Assessing Aggregated Impacts of Distributed Energy Resources (DERs): A Building Stock Model Approach

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Abstract

Current simulations of DER impacts rely on detailed power system models or optimization algorithms, with less emphasis on coupling aggregate impacts to building models. We demonstrate that a building stock model approach can be applied with free, publicly available tools to aggregate impacts of DER using physics-based building models while generating insights with the granularity of hourly building simulations. We have used BEopt (EnergyPlus) and SAM to simulate various PV and battery storage deployment scenarios with a building stock model approach for the Northwest U.S. This approach was used to assess both local and regional load impacts with site-level granularity (e.g. available regional demand reduction potential for DER and site-level battery performance).

Introduction

Distributed energy resources (DERs) have historically been described as relatively small-scale generation and storage assets that if aggregated can satisfy electricity demand at scales comparable to larger, centralized generators and provide electrical power to a transmission or distribution system. In recent years, DER technologies such as solar photovoltaics (PV) and battery storage have proliferated, driven by state energy and environmental policies, increasingly favourable economics and incentives, and consumer preferences. During this time, various stakeholders including regulators, grid operators, utility companies, and customers have recognized that DERs can play a significant beneficial role in a modern electrical grid, given the many benefits that DERs can provide from the site-level, to a utility-territory scale, to a regional scale.

Background

There is growing interest in DER impacts (both individual and aggregated) by a variety of grid stakeholders, including regulators and grid operators, and for a variety of objectives. The Federal Energy Regulatory Commission (FERC) issued a Notice of Proposed Rulemaking (NOPR) in November 2016 proposing amended regulations to “remove barriers to the participation of electric storage resources and distributed energy resource aggregations in the capacity, energy, and ancillary service markets operated by regional transmission organizations (RTO) and independent system operators (ISO) [i.e. organized wholesale electric markets]” (FERC, 2016). Recognizing the rapidly changing landscape for electricity generation, delivery, and use, the National Association of Regulatory Utility Commissioners also recently published a manual to assist regulators in rate design and compensation policies for DER (NARUC, 2016). For instance, the designation of “peak load” (e.g. non-coincident customer peak, coincident system peak, etc.), which is typically affected by DER (at all levels), is identified as an important factor in rate design. The Electric Power Research Institute (EPRI) has worked with Midcontinent Independent System Operator (MISO) and others over at least the last four years to incorporate demand-side resources (e.g. energy efficiency programs and DER impacts) into system planning and reliability models (EPRI, 2015). In compliance with FERC Orders 890 and 1000 that stipulated coordination, transparency, and other methodological principles for transmission planners, various grid operators now have stakeholder committees to coordinate system planning and address DER-related issues at regional scales.

For power planners, policy makers, researchers, and DER vendors, assessing impacts of DER in aggregate while capturing the realistic diversity of building performance has remained complex and costly—particularly in the context of integrated resource planning (IRP) and other long-term planning activities (e.g. transmission expansion planning). Existing methodologies such as hosting capacity analysis (HCA) and EPRI’s distribution resource integration and value estimation (DRIVE) have been used in jurisdictions such as California, New York, and by utilities such as Xcel Energy, for identifying optimal locations for DER interconnection—and these methodologies continue to warrant improvement to achieve a balance between accuracy and ease of application (Trabish, 2017). Moreover, existing resource planning and DER simulation tools are often proprietary

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and expensive to apply, with some relying on bottom-up simulation of electrical flows in network/graph-theoretic models (e.g. OpenDSS, GridLAB-D, etc.) or optimization algorithms (e.g. dynamic programming algorithms in EPRI's EGEAS tool), while others rely on top-down statistical models, with limited fidelity to building and system-level physics and performance. Saif et al. (2013) provide a basic overview of simulation-based optimization approaches for allocating DERs, while network models have begun to include more novel approaches from areas such as game theory (Belenky, 2015). However, to the authors' knowledge, there are no public-domain methods or models that address aggregation of site-level DER impacts to allow for large-scale, steady-state DER impact assessment (e.g. for utility-territory, state-level, or regional resource planning).

