Title
Grid Value of Residential Battery Storage When Operated for Solar Self-Consumption

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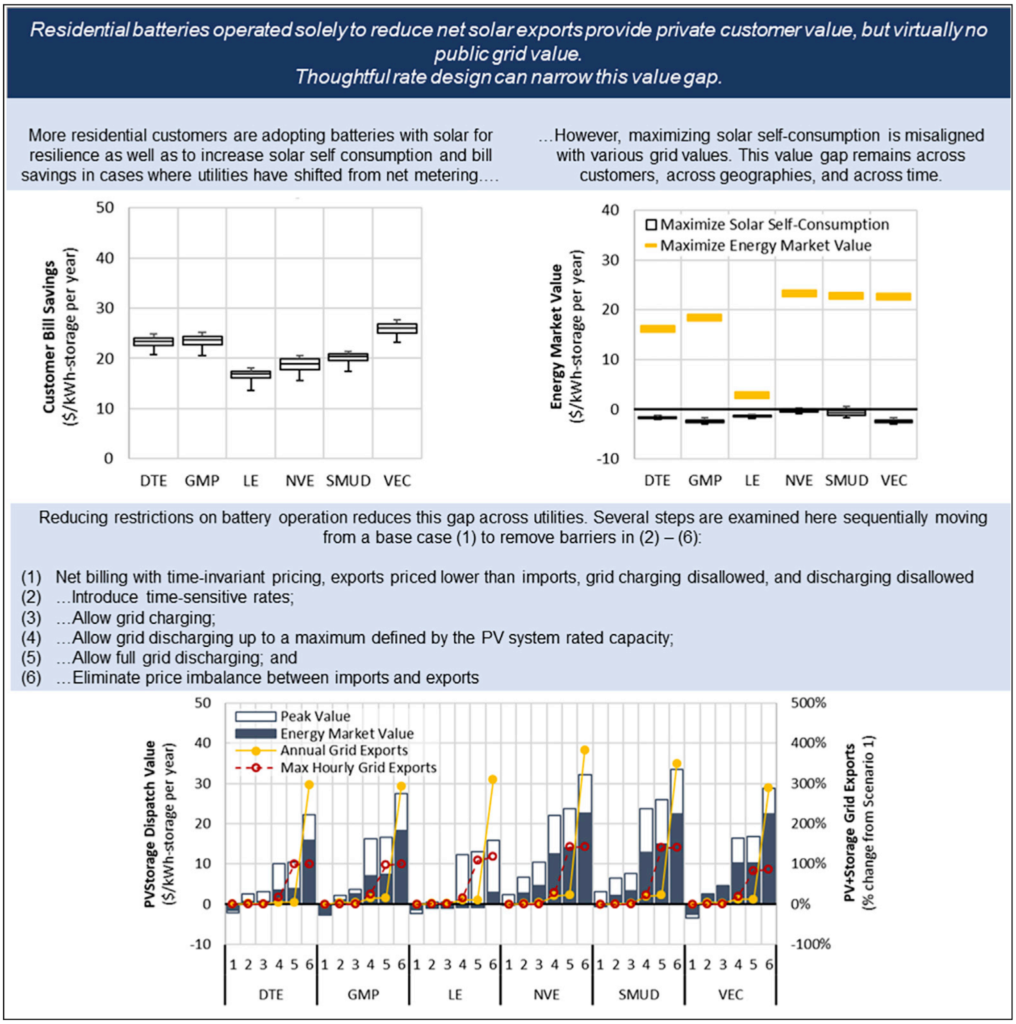

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Highlights

Residential batteries maximizing PV self-consumption provide near-zero grid value

The value gap is largely owing to discharge constraints and idle batteries on peak days

This value gap persists across customers, location, and time

Improved utility rate and program design features can better capture grid value

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Private vs. public value of U.S. residential battery storage operated for solar self-consumption

Sydney Forrester,[1] Galen Barbose,[1,2,*] and Cesca Ann Miller[1]

SUMMARY

Compensation structures for residential solar are evolving toward a model that incentivizes using battery storage to maximize solar self-consumption. Using metered data from 1,800 residential customers across six U.S. utilities, we show that batteries operated solely in this manner provide customer bill savings up to $20–30 per kWh of storage capacity annually, but virtually no grid value. Relative to market-based dispatch, this value gap remains across customers and will become more severe over time, insofar as increased renewable energy penetration leads to more volatile wholesale prices. This inefficiency primarily stems from residential batteries largely sitting idle on peak days. We show that incentivizing storage customers to respond to market prices, particularly on peak days, would enhance both private and public value. Unconstrained grid discharging increases exports to distribution networks, but 50–70% of the potential market value could be achieved without materially degrading solar self-consumption levels or increasing local grid stress.

INTRODUCTION

As direct subsidies phase down, the continued viability of the residential solar photovoltaic (PV) market will increasingly depend on how distributed solar generation is compensated. In the United States, net energy metering (NEM) has been the dominant compensation structure, whereby solar exports to the grid are credited against consumption at the full retail electricity price (Blackburn et al., 2014; Darghouth et al., 2016). This has primarily occurred in conjunction with volumetric retail electricity tariffs with little or no temporal variation. Although distributed solar boasts many benefits, this compensation structure has raised a number of concerns, including the potential for cost-shifting to non-solar customers (Blackburn et al., 2014; Brown and Sappington, 2017; Costello, 2015; Geffert and Strunk, 2017; Picciariello et al., 2015; Satchwell et al., 2015; Sergici et al., 2019). Consequently, many states and utilities are engaged in efforts to reform distributed solar compensation rules to better align with value (Geffert and Strunk, 2017; NC Clean Energy Technology Center, 2021; Sergici et al., 2019).

Net billing has become the de-facto NEM successor in many U.S. states. Net billing allows customers to offset consumption with contemporaneous solar generation, but any surplus generation exported to the grid (typically netted at an hourly interval or less) is credited at a grid export rate below the full retail electricity price, often tied to the utility's avoided costs (NC Clean Energy Technology Center, 2021; Sergici et al., 2019). Currently, some variation of net billing has been adopted in ten U.S. states and has been recently proposed in at least five others (NC Clean Energy Technology Center, 2021). Similar pricing structures have been common outside the U.S. for many years, often under feed-in tariffs that provide sub-retail pricing for exported solar generation (International Renewable Energy Agency, 2019; Masson et al., 2016; Ossenbrink, 2017). The key feature of this type of pricing structure is the asymmetry between export and consumption prices, incentivizing solar customers to minimize grid exports or, equivalently, to maximize solar self-consumption. See Figure S1 for a schematic illustrating the difference between net billing vs. NEM structures.

Concurrent with these regulatory reforms have been rising rates of co-adoption of battery storage by residential solar customers. Currently, 13% of new residential solar installations in the U.S. are now being paired with storage, up from close to 0% five years ago and projected to reach 30% over the next five years (Wood Mackenzie, 2022). To date, virtually all of this growth consists of 2-h duration lithium-ion batteries, typically sold in 5 kW peak power increments. These trends have been driven to a significant degree by customer demand for backup power, but also by direct financial opportunities (Green and Staffell,

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2017). Utilities in a number of states have begun offering programs that provide customers payment for various grid services, such as local congestion relief or peak shaving, and U.S. federal energy regulators have established guidelines for grid operators to provide distributed resources access to wholesale power markets (Forrester and Cappers, 2021). However, the primary source of direct financial benefit in most regions has been retail rate arbitrage via time-of-use (TOU) tariffs or, increasingly, net billing structures that reward the use of storage for solar self-consumption.

Various studies have evaluated the economics of storage for residential solar self-consumption, from different perspectives. For example, Green and Staffell (2017) show that storage installed for solar self-consumption is uneconomic from the private customer perspective, under the U.K. feed-in tariff structure in place at the time (Green and Staffell, 2017). Others, such as Schill et al. (2017) and Say et al. (2020), simulate power system expansion and costs with large amounts of residential storage deployed for solar self-consumption (in Germany and Australia, respectively) and show how it increases total costs, including storage capital costs, relative to the least-cost expansion pathway (Say et al., 2020; Schill et al., 2017). Meanwhile, Fares and Webber (2017) show how storage used for self-consumption increases household energy consumption and power sector emissions for a sample of customers in Texas (Fares and Webber, 2017). A number of studies explore the implications of retail pricing structure, such as Klein et al. (2019), which evaluates the wholesale energy market value of residential storage under rates with time-varying prices and fixed network charges, focusing on the German market (Klein et al., 2019). Finally, other studies have focused on local distribution network impacts, for example by showing how existing tariffs may fail to incentivize charging from solar at times that provide the greatest benefit from relieving over-voltage conditions, or may even exacerbate those conditions (Angenendt et al., 2018; Moshövel et al., 2015; Pena-Bello et al., 2017; Ratnam et al., 2015).

Our analysis brings together many of these threads, drawing on a diverse empirical dataset to examine outcomes and implications within the present-day U.S. context, while exploring interactions with other key features of the regulatory landscape. Relying on metered electricity load data from roughly 1,800 U.S. residential customers from six utilities, we quantify the value of storage operated for solar self-consumption from both the private customer and power system perspectives, considering wholesale energy costs as well as "peak-related" system costs across the generation, transmission, and distribution systems. In doing so, we show how storage operated under net billing structures in the U.S. provides virtually no value to the power system. Though this outcome moderates slightly in futures with higher grid-penetration of renewables, the gap relative to more socially optimal dispatch widens as a result of increasing price volatility. We show how this inefficiency manifests both as a misalignment in the timing of storage dispatch, as well as the tendency of storage operated for solar self-consumption to largely stand idle on peak-load days. We explore how these dynamics are the composite effect of three factors: asymmetric pricing for grid exports and consumption, time-invariant pricing, and constraints (either policy-related or physical) on charging or discharging storage directly to the grid. In doing so, we identify features of a pricing structure that would incentivize much more beneficial storage operating behavior without materially degrading solar self-consumption levels or imposing significantly greater stress on local distribution networks.

