Savings in Action: Lessons from Observed and Modeled Residential Solar Plus Storage Systems

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List of Acronyms and Abbreviations

AC	alternating current
APS	Arizona Public Service
AVERT	AVoided Emissions and geneRation Tool
CO_2	carbon dioxide
DC	direct current
DG	distributed generation
EPA	Environmental Protection Agency
HVAC	heating, ventilation, and air conditioning
kW	kilowatt
MACRS	Modified Accelerated Cost Recovery System
MWh	megawatt-hours
NREL	National Renewable Energy Laboratory
O	off-peak
O&M	operation and maintenance
OCHRE	Object-oriented Controllable High-resolution Residential Energy
P	peak
PV	photovoltaics
REopt	Renewable Energy Integration & Optimization
S+S	solar and storage
SD	standard deviation
SOP	super off-peak

Executive Summary

The electric grid is rapidly evolving as small-scale, demand-side resources play increasingly important roles in grid operations and decarbonization. Maximizing the potential of demand-side resources involves incentivizing electricity customers to use those resources in ways that benefit the broader electric grid. These incentives depend largely on the electricity cost savings that customers can realize by adopting demand-side resources. Determining these potential cost savings is a complex task. Cost savings depend on numerous factors, including the characteristics of different technologies, the algorithms that control these devices, system performance, customer behavior, electricity rate structures, and climatic factors. Another challenge is that estimated cost savings are frequently based on modeled rather than observed system performance, particularly in the literature.

In this study, we begin to fill the gap in empirical research of demand-side resources using data from a new-construction residential community equipped with rooftop solar and storage (S+S) in Arizona. We use these data to analyze the factors that determine customer electricity cost savings and emissions impacts of S+S in the real world. We then compare these data to modeled system performance to understand how models deviate from real-world outcomes. Based on these findings, we explore ways to improve such models and, conversely, use modeled results to suggest improvements to actual S+S deployment. The results of these analyses can be summarized in four key findings.

Rate structures play a central role in the grid and customer value of demand-side resources. In the Arizona case study, the local utility enrolled all households in the community in an experimental rate designed for customers with demand-side resources. The data show that the distributed generation rate benefited the grid by reshaping customer grid demand profiles, especially by reducing demand during grid peak periods. At the same time, the challenge associated with reducing demand charges in the pilot rate plan eroded the customer cost savings from S+S adoption. The resulting erosion of customer value caused at least some community members to switch back to a time-of-use rate plan that was less beneficial to grid operations. In this case study and in other circumstances, there is a tension between designing rates that benefit the electric grid and providing incentives that induce customers to adopt demand-side resources.

Certain customers can benefit more from demand-side resource adoption than others. Electricity cost savings varied significantly across households in our case study, even though the newly constructed, energy efficient homes were all equipped with similar S+S systems. Household-level factors that drive cost savings include total electricity demand, demand profiles (e.g., more use during on-peak hours), and differences in home square footage.

Modeled battery dispatch and sizing reveals opportunities for additional cost savings. Modeled results show that current battery systems in the community could further reduce demand charges by moderating their discharge during the peak demand period rather than attempting to reduce demand to zero. However, changes to the dispatch strategy may require software developments and updates that come at an added cost. Under the experimental rate, which has a high demand charge and low energy cost, the modeled optimal battery sizes are slightly smaller than those currently installed and the modeled results suggest that solar PV is not cost-effective. Indeed, our modeling suggests certain electricity rates may eliminate entirely

the rate incentives to adopt solar. Again, this outcome reflects the challenge of designing rates that incentivize demand-side services without eliminating incentives for demand-side resource adoption. At the same time, although the cost savings from deploying battery storage alone are marginally higher than those associated with deploying solar PV and battery storage, storage alone does not provide non-cost benefits such as emissions reduction. The optimized results highlight potential opportunities to improve deployed system design and controls, while accounting for real-world constraints.

Optimal dispatches can reduce grid emissions and maximize bill savings.
Grid emissions reductions can be a co-benefit of deploying S+S. Though this was not an explicit goal of the community in our case study, our analysis quantified the emissions impact of the actual and modeled battery systems, and we determined the battery dispatch that co-optimizes customer and emissions costs. When accounting for hourly emissions costs, the modeled batteries charge more with midday zero-carbon solar output or lower-emissions grid electricity, on average, similar to the currently installed systems, rather than directly following the peak demand period. However, achieving the modeled emissions reduction would require granular, real-time emissions information to allow the battery dispatch to mirror the highly variable grid emissions rates. Furthermore, the emissions offset by the battery varies depending on the data set and emissions metric used. Importantly, accounting for grid emissions has minimal impact on utility cost savings, suggesting emissions reduction strategies need not be at odds with bill savings strategies. Policymakers and rate designers could leverage this fact by implementing measures to incentivize developers to dispatch demand-side resources to simultaneously reduce grid emissions and maximize customer savings.

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1 Introduction

The electric grid is built on a top-down model of large-scale, centralized assets serving end-use customers. However, various technological and market innovations have increased the viability of a bottom-up model with small-scale, distributed assets providing services to the grid. The emerging distributed model leverages the capabilities of demand-side resources such as rooftop solar photovoltaics (PV), batteries, building energy management systems, energy efficiency investments, and electric vehicles.[1] Demand-side resources can provide grid services and help decarbonize grids more quickly and cost-effectively (Jenkins, Luke, & Thernstrom, 2018). Yet, demand-side services remain a largely untapped resource (O'Shaughnessy & Shah, 2021).

Though demand-side resources can provide benefits to both customers and utilities, maximizing the potential of demand-side resources involves resolving two challenges. The first challenge is deployment. Unlike centralized grid assets, demand-side resource deployment depends on the idiosyncratic decisions of millions of individual actors (Wolskea, P., & T., 2017). Further, even when demand-side resources are deployed, those resources are not necessarily used in ways that benefit the grid or drive decarbonization. Operating demand-side resources for the grid's benefit can, in certain cases, directly conflict with the private use cases of those resources. For instance, dispatching a battery to provide reserve capacity reduces the ability of the battery to provide home backup power. The second challenge is therefore incentivizing demand-side resource owners to use those resources in ways that provide grid value (Cook, Ardani, O'Shaughnessy, Smith, & Margolis, 2018). The lack of incentives can result in inefficient and inequitable outcomes, with the possibility of demand-side resource adopters shifting some grid costs onto non-adopters in the long term (Morstyn, Farrell, Darby, & M., 2018).

The adoption of demand-side resources largely depends on the economic perceptions of electricity customers. All else being equal, customers are more likely to adopt demand-side resources and provide demand-side services if these decisions yield larger electricity cost savings. However, determining the potential cost savings of investments in demand-side resources and services is a complex task. The electricity cost savings of demand-side resource adoption depend on the characteristics of different technologies, the algorithms that control these devices, system performance, customer behavior, electricity rate structures, and climatic factors. Additionally, estimated cost savings are frequently based on modeled rather than observed system performance, particularly in the literature (O'Shaughnessy, Cutler, Ardani, & Margolis, 2018).

In this study, we begin to fill the gap in empirical research of demand-side resources using data from a new-construction residential community equipped with rooftop solar PV and batteries in Arizona. We use these data to analyze the factors that determine customer electricity cost savings in the real world (Section 3). We then compare these data to modeled system performance to understand how models deviate from real-world outcomes and explore ways to both improve such models and increase deployment of solar and storage (S+S) systems (Sections 4–5). We also explore how different objectives affect S+S dispatch, namely objectives to minimize customer costs relative to objectives to minimize both customer costs and grid emissions.

[1] Other terms that are often used to refer to demand-side resources include "distributed" and "behind the meter."

2 Mandalay Homes Case Study

We use data from a community of newly constructed residential homes in Clarkdale and Prescott, Arizona, about 110 miles north of Phoenix. The community was built by Mandalay Homes, a construction firm specializing in high performance and energy-efficient homes. At the time of our analysis, this community comprised 107 owner-occupied housing units equipped with solar plus storage (S+S). Home sizes range from about 1,340 square feet to about 4,330 square feet. Most homes were equipped with 1.86-kW PV systems, though seven homes were equipped with larger systems ranging from 2.48 kW to 4.5 kW. Similarly, all homes were equipped with 5 kW/10 kWh sonnen batteries, with a single exception of a home equipped with a 6 kW/12 kWh battery. The batteries and PV had separate inverters. All homes have an air-source heat pump and a heat pump water heater. Currently, the homes control their two-stage air source heat pump to only operate in stage 1 (at a lower speed and therefore lower power consumption) during peak demand periods, but otherwise no equipment automatically changes behavior in response to utility rates.

sonnen provided data on home energy use as well as S+S system performance. The data included household demand, grid demand (electricity met by grid), solar generation, battery power, and battery state-of-charge. We leverage the difference between household demand and grid demand to estimate customer electricity payments under various scenarios.

Arizona Public Service (APS) is the electricity provider for the Mandalay Homes community. APS enrolled customers in the community in an experimental rate schedule designed exclusively for customers with "two or more qualifying… on-site technologies." For simplicity, we refer to this pilot rate as the distributed generation (DG) rate. The DG rate was designed to "test the ability and desire of participating residential customers to reduce On-Peak energy and demand usage through multiple behind-the-meter technologies." That is, the DG rate was designed to incentivize demand-side resource operations that benefit the grid. Households without S+S (two qualifying technologies) are ineligible for the DG rate. As a result, we calculate customer payments under a "standard" rate representing what the customers would have paid if not for S+S adoption. We base the standard rate on the APS Saver Choice rate schedule (APS, 2021). Some of the Mandalay Homes customers switched rates during the case study period. For simplicity, we present hypothetical results for customers that remained on the same rate schedule (the DG rate or the standard rate) during the full study period.

Table 1 summarizes the DG and standard rates. In both cases, peak periods apply from 3 p.m. to 8 p.m. on non-holiday weekdays. Both schedules set separate rates in summer (May-October) and winter. The standard rate also includes a super off-peak period from 10 a.m. to 3 p.m. during the winter months. The DG rate levies a demand charge ($/kW) based on the customer's highest demand in a 1-hour window during peak periods within the month. The DG rate also charges time-of-use volumetric ($/kWh) rates, but these rates are relatively low given that most utility costs are recouped through demand charges. In contrast, the standard rate does not levy any demand charges and instead recoups costs through time-of-use volumetric rates that are 2–4 times higher than the rates in the DG rate. As a result, customer peak *demand* (kW) drives customer costs in the DG rate, while customer *energy* use (kWh) drives customer costs in the standard rate. PV exports are credited at net billing rates set by APS. This rate fell slightly from $0.116/kWh to $0.104/kWh at the end of 2019. However, to remove this temporal variation from our analysis, we assume that all systems are credited at the $0.104/kWh rate. The standard rate also includes a monthly grid access charge of $0.93/kW of PV capacity. In absence of customer utility bills, we estimate utility payments for each home using household net load data under the two rate structures.

Table 1. DG and Standard Rates

P = peak; O = off-peak; SOP = super off-peak

Rate	Summer		Winter		Service ($/day)	PV Export ($/kWh)
	Demand ($/kW)	Energy ($/kWh)	Demand ($/kW/ month)	Energy ($/kWh)		
DG	P: 20.25 O[a]: 6.50	P: 0.058 O: 0.048	P: 14.25 O[a]: 6.50	0.048	0.493	0.104
Standard		P: 0.243 O: 0.109		P: 0.231 O: 0.109 SOP: 0.032	0.427	0.104

[a] Off-peak rates only apply to demand above 5 kW.

All the community's batteries follow the same dispatch algorithm. This approach takes battery state of charge, time of day, PV output, and home electricity use into account, and controls the battery with a smart self-adjusting algorithm to obtain key parameters (e.g., fully charged by 2:59 p.m.). The strategy for the DG rate, summarized in Table 2 and illustrated in Figure 1, is intended to reduce demand charges by discharging during the peak demand period

Table 2. Overview of Current sonnen Dispatch Strategy

Time	Dispatch Algorithm
1 a.m. – 6:29 a.m.	Grid power used to charge battery to 15%, power home loads, and charge electric vehicle (predictive weather analytics regarding PV production).
6:30 a.m. – 9:59 a.m.	PV self-consumption; charge battery to 40%.
10 a.m. – 2:59 p.m.	PV self-consumption; charge battery to 80%. Charge battery to 100% by 2:59 p.m.
3 p.m. – 10 p.m.	Discharge battery to home loads, driving load to zero (no grid export). Deploy smart demand control/load shedding (air-source heat pump). If excess battery capacity available, unit can serve as demand response asset.
10:01 p.m. – 12:59 a.m.	Grid power used to power home loads.