We propose a stock model approach as a contribution to fill the current gaps in the literature and in practice regarding DER impact assessment in the public domain. Building stock model approaches have a long history of use in resource forecasting and energy efficiency/conservation planning. Kavgic et al. (2010) have provided an extensive overview of building stock models. The methods presented in this paper highlight the advantages of a building stock model approach, which can provide an effective balance between the rigor of physics-based simulations and the simplicity of representing an entire building stock using a representative set of building prototypes (as demonstrated by Foliente and Seo [2012] for energy use and carbon emission scenarios).

In this paper, we demonstrate that our building-stock model approach can be readily adopted to (i) generate assessments of large-scale impacts of DER for planning and (ii) identify scenarios in which more sophisticated models and simulations may be warranted (e.g. for localized impact assessments or for detailed power system design).

Methods

The methods used for the analysis (along with their required inputs) are outlined in Figure 1 below.

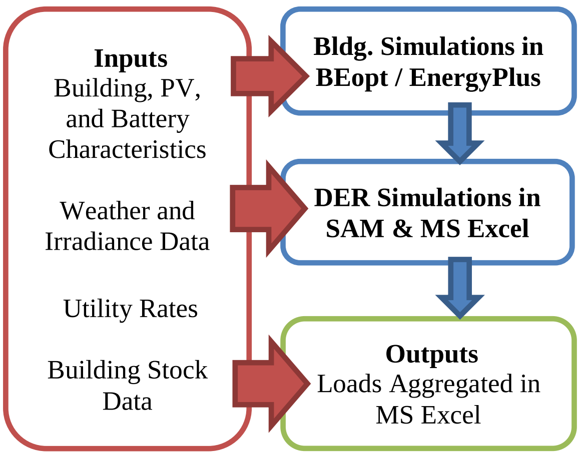

Figure 1: Flowchart of Methods and Tools Used

Building Prototype Simulation

To simulate DER impacts from a representative customer population across an entire region, whole-building energy simulations were completed by developing prototype models for residential homes in the Pacific Northwest (PNW) region. Even though this region is not optimal for solar PV deployment given its relatively low solar resource of between 3.4 and 4.4 sun-hours per day (kWh/m^2-day), this region and population were selected for illustrating our methods due to the quality of publicly available building stock data for the region. Free, publicly available simulation tools were used for this paper to facilitate replicability. BEopt™ (v.2.6.01) was used as the front-end building energy simulation tool, with EnergyPlus™ (v.8.5) as the simulation engine.

A set of three (3) single family building prototypes were developed by modifying a default BEopt building (Wilson, 2014) with envelope and equipment parameter data for weatherized homes available in the Simplified Energy Enthalpy Model (SEEM) program from the Northwest Power and Conservation Council's (NWPCC) Regional Technical Forum (RTF) (SEEM, 2016). The prototypes varied based on building size and configuration (1,344 ft^2 with crawlspace [1344C prototype code]; 2,200 ft^2 with crawlspace [2200C]; and 2,688 ft^2 with basement [2688B]) and were simulated with three (3) electric heating systems (electric forced air furnace [eFAF], air-source heat pump [ASHP], and zonal electric heat [ZONL]) across five (5) representative cities (Portland, OR; Seattle, WA; Boise, ID; Spokane, WA; Kalispell, MT). Although the majority (64%) of residential homes in the PNW region have natural gas-fired furnace heat (Ecotope, 2012; RTF, 2016), homes with electric heating were chosen as the likely installers of PV and battery storage due to heating being the dominant end use in the region. Detailed model calibration to actual home usage data was not performed, but our approach could accommodate calibration.

DER Simulation

Impacts of PV and battery storage were then simulated using the System Advisor Model (SAM, v.2016.3.14), a free, publicly available tool from the National Renewable Energy Laboratory (NREL). This tool allows for the import of hourly whole-building electric energy consumption outputs from building simulations and performs analysis of distributed energy resources such as PV and energy storage. Detailed performance models for the PV and energy storage systems modelled in SAM are publicly available (NREL, 2010).

