}) \).

To represent the storage as batteries we assume that a device can cycle at 85% of its nominal rated capacity (therefore \( \text{SOC}_{\text{min}} = 0.15\text{SOC}_{\text{max}} \)) and has a lifetime of 3000 cycles. We then count the Equivalent Full Cycles of each user’s storage device over the simulation period (1 month) and extrapolate to estimate the battery lifetime. The battery must be replaced at the end of its lifetime.

A consumer’s net electrical demand including solar and storage at any time period \( t \) is then expressed as \( d_i(t) - s_i(t) + \text{ES}_i(t) \), where \( d_i \) is consumer \( i \)'s actual demand, \( s_i \) is their solar generation and \( \text{ES}_i \) is the action of their battery. We assume that the majority of the consumers’ electricity bills are composed of the price of electrical units of energy, rather than other charges (for example charges relating to peak power usage or fixed charges). We consider billing arrangements which can have either a Net Energy Metering (NEM) or a Feed In Tariff (FIT) structure and have a price for electricity, \( p(t) \). Under NEM the consumer is charged for the net cost of the energy that they use — that is to say that the consumer’s cost at each period is:
The net demand \([d_i(t) - s_i(t) + ES_i(t)]\) can be either positive or negative at each period, where a negative net demand represents exported electricity. If the user exports sufficient power to the grid their total cost may be negative — implying a reimbursement rather than a payment for their electricity bill. Under the FIT strategy, PV energy used locally displaces the need to buy grid electricity, and exported electricity is rewarded at the FIT export rate \((p_{EX})\). Energy used locally may receive also receive an additional bonus \((p_{SC})\). Therefore the cost at each period depends on whether energy is being imported or exported and is expressed conditionally as:

\[
C_i(t) = [d_i(t) - s_i(t) + ES_i(t)]p(t) - [d_i(t) + ES_i(t)]p_{SC} \quad \text{for} \quad d_i(t) + ES_i(t) \geq s_i(t) \quad (7)
\]

\[
C_i(t) = [d_i(t) - s_i(t) + ES_i(t)]p_{EX} - [d_i(t) + ES_i(t)]p_{SC} \quad \text{for} \quad d_i(t) + ES_i(t) < s_i(t) \quad (8)
\]

We also stipulate that the storage is not allowed to sell power back to the grid at the market price \(p(t)\) — engaging in arbitrage — the battery can only be used to increase or reduce consumption. The operation of the energy storage module is then driven by the price \(p(t)\) and the problem of minimizing a consumers electricity bill can then be framed as follows:

\[
\text{Minimise : } \sum_{t=t_0,...,t_N} C_i(t) \quad (9)
\]

To perform the minimization we assume the electricity price and the consumer’s demand are known throughout the optimization period — the effect of these assumptions are discussed in Supplementary note 3. The operation of the scheduling algorithm is then summarized as follows:

1. The algorithm searches the time-series of grid electricity price for the highest price and denotes this MAXhour.
2. A range around MAXhour in which it is physically possible for the device to charge is established. This range spans between the last time before MAXhour that the battery was fully charged and the time period before the last period after MAXhour (including MAXhour) when the battery was empty. If there are no times before MAXhour when the battery was fully charged then the start of the range is simply the first time period.
3. The minimum price within this range in the electricity buy-price timeseries is located and denoted MINhour (electricity can either be bought from the consumer’s PV or the grid and the cost depends on the tariff policy).
4. The cost of operating the battery between MINhour and MAXhour is calculated and if it results in a net cost reduction for the consumer then the operation is added to the battery’s schedule at the maximum level that doesn’t violate any constraints. Namely, Eqs. 2-3 and provided that the action doesn’t reduce the consumer’s demand below zero at any period. If there is no cost reduction then MAXhour and MINhour are removed from the time series.
5. The algorithm then checks if the battery operation is at the maximum allowed level at either MAXhour or MINhour and if so removes these hours. These are marked and excluded from any further searches.
6. The process 1-5 is repeated until all hours have been considered and excluded.

A full-length description of the algorithm’s operation are given in Supplementary note 3.

Calculating a consumers economic benefits

The total benefit from either a PV-only or a PV-storage installation for a consumer \( i \) is expressed by either equation 10 or 11 respectively.

\[
B_{PV,i} = \sum_{t=1}^{t_{max}} [d_i(t)p(t) - C_{PV,i}(t)] \quad (10)
\]

\[
B_{PV_B,i} = \sum_{t=1}^{t_{max}} [d_i(t)p(t) - C_{PV_B,i}(t)] \quad (11)
\]

Here \( d_i(t) \) is the consumer’s actual demand at time period \( t \), \( p(t) \) is the price of electricity at \( t \), \( C_{PV,i}(t) \) is the cost of meeting the consumer’s electrical demand at \( t \) when they have PV installed and \( C_{PV_B,i}(t) \) is the cost when they have a PV-battery system. For residential users, the payback period is the most appropriate economic metric to use and is most often quoted in the sale of solar panels or building energy efficiency measures. The similarity of the Cambridge consumer’s monthly usage distributions throughout the year means that we can extrapolate the results of our monthly simulations to obtain representative annual values. Including operation and maintenance costs and extrapolating up from our monthly simulation leads to a yearly saving of \( 12B_{PV,i} - OMPV \) for PV or \( 12B_{PV_B,i} - OMPV -OMB \) for a PV-battery system. Where \( OMPV \) and \( OMB \) are the yearly maintenance costs for PV and solar panels respectively, assumed here at $20/kW/year for solar and $10/kW/year for storage [37]). To calculate the payback period we sum the yearly cumulative costs until they equal zero, noting that there will be an initial upfront cost at year zero corresponding to the capital costs of the PV or coupled PV-battery system, yearly maintenance costs and a replacement battery cost each time the battery surpasses its lifetime. The lifetime is calculated by extrapolating the consumers monthly equivalent full cycles.

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Author contributions statement

M.C.G and E.B conceived the experiment(s) and wrote the paper. E.B. and S.A. conducted the experiment(s), E.B., S.A. and M.C.G analyzed the results. All authors reviewed the manuscript.
Additional information

See additional document Supplementary Information for “Economic and environmental benefits of PV-battery systems for residential consumers in different pricing scenarios”.

References


[34] Per Sebastian Skardal and Alex Arenas. “Control of coupled oscillator networks with application to microgrid technologies”. In: Science advances 1.7 (2015), e1500339.


[37] NREL. Distributed Generation Energy Technology Operations and Maintenance Costs. 2016. URL: http://www.nrel.gov/analysis/tech%7B%5C_%7Dcost%7B%5C_%7Dom%7B%5C_%7Ddg.html.