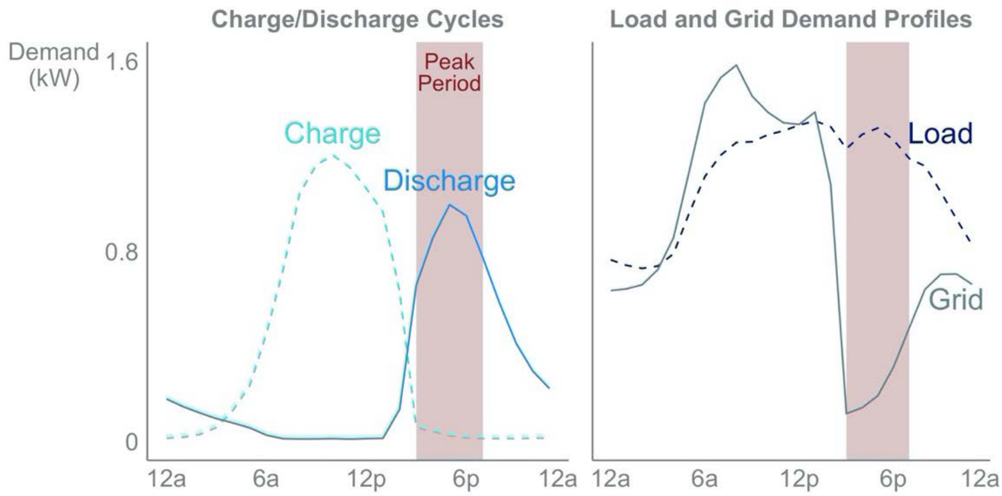

Figure 1. Average hourly charge/discharge (left) and load/grid demand profiles (right)

Figure based on average values for all homes and all hours in the data

3 Analysis of Customer Bill Savings

In this section, we use the Mandalay Homes and sonnen data to estimate customer bill savings under various scenarios. We then analyze how several factors can explain differences in bill savings across customers.

3.1 Data and Scenarios

To compare energy performance across units, we restrict our sample for this analysis to 76 units with continuous data available for at least 6 months from 2018 through 2020.[2] We then compile data into monthly estimates for energy use and bill savings. From the 76 batteries in the sample, we estimate bill savings for 865 months. This data sample (N=865) is the basis for the analyses in this section.

The S+S systems in this community reduce customer bills by reducing their demand charges and, to a lesser extent, their energy charges. We can estimate the value of these bill savings by estimating customer payments under a counterfactual scenario where the homes were not equipped with S+S using the total rather than the grid demand. However, in that hypothetical scenario, the homes would not qualify for the DG rates which, by definition, require homes to have two qualifying technologies. As a result, the more relevant counterfactual is a scenario where the Mandalay Homes were not equipped with S+S and paid standard rates. That is, community bill savings are equal to the difference between what the customers actually pay and what they would have paid under standard rates without S+S systems. A third counterfactual scenario is one in which customers adopt S+S but remain under standard rates. Figure 2 illustrates the four combinations of S+S adoption and rate structures:

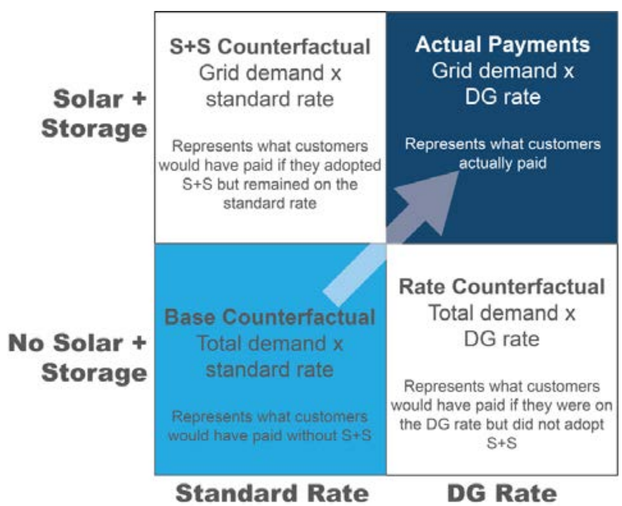

Figure 2. Counterfactual scenarios for estimating customer savings

The shift from the bottom left to the top right of Figure 2 is the basis for realized customer bill savings in the community. Nonetheless, differences between payments under all four potential combinations provide further insights into the factors that affect customer bill savings under S+S

[2] The dropped units do not vary from the sample in terms of home size, PV capacity, or battery capacity.

adoption. From these four technology and rate structure regimes, we analyze customer bill savings under five scenarios:

- **Scenario A – S+S adoption (standard rate):** Moving from the Base Counterfactual (bottom left of Figure 2) to the S+S Counterfactual (top left). This scenario represents what a customer could save by adopting S+S by staying on standard rates.
- **Scenario B – Rate change (no S+S):** Moving from the Base Counterfactual (bottom left) to the Rate Counterfactual (bottom right). This scenario represents how the rate change affects the bill payments of households without S+S.
- **Scenario C – S+S adoption (DG rate):** Moving from the Rate Counterfactual (bottom right) to the Actual Payments (top right). This scenario represents what a customer already on the DG rate saves by adopting S+S.
- **Scenario D – Rate change (with S+S):** Moving from the S+S Counterfactual (top left) to the Actual Payments (top right). This scenario represents how the rate changes affects the bill payments of households with S+S.
- **Scenario E – S+S adoption with rate change:** Moving from the Base Counterfactual (bottom left) to the Actual Payments (top right). This scenario represents the combined impact of S+S adoption and the rate change on customer bill payments.

3.2 Customer Bill Savings

Mandalay Homes customers save money on their electricity bills due to reduced grid consumption from the solar systems and the reshaped load profiles enabled by the batteries. Hypothetically, if customers adopted the S+S systems but remained on the standard rate (Scenario A), the average customer would save around $30/month. Similarly, for customers that are already on the DG rate (Scenario C), the average customer savings from S+S adoption are around $50/month (Figure 3). That is, customers always save money as a result of S+S adoption holding rates constant.[3] Recall that savings under the standard rate (Scenario A) are primarily driven by energy charges, while savings under the DG rate (Scenario C) are primarily driven by demand charges.

[3] As illustrated in Figure 3, there are a few outlier months in which savings were negative as a result of battery operations, but these occasional anomalies are more than offset on an annual basis, such that customer savings are always positive.

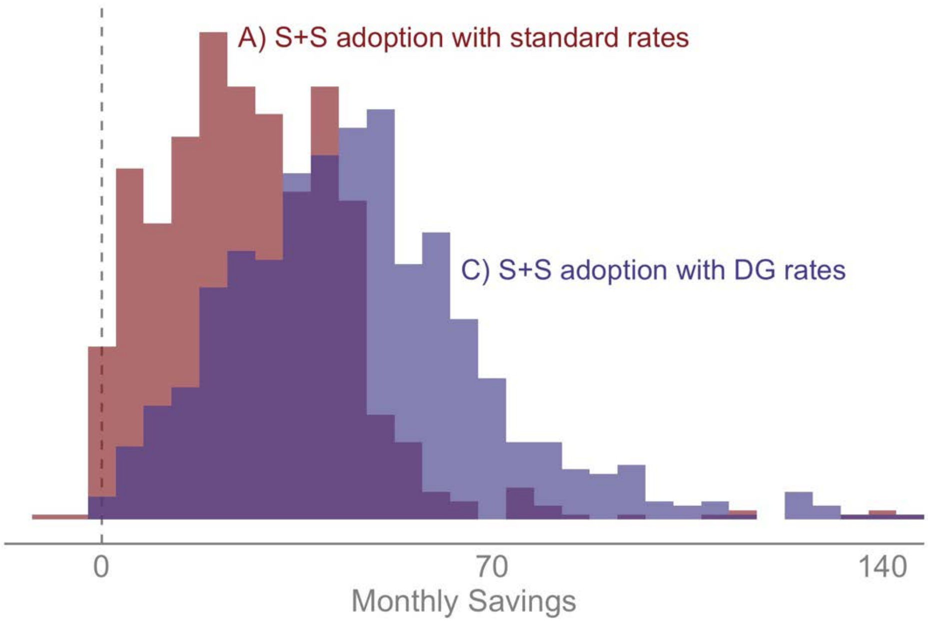

Figure 3. Hypothetical distributions of customer bill savings from S+S adoption

Heights on the y-axis correspond to the shares of months that achieved the savings along the x-axis.

The S+S savings described above are hypothetical in that they do not account for the Mandalay Homes customers' shift from standard to DG rates. Some Mandalay Homes customers can save money by simply switching from standard to DG rates (discussed further in Section [3.3]). However, the demand charges in the DG rates increase costs for most customers in most months. Hypothetically, shifting a customer without S+S on standard rates to DG rates (Scenario B) would increase that customer's monthly bills by around $30/month, on average. The S+S systems mitigate but do not fully offset the impacts of the rate change on customer bills. Shifting a customer with S+S on standard rates to DG rates (Scenario D) would increase that customer's monthly bills by around $10/month, on average (Figure 4). There is some seasonality to these results. Customer costs increased in about 62% of APS-defined summer months in Scenario D, compared to about 54% of winter months.

Figure 4. Hypothetical distributions of customer bill savings or increases when shifting from standard to DG rates

The plot is a histogram. Heights on the y-axis correspond to the shares of months that achieved the savings along the x-axis.

The net result of these changes on customer bills is illustrated in Figure 5 and summarized in Table 3, on the following page. S+S adoption reduces customer bills, but at least some of those savings are offset by the rate change. The combined effects of S+S adoption and the rate change yield an average monthly bill saving of about $10/month. The DG rate erodes customer bill savings because the rate design is relatively challenging. The monthly peak demand charge is set based on the home's peak demand in a single hour each month. For customers with S+S, the peak demand charge effectively represents the hour in which the battery's algorithm performed the worst, i.e., the hour in which the battery was least capable of minimizing peak energy demand. As a result, Mandalay Homes customer cost savings are largely determined by how well the homes are able to ride through each 5-hour peak period.

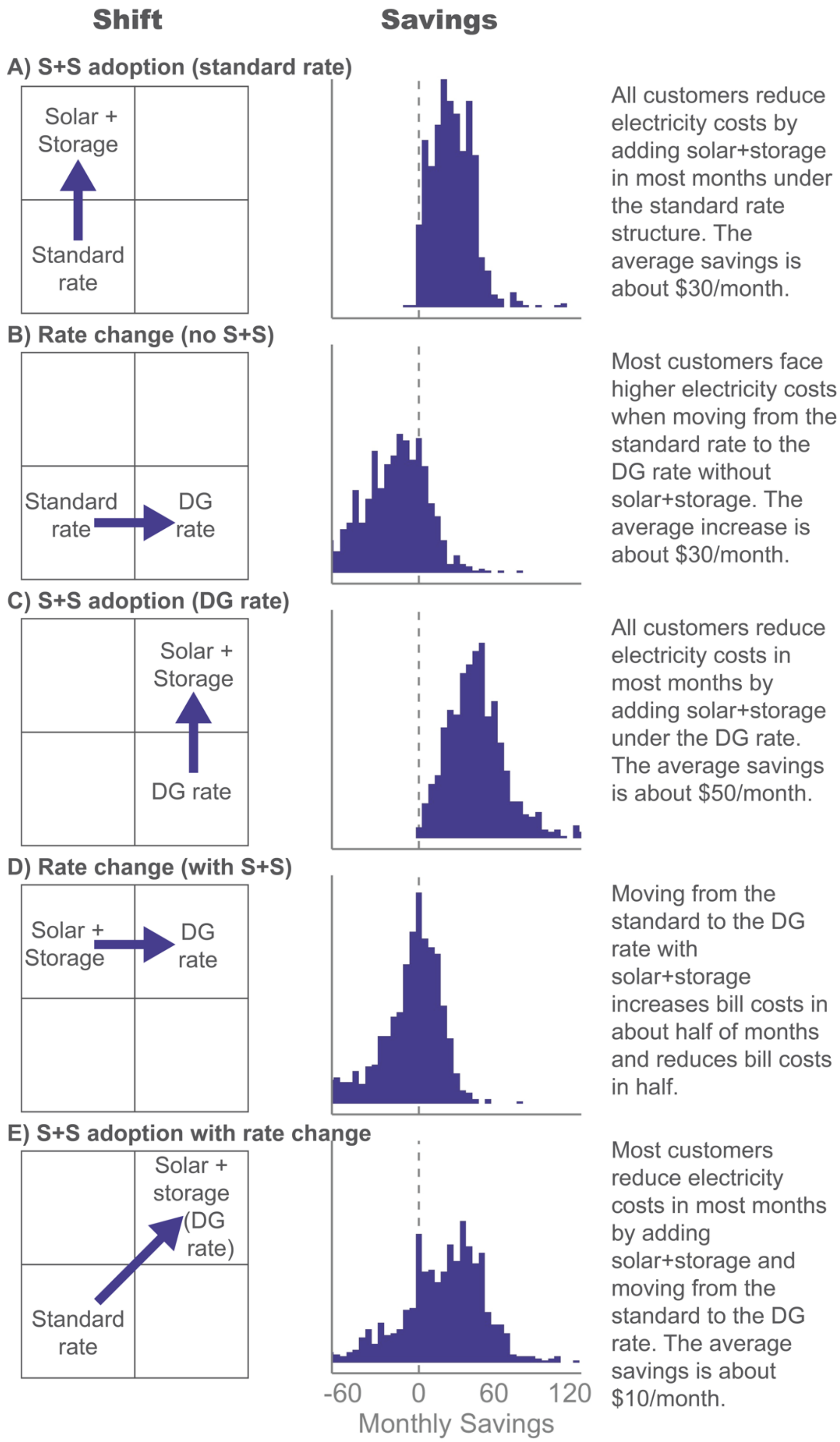

Figure 5. Estimated annual savings in shifts between S+S and rate scenarios

Table 3. Summary of Statistics for Estimated Customer Savings in Five Scenarios

Scenario	Mean	P25	Median	P75
A	27.5	14.6	25.6	38.4
B	-33.1	-48.4	-21.3	-3.2
C	46.9	30.2	44.4	58.9
D	-13.6	-23.1	-2.8	8.6
E	13.8	-2.0	21.4	40.5

