Metrics and Analytical Frameworks for Valuing Energy Efficiency and Distributed Energy Resources in the Built Environment

Preprint

Monisha Shah, Dylan Cutler, Jeff Maguire, Zac Peterson, Xiangkun Li, Josiah Pohl, and Janet Reyna

National Renewable Energy Laboratory

Presented at the 2020 ACEEE Summer Study on Energy Efficiency in Buildings
August 17-21, 2020

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-6A20-77888
October 2020

Metrics and Analytical Frameworks for Valuing Energy Efficiency and Distributed Energy Resources in the Built Environment

Preprint

Monisha Shah, Dylan Cutler, Jeff Maguire, Zac Peterson, Xiangkun Li, Josiah Pohl, and Janet Reyna

National Renewable Energy Laboratory

Suggested Citation
Shah, Monisha, Dylan Cutler, Jeff Maguire, Zac Peterson, Xiangkun Li, Josiah Pohl, and Janet Reyna. 2020. *Metrics and Analytical Frameworks for Valuing Energy Efficiency and Distributed Energy Resources in the Built Environment: Preprint*. Golden, CO: National Renewable Energy Laboratory NREL/CP-6A20-77888.
https://www.nrel.gov/docs/fy21osti/77888.pdf.

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-6A20-77888
October 2020

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

NOTICE

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

NREL prints on paper that contains recycled content.

Metrics and Analytical Frameworks for Valuing Energy Efficiency and Distributed Energy Resources in the Built Environment

Monisha Shah, Dylan Cutler, Jeff Maguire, Zac Peterson, Xiangkun Li, Josiah Pohl, and Janet Reyna, National Renewable Energy Laboratory

ABSTRACT

This paper summarizes efforts to develop new, and enhance existing, analytical frameworks and metrics to quantify the value that grid-interactive efficient homes with solar (GEB-solar homes) can provide. Industry is working to characterize and understand these capabilities and benefits, but existing analytical frameworks for evaluating energy efficiency (EE) are often siloed from those that evaluate distributed energy resources (DERs).

Five metrics were adapted from an extensive literature review and applied to case studies of a modeled home in Riverside, California: *ramp up/down, cover factor demand/supply, and curtailable load*. Eight different technology scenarios were analyzed using a connected suite of building, site, and grid models (BEopt, REopt, ReEDS, and PLEXOS). Additionally, time-varying marginal electricity costs were developed, based on NREL's 2018 Standard Scenarios. These marginal costs were used to generate time-varying proxy retail rates, and were also applied directly to calculate a new grid alignment metric.

In the results, a more integrated combination of GEB-solar technologies led to a higher cover factor demand—the percentage of gross home load covered by on-site solar—however, a benchmark was required to determine what range of cover factor was "best" for given grid conditions. To that end, a grid alignment cost metric was applied to the case study scenarios. The average cost to serve the net load of the home decreased from a median of ~$0.24/kWh to ~$0.10/kWh when the most integrated technology scenario was optimized towards the grid pricing proxy versus the time-of-use (TOU) rate.

Introduction

This work focuses on analytical frameworks for valuing grid-interactive efficient single-family residential buildings with solar, GEB-solar homes, which, in aggregate, could provide substantial grid-oriented services. GEB-solar can impact the local and bulk power grids in positive and negative ways. Industry is working to characterize and understand these impacts, capabilities, and benefits as described by NASEO-NARUC (2019). To date, there has been limited development of metrics or analytical approaches for assessing the value that buildings harnessing EE, flexible loads (FLs), battery energy storage systems (BESS), and photovoltaics (PV) can provide to different energy sector stakeholders, such as building owners, distribution utilities, grid operators, and society (Shah et al. 2018). Existing analytical frameworks for evaluating the costs and benefits of EE are often siloed from those that evaluate DERs and are often not equipped to consider the cost and benefits of these resources as a combined package. Consequently, decision makers may even view resources such as EE and PV as competing, rather than considering the combined value of pairing these assets together (Perry et al. 2019). New analytical frameworks and metrics must be developed, or existing ones enhanced, to more accurately quantify the value buildings can provide to different energy system actors, particularly in a temporally and spatially specific context.

In this analysis, we highlight the relevant benefits by stakeholder group, evaluate the metrics that have heretofore been used to quantify these benefits, and evaluate select metrics (including a newly developed grid-centric metric) through a new analytical modeling framework. The first two sections of the paper cover value streams and a review of existing metrics for GEB-solar. The last two sections outline the case studies for a modeled single-family home in Riverside, California, that were performed with a connected suite of building, site, and grid models (BEopt, REopt, ReEDS, and PLEXOS) and the associated results and conclusions.

Potential Value Streams of GEB-Solar Homes

The enhanced capabilities of GEB-solar buildings, including flexibility, can provide a spectrum of benefits to various stakeholders in the energy system (Carmichael et al. 2019; DOE 2019). This project explores new and existing methods for valuing these benefits for three main stakeholder groups: building owners/occupants, utility or grid actors, and society as a whole.

From the bulk power system perspective, aggregates of single-family homes have the potential to provide a number of grid services. For example, a group of houses could provide capacity during peak times at the bulk power level by reducing net load based on a signal from grid operators. GEB-solar can provide transmission congestion relief by exporting energy to provide electricity in constrained areas. In addition, a group of homes could shift energy consumption to time periods with overgeneration of PV. Another way GEB-solar could provide value is through operational cost savings (e.g., power plant fuel, O&M, and startup costs) by enhancing the ability of a building to reduce energy requirements during times with high marginal cost of generation.

The distribution system has needs unique from the bulk power system. One of the most significant ways a GEB-solar can support the distribution system is by managing the real/reactive power output from inverter-based devices like PV coupled to the grid. Doing so can aid in mitigating voltage violations (unrelated to PV), decrease distribution grid energy losses, and reduce or defer distribution system infrastructure upgrades. Additionally, GEB-solar can reduce distribution system congestion by curtailing net load or increasing or decreasing the export of on-site generation during times of congestion.