RESULTS

Customer-value of storage operated for solar self-consumption

Owing to timing differences between solar generation and customer consumption, residential PV systems typically export a substantial portion of their generation to the grid. To illustrate, Figure 1A shows annual exports for varying PV system sizes, based on metered, hourly interval load data and simulated solar production data for residential customers of six U.S. electric utilities: Detroit Edison (DTE), Green Mountain Power (GMP), Lakeland Electric (LE), Nevada Energy (NVE), the Sacramento Municipal Utilities District (SMUD), and Vermont Electric Cooperative (VEC). Further details on these data are provided in Figure 9 and Table 2 and 3. Across the typical PV system size range and the full set of households, between 47 and 72% of annual generation is exported to the grid (Angenendt et al., 2018). Those values, which are based on exports netted over hourly intervals, would be slightly higher if netted over shorter intervals or instantaneously, as is common practice under many net billing tariffs (see Figure S2).

Solar customers have various options for managing grid exports, including shifting certain end-use loads (e.g., electric heating, cooling, and electric vehicle charging) to coincide with solar production. None of those strategies, however, are likely to offer the same efficacy as battery storage, which can be used to

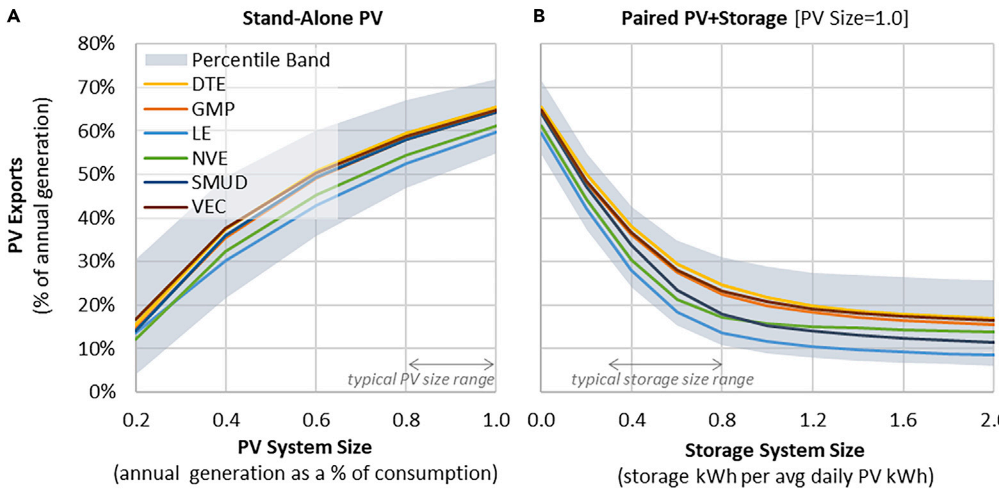

Figure 1. Solar PV grid exports with and without battery storage

(A) shows annual PV exports for systems without storage, across varying PV system sizes, while (B) presents annual PV exports for a relatively large PV system paired with battery storage of varying sizes and operated only to maximize solar self-consumption. PV export percentages are calculated as the sum total of exports within each hourly interval over the course of the year, divided by total annual solar generation. Solid lines represent median values across all customers of each utility, while the percentile bands represent the 5th to 95th percentile range across all customers of all utilities. Solar and storage system sizes are both denoted in normalized units, as described in the axis titles. The figures identify typical ranges for solar and storage system sizes, based on recent market data. Commercially available residential batteries are almost exclusively of approximately 2-hour durations, which is the assumption used for this article. (see STAR Methods for further details).

absorb surplus solar generation during the middle of the day and discharge later to serve customer load (Bronski et al., 2015; Cappers et al., 2013; Luthander et al., 2015). As shown in Figure 1B, storage systems at the upper end of typical size ranges (Darghouth et al., 2020) can reduce solar exports to 11–31% of annual solar generation, based on the percentile range across all households, compared to 55–72% for the same sized solar PV system without storage. Larger batteries would reduce exports furthermore, but with rapidly diminishing returns owing to limits on the amount of nighttime load available for discharging. Additional details on customer-level variability in export levels are provided in Figure S3.

Customer economics of storage for solar self-consumption are driven by the pricing differential between solar exports and self-consumption. Solar export prices set by utilities and regulators are rarely based purely on economics, but rather often reflect some compromise among competing interests or objectives. Abstracting from those considerations, we consider the simple case where export prices are based on average wholesale energy market prices, and self-consumption prices are based on average retail rates for each utility during the particular historical periods analyzed. This yields a relatively wide pricing differential and arbitrage opportunity for storage.

As shown in Figure 2A, annual customer bill savings range from $19–33 per kWh of storage capacity for storage systems at the smallest end of the size range considered, and decline steadily with increasing size (see Figure S4 for sensitivities around PV sizing). Some spread exists across utilities, partly reflecting differences in the size of the transmission and distribution components in retail rates, but as shown in Figure 2B, variations across individual customers of each utility are quite narrow. Given current residential battery storage costs of $700–1,300 per kWh, installing storage solely for solar self-consumption in the U.S. clearly is not an economical customer investment at present, even considering current federal tax incentives (with simple payback periods well beyond the expected 10-year lifetime of a battery) (Barbose et al., 2021b). Rather, residential storage adoption has been and likely will continue to be, driven by a multitude of value streams, of which solar self-consumption may be one key element.

Energy market value of storage operated for solar self-consumption

The value of the electric system of storage operated for solar self-consumption is a composite of various components. At the bulk power system level, marginal changes in operating costs can be measured using

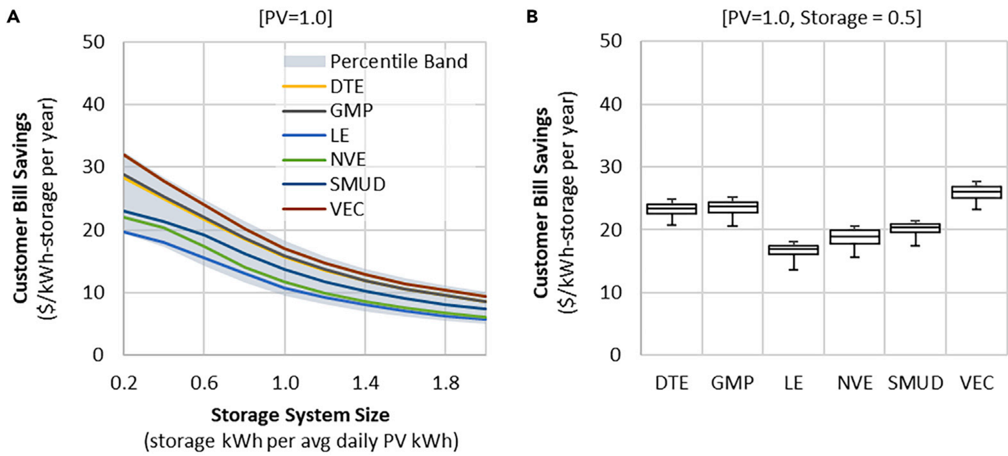

Figure 2. Customer bill savings from operating storage for solar self-consumption

(A) shows annual bill savings across a range of storage system sizes, while (B) presents the distribution in bill savings across customers of each utility, for a storage system sized at 50% of average daily PV generation. Both figures are based on a PV system sized to meet 100% of annual customer consumption. See Table 5 for the equivalent PV and storage system sizes in kW and kWh units for the standard system configuration used in panel (B). The bill savings in both figures are based on arbitraging solar export quantities between average retail and wholesale prices for each utility (see Table 6), with the constraint that only 80% of storage energy capacity can be utilized, in order to maintain minimum and maximum states of charge on the battery. In (A), the solid lines represent median values across all customers of each utility, while the percentile band represents the 5^{th} to 95^{th} percentile range across all customers of all utilities. In (B), the boxes present the 25^{th} to 75^{th} percentile range, and the error bands show the 5^{th} and 95^{th} percentile values across customers of each utility. See Figure 1 caption for the explanation of normalized units used for PV and storage system sizing.

energy-market prices. We evaluate these cost savings using historical energy market prices for the six utilities above, initially considering the most common scenario (in the U.S.) of time-invariant residential retail rates. In this case, customers seeking solely to maximize solar self-consumption will operate their storage systems by charging from surplus solar generation and discharging to meet the net load as soon and as quickly as possible each day, until the state-of-charge (SOC) limit is reached (see Figure 10). We benchmark those results against the energy market value of storage if it were instead dispatched directly against wholesale energy prices, thereby maximizing its energy market value. Under each set of storage dispatch profiles, we compute the energy market value by applying hourly energy market prices to storage discharging and charging in each hour, relying on historical market prices for the same period over which the load data were collected (see Table 4 for the pricing nodes used). The average daily dispatch patterns and wholesale prices are summarized in Figure 3.

The results of this comparison are stark. As shown in Figure 4, storage dispatched to maximize solar self-consumption under time-invariant net billing rates yields a slightly negative energy market value—that is, leads to an increase in costs in the short term. This outcome is remarkably consistent across storage system sizes, utilities, and customers, despite widely varying customer load shapes and wholesale pricing patterns. In comparison, dispatching storage to maximize its energy market value yields an annual value of $16–23 per kWh of storage capacity, for five of the six utilities, which, by chance, is roughly on par with the customer bill savings from operating storage for solar self-consumption. The energy market value for LE is much lower, owing partly to the fact that this utility is not part of a centralized power market, and therefore the energy value is based on hourly marginal operating costs, rather than market-clearing prices, which tend to be more volatile.

The disparity in energy value between these two dispatch cases stems from a persistent misalignment in the *timing* between storage dispatch and marginal system costs. As shown in Figure 3, the timing of discharge coincides loosely with high energy prices for most of the utilities, though typically extends into lower priced hours later in the evening. Charging times, in contrast, coincide quite poorly with the lowest prices of the day, which typically occur in the middle of the night, rather than mid-morning when charging from surplus solar tends to occur.

