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The impacts of storing solar energy in the home to reduce reliance on the utility

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There has been growing interest in using energy storage to capture solar energy for later use in the home to reduce reliance on the traditional utility. However, few studies have critically assessed the trade-offs associated with storing solar energy rather than sending it to the utility grid, as is typically done today. Here we show that a typical battery system could reduce peak power demand by 8–32% and reduce peak power injections by 5–42%, depending on how it operates. However, storage inefficiencies increase annual energy consumption by 324–591 kWh per household on average. Furthermore, storage operation indirectly increases emissions by 153–303 kg CO_2, 0.03–0.20 kg SO_2 and 0.04–0.26 kg NO_x per Texas household annually. Thus, home energy storage would not automatically reduce emissions or energy consumption unless it directly enables renewable energy.

In recent years, there has been growing interest in storing energy produced from rooftop photovoltaic panels in a home battery system to minimize reliance on the electric utility[1]. A number of vendors have sought to capture this emerging market, including electric vehicle market leader Tesla and German home energy storage provider Sonnenbatterie[2,3]. Notably, Tesla has partnered with Green Mountain Power, one of the largest electric providers in the state of Vermont, to offer home storage to its customers; and Sonnenbatterie has partnered with Sungevity, the largest private solar company in the United States[4,5].

While there is a growing market for home energy storage for rooftop solar panels, storage is not strictly required to integrate rooftop photovoltaic systems with the grid. A study on the impacts of rooftop photovoltaic panels in California found that even at 100% penetration (measured as the ratio between nameplate capacity and peak system demand), the utility Pacific Gas and Electric (PG&E) could maintain adequate voltage levels in its system by increasing the number of transformer tap changing operations at a cost of US$442,000 annually—or 0.007% of its US$6 billion annual operation and maintenance budget[6,7]. These findings align with previous findings on the impact of high photovoltaic penetration in distribution circuits in California[8]. Furthermore, a number of studies have shown that upgrading conductors, upgrading the transformer, or incorporating 'smart' photovoltaic inverter control could be used in lieu of storage to maintain adequate system voltage[9–14]. Even if energy storage were needed to integrate rooftop solar panels, it is not clear that it would have to be installed at the household level.

Despite the fact that energy storage is rarely required to integrate rooftop solar panels, there is significant interest in capturing on-site solar generation to minimize reliance on the electricity utility and injections of solar energy to the grid. This application has been studied extensively in the literature[15–21], and it is the primary value proposition offered to residential customers by home energy storage vendors[2,3,22].

While a number of studies have assessed the benefits of energy storage that captures rooftop solar energy to mitigate overvoltage in the distribution grid and hedge utility tariffs[20,23,24], the amount of energy consumed by the battery during operation and the corresponding emissions footprint is typically neglected. One notable exception is a 2013 study that found lead-acid batteries used with solar panels in the UK would increase both primary energy consumption and carbon dioxide emissions[25].

In this paper we critically assess the trade-offs of using lithium-ion battery storage to capture solar energy and minimize reliance on the utility. We build on previous work by using measured electricity use and production data from 99 Texas households to understand how adding energy storage would impact power demand, energy consumption, electricity service costs, and emissions of CO_2, SO_2 and NO_x from the electricity system. We consider two different storage operation models and compare their impacts. We also perform a sensitivity analysis considering various storage efficiencies, storage energy capacities, and storage power capacities to understand the impact of energy storage under different scenarios.

Energy storage system model

The energy storage application considered in this paper is minimizing the interaction between a household and the utility by minimizing power draws from and injections to the utility grid for the benefit of the electricity customer in terms of increased solar energy self-consumption, independence from the utility, and reduced sensitivity to grid outages. This application has been studied extensively in the literature, and is the primary value proposition offered to residential customers by home energy storage vendors[2,3,15–20,22].

We utilize electricity data directly measured from 99 Texas households over calendar year 2014 to reveal how home storage would operate with solar panels to minimize reliance on the utility. These data track electricity use and solar production with a one-minute time resolution, allowing us to reveal how storage could respond to short-duration power fluctuations. The data were collected on a voluntary basis by the non-profit entity Pecan Street and are freely available to university researchers through an online portal[26]. Summary statistics for the 99 households in the sample are provided in Supplementary Table 1.

We model home energy storage operation using two different methods: a 'target zero' approach where the battery does not have information about the future level of solar generation or electricity demand and seeks to reduce injections to and demand from the grid to zero at all times; and a 'minimize power' approach where the battery system has perfect information about the future level of electricity demand and solar generation over the day, and plans its

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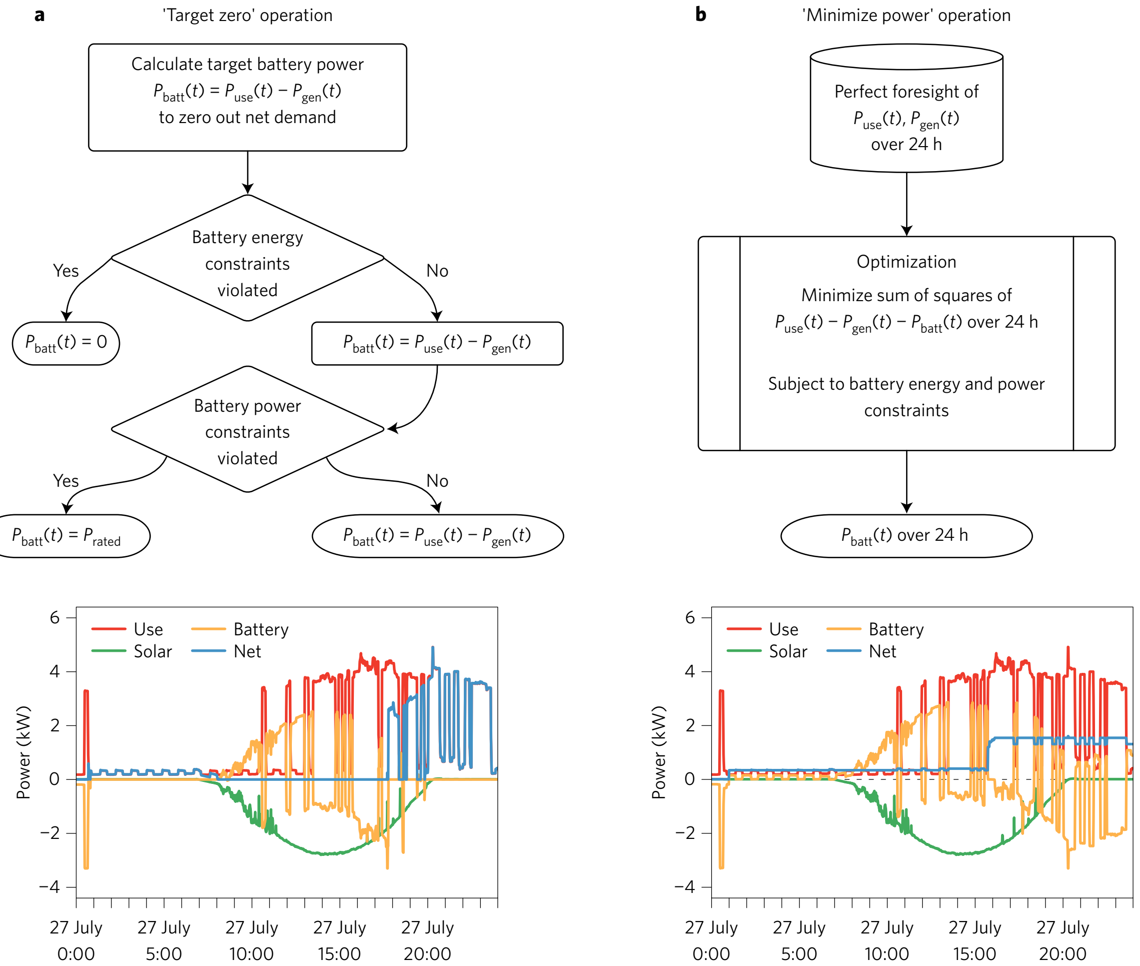

