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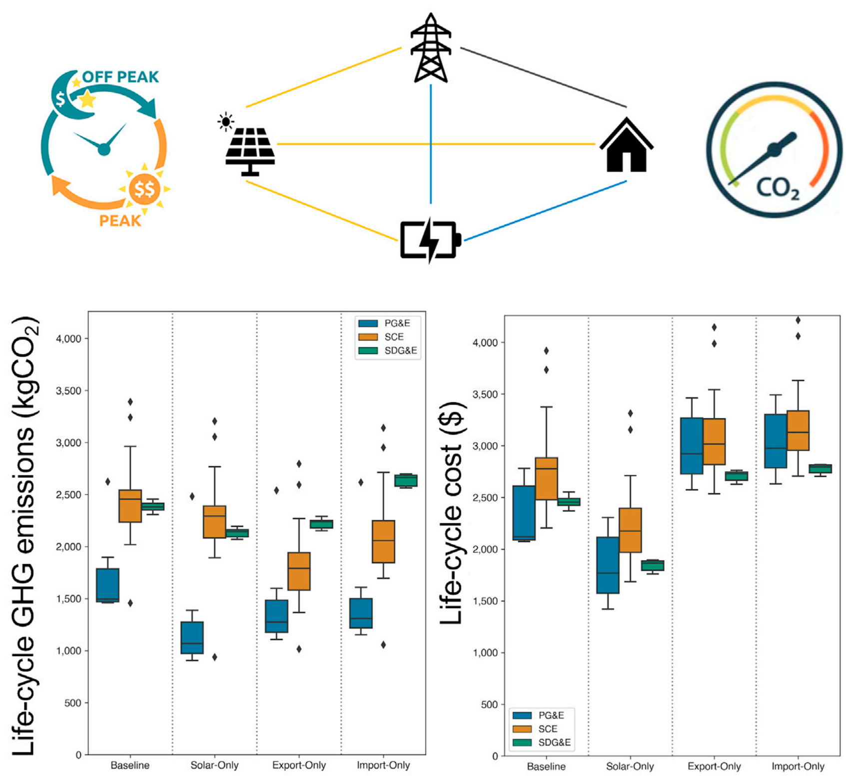

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Highlights

First study assessing residential solar-plus-storage systems using lifecycle approach

PV reduces lifecycle cost and emissions while solar-plus-battery has mixed impacts

Emissions depend on operation mode, tariff structure, and marginal emission factors

Tariff reform and reduction in embodied emissions and cost of battery are needed

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Lifecycle cost and carbon implications of residential solar-plus-storage in California

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SUMMARY

Capacities of residential photovoltaics (PV) and battery storage are rapidly growing, while their lifecycle cost and carbon implications are not well understood. Here, we integrate PV generation and load data for households in California to assess the current and future lifecycle cost and carbon emissions of solar-plus-storage systems. Our results show that installing PV reduces \$180–\$730 and 110–570 kgCO_2 per year per household in 2020. However, compared to solar-only system, adding battery storage increases lifecycle costs by 39%–67%, while impact on emissions is mixed (−20% to 24%) depending on tariff structure and marginal emission factors. In 2040, under current decarbonization and cost trajectories, solar-plus-storage leads to up to 31% higher lifecycle costs and up to 32% higher emissions than solar-only systems. Designing a tariff structure with wider rate spreads aligned with marginal carbon emissions, and reducing the costs and embodied emissions of batteries are crucial for broader adoption of low-carbon residential solar-plus-storage.

INTRODUCTION

Variable renewable energy (VRE) such as solar and wind, is experiencing accelerated expansion with decreasing costs. However, the variability of VRE generation poses a major challenge to the low-carbon transition. Energy storage provides various benefits ranging from smoothing renewable generation, reducing curtailment, improving the reliability of operating transmission and distribution grids, deferring or substituting costly investments in infrastructure, and peak shaving, among others (Arbabzadeh et al., 2019; California Independent System Operator, 2019; Craig et al., 2018; O'Shaughnessy et al., 2018).

For households, residential battery storage, typically coupled with rooftop solar photovoltaic (PV), can increase PV self-consumption, save electricity bills, and provide backup power during outages (O'Shaughnessy et al., 2018). The capacity of behind-the-meter batteries with rooftop PV is estimated to dramatically increase and match that of utility-scale batteries by 2030 globally (International Renewable Energy Agency, 2019). In the U.S., one-quarter of new residential PV systems are expected to be paired with storage by 2025. Among U.S. states, California represents the largest market with 38% of nation-wide residential PV installations between 2016 and 2020, and is driving the growth of solar-plus-storage systems (Solar Energy Industries Association, 2021).

Understanding the implications of residential solar-plus-storage systems on greenhouse gas (GHG) emissions from a lifecycle perspective is important to avoid unintended consequences or problem shifting. Battery storage has the potential to address the intermittency problem of solar PV, therefore, contributing to GHG emissions reduction through replacing carbon-intensive, fossil fuel-based electricity with renewable electricity. However, the potential for additional battery storage to reduce GHG emissions should be weighed against the additional GHG emissions from battery production, the point of which has not been examined in the literature. On the one hand, use-phase studies often employ optimization models to quantify operational emissions with little consideration of the embodied impacts from battery production (Elzein et al., 2019; Ren et al., 2020). On the other hand, life cycle assessment (LCA) studies generally limit the scope to the production phase or make oversimplified assumptions on battery cycling during the use phase (Mayer et al., 2020; Petrelli and Melià, 2019). Stationary applications of battery storage, especially in the residential sector, are notably underevaluated compared with mobile applications such as electric vehicles (Le Varlet et al., 2020).

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Additionally, existing literature on the operational emissions of residential battery storage is largely limited to retrospective analyses. Some studies conclude that residential battery storage increases total emissions when performing energy arbitrage (charge when electricity price is low and discharge when it is high), mainly owing to energy losses during battery cycling (Babacan et al., 2018; Fares and Webber, 2017; Fisher and Apt, 2017; Hittinger and Ciez, 2020). These analyses often use a set of short-run marginal emission factors (MEFs) derived through regression models based on empirical fossil generation data, which do not take nuclear and renewable generators into account (Center For Climate and Energy Decision Making, 2019; Siler-Evans et al., 2012). This approach is less applicable to the regions with large portions of VRE such as California and Mid-West, where VRE is often on the margin (Fisher and Apt, 2017; Li et al., 2017). Including non-emitting generators in the regression model for a high-wind-penetration area is shown to have about 30% discrepancy in short-run MEFs compared with the MEFs based on fossil fuels only (Li et al., 2017), and such MEFs are frequently used in recent studies (Gai et al., 2019; Thind et al., 2017).

While suitable for retrospective analyses, short-run MEFs are unable to inform the impacts of battery storage on GHG emissions, as the share of VRE in the electric grid increases rapidly. Energy storage systems can induce structural changes in grid infrastructure by changing demand profiles (Bistline and Young, 2020). Short-run MEFs evaluate the operational response to a marginal load change, assuming that the underlying grid composition is fixed (Hawkes, 2010; Yang, 2013). In comparison, long-run MEFs account for the structural changes of the electricity system, such as capacity investments of VRE and retirement of fossil fuel power plants, which are more suitable for prospective analyses (Chalendar and Benson, 2019; Gagnon et al., 2020; Hawkes, 2014; Soimakallio et al., 2011; Yang, 2013).

Here, we evaluate the lifecycle GHG emissions and costs of installing and operating solar-only and solar-plus-storage systems in 52 representative households across California. We optimize the operation of residential solar-plus-storage systems with two power modes in three utility areas for the current time (2020) and a highly decarbonized future (2040) and calculate the emissions based on long-run MEFs. By comparing their lifecycle costs and GHG emissions, we explore if adding storage can further reduce cost and emissions and under what conditions would solar-plus-storage outperform solar-only systems.