For each of the 45 prototypes across size, heating system, and city, batch parametric simulations were performed to vary the PV capacity (0, 5, 10, and 15 kW), lithium ion battery capacity (0, 3, 6, and 12 kWh capacity with 48V bank voltage), and different battery dispatch methods. All other battery and PV performance characteristics were kept at the defaults provided in SAM. Each combination of DER characteristics used in each simulation run represents a DER deployment scenario.

Furthermore, representative electric rate structures were chosen for electric utilities that are the primary electricity providers in the respective locations simulated. Where possible (as in the case of Portland, Seattle, and Kalispell), a time-of-use (TOU) rate structure was chosen. For Seattle and Spokane, however, only residential block rates were available through the U.S. Utility Rate Database (U.S. DOE, 2016). None of these residential electric rate structures included a demand charge, which dampens the economic impact of battery storage by negating the effect of demand limiting.

Typical meteorological year (TMY3) weather data was used for each representative city to simulate ambient conditions for a typical year. A number of outputs were selected from each SAM simulation run, including hourly values for the electricity supplied to the home from the grid, hourly values for the percentage charge of the battery, hourly output of the PV system, and single annual values for parameters such as the annual net cost savings for the customer.

Battery Dispatch Methods

The SAM software provided three (3) automated battery dispatch methods: Peak Shaving 1-Day Look Ahead (1DA), Peak Shaving 1-Day Look Behind (1DB), and Automated Grid Power Target (AGPT). The impact of statistical battery dispatch methods was also investigated based on probabilistic methods developed by A. Duer (2016).

For the 1DA battery dispatch method, the solar resource and building load data are analysed a day ahead (with perfect knowledge) and the DER system is simulated to minimize grid power consumption and peak demand for the building. For the 1DB dispatch method, the previous day's solar resource and load data are analysed and the DER system is simulated to minimize grid power consumption peak demand. For the AGPT dispatch method, the simulation operates the system to shave demand and meet a flat grid power target of 1 kW per building at every hour of the year (DiOrio, et. al., 2016).

The fourth battery dispatch method considered was a probabilistic forecasting (PF) method that is composed of two parts: one to predict forward usage and another to optimize that usage as much as possible given the constraints of the battery capacity, forward usage, and load uncertainty (Duer, 2016).

The first part of the PF dispatch method uses historical load, weather, irradiance, and calendar data to construct a multivariate regression model to create an hourly energy consumption forecast. The PF method then involves using historical usage data to derive a regression model with the form of Equation (1) below:

$$kW = b_1 * temp + b_2 * CDD + b_3 * HDD + b_4 * Irradiance + b_5 * MonthlyIndicator + b_6 * HourlyIndicator \quad (1)$$

For Equation (1) above, the monthly and hourly indicators were one-hot encoded variables of m1 to m11 and h1 to h23, respectively. The last month and hour indicators are dropped from the model to avoid collinearity. Once the forecast is derived, the forecasting error can then be evaluated to establish a standard deviation. Using the standard deviation and the confidence value provided by the user, the forecast is then adjusted such that the true load is likely to be below the forecast. To give a concrete example, given a 95% confidence value, the forecast will be adjusted upward such that there is a 95% probability that the true load will be below the forecasted load. A similar situation holds true for the PF 80% case. The perfect knowledge case, however, presumes complete certainty in the forecast and allows the optimization routine to aggressively optimize the day's peak load.

The second part of the PF dispatch method is optimization. This part takes the forward forecast provided by the previous part and attempts to optimize battery operation. For periods where forecasted energy usage is lower than the daily demand, the PF method will attempt to charge the battery if there is available capacity. For periods where the forecasted energy usage is greater than daily demand, the PF method iteratively attempts to bring peak period(s) down to the next highest peak in forecast. For example, if the three highest periods are 5 kW, 4.50 kW, and 4 kW, the optimization routine first attempts to deploy 0.5 kW into the first period to reduce the total peak to 4.50 kW. If that succeeds, then it will attempt to deploy 1.00 kW and 0.50 kW into the highest and second highest periods. This process continues until the battery is unable to reduce the peak further in full increments. If there is energy left in the battery, the battery will then attempt to step down each of the peak periods by 0.1 kW until it is no longer able to reduce the building's peak. To return to our example, if our battery has a capacity of 0.75 kWh, the first iteration will reduce the 5.00 kW peak to 4.50 kW, leaving 0.25 kW, which is not enough to drive the two highest periods to 4.00 kW. In this case, the regression model will deploy 0.1 kW into each of the two highest periods to reduce total peak to 4.40 kW and stop optimizing.