Figure 1 | Storage operation model control logic and sample outputs. a, The 'target zero' method steps from one minute to the next with no foresight of future electricity demand or solar generation, and seeks to set net grid demand to zero whenever possible without violating the battery's energy and power constraints. **b**, The 'minimize power' method has perfect day-ahead foresight of electricity demand and solar generation, and uses an optimization program to minimize the sum of squares of net grid demand over the entire day. Sample outputs for each method are shown below the flowcharts, with storage discharging given a negative sign and storage charging given a positive sign.

operation to minimize the sum of the squares of net power demand from the utility over the entire day. Besides the level of foresight, the primary distinction between these two methods is that 'target zero' seeks to maximize the number of hours during which the household is completely independent from the grid, while 'minimize power' seeks to minimize the magnitude of grid power demand over every minute of the day with equal weights placed on each minute, so that the household is resilient to a grid outage regardless of when it occurs. Furthermore, the 'target zero' mode restricts the battery system to charge only with solar power, while the 'minimize power' mode allows the battery to charge with grid or solar electricity to minimize demand over the day. Figure 1 illustrates the control logic of each operational method and shows sample outputs for one household.

These two operational methods were selected because they represent plausible yet distinct methods for storing solar energy in the home to reduce reliance on the utility. 'Target zero' prioritizes being as independent as possible during the current minute, while 'minimize power' prioritizes being as independent as possible over the entire day. By considering these two plausible yet distinct operational strategies, we can show the range of impacts that would be expected for storage systems that operate somewhere between the no foresight and perfect foresight extremes represented by 'target zero' and 'minimize power,' respectively.

Note that both of these operational modes take a customer-centric perspective that seeks to minimize interaction with the utility as much as possible. Neither operational method explicitly considers other grid-level services that could be offered by distributed energy storage or the potential economic benefits of those services. While we are aware of the fact that the methods of storage operation selected are not optimal from a purely economic or system perspective, our objective is to assess the specific impacts of storing solar energy in the home to minimize reliance on the utility, because this application is the primary value proposition offered to residential customers by storage vendors[2,3,22]. The details of each of these operational models are provided in the Methods.

For both operational models, three parameters define the home energy storage system: its power capacity (P_{rated}) in kilowatts, its energy capacity (E_{rated}) in kilowatt hours, and its roundtrip (a.c. to a.c.) energy efficiency (η_{rt}). For the base case battery system considered, we set these parameters equal to $P_{rated} = 3.3$ kW, $E_{rated} = 7$ kWh and $\eta_{rt} = 85\%$, corresponding to the parameters announced for a common home battery system for daily cycle applications[3]. We also consider a range of power capacities $P_{rated} = 1$–7 kW, energy capacities $E_{rated} = 1$–7 kWh, and roundtrip efficiencies $\eta_{rt} = 70$–100% in our sensitivity analysis, as discussed in Supplementary Note 1.

Power demand and energy consumption impacts

Figure 2 illustrates the effect that home energy storage has on the aggregate net power demand (electric load minus solar generation)

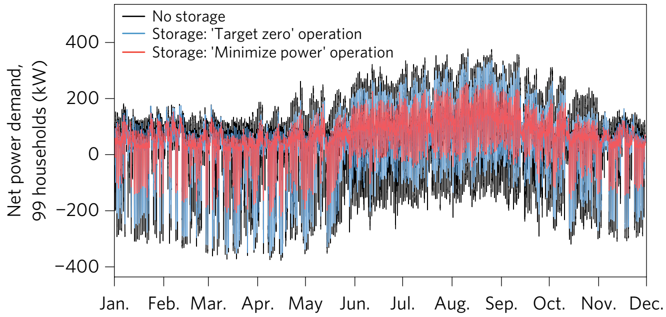

Figure 2 | Aggregate power demand impact of adding energy storage. Energy storage reduces the magnitude of power flows in the local utility grid by storing produced solar energy for later use in the home. When storage operates under the 'target zero' mode (shown in blue) with no foresight of future electricity demand or solar generation, it reduces the maximum aggregate power demand for the 99 households by 8% and the maximum magnitude of reverse power flows by 5%. When storage operates under the 'minimize power' mode (shown in red) with perfect foresight, it reduces peak power demand by 32% and reduces the maximum magnitude of reverse power flows by 42%.

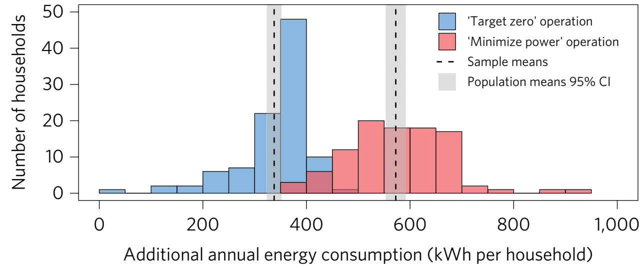

Figure 3 | Energy consumption impact of adding energy storage. The increase in energy consumption observed across the 99-household sample is shown using a histogram. The dashed lines indicate the mean increase across the sample, and the shaded areas indicate 95% confidence intervals of the expected mean across all households computed using a Student's *t*-test. The average additional energy consumption caused by home energy storage is 338 ± 14 kWh under the 'target zero' operating scenario and 572 ± 19 kWh under the 'minimize power' operating scenario.

for the 99 households considered. When home energy storage operates according to the 'target zero' mode, the aggregate peak demand is reduced by 29 kW or 8% from a value of 378 kW without storage to a value of 349 kW with storage. Under the 'minimize power' operating mode, energy storage reduces the level of peak demand by 121 kW or 32%. Likewise, the maximum magnitude of reverse power flows is reduced by 17 kW or 5% when storage operates in the 'target zero' mode versus 158 kW or 42% when storage operates in the 'minimize power' mode. The results shown in Fig. 2 are for the base case battery system considered ($P_{\mathrm{rated}} = 3.3$ kW, $E_{\mathrm{rated}} = 7$ kWh and $\eta_{\mathrm{rt}} = 85\%$). Supplementary Figs 6–8 show how changing the power capacity, energy capacity, and efficiency of the storage systems affects their ability to reduce aggregate peak demand and injections.