RESULTS

Operation modes

We estimate the lifecycle GHG emissions and cost of households under three operation modes—Solar-Only, Export-Only, and Import-Only. These are the most common residential self-generation configurations that are compliant with the current California Net Energy Metering (NEM) policy. Solar-Only refers to the case when households install only rooftop solar PV systems (Figure 1A). In Export-Only mode, households install solar-plus-storage systems, in which the battery storage only charges from solar PV and the battery can discharge and export to the grid besides meeting the on-site load (Figure 1B). In Import-Only mode, households install solar-plus-storage systems where the battery can charge from solar PV or the grid, but the battery can only discharge to meet the on-site load (Figure 1C). For both Export-Only and Import-Only modes, we assume that the households dispatch batteries to minimize their annual electric utility cost (*minCost*). Unconstrained mode, in which the battery can charge and discharge without direction limitation, is currently not allowed in California. Nevertheless, we explored this mode and show the results in the Supporting Information. We model the hourly PV generation, grid electricity consumption, and battery dispatch for each sampled household through optimization.

We use the default time-of-use (ToU) tariffs for NEM participants in 2020 from three major utility companies in California—Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric Company (SDG&E)—with hourly rates shown in Figure 2. We describe the selected ToU plan of PG&E (E-TOU-D) as "*Narrow-Spread*" because it sets small price differences between on-peak and off-peak hours and has a flat rate for weekends. Conversely, the ToU plan of SCE (TOU-D-4-9PM) maintains a significant and consistent gap between on-peak and off-peak hours across all seasons, so it is coded as "*All-Season Wide-Spread*". The ToU plan of SDG&E (DR-SES) has very little daily variation during wintertime but has a much larger gap between on-peak and off-peak hours during summertime; therefore, we call it "*Summer-Only Wide-Spread*".

We collect the hourly electric load for typical three-bedroom houses across California, with the annual load varying by local climate (7,500–13,000 kWh) (Office of Energy Efficiency & Renewable Energy (EERE), 2013).

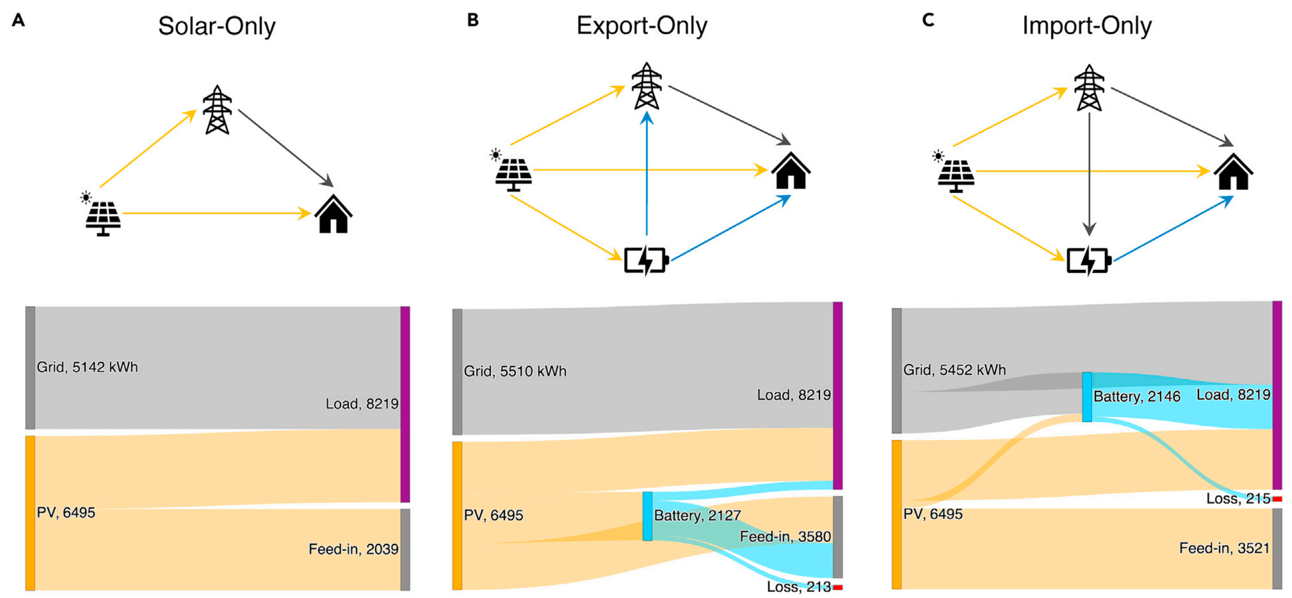

Figure 1. Illustration of different power control modes of solar-only or solar-plus-storage systems and resulting annual electricity flow for an example household

(A–C) (A) Solar-Only mode, (B) Export-Only mode, and (C) Import-Only mode. Shown in Export-Only and Import-Only modes are optimized electricity flows under an objective of minimizing annual utility cost.

We simulate a 4-kilowatt (kW) solar PV system, coupled with lithium-ion battery storage with usable capacity of 13.5 kilowatt h (kWh) and round-trip efficiency of 90% (Tesla, 2019). This system size is typical for a three-bedroom house and would ensure that the PV generation does not exceed the on-site load, as required by the state's NEM policy (California Public Utilities Commission, 2020). Depending on the location of the houses, the solar PV generation ranges between 5,000–7,300 kWh/year.

In Solar-Only mode, 33%–40% of the household's on-site load is met by solar PV, with the remaining demand met by the grid. Surplus PV generation is fed back to the grid (33%–60% of annual PV generation, depending on the location and load size), and the household receives financial credits for feed-in. The annual PV-to-load ratio of the sampled households ranges between 53% and 90% with a mean value of 75%.

In Export-Only mode, the electricity flows of households using SCE *All-Season Wide-Spread* show a contrasting pattern with the others (Figure 3B). Particularly, 72% of PV generation is used to charge batteries in SCE on average, with the rest serving on-site load directly (26%) or feeding back to the grid (2%). In comparison, only 20% of PV generation is stored in households using PG&E *Narrow-Spread*, with a higher percentage used on site (44%) or fed back to the grid (36%). For SDG&E *Summer-Only Wide-Spread*, the average percentage of PV generation used for battery charging, on-site consumption, and feed-in is 32%, 36%, and 32%, respectively. Across all three areas, most of the electricity stored in batteries (61%–86%) is discharged to the grid in exchange for credit, mostly during peak hours when retail rates are high.

In Import-Only mode, 33%–56% PV generation is used for on-site consumption, greater than in Export-Only mode. The portion of PV generation stored in batteries is low for PG&E *Narrow-Spread* and SDG&E *Summer-Only Wide-Spread* (7% and 5% on average, respectively) but is much greater for SCE *All-Season Wide-Spread* (34%). For households served by SDG&E, batteries charge mostly from the grid at nighttime rather than from solar PV. However, in SCE area, households charge more during the day from both on-site PV and the grid. Across all areas, batteries discharge in late afternoon and early night to displace expensive grid electricity. For detailed battery dispatching and state-of-charge curve, see Figures S3–S11.