Post-Processing and Aggregation

After hourly profiles of electricity from the grid and battery percentage charge were output for each prototype and DER simulation run, aggregated load profiles for each DER deployment scenario were developed via building stock weights with saturation data from the Northwest Residential Building Stock Assessment (RBSA) to result in weighted-average load profiles for a representative electrically-heated home in the PNW region, accounting for building type size, heating system, and location (Ecotope, 2012; RTF, 2016). These values were then be multiplied by the total number of electrically heated single family homes in the PNW region (594,117 homes) to result in an estimated total impact on the region for each combination of PV capacity level, battery storage capacity level, and battery discharge method. The weights used to calculate aggregated values can be seen in Table 1 below, where ASHP is an air-source heat pump, eFAF is an electric forced-air furnace, and ZONL is zonal heat.

Table 1 : Building Stock Weights Used for Aggregation

Location	HVAC System	Prototype		
		1344c	2200c	2688b
Portland	ASHP	1.5%	2.9%	1.4%
Portland	eFAF	1.2%	0.4%	0.6%
Portland	ZONL	6.8%	0.2%	1.0%
Seattle	ASHP	3.7%	7.2%	3.6%
Seattle	eFAF	3.0%	0.9%	1.5%
Seattle	ZONL	17.0%	0.6%	2.6%
Boise	ASHP	1.2%	2.3%	1.1%
Boise	eFAF	1.0%	0.3%	0.5%
Boise	ZONL	6.0%	0.2%	0.9%
Spokane	ASHP	2.1%	4.1%	2.0%
Spokane	eFAF	1.9%	0.6%	0.9%
Spokane	Zonl	11.7%	0.4%	1.8%
Kalispell	ASHP	0.2%	0.4%	0.2%
Kalispell	eFAF	0.3%	0.1%	0.2%
Kalispell	Zonl	2.9%	0.1%	0.4%

The hourly data was analysed in the Energy Charting and Metrics (ECAM) tool to develop average hourly load profiles along with box plot percentile ranges. A variety of other metrics were used to compare values across each DER combination, including ramp rates, demand reduction potential, and others.

Results and Discussion

After aggregated load profiles and other impact results were determined for each DER simulation run, they were summarized and assessed for trends and scenarios warranting more detailed analysis. For instance, the building load profile outputs generated for each DER simulation run were investigated to examine the impact of a change in PV or battery capacity or a change in battery dispatch method on the building load to be satisfied by the utility grid. These load profiles were also analysed on an annual and peak day basis and by location.

The main DER impact investigated in this analysis was the electric load (kW) from the grid, which is the load that the utility would provide to a Pacific Northwest home at each hour of a typical year. Note that the annual electricity load from the grid is not on a net basis but is calculated as the sum of the total load that the utility must provide to the home when electricity demand exceeds solar generation. When solar generation exceeds the demand of the home, the electricity from the grid is zero (not negative); this allows for an analysis of power demand requirements from the utility perspective. However, the electricity rates, monetary valuation of annual electricity bills, and cost savings from the analysis does account for end-of-year net metering.

Overall, the addition of PV and storage were found to significantly impact the load profile and electricity bill of the home. For instance, the SAM portion of the analysis found that if 12 kWh batteries were added to every electrically heated single family home in the region would result in approximately $3 million in customer bill savings per year if the battery were controlled with the AGPT dispatch method and approximately $700,000 in savings per year if the battery were controlled with the 1DB dispatch method. It could be seen that even a 3-kWh battery in every home controlled with AGPT would result in almost as much bill savings ($0.9 million per year) as 12 kWh batteries controlled with the 1DA dispatch method ($1.3 million per year). If 5 kW of PV capacity was added however, the regional electricity bill savings increased considerably (to an average of $322 million per year) but no longer differed significantly across battery sizes and battery dispatch method.