Homeowners can accrue value from GEB-solar through utility bill cost savings, monetary compensation for providing grid services, or through non-monetary values such as improved comfort or resiliency. For example, a utility bill management strategy could utilize storage or load scheduling to shift energy consumption to lower-cost time periods or simply reduce consumption during high-cost time periods (assuming the retail tariff provides some time-based price differentiation or demand charge component). Either would result in reduced utility bills, assuming the price differential is large enough to make up for any roundtrip efficiency or other losses. New revenue streams can be developed by participating in demand response events which compensate for managed energy consumption based on temporal parameters. GEB-solar with storage can also provide increased resiliency by supporting critical loads during a grid outage, allowing occupants to continue operations. This capability will depend on inverter technology, islanding technology, and presence of AC-coupled batteries, as most solar inverters are not able to generate during grid outages for safety purposes.

From the societal perspective, GEB-solar could also provide value by reducing the greenhouse gas emissions, reducing criteria pollutants, and increasing system resiliency. One aspect of greenhouse gas and criteria pollutant reduction is reducing total annual energy consumption (Langevin et al. 2019), but grid emissions also vary on a temporal basis (Vuarnoz et al. 2018). BESS and/or FL in tandem with EE and PV could be optimized to shift energy consumption to a less carbon-intensive time period or to self-consume during carbon-intensive periods on the grid. Additionally, GEB-solar homes could provide flexibility to markets with high penetrations of variable resource renewable generation or provide low carbon electricity by exporting on-site renewables. Finally, benefits of generation sited near to load, and more controllability on the load side, could provide additional resiliency to the system. Capturing these benefits for GEB-solar requires the application of either existing or new metrics and analytical frameworks to measure the building capabilities needed to provide these benefits.

Existing Metrics and Analytical Frameworks

A literature review was conducted to collect existing metrics that could quantify the value streams associated with GEB-solar and measure the building capabilities needed to provide them. A wide net was cast across five different bodies of literature: zero energy buildings, grid impact, demand response, value of DERs, and bulk power system; and from that search we identified over 125 potentially relevant metrics.

Most of the metrics identified through literature review fell into two high-level categories: (1) operational metrics; or (2) asset metrics. Asset metrics—"leading" metrics—measure potential performance, evaluating the theoretical or technical potential of a GEB-solar depending on its design characteristic. Operational metrics—also referred to as "lagging" metrics—measure past performance, typically based on empirical data. Metrics were also categorized as: directly applicable to GEB-solar, indirectly applicable (i.e., requiring minor adaptations before being used to evaluate a GEB-solar home), or out-of-scope. Out-of-scope metrics were those that measured impacts not considered in this analysis. Five metrics were selected to test their effectiveness through the case study analysis, and these are described in more detail below.

Ramp up/down. The ramp up/down metric was adapted from the bulk power flexibility literature from a metric called "maximum ramp rate in net load" (GMLC 2020) and is usually a maximum value calculated over all hours of the year. To avoid outliers, the metric can also be calculated as the mean of the absolute value of the top 1% largest ramps over the year.

$$R_i = P_i - P_{i-1} \quad i = 1, 2, \ldots, 8760 \qquad \textit{(Eq. 1)}$$

The *ramp* metric (in kW/hr) was calculated by subtracting the net load[1] (in kW) for each hourly time step by the net load of the previous time step for the entire year. This is seen in Eq. 1, where R_i is the ramp for the time step, P_i is the power at the time step, P_{i-1} is the power at the previous time step, and this was considered on an hourly basis.

The ramp metric measures the change of net load (e.g., kW) for a given time step (e.g., 1 hour) over a time period (e.g., 1 year), units kW/hr. Ramp could be a useful metric in understanding how variable the net load of a building might be and quantifying the magnitude. The ramp metric could be used to ascertain building performance against other grid behaviors. For example, it may be useful to measure ramp for a building during a time of day when system-wide ramps in load are occurring. The ramp metric could also be useful in determining

[1] Net load refers to the gross load of a GEB-solar home minus any on-site generation used to meet gross load, including on-site solar electricity stored in the BESS and discharged to meet on-site loads at a later time.

opportunities for smoothing the load profile to reduce demand charges through storage or FL capabilities. If the ramp metric were calculated for individual technologies in the building instead of for the whole building, one may be able to determine how different equipment contribute to rapid changes in net load in a building.

Curtailable load. Curtailable load measures the absolute *decrease* in net load a building can provide during a time step (e.g., 1 hour), in units of kW. This metric originates from the bulk power system literature and was originally defined as the ramp capability of a dispatchable fleet over various time periods (GMLC 2020). For a building, curtailable load would need to consider all FLs in the building operating during the time step of interest while taking into account thermal comfort requirements. This metric could be calculated on an asset basis and provide the potential to curtail net load or on an operational basis and provide the actual net load that was curtailed due to economic drivers or building controls. Curtailable load can be considered over various time scales, and measurement becomes more complex when storage is included. This information could be helpful to utilities who may need to curtail load during times of system peak or to building owners who seek to curtail loads to avoid high demand charges or TOU rates.

Cover factor supply/demand. Cover factor demand and supply are derived from the net zero energy buildings literature and are usually calculated on an annual basis (Verbruggen et al. 2011). Both of these metrics are unit-less and vary from 0 to 100%. *Cover factor supply* (CF_s) measures the ratio of on-site generation consumed by the building to gross on-site generation. A CF_s of 100% means the building is consuming all on-site generation, whereas a cover factor of 0% means the building is exporting all on-site generation. This metric can indicate the amount of electricity the building is exporting during a given time period and also provide a sense for what percentage of the on-site electricity is being used for self-consumption. CF_s is normally calculated on an annual basis (Eq. 2) but can be modified for different time periods (e.g., a daily time period).

$$CF_s = \frac{Consumed\ onsite\ PV\ generation}{Gross\ onsite\ PV\ generation} x100 \qquad \textit{(Eq. 2)}$$

Cover factor demand (CF_d) measures the ratio of total on-site generation serving load to the gross load of the building. This metric provides insights on both load matching[2] or self-consumption,[3] as well as how reliant the building is on electricity from the grid. For example, a building with CF_d of 100% on an annual basis means the building is a zero-energy building over the course of a year, whereas a cover factor of 0% means the building lacks on-site generation or the generation is completely misaligned with demand, and is thus fully reliant on the grid. This metric can be modified as needed to consider how different net load components (e.g., electrochemical storage, thermal storage, FLs) change the cover factor. For this analysis, CF_d was calculated by dividing the annual on-site generation consumed by the building by the building's gross load for the entire year (Eq. 3). The gross load in the scenarios includes the consumption from the traditional loads (e.g., lighting, appliances), as well as consumption from the battery system and FLs (if applicable).

---

[2] Managing energy consumption to match with energy supply.