3.3 Analysis of Drivers of Bill Savings

One striking characteristic of customer savings is the significant variation in savings across the homes, despite the fact that the homes are equipped with similar S+S systems. Here, we explore the factors that could explain these ranges in customer savings. Using available data, we identify five variables that could affect customer bill savings. We organize these variables into two groups: *structural* characteristics that are constant features of each home (home size and PV system size), and *load profile* characteristics that vary over each month and describe how different customers use electricity (total use, peak demand, and % of demand occurring during peak periods) (Table 4). We also explore the seasonality of customer bill savings by analyzing differences in savings across the seasons as defined by APS: summer (May-October) and winter (November-April).

Table 4. Summary of Statistics for Explanatory Variables

Variable	Definition	Mean (SD)
Structural Characteristics		
Home square feet	Home area in thousand square feet	1.82 (0.46)
PV system size	PV system size (kW)	1.98 (0.43)
Load Profile Characteristics		
Total use	Total household monthly electricity use (MWh)	0.66 (0.43)
Peak demand	Household peak demand during peak period (kW)	4.06 (2.20)
Percentage of demand on-peak	Percentage of customer demand that occurs during on-peak hours	0.18 (0.06)

We estimate the impacts of the different factors on customer bill savings through ordinary least squares regression. The regression allows us to isolate associations between individual variables and bill savings while holding other factors constant. We test the following model for each of the five scenarios:

$$sav_{x,h,m} = S_h\beta_S + L_{h,m}\beta_L + u_m\beta_u + \beta_0 + \varepsilon$$

Where $sav_{x,h,m}$ is the estimated bill savings in scenario x in household h in month m, S_h is a vector of the two structural variables (home size, PV system size) for household h, $L_{h,m}$ is a vector of the three customer load variables (total use, peak demand, % on-peak) for household h in month m, u_m is a dummy variable indicating whether month m is in the APS-defined summer months (May-October), β_S, β_L, and β_u are vectors of coefficients representing the impacts of the structural variables, load profile variables, and season (respectively) on bill savings, β_0 is a constant, and ε is an error term.

Before proceeding to the results, three limitations are worth noting. First, most of the homes are equipped with S+S systems with the same capacity. In the case of the batteries, there is too little variation in system capacities to include a variable for battery storage in the model. Though we include PV in the model, the lack of variation in system sizes could cause the model to underestimate the impacts of differences in PV system size on customer bill savings. Further, one potentially relevant metric is the contribution of PV output to on-peak demand, a function of PV system size and system orientation. Again, we excluded this variable due to lack of variation in the S+S systems. Second, we are only able to control for variables for which we have data. Omitted variables could bias some of the results from the model. In particular, occupant behavior, which we do not have insight into, can have a substantial impact on cost savings. Homeowners may choose to prioritize comfort and set their thermostats such that they consume more energy than others, be home during the day or away at work, run a home business, or do some other behavior that has a substantial impact on their energy use. These idiosyncrasies are not reflected in the model. Third, our results are based on estimated cost savings rather than actual, reported cost savings. This was a deliberate choice to be able to compare savings across real-world load profiles for rate structures that remained constant. Further, our research objective is to analyze the factors that affect bill savings, not to develop precise empirical estimates of the bill savings of specific customers.

Table 5 presents the results. The key results are for Scenarios A, C, and E, which reflect the impacts of the variables on bill savings from S+S adoption. However, we use results from Scenarios B and D to help contextualize some of these associations in Scenarios A, C, and E. To facilitate comparison across the factors, we use standardized values for each variable except the summer dummy variable, so that each coefficient represents the impact of a standard deviation change in each variable on bill savings. For instance, in the model for Scenario E, the coefficient on total use suggests that a standard deviation increase in total use is associated with an $33.14 increase in monthly bill savings, holding the other factors in the model constant. The reader can reference Table 4 for the standard deviation values. In this example, a standard deviation in total use is 0.43 MWh. The reader can then easily estimate the impact of a unit change: e.g., a 1 MWh increase in total use is associated with about an $77 increase in monthly bill savings in Model (3). Note that we omit the PV system size variable from Scenario B, given that the scenario is based on a hypothetical scenario without a PV system.

Table 5. Regression Results (Y=Customer Savings [$/month])

(robust standard errors in parentheses; N=865)

	Scenario A: S+S adoption w/ standard rate	B: Standard to DG rate (no S+S)	C: S+S adoption w/ DG rate	D: Standard to DG rate (with S+S)	E: S+S adoption with rate change
Home square feet	-0.96	0.47	-3.98*	-2.10*	-3.07*
	(0.51)	(0.28)	(1.02)	(0.74)	(1.03)
PV system size	3.43*	‡	6.79*	2.29*	5.72*
	(0.69)		(1.35)	(0.94)	(1.25)
Total use	14.31*	36.35*	-3.40*	18.83*	33.14*
	(0.73)	(0.60)	(1.31)	(1.21)	(1.47)
Peak demand	-2.24*	-49.26*	11.56*	-35.49*	-37.73*
	(0.43)	(0.84)	(1.49)	(1.85)	(2.02)
% demand on-peak	1.33*	5.74*	-1.36	3.02*	4.35*
	(0.50)	(0.61)	(0.86)	(0.79)	(1.01)
Summer	10.58*	-10.43*	13.91*	-7.17*	3.41
	(0.93)	(0.99)	(1.64)	(1.49)	(1.84)
R-squared	0.73	0.95	0.37	0.73	0.76

* $p<0.05$; ‡ Omitted

All the variables are associated with statistically significant impacts on bill savings under most scenarios.

Home square feet: Bill savings are generally slightly lower in larger homes. The regression results suggest that larger homes achieve lower bill savings, all else equal. One hypothesis for the negative coefficients is that larger homes require more electricity to keep cool during summer peaks, meaning that the batteries are less able to ride out the 5-hour peak period that determines customer demand charges.

PV system size: Larger PV systems are associated with greater bill savings. The regression yields the expected result that larger PV systems are associated with higher bill savings. The results suggest that PV system size has a greater impact on bill savings under DG rates than under standard rates.

Total use: Higher total use is generally associated with greater bill savings. As expected, the model for Scenario A suggests that higher total use is associated with greater bill savings from S+S adoption under standard rates. Similarly, Scenario B suggests that customers with higher total use save money by switching rates even without adopting S+S. This occurs because customers with high *energy* use pay relatively high energy charges under the standard rate. By switching to DG rates with lower energy charges, high energy use customers can significantly lower their energy payments. The net impact of these two results is a strong positive correlation between total use and bill savings in Scenario E: the model indicates that customers adopting S+S and switching rates save about $77 more for each additional MWh of total use.[4] However, the results in Scenario C suggest that higher total use reduces bill savings from S+S adoption for customers that are already on DG rates. That result suggests that high total use undermines the ability of the S+S systems to offset customer peak energy and demand charges.

Peak demand: Higher peak demand is generally associated with lower bill savings. Higher peak demand is associated with significantly lower savings in every scenario except Scenario C. The result in Scenario B is illustrative: for customers without S+S, switching from standard to DG rates increases customer bills by about $22 for each additional kilowatt of peak demand. These higher costs reflect the higher demand charges that these customers incur to pay for that peak demand. S+S adoption can mitigate but not fully offset those costs. High peak demand makes it more difficult for the home batteries to ride out peak periods, such that customers with large peak demand realize less savings from S+S adoption. Figure 6 illustrates this by comparing the grid demand profiles of households with peak demand above and below 4 kW. The figure shows how grid demand rises much more rapidly during the peak period for those households with higher peak demand. Importantly, this result does not imply that customers with high peak demand lose money by S+S adoption, only that those customers realize less savings than customers with lower peak demand. The exception is Scenario C. For customers that are already on DG rates and already paying demand charges, S+S adoption can only reduce those demand charge payments.

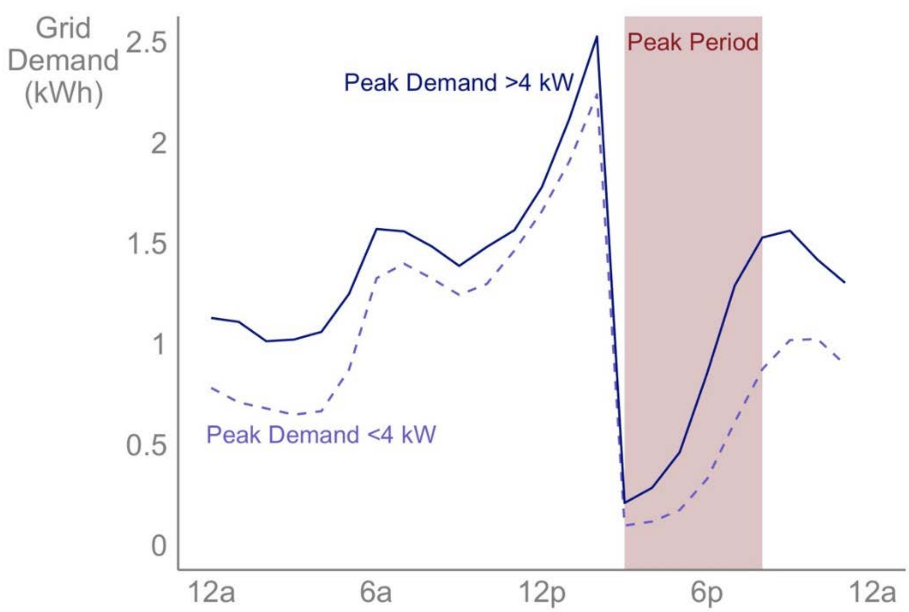

Figure 6. Grid demand profiles for households with peak demand above and below 4 kW

Based on average profiles for 65 households in August 2020

Percentage of customer demand occurring during on-peak period: Higher peak energy use is associated with higher bill savings from rate switching, but not S+S adoption. In contrast to peak

[4] In the text, we convert all coefficients into the units of the variables. Here, Table 5 shows that total use is associated with $33.14/month increase per standard deviation. There are 0.43 MWh per standard deviation (see Table 4), yielding an impact of about $77/MWh.

demand, peak energy use is associated with greater bill savings in Scenarios B, D, and E, though the magnitude of this relationship is much weaker than for peak demand. The fact that the result in Scenario A is insignificant suggests that peak energy use affects bill savings from rate switching but not necessarily from S+S adoption. Again, the results for Scenario B are illuminating: customers with high peak energy use can save money just by switching from standard to DG rates. This occurs because high-peak use customers pay significantly less for peak energy under the DG than under the standard rate. As a result, the model suggests that customers with high peak energy use save money when rate switching and adopting S+S (Scenario E), but those savings are largely due to the rate switching rather than the S+S adoption.

Summer: S+S adoption generates higher bill savings in the summer months, but these savings can be offset by challenging rate structures. The model shows that bill savings from S+S adoption are higher in the summer than in the winter. However, these additional savings are largely offset by the higher costs stemming from switching from the standard to the DG rate. The net result is a statistically insignificant difference between bill savings in the summer and in the winter. Further, summer conditions (long days, high air conditioning demand) augment the effects of other variables in the regression. We tested the impacts of summer conditions on the other factors by interacting the summer variable with the total use and peak demand variables. In this model, the summer dummy variable remains statistically insignificant for Scenario E savings, but summer conditions still affect the impacts of total use and peak demand on Scenario E savings. The model shows that an additional megawatt-hour of total use is associated with about $9.6/month of additional savings in the winter but $15.4 of additional savings in the summer, and that an additional kilowatt of peak demand is associated with about $57 less savings in the winter and $89 less savings in the summer.