Load Profiles

The consumption of residential homes in the Pacific Northwest is dominated by heating requirements, with a regional average of 4,640 heating degree-days as compared to 128 cooling degree-days. Thus, loads are much higher in the winter. Average daily loads are also dominated by a sharp morning peak and a plateauing evening peak. Figure 2 shows the average daily load profile (electricity from grid) of a weighted average single family home in the PNW region on an annual basis and for the coldest and hottest months (January and August).

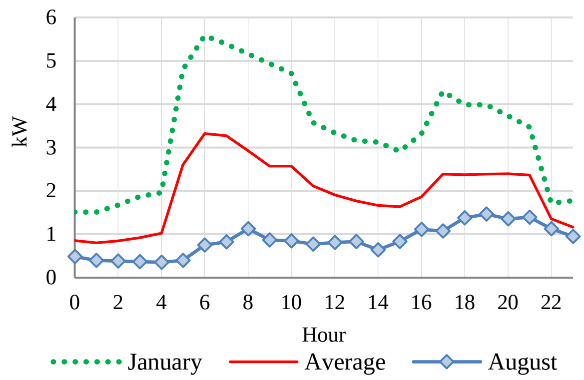

Figure 2: Seasonal Load Profile Comparison of Typical PNW Home without PV or Battery Storage

One can observe from Figure 2 that the home without DER already exhibits a decrease during the middle of the day due to occupancy, which is only exacerbated by the addition of solar PV capacity. The sharp rise in consumption between the hours of 4 and 6 AM (with a morning peak at 6 AM) and the evening peak at 5 PM are notable as well. The difference in consumption at various times of the day is most evident during the coldest month, where heating dominates the electric load.

The relative variability of a load magnitudes can be quantified by using the differences between morning (4 AM to 10 AM) and evening (4 PM to 10 PM) peaks versus night-time (10 PM to 4 AM) and midday (10 AM to 4 PM) troughs. The rate of load change between the night-time trough and the morning peak can then be considered the morning ramp rate, and the rate of load change between the midday trough and the evening peak can be considered the evening ramp rate (kW per 6-hour period). These ramp rates are useful for utility resource planning purposes since the increase in building load must be met with an increase in electricity generation. For the baseline home without DER in Figure 2 above, the morning ramp rate for the average annual daily load is 0.42 kW/hr, while the average morning ramp rate for the month of January is 0.68 kW/hr.

With the addition of battery and PV capacity, the load profile changes dramatically. Figure 3 depicts the average annual profile of a baseline home, a home with no PV but 12 kWh of battery storage, and a home with 15 kW of PV and 12 kWh of battery storage. All storage in this example is controlled with the probabilistic forecast method with perfect knowledge. The DER combinations are labelled “PV#_B#”, where “PV#” signifies the PV capacity in kW and “B#” signifies the battery capacity in kWh.

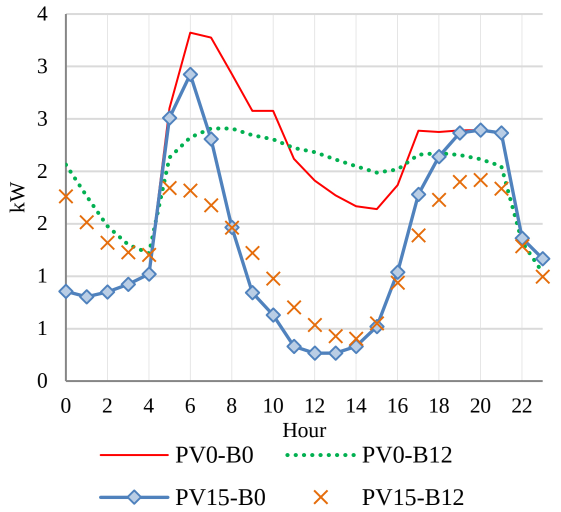

Figure 3: Annual Average Load Profile Comparison of Typical PNW Home with and without PV and Battery Storage; Probabilistic Forecast (Perfect Knowledge) Dispatch Method