The change in aggregate power demand is an important metric for the utility, which must size distribution equipment to meet the expected maximum magnitude of net electricity demand. However, residential electricity customers are not typically billed for their demand in kilowatts, but rather for their cumulative energy consumption in kilowatt hours. Thus, we consider the energy consumption impact of home storage on a customer-by-customer basis. Figure 3 illustrates the change in annual energy consumption from the addition of storage for each of the 99 households when it is operated under the two operating modes considered. Because home energy storage consumes some energy every time it charges and discharges, annual energy consumption increases for every household. The mean increase in annual energy use across the 99 households is 338 kWh when storage operates in the 'target zero' mode and 572 kWh when storage operates in the 'minimize power' mode, illustrated by the dashed vertical lines in Fig. 3. This increase is equal to 8% and 14%, respectively, of the average annual net energy consumption of sampled households. We compute 95% confidence intervals for the corresponding population means using a Student's *t*-test, resulting in an estimated mean additional annual energy consumption of 338 ± 14 kWh under the 'target zero' operating scenario and 572 ± 19 kWh under the 'minimize power' operating scenario. Supplementary Figs 9–11 show how changing the power capacity, energy capacity, and efficiency of the storage system considered affects the mean increase in energy consumption. Note that the average increase in energy consumption caused by adding storage is small compared with the average decrease from adding solar panels in the first place, as discussed in Supplementary Note 2 and illustrated in Supplementary Fig. 32. Thus, energy storage that directly enables rooftop photovoltaic panels could lead to a decrease in net household energy consumption, although energy storage is typically not required[6–8].

Economic impacts

In addition to the impact that home energy storage would have on electricity demand and consumption, we also consider the impact that storage used to isolate customers from the utility and increase solar self-consumption would have on the cost of electricity service to the customer. Note that we did not explicitly consider a particular utility tariff structure when selecting the objective function for storage operational management, because our goal is to show the economic impact of storage used to isolate a customer with solar panels from the utility without binding storage operation to a particular utility's tariff. We consider the economic impact of storage used in Austin, Texas (where the home electricity data used in this paper were collected), other areas of Texas, and the states of Hawaii and California, which have seen a significant penetration of rooftop solar panels and are strong candidates for early home energy storage deployments.

Table 1 shows the average annual customer benefit and present value calculated across our 99-household sample for the base case 3.3 kW, 7 kWh, 85% efficient energy storage system considered. Results are shown for seven different Texas utility tariffs[27–37], as well as four Hawaiian Electric Company (HECO) tariffs[38–42] and three California tariffs[43–48]. Note that Hawaii and California are shown only for illustration, as storage that operates in these regions would see different patterns of electricity use and generation than those observed from our sample of Texas households. For each tariff, the approximate consumption tariff and feed-in tariff are shown in US cents per kilowatt hour. These approximate values are based on the average monthly consumption and production measured across our sample. The values shown for the average annual customer benefit and present value are calculated on the basis of each household's precise monthly electricity use and each utility's precise tariff structures, which typically include volumetric tiered rates, seasonal rates, and other subtleties that would be difficult to summarize here. We refer the reader to the citations provided for each tariff in Table 1.

In general, using storage to increase solar self-consumption provides a financial benefit when the consumption tariff is higher than the feed-in tariff. The maximum present value that could be realized in Texas is US\$95 kWh^{-1} of storage capacity. If Texans were exposed to Maui's electric rates, the maximum would increase to US\$287 kWh^{-1}. The minimum present value observed under Texas electricity tariffs is −US\$60 kWh^{-1}. If Texans were exposed to California's electric rates, the minimum would fall to −US\$143 kWh^{-1}. The installed cost of a lithium-

Table 1 | Economic impacts of adding energy storage.

Electric utility	Tariff name	Approximate consumption tariff (US¢ kWh^{-1})	Approximate feed-in tariff (US¢ kWh^{-1})	'Target zero' Average annual benefit (US\$ yr^{-1})	'Target zero' Ten-year present value (US\$ kWh^{-1})	'Minimize power' Average annual benefit (US\$ yr^{-1})	'Minimize power' Ten-year present value (US\$ kWh^{-1})
Austin Energy	Value of Solar[27,28]	9.0	10.9	−31	−32	−57	−58
San Antonio – CPS Energy	Net Energy Metering[29,30]	9.8	9.8	−27	−27	−49	−50
MP2 Energy + Oncor	Net Energy Metering[31–33]	10.1	10.1	−34	−35	−58	−60
MP2 Energy + Oncor	Net Energy Buyback[33,34]	8	3.6	78	80	57	58
MP2 Energy + Centerpoint	Net Energy Buyback[33,34]	8.8	3.6	93	95	70	72
TXU Energy + Oncor	Clean Energy Credit[33,35,36]	11.4	7.5	50	51	24	25
TXU Energy + Centerpoint	Clean Energy Credit[33,35,37]	9.9	7.5	21	21	−1.9	−1.9
HECO – Hawaii/Oahu	Customer Grid Supply[38,39]	22.4	15.1	107	110	58	59
HECO – Maui	Customer Grid Supply[38,40]	33.8	17.16	280	287	207	212
HECO – Molokai	Customer Grid Supply[38,41]	39.0	24.07	251	258	165	169
HECO – Lanai	Customer Grid Supply[38,42]	43.4	27.88	233	239	140	143
California – PG&E	Net Energy Metering[43,44]	28.1	28.1	−72	−74	−140	−143
California – SDG&E	Net Energy Metering[45,46]	27.9	27.9	−71	−73	−139	−143
California – SCE	Net Energy Metering[47,48]	20.9	20.9	−55	−57	−105	−107

We use utility tariffs from Texas, Hawaii and California to show how storage operating as described in this paper would affect the cost of electricity service to customers. Note that the Hawaii and California cases are shown only for illustration, because storage would see different load and generation profiles than those observed from our sample of Texas households. The installed price of a home energy storage system would have to fall below US\$100 kWh^{-1} to provide a benefit under current Texas electricity tariffs.

ion battery system used for residential applications ranges from approximately US\$700–US\$1,800 kWh^{-1} of storage capacity, where US\$700 kWh^{-1} represents a low cost estimate for a market-leading storage vendor in 2016 and US\$1,800 kWh^{-1} represents the high cost estimate reported to the US Department of Energy in 2013 for its Energy Storage Handbook[49,50]. Thus, under no scenario considered here could storage provide sufficient direct economic benefit to the customer to offset its upfront cost. The installed price would have to fall below US\$100 kWh^{-1} of storage capacity to provide a benefit under current Texas electricity tariffs. Details of the economic calculations carried out to obtain the data given in Table 1 are provided in the Methods. The complete range of customer benefits calculated across our 99-household sample for each utility tariff is provided in Supplementary Figs 14–27.