4 Analysis of System Performance

In this section, we compare observed versus modeled, theoretically optimal S+S system performance. The purpose of this task is to better understand differences in the performance of deployed residential solar PV, battery storage, and flexible building loads as compared to the performance of these systems in energy models and tools. This understanding can help improve the models to better reflect real-world performance, provide validation of existing models, and inform the sizing and dispatch of deployed systems. We compare empirical performance data from the Mandalay Homes community to modeled performance using optimization tools developed at the National Renewable Energy Laboratory (NREL). We use the empirical data to validate NREL models to ensure accurate representation of the Mandalay Homes and technologies installed and make improvements to the models accordingly (see Appendix B). We subsequently use these models to assess the potential energy bill and carbon dioxide (CO2) emissions savings from optimized battery dispatch strategies, as well as savings achievable through cost-optimal system sizing, compared to deployed systems. This workflow is summarized in Figure 7.

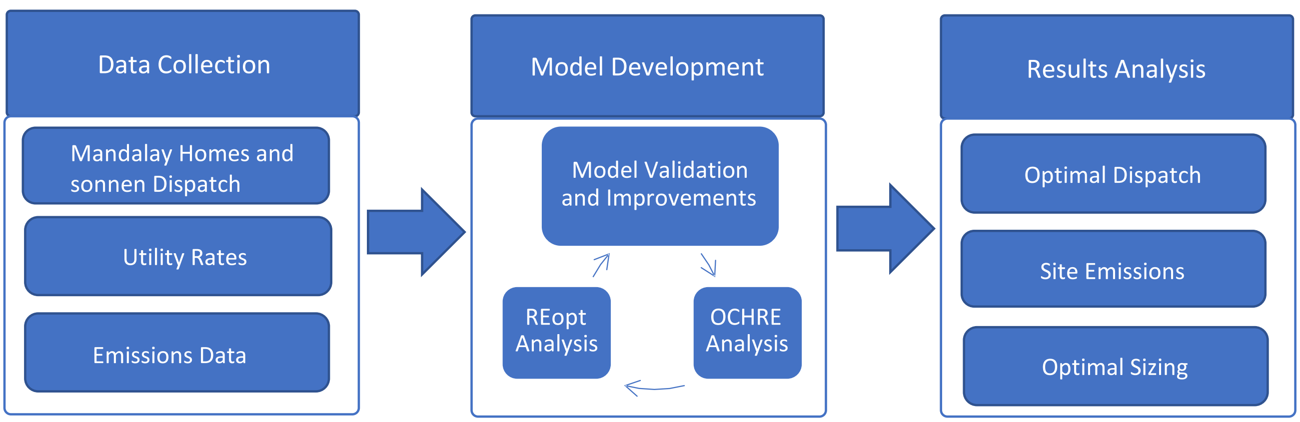

Figure 7. Analysis process for Mandalay Homes data

4.1 Data

For this analysis, we select five representative homes to analyze in depth. These homes were chosen for data completeness and to provide a range of home sizes and energy consumption.[5] Table 6 displays relevant information for each home analyzed. In addition, a representative home was modeled based on a floorplan provided by Mandalay Homes that is typical for some of the homes within the community.

Table 6. Key Attributes for Homes Evaluated

Home ID	Size (sq. ft.)	2019 Energy Use (kWh)	2019 Peak Demand (kW)	2019 Average Load (kW)	2019 PV Output (kWh)
A	1,341	8,255	7.0	0.94	2,986
B	1,692	10,102	7.7	1.15	3,117
C	1,832	7,523	8.8	0.86	3,044

[5] We selected houses with at least some data in every hour of the year 2019 (i.e., without missing data for more than one hour) and houses with typical seasonal patterns (i.e., more load in winter and summer due to HVAC).

Home ID	Size (sq. ft.)	2019 Energy Use (kWh)	2019 Peak Demand (kW)	2019 Average Load (kW)	2019 PV Output (kWh)
D	1,870	12,341	9.4	1.41	2,946
E	Unknown	10,991	8.6	1.25	2,359
Modeled home	2,200	11,081	6.7	1.26	N/A

The DG rate described in Table 1 was used to calculate energy costs and savings for the modeled scenarios.[6] This analysis assumes the homes have not switched to a different rate structure since the S+S systems were deployed.

4.2 OCHRE and REopt Models

The Renewable Energy Integration & Optimization (REopt) model is a mixed-integer model that determines the cost-optimal deployment of distributed energy technologies while adhering to operational constraints (Cutler, et al., 2017). The model identifies the system sizes and dispatch strategies that minimize the life cycle cost of energy over the financial life of a project. In this work, we primarily use REopt to determine the cost-optimal S+S system sizes and battery dispatch strategies for specific homes. For these homes, we compare the system sizing, battery dispatch, cost savings, and emissions savings in the actual and optimized cases. Separately, REopt is used in conjunction with the Object-oriented Controllable High-resolution Residential Energy (OCHRE) model to validate the OCHRE-REopt workflow using data from the homes.

OCHRE is a residential energy model that simulates energy consumption and occupant comfort with a reduced-order resistance capacitance network approach[7] (Blonsky, et al., 2021). OCHRE is designed to be used as an underlying model for energy control and optimization applications and includes controllable models for heating, ventilation, and air conditioning (HVAC) equipment, water heaters, electric vehicles, PV, and batteries.

Here, OCHRE is combined with REopt to optimize HVAC, water heater, and battery dispatch to provide demand response and assess their impacts on occupant comfort. OCHRE was also used to generate reduced-order models for REopt and to assess the performance of the home's HVAC controls. A single OCHRE model was generated to represent a typical home in the Mandalay Homes community.

While OCHRE has previously been validated against detailed, physics-based models such as EnergyPlus (Blonsky, et al., 2021), the high-resolution data provided by sonnen presented a unique opportunity to validate the OCHRE-REopt modeling workflow against empirical data. In Appendix B, the OCHRE HVAC model was validated against whole home power data and compared with REopt HVAC dispatch results.[8]

[6] The export rate used in REopt modeling assumed true net metering, rather than $0.104/kWh, in order to accurately represent true power flows (by removing incentive for the PV generation to exclusively export to the grid).

[7] A reduced-order resistance capacitance network model, also referred to as an equivalent circuit model, represents a building's physical construction and the associated heat transfer as a series of resistors and capacitors.

[8] As part of this project, we made several improvements to REopt and OCHRE based on comparisons of observed and modeled system performance. We document these improvements and how they affect our analysis in Appendix B.

5 Mandalay Homes Actual versus Optimal Dispatch and Sizing Results

For each of the five homes evaluated, we compare actual outcomes to REopt optimal outcomes under three scenarios:

- Actual system sizes with bill savings-optimal dispatch (Section 5.1)
- Actual system sizes with bill savings- and emissions-optimal dispatch (Section 5.2)
- Optimized system sizes and bill savings-optimal dispatch (Section 5.3).

REopt has perfect foresight of home load and can optimally charge and discharge the battery in each hour. Thus, REopt provides an upper bound of theoretical cost savings and emissions benefits of S+S. Comparing the optimized dispatch given by REopt to the actual dispatch from sonnen provides insight into how control algorithms can be modified to increase customer savings and emissions benefits, as well as how grid modeling can better incorporate on-the-ground realities.

Note that bill savings are calculated assuming the customer is on the DG rate (with a demand charge) for the baseline case and the case with the S+S system. This is equivalent to Scenario C in Section 3.

5.1 Savings from Bill Savings-Optimal Dispatch

Table 7 compares estimated energy bills versus optimized energy bills given the bill savings-optimal dispatch strategy for each of the five homes.[9]

With the actual systems, these homes paid an average of $394 in energy charges and $516 in demand charges in year one. On average across the five homes, the bill savings-optimal dispatch results in a 6% ($22) reduction in year one energy charges and 73% ($374) reduction in year one demand charges. The reduction in energy charges is relatively small because the difference between on- and off-peak energy cost is only one cent, therefore there is little room to increase savings. Each of the homes currently incur on-peak demand charges in every month of the year while the optimized dispatch avoids on-peak demand charges in 6–12 months of the year, depending on the home, and reduces demand charges in other months. The homes incur off-peak demand charges 5–12 months of the year, whereas the optimized dispatch eliminates off-peak charges in four of the five homes.

[9] Actual energy bills are calculated using each home's net load (which accounts for solar production and battery dispatch) under the DG rate tariff. Optimized energy bills are calculated using each home's gross load, fixing the PV and battery sizes to the true sizes, and allowing REopt to optimally dispatch the battery to minimize the life cycle cost of energy.

Table 7. Year One Energy and Demand Charges from Actual versus Optimized Dispatch Strategy for Five Homes

	Annual Energy Charges			Annual Demand Charges			Months with On-Peak Charges	Months with Off-Peak Demand Charges
Home ID	**Actual**	**Optimized**	**Reduction**	**Actual**	**Optimized**	**Reduction**	**Actual/optimized**	**Actual/optimized**
A	$326.19	$306.30	6%	$383.61	$88.85	77%	12|6	5|0
B	$385.49	$377.12	2%	$446.64	$126.02	72%	12|10	6|0
C	$289.77	$271.88	6%	$541.57	$114.73	79%	12|7	7|2
D	$507.29	$484.43	5%	$874.26	$284.53	67%	12|12	12|0
E	$462.75	$422.84	9%	$335.31	$96.82	71%	12|7	9|0
Average (± SD)	**$394 (± $91)**	**$372**	**6% (± 2%)**	**$516 (± $214)**	**$142**	**73% (± 5%)**	**12|8.4**	**7.8|0.4**

The primary revenue stream for the batteries is reducing net load during the peak demand period, which occurs on non-holiday weekdays between 3 p.m. and 8 p.m. Figure 8 displays the average summer weekday load for the five buildings analyzed for each hour of the day. The three lines represent the baseline building load (i.e., without solar or storage), the actual net building load (accounting for PV and actual battery dispatch), and the optimized net load (accounting for PV and the bill savings-optimal battery dispatch). One notable trend is that sonnen charges the battery in the middle of the day while REopt charges the battery at night once the demand charge period ends.[10] The other notable trend is that the actual net load is higher at the end of the demand period than the bill savings-optimal net load.

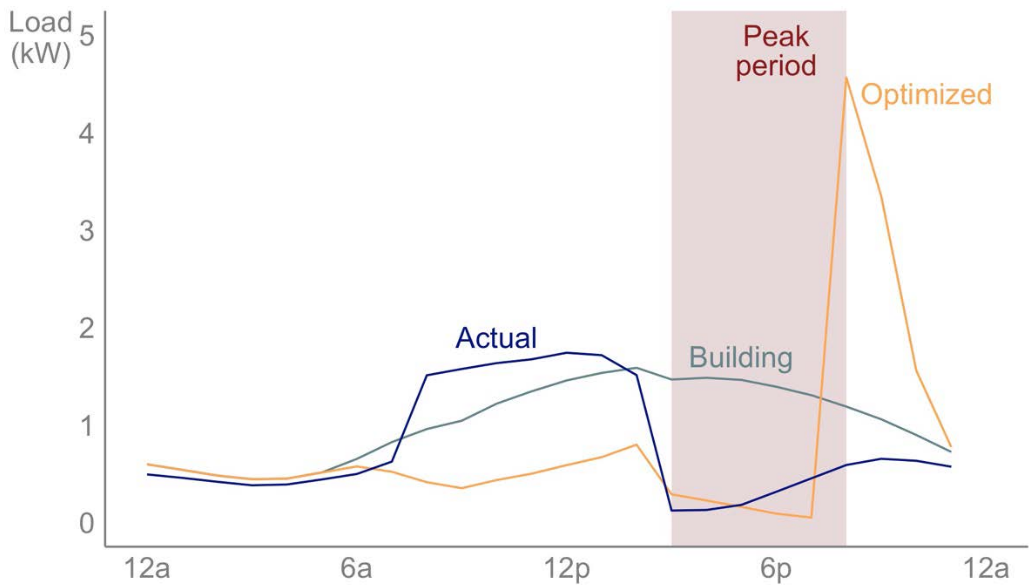

Figure 8. Average hourly gross and net loads for weekday hours between May and November

It is worth noting that the occupants of two of the homes alter their behavior before and during the peak demand period by, for example, precooling or preheating the home, which leads to a drop in building load during the demand period. This demonstrates how reduction in grid consumption can come from both installed systems such as PV and batteries, and from behavioral components such as changing thermostat setpoints or changing heat pump settings. It also points to the importance of integrating building models such as OCHRE with energy resource tools such as REopt to convey a complete picture of building flexibility.