Figure 3 details the typical average daily load profiles that a utility would expect to see should a single-family home in their service area add battery storage or solar and control the batteries with the probabilistic forecast dispatch method. The addition of a battery significantly reduces the morning peak, flattens the overall daily load profile, and reduces the morning ramp rate from 0.42 to 0.23 kW/hr. While the addition of solar on top of the battery results in lower peaks and a lower morning ramp rate of 0.14 kW/hr, a large PV capacity addition also results in a greater evening ramp rate of 0.25 kW/hr (a ramping increase of 0.12 kW/hr from the baseline PV0-B0 case) thereby creating the dreaded “duck curve.” If a baseline home only had a PV capacity addition without a battery, the morning peak would slightly decrease from the PV0-B0 case while the evening peak would remain the same. Furthermore, the morning ramp rate would decrease from 0.42 to 0.35 kW/hr, while the evening ramp rate would increase from 0.13 to 0.35 kW/hr. Thus, the shape of the “duck” is exacerbated if there is no battery storage present to lower the morning and evening peaks. The results in Figure 3 show that while the probabilistic forecast method primarily addresses battery discharge optimization from the customer side, it also aligns with utility needs by discharging the battery as appropriate and reducing the ramp rates when a battery is present.

When aggregated for the region, the load profile results allowed for the calculation of the average daily demand reduction potential, or difference in demand between the baseline PV0-B0 case and each proposed PV-battery case, during the peak hour of 6 AM. From the utility standpoint, this is a useful metric that can help determine the typical demand reduction expected during this hour across the year if a customer installs a specified amount of solar and battery storage; these aggregate peak-period demand reductions were calculated for each DER deployment scenario for the Pacific Northwest region. Table 4 in the Appendix of this report provides average aggregated daily peak-period demand reduction (in MW) across battery and PV capacities, battery dispatch methods, and representative cities in the PNW region.

Peak Day Analysis

The methods outlined in this study can also be used to identify and isolate specific days and hours to investigate differences between the performance of battery dispatch algorithms. To evaluate a representative peak day, weighted typical weather data for the PNW region was analysed to determine the HDD for each day of the year and a “peak cold day” of January 8 was chosen as the third consecutive coldest day of the year. Though this day is only the 9th highest in daily energy consumption, it is nevertheless in the 98th percentile of daily energy across the year.

Figure 4 compares the load profile of the typical, weighted average PNW home with 15 kW of PV and 12 kWh of battery storage on the peak cold day for the three automated battery dispatch methods available in the SAM software: 1-Day Ahead (1DB), 1-Day Behind (1DB), and Automated Grid Power Target (AGPT). The kW axis in the figure is truncated at 1.5 kW to more clearly show the differences across the dispatch methods during the morning and evening peaks.

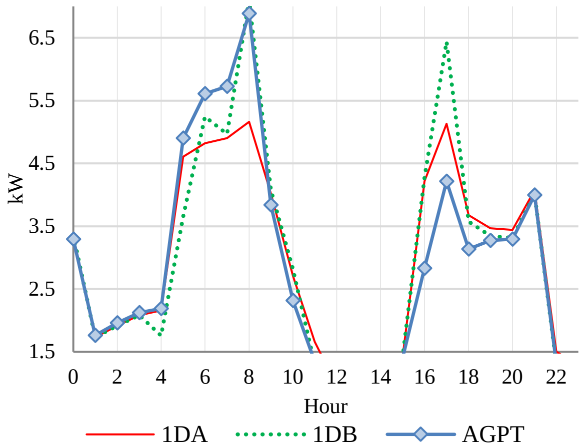

Figure 4: Comparison of SAM Dispatch Methods for a Typical PNW Home with 15 kW of PV and 12 kWh of Battery Storage During the Peak Cold Day

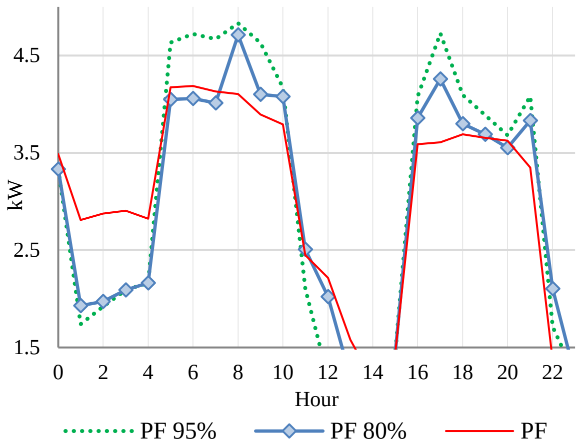

Figure 5: Comparison of Three PF Dispatch Methods for a Typical PNW Home with 15 kW of PV and 12 kWh of Battery Storage During the Peak Cold Day