The differences in battery dispatching patterns can be attributed to the ToU tariff structures. PG&E *Narrow-Spread* offers little incentive for households to dispatch batteries (except for summer weekdays), given that the energy loss during cycling leads to higher electricity consumption. For SDG&E *Summer-Only*

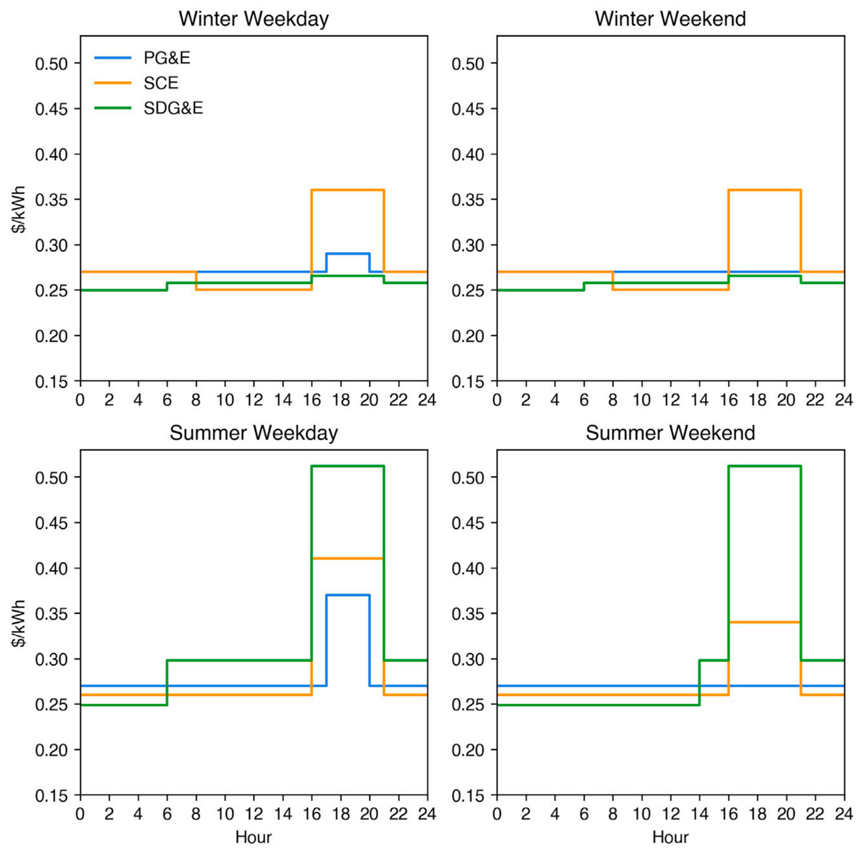

Figure 2. Time-of-Use Rates by Utility Company in California (2020)
PG&E: E-TOU-D *(Narrow-Spread)*. SCE: TOU-D-4-9PM*(All-Season Wide-Spread)*. SDG&E: DR-SES *(Summer-Only Wide-Spread)*. Summer is June–September for PG&E and SCE but June–October for SDG&E.

Wide-Spread, off-peak rates are lower during nighttime (0–6 a.m.) than daytime (6 a.m.– 4 p.m.), which results in frequent charging from the grid at night and more PV feed-in during the day in the Import-Only mode. Conversely, SCE *All-Season Wide-Spread* maintains an intraday differential all year round and sets the lowest rate during off-peak hours (8 a.m.–4 p.m.) in winter, which encourages more PV generation to be stored and later discharged during peak hours. Consequently, the battery storage at our modeled households is served by SCE cycle more frequently than those served by other utilities.

Annual lifecycle cost and GHG emissions

We calculate the resulting lifecycle cost and GHG emissions after optimizing the solar-plus-storage systems for one year under the *minCost* (minimizing utility cost) objective for each household. Annual lifecycle cost consists of annualized capital cost of the device(s), utility cost based on ToU rates, credits from feed-in, and extra cost from imposing a carbon price in addition to ToU charges (when assumed). Under the current NEM program in California, residential customers who produce surplus renewable electricity and feedback into grid receive a financial credit on electricity bills at the same retail rate that they would have paid without the renewable generator (California Public Utilities Commission, 2020). Annual lifecycle GHG emissions include the annualized embodied emissions of the system, lifecycle emissions from grid electricity usage, and avoided emissions from feed-in.

Figure 4 shows the annual lifecycle GHG emissions and cost of all sampled households in different scenarios. Baseline scenario assumes households have no PV or storage installed. Compared to the baseline scenario, installing Solar-Only systems lead to 110–570 kgCO_2 (or 5%–39%) reduction. Across all scenarios, lifecycle GHG emissions of households in PG&E area are lower than those in the other two areas (Figure 4A), owing to fewer cooling degree days (less need for air-conditioning) and a lower carbon grid. There is a

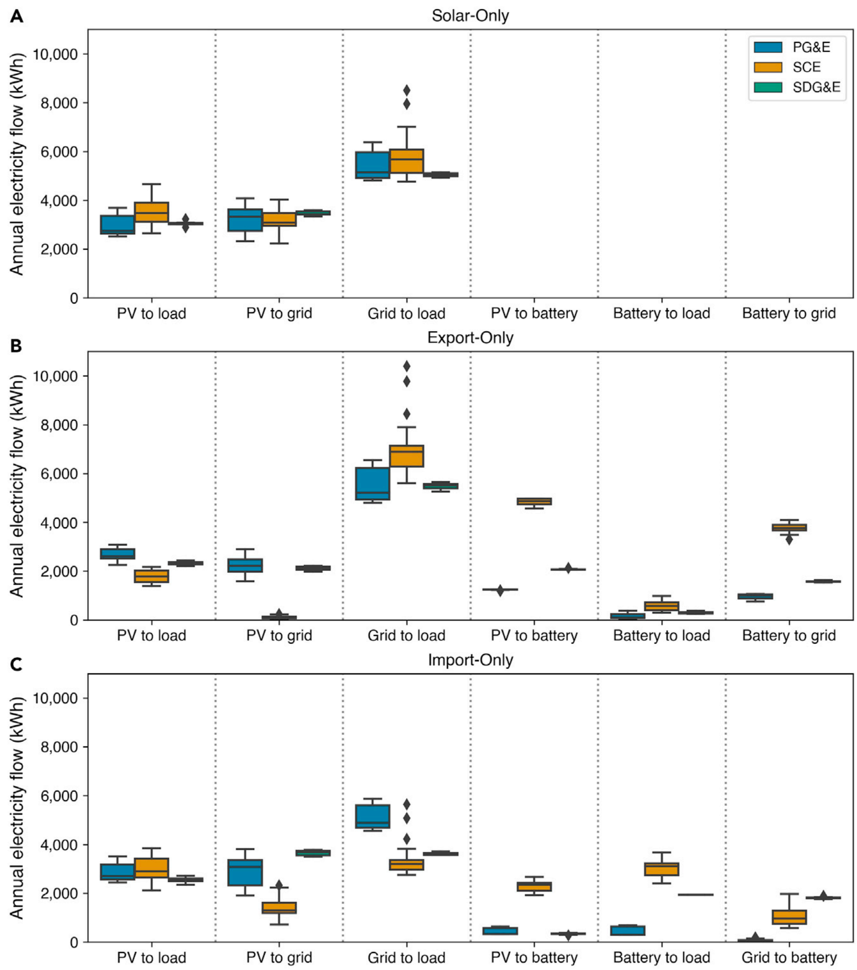

Figure 3. Annual electricity flows of all sampled households in California by utility area in different scenarios

(A–C) (A) Solar-Only, (B) Export-Only, and (C) Import-Only. Solar-Only—households adopt only solar PV systems. Export-Only— households adopt solar-plus-storage systems with Export-Only mode. Import-Only—households adopt solar-plus-storage systems with Import-Only mode. Results for Export-Only and Import-Only modes are optimized under an objective of minimizing annual utility cost.

larger variation in emissions among households served by SCE due to a greater variation in climate and load size within the utility area.

For households with PG&E *Narrow-Spread*, installing solar-plus-storage systems results in 2%–27% higher lifecycle GHG emissions in 2020 than the Solar-Only scenario, due to a lack of tariff incentives for battery dispatch and a lower-carbon grid mix. For SCE *All-Season Wide-Spread*, installing solar-plus-storage systems can reduce more GHG emissions from the baseline than installing only solar PV. This is because these households fully utilize batteries by charging from on-site PV and discharge during peak time to replace generation from mostly natural gas peaker plants. Reduction of emissions in Export-Only mode is greater because more stored electricity can feed back to the grid. For SDG&E *Summer-Only Wide-Spread*, Import-Only mode leads to a 9%–12% increase in lifecycle GHG emissions from the baseline, owing to nighttime charging from the grid when marginal costs are low while marginal emissions are high from the mostly fossil fuel-based generation.