The sonnen dispatch algorithm charges the battery in the middle of the day, as is seen from the actual midday net load being above the building load (Figure 8). In the bill savings-optimal dispatch, REopt prefers quickly recharging the battery (without exceeding off-peak demand thresholds) so that battery capacity is available in the event of a power outage. This results in a large spike in optimized net load directly at the end of the demand period. From a bill-savings perspective, the cost to charge is the same during the middle of the day as it is at night, but there may be resilience benefits of charging at night. Alternatively, there may be alignment with

[10] Individuals interviewed for this study that were involved in the project, suggested that one reason for charging the batteries during the day is to align demand with solar generation on the larger grid, though this was not an explicitly stated goal of the dispatch.

emission reduction opportunities to charge during the middle of the day, when there is more solar on the wholesale market. We explore these potential emissions benefits further in Section 5.2.

The trend of optimized net load being higher than actual net load in the initial peak hours and then lower in the later peak hours is due to the sonnen dispatch algorithm attempting to drop net load to zero but not always having enough energy to do so for the entire period. The demand charge is calculated based on the maximum hourly net load for each month, so failing to adequately reduce load for one hour of the peak hours impacts savings for the entire month.

Figure 9 shows the hourly net load during the August demand periods for Home A with the net load resulting from the bill savings-optimal dispatch in orange and from the actual dispatch in blue. We also show the home's electricity consumption in grey, referred to as "Building." During certain days (Week 1, Monday–Wednesday for example) the building load is low enough that the battery can eliminate grid demand, indicated by a flat line in both the optimized and actual cases. Other days, the building load is high enough that the battery cannot eliminate demand across the entire demand period. On these days, REopt dispatches the battery to minimize the net load across all demand hours. On Thursday in Week 1, the optimized net load is reduced to 1.54 kW across all peak hours, which sets the optimized demand charge for the month.

Changing the dispatch strategy to target a monthly peak net load above zero (such as 1.54 kW in the above discussion) is well within the capabilities of the hardware and controllers but would require additional software updates and development. The optimal target varies by month and by home consumption, and the correct value to target is not known ahead of time; factors that make it challenging to optimally dispatch the system. At the same time, the savings potential from dispatching closer to the theoretical optimal may justify the costs of developing a more sophisticated dispatch strategy.

The shaded red regions in Figure 9 denote hours in which the actual battery reaches a zero state of charge by the end of the hour. When the battery reaches its minimum state of charge, it can no longer discharge to reduce the peak load. This is most impactful in the final Friday of the month, where net load spikes to 3.86 kW in the final hour and sets the demand charge for the entire month.

In some hours, such as the second hour of the first Tuesday, the actual net load exceeds the optimized load even though the battery still has charge. This is likely due to REopt using hourly load data, which smooths intra-hour peaks that exceed the battery's inverter capacity. In other words, even though the average load within an hour is below the 5-kW battery capacity, some periods within the hour may exceed this capacity limit. Such intra-hour variability indicates the benefit of using subhourly load data when modeling demand charges.

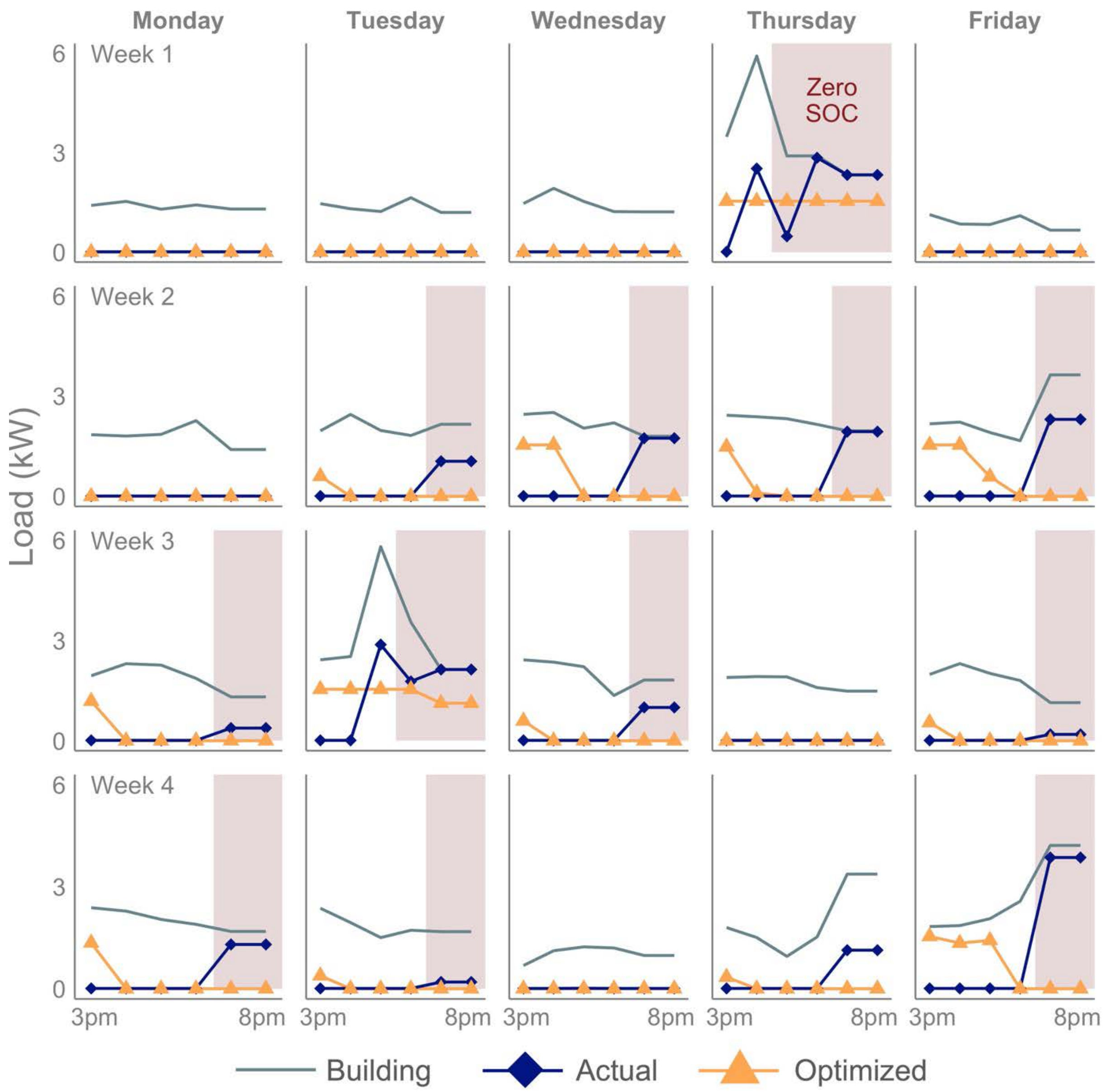

Figure 9. Hourly net loads during demand periods in August for Home A

The first Monday is August 5, 2019. The shaded areas denote hours with actual battery dispatch ending state of charge of zero.

Several additional differences between the bill savings optimal and actual net load point to the types of challenges developers face in designing a simple yet effective dispatch strategy. Unlike the theoretical optimal, where the battery can respond at every hour of the year using perfect forecasts of future load, actual developers must work within the limitations of limited data along with system and controller limitations.

One example of such constraints is seen by the sonnen dispatch strategy discharging the battery during the weekend days, even though there is no savings associated with doing so. While discharging during the weekend can add to total electricity costs due to the round-trip efficiency of the battery these costs are traded against the benefits of simplifying the controller algorithm by not having to differentiate between weekends and weekdays.

Another example of challenges facing developers is from off-peak demand charges. Figure 10 shows the maximum monthly peak and off-peak actual and optimized net load for Home A. While most demand charges are incurred during the peak period, there is an additional demand charge for loads above 5 kW during off-peak hours. The optimized dispatch strategically charges and discharges the battery to keep off-peak loads under the 5-kW threshold. Note that charging the 5-kW or 6-kW batteries at maximum power would increase the net load to or above this off-peak threshold. The actual dispatch charges in the middle of the day and discharges during the peak hours, and it does not consider these additional demand charges. This can become costly during the winter months where space heating can increase loads during off-peak hours. For example, load from Home D spiked to 9.4 kW at 9:00 a.m. on January 16 and the actual dispatch was set to charge the battery at this time, raising net load to 10.5 kW. The annual cost of the off-peak demand charges ranges from $35 for the smallest of the five homes analyzed to $147 for the largest home and contributes to a meaningful portion of the additional savings from the bill savings-optimal dispatch.

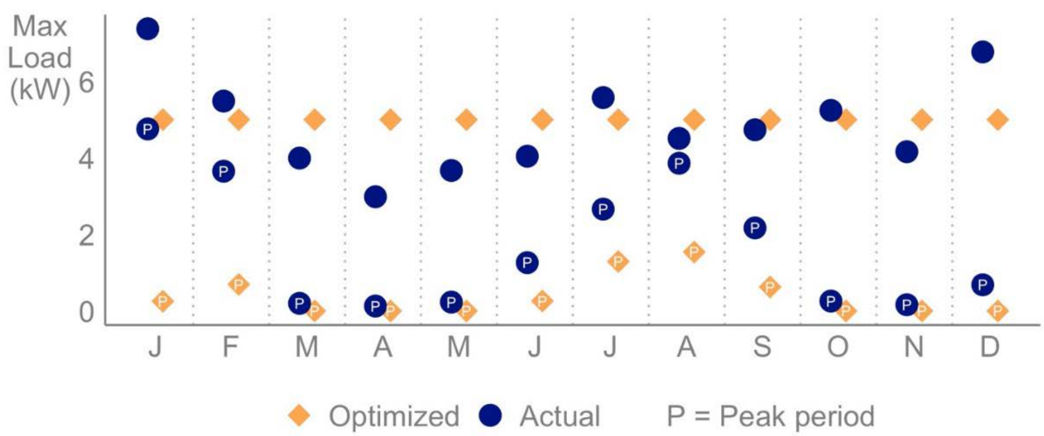

Figure 10. Monthly peak and off-peak load for Home A

5.2 Accounting for Emissions Costs

The REopt bill savings-optimal dispatch strategy is based on minimizing utility charges with a secondary objective of keeping the battery at a high state of charge. The sonnen dispatch strategy, which includes charging the battery midday, could potentially have a complementary emissions benefit if high midday solar output on the wholesale electricity system lowers the emissions intensity of grid power during those times. We therefore explore the CO_2 emissions impact of the sonnen and REopt dispatch strategies, and additionally assess how REopt's optimal dispatch changes when accounting for CO_2 emissions costs from the building's energy consumption.

Emissions costs are calculated as the building's net load (i.e., grid purchases) multiplied by the hourly emissions intensity of the grid and the U.S. Environmental Protection Agency's (EPA's) social cost of CO_2 ($51/t in year one of the analysis) (United States Government Interagency Working Group on Social Cost of Greenhouse Gases, 2021). We assume avoided emissions costs are a social good (i.e., not monetized by the customer) that nonetheless impact the model's objective function along with customer bill savings. We compare results using marginal emissions factors for grid-purchased electricity from NREL's Cambium data set (using 2020 data at the balancing authority scale) (Gagnon, Frazier, Hale, & Wesley, 2020) and the EPA's AVoided Emissions and geneRation Tool (AVERT) data set (using 2019 data at the region scale) (U.S. Environmental Protection Agency, 2020). Though marginal emissions factors are most appropriate when assessing how a change in load affects the bulk power system, we also illustrate emissions impacts determined using average emissions factors from Cambium.[11] These comparisons illustrate the sensitivity of optimal dispatch and emissions to the grid emissions data source and type. Appendix A contains details regarding these data sources and the methods used to calculate emissions costs.

Regardless of data source or emissions factor type, the optimal battery dispatch changes when emissions costs are incorporated into the REopt objective function. With emissions in the objective, REopt optimally dispatches the battery to avoid grid purchases during high-emissions hours and to make grid purchases (including charging the battery) during low-emissions hours. In all cases, accounting for emissions costs results in more midday charging as compared to the bill savings-optimal dispatch, and a less pronounced spike in charging immediately following the peak demand period (at 8 p.m.). Accounting for emissions costs, which vary hour by hour, also results in significantly greater variability in the bill savings- and emissions-optimal dispatch strategy as compared to the actual and bill savings-optimal dispatch strategies. Figure 11 shows the hourly average actual dispatch (blue) compared to the bill savings- and emissions-optimal dispatch (orange) and the emissions rates (purple) for each emissions scenario and for the bill savings-only optimization.