[3] Maximizing consumption of energy generated on-site.

$$CF_d = \frac{Consumed\ onsite\ PV}{Gross\ load} x100 \qquad \textit{(Eq. 3)}$$

Case Studies

To evaluate the applicability and usefulness of existing and new metrics, an analysis workflow was developed to assess the interactions between PV, EE, FL, and BESS in a modeled single-family home in Riverside, California. The analysis workflow allowed the project team to study simulated home design and operations with respect to grid information. Existing metrics identified through the literature review were calculated using this analysis workflow to begin assessing their applicability and effectiveness in measuring the various benefits of GEB-solar. The analysis workflow (Figure 1) included two models developed by the National Renewable Energy Laboratory, the Building Energy Optimization (BEopt) (BEopt 2014) and the Renewable Energy Optimization (REopt) (Cutler et al. 2017) models, which were both deployed to determine cost-optimal adoption and operation of EE, FL, and DER technologies in homes.

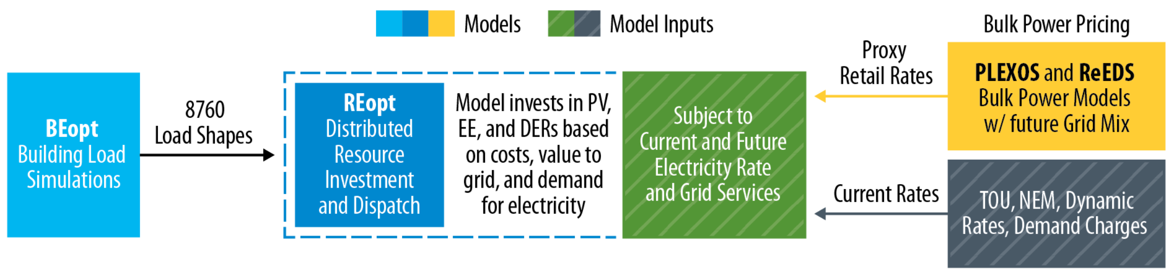

Figure 1. Analysis workflow for evaluation of customer investment decisions

Home EE and DER investment and operation models. ***BEopt*** is a physics-based building energy modeling platform for residential buildings that finds cost-optimal combinations of building equipment and technologies. The major limitations to BEopt with regards to this project are the limited options for modeling FLs and the inability to model battery storage. ***REopt*** is a techno-economic optimization model that can optimally size and dispatch mixes of generation and storage technologies to minimize the cost of energy for a site. It is formulated as a mixed integer linear program (MILP), with the objective function being the minimization of the life cycle cost of energy for a specific site or building. The limitation to REopt in the context of this project is that it simplifies the building load modeling and cannot fully simulate and compare EE improvements with renewable energy or storage options. While both of these models optimally select combinations of technologies to minimize the life cycle cost of energy for a site, neither contains the complete set of technologies that were of interest for this project. Using a coordinated model workflow, these two models were utilized in conjunction, with data being passed from BEopt into REopt, enabling a more complete evaluation of the technological space under consideration.

These two models approach the control of dispatchable technologies in very different ways. BEopt uses algorithmic approaches for how to control a single technology (e.g., HVAC systems or smart appliances). These are typically schedule-based and are input based on analysis of the TOU rate. REopt, on the other hand, dispatches a suite of technologies to minimize cost of electricity for the homeowner and considers the technical capabilities and cost/benefit trade-off (as formulated in the optimization constraints) as it optimally dispatches any combination of the technologies selected by the model using perfect foresight. This approach reflects a centralized controls approach—similar to what an advanced home energy management system (HEMS)[4] would attempt to deliver—and may be considered to represent a theoretical upper bound. Actual operation of an integrated HEMS would depend on how the system was programmed and its ability to coordinate the loads with uncertain forecasts. To adequately capture a range of approaches to controls, both types of device controls were included in the modeling framework.

	BEopt		REopt		
Scenario	Energy Efficiency (no controls)	Flexible Loads (Schedule-based controls)	Flexible Loads (Advanced controls)	PV	BESS
no FL	●				
FL-Sch	●	●			
PV	●			●	
FL-Sch/PV	●	●		●	
PV/BESS	●			●	●
FL-Sch/PV/BESS	●	●		●	●
FL-Adv	●		●		
FL-Adv/PV/BESS	●		●	●	●

Figure 2. Summary of technology combination scenarios

BEopt was utilized to suggest optimal packages of energy efficient and FL technologies that minimize life cycle costs for the homeowner when designing a single-family home. With EE and, in some scenarios, FLs modeled in BEopt, the top 100-200 performing sets of technology combinations were sent to REopt to find optimal combinations of PV and BESS to minimize cost to the homeowner. Additionally, for coordinated controls scenarios, the FLs were characterized in BEopt but then modeled explicitly in REopt using state space modeling of resistance-capacitance networks to allow for coordinated dispatch.[5] This approach allows for the exploration of a full range of EE, FLs, BESS, and PV, but because of the sequential nature of the modeling flow, not everything is co-optimized in the same platform.

Time-varying Marginal Grid Costs. To determine the grid value of different demand-side technologies when the technology owner is operating it in their own self-interest, the project team used two models to generate time-varying marginal costs of electricity, using NREL's 2018 Standard Scenarios to characterize future bulk power system scenarios.[6] Using the capacity investments from the 2018 NREL Standard Scenarios Mid-Case, we used PLEXOS, a commercial production cost model, to obtain hourly marginal costs of energy and ancillary services for the projected 2040 system. We then constructed a total marginal electricity cost by

[4] Home energy management systems exist but are not widely deployed in US homes. For more information see: https://www.energystar.gov/products/shems_key_product_criteria

[5] A resistance-capacitance network is an equivalent circuit representation of the thermal flows through a building. This can be represented in a state-space formulation, which is linear set of equations that can be embedded in a MILP.

[6] NREL's Standard Scenarios is an annual product that uses the ReEDS capacity expansion model to project the evolution of the bulk power system through 2050 under a range of potential futures (Cohen et al. 2019; Cole et al. 2018).

allocating the marginal cost of capacity (from the ReEDS model) to the top 40 net-load hours.[7] Lastly, to construct a time-varying proxy retail rate for this future scenario, we took the marginal cost patterns described above and scaled them up, such that the same amount of revenue would be collected from that load profile as the revenue collected from the actual retail rate's energy prices.[8] These proxy retail rates could then be used in BEopt and REopt to influence technology investment and operations decisions.