Although solar-plus-storage systems may reduce lifecycle GHG emissions, they result in 4%–49% higher lifecycle costs compared to the baseline in 2020 without subsidy (Figure 4B) because the annualized capital cost of battery storage exceeds the savings on utility bills from optimizing the battery operation. Solar-Only

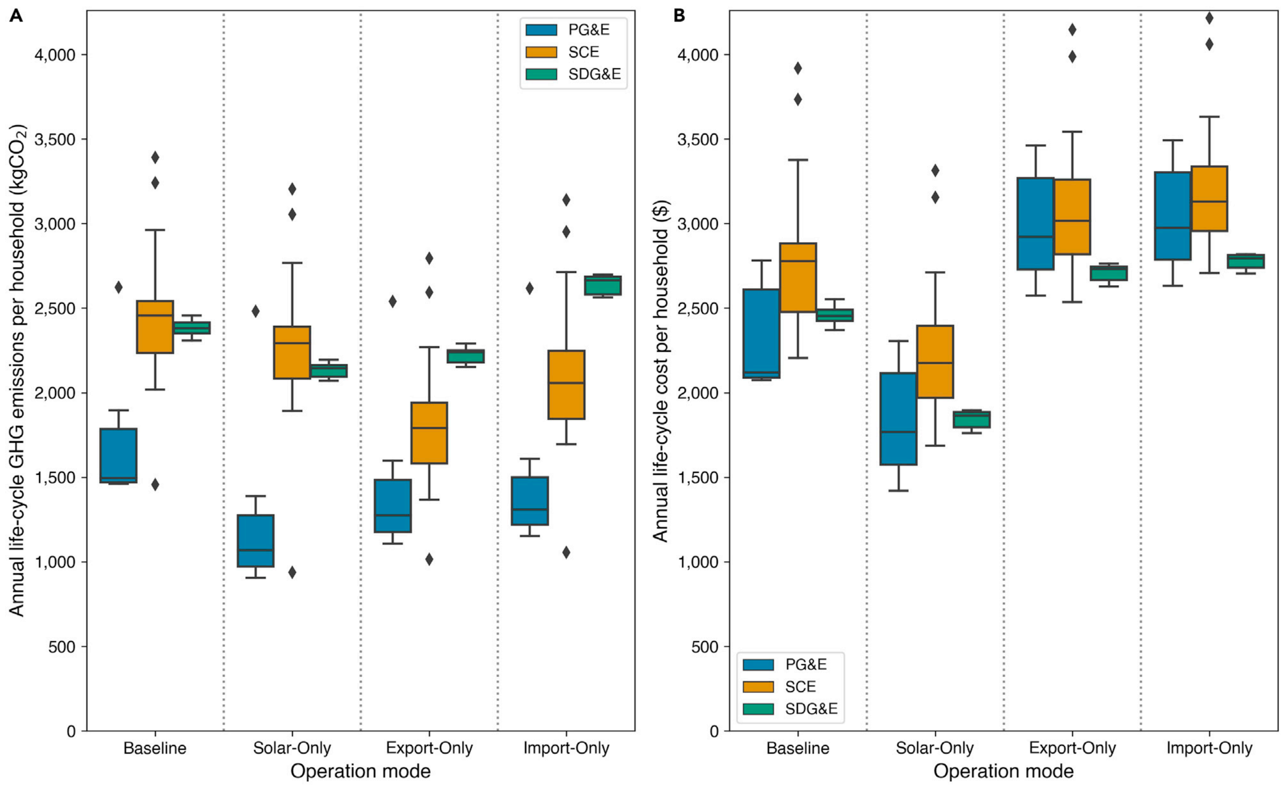

Figure 4. Lifecycle GHG emissions and cost of sampled households in 2020 by utility area in different scenarios

(A and B)(A) Annual lifecycle GHG emissions and (B) annual lifecycle cost. Baseline—households have no PV or storage. Solar-Only—households adopt only solar PV systems. Export-Only—households adopt solar-plus-storage systems with Export-Only mode. Import-Only—households adopt solar-plus-storage systems with Import-Only mode. Results for Export-Only and Import-Only modes are optimized under an objective of minimizing annual utility cost for the household.

mode, however, outperforms both modes of the solar-plus-storage systems by decreasing the lifecycle costs from the baseline scenario by 8%–32% (or \$180–\$730) across all utility areas in 2020.

Breakdown of the lifecycle GHG emissions and cost for representative households with similar annual loads served by each utility is shown in Figures S12–S14. Unconstrained mode leads to slightly lower lifecycle costs for households than Export-Only and Import-Only modes in both 2020 and 2040, but it may lead to more lifecycle emissions than Export-Only mode. A sensitivity analysis on using half- and double-size battery storage is shown in Figure S18. In general, as we increase the battery size from 2.5 kW (0.5X) to 10 kW (2X), the lifecycle GHG emissions increase as the embodied emissions of battery grows, with the exception of SCE, for which the 0.5X case leads to the highest lifecycle emissions. Similarly, the lifecycle cost increases with battery size owing to higher annualized capital cost.

Comparing solar-plus-storage with solar-only systems

The cost of battery storage is expected to decrease, making solar-plus-battery systems increasingly competitive compared with solar-only systems. In addition, the grid will be increasingly decarbonized. These dynamics will significantly affect the extent to which residential solar-plus-storage systems reduce lifecycle GHG emissions and costs, especially when compared with solar-only systems.

We present results from both 2020 and 2040 scenarios to highlight their differences (Figure 5). For 2040, we use estimated long-run MEFs of the grid (National Renewable Energy Laboratory, 2020a) and estimated embodied emissions and capital costs of the systems. For 2040, we keep ToU tariff and load profiles unchanged from 2020, with a goal to illustrate the impacts of electric grid decarbonization on the lifecycle GHG emissions of the systems. We acknowledge that electricity rates would change in the future, and