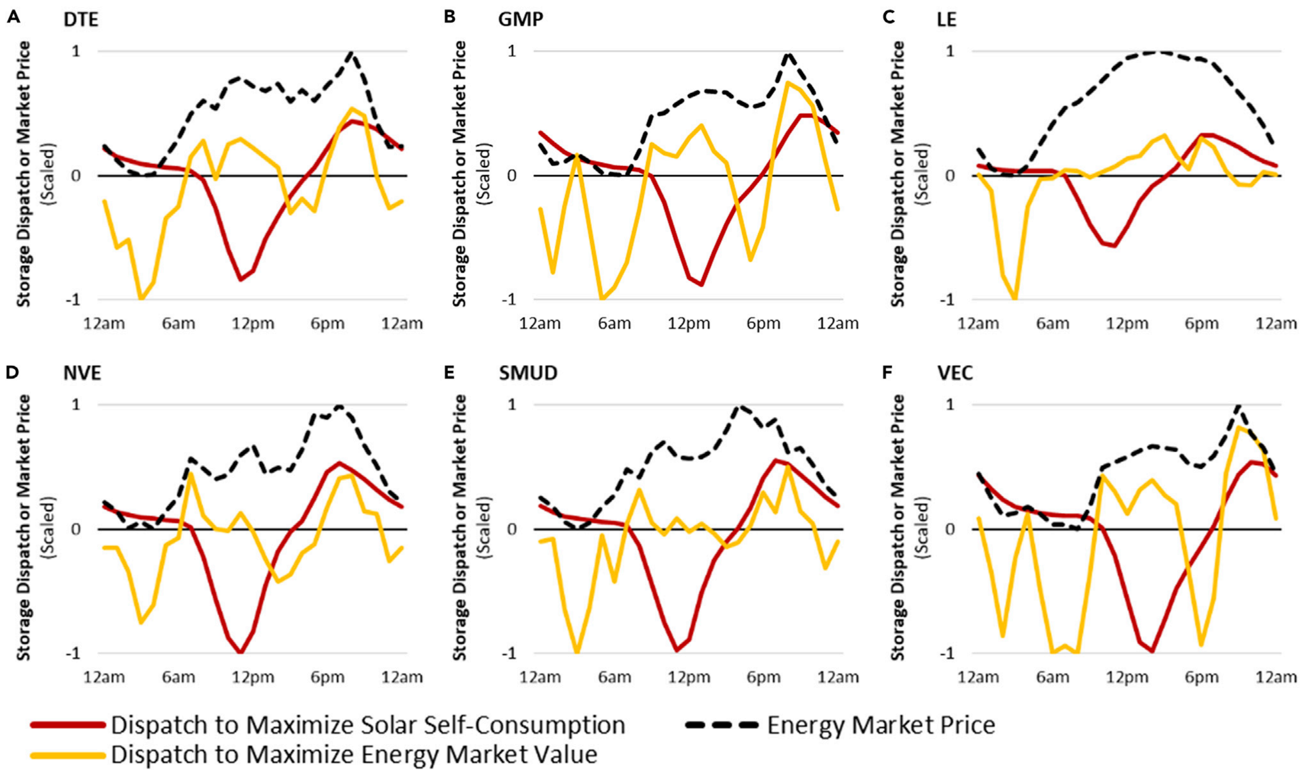

Figure 3. Annual average storage dispatch profiles under alternate dispatch schemes

The figures present annual average storage dispatch profiles for each of the six utilities (panels A-F, respectively), averaged across all customers and all days of the year, along with annual average energy market prices in each hour. Storage dispatch profiles are represented with a positive value for discharging and a negative value for charging, and are normalized to the maximum absolute value of each profile. Similarly, energy market prices are normalized to a max = 1 and min = 0. Note that our simulation of market-based dispatch does not account for cycling fatigue, and therefore tends to produce multiple cycles per day; other studies have shown that accounting for cycling fatigue significantly reduces cycling frequency, but has only a negligible impact on overall market value (Montanes et al., 2022).

Peak value of storage operated for solar-self consumption

A variety of power system costs at the bulk generation and transmission system level, as well as the local distribution network level, are driven by peak demand. Here we consider the value of residential storage in reducing these various peak-related costs (as a composite concept) when operated for solar self-consumption compared to dispatch schemes that instead optimize for peak value. That value is essentially the product of two factors: (a) the coincidence between storage dispatch and system peak and (b) the marginal costs of meeting peak demand.

Coincidence with system peak demand can be measured in various ways. We do so in terms of storage capacity factors during peak load hours, for both the bulk power system and local distribution network, over peak periods of varying durations (from the top-10 to top-100 h). This approach corresponds to how generation and transmission capacity costs are often allocated to network users, and how end-use customers are often compensated under peak demand reduction programs. Figure 5A shows capacity factors under each of these peak-period definitions. Though there are some notable differences across utilities and individual customers, capacity factors are generally <20% relative to bulk-system peak periods and <30% for distribution-system peak periods. The values are higher in the latter case, as the distribution feeder loads in our analysis are assumed to be populated by residential customers.

While it would be tempting to attribute this disconnect to a simple misalignment between the timing of storage discharge and system needs, as in the case of the energy value, that is not the primary factor. Rather, the primary cause is that storage operated solely for solar self-consumption tends to stand idle on peak load days. This occurs for the simple reason that individual residential loads tend to peak on the same days when the power system peaks, and relatively little surplus solar energy is, therefore, available

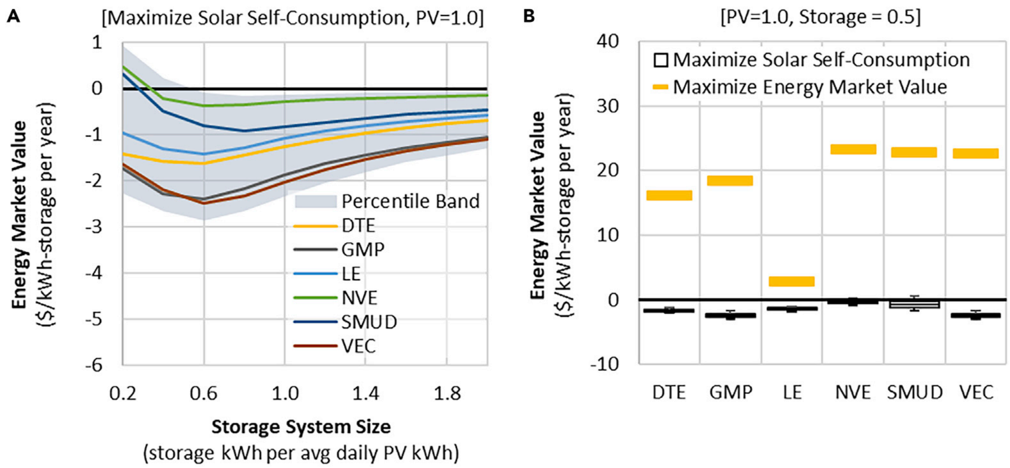

Figure 4. Energy market value of storage operated to maximize solar self-consumption

(A) shows the energy market value of storage dispatched to maximize solar self-consumption under time-invariant net billing rates, across a range of storage sizes, while (B) compares the energy value of that dispatch scheme, for a standard system configuration, to one in which storage is dispatched to maximize its energy market value. The energy value in that latter case is invariant across system sizes and customers, and thus a single point value is provided for each utility. See Figures 1 and 2 captions for further explanations of figure construction and nomenclature.

on those days to fuel storage dispatch. This is illustrated in Figure 6, which shows storage dispatch profiles on each utility's single peak-load day. As shown, storage cycling under self-consumption-based dispatch is quite shallow compared to market-based dispatch, where storage is fully discharged to its maximum power capability during the system's peak hour. In addition, the timing of discharge is also generally misaligned with peak demand, though the degree of misalignment differs across utilities. In the case of NVE and

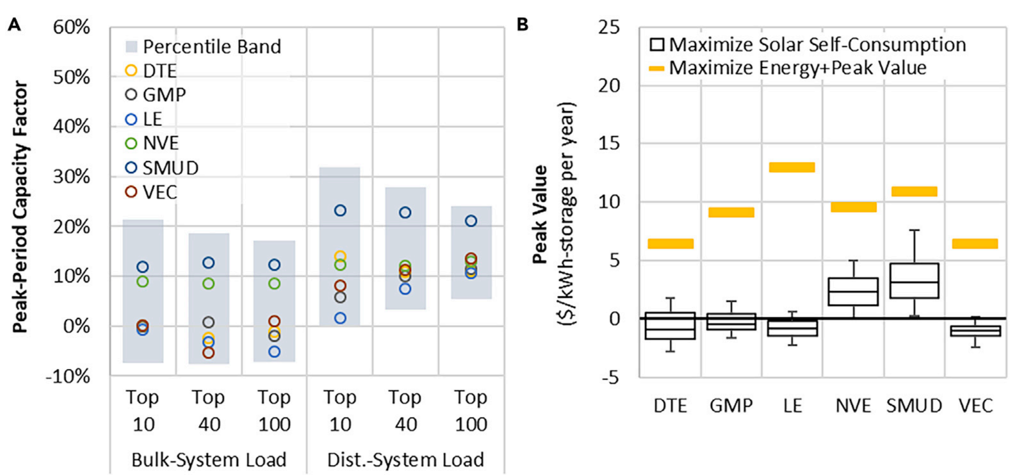

Figure 5. Peak-period capacity factors and peak value of storage operated for solar self-consumption

(A) shows peak-period capacity factors of storage operated for solar self-consumption under alternate peak-period definitions, based on either the bulk-power system load or the local distribution system load, and across the top-10, -40, or -100 hours. The circles represent median values for each utility, while the percentile bands show the range between the 5th to 95th percentile across all customers of all utilities.

(B) compares the peak value of storage dispatched for solar self-consumption relative to its value if dispatched to maximize its combined peak and energy-market value. Those peak values are based on a $50/kW-yr marginal capacity cost, allocated across the top-40 bulk-power system load hours. This is operationalized within the dispatch logic and dispatch value calculations by distributing the marginal capacity cost across the top-40 load hours, in the form of a per-kWh adder layered on top of the energy price. In (B), the boxes present the 25th to 75th percentile range, and the error bands show the 5th and 95th percentile values across customers of each utility. Both figures are based on the standard PV + storage system configuration assumed elsewhere; Figure S5 presents a sensitivity case across a range of both PV and storage system sizes.