Electricity system emissions impacts

In addition to the impact that home energy storage has on electricity demand and consumption, we also consider the indirect impact it would have on electricity system emissions. As the households in the data set are located in Texas, we use marginal emissions factors calculated for the Texas electricity system from US Environmental Protection Agency emissions monitoring data to approximate the change in emissions associated with the hourly changes in electricity demand caused by home energy storage[51,52]. These data report the emissions in kilograms of CO_2, SO_2 and NO_x per megawatt hour of marginal change in electricity consumption at 5% quantiles of fossil generation online measured in gigawatts. We use these data to approximate marginal emissions factors for each hour of the year by comparing them with the measured hourly level of fossil generation in the Texas electricity system over 2014[53]. The resulting hourly marginal emissions factors are used to calculate how adding home energy storage would impact annual emissions for each household considered. The Methods discusses these calculations in detail. Marginal emissions factors for the Texas electricity system are provided in Supplementary Figs 28–31.

We find that the addition of energy storage to a household with existing rooftop solar panels in the Texas electricity system would increase annual emissions of CO_2, SO_2 and NO_x for an average household. When storage operates under the 'target zero' mode, its mean emissions impact is 160 ± 7 kg CO_2, 0.05 ± 0.02 kg SO_2 and 0.05 ± 0.01 kg NO_x per household per year. When storage operates under the 'minimize power' mode its mean emissions impact increases to 290 ± 13 kg CO_2, 0.16 ± 0.04 kg SO_2 and 0.24 ± 0.02 kg NO_x per household per year. The complete range of emissions impacts across the 99-household sample is illustrated in Fig. 4. A sensitivity analysis of emissions impacts to energy storage system parameters is provided in Fig. 5 and Supplementary Figs 12 and 13. Note that while adding storage to homes with existing solar panels leads to an increase in emissions on average, the observed increase is smaller than the average decrease in emissions caused by adding solar panels in the first place, as discussed in Supplementary Note 2 and illustrated in Supplementary Figs 33–35. However, energy storage is typically not required to integrate solar panels[6–8].

The change in grid emissions from the addition of home battery energy storage is caused by two separate factors: the additional energy consumption required to cover storage inefficiencies, and the fact that storage shifts electricity demand in time, and alters which generators are used to provide energy not produced from rooftop solar panels.

To gauge how much of the emissions impact of home energy storage is caused by its energy consumption versus its temporal impact on electricity demand, we test the sensitivity of the CO_2, SO_2 and NO_x emissions impact to storage system a.c.–a.c. roundtrip efficiency. The results of this analysis are illustrated in Fig. 5. The mean emissions impacts calculated across our sample of 99 households are illustrated by the solid lines, and 95% confidence intervals of the corresponding population means are illustrated by the shaded areas around each line. We also calculated the sensitivity of the emissions impacts to the storage system's power capacity and energy capacity. These results are provided in Supplementary Figs 12 and 13.

Under the 'target zero' operating scenario, storage could reduce SO_2 and NO_x emissions if its a.c.–a.c. roundtrip efficiency exceeds 90%. However, it could not reduce CO_2 emissions unless its efficiency approaches 100%. The sensitivity of emissions to energy efficiency changes under the 'minimize power' operating scenario because the battery charges and discharges at different times of day. Under this operating scenario, storage could reduce SO_2 emissions if a.c.–a.c. roundtrip efficiency exceeds 95%, but it could not reduce NO_x emissions even if efficiency equals 100%, because it shifts more energy production to natural gas combustion turbines.

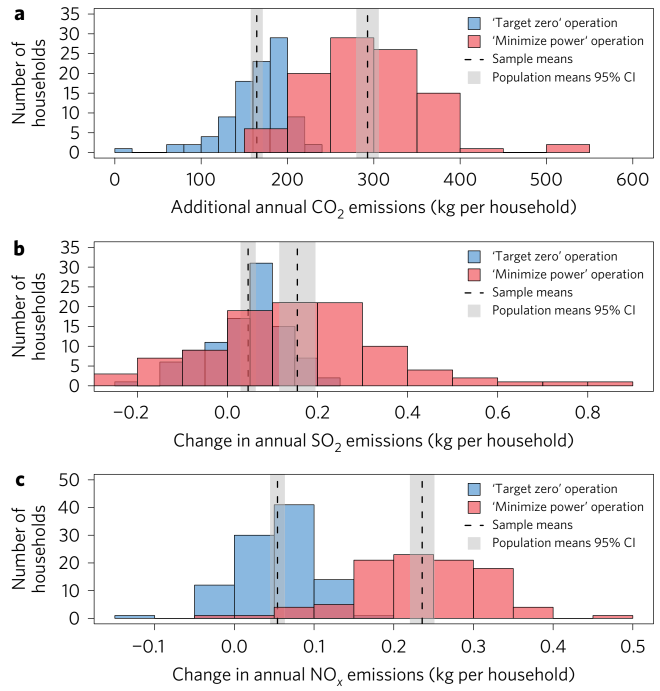

Figure 4 | Emissions impacts of adding energy storage. a–c, The change in electricity system CO_2 (**a**), SO_2 (**b**) and NO_x (**c**) emissions observed across the 99-household sample shown using histograms. The dashed lines indicate the mean impacts observed across the sample, and the shaded areas indicate 95% confidence intervals of the expected mean across all households computed using a Student's *t*-test.

For reference, reported a.c.–a.c. roundtrip efficiencies from Li-ion energy storage vendors range from 80–93%, although these estimates might be optimistic because they are reported values and not measured from the field[49]. A roundtrip efficiency exceeding 90% would be difficult to achieve due to losses in the battery pack itself, additional losses in the power conditioning system that converts the battery's d.c. electricity into a.c. electricity suitable for the grid, and supplemental energy required for thermal controls to maintain an acceptable battery pack temperature. Thus, adding home energy storage to households with existing photovoltaic panels in Texas would most likely lead to an increase in CO_2, SO_2 and NO_x emissions .

Discussion and conclusions

Our findings on the power demand impact of home energy storage show that it could be a useful tool to reduce the magnitude of power flows in the utility grid. This reduction would benefit the utility in two ways: it would reduce the required capacity of electric delivery equipment such as substations and transformers[54], and it would reduce the need for new generation capacity to reliably meet peak electricity demand[55]. These benefits are greater when home energy storage operates in a way that minimizes the magnitude of households' individual power flows (our 'minimize power' scenario) versus when home energy storage operates in a way that seeks to reduce power flows between the household and the utility to zero whenever possible (our 'target zero' scenario). Note that these benefits arise even though storage operates from a customer-centric perspective that seeks to minimize customers' reliance on the electric utility. If storage operated to explicitly benefit the utility without trying to isolate customers, there would be a greater benefit to the utility.