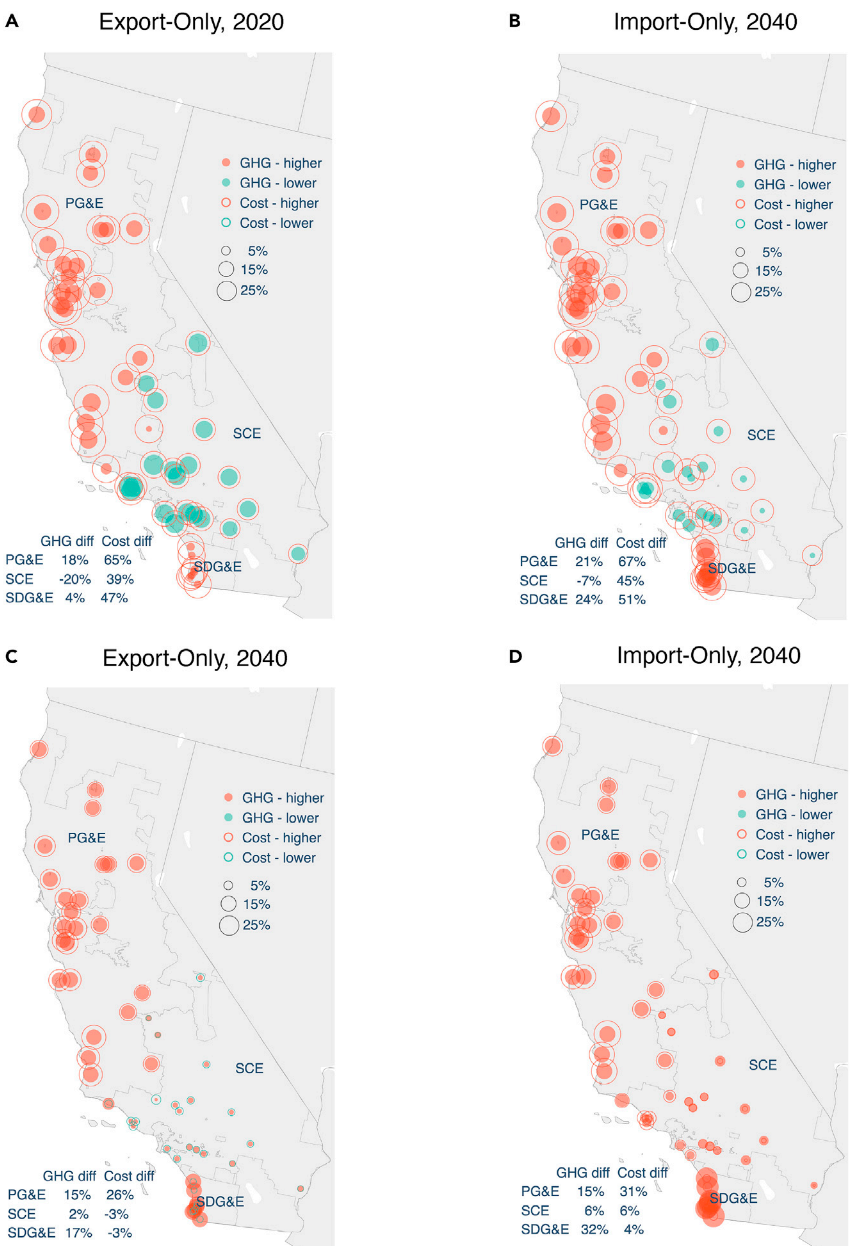

Figure 5. Differences in annual lifecycle GHG emissions and costs between adopting solar-plus-storage systems and adopting solar-only systems for households in California

(A–D)(A) Export-Only mode, 2020; (B) Import-Only mode, 2020; (C) Export-Only mode, 2040; and (D) Import-Only mode, 2040. Results for solar-plus-storage systems are optimized under the objective of minimizing annual utility cost. The tables in lower left summarize average differences for households by utility area. Red color indicates that solar-plus-storage systems lead to higher lifecycle emissions or cost and green means the opposite. Solid circles represent differences in lifecycle GHG emissions, and hollow circles represent differences in lifecycle costs.

potentially be more aligned with the MEFs of the grid as decarbonization progresses. Therefore, as an alternative to today's ToU, we evaluate the performance of the systems with real-time retail prices, which reflect wholesale electricity prices in 2040 (see Figure S17 for results).

To understand if a carbon price can change dispatch behaviors, we also consider a carbon price of \$51/tonne CO_2 in 2020 and \$73/tonne CO_2 in 2040 (Interagency Working Group on Social Cost of Greenhouse Gases, United States Government, 2021), charged in addition to the utility bills of households under the *minCost* objective, to account for the social cost of carbon. An additional objective of minimizing operational GHG emissions (*minGHG*) is also evaluated. Results of these two scenarios are shown in Figures S15 and S16.

Export-Only mode leads to lower lifecycle costs and GHG emissions compared with Import-Only mode across all utilities in both 2020 and 2040. With Export-Only mode, households using SCE *All-Season Wide-Spread* can have on average 20% lower lifecycle GHG emissions than Solar-Only scenario in 2020, but with 39% higher lifecycle costs (Figure 5A). For PG&E *Narrow-Spread*, there are on average 18% higher lifecycle emissions because the small reduction in operational emissions from infrequent dispatching of batteries cannot offset their embodied emissions (Figure S12A). The lifecycle cost is much higher as the small price difference between peak and off-peak hours and the narrow peak-hour window of the ToU result in little savings in utility cost, in addition to the relatively high cost of battery storage. For SDG&E *Summer-Only Wide-Spread*, the emissions and cost reduction from the operational phase cannot offset the annualized embodied emissions and capital cost either. With Import-Only mode (Figure 5B), households served by SCE have lower emissions reduction potential than when Export-Only mode is adopted. For SDG&E, solar-plus-storage systems with Import-Only modes lead to an average of 24% higher lifecycle GHG emissions than solar-only systems.

The distinct results across utility areas can again be explained by their ToU plans, MEFs, and climates. SCE *All-Season Wide-Spread* provides higher incentives for battery dispatch and encourages more charging from on-site solar PV or from the grid during daytime. In comparison, SDG&E *Summer-Only Wide-Spread* incentivizes nighttime charging when MEFs are the highest. In 2020, the variations in MEFs of PG&E area are lower than those of SCE and SDG&E, owing to a higher portion of non-solar renewable energy, such as wind, hydro, and geothermal as marginal generation mix.

In the future, to meet decarbonization targets, more renewable energy and energy storage capacity will be added to the grid. Figures 5C and 5D show the modeled results for 2040 using the estimated capital cost, embodied emissions, and MEFs in 2040. The differences in lifecycle GHG emissions between solar-plus-storage and Solar-Only systems (2%–32%) are higher than 2020, but the differences in lifecycle cost are lower and could potentially be negative (−3% with Export-Only mode) owing to a lower cost of battery storage. With an increasingly decarbonized grid and growing utility-scale storage, the long-run MEFs in the future are much lower and with less variations than those in 2020 (Figures S1 and S2). This change leads to smaller or no reduction in operational GHG emissions from dispatching residential battery storage with the evaluated modes, in addition to their lower but non-trivial embodied emissions in 2040 (Figures S12B–S14B).

Applying a carbon price can reduce the lifecycle emissions of solar-plus-storage systems, especially with Import-Only mode (Figure S15). This is because battery charging is discouraged when carbon-intensive fossil fuels are on the margin, which would incur higher cost for the household. Under *minGHG* objective (minimize annual operational GHG emissions), the lifecycle GHG emissions reduction is much higher for solar-plus-storage systems, but with higher lifecycle cost compared to the *minCost* scenario (Figure S16). As shown in Figure S17, real-time pricing improves upon ToU scenario by reducing both lifecycle GHG emissions and cost in 2040 in both operation modes, showing that MEF-aligned retail prices have the potential to achieve both goals. But, the annualized lifecycle GHG emissions remain greater for solar-plus-storage compared to solar-only installations.

DISCUSSION

Our results show that installing residential solar PV systems in 2020 has the potential to significantly reduce both lifecycle GHG emissions and utility costs of households, using today's ToU rates and NEM policy. Compared with solar-only systems, solar-plus-storage systems are expected to result in 39%–67% higher lifecycle costs for households across California, while their impacts on the lifecycle GHG emissions are mixed, ranging from −20% to 24%, depending on the utility area and operation mode. In 2040, however, solar-plus-storage leads to −3% to 31% higher lifecycle costs and 2%–32% higher emissions than solar-only systems.

ToU tariff design determines residential battery dispatch patterns as households seek to minimize their utility cost. A larger price spread creates cost arbitrage opportunities and motivates households to move toward low-carbon consumption during off-peak hours. To minimize lifecycle GHG emissions, ToU structure should also reflect the marginal emissions of electricity generation in the grid in such a way that households are encouraged to store low-carbon electricity when VRE generation is abundant, and avoid consuming grid electricity when MEFs are high. The NEM policy may change in the future and a lower credit for feed-in could reduce the value of residential solar PV.

Applying a carbon price can improve the alignment between electricity prices and marginal emission factors of the grid and therefore enhance the GHG emissions mitigation potential of solar-plus-storage systems. It would enable more solar PV generation to be shifted and discourage energy consumption from the grid when fossil fuel generators are on the margin. Alternatively, real-time pricing, which is based on the real-time marginal generation cost with a higher temporal resolution than ToU (Matisoff et al., 2020), is more effective in aligning economic and environmental goals as the capacity of low-carbon energy expands, as our supporting analysis shows.