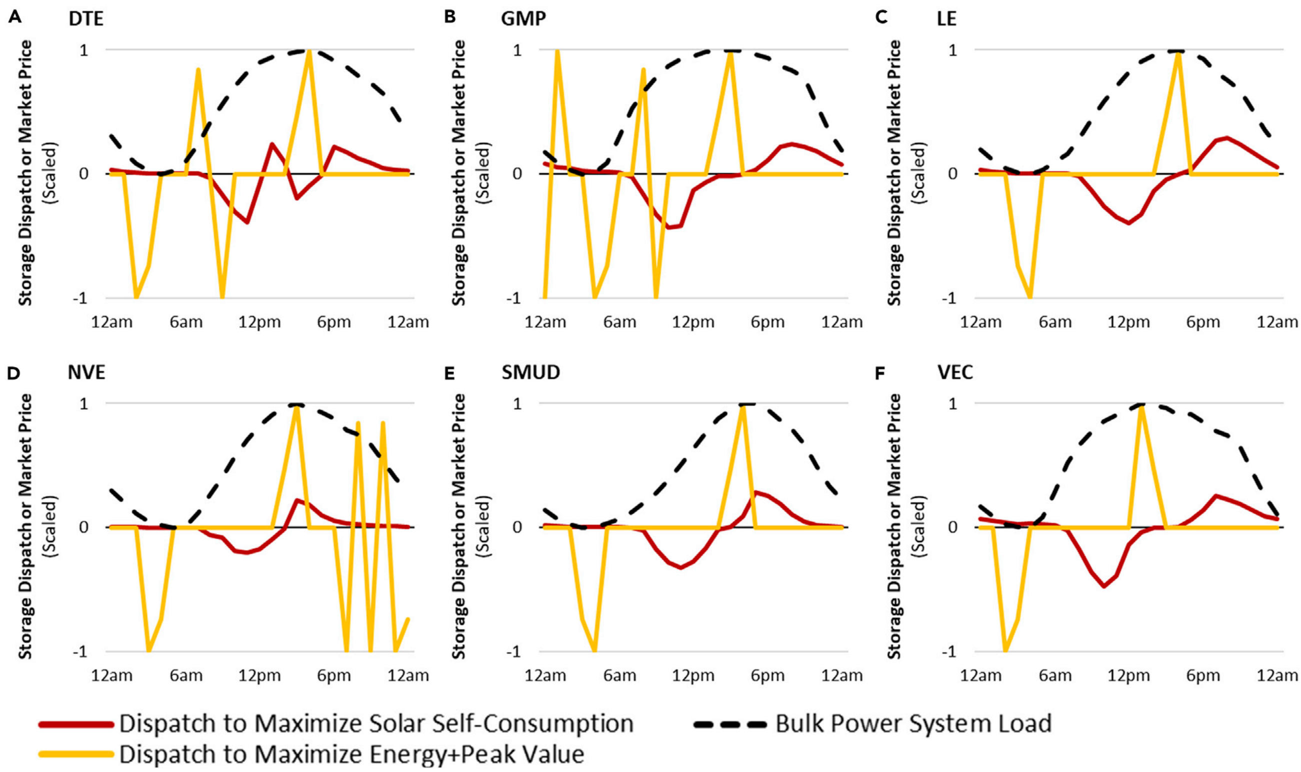

Figure 6. Peak-day storage dispatch profiles under alternate dispatch schemes

The figures present storage dispatch profiles for each of the six utilities (panels A-F, respectively), on their single peak-load day, averaged across all customers and all days of the year, along with the system load profile for that day. Storage dispatch profiles are represented with a positive value for discharging and a negative value for charging, and are normalized to the maximum absolute value of each profile. Similarly, system loads are normalized to a max = 1 and min = 0. These results are based on the standard PV + storage system configuration used elsewhere.

SMUD, both have heavy residential cooling loads that shift the timing of storage discharge to partially overlap with the system peak, leading to the non-zero capacity factors observed in Figure 5A.

The efficiency implications of these dynamics are illustrated in Figure 5B, which compares the peak value of the storage dispatch profile when operated for solar self-consumption vs. when operated to maximize its peak plus energy value. For the purpose of this comparison, we rely on a peak period defined over the top-40 bulk system net-load hours for each utility and a marginal cost of $50/kW-year to meet peak demand. That latter value corresponds roughly to prices currently observed in many U.S. generation capacity markets and is within the range observed in other bulk power and distribution system peak-load reduction applications (see Table S4).

Consistent with the capacity factor results, the peak value of storage operated for solar-self consumption is roughly zero for virtually all customers of four of the six utilities. For NVE and SMUD, values are generally positive and exhibit greater spread across customers, but are well below the potential when dispatched to maximize peak value, which is represented in our dispatch model as an increase in the hourly market price during peak period hours (see STAR Methods). Of particular note is that the potential peak values, when combined with the potential energy market values illustrated earlier (Figure 4B), are greater than the upper bound of bill savings that customers generate by managing solar self-consumption under net billing rates (Figure 2B). This suggests the potential for a significant Pareto improvement by replacing inefficient net billing structures with market-based pricing for storage.

Decomposing the value gap

The preceding analysis points to two key sources of inefficiency in typical net billing structures for distributed solar and storage: (1) the asymmetry in pricing between exports and self-consumption and (2) time-invariant pricing for both exports and self-consumption. Later in discussion, we disentangle the relative

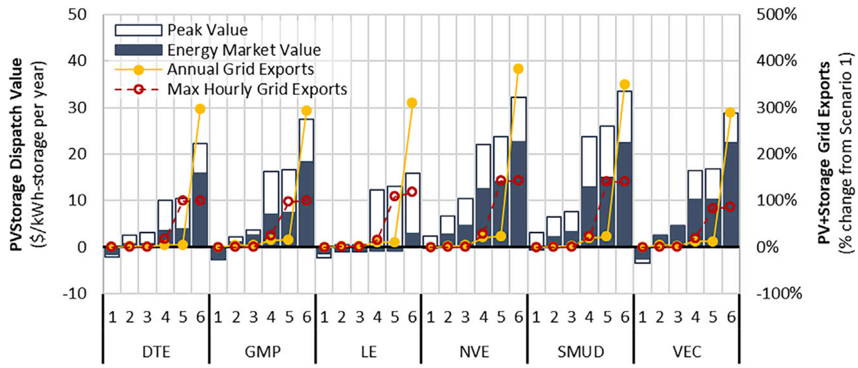

Figure 7. Storage dispatch value and grid exports under sequential tariff scenarios

Numbers along the x-axis refer to the scenarios described above. Plotted values are medians across all customers of each utility. Annual grid exports and maximum hourly grid exports are denominated as a percentage change from Scenario 1.

effects of each of those factors, along with a separate set of issues related to constraints on whether storage can charge from or discharge to the grid. Those constraints can arise separate from any price-based effects, as a result of interconnection limits, tariff provisions, tax incentives, or inverter sizing (in the case of DC-coupled systems).

To isolate the relative significance of each of these factors, we compare the market value of storage dispatch profiles across a structured sequence of scenarios that move incrementally from standard net billing with time-invariant pricing to full market-based dispatch. The sequence of scenarios is as follows:

- Scenario 1: Net billing with time-invariant pricing
- Scenario 2: Hourly varying prices for both exports and consumption, with a fixed volumetric adder for network costs applied to consumption prices, and no grid charging or discharging allowed
- Scenario 3: Same as Scenario 2, but with grid charging allowed and no grid discharging
- Scenario 4: Same as Scenario 3, but with limited grid discharging, such that hourly PV + storage exports are capped at PV nameplate capacity (essentially a lower bound for DC-coupled systems when the inverter is sized to the PV component)
- Scenario 5: Same as Scenario 3, but with no constraints on grid discharging
- Scenario 6: Full market-based dispatch (i.e., same as Scenario 5, but with no T&D adder)

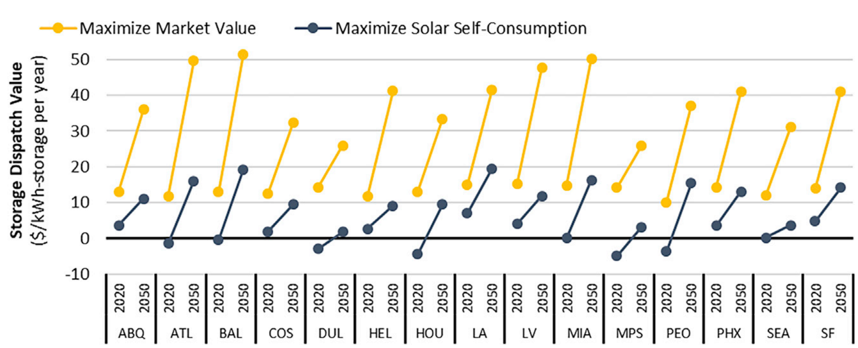

Figure 8. Changes in storage dispatch value under a low renewables cost future

The figure shows changes in projected storage dispatch value from 2020 to 2050 when operated either to maximize solar self-consumption under a net billing tariff with time-invariant rates or to maximize its market value. The value under each dispatch scheme and time period is computed for 24 distinct residential load profiles in each of the 15 locations shown, and the values plotted are averages across those individual profiles. These results are based on our standard system configuration.

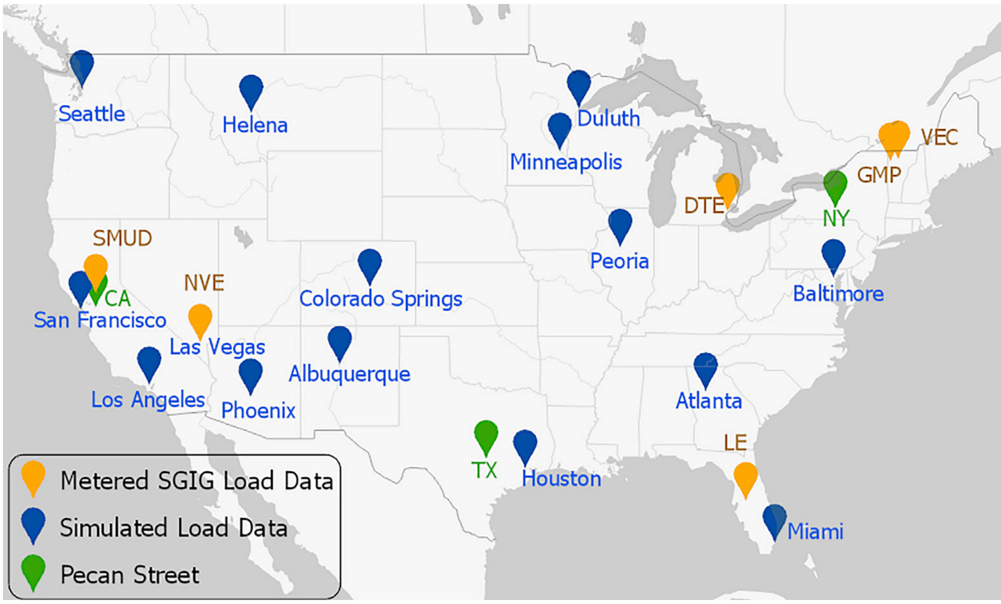

Figure 9. Customer load data locations

The map identifies the locations represented among the three sources of customer load data used within this analysis. For the metered SGIG load data, the locations are based on utility service territories, while the simulated load data are for particular cities, and the Pecan Street data come from three different states (with individual customers dispersed across those states). The core analysis utilizes the metered SGIG data while the forward-looking analysis is based on the simulated load data. Pecan Street data are used in Figure S2 to illustrate the impacts of using data netted at hourly versus 1-min intervals.