While home energy storage is a useful tool to reduce power flows in the distribution system, our findings indicate that it would increase net energy consumption due to energy storage inefficiencies. Under common net-metering tariffs, which credit customers for solar energy at a rate equal to the rate charged for energy consumption, the increase in energy consumption from storage leads to an increase in customers' utility bills, as shown in Table 1. However, in areas where the tariff charged for consumption is higher than the feed-in tariff for solar energy, the addition of storage can provide an economic benefit to the customer, despite the fact that it leads to higher consumption overall. These instances mirror the current situation in Germany, where the feed-in tariff decreased in 2012 below the rate charged for electricity consumption, creating an incentive for home storage[23]. Under current Texas utility tariffs, the base case energy storage system has a maximum present value of US\$95 kWh^{-1} for a typical household. This value is much lower than the current installed cost of a home energy storage system (US\$700–US\$1,800 kWh^{-1} of storage capacity[49,50]), so storage could not provide a direct economic benefit to Texas customers under current tariffs. It is worth noting that the customer benefit of adding energy storage was found to be higher when it operates according to the 'target zero' approach, even though this approach provides less benefit to the utility in terms of reduced power demand and injections. This finding indicates that it might be useful for utilities to institute demand charges for residential customers with energy storage to explicitly incentivize reducing power demand and injections.

Because energy storage decreases kilowatt power flows in the utility grid but increases kilowatt hour sales of electric energy, it would be in the utility's interest for consumers with solar panels to install home storage. While adding storage does reduce a customer's reliance on the utility, previous analysis has shown that mass defection from the utility is unlikely due to the high cost required for sufficient photovoltaic panels and battery storage to be 100% independent, and the advantages of an interconnected grid that can balance customers' generation with demand and enable customer-producers to sell excess electric energy[56]. Thus, it is possible that energy storage could provide a solution to the disruption of utility business models with rising use of distributed generation[57]. Future work should investigate the potential for energy storage to benefit utilities in this way.

Our findings on the emissions impact of adding energy storage to Texas households with existing photovoltaic panels indicate that it would increase overall electricity system CO_2, SO_2 and NO_x emissions due to time-shifting of electric demand and the additional electric energy required to cover storage system inefficiencies. Changing the local electricity generation mix would alter the emissions impact of home energy storage, but it is unlikely that storage could decrease emissions unless it directly enables new installation of non-emitting generators or enables production from non-emitting sources that otherwise would have been curtailed. This finding aligns with previous work that has examined the system impacts of bulk electricity storage used for price arbitrage in wholesale electricity markets[58].

While rooftop photovoltaic systems deployed on the US grid today do not require home energy storage, there are limited instances where storage might enable wider use of photovoltaic panels. For example, in October 2015 the Public Utilities Commission of Hawaii ended its net-energy metering programme due to concerns about the impact of growing use of rooftop solar panels on electric grid operations and utility rates[59]. The net-metering tariff was replaced with a 'self-supply' tariff for customers that use all of their produced solar energy on site, and a 'grid-supply' tariff that pays a price lower than the retail electric price for energy sent to the grid from solar panels[59]. There is no limit to the number of customers that can install solar panels under the self-supply tariff, but installations under the grid-supply tariff are capped[59]. Thus, for the case of Hawaii, home storage could enable more customers to connect solar panels under the self-supply tariff, and indirectly decrease electricity system emissions. However, it is worth noting that the rule change in Hawaii was driven by both technical issues associated

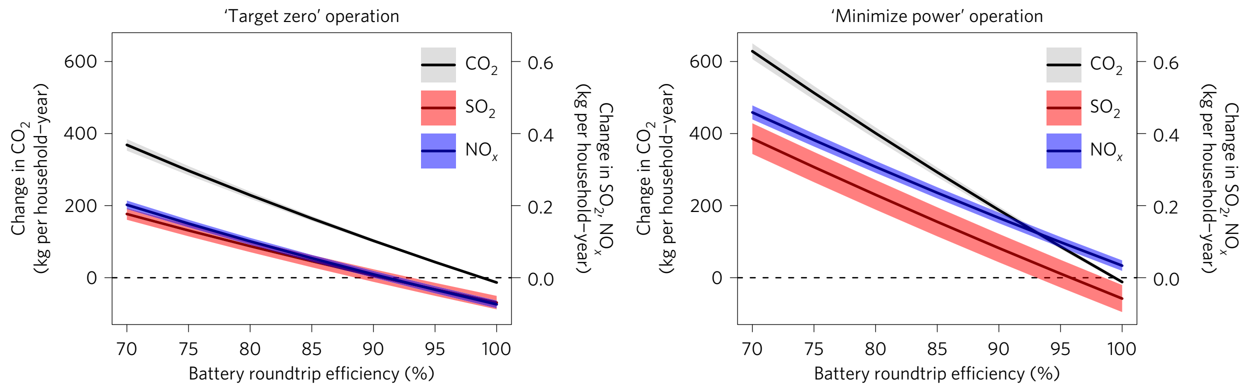

Figure 5 | Sensitivity of emissions impacts to storage roundtrip efficiency. We test the sensitivity of the CO_2, SO_2 and NO_x emissions impact of home energy storage versus its roundtrip efficiency by repeating our analysis for values of roundtrip energy efficiency η_{rt} ranging from 70–100%. The solid lines are the mean emissions impacts observed across the 99-household sample, and the shaded areas are 95% confidence intervals calculated for the corresponding population means.

with integrating solar panels and economic solvency issues related to net-metering tariffs. Further, Hawaii is a unique case where high electricity prices, exceptional solar resources, and a progressive energy policy make rooftop solar very attractive to consumers, yet the islands' small grid and isolation from the mainland exacerbate integration challenges[9].

In the future, regulators, policymakers and other decision-makers should seek to evaluate the impacts of energy storage separately from the impacts of photovoltaic panels or other renewable energy sources. Because energy storage is an energy consumer and not a producer, it would most likely not reduce emissions or primary energy consumption unless it directly enables intermittent renewable energy. It would be useful for future research to assess the cost-emissions trade-off associated with using energy storage to integrate intermittent renewable resources versus other sources of flexibility such as dispatchable generation, transformer tap-change operations, advanced inverters, controllable loads, and other sources of power and voltage control.