Assuming current lifecycle costs and rate structures, solar-plus-storage systems do not offer savings for most households in California, unless subsidies or tax breaks are implemented. The savings in utility bills through battery arbitrage often cannot compensate for the high upfront cost. However, direct financial incentives such as the Self-Generation Incentive Program in California and the federal investment tax credit (Zinaman et al., 2020) have been used to ease the financial burdens of households and have driven large-scale uptake of such systems. Current NEM policy in California has also motivated the adoption, although a re-evaluation on the feed-in rates is argued as it raises social equity issues (Lukanov and Krieger, 2019). Declining costs of battery storage due to technology improvement and economies of scale would further expedite the installation of solar-plus-storage systems, along with the rapidly growing needs for battery storage as backup power in cases of power outage due to extreme weather events (International Renewable Energy Agency, 2017; Schmidt et al., 2019).

The net GHG emissions from a solar-plus-storage system are determined not only by operational parameters including the marginal electricity generation, ToU rate structure, load profile of the household, and operation mode but also embodied emissions owing to materials production and manufacturing of the system, which contributes as a significant portion. For solar-plus-storage systems to mitigate lifecycle GHG emissions, reducing upstream emissions by advancing energy efficiency and materials efficiency during production, improving round-trip efficiency during operation, and increasing end-of-life reuse and recycling are essential.

In the long run, as a growing portion of VRE and utility-scale storage capacities added to the electricity systems, the MEFs of the grid become lower and less variable, leaving smaller opportunities for residential battery storage to reduce emissions with the two operation modes evaluated. However, with the marginal generation cost and marginal emissions of the grid becoming increasingly temporally aligned owing to the growing penetration of VRE in California, residential battery storage has the potential to reduce utility bills and emissions simultaneously in the future with an unconstrained operation mode.

Distributed energy resources can reduce the total cost and emissions of electricity systems by providing stacked benefits (Clack et al., 2020). Especially, solar-plus-storage can reduce utility-observed peak, prevent curtailment, defer distribution system upgrades, and improve energy resilience. Our study highlights the importance of ToU tariff with wider rate spreads reflective of MEFs, rapid cost reduction of and subsidy for battery storage, and adoption of carbon prices in reducing lifecycle GHG emissions and cost through residential solar-plus-storage systems.

Limitations of the study

There are limitations with the methodology and data used in this study. First, we use the current ToU rates and NEM policy in California, which is subject to change in the future. The conclusions we draw here may not be applicable to regions with substantially different tariff designs or feed-in policies. Second, there are some limitations on the emission factors used, such as omission of transmission losses and distortion of data in the event of outages in the Cambium tool, as described in the reference (Gagnon et al., 2020). Third, although we used the most recent and best available data, there are uncertainties around the future costs and embodied emissions of solar PV and battery systems, depending on technology development and policy implementation, etc. Fourth, in our model, we assumed perfect information of the emissions factors of the grid for optimization. However, this information would not be known to the households until advanced technology which can quickly predict marginal generator(s) is in place. Furthermore, our model is limited to optimize individual households with commonly used power modes currently and cannot simulate complex grid-level power management with households running systems with mixed sizes and operation modes. Lastly, the weather data used by Cambium is 2012, while the load data we used is based on TMY 3 dataset, which is a condensation of several historical years to represent the weather of a typical year.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCE TABLE
- RESOURCE AVAILABILITY
  - Lead contact
  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - Residential load profiles
  - System design
  - Emission factors
  - Capital cost and utility cost
  - Embodied GHG emissions
  - Optimization model
  - Life-cycle cost and GHG emissions
  - Real-Time Pricing in 2040

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2021.103492.

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AUTHOR CONTRIBUTIONS

Conceptualization: J.Z., S.S., and R.D.; Investigation & Methodology: J.Z., Z.L., R.D., S.S., and E.M.; Formal Analysis & Visualization: J.Z.; Writing – original draft: J.Z.; Writing – review & editing: R.D., E.M., and S.S.; Supervision: S.S.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

One or more of the authors of this paper self-identifies as an underrepresented ethnic minority in science. One or more of the authors of this paper self-identifies as a member of the LGBTQ + community.

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SUPPORTING CITATIONS

The following references appear in the Supplemental Information: Barbose et al. (2020); Darghouth et al. (2020), Tesla (2019); Tesla Powerwall Limited Warranty (USA), 2017; Gilman et al. (2018); Gilman et al. (2018); Jordan and Kurtz (2013); Powerwall - Tesla (2020); Schmidt et al. (2017); Barbose et al. (2020); National Renewable Energy Laboratory (2020b); Ellingsen et al. (2014); International Energy Agency (2020); Le Varlet et al. (2020); Intergovernmental Panel on Climate Change (2014); International Energy Agency (2020); Yao et al. (2014); Intergovernmental Panel on Climate Change (2014); National Renewable Energy Laboratory (2020a).

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STAR★METHODS

KEY RESOURCE TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
Python version 3.7	Python Software Foundation	https://www.python.org
Optimization algorithm	This study	See methodology and supplemental information. Code available at https://github.com/cetlab-ucsb/residential_solar_storage
System advisor model (SAM)	National Renewable Energy Laboratory	https://sam.nrel.gov/
Other		
Residential load data	OpenEI.org	https://dx.doi.org/10.25984/1788456
Marginal emission factors data	National Renewable Energy Laboratory	https://cambium.nrel.gov/

RESOURCE AVAILABILITY

Lead contact

Requests for further information should be directed to the lead contact, Sangwon Suh (suh@bren.ucsb.edu).

Materials availability

This study did not generate new physical materials.

Data and code availability

- This paper analyzes existing, publicly available data. These accession numbers for the datasets are listed in the Key Resources Table.
- All original code has been deposited at https://github.com/cetlab-ucsb/residential_solar_storage and is publicly available as of the date of publication.
- Any additional information is available from the Lead Contact upon request.

METHOD DETAILS

Residential load profiles

The residential load profiles in the U.S. are selected from a dataset in OpenEI (Office of Energy Efficiency & Renewable Energy (EERE), 2013). The dataset has a total of 961 load profiles of households in different cities across the United States. Base Load scenario is selected for our analysis, in which the hourly load profiles for a typical one-story house with three bedrooms are simulated using Typical Meteorological Year 3 (TMY 3) weather data. We use the electricity load profiles of 52 households which fall in the electricity service territory of the three major utility companies, PG&E, SCE, and SDG&E in California. We keep the households' load profiles constant for 2020 and 2040 with a purpose to examine the impacts of electric grid transformation on the life-cycle GHG emissions of solar-only or solar-plus-storage systems, and future changes in climates are not considered.

System design

We use the PVWatts simulation tool in System Advisor Model (SAM) model to generate hourly solar PV outputs (Freeman et al., 2018). We assume that the capacity of the solar PV system is 4 kWdc, which is a reasonable size for a three-bedroom house. The PV panels are assumed to have a tilt angle of 20°, an azimuth of 180° and total system losses of 14.08%, which are common settings according to historical data (Barbose et al., 2020; Gagnon et al., 2016). To generate solar PV outputs for households at different locations, the respective weather files are required in SAM model. We downloaded the TMY 3 weather files

(Wilcox and Marion, 2008) from National Solar Radiation Database (NSRDB) (National Solar Radiation Database - Archives, 2021). We modified the LK code script provided by SAM model, ran a sequential batch of simulations iterating the weather files of California TMY 3 locations, generated and exported the hourly solar PV outputs for each household. A degradation rate of 0.5% per year and a lifetime of 25 years is assumed for the solar PV system (Jordan and Kurtz, 2013).

We use the specifications of Tesla Powerwall II to simulate the battery storage system. We assume that one battery is used in the solar-plus-storage systems, with an usable energy capacity of 13.5 kWh and a power rating of 5 kW (Tesla, 2019). The warranty states that the battery system has no less than 70% energy retention at ten years following the installation date, with an operating limitation of 37.8 MWh of aggregate throughput (Tesla Powerwall Limited Warranty (USA), 2017). Based on this, a degradation rate of 3.89% per year is assumed for the battery system for 10 years of lifetime and a limit of aggregate yearly discharge is set as one constraint.