Further details are provided in Table 7. Several additional scenarios are presented in Figures S7 and S8 (one with time-of-use rates and another where we reverse the sequence in which grid charging and discharging constraints are lifted). The market value in this comparison includes both an energy market value and a separate peak value, based on the same set of assumptions as in Figure 5B. We also compare total annual grid exports, in order to show changes in solar self-consumption levels, as well as changes in the maximum hourly grid exports, which provide an indication of potential impacts on the local distribution network.

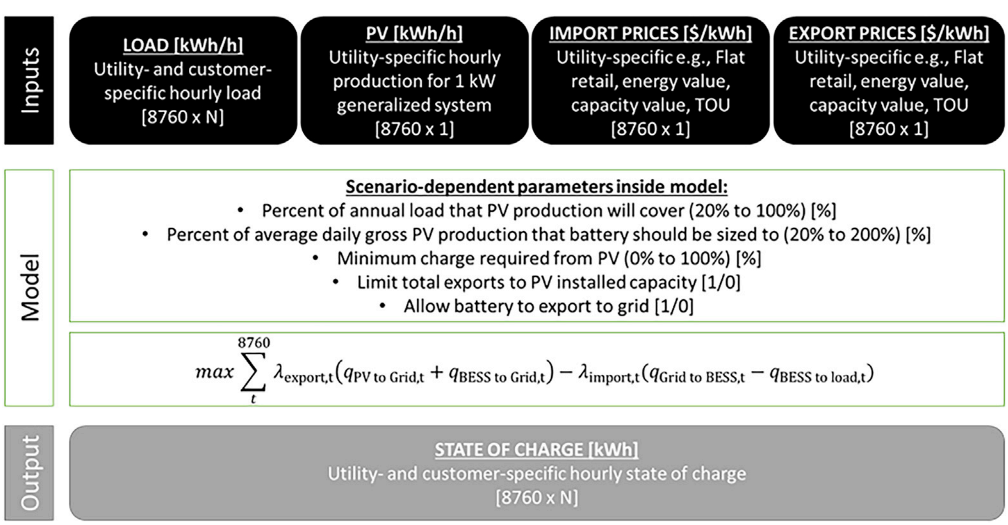

Figure 10. Model inputs, scenario parameters, and outputs

Table 1. Price variability and storage capacity factors over time

Location	Coefficient of variation for hourly market prices		Average storage capacity factor in top-40 h			
			Maximize solar self-consumption		Maximize market value	
	2020	2050	2020	2050	2020	2050
Albuquerque, NM	2.5	6.5	17%	19%	36%	59%
Atlanta, GA	2.2	5.3	−5%	23%	30%	71%
Baltimore, MD	2.1	5.2	0%	25%	30%	71%
Colorado Springs, CO	2.4	6.4	11%	17%	50%	46%
Duluth, MN	2.7	8.5	−6%	3%	35%	46%
Helena, MT	2.5	7.1	18%	19%	54%	76%
Houston, TX	1.9	6.7	−15%	18%	45%	62%
Los Angeles, CA	2.7	5.4	27%	29%	50%	60%
Las Vegas, CA	2.8	6.8	17%	19%	54%	76%
Miami, FL	2.1	5.1	5%	21%	45%	82%
Minneapolis, MN	2.7	8.5	−9%	5%	35%	46%
Peoria, IL	2.0	6.4	−12%	21%	24%	53%
Phoenix, AZ	2.7	5.9	12%	18%	36%	59%
Seattle, WA	2.8	6.1	5%	8%	58%	62%
San Francisco, CA	2.6	5.3	20%	21%	50%	60%
Average	*2.5*	*6.3*	*6%*	*18%*	*42%*	*62%*

Coefficient of variation provides a rough measure of overall price variability, and is calculated here based on the sum total of hourly energy plus capacity prices. Storage capacity factors are the averages across the 24 customer load profiles at each location and are calculated over the top-40 net-load hours, as the average net storage discharge during those hours divided by the nameplate storage power capacity. Even under market-based dispatch, capacity factors are constrained by the minimum and maximum state of charge limits assumed for the batteries. The values presented in the table are the averages across 24 customer load profiles at each location.

The results of this sequential analysis are summarized in Figure 7. Several key findings emerge. First, the effect of time-invariant pricing on storage dispatch patterns for solar self-consumption is relatively small in isolation, as evident by the small changes in value from Scenarios 1 to 2. That is, even in the best-case scenario when charging from solar and discharging to serve onsite load occur at the best available times from a bulk power system perspective, operating storage simply to maximize solar self-consumption yields little to no value.

Second, restrictions on grid discharging can significantly constrain the realization of market value from time-varying pricing, whereas restrictions on grid charging are not nearly so impactful. This is particularly acute for peak-related value, which is concentrated (by definition) within a relatively small set of hours; capturing that value requires that storage can freely discharge during those hours. The same is true to a lesser extent for energy value as well. Grid discharge outside of those peak load or peak pricing hours is quite limited, as evident by the negligible change in annual grid export levels between Scenario 3 and Scenarios 4 and 5, indicating that solar self-consumption levels are virtually unchanged.

Yet, allowing storage to discharge to the grid raises the possibility of added stress on the local distribution network, particularly on feeders with large amounts of distributed PV and storage. What is notable is that the "limited" grid discharging case (Scenario 4) achieves almost equivalent value to full discharge (Scenario 5), but with a substantially smaller increase in the maximum hourly export levels. In the case of Scenario 4, the median dispatch value across the utilities ranges from \$10–23 per kWh of storage capacity and roughly 50–70% of the potential value under full market-based dispatch.

Finally, the incremental effect of asymmetric pricing—represented here as a fixed adder applied to hourly market prices charged for consumption—is to suppress much of the routine daily energy-arbitrage cycling that would occur under full market-based dispatch. This can be inferred from the large uptick

Table 2. Time series data used within the analysis

Data type	Source	Description	Use
Customer load profiles	Smart Grid Investment Grant (SGIG) Consumer Behavior Studies (Cappers et al., 2013)	Metered, hourly-interval loads for a sample of 1,749 customers in six utility service territories, collected from 2012 to 2013	Used to represent customer loads in the core analysis
	Simulated load data (Darghouth et al., 2020)	Simulated, hourly loads for 24 different residential building types in 15 cities, modeled with the U.S. DOE's EnergyPlus building simulation model, using 2012 weather data	Used in the forward-looking analysis, in conjunction with the Cambium market price forecasts, also based on the 2012 weather year
	Pecan Street (Pecan Street Inc., n.d.)	Metered, 1-minute-interval net load data for a sample of 265 solar customers in 3 states, from 2020	Used in the sensitivity analysis in Figure S2, to illustrate the impact of netting interval on measured PV exports
Solar generation profiles	Simulated solar generation profiles (National Renewable Energy Laboratory, 2020)	Hourly solar PV production, simulated using NREL's System Advisory Model (SAM), for each of the locations and time periods represented within the SGIG and simulated load data	Used to represent hourly solar generation in the core analysis (paired with SGIG load data) and in the forward-looking analysis (paired with simulated load data)
	Pecan Street (Pecan Street Inc., n.d.)	Metered, 1-minute-interval solar generation data for a sample of 265 solar customers in 3 cities, from 2020	Used in the sensitivity analysis in Figure S2, to illustrate the impact of netting interval on measured PV exports
Utility system load profiles	ABB Ventyx Velocity Suite (Hitachi, n.d.)	Hourly loads for the balancing authority and time period corresponding to each SGIG dataset	Used to identify the top load hours, over which marginal generating capacity costs were allocated for peak value in the main analysis
Historical energy market prices	ABB Ventyx Velocity Suite (Hitachi, n.d.)	Hourly real-time energy market prices (or, for Lakeland Electric, utility hourly system lambda values)	Used to represent the marginal energy value in the core analysis
Simulated energy and capacity market prices	NREL Cambium (Gagnon et al., 2020)	Simulated hourly marginal energy and capacity prices, under NREL's 2020 Standard Scenarios Mid-Case, for each year from 2018 to 2040, in each of the balancing areas corresponding to the 15 locations covered by the DOE Proto-type Building Models	Used to represent marginal energy and peak values (generation capacity value) in the forward-looking analysis

in annual grid exports from Scenarios 5 to 6. This has no effect on peak value, but reduces realized energy market value by \$4–12 per kWh of storage across the six utilities. The magnitude of this effect depends on the size of the diurnal spread in energy prices, and how that compares to the pricing asymmetry between exports and self-consumption. To the extent the latter exceeds the former, it will suppress energy price arbitrage.

Assessing the persistence of the value gap in high-solar futures

There is reason to suspect that the inefficiency of storage operation for solar self-consumption could become less acute over time, particularly with rising grid-penetration of solar (both distributed and utility-scale). In such a future, energy market prices will resemble the proverbial "duck curve": low during the middle of the day when aggregate solar generation on the grid is peaking, and high during late afternoon and evening hours after solar generation has ramped down and the utility system's net load is at its peak (Seel et al., 2018). This price profile may coincide reasonably well with the dispatch profile of storage

Table 3. SGIG data used in this analysis

Utility	State	Start date	End date	Sample size	Percent of hours interpolated
Detroit Edison (DTE)	MI	09/09/2012	09/08/2013	229	0.02%
Green Mountain Power (GMP)	VT	5/16/2012	5/16/2013	294	0.45%
Lakeland Electric (LE)	FL	4/16/2012	4/16/2013	284	0.74%
NV Energy (NVE)	NV	1/1/2013	12/30/2013	342	0.00%
Sacramento Municipal (SMUD)	CA	1/1/2012	12/30/2012	300	0.03%
Vermont Elect. Co-ops (VEC)	VT	12/22/2012	12/22/2013	300	0.20%

operated to maximize solar self-consumption, where storage typically charges from exports during the middle of the day, and discharges to meet onsite load during late afternoon and evening hours (as observed earlier in Figures 3A–3F).