Eight technology scenarios were studied in the analysis workflow (Figure 1); all scenarios included traditional EE measures that lower overall energy consumption but do not allow for load shifting. The "no FL" scenario refers to scenarios with only traditional EE upgrades and no FL options. The "FL-Sch" scenario includes the FL options included in BEopt, such as certain household appliances or the HVAC systems with manually programmed operating schedules around the peak periods of a local TOU rate. Since flat rates do not incentivize load shifting and the time-varying marginal grid costs do not align well with scheduled control, they were not applied to the FL-Sch scenarios. Finally, the "FL-Adv" technology scenarios include FLs for which the operations are optimized in REopt based on the rate structure, other incentives and, when available, with PV and battery sizing and dispatch decisions. This approach maximizes synergies across flexible residential assets.

In the analysis, several economic and technology assumptions were taken. The analysis period was 30 years, and the technologies were assumed to be owned by the building owner. The PV and battery systems were assumed to utilize the Investment Tax Credit at 30% and 26.25% respectively and grid charging was allowed, as well as the 5-year Modified Accelerated Cost Recovery System (MACRS) depreciation deduction. The PV systems were assumed to have an installed cost of $2.80/W-DC (Fu et al. 2017) with an O&M cost of $20/kW/year. The battery costs were assumed to be $930/kWh + $1,115/kW, with a single replacement occurring during the analysis time period with a cost of $471/kWh + $565/kW[9] (WMPR 2018).

BEopt and REopt were both exposed to a suite of utility tariffs to understand what technologies (and operational approaches) provided the most value to the homeowner. Four sets of rate structures were applied to the scenario analysis: a flat volumetric rate, a 2018 TOU rate for Southern California Edison (SCE),[10] the net metering rate for SCE in 2018, (NREL 2018) and the aforementioned proxy retail rate based on the projected 2040 system. This last rate was included to provide the most direct, price-based communication of grid needs to the homeowner-focused modeling workflow.

A distinct single-family home model was developed for Riverside, California, and location-specific weather files were used to model realistic conditions. Riverside is simulated in the SCE service territory, which is part of the California Independent System Operator, and is located in IECC climate zone 3B. By design, BEopt selects packages of energy efficient technologies based on capital cost, installation costs, equipment lifetime, and electricity rates to minimize life cycle costs. For Riverside, 24 potential efficiency measures in nine major technology categories were considered: thermal mass (3), wall insulation (2), wall sheathing (4),

[7] The future marginal electricity costs were developed with a prototype version of a grid model post-processing tool called Cambium (Hale et al., 2019)

[8] This should not be mistaken for a maximally economically efficient pricing scheme. It would be by chance if the actual costs that create the difference between wholesale and retail rates followed the patterns of the marginal costs.

[9] Battery costs are assumed to decline at a rate of 6%/year (Manghani, R. 2014. *The Future of Solar-Plus-Storage in the U.S.* Boston: GTM Research)

[10] SCE rate: TOU-D-T-Region 10 (https://openei.org/apps/USURDB/rate/view/586be52d5457a30d661c9607#1__Basic_Information).

ceiling insulation (3), windows (1), basement/floor insulation (3), infiltration (3), ventilation (1), space conditioning (2), and lighting (2). The base model was an all-electric home to focus on exploration of the electric impacts of space conditioning upgrades/controls. The capital and installation costs, as well as the expected lifetime of each of these technologies, are standard to BEopt and come from the National Residential Efficiency Measures Database (NREL 2018).

Results

Though all the of the metrics described above were applied in the case study, a few will be highlighted in this report. The application of *cover factor demand*, a metric that can measure building capabilities of both load-matching and self-consumption, and the results of a *grid alignment* metric will be explained.

Impact of control options. One component of the scenario analysis was to explore how different types of control options—scheduled controls (BEopt) and advanced dispatch controls (REopt), which more closely integrate EE and DER options—could impact the value of GEB-solar and, in particular, the contribution of solar to that value. Figures 3 and 4 compare the impact of these control options, with and without solar and storage, respectively, in diagrams displaying the dispatch results for 1 week in early June for the modeled home in Riverside, California (the optimal EE package generated by BEopt).

In Figure 3, we show the impact of the two control options (smart water heaters and HVAC) without any PV or BESS. The scheduled controls minimize HVAC use during peak pricing, as opposed to the advanced controls, where the HVAC is either turned off or precooled. Note that REopt, with its more advanced dispatch, was allowed to choose different setpoints from BEopt so long as it maintained thermal comfort (leading to a precooling strategy), whereas BEopt was scheduled to turn HVAC off at certain times and temperature would drift accordingly. Additionally, the scheduled controls do not include water heater control, where the advanced controls model does (note shifting of the DHW [yellow area] out of peak-pricing periods in the lower tile of the figure). The scheduled controls include appliance control where the advanced controls approach does not (note shifting of the light blue area out of peak-pricing periods in the upper tile of the figure). Despite these differences, the two controls approaches, in Figure 3, result in relatively similar net load profiles (solid black trace), with the largest change being the advanced controls shifting of the DHW load.

Next, Figure 4 mirrors the dispatch differences between the two controls approaches from Figure 3 but now includes the cost-optimal configurations for PV and BESS systems. In these instances, the advanced controls shift a large amount of load into the hours where the PV system is generating electricity, enabling a larger system size (3.3 kW vs. 5.4 kW for scheduled and advanced controls, respectively). The scheduled controls optimally select a larger BESS, whereas the advanced control selects a smaller system and utilizes the enhanced load coordination to effectively utilize more of the cost-effective PV. Net load is also more consistently low and smooth with the advanced controls. The detailed comparison of these two approaches highlights the ability of the controls to impact both system sizing and resulting metrics characterizing the operation of these buildings.