Two power control configurations are modeled for residential solar-plus-storage systems, Export-Only (also known as No Grid Charging) mode and Import-Only (or No Storage Export) mode that are NEM-eligible, based on a recent rule made by California Public Utilities Commission (California Public Utilities Commission, 2019). An unconstrained mode is evaluated in the Supporting Information.

Emission factors

For emission factors of the grid in 2020 and 2040, we use the Average Emission Rates (AER) and Long-Run Marginal Emission Rates (LRMER) from a mid-case scenario in the Cambium tool developed by National Renewable Energy Laboratory (NREL) (Gagnon et al., 2020). AER is the average CO_2 emission intensity of the grid weighted by the generation amount of each technology during an hour, calculated by dividing the total system emissions by the total system supply. LRMER is the CO_2 emission rate of the mixture of generation that would serve a persistent change in end-use demand, taking into account any structural changes to the grid in response to the change in demand (Gagnon et al., 2020). The emission factors for three balancing areas are used, defined as p9, p10 and p11 in Cambium, which covers PG&E, SCE and SDG&E, respectively. There is a slight misalignment in the borderline of the former two areas, i.e., Santa Barbara weather station lies in p9 but is exposed to the ToU rates of SDG&E while Bakersfield station is located in p10 but exposed to the ToU rates of PG&E. Based on the Cambium model, the portion of electricity generated from variable renewable energy (VRE, i.e., solar and wind) in the total generation for p9, p10 and p11 area is 17%, 36% and 28% in 2020, respectively. The VRE portion is projected to increase to 23%, 64% and 64% in 2040, respectively. Representative hourly AER and LRMER values by season in 2020 and 2040 are shown in Figures S1 and S2.

We use AER to calculate the GHG emissions for the baseline scenario, when households have no solar PV or battery system, assuming that they consist part of the existing end-use demand. When households install new solar PV or solar-plus-storage systems, we apply LRMER to the change in net load and feed-in. As a significant number of households install solar-only or solar-plus-storage systems, the new loads or change in load curves would induce structural change in the electricity supply infrastructure within a balancing area. Specifically, the addition of battery storage can help reduce peak demand of the grid and hence the need for fossil fuel peaker plants, enable the storage of more renewable energy and induce higher electricity consumption due to internal energy loss, which combined can alter both the structure and operation of the grid (Yang, 2013).

Capital cost and utility cost

Capital cost is a major component of the life-cycle cost for a household adopting NEM-eligible systems. We assume that the installation cost of residential solar PV systems in California is $3.75/W in 2020, given that the median installed price of such systems before incentives in California was $3.81/W in 2019, and we assume a same price drop (−1.7%) for 2019-2020 with that in 2018-2019 (Barbose et al., 2020). The unit cost is assumed to decrease to $1.41/W in 2040, excluding subsidy or tax rebates, based on the projected cost decrease in NREL Annual Technology Baseline (ATB) on residential solar PV (National Renewable Energy Laboratory, 2020b). For residential battery storage, we use the empirical cost data in 2020 ($670/kWh usable capacity (Powerwall | Tesla, 2020)) and the trend projected in ref (Schmidt et al., 2017) to estimate the cost in 2040 ($185/kWh). All costs in this analysis are in 2019 U.S. dollars. For a detailed list of assumptions on key technical, cost and unit emissions parameters, see Table S1.

Using a life-cycle perspective, we calculate the annualized capital cost of solar PV and battery system based on their lifetimes, shown in Equation 1. Salvage value of the system is not considered.

$$Annual\_cap\_cost_i = Cap\_cost_i \times \frac{r}{1-(1+r)^{-Y_i}} \quad \text{(Equation 1)}$$

In the equation, $i$indicates the device, i.e., solar panels or battery storage. $Cap_cost_i$is the total installed cost of the device,$r$is the assumed discount rate (6.1%) (Feldman et al., 2021) and $Y_i$is the lifetime of solar PV (25 years) or battery storage system (10 years).Annualized cost would be more if a higher discount rate is used.

The NEM Program 2.0 in California allows households with PV panels to export surplus self-generated electricity to the grid and apply credits equivalent to retail prices to reduce their bills on a monthly-basis (California Public Utilities Commission, 2020). We collected the default ToU tariffs in 2020 for NEM participants from three utility companies, i.e., E-TOU-D plan by PG&E (Pacific Gas and Electricity, 2020), TOU-D-4-9PM by SCE (Southern California Edison, 2020) and DR-SES by SDG&E (San Diego Gas and Electric Company, 2020), respectively. In a typical ToU rate structure, a high rate is charged during the peak time (4-9 p.m. or 5-8 p.m.), and lower rates are applied to other hours of the day, which are off-peak or super off-peak times. We did not model the households served by other smaller utility entities. Non-bypassable charges and ontime interconnection fees are not included in our cost analysis.

Embodied GHG emissions

There are extensive LCA studies of battery or battery systems, with a heavier focus on mobile applications (i.e. electric vehicles) than on stationary applications (grid-scale and residential batteries) (Pellow et al., 2020; Le Varlet et al., 2020). Most of the LCA studies have a system boundary of cradle-to-gate, leaving out the use and end-of-life phase due to complexity and lack of data (Peters et al., 2017). For example, a recent LCA study on commercialized residential battery systems reported that the cradle-to-gate GHG emissions are around 200 kg CO_2e per kWh of usable storage capacity(Le Varlet et al., 2020). In our analysis, we use this data to estimate the total embodied GHG emissions of a battery storage system based on its usable storage capacity.

We calculate the annualized embodied emissions of battery storage based on its lifetime, assuming an equal allocation to each year throughout a 10-year lifetime Equation 2.

$$Annual\_emb\_CHG_i = \frac{Emb\_CHG_i}{Y_i} \quad \text{(Equation 2)}$$

Emb_CHG_irepresents the total embodied emissions of device i(solar PV or battery storage)Y_i and is the lifetime of the device (25 years for solar PV and 10 years for battery storage). For solar PV, the unit life-cycle GHG emissions is 48 gCO_2e per kWh of electricity output (Intergovernmental Panel on Climate Change, 2014), and the total life-cycle GHG emissions of a 4-kW solar PV system are calculated by multiplying this unit embodied emissions with the average lifetime total output of the sampled households (in kWh).

We also estimated the embodied emissions of solar PV and battery storage for 2040. The International Energy Agency projects that the global average carbon intensity of power generation would decrease from 440 gCO_2/kWh in 2020 to 282 gCO_2/kWh in 2040 (International Energy Agency, 2020) in a Stated Policies Scenario (STEPS). In the STEPS scenario, future carbon intensities of the U.S. grid are aligned with those modelled in Cambium mid-case scenario. Electricity consumption contributes to 53% and 64% to the life-cycle GHG emissions of a battery pack (Ellingsen et al., 2014) and a solar PV module (Yao et al., 2014), respectively. Assuming that the GHG emissions from non-electricity processes stay unchanged, we estimate that the embodied emissions of battery storage would decrease from 200 to 162 $kgCO_2$e per kWh usable capacity and the embodied emissions of solar PV would decrease from 48 to 37 gCO_2/kWh output from 2020 to 2040.

In Cambium, the emissions rates only account for emissions of electricity generation during the operational phase. So, we calculated the indirect GHG emissions of the grid, i.e., the infrastructure and supply chain emissions for all generation technologies and added them to the model. The indirect emissions factors of the grid by balancing area for 2020 and 2040 are listed in Table S1.