Methods

Summary. This paper approximates the impacts of home energy storage using a sequence of five steps. First, electricity use and solar production data for a particular household are downloaded from Pecan Street's Dataport website[26]. Second, the data are entered into a program that plans the operation of home energy storage based on the observed level of electric load and solar generation. Third, the revealed charging and discharging behaviour of home energy storage is used to calculate its impact on electrical power demand and energy consumption. Fourth, electricity tariffs from Texas, Hawaii and California are used to calculate the economic impact of home energy storage. Fifth, a data set of marginal emissions factors for the Texas electricity system is used to approximate the emissions impact of adding home energy storage[51,52]. The following subsections explain the methods associated with each of these steps in detail.

Electricity use and production data. To show how energy storage could respond to a household's electricity consumption and solar production to minimize interaction with the utility, we use electricity data collected by Pecan Street from residential electricity customers[26,60]. Each of the customers provides their data to Pecan Street on a voluntary basis. Many of the participants in the data collection programme are knowledgable about energy and take active steps to reduce their energy use and environmental impact. Previous analysis of the study participants revealed a negative correlation between the score obtained on an energy knowledge quiz and the homeowner's overall electricity consumption[60]. We believe the demographics of the participants resemble the demographics of likely home energy storage early adopters.

Electricity use and production data are downloaded from Pecan Street's Dataport website[26]. The data track electricity use and production in kilowatts at a one-minute time resolution, allowing us to examine how energy storage could respond to short-duration fluctuations in electricity demand and solar production. The data collected from each household are screened according to the following algorithm. First, the number of minutes over the year for which no recorded value of electricity use or solar generation exists is calculated for each household, and households with missing data points are excluded from the data set (38 households in total). Second, the number of minutes for which the recorded value of electricity use is equal to zero is calculated for each of the households, and households with greater than 1,440 min (one cumulative day over the year) of electricity use equal to zero are excluded from the data set (22 households in total). Finally, we generate time series plots showing the minute-by-minute level of electricity demand and solar generation measured from each of the remaining households over 2014. We examine each of these plots visually, and eliminate an additional 13 households from the data set on the basis of anomalous solar generation or electricity consumption behaviour.

After the screening process is complete, the verified data set contains residential electricity use and solar generation data for 99 households, a sufficient sample to examine the expected impact of home energy storage. The data set is organized into data files that can be queried and then entered into the optimization program that is used to plan the operation of home battery energy storage. Summary statistics for each of the 99 homes from which data were collected for this study are provided in Supplementary Table 1.

Energy storage operational management. We model home energy storage operation using two different methods: a 'target zero' approach where the battery does not have information about the future level of solar generation or electricity demand and seeks to reduce the power flows between the household and the grid to zero without regard for how its present actions might affect future reliance on the utility; and a 'minimize power' approach where the battery system has perfect information about the future level of electricity demand and solar generation over the day, and plans its operation to minimize the magnitude of power flows between the home and the utility grid over the entire day. The details of each of these operational models are provided in the following sections.

'Target zero' operational model. The 'target zero' model for operational management of home energy storage considers variables defined over three sets: H:{1,2, …, 99}, representing the numerical identifier of the household where the energy storage system is operating; d:{1,2, …, 365}, representing the day of the year; and m:{1,2, …, 1440}, representing the minute of the day.

The model considers an energy storage device with a rated power P_{rated}, a rated energy capacity E_{rated}, and a roundtrip efficiency η_{rt}. P_{rated} and E_{rated} are selected to correspond to the specifications announced for Tesla's 'Powerwall' home battery system for daily cycle applications: P_{rated} = 3.3 kW, E_{rated} = 7 kWh (ref. 3). We assume a roundtrip a.c.–a.c. efficiency η_{rt} = 85% based on the 92% d.c.–d.c. efficiency announced for the Powerwall and an assumed d.c.–a.c. converter efficiency of 96%[3,49,61,62].

The model steps from one minute of the year to the next, and uses the following algorithm to decide the level of battery power. First, the target battery power for household H during the day of the year d and the minute of the day m is calculated as the instantaneous net power demand of the household during the current minute, which is equal to the measured level of electricity use $P_{use}(H, d, m)$ minus the measured level of electricity generation $P_{gen}(H, d, m)$ as given in equation (1). The parameters $P_{use}(H, d, m)$ and $P_{gen}(H, d, m)$ come from the home electricity data set discussed in the previous section. Second, the target power is compared with the rated power of the battery system. If the target power exceeds the rated power, then the magnitude of the target power is reduced to the rated power level. Third, the level of stored energy at the end of the current minute as a result of the applied target power is calculated. If the level of stored energy violates the battery system's limits, then the battery power during the minute is set equal to zero. Otherwise, the battery power during the minute is set equal to the target power level.

This control logic is defined in equation (2). Positive values of $P_{bat}(H, d, m)$ indicate discharging while negative values indicate charging. The relationship between the applied battery power and the level of stored energy during minute m is defined by equations (3)–(6). Equation (3) estimates the instantaneous amount of stored energy as a function of the initial energy stored at the beginning of the day, $E_{bat,i}(H, d)$, and the change in the amount of energy stored during each prior minute of the day, $\Delta E_{bat}(H, d, m)$. Equation (4) defines $E_{bat,i}(H, d)$. The initial amount of energy stored at the beginning of the first day of the year is set equal to one half the system's rated energy capacity. For subsequent days, it is set equal to the amount of energy stored at the end of the prior day. Equation (5) defines $\Delta E_{bat}(H, d, m)$ as a function of the amount of power applied to the battery. The constant Δt represents the duration of the one-minute time step, and is set equal to (1/60) to integrate the kilowatt power flow to/from the battery into kilowatt hours of energy. The constant κ represents the energy losses during charging and discharging, and is defined in equation (6). When the battery is discharging, more energy is extracted from the storage device than is delivered to the grid, so κ is equal to $1/\sqrt{\eta_{rt}}$ and greater than 1. When the battery is charging, less energy enters the storage device than is extracted from the grid, so κ is equal to $\sqrt{\eta_{rt}}$ and less than 1. Put together, the values defined for κ in equation (6) set the net roundtrip energy storage efficiency to be equal to η_{rt} and equally impose energy losses on charging and discharging. Previous work has used a similar formulation to model storage energy losses[58,63].

$$P_{target}(H,d,m) = P_{use}(H,d,m) - P_{gen}(H,d,m) \quad (1)$$

$$P_{bat}(H,d,m) = \begin{cases} \min(P_{target}(H,d,m), P_{rated}) & \text{if } P_{target}(H,d,m) > 0 \quad \text{(net consumer)} \\ & \text{and } 0 \le E_{bat}(H,d,m) \\ \max(P_{target}(H,d,m), -P_{rated}) & \text{if } P_{target}(H,d,m) < 0 \quad \text{(net producer)} \\ & \text{and } E_{bat}(H,d,m) \le E_{rated} \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

$$E_{bat}(H,d,m) = E_{bat,i}(H,d) + \sum_{\mu=1}^{m} \Delta E_{bat}(H,d,\mu) \quad (3)$$

$$E_{bat,i}(H,d) = \begin{cases} E_{rated}/2 & \text{if } d = 1 \\ E_{bat}(H, d-1, m=1{,}440) & \text{if } d \ne 1 \end{cases} \quad (4)$$

$$\Delta E_{bat}(H,d,m) = -P_{bat}(H,d,m)\kappa\Delta t \quad (5)$$

$$\kappa = \begin{cases} 1/\sqrt{\eta_{rt}} & \text{if } P_{bat}(H,d,m) > 0 \quad \text{(discharging)} \\ \sqrt{\eta_{rt}} & \text{if } P_{bat}(H,d,m) < 0 \quad \text{(charging)} \end{cases} \quad (6)$$

The control logic is applied using a for loop, which steps from one minute to the next and assigns the battery power during minute m according to equation (2). Sample input parameters and results from the operational model are provided in Supplementary Figs 2–5.