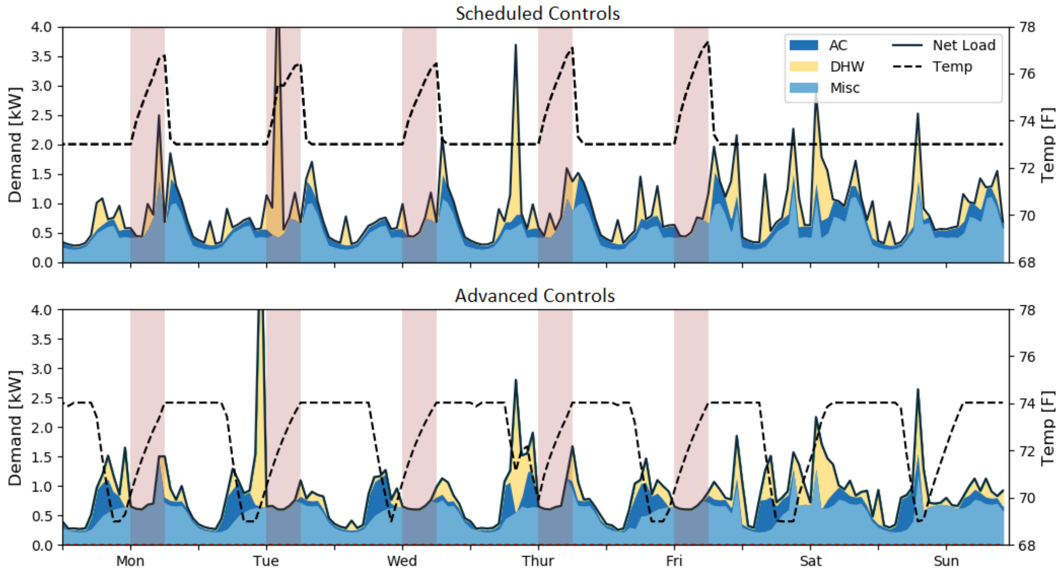

Figure 3. A week of operations comparing the scheduled (top) and advanced (bottom) controls. The profiles are for just EE and FLs (no PV or BESS). Light red bands show peak-pricing periods.

Solar and storage sizing. Building on the previous section, the scenarios with scheduled controls lead to a slight decrease in both average PV and battery sizes as compared to scenarios with only traditional EE. This is likely due to high-cost peak periods in the TOU rate aligning well with peak PV generation hours, so by scheduling FL outside of peak TOU periods, the direct value of PV generation is reduced.[11] It is not cost-effective for a homeowner to invest in a larger storage system to shift the electricity generated by the PV system to match the new load schedules, so the technology sizes decrease; however, when advanced control is available, there is a noticeable increase in average PV size with a corresponding decrease in battery size. The increase in building load flexibility allows for better utilization of renewable energy integration. PV sizes increase as load can be dynamically shifted to match daily generation profiles, reducing the need for grid purchases. Simultaneously, the increased flexibility allows the building to act as a storage unit itself, through space temperature and hot water temperature setpoint modification, reducing the need for additional electrochemical storage capacity to align on-site consumption with self-generation.

[11] This results from the EE being implemented/controlled separately from the PV/BESS. The scheduled controls are not aware of potential PV generation, therefore only reducing load in the high value periods, and thus the PV system is optimally sized smaller.

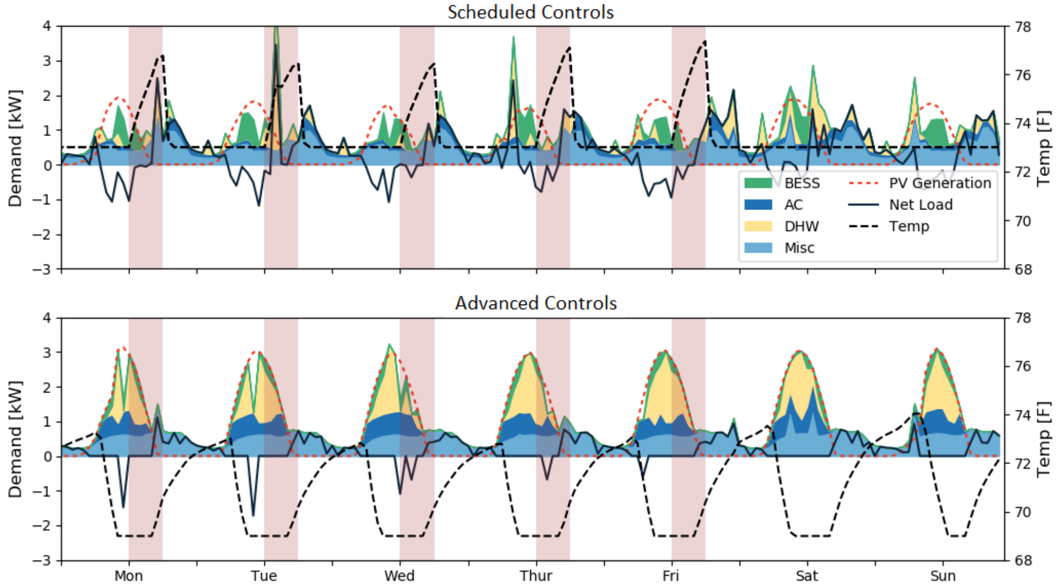

Figure 4. A week of operations comparing the scheduled (top) and integrated (bottom) controls with optimal PV and BESS sizes included. Light red daily bands show peak-pricing periods.

The solar and storage sizing is not just affected by available control options but also by the type and shape of the rate structures in place. When comparing the sizing results under the TOU rate with the proxy retail rate, we see that PV sizes are reduced (for a given control strategy, e.g., FL-Adv TOU and the proxy retail rate) when optimized under the proxy retail rate. Because the proxy retail rate reflects future marginal costs, and the grid's generation mix is expected to evolve to contain more low marginal cost renewables, daytime prices are driven down, decreasing the value of behind-the-meter PV generation. On the other hand, the real-time nature of the proxy retail rate, with greater volatility and larger price differentials, allow for more arbitrage opportunities causing battery sizes to increase relative to TOU sizing across all control approaches.

Building capability results. Though all the building capability metrics described above were calculated using the analysis workflow, this section will discuss the CF_d metric results, as it is a metric well-suited to assess load-matching and self-consumption, which are unique building capabilities for GEB-solar homes. First, the annual CF_d results for the California TOU scenarios are summarized in Figure 5. The scenarios without PV are not included in the graph because they would have a 0% cover factor demand. Each boxplot within the chart represents results for a ~100-200 combination of technologies (depending on BEopt optimization search path), ranging from only EE options without FLs or controls to full PV/battery/FLs/advanced controls. Each boxplot may represent different cost-optimal combinations of EE or FL technologies, as well as different sizes of solar and storage.