[11] AVERT accounts only for fossil generation and thus does not report average emissions factors for the grid.

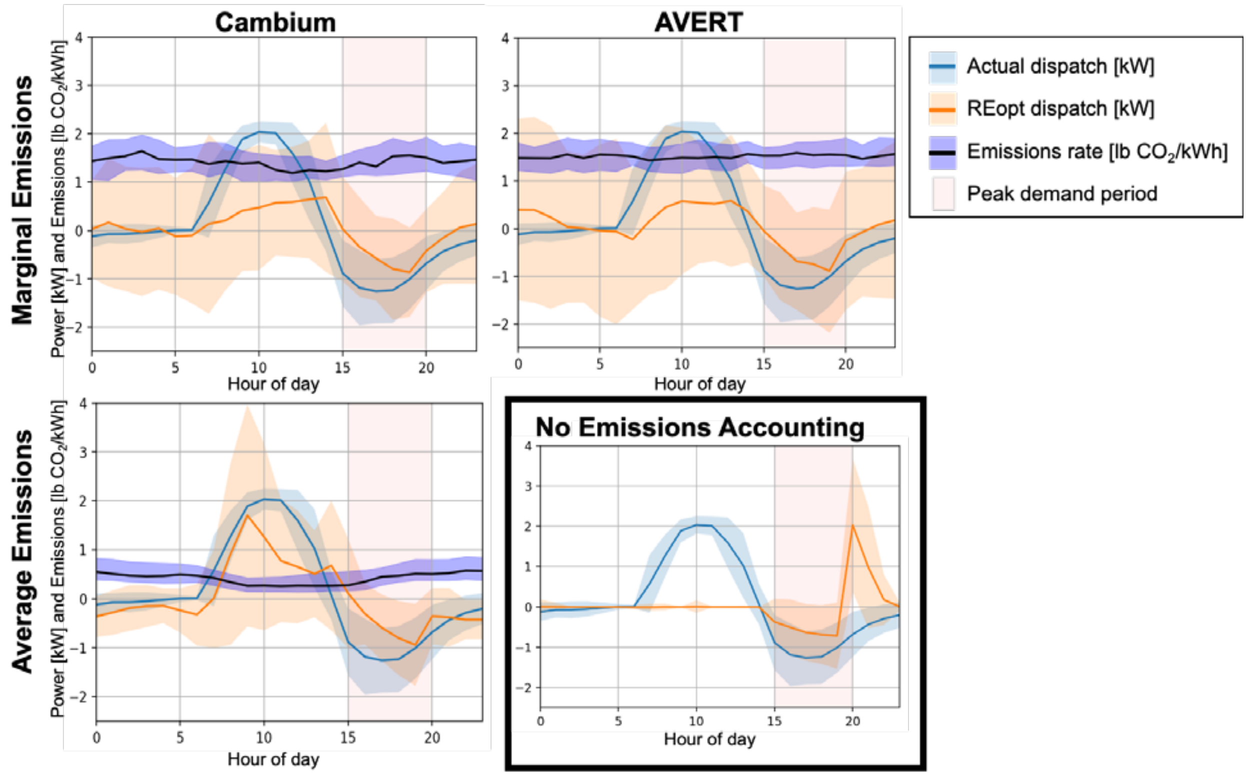

Figure 11. Daily actual battery dispatch (blue) and REopt bill savings- and emissions-optimal dispatch when using varying emissions data sets (orange) for Home A

Emissions rates as reported by AVERT and Cambium are shown in purple. Solid lines represent mean values for each hour of the day and the shaded regions extend one standard deviation from the mean. The on-peak demand period (3 p.m.–8 p.m.) is shaded in pink.

While the bill savings- and emissions-optimal dispatch strategy more closely resembles the actual dispatch regardless of emissions scenario, the resulting CO_2 impacts vary widely depending on the data source and emissions type considered (Figure 12).

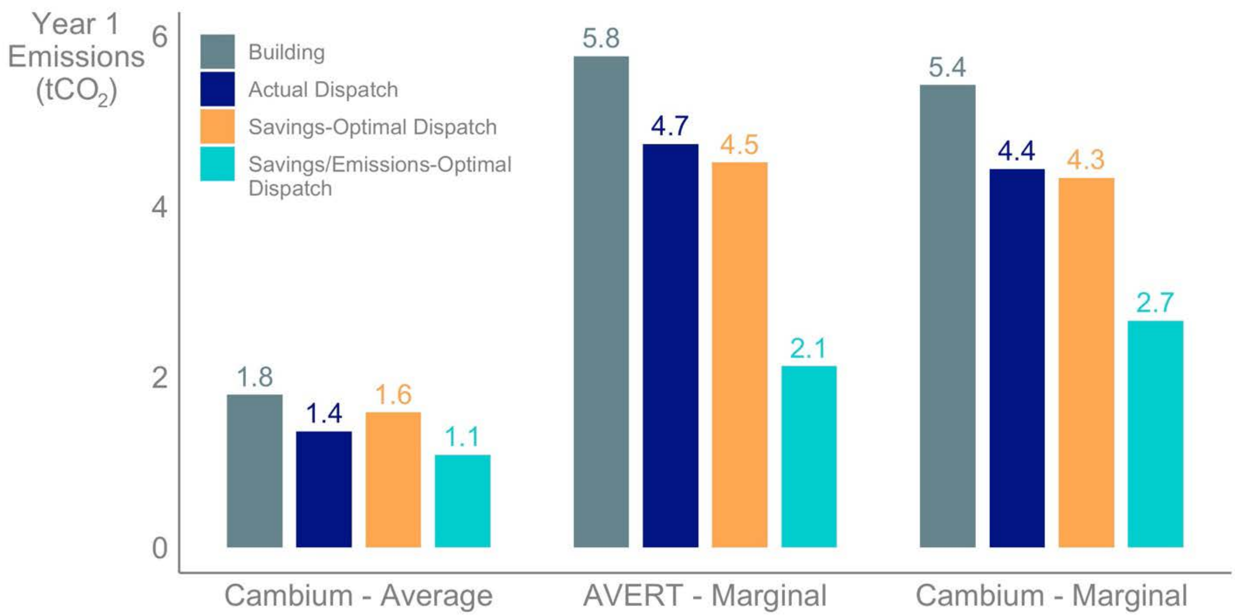

Figure 12. Year 1 CO_2 emissions from Home A from the baseline building load, the actual net load (including PV and sonnen battery), the optimized building load (for bill saving), and the optimized building load (for bill and emissions savings) using Cambium and AVERT average and marginal emissions factors

For Home A, the actual dispatch reduces CO_2 emissions by 14% as compared to REopt's bill savings-optimal dispatch, using Cambium average emissions data. This is because Cambium average emissions data reflects a consistent midday dip in emissions intensity when the sonnen battery charges. However, using marginal emissions rates indicates that the actual dispatch *increases* CO_2 emissions by 5% (using AVERT) or 2% (using Cambium) as compared to the bill savings-optimal dispatch. In all cases, the bill savings- and emissions-optimal dispatch reduces CO_2 emissions as compared to both the actual dispatch (by 20%–55%, depending on the data source) and the bill savings-optimal dispatch (by 31%–53%).

Marginal emissions rates are most appropriate to use to determine a new battery dispatch strategy, since the dispatch will result in a change in load that affects the grid at the margin. Our results indicate that a bill savings- and emissions-optimal dispatch would on average utilize more midday charging than the bill savings-optimal dispatch and less midday charging than the actual dispatch. However, REopt can achieve the significant emissions reductions shown in Figure 12 largely due to its perfect foresight of emissions and ability to tailor the hourly battery charging and discharging accordingly. This type of dispatch would only be feasible for the homes with real-time information regarding grid emissions intensities and the ability to respond to such information.

Notably, demand savings are unaffected by the co-optimization for bill savings and emissions costs. That is, the battery can be dispatched to minimize emissions costs without reducing customer bill savings from demand charge reductions. Accounting for emissions costs has a modest impact on energy charge savings, but because energy charges account for such a small portion of customer bills these impacts have a small overall effect on customer savings. As a result, our results suggest that the battery dispatches can be reshaped to minimize grid emissions with little impact on customer bill savings.

5.3 Cost-Optimal System Sizes

All the homes at the Mandalay Homes community were equipped with S+S systems of similar capacities, mostly 5 kW/10 kWh batteries with 1.86-kW PV systems. Larger systems could further reduce energy and demand charges while smaller systems would reduce upfront capital costs. To calculate cost-optimal system sizes over the analysis period (including capital and O&M [operation and maintenance] costs, as well as lifecycle bill savings), we modeled cost-optimal system sizes in REopt assuming a PV cost of $2,490/kW and a battery cost of $581/kW–$544/kWh. The battery life is assumed to be 10 years and the DG rate (Table 1) was used to calculate utility costs. Additional assumptions can be found in Appendix A.

Table 8 displays the cost-optimal battery power and energy capacities. We let the model size the power and energy capacities independently rather than specifying a ratio. The cost-optimal systems did not include PV, so we also model optimal battery sizing with the PV sizes fixed at 1.86 kW.[12] Across both scenarios (with and without PV), the cost-optimal battery systems are smaller than the ones currently installed, ranging from 1.15–4.98 kW and 2.21–9.26 kWh compared to the actual 5 kW/10 kWh system sizes. Without the 1.86-kW PV system, slightly larger battery systems are cost-optimal (on average, 0.78 kW/0.36 kWh larger than those with PV). As with the currently installed systems, the duration is around 2 hours. Total cost savings are calculated based on the difference in net present value of capital, O&M, and energy costs for a house with and without S+S. On average, the optimized system sizes result in 20% cost savings (without PV) and 23% cost savings (with PV) as compared to the business-as-usual case with no S+S.

The cost-optimal S+S systems offer a best-case benchmark on sizing and savings, but there are additional considerations for implementation. Battery system sizes do not come in the exact sizes recommended by the model, and it is likely that the installed systems are the most cost-optimal commercially available sizes, particularly considering cost savings that can results from purchasing multiple similarly-sized systems. In addition, modeling the load of new homes prior to construction is difficult, making system sizing for new construction a challenge. Finally, REopt has perfect foresight when sizing and dispatching the systems. The cost-optimal capacities represent the technical minimum size to achieve savings.

Table 8. Cost-Optimal Battery and PV Sizing

	Cost-Optimal Sizing (0 kW PV)				Cost-Optimal Sizing with Fixed PV (1.86 kW PV)			
Home ID	**Power (kW)**	**Energy kWh**	**Duration (hours)**	**Total Cost Savings**	**Power (kW)**	**Energy (kWh)**	**Duration (hours)**	**Total Cost Savings**
A	3.82	5.88	1.54	28%	3.55	5.80	1.63	25%
B	3.77	5.95	1.58	23%	3.79	6.01	1.59	19%
C	3.64	6.27	1.72	25%	3.48	6.13	1.76	21%
D	4.84	8.97	1.85	26%	4.98	9.26	1.86	24%

[12] The R-tech rate specifies the system must have at least a 2 kW-DC PV system, which, because PV panels are oversized relative to inverter capacity, roughly aligns with the 1.86 kW-AC system installed

	Cost-Optimal Sizing (0 kW PV)				**Cost-Optimal Sizing with Fixed PV (1.86 kW PV)**			
Home ID	**Power (kW)**	**Energy kWh**	**Duration (hours)**	**Total Cost Savings**	**Power (kW)**	**Energy (kWh)**	**Duration (hours)**	**Total Cost Savings**
E	2.21	4.86	2.20	14%	1.15	2.93	1.84	11%
Average	**3.66**	**6.39**	**1.75**	**23%**	**2.88**	**6.03**	**1.74**	**20%**

Percentage total cost savings are calculated as the change in life cycle cost relative to the business-as-usual case (no S+S) for each home.

6 Conclusions

The electric grid is evolving to accommodate a growing number of cost-effective demand-side resources and services. The future impact of demand-side resources on grid operations and the associated emissions depends on the financial incentives for customers to adopt and use these resources. These incentives largely depend on the potential electricity bill savings that can accrue from demand-side resource adoption. Projecting bill savings is a complex task, and many analyses of bill savings rely on modeled results. Here, we explored these complexities through analyses of observed and modeled S+S system performance in a case study community in Arizona. To conclude, we discuss some of the implications of these results for demand-side resource policy, emissions reductions, and technology development.

The two analyses in this study show a significant difference in actual savings and optimal savings for S+S systems. Actual energy bill savings when using the DG rate (Section 3.2, Scenario C) are about $50/month on average, and battery controls optimized for bill savings (Section 5.1) show the potential to increase savings by an additional $33/month on average.