'Minimize power' operational model. Like the 'target zero' model, the 'minimize power' model considers variables defined over three sets: H:{1,2, …, 99}, representing the numerical identifier of the household where the energy storage system is operating; d:{1,2, …, 365}, representing the day of the year; and m:{1,2, …, 1440}, representing the minute of the day. A nonlinear optimization program is used to plan the operation of home energy storage.

The decision variable for the optimization program is the level of battery power $P_{bat}(H, d, m)$ during each minute m of operating day d for household H, with negative values of $P_{bat}(H, d, m)$ indicating charging and positive values indicating discharging.

The objective of the optimization program is to minimize the magnitude of power flows between a household and the grid by scheduling the battery charging and discharging power over the day. Thus, we define the objective function to be minimized as the sum of the squares of the net power flow between household H and the grid during each minute m of day d, as given in equation (7). The net power flow during each minute is equal to the measured level of electricity use $P_{use}(H, d, m)$, minus the measured level of electricity generation $P_{gen}(H, d, m)$, minus the battery power decision variable $P_{bat}(H, d, m)$. The optimization program is executed separately for each household H and each day d to minimize each household's interaction with the utility during each day of the year.

$$f_{Obj}(H,d) = \sum_{m=1}^{1{,}440} (P_{use}(H,d,m) - P_{gen}(H,d,m) - P_{bat}(H,d,m))^2 \quad (7)$$

An important constraint on the battery system's operation is that the instantaneous amount of energy stored in the battery system must be within its rated energy storage capacity, E_{rated}. We impose an equality constraint within the optimization program to define a dependent variable $E_{bat}(H, d, m)$, which represents the amount of energy stored in the battery at the end of minute m. The relationship between the decision variable $P_{bat}(H, d, m)$ and the dependent variable $E_{bat}(H, d, m)$ is defined as given in equations (3)–(6) discussed in the previous section. As equation (6) has a conditional definition based on the sign of the decision variable $P_{bat}(H, d, m)$, it must be defined within the optimization program using either an integer variable or a smooth functional approximation of the discontinuous conditional constraint so that the solver can traverse the solution space. We approximate equation (6) using the smooth, continuous hyperbolic tangent function given in equation (8). Supplementary Fig. 1 compares equation (6) and (8).

$$\kappa \approx \left(\frac{1}{2}\left(\frac{1}{\sqrt{\eta_{rt}}} + \sqrt{\eta_{rt}}\right) - \frac{1}{2}\left(\frac{1}{\sqrt{\eta_{rt}}} - \sqrt{\eta_{rt}}\right) \tanh(-50P_{bat}(H,d,m)) \right) \quad (8)$$

Within the optimization program, the battery power $P_{bat}(H, d, m)$ and the amount of energy stored in the battery $E_{bat}(H, d, m)$ are constrained according to the technical limits of the energy storage system. The magnitude of the battery power is constrained to be less than or equal to the rated power capacity P_{rated} according to equation (9). The amount of energy stored is constrained to be greater than or equal to zero and less than or equal to the rated battery energy capacity E_{rated} according to equation (10).

$$-P_{rated} \le P_{bat}(H,d,m) \le P_{rated} \quad (9)$$

$$0 \le E_{bat}(H,d,m) \le E_{rated} \quad (10)$$

We implement the optimization using the General Algebraic Modeling System (GAMS)[64]. Within GAMS, the interior point nonlinear optimization solver is used[65].

The values of the parameters $P_{use}(H, d, m)$, $P_{gen}(H, d, m)$, P_{rated}, E_{rated} and η_{rt} are passed to GAMS using the R programming package gdxrrw[66]. The parameters $P_{use}(H, d, m)$ and $P_{gen}(H, d, m)$ come from the data set discussed in the previous section. The parameters P_{rated} and E_{rated} are selected to correspond to the specifications announced for Tesla's Powerwall home battery system for daily cycle applications: P_{rated} = 3.3 kW, E_{rated} = 7 kWh. We assume a roundtrip a.c.–a.c. efficiency η_{rt} = 85% based on the 92% d.c.–d.c. efficiency announced for the Powerwall and an assumed d.c.–a.c. inverter efficiency of 96%[3,49,61,62].

R is used to obtain and store the solution to the optimization program computed by GAMS. Sample input parameters and results for the optimization program are provided in Supplementary Figs 2–5. We solve the optimization program over the set of all households H in parallel. For each household, the optimization problem is solved for each of the 365 days of the year d in series.

Calculation of power demand and energy consumption impacts. Once the charge–discharge pattern of home energy storage has been calculated for each day of 2014 for each of the 99 households in our data set, we can calculate the impact that home energy storage would have on electrical power demand and annual energy consumption.

The aggregate power demand with no storage $P_{grid}^{NS}(d, m)$ is calculated by summing the electricity use and solar generation measured from each household H according to equation (11). Likewise, the aggregate power demand with storage $P_{grid}^{S}(d, m)$ is calculated according to equation (12). The calculated values of $P_{grid}^{NS}(d, m)$ and $P_{grid}^{S}(d, m)$ are illustrated in Fig. 2.

$$P_{grid}^{NS}(d,m) = \sum_{H=1}^{99} P_{use}(H,d,m) - P_{gen}(H,d,m) \quad (11)$$

$$P_{grid}^{S}(d,m) = \sum_{H=1}^{99} P_{use}(H,d,m) - P_{gen}(H,d,m) - P_{bat}(H,d,m) \quad (12)$$

As residential electricity customers are typically billed for their kilowatt hour consumption, we calculate the impact that the addition of home energy storage would have on annual energy consumption for each of the households in our data set. The change in net energy consumption over the year for each household $\Delta E_{cons}(H)$ from the addition of home energy storage is calculated by integrating the flow of power in and out of the storage device according to equation (13), where Δt is set equal to (1/60) to convert the kilowatt power flows in/out of the battery during each minute m into kilowatt hours of energy. Note that a negative sign is added to the summation because positive values of P_{bat} indicate discharging and negative values indicate charging.

$$\Delta E_{cons}(H) = \sum_{d=1}^{365} \sum_{m=1}^{1{,}440} -P_{bat}(H,d,m)\Delta t \quad (13)$$

Figure 3 illustrates the change in energy consumption from the addition of home energy storage for each of the 99 households in the data set. The mean additional energy consumption is calculated by taking the average of $\Delta E(H)$ over all H, and a 95% confidence interval for the mean is calculated using a Student's t-test with 98 degrees of freedom.