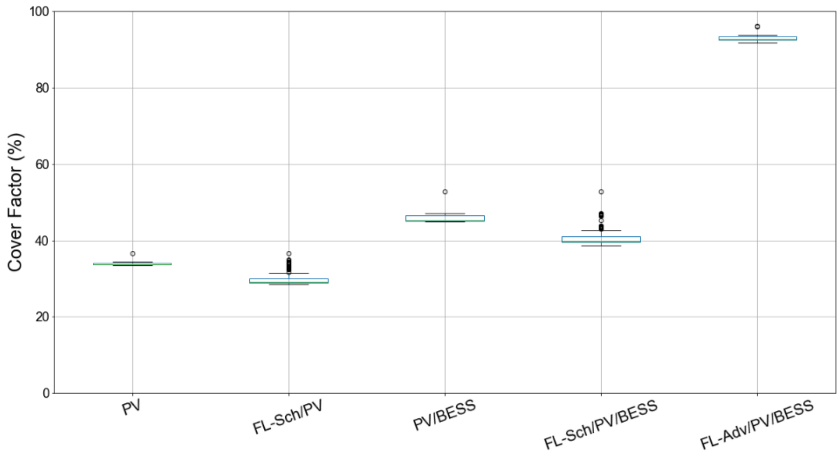

Figure 5. Cover factor demand, TOU rate

The small interquartile range seen in all scenarios suggests consistency of the cover factor value between the buildings in each scenario, highlighting the fact that FL and DER having a much larger impact than static EE measures for this metric. The results demonstrate that as the FL controls become more advanced, and BESS is deployed, the cover factor demand increases. The scenario with FL-Adv and BESS has a cover factor demand of over 90%, illustrating that the building is close to consuming zero energy from the grid on an annual basis. Interestingly, the scenarios with scheduled FLs have a lower cover factor than the comparable scenario without FLs. This is likely because the TOU peak is aligned with peak solar generation, and the scheduled controls move those loads to off-peak periods.

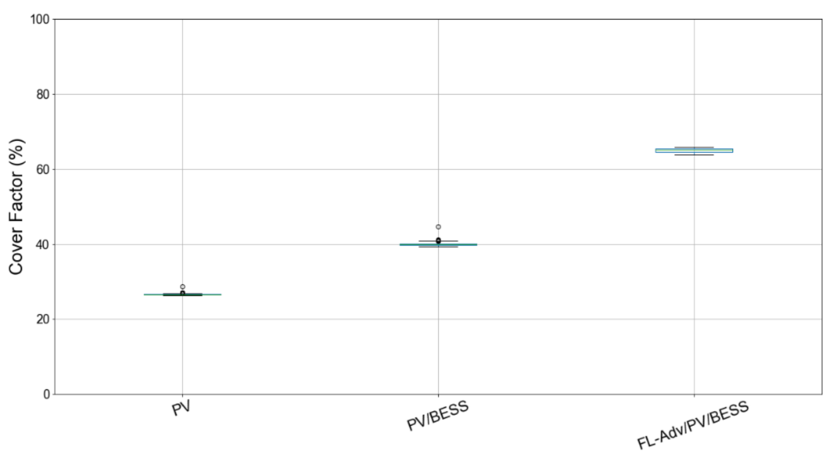

Figure 6. Cover factor demand, proxy retail rate

The amount of PV deployed also plays a role in the magnitude for the cover factor. The median PV system size for the FL-Adv scenarios was approximately 5.5 kW, but for all other scenarios the median PV system size was close to 3.5 kW. The larger system size is likely due to the FL-Adv being able to shift the loads to be coincident with the on-site generation. The proxy retail rate scenarios only include the technology packages with PV and do not include the FL-Sch (Figure 6). CF_d increases as BESS and FL-Adv are added, which is similar to the TOU scenarios. The PV system size also plays a large role in these results with the higher cover factor associated with a higher PV system size. Calculating CF_d for a particular design and operation of a home could indicate which homes might be best suited to minimize utility bill savings for customers but may need to be considered against the life cycle cost of the technology investments. Similarly, a high CF_d could also indicate which homes are best suited to address local distribution peak shaving, especially if designed against a TOU set by the distribution utility.

A high CF_d might also indicate which homes are best suited to minimize export impacts on the local grid or reduce net load during periods of peak demand on the bulk power grid. Although the project team could measure the building capability metrics in the case studies, there was still a need for context: Was a cover factor demand of 70% good, and in which instances? The project team needed to develop a benchmark for a GEB-solar home that could be considered an ideal grid asset under a given set of grid conditions.

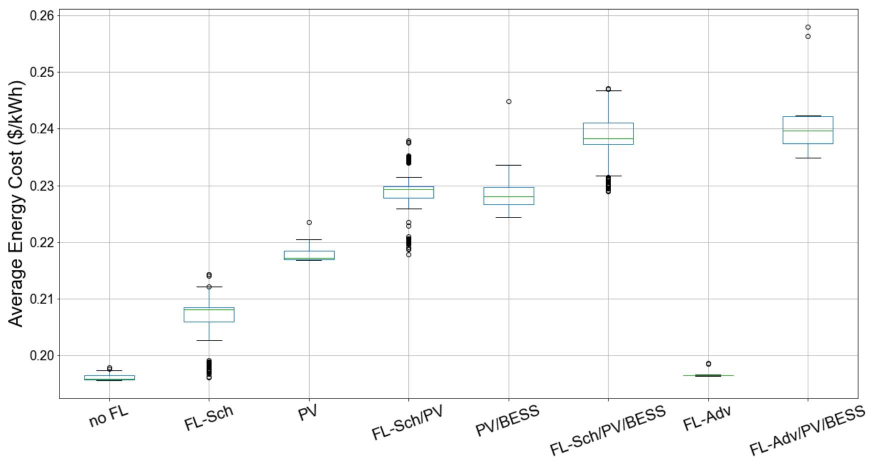

Figure 7. Average grid alignment cost for Riverside, California (TOU rate)

Grid alignment results. To that end, a *grid alignment* metric was developed and applied to the case studies to provide a benchmark for which homes might be best aligned with a future bulk power grid from a cost and emissions perspective. To explore this metric, we introduce the average marginal cost metric ($C_{p,avg}$), and then discuss the associated results. This metric is calculated by multiplying the hourly net loads for each version of the Riverside home with the technology scenarios conducted with BEopt and REopt (Fig. 1) against the proxy retail rate pricing in each hour and then normalizing this by the annual electricity demand of the home to demonstrate the average cost of serving this load from the grid perspective:

$$C_{p,avg} = \sum_{t=1}^{8760} \frac{E_t}{E_{annual}} \cdot c_t \qquad \textit{(Eq. 4)}$$

Where E_t is the net load for time step *t* (in units of kWh), E_{annual} is the total annual energy consumption of the home, and c_t is the proxy retail rate price for time step *t.*[12]

Figure 7 shows the result for average grid cost for Riverside, California, when the EE and DER assets were selected and optimized for the TOU rate. In each graph, results are presented in boxplot form, where the underlying data are the average marginal cost metric results for every

[12] We note that in this metric we are concerned with energy (thus the unit of kWh for the hour), whereas in Equation 1 we evaluate based on kW given that it is a ramping metric focused on power. These are both able to be used because it is an hourly model and the kW for the hour is equal to the energy in kWh for that hour.

building design selected during the BEopt optimization (and subsequently passed to REopt for DER optimization).