To test this hypothesis, we compute storage dispatch value under both net billing with time-invariant pricing and market-based dispatch, using modeled hourly market prices generated from the National Renewable Energy Laboratory (NREL)'s Cambium model, which includes both a capacity expansion module and an hourly production cost model of the U.S. electric power system, disaggregated into separate 134 balancing areas (Gagnon et al., 2020). We rely specifically on hourly energy and capacity prices from the 2020 Cambium "Low Renewables Cost" case, where U.S. solar generation rises from 4% of total electricity generation in 2020 to 29% in 2050, while combined solar-plus-wind penetration reaches 60% of electricity generation. We compute storage dispatch using simulated hourly residential load profiles and solar generation profiles for specific 15 cities for a standard set of residential building models that were available for the same weather year (Darghouth et al., 2020). The same default PV and storage system sizes are assumed here as in the previous section.

As shown in Figure 8, the market value of storage operated for solar self-consumption rises over time, consistent with the expectations above. On average across the 15 study locations, market value increases by about \$10 per kWh of storage capacity annually over the 2020–2050 time frame, reaching \$2–19 per kWh depending on the location. Yet, the value under market-based dispatch rises by an even greater amount, by roughly \$26 per kWh on average, reaching \$26–51 per kWh in 2050. Thus, the value gap widens and storage operated for solar self-consumption becomes increasingly inefficient from a bulk power system perspective as grid-penetration of renewables grows.

The basic reason for this widening gap is that market prices become significantly more variable over time with more extreme price spikes, which manifest in NREL's Cambium model partly in terms of increasing generation capacity prices during the top-40 h. This dynamic has been documented elsewhere in the literature, and can be seen in Table 1 as well as a further broken-down summary in Table S2, which shows a steep rise in the coefficients of variation of hourly prices (Jenkin et al., 2016; Seel et al., 2018). At the same time, storage discharge during high-price periods increases at a greater rate when dispatched directly against market prices than when dispatched for solar self-consumption. This can be seen by comparing average storage capacity factors during the highest priced hours and reflects the dynamic discussed previously, where storage operated for solar self-consumption tends to have shallow cycles on peak load days, owing to the limited quantity of surplus solar available for charging.

Table 4. ABB Ventyx Velocity Suite transmission zones and energy pricing nodes used for each SGIG utility

Utility	Transmission zone	Representative energy market price node
DTE	Detroit Edison Company	DECO.RES.CNE
GMP	ISO-NE – Vermont	LD.N_RUTLND46
LE	Florida Municipal Power Pool (FMPP)	n/a (used published system lambda for FMPP)
NVE	Nevada Power Co	SUMMIT_ASR-APND
SMUD	Balancing Authority of Northern California	HURLEYS_2_N001
VEC	ISO-NE – Vermont	LD.STOWE 34.5

Table 5. Solar and storage system sizes under standard Configuration assumptions

Load data	Utility/Location	PV system size (kW)	Storage size (kWh)
SGIG	DTE	6.6 (2.9–14.4)	11.8 (5.2–25.8)
	GMP	4.9 (2.0–10.7)	8.6 (3.4–18.7)
	LE	8.1 (2.5–15.9)	18.0 (5.5–35.2)
	NVE	7.9 (2.6–21.4)	18.2 (6.0–49.3)
	SMUD	4.6 (1.7–10.2)	10.7 (4.1–23.8)
	VEC	5.9 (3.0–11.7)	9.8 (4.9–19.3)
Simulated	Albuquerque, NM	4.4 (3.2–7.6)	11.5 (8.4–20.0)
	Atlanta, GA	5.1 (3.9–8.2)	10.8 (8.1–17.1)
	Baltimore, MD	5.7 (4.0–10.3)	11.3 (8.0–20.5)
	Colorado Springs, CO	4.7 (3.2–8.9)	11.4 (7.7–21.4)
	Duluth, MN	7.2 (3.9–15.8)	13.3 (7.2–29.3)
	Helena, MT	6.7 (3.8–14.2)	12.1 (6.9–25.8)
	Houston, TX	5.6 (4.5–7.3)	12.0 (9.6–15.6)
	Los Angeles, CA	4.3 (3.3–6.5)	10.5 (8.1–15.8)
	Las Vegas, CA	4.8 (3.6–7.6)	12.1 (9.2–19.1)
	Miami, FL	5.9 (4.9–6.8)	13.4 (11.2–15.6)
	Minneapolis, MN	6.7 (4.0–14.0)	12.8 (7.7–27.0)
	Peoria, IL	5.9 (4.0–11.0)	12.0 (8.1–22.5)
	Phoenix, AZ	5.4 (4.4–7.0)	13.7 (11.2–17.8)
	Seattle, WA	7.2 (4.7–14.0)	10.3 (6.8–20.0)
	San Francisco, CA	3.8 (2.7–7.6)	8.8 (6.3–17.4)

Solar and storage system sizes are provided in terms of medians (and 5th-95th percentile values), across all customers in each location, under our standard system configuration, which assumes that each PV system is sized to generate the equivalent of 100% of each customer's annual energy consumption and each storage system is sized so that its energy capacity is equal to 50% of average daily solar generation.

DISCUSSION

This study highlights a key shortcoming in current tariff reforms for residential solar PV that will become increasingly problematic as residential battery storage becomes more prevalent. Those reforms encourage the use of storage to maximize solar self-consumption. Yet, as we show, storage operated solely for that purpose provides effectively no value to the power system in terms of avoided energy or peak-demand-driven costs. This finding is highly consistent across individual customers and utilities. A significant source of this deficiency is that storage operated only for solar self-consumption largely sits idle on peak-load days. Moreover, as grid-penetration of renewables grows over time, the shortcomings of operating storage for solar self-consumption may become more severe, insofar as electricity prices become more volatile and/or a larger portion of system costs is recovered through capacity-based markets and other peak-driven programs.

Table 6. Consumption and export prices for time-invariant net billing

Utility	Retail rate ($/kWh)	Export price ($/kWh)	Pricing delta ($/kWh)	Pricing delta (% of Export price)
DTE	0.153	0.037	0.116	314%
GMP	0.170	0.054	0.116	215%
LE	0.106	0.033	0.073	221%
NVE	0.122	0.038	0.084	221%
SMUD	0.124	0.033	0.091	276%
VEC	0.187	0.059	0.128	217%

Table 7. Net billing tariff design scenarios

Scenario number	Description	Pricing basis		Charging & discharging constraints	
		Consumption λ_{import}	Grid exports λ_{export}	Max. export to grid	Min. charge from PV
Primary scenarios (presented in section Decomposing the value gap)					
1	Net billing with time-invariant pricing (base-case design)	Annual Average Retail Price	Annual Average Solar Market Value	0%	100%
2	Net billing with hourly pricing for consumption and exports	Hourly Export Price + Pricing Delta[a]	Hourly Energy + Peak Capacity	0%	100%
3	Scenario 2 with no grid charging constraint	Same as Scenario 2	Same as Scenario 2	0%	0%
4	Scenario 2 with no grid charging constraint; discharging such that solar-plus-storage exports do not exceed rated PV capacity	Same as Scenario 2	Same as Scenario 2	PV kW	0%
5	Scenario 2 with no grid charging or discharging constraint	Same as Scenario 2	Same as Scenario 2	100%	0%
6	Market-based dispatch	Hourly Energy + Capacity	Same as Scenario 2	100%	0%
Secondary scenarios (presented in Supplementary Figures S7 and S8)					
7[b]	Net billing with time-of-use (TOU) rates for consumption and exports	Export Price + TOU Pricing Delta	TOU-Average Energy Prices	0%	100%
8	Scenario 2 with no grid discharge constraint	Same as Scenario 2	Same as Scenario 2	100%	0%

[a]Values for the Pricing Delta in Scenarios 2–5 are provided above in Table 6, by utility.
[b]Details on the construction of TOU-based rates for Scenario 7 are provided in Supplementary Table S1.

One direct implication of these findings is that storage investments made purely or primarily on the basis of managing solar self-consumption are not an efficient use of capital from a societal perspective. We also show that it is inefficient from the individual customer perspective, though the private bill savings value may be enough to drive adoption when combined with the resilience value from backup power or other revenue streams.

A second implication, germane especially in the U.S. context, is that battery storage may subvert the intent of current NEM reforms and could perpetuate regressive outcomes. Customers operating storage for solar self-consumption receive a private benefit in the form of a reduction in their annual utility bills. Across the utilities in our analysis, that benefit amounts to roughly $20 per kWh of storage capacity (i.e., $200 per year for a typical 10 kWh storage system). Yet, no commensurate cost savings accrue to the utility or its ratepayers. Moreover, as shown elsewhere, households co-adopting storage with solar tend to skew even more heavily toward higher incomes than do solar adopters in general, potentially exacerbating any regressive patterns in the cost-shifts (Barbose et al., 2021c). These effects may be further amplified if the storage equipment is partially financed through taxpayer- or utility ratepayer-funded incentives.

Compensating customers for operating storage in response to market prices can create a win-win, providing benefits to the power system while offering commensurate financial returns to PV + storage adopters (or their aggregators) that exceed what they would receive from simply maximizing solar self-consumption. However, that outcome is conditional on customers being allowed to discharge storage to the grid. Unrestricted market response would significantly increase exports, which could impose stress on the local distribution network under certain conditions. As we show, though, a significant portion of the potential market value could be achieved without significantly increasing exports, by relying on pricing or programmatic incentives that target storage discharge during narrow peak demand periods.

Limitations of the study

While this study utilizes empirical, metered data for customer load as well as empirical data for historical wholesale energy prices (or system lambdas in the case of Lakeland Electric), capacity markets are not universal and have heterogeneity between compensation levels, participation rules, and more. For this study, we applied a uniform method to determine "peak value." Owing to this stylized approach, it does not accurately represent the value that residential batteries may get in present-day capacity markets or in other peak service programs.