Calculation of economic impacts. To assess the impact that adding energy storage would have on the annual cost of service under different electricity tariffs, we first calculate the monthly energy consumption from the grid and energy injection to the grid for each of the 99 households in our data set with and without energy storage added. Then, we create custom functions using the R programming package that calculate the annual cost of service as a function of monthly consumption and production for each of the 14 utility tariffs identified in Table 1[67]. While some of the tariffs charge a fixed US cent per kilowatt hour rate for energy consumed and energy produced, most of the utility tariffs include volumetric tiered charges, seasonal peak charges, or other subtleties that would be difficult to compactly summarize here. We refer the reader to the utility tariffs cited in the references and identified in Table 1[27–48]. We use the custom R functions to calculate the annual cost of service for each of the 99 households in our data set with and without energy storage, and then calculate the annual benefit from energy storage as the difference between the cost of service with no energy storage installed and the cost of service with energy storage installed. The annual benefit for each of the 99 households under each of the utility tariffs considered is illustrated in Supplementary Figs 14–27.

Once the average annual benefit from the addition of energy storage is calculated for each one of the utility tariffs considered and for both storage operational modes considered, we calculate the present value of the energy storage system assuming a ten-year lifetime, a 10% discount rate, and a 2.5% inflation rate[3,68]. These assumptions result in a present worth factor of 7.17, as given in equation (14). We multiply this present worth factor by each average annual benefit in Table 1 and then divide by the base case energy capacity $E_{\text{rated}} = 7\,\text{kWh}$ to obtain the present value in US dollars per kilowatt hour for each utility tariff.

$$\text{PW}_{\text{factor}} = \sum_{y=1}^{10} \frac{(1+0.025)^{y-0.5}}{(1+0.10)^{y-0.5}} = 7.17 \tag{14}$$

Marginal emissions data and estimation of emissions impacts. To calculate the emissions impact of adding home energy storage to households with existing solar panels, it is important to consider which generating units would respond to a change in electricity demand at the particular times when energy storage charges and discharges, because those generators might have different emissions.

Electricity generators are scheduled by the grid operator according to their marginal operating cost, with the least costly generators dispatched first to minimize overall production costs. As a rule of thumb, wind, solar, hydroelectric and nuclear generation are dispatched first, followed by coal, and then natural gas generation. The precise order that generators are dispatched depends on a number of factors, such as their individual efficiency, fuel price, maintenance requirements, electricity transmission constraints, and other factors.

To estimate the emissions associated with the marginal change in electricity demand caused by home energy storage, we use marginal emissions factors calculated for the Texas electricity system from US Environmental Protection Agency Continuous Emissions Monitoring System (CEMS) data[51,52]. These data estimate the change in CO_2, SO_2 and NO_x emissions associated with a change in electricity demand at 5% quantiles of fossil generation online. These data show that when the total fossil generation online is at its minimum, the marginal CO_2 and SO_2 rates are at their maximum because more of the generators responding to a marginal change in electricity generation are coal steam units. Likewise, when the total fossil generation online is at its maximum, the marginal NO_x rate is at its maximum because more of the generators responding to a marginal change in electricity demand are natural gas combustion turbines. The data are available online from the Carnegie Mellon Center for Climate and Energy Decision Making, and provided in Supplementary Fig. 28[52]. We estimate hourly marginal emissions factors by comparing the recorded hourly level of fossil generation over 2014 in Texas to the marginal emission factors calculated for various levels of fossil generation and interpolating linearly. The hourly marginal emissions factors are illustrated in Supplementary Figs 29–31.

Once hourly marginal emissions factors for CO_2, SO_2 and NO_x have been estimated, we calculate the annual emissions impact of adding home energy storage to households with existing solar panels according to equations (15)–(17), where MEF(h) is the marginal emissions factor in kilograms per kilowatt hour at hour h, $P_{\text{bat}}(H, d, m)$ is the battery power for household H on day d at minute m in the corresponding hour h, and Δt is set equal to (1/60) to convert the kilowatt power flow in and out of the battery system into kilowatt hours.

$$\Delta\text{CO}_2(H) = \sum_{d=1}^{365}\sum_{h=1}^{24}\sum_{m\in h} -P_{\text{bat}}(H,d,m)\Delta t\,\text{MEF}_{\text{CO}_2}(h) \tag{15}$$

$$\Delta\text{SO}_2(H) = \sum_{d=1}^{365}\sum_{h=1}^{24}\sum_{m\in h} -P_{\text{bat}}(H,d,m)\Delta t\,\text{MEF}_{\text{SO}_2}(h) \tag{16}$$

$$\Delta\text{NO}_x(H) = \sum_{d=1}^{365}\sum_{h=1}^{24}\sum_{m\in h} -P_{\text{bat}}(H,d,m)\Delta t\,\text{MEF}_{\text{NO}_x}(h) \tag{17}$$

The result of equations (15)–(17) is an estimate of the annual change in CO_2, SO_2 and NO_x emissions in kilograms caused by the addition of home energy storage. Note that no emissions credit is given for grid energy consumption offset by the solar panels because our objective is to analyse the impact of adding energy storage to a household with existing solar panels. The emissions impact of home energy storage for each household in our sample is shown in Fig. 4. The mean emissions impact is calculated by taking the average of the $\Delta\text{CO}_2(H)$, $\Delta\text{SO}_2(H)$ and $\Delta\text{NO}_x(H)$ over each of the 99 households in our sample H. We calculate a 95% confidence interval on the population mean using a Student's t-test with 98 degrees of freedom.

Data availability. To calculate the results presented in this paper, we draw on the database of household electricity use and production available through Pecan Street's Dataport website[26]. Supplementary Table 1 provides the unique data identifiers and summary statistics for each of the 99 households considered in this study. The marginal emissions factors data used to calculate the emissions impacts presented in Fig. 4 are available online from the Carnegie Mellon Center for Climate and Energy Decision Making[51,52]. Additionally, the US Environmental Protection Agency Continuous Emissions Monitoring System (CEMS) data originally used to calculate marginal emissions factors are available online through the Air Markets Program Data website[69]. Any intermediate data not available from the sources described above, and not included in this article or its Supplementary Information, are available from the authors on request.

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Author contributions
R.L.F. identified the research question, curated the data used, designed the research methods, analysed the numerical results, and prepared the manuscript. M.E.W. contributed to identifying the research question, interpreted the results, prepared the manuscript, and provided institutional and material support for the research.

Additional information
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