The average marginal cost increases with larger numbers of—and more integrated control of—DER and EE technologies. While the optimization models are effectively reducing the total cost of utilities for the homeowner, the reduction in utility purchases is happening at times when the grid's cost of delivering that energy (as expressed by the proxy retail rate) are the highest. Therefore, the BEopt and REopt models have effectively minimized cost for the homeowner by moving consumption out of the high-price period of the day based on the 2018 TOU price (see Fig. 7). This has effectively moved the power consumption into times that are more costly from the future grid perspective. Figure 8 shows the daily average proxy retail rate profile for all hours of the year in comparison with the on-peak period from the SCE 2018 TOU rate. We note that the on-peak period for the TOU rate (shown in the band covering 12 p.m.-6 p.m.) covers the hours with the lowest marginal grid costs on average. This difference in price shapes affect the investment and operation of the suite of technologies analyzed in this work. Figure 9 shows similar boxplot results for the scenarios that were designed against the proxy retail rate.

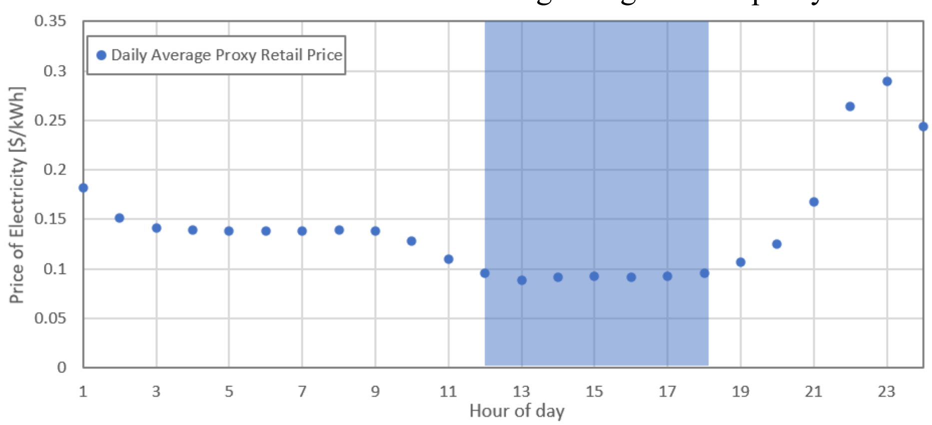

Figure 8. Comparison of daily average proxy retail rate for 2040 vs. SCE 2018 TOU rate (on-peak, 12 p.m.-6 p.m.)

For the marginal costs, similar to the previous scenarios, the scheduled controls were not run under this pricing scenario. We note that when the customer-facing models are optimized against the proxy retail rate, the trends seen in Figure 9 reverse themselves: the average marginal cost metric now decreases in line with more technologies and advanced controls. This demonstrates the ability to align the objectives of the customer and the grid, with the increasingly dispatchable, responsive controls of the DER technologies being operated to minimize energy consumption during high marginal cost periods for the bulk power system. Additionally, we note that the y-axis scales are different between Figure 7 and Figure 9, and the average cost to serve the net load of the home shifts from a median of ~$0.24/kWh to ~$0.10/kWh when the most integrated combination of PV, battery, and FL control is optimized towards the TOU rate versus the marginal grid costs, respectively.

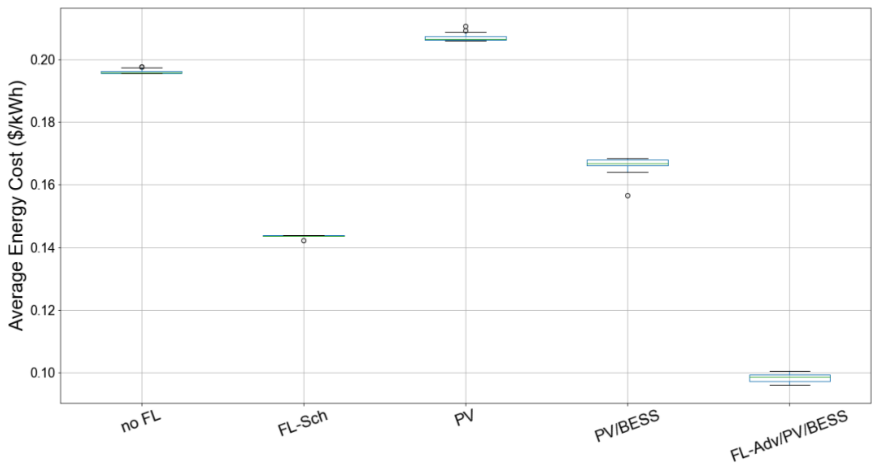

Figure 9. Average grid alignment cost for results optimized (proxy retail rate)

Conclusions

In this work, we developed a modeling methodology to evaluate the value of GEB-solar homes from multiple perspectives, including: the homeowner, the bulk power system, and society. To achieve this multi-perspective analysis, we combined models from several sectors: building energy modeling and EE (BEopt), DER optimization and dispatch (REopt), capacity expansion (ReEDS), and unit commitment and dispatch (PLEXOS). We utilize the model outputs to assess several metrics to better understand how to quantify GEB-solar contributions.

Based on the research and analysis undertaken, we drew several overall conclusions from the work. First, though the literature review resulted in over 125 metrics, only one-fifth of the metrics were readily applicable to GEB-solar homes and, even then, there were still building capabilities of interest that could not be readily measured from existing metrics. Second, although the project team could measure the building capability metrics in the case studies, there was still a need for context. Was a cover factor demand of 70% good, and in which instances? A grid alignment metric was developed and applied to provide a benchmark for which homes might be best aligned with the bulk power grid from a cost and emissions perspective.