Additionally, this study focuses primarily on wholesale market value though also addresses peak value in terms of transmission, distribution, and capacity on both the bulk and distribution system level. Residential batteries are participating in wholesale markets via aggregations in small numbers, though recent advances in market participation rules, metering, and telemetry may lead to higher levels. Even so, this study does not directly address very location-specific distribution network constraints. In some cases, Scenario 5 (see Figure 5) would not be feasible owing to impacts on voltage, equipment overload, and so forth.

Lastly, this study focuses on common residential solar and battery sizing currently seen on the market. Additionally, residential batteries may not be adopted solely for economic reasons, as many customers have attached batteries to solar for outage resilience. As such, we do not focus on system size optimization.

STAR★METHODS

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

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
  - Lead contact
  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - SGIG load data
  - Simulated load data
  - Pecan Street load and solar production data
  - Simulated solar generation profiles
  - Utility system load profiles
  - Historical energy market prices
  - Simulated energy and peak (generation capacity) market prices
- QUANTIFICATION AND STATISTICAL ANALYSIS
  - Objective: Maximize total revenue

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.104714.

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AUTHOR CONTRIBUTIONS

Conceptualization G.L.B and S.P.F; Methodology G.L.B and S.P.F; Validation G.L.B., S.P.F., and C.A.M.; Formal Analysis G.L.B and S.P.F; Resources C.A.M. and S.P.F.; Data Curation C.A.M. and S.P.F.; Writing – Original Draft G.L.B., S.P.F., C.A.M.; Writing – Review and Editing G.L.B. and S.P.F.; Supervision G.L.B.; Project Administration G.L.B.; Funding Acquisition G.L.B.

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The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Input data to battery dispatch models	This paper	https://doi.org/10.6084/m9.figshare.20083910
Software and algorithms		
Simulated hourly solar generation data	National Renewable Energy Laboratory System Advisory Model	https://sam.nrel.gov/
Linear optimization and non-optimization battery dispatch models	This paper	https://doi.org/10.6084/m9.figshare.20083910
Other		
Empirical metered hourly residential customer load data	Smart Grid Investment Grant	https://www.osti.gov/servlets/purl/1171525
Simulated hourly residential customer load data	Developed from Department of Energy Energy + Residential Proto-type Building Models	https://doi.org/10.1016/j.enpol.2020.111766
Empirical metered 1-min residential customer load and solar generation data	Pecan Street	https://dataport.pecanstreet.org/
Empirical hourly utility bulk system load profile	Nodal Load via ABB Ventyx Velocity Suite	https://www.hitachienergy.com/us/en/offering/product-and-system/energy-planning-trading/market-intelligence-services/velocity-suite

RESOURCE AVAILABILITY

Lead contact

Further information requests or questions should be directed to the lead contact, Galen L. Barbose (glbarbose@lbl.gov).

Materials availability

Not applicable.

Data and code availability

- Raw, nonproprietary model input data that support the analysis are available for download as of the date of publication. DOI is listed in the key resources table
- Original code for battery dispatch is available for download as of the date of publication. DOI is listed in the key resources table
- Any additional information is available from the lead contact upon reasonable request

METHOD DETAILS

The analysis required integrating several types of time-series data—customer load profiles, solar generation profiles, utility system load profiles, and electricity market prices—across a discrete set of locations and time periods. The choice of study locations and time periods was driven by the available customer load data (see Figure 9). The datasets for each location are summarized in Table 2, and described further below. In describing the role of each dataset within our analysis, we refer variously to the "core" analysis and to the "forward-looking" analysis, where the former refers to results presented through Figure 7, while the latter refers to the results presented in Figure 8. Other data are used exclusively within analyses presented within the Supplementary Information sections, as noted.

SGIG load data

The core analysis relies on metered, hourly interval load data for a sample of residential customers, collected under the Smart Grid Investment Grant (SGIG) program's Consumer Behavior Studies (Cappers et al., 2013). Those studies consisted of a set of electricity pricing pilots with 10 utilities, conducted over the 2010–2015 period. Interval load data were collected both from customers participating in pilot rate structures as well as from a randomly selected set of control group customers that remained on each utility's standard, time-invariant residential rate. None of the customers had rooftop solar or any other distributed generation resource. For the purpose of the present study, we used data only from the control group. Those data were down-selected based on a number of criteria. First, the maximum hourly load, average annual load, ratio of maximum load value to mean load, and maximum difference between two adjacent load values were calculated for each customer. Customers were removed from the sample if any of the preceding metrics were three times greater than the median value for all customers of the same utility, or if data gaps larger than three consecutive hours were present. We then eliminated those utilities with fewer than 100 customers in the remaining sample, leaving six remaining utilities (see Table 3). Two of those utilities, SMUD and VEC, had a far greater number of customers than the other utilities; we therefore randomly selected 300 customers out of the remaining set for each of these two utilities, in order to maintain a roughly equivalent number of customers in the final sample for all six utilities. Finally, for each utility, we then selected the single, consecutive 8760-h period within the sampling interval with the fewest missing values, and linearly interpolated all missing data, which represented less than 1% of hours in all cases.

Simulated load data

For the forward-looking analysis presented in the section entitled Assessing the persistence of the value gap in high solar futures, we use simulated hourly residential load data. The rationale is that this analysis relies on modeled electricity market prices developed using utility system level load shapes from 2012 (see the description of Historical Energy Market Prices for further details), necessitating a corresponding set of residential customer load data for 2012. Given the impracticality of obtaining residential customer load data across multiple locations for that specific time period, we instead opted to rely on an existing set of simulated load profiles for single-family residential buildings, developed through a previous study (Darghouth et al., 2020). These load profiles were developed using the Department of Energy's Energy + Residential Proto-type Building Models (Mendon and Taylor, 2014) across 15 U.S. cities (see Figure 9). For each location, separate load profiles were developed for 24 distinct building stock configurations, which included variations related to foundation (crawl-space versus slab), heating equipment (gas furnace, oil furnace, electric resistance heating, or electric heat-pump), and building efficiency (based on the International Energy Conservation Code's 2006, 2009, or 2012 standards).

Pecan Street load and solar production data

The core analysis relies on metered hourly-interval data. However, many net billing schemes are based on solar grid exports measured over shorter time intervals or instantaneously. In order to assess whether the hourly granularity of our core analysis significantly impacts our findings, the analysis in Figure S2 leverages a dataset of 1-min interval load data to compare PV grid export levels when measured over hourly vs. 1-min intervals. The load data, obtained from Pecan Street (Pecan Street Inc., n.d.), consists of 1-minute-interval, metered solar production and net load from 265 residential customers located in three states: Texas ($n = 195$), New York ($n = 59$), and California ($n = 11$). The data cover different date ranges for each customer; for consistency and simplicity, we use data for calendar-year 2020.

Simulated solar generation profiles

For all analyses presented in the main body of the paper, we rely on simulated hourly solar generation profiles, developed using NREL's System Advisory Model (SAM) (National Renewable Energy Laboratory, 2020). We developed those profiles for the specific locations and time periods corresponding to the SGIG and simulated load data, using SAM's default settings for all PV system parameters (e.g., equipment type, losses, and panel orientation). For each location and time period, we developed a single profile based on a 1-kW system, and then scaled the hourly generation profile up or down for each customer, as described below in *Solar-plus-Storage Configuration*. Though not included within this paper, we also developed a set of solar generation profiles with west-facing panels (rather than south-facing, as assumed within the model's default settings). The solar export levels with west-facing panels differed only marginally (<1%) from south-facing panels, and the results were therefore deemed unworthy of inclusion.

Utility system load profiles

As described below in Development of hourly peak value price profiles, hourly peak prices in the core analysis were developed by distributing a single annual marginal generation capacity cost for each utility across its top-40 load hours during the one-year period of the corresponding SGIG customer load data. Those top-40 h are based on historical load data obtained from ABB's Ventyx Velocity Suite (Hitachi, n.d.), for the Transmission Zone corresponding to each utility in the SGIG dataset (see Table 4).

Historical energy market prices

The core analysis relies on historic energy market prices, sourced from the Ventyx Velocity Suite price portal (Hitachi, n.d.), for the locations and time periods corresponding to each SGIG utility's load data. For all utilities other than Lakeland Electric (which does not reside within, or adjacent to, an organized power market), these data consist of hourly averages of the 5-min real-time market price for a representative node within or, in the case NVE and SMUD, adjacent to the utility's service territory (see Table 4). For Lakeland Electric, the data instead consist of hourly system lambda values for the Florida Municipal Power Pool balancing authority, which represent the marginal energy cost in each hour.

Simulated energy and peak (generation capacity) market prices

The forward-looking analysis relies on a preexisting set of simulated hourly energy and capacity prices for the years 2020–2040, developed by NREL using its Cambium model, which combines NREL's capacity expansion model (the Renewable Energy Deployment System) with a detailed production cost model (Energy Exemplar's Plexos model) (Gagnon et al., 2020). NREL has published model outputs for a variety of scenarios. The hourly prices used within our analysis are from the 2020 Standard Scenarios Mid-Case scenario, and consist of energy and capacity prices for the 15 balancing authority regions corresponding to the cities represented among the simulated customer load profile data. Further details on the model structure and scenario assumptions are available through NREL's published documentation (Cole et al., 2020).

Development of Hourly Peak Value Price Profiles

Hourly peak values within the core analysis were demonstrated by stipulating an annual marginal generation capacity cost of $50/kW-year for all utilities, and then allocating that annual cost across the top-40 load hours of the transmission load zone for each respective utility. This approach is similar to that taken in a number of other recent studies (Gorman et al., 2021; Kim et al., 2021; Seel et al., 2020) and is intended to facilitate comparison across regions, some of which may not have formal capacity markets, and where they do, those markets can vary widely in terms of their respective structure, compensation levels, and participation rules. The specific choice of $50/kW-year was based on its similarity to currently observed capacity market prices in most organized capacity markets, though prices in MISO, which operates a voluntary capacity market, are considerably lower (Mills et al., 2021). The choice of the top-40 h was made to maintain consistency between the core analysis and the forward-looking analysis, which relies on Cambium capacity prices that are also based on the top-40 net-load hours (Gagnon et al., 2020). Following the Cambium methodology, capacity costs were allocated across those top-40 h on a weighted basis, based on the relative load levels in each of those hours.