Adopter cost savings are highly variable.
The Mandalay Homes community case study illustrates how similar homes equipped with similar technologies can experience significantly different cost savings from demand-side resource adoption. This range of cost savings reflects a host of household-level differences, including home size, total electricity use, occupant behavior, and load profiles. These results illustrate the difficulty in predicting building loads, optimally designing S+S systems to achieve customer bill savings, and predicting expected savings for prospective S+S adopters.

Rate design to incentivize demand-side services may conflict with incentives for adoption.
The DG rate in the Mandalay Homes case study was designed to induce demand-side resources to operate in ways that benefit the grid. The load profile data suggest the DG rate is highly effective in achieving this objective through the implementation of a demand charge. The homes use significantly less electricity during grid peak times. Although estimating the grid values of these systems was not in the scope of this report, it is reasonable to conclude that the community's S+S systems reduced system costs by reducing peak load. At the same time, the DG rate has a lower energy cost component, which erodes cost savings from S+S adoption, particularly impacting the savings from PV. Indeed, the REopt modeling suggests the DG rate may eliminate entirely the rate incentives to adopt PV. This outcome reflects an underlying tension in demand-side resource rate design: designing a rate that incentivizes demand-side services without eliminating incentives for demand-side resource adoption. Future work could explore this tension and how rate design might achieve a balance to motivate efficient levels of demand-side resource adoption and the optimal provision of demand-side services.

Discharge strategies in observed versus modeled homes generally align, but there is room for improvement in the execution of a strategy.
The actual and modeled bill savings-optimal battery dispatch strategies generally align, as both aim to minimize demand during the on-peak period. However, the actual systems discharge to reduce net demand to zero during the demand period. This causes the batteries to occasionally run out of energy before the peak period is over and therefore result in high demand charges based on increased consumption in the last hour of the on-peak period. The data show that

certain households are more likely to encounter this problem than others, particularly those with higher peak energy demand. Instead, the dispatch strategy could aim to minimize the maximum demand incurred over the entire on-peak period (discharging less energy per hour, over a longer period). Additional savings could be gained by not exceeding 5-kW peak load during off-peak periods, below which demand charges are not incurred, and by not discharging the battery during the weekend, when no peak demand charges are incurred. Though the optimal savings are not achievable in practice due to the need for perfect load forecasting, there is still significant potential for increased savings with improved controls.

Optimal dispatches can reduce grid emissions and maximize bill savings.
The actual battery systems charge during the day while the modeled, bill-savings optimal systems charge at night. Though this does not significantly impact economics, it could impact the carbon emissions of the homes. We determine that the actual systems reduce emissions more than the bill-savings optimal dispatch when using *average* emissions factors but not when using *marginal* emissions factors. Co-optimizing for bill savings and emissions costs results in more midday charging, like the actual dispatch, but with significant variability in day-to-day charging. Due to this variability, implementing a dispatch strategy to minimize emissions alongside bill savings would require real-time communication of emissions rates and the ability to respond to such information. Further, our results show that dispatching to reduce grid emissions can be achieved with minimal impacts on customer bill savings. Policymakers and rate designers could leverage this fact by implementing measures to incentivize developers to dispatch demand-side resources to simultaneously reduce grid emissions and maximize customer savings.

Cost-optimal battery capacities are similar to those installed, but solar PV is excluded from cost-optimal systems.
When the REopt model is allowed to size PV and battery storage, only battery storage is cost-effective under the DG rate. This is likely because batteries can effectively mitigate the DG rate's high demand charges but low energy costs undermine the economics of PV. The cost-optimal battery storage sizes and durations are similar to those installed. Battery system sizes do not come in the exact sizes recommended by the model, and the installed systems are likely the most cost-optimal commercially available sizes. Including PV at the existing sizes (and optimally sizing battery storage) results in only a small reduction in savings but provides non-cost benefits such as emissions reduction.

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Appendix A. REopt Analysis and Results

Table A-1 describes the analysis assumptions used in the REopt model.

Table A-1. REopt Analysis Assumptions

PV Parameters	**Value**	**Reference**
Array type	Rooftop, fixed	(Dobos, 2014)
Array azimuth	Multifaceted roof modeled based on typical home built by Mandalay Homes	—
DC-to-AC size ratio	1.2	(Dobos, 2014)
System losses	14%	(Dobos, 2014)
Capital cost	$2,490/kW-DC	(National Renewable Energy Laboratory, 2020)
O&M cost	$19/kW/year	(National Renewable Energy Laboratory, 2020)
Incentives	5 years MACRS[a] (100% bonus depreciation); 26% federal investment tax credit	(Anderson, et al., 2021)
Battery Parameters	**Value**	**Reference**
Rectifier efficiency	96%	(Patsios, et al., 2016)
Round-trip efficiency	97.5%	(Patsios, et al., 2016)
Inverter efficiency	96%	(Patsios, et al., 2016)
Minimum state of charge	20%	(Patsios, et al., 2016)
Battery life	10 years	(DiOrio, Dobos, & Janzou, 2015)
Energy capacity cost[b]	$544/kWh	(Boomberg New Energy Finance, 2020)
Energy replacement cost[b]	$302/kWh	(Boomberg New Energy Finance, 2020)
Power capacity cost[b]	$581/kW	(Boomberg New Energy Finance, 2020)
Power replacement cost[b]	$323/kW	(Boomberg New Energy Finance, 2020)
Incentives	5 years MACRS (100% bonus depreciation); 23.4% federal investment tax credit	(Anderson, et al., 2021)
General Economic Parameters	**Value**	**Reference**

PV Parameters	Value	Reference
Analysis period	25 years	(National Renewable Energy Laboratory, 2020)
Ownership model	Direct ownership	—
Host discount rate (nominal)	5.5%	(National Renewable Energy Laboratory, 2020)
Host effective tax rate	26%	(Anderson, et al., 2021)
Electricity cost escalation rate (nominal)	2.3%	(Energy Information Administration, 2020)
O&M cost escalation rate	2.5%	(National Renewable Energy Laboratory, 2020)
Net metering limit	1,000 kW	—
Health and Climate Parameters	**Value**	**Reference**
Social cost of CO_2 in first year	$51/ton	(Interagency Working Group on Social Cost of Greenhouse Gases, 2021)
Annual escalation of social cost of CO_2	1.78%	(Interagency Working Group on Social Cost of Greenhouse Gases, 2021)
Carbon emissions	AVERT 2019 hourly data set (marginal) for Southwest region Cambium 2020 hourly data set (marginal and average) for balancing area 28	(EPA, 2020) (Gagnon, Frazier, Hale, & Wesley, 2020)

[b] Use useful capacity

MACRS is the Modified Accelerated Cost Recovery System.

Appendix B. Model Validation Results

The following improvements were made to the OCHRE-REopt modeling workflow based on the Mandalay Homes data set to enable a more accurate comparison of the actual and modeled homes and to validate the workflow for future flexible load modeling efforts. Applicable improvements will continue to be utilized in future modeling efforts.

Accounting for the Cost of Carbon in REopt

The battery dispatch in REopt is optimized to minimize overall energy costs by shifting grid purchases to lower-cost periods. The dispatch is also adjusted to incentivize keeping the battery at a high state of charge when it does not impact the overall cost. This may be beneficial for resilience considerations, where a higher battery state of charge results in a higher probability of riding through a grid outage. In contrast, the battery dispatch strategy implemented in the homes built by Mandalay Homes could reduce both demand charges and the emissions intensity of the buildings' energy consumption (see Table 2). Due to the difference in dispatch strategy between REopt and sonnen, we assess how REopt's cost-optimal battery dispatch changes when accounting for carbon dioxide (CO_2) emissions from the building's energy consumption.

To this end, we incorporate CO_2 emissions costs into the model's objective function, so that the new objective minimizes life cycle emissions costs in addition to energy costs. Emissions costs are calculated as the building's net load multiplied by the hourly emissions intensity of the grid and the EPA's social cost of CO_2 ($51/t in year 1) (United States Government Interagency Working Group on Social Cost of Greenhouse Gases, 2021). We assume the social cost of CO_2 escalates at the rate estimated by the EPA (United States Government Interagency Working Group on Social Cost of Greenhouse Gases, 2021). The grid emissions factors are assumed to remain constant throughout each projects' financial lifetime.

We assess the sensitivity of our results to two main assumptions regarding the emissions intensity of the grid:

1. **Average versus Marginal Emissions Rate:** Marginal emissions factors represent the emissions intensity of the marginal generator and are most appropriate to use if the load under consideration represents an incremental change in demand (Ryan, Johnson, & Keoleian, 2016) (Ryan, Johnson, & Keoleian, 2016). Average emissions factors represent the average emissions intensity of the grid and are most appropriate to use if the load represents existing demand and is not considered a change from the baseline load (Ryan, Johnson, & Keoleian, 2016)
2. **AVERT versus Cambium Emissions Data Set:** Emissions factors also vary based on the underlying grid model and corresponding geographic and temporal resolution. In this study, we compare results obtained using marginal and average emissions factors from the EPA's AVoided Emissions and geneRation Tool (AVERT) (U.S. Environmental Protection Agency, 2020) as well as NREL's Cambium database (Gagnon, Frazier, Hale, & Wesley, 2020). AVERT data are at the regional scale for 2019 and Cambium data are at the balancing authority scale for 2020. A key difference between these data sets is that the AVERT data set was developed to represent the current utility grid mix while Cambium was developed to represent the future grid under difference scenarios.

Marginal and average emissions factors from Cambium and AVERT are shown in Figures B-1 and B-2 and are compared in Table B-1.

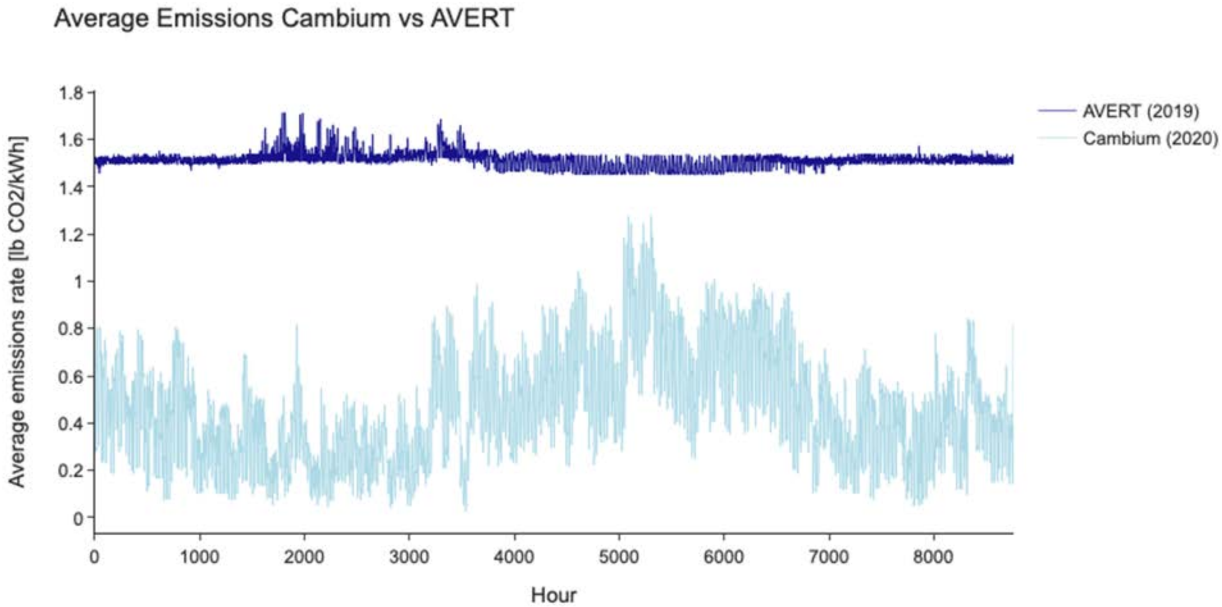

Figure B-1. Marginal emissions factors for AVERT and Cambium

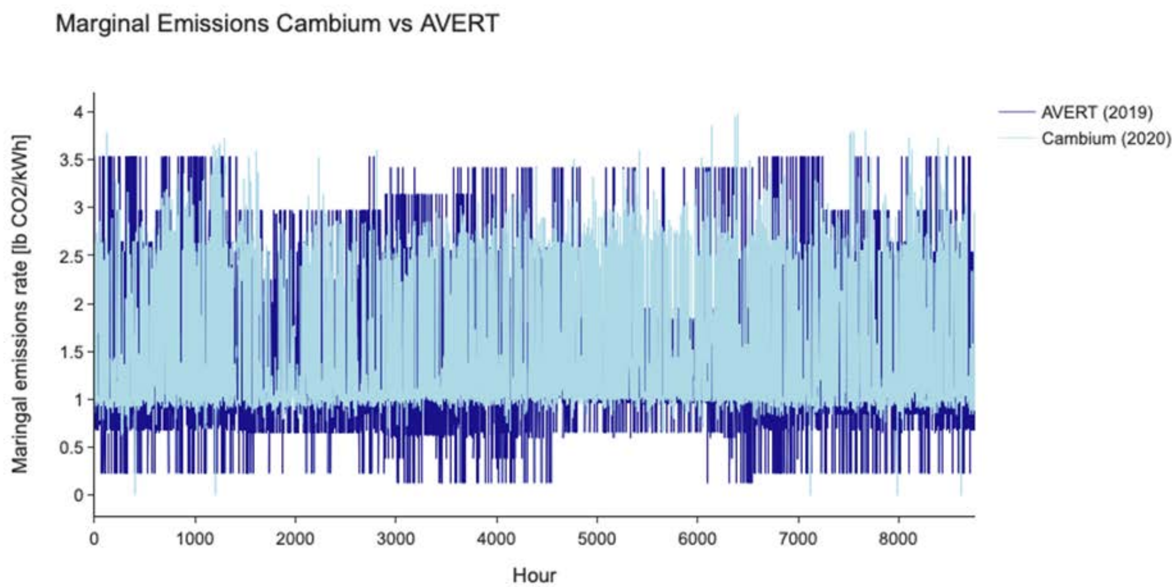

Figure B-2. Average emissions factors for AVERT and Cambium

Table B-1. Annual Mean of Hourly Marginal and Average Grid Emissions Rates from Cambium (at the Balancing Area Scale, for 2020) and AVERT (at the Regional Scale, for 2019)