In this work, there was still a need to more clearly capture the strengths and weaknesses of the grid alignment approach and, more specifically, explore the types of costs and emissions utilized therein. Additionally, the current grid alignment methodology incorporates many grid events (e.g., capacity costs, duck curve ramping, PV curtailment events, and so on) during which a building strategy of self-consumption might be needed. These grid events could be more specifically isolated in the grid alignment methodology and used to benchmark the building capability metrics. It would also be valuable to understand "at what cost" the building capabilities and grid alignment values of a GEB-solar home are from the owner perspective. For example, is it beneficial to increase grid alignment slightly, but result in a huge capital expenditure for the homeowner? A benefit-cost approach could be constructed to better understand this trade-off in future work. Finally, the results here are drawn from a small set of case study scenarios. These should be expanded, and associated metrics should be stress tested across a much larger set of locations and building designs.

References

BEopt. 2014. "Home." https://beopt.nrel.gov/.

Carmichael, Cara, Matt Jungclaus, Phil Keuhn, and Kinga Porst Hydras. 2019. *Value Potential for Grid-Interactive Efficient Buildings in the GSA Portfolio: A Cost-Benefit Analysis.* Basalt, CO: RMI (Rocky Mountain Institute). https://rmi.org/insight/value-potential-for-grid-interactive-efficient-buildings-in-the-gsa-portfolio-a-cost-benefit-analysis/.

Cohen, Stuart, Jon Becker, Dave Bielen, Maxwell Brown, Wesley Cole, Kelly Eurek, Will Frazier, Bethany Frew, Pieter Gagnon, Jonathan Ho, Paige Jadun, Trieu Mai, Matthew Mowers, Caitlin Murphy et al. 2019. *Regional Energy Deployment System (ReEDS) Model Documentation: Version 2018*. NREL/TP-6A20-72023. Golden, CO: NREL. https://www.nrel.gov/docs/fy19osti/72023.pdf.

Cole, Wesley, Will Frazier, Paul Donohoo-Vallett, Trieu Mai, and Paritosh Das. 2018. *2018 Standard Scenarios Report: A U.S. Electricity Sector Outlook*. NREL/TP-6A20-71913. Golden, CO: NREL. https://www.nrel.gov/docs/fy19osti/71913.pdf.

Cutler, D., D. Olis, E. Elgqvist, X. Li, N. Laws, N. DiOrio, A. Walker, and K. Anderson. 2017. *REopt: A Platform for Energy System Integration and Optimization*. NREL/TP-7A40-70022. Golden, CO: NREL. https://www.nrel.gov/docs/fy17osti/70022.pdf.

Fu, Ran, David Feldman, Robert Margolis, Mike Woodhouse, and Kristen Ardani. 2017. *U.S. Solar Photovoltaic System Cost Benchmark: Q1 2017.* NREL/PR-6A20-68580. Golden, CO: NREL. https://www.nrel.gov/docs/fy17osti/68580.pdf.

GMLC (Grid Modernization Lab Consortium). 2020. "Grid Modernization: Metrics Analysis (GMLC1.1)." https://gmlc.doe.gov/projects/1.1.

Hale, Elaine, Wesley Cole, and Pieter Gagnon. 2019. "The Evolving Nature of Grid Energy." Presented at Greenbuild International Conference and Expo 2019. Atlanta, Georgia, November 19-22, 2019.

Langevin, Jared, Chioke B. Harris, and Janet L. Reyna. 2019. "Assessing the Potential to Reduce U.S. Building CO2 Emissions 80% by 2050." *Joule* 3, no. 10 (October 2019): 2403–24. https://doi.org/10.1016/j.joule.2019.07.013.

NASEO-NARUC, Grid-interactive Efficient, and Buildings Working Group. 2019. *Grid-Interactive Efficient Buildings: State Briefing Paper.* https://naseo.org/data/sites/1/documents/publications/FINAL-GEB-NASEO-report-full.pdf.

NREL (National Renewable Energy Laboratory). n.d. "Utility Rate Database | Open Energy Information." Accessed 2018. https://openei.org/wiki/Utility_Rate_Database.

NREL. n.d. "National Residential Efficiency Measures." Accessed 2018. https://remdb.nrel.gov.

NREL. n.d. "REopt Energy Integration & Optimization Home." Accessed March 27, 2020. https://reopt.nrel.gov/.

Neukomm, Monica, Valerie Nubbe, and Robert Fares. 2019. *Grid-Interactive Efficient Buildings Overview.* DOE/EE-1968. Washington, D.C.: DOE. https://www.energy.gov/sites/prod/files/2019/04/f61/bto-geb_overview-4.15.19.pdf.

Perry, Christopher, Harry Misuriello, and Jennifer Amann. 2019. *Solar PV and Energy Efficiency in Residential Building Codes*. ACEEE. https://www.aceee.org/sites/default/files/solar-and-ee-042519.pdf.

Shah, Monisha, Dave Roberts, Eric Wilson, Dylan Cutler, Ben Polly, Elaine Hale, Janet Reyna, Annabelle Pratt, Mark Ruth, and Elaine Ulrich. 2018. *Valuing Energy Efficiency and Distributed Energy Resources in the Built Environment: Preprint.* NREL/CP-6A20-71701. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy18osti/71701.pdf.

Verbruggen, B., R. De Coninck, R. Baetens, D. Saelens, L. Helsen, and J. Driesen. 2011. "Grid Impact Indicators for Active Building Simulation." In ISGT 2011: 1–6. https://doi.org/10.1109/ISGT.2011.5759161.

Vuarnoz, D., S. Cozza, T. Jusselme, G. Magnin, T. Schafer, P. Couty, and E-L. Niederhauser. 2018. "Integrating Hourly Life-Cycle Energy and Carbon Emissions of Energy Supply in Buildings." *Sustainable Cities and Society* 43 (November 2018): 305–16. https://doi.org/10.1016/j.scs.2018.08.026.

WMPR (Wood Mackenzie Power & Renewables / Energy Storage Association). 2018. "U.S. Energy Storage Monitor Q4 2018 Full Report." https://www.woodmac.com/reports/power-markets-u-s-energy-storage-monitor-q4-2018-37185.