In addition, we analyzed how the capacity credit of battery dispatch would shift if peak-load hours were defined instead across the top-10 and top-100 h, as shown in Figure 5. We found that the peak value of storage was relatively insensitive to how narrowly the peak-load hours were defined, consistent with a recent study's findings (Schleifer et al., 2021). Further, to capture potential value to the distribution system, we explored the battery operation's capacity credit for a residential feeder's peak by summing all customers, by utility, and identifying the top-10, top-40, and top-100 h as proxy for retail utility programs or tariff designs such as demand response programs, non-wires alternatives, or critical peak pricing riders. Table S4 shows a survey of prices and peak period definitions across various markets and programs at bulk generation, bulk transmission, and local distribution levels.

Solar-plus-storage system configuration

PV system sizes are denoted in this analysis as the ratio of annual solar generation to each customer's annual consumption, a standard approach used to normalize PV system sizes across customers with varying consumption levels (Darghouth et al., 2016). The standard base-case configuration assumes PV systems sized to generate 100% of each customer's annual consumption (denoted in the text as PV size = 1.0), consistent with available data suggesting that residential PV systems in the U.S. are typically sized to generate 80–100% of annual consumption (EnergySage, 2021; Verdant, 2021). Applying that PV sizing ratio to the set of customers within the SGIG and simulated load samples yields median PV system sizes ranging from 3.8–8.1 kW across analysis locations (see Table 5), which is again consistent with recent market data showing that median residential solar PV system sizes ranged from 5.4–10.6 kW across U.S. states in 2020 (Barbose et al., 2021a). Additional sensitivities were performed with PV system sizes ranging from 20–80% of each customer's annual consumption (denoted as 0.2–0.8). To create solar generation profiles for each customer and PV sizing assumption, the 1-kW solar PV generation profile simulated for each customer location (as described above in *Data Overview*) was scaled up or down so that the annual generation yielded the specified PV system size ratio. As noted earlier, all other PV system design assumptions were based on SAM default values.

Battery storage system sizes are denoted in this analysis as the ratio of energy storage capacity in kWh to each customer's average daily solar generation. The standard base-case configuration assumes storage system capacity equivalent to 50% of average daily solar generation (denoted in the text as battery size = 0.5), yielding median battery sizes of 8.6–18.2 kWh across analysis locations, for a PV system sized at 1.0 (see Table 5). These battery sizes are consistent with recent market trends, which show that paired residential solar-plus-storage systems in the U.S. typically include a single battery of 10–13.5 kWh in capacity, though dual-battery systems with storage capacity up to 27 kWh are also common, and battery storage capacity typically represents 30–80% of average daily solar generation (Barbose et al., 2021b). Additional sensitivities were performed for storage systems ranging in size from 20–200% of each customer's average daily solar generation (denoted as 0.2–2.0). Beyond the battery sizing assumptions, our analysis assumes 2-h duration (Barbose et al., 2021b), a round-trip efficiency of 85% (National Renewable Energy Laboratory, 2021), and state of charge constraints set at a minimum of 10% and maximum of 90%. The duration assumption effectively means that the storage rated power capacity (in kW) is half of its energy capacity (in kWh).

Net billing tariff design scenarios

The base-case net billing tariff assumed within our analysis consists of a single, time-invariant retail electricity price (in \$/kWh) applied to net consumption in each hour and a separate, time-invariant grid export price (in \$/kWh) applied to net exports in each hour. In other words, in each hour, a solar customer is either a net consumer or a net producer, and is charged for its net consumption or credited for its net generation at the corresponding price. For the purpose of modeling storage dispatch under this tariff design, the relevant quantity is the difference between the two prices, which defines the arbitrage opportunity. Most important is whether that pricing difference is larger or smaller than the threshold level required to offset round-trip efficiency (RTE) losses of the battery. Given our 85% RTE assumption, that threshold level is equal to 15% of the export price. Any pricing difference larger than that level will induce storage cycling to arbitrage surplus solar energy between grid export and consumption prices.

For the core-analysis using the SGIG load data, we specify consumption prices based on each utility's average retail electricity price, and export prices are based on the market value of the solar generation profile (see Table 6). Retail rates are based on data from the U.S. Energy Information Administration (U.S. Energy Information Administration, 2021) for residential customers of each utility over the time period of the SGIG data, while the solar market value was computed by applying hourly energy market prices to the solar generation profile for each utility. The resulting price differences for the six utilities are all well above the 15% minimum threshold required to induce storage cycling.

The section entitled Decomposing the value gap introduces a series of intermediate tariff designs that step incrementally from our base-case net billing design with time-invariant prices to market-based dispatch, where storage is dispatched directly against hourly energy and peak prices with no constraints on grid charging or discharging. Those intermediate tariff design scenarios are summarized in Table 7 (see Scenarios 2–5). As shown, the first incremental step in Scenario 2 is to replace the time-invariant consumption and export prices of the base-case design (Scenario 1) with hourly varying prices, while maintaining the same pricing delta between consumption and exports shown in Table 7. Scenario 3 eliminates the constraint on grid charging, while Scenario 4 eliminates the constraint on grid discharging up to solar nameplate capacity and Scenario 5 eliminates the grid discharging constraint completely. Finally, Scenario 6 eliminates the asymmetric pricing between consumption and exports. Several additional intermediate tariff designs (Scenarios 7 and 8) are explored in Figures S7 and S8.

QUANTIFICATION AND STATISTICAL ANALYSIS

For the base-case net billing design (Scenario 1), the model requires no optimization, but rather simply steps through each hour of the year sequentially, charging the battery in any hour with solar exports and remaining battery capacity, and discharging in any hour with net load and stored energy in the battery available, subject in both cases to the minimum and maximum state of charge (SoC) limits noted previously and accounting for RTE losses.

All other scenarios, however, require linear optimization to maximize the market value of battery storage dispatch, with perfect foresight and subject to various parameters and constraints, as summarized in Figure 10 and outlined further below:

Specifically, the model uses dual simplex linear optimization via MATLAB software. The only required initial condition is state of charge, which is set as full for all runs. Additional runs with different initial values were not considered due to the negligible impact on overall findings, only affecting a small number of hours of the total 8,760. The objective and parameters are outlined as such:

Objective: Maximize total revenue

Solar flows first to existing load and the remaining flows either to the grid for an export price or to the battery at $0 monetary cost. If the battery does not charge from solar, it can charge from the grid at the import price. When it exports, it can either reduce net load at that hour at the negative import price, consistent with typical net metering or net billing rules, or can dispatch to the grid at the export price. Though results focus on battery activity solely, the optimization takes the entire hybrid solar and battery into account.

$$\max \sum_{t}^{8760} \lambda_{\text{export},t}\left(q_{\text{PV to Grid},t} + q_{\text{BESS to Grid},t}\right) - \lambda_{\text{import},t}\left(q_{\text{Grid to BESS},t} - q_{\text{BESS to load},t}\right)$$

Subject to:

1. All kWh/h flows are positive

$$\left\{q_{\text{BESS to load, }t},\ q_{\text{BESS to Grid, }t},\ q_{\text{PV to Grid, }t},\ q_{\text{Grid to BESS, }t},\ q_{\text{PV to BESS},t}\right\} \geq 0$$

2. Battery state of charge maintained within limits

$$\widehat{S}_i * 10\% \leq \text{State of Charge }(\text{SoC}_{t,i})\ [\text{kWh}] \leq \widehat{S}_i * 90\%$$

3. Battery discharge to load limited by the customer's net load in a given hour

$$0 \leq q_{\text{BESS to load, }t,i} \leq \max\left\{0, (\text{kWh}_{\text{load}} - \text{kWh}_{\text{PV}})_{t,i}\right\}$$

4. Limits on discharge/charge rate to power capacity of battery

$$q_{\text{BESS to load, }t} + q_{\text{BESS to grid, }t} \leq Q_{\text{BESS}}[\text{kW}]$$
$$q_{\text{PV to BESS, }t} + q_{\text{Grid to BESS, }t} \leq Q_{\text{BESS}}[\text{kW}]$$

5. Limits on amount of charging from PV (see Table 7 "Min. Charge from PV" column)

$$\frac{q_{\text{PV to BESS, t}}}{q_{\text{Grid to BESS, t}} + q_{\text{PV to BESS, t}}} \leq \text{min. charge from PV } [\%]$$

6. Battery losses due to roundtrip efficiency (ε_{RTE}) [kWh]

$$q_{\text{ BESS loss, t}} = \left(1 - \sqrt{\varepsilon_{\text{RTE}}}\right) * \left(q_{\text{Grid to BESS, t}} + q_{\text{PV to BESS, t}}\right) + \left(\frac{1}{\sqrt{\varepsilon_{\text{RTE}}}} - 1\right) * \left(q_{\text{BESS to Grid, t}} + q_{\text{BESS to load,t}}\right)$$

7. SoC energy balance due to existing balance and subsequent charging, discharging, and losses [kWh]

$$\text{SoC}_{\text{ t+1}} = \text{SoC}_{\text{t}} + q_{\text{PV to BESS, t}} + q_{\text{Grid to BESS, t}} - q_{\text{BESS to load, t}} - q_{\text{BESS to Grid, t}} - q_{\text{BESS loss, t}}$$

8. All net solar exports must flow to the battery or grid (note that even when batteries are not allowed to export to the grid as in Scenarios 1–3, 6, and 7, excess solar export is permitted)

$$\max\left(0, q_{\text{PV,t}} - q_{\text{load,t}}\right) = q_{\text{PV to BESS, t}} + q_{\text{PV to Grid, t}}$$

9. Limits on total exports to nameplate capacity (constraint removed in Scenarios 4 and 5):

$$q_{\text{PV to Grid, t}} + q_{\text{BESS to Grid, t}} \leq Q_{\text{PV}}[kW]$$

10. Disallowing battery export to grid (constraint removed in Scenarios 4, 5, and 8)

$$q_{\text{BESS to Grid,t}} = 0$$

Where:

λ is import (≤ 0) or export price (≥ 0) $\left[\frac{\$}{\text{kWh}}\right]$ for hour t (see Table 7 for all scenarios).

q is energy flow to and from load, grid, PV, or BESS for hour t and customer i [kWh].

$\hat{S}$ is battery capacity [kWh] for customer i.

Q is installed capacity for PV or BESS system for customer i[kW].

ε_{RTE} is battery roundtrip efficiency [%].