Emissions	Cambium (Balancing Area 28, 2020) [lb CO_2/kWh]	AVERT (Southwest Region, 2019) [lb CO_2/kWh]
Average emissions	0.46	1.51
Marginal emissions	1.44	1.54

The annual mean of the Cambium *average* emissions rates is 70% lower than that of AVERT, whereas the mean of the *marginal* emissions rates from Cambium is only 6% lower than that of AVERT. Because the average values from the AVERT data set are based only on fossil-based generation while the Cambium data set represents the total grid mix, AVERT average emissions factors are not necessarily representative of an existing load's emissions impact. While the values are shown here for illustrative purposes, they are not included in the results section of this paper. Cambium *average* emissions rates indicate lower emissions intensity midday, likely due to increased solar generation, whereas the AVERT average emissions data does not, due to the fact that only fossil generation is captured. AVERT shows greater seasonal variability in marginal emissions factors, while Cambium indicates greater seasonal variability in average emissions factors.

Considering the wide range of emissions factors estimates under differing factor type and data set assumptions, we present the cost-optimal battery dispatch strategy and resulting emissions impacts for a single home using marginal emissions factors from both AVERT and Cambium and average emissions factors from Cambium.

PV Considerations in REopt

The solar PV generation collected from the homes differed from that reported in REopt for a system of the same size. The actual PV generation peaks at different times of day, often earlier and at a higher average power than the modeled peak in REopt. This was attributed to the panel type and orientation; the homes built by Mandalay Homes have bi-facial panels, and variable roof (and therefore solar panel) orientation. To address this in the model, we adjusted the angles and array types of the modeled systems to better align with the deployed systems.

Optimal HVAC and Water Heating Dispatch in REopt

Outputs from the OCHRE model were used to enable flexible load modeling in REopt. An RC model from OCHRE was used to model a home's thermal envelope and, along with the HVAC efficiency and capacity characterization, to enable REopt to dispatch the system to minimize the cost of electricity purchases (while not exceeding comfort tolerances). A similar framework was extended to capture the performance of the water heating system, in this case a heat pump water heater. The amount of energy delivered and consumed by the HVAC and water heating systems when redispatched in REopt matched OCHRE outputs nearly perfectly during validation as shown in Figure B-3. This indicates that the optimal dispatch achieved in REopt results in similar performance as using the setpoints in OCHRE. For the homes in this analysis, we only have whole home power without HVAC consumption disaggregated and also do not have information on the HVAC setpoints, so no comparisons of the field and modeled HVAC power consumption were done. Still, this enhancement will enable future high-fidelity modeling of flexible loads in REopt.

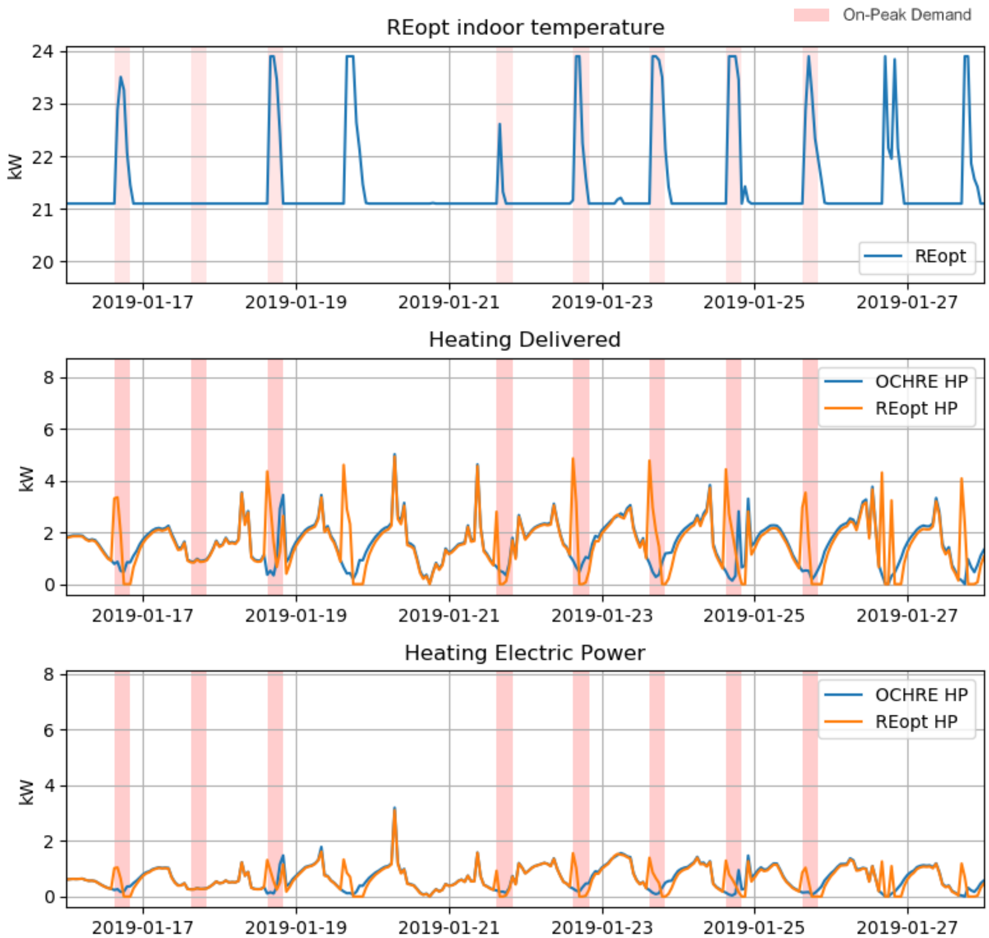

Figure B-3. Comparison of HVAC dispatch in REopt and OCHRE

Thermostat and Thermal Mass in OCHRE

HVAC equipment cycling frequency is important for understanding high-resolution home power consumption, but it is not incorporated into many building models. Previously, OCHRE modeled HVAC equipment that cycled too frequently when compared to the field data from the Mandalay Homes community, causing large fluctuations in house power. Based on recent research (Cetin, Fathollahzadeh, Kunwar, Do, & Tabares-Velasco, 2019) and data from the Mandalay Homes community, OCHRE's model was updated to reduce HVAC cycling to more realistic levels by increasing the amount of thermal mass in the building to better reflect actual amounts of furniture in homes.

HVAC Control in OCHRE

OCHRE's HVAC model included control methods for setting a thermostat setpoint and for directly controlling the HVAC duty cycle. The homes in this analysis use two-speed heat pumps with a unique control strategy that disables the higher speed during peak hours to reduce demand at those times. This control strategy was implemented in OCHRE and was shown to reduce HVAC consumption during peak hours.

Figure B-4 shows the HVAC power and indoor temperatures (as modeled in OCHRE) with and without the new control strategy. The controls reduce HVAC cycling and peak power consumption, while having very little impact on overall energy consumption or occupant discomfort.

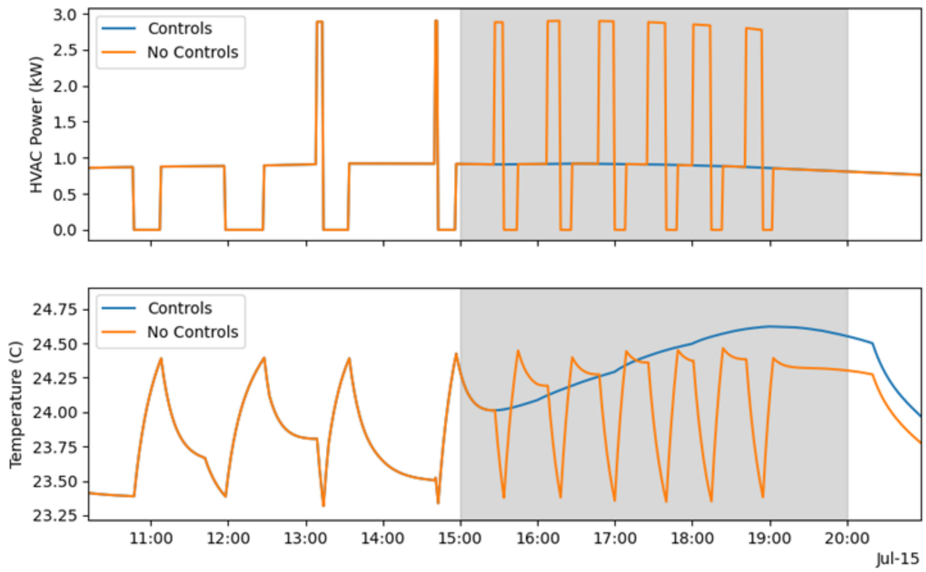

Figure B-4. OCHRE HVAC power and indoor temperature with and without the two-speed HVAC control strategy

The OCHRE house model with these HVAC controls was validated against field data from the homes in this analysis as shown in Figure B-5. On a hot summer day, the main component of total house load is air conditioning from the air source heat pump. OCHRE's HVAC model has a similar cycling frequency and duty cycle as many of the homes in the field.

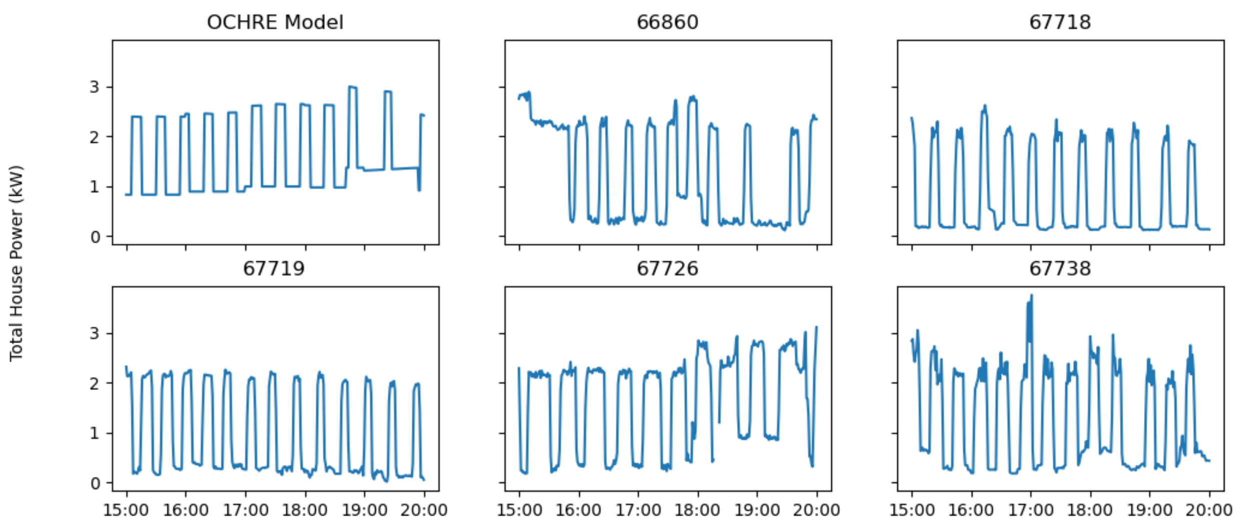

Figure B-5. Total house power for the modeled OCHRE home and five Mandalay homes on a hot summer day