Optimization model

The optimization model dispatches battery storage under two separate objectives: minimizing annual utility cost (*minCost*) and minimizing annual operational emissions (*minGHG*) of the solar-plus-storage system. In addition, we optimize utility cost considering a carbon price that is equivalent to the social cost of carbon (\$51/tonneCO_2 for 2020 and \$73/tonneCO_2 for 2040) (Interagency Working Group on Social Cost of Greenhouse Gases, United States Government, 2021). Under the *minCost* objective, since a certain electricity rate spans across a number of hours, the optimization model may have multiple solutions for a minimal total cost, but the resulting GHG emissions would vary slightly. This difference is small (0.3% for Import-Only scenario and 1.7% for Export-Only scenario on average in 2020), and we show the upper bounds of the life-cycle emissions in the main text. For solar-only systems, no optimization is required. We built the optimization model using Pyomo in Python and solved it as a Mixed Integer Problem using Gurobi Optimizer 9.0.3.

We calculate the life-cycle cost and GHG emissions of the systems based on the optimal battery dispatching solution under a *minCost* objective Equation 3. In an alternative scenario where there is a carbon price, we assume that the carbon cost is charged based on the household's net grid consumption and the hourly average emission factor of the grid:

$$\min Cost = \sum_{h=1}^{8760} ToU_h \times \left(E_{net\_load,h} - E_{feed-in,h}\right) + C\_price \times \left(AEF_h \times E_{net\_load,h}\right) \qquad \text{(Equation 3)}$$

$ToU_h$is the Time-of-Use rate in hour (\$/kWh), $E_{net_load,h}$is the net load of the household in hour (kWh) and $E_{feed\text{-}in,h}$is the surplus electricity fed back to the grid in hour (kWh), $AEF_h$is the average emission factor of the grid in hour h(kgCO_2e/kWh) *C_price*and is the carbon price (0 or social cost of carbon).

We also minimize the annual operational GHG emissions for the solar-plus-storage system, applying MEFs to the change in net load. The objective function is shown in Equation 4, where$E_{load,h}$ is the original load of the household in the baseline scenario in hour (kWh) and $MEF_h$is the long-run marginal emission rates of the grid in hour (kgCO_2e/kWh):

$$\min GHG = \sum_{h=1}^{8760} AEF_h \times E_{load,h} + MEF_h \times \left(E_{net\_load,h} - E_{load,h} - E_{feed-in,h}\right) \qquad \text{(Equation 4)}$$

There are a series of constraints in our optimization model. In Export-Only mode, batteries can charge from solar PV only and export to the grid. In Import-Only mode, batteries can charge from both solar PV and the grid but can only discharge to serve on-site load. With an Unconstrained mode (explored in Supporting Information), there are no direction limits to battery charging or discharging. In all modes, the battery system is set to be 50% charged in the first hour of the year. We assume a 90% round-trip efficiency and impose equal amounts of energy loss during battery charging and discharging. There are other technical constraints for the battery system, for example, the household cannot send surplus PV generation to the grid and pull power from the grid at the same time. There is a yearly discharge limit which allows the battery system to meet the requirement specified in warranty. In addition, the household's load must be met in any hour and the balance of solar PV output must be maintained. For a full list of constraints with notations, see TablesS2–S5.

Life-cycle cost and GHG emissions

In the baseline scenario when households have no solar PV or battery storage installed, annual cost only consists of utility cost, and carbon cost if assumed. When households install only solar PV systems, the annual life-cycle cost includes net utility cost, carbon cost (if any) and the annualized capital cost of solar PV. When households install solar-plus-storage systems, the annual life-cycle cost include the aforementioned components plus the annualized capital cost of battery system:

$$Lifecycle\_Cost_{baseline} = \sum_h ToU_h \times E_{load,h,y} + C\_price \times \left(lcAEF_h \times E_{load,h}\right) \qquad \text{(Equation 5)}$$

$$\begin{aligned} Lifecycle\_Cost_{solar-only} = &\sum_h ToU_h \times \left(E_{net\_load,h,y} - E_{feed-in,h,y}\right) \\ &+ C\_price \times \left[\left(lcAEF_h \times E_{net\_load,h}\right) + Annual\_emb\_GHG_{PV}\right] + Annual\_cap\_cost_{PV} \end{aligned} \qquad \text{(Equation 6)}$$

$$\begin{aligned} Lifecycle\_Cost_{solar+storage} = &\sum_h ToU_h \times \left(E_{net\_load,h,y} - E_{feed-in,h,y}\right) + C\_price \times \left[\left(lcAEF_h \times E_{net\_load,h}\right)\right. \\ &\left. + Annual\_emb\_GHG_{PV} + Annual\_emb\_GHG_{storage}\right] + Annual\_cap\_cost_{PV} + Annual\_cap\_cost_{storage} \end{aligned} \qquad \text{(Equation 7)}$$

The life-cycle GHG emissions of households in the baseline scenario are the direct and indirect GHG emissions from grid electricity consumption. epresents the life-cycle average emission factors in hour including the embodied emissions of grid infrastructure. The life-cycle GHG emissions in Solar-Only scenario include the GHG emissions from grid electricity use, GHG emissions avoidance due to feed-in and the embodied emissions of solar PV. In solar-pus-storage scenario, besides these components, embodied emissions of battery storage are added.

$$Lifecycle\_GHG_{baseline} = \sum_{h,y} lcAEF_h \times E_{load,h} \quad \text{(Equation 8)}$$

$$Lifecycle\_GHG_{solar-only} = \sum_{h,y} lcAEF_h \times E_{load,h} + MEF_h \times \left(E_{net\_load,h} - E_{load,h} - E_{feed-in,h}\right) + Annual\_emb\_GHG_{PV} \quad \text{(Equation 9)}$$

$$Lifecycle\_GHG_{solar+storage} = \sum_{h,y} lcAEF_h \times E_{load,h} + MEF_h \times \left(E_{net\_load,h} - E_{load,h} - E_{feed-in,h}\right) + Annual\_emb\_GHG_{PV} + Annual\_emb\_GHG_{storage} \quad \text{(Equation 10)}$$

The annual life-cycle cost and GHG results in three scenarios are therefore calculated and compared, shown in the main text.

Real-Time Pricing in 2040

In the main text, we assumed the same ToU rates from 2020 to calculate the life-cycle GHG emissions and cost for 2040. However, as we stated, rate reform is under discussion and will likely occur in the future. We therefore develop a set of Real-Time Pricing (RTP) based on the marginal electricity generation cost in 2040, assuming that the carbon cost is internalized in generation cost in the future. In other words, marginal generation cost is reflective of the marginal emissions –RTP is low when renewable energy is on the margin and high when fossil fuels are on the margin.

Cambium provides modelled results for end-use load, generation, imports/exports and generation cost. We use the ToU rates of today to calculate a target total revenue for a certain balancing area, and assume that using a set of RTP would achieve the same target revenue. Equation 11 shows the calculation of RTP:

$$RTP_{i,h} \times Load_{i,h} = Gen\_cost_{i,h} \times \left(Gen_{i,h} + Import_{i,h} - Export_{i,h}\right) + Other\_cost_{i,h} \quad \text{(Equation 11)}$$

In Equation 11, $Load_{i,h}$(MWh) is the end-use load in balancing area $i$in hour h, $Gen\_cost_{i,h}$ is the electricity generation cost ($/MWh), $Gen_{i,h}$is the generation amount (MWh), $Import_{i,h}$is the amount of imported electricity, and $Export_{i,h}$is exported electricity (MWh). $Other_cost_{i,h}$is all other cost including the fixed cost from electricity generation infrastructure, which we assume is proportional to the end-use load in that hour:

$$Other\_cost_{i,h} = \left[\sum_{h=1}^{24\times365} ToU_{i,h} \times Load_{i,h} - \sum_{h=1}^{24\times365} Gen\_cost_{i,h} \times \left(Gen_{i,h} + Import_{i,h} - Export_{i,h}\right)\right] \times \frac{Load_{i,h}}{\sum_{h=1}^{24\times365} Load_{i,h}} \quad \text{(Equation 12)}$$

Then we use the derived hourly RTP to model the 2040 results and compare with those using today's ToU, shown in Figure S17.