During the peak cold day, the baseline PV0-B0 home (not shown) has peaks of 7.2 kW at 8 AM and 6.4 PM at 5 PM. As seen in Figure 4, the morning peak is barely lowered by the 1DB (reduction of 0.1 kW) and AGPT (reduction of 0.3 kW) dispatch methods. The ineffectiveness of the 1DB method to reduce the 8 AM peak on January 8 can be explained by the peaks on January 7, where the morning peak occurred at 6 AM and the 5 PM evening peak was much lower (4.2 kW). Since the 1DB dispatch method operates the battery dispatch based on the previous day, it decreases the demand at 6 AM but was not able to foresee an increase in demand at 8 AM. While the AGPT method is adept at lowering the evening peak by 2.2 kW below the original evening peak, the 1DB method does not impact the evening peak whatsoever since it was not flagged as significant from the day before. Dispatching the battery with 1DA seems to be the more optimal method since it decreases both morning and evening peaks. While the evening ramp rate for the 1DA method is 0.19 kW/hr greater than the evening ramp rate for the AGPT method, the 1DA morning ramp rate is also 0.32kW/hr lower than the rate for AGPT, thereby reducing overall load variability. However, the success of the 1DA method relies on perfect knowledge of the future, which is improbable.

The probabilistic forecast analysis conducted in this study allowed for the investigation of how the variations of the dispatch method's risk tolerance impact the performance of the battery and the resulting load. Figure 5 compares the load profile of a PV15-B12 home during the peak cold day for three probabilistic forecast (PF) dispatch methods: one with perfect knowledge of the future, one at 80% confidence and another at 95% confidence. The kW axis in the figure is truncated at 1.5 kW to more clearly show the differences across the dispatch methods during the morning and evening peaks.

Figure 5 shows that as the probabilistic algorithm's knowledge of the future load becomes more certain, the morning and evening ramp rates decrease and the relative shape of the peak periods flatten out. The dispatch method with perfect knowledge of the future results in significantly flattened load since the method does not attempt to keep any energy in reserve for un-forecasted spikes in usage. The 95% PF case introduces the concept of uncertainty into the forecast: knowing that the forecasted load contains uncertainty, it assumes future usage will be at 95% confidence and plans accordingly. This causes the PF regression model to be more conservative as predicted usage is higher, resulting in more need to dispatch and less opportunity to recharge. The 80% PF case involves relaxing this rule to 80% confidence and the battery can then deploy more freely. The results show that the 80% PF case can reduce the morning ramp rate by discharging more energy in the morning but is then faced with a depleted battery and cannot further flatten the peak at 8 AM. With perfect knowledge of the future load, the battery operated in the PF case charges more during pre-peak hours (1 AM to 4 AM), can reduce ramp rates, and flattens all the peak period loads by discharging the battery accordingly. The 95% PF case does not suppress the load as much during the morning peak but maintains a flatter load shape during this time. Table 2 provides the demand reduction potential during the 6 AM hour for a typical home on the peak cold day, shown for the median of the three probabilistic forecast methods. As can be seen, the battery addition is the single most critical factor in reducing this early morning peak.

Table 2: Per-Home Demand Reduction Potential on Peak Cold Day at 6 AM for Typical Home in the Region; Median of PF Methods, in kW

Battery Capacity	PV 0 kW	PV 5 kW	PV 10 kW	PV 15 kW
3 kWh	0.15	0.16	0.17	0.17
6 kWh	0.51	0.64	0.70	0.70
12 kWh	0.98	1.23	1.34	1.45

Locational Differences

Differences between locations and the impact of utility rate structures on load profiles could also be investigated through the location-specific data developed as part of the building stock analysis. Portland and Seattle were chosen for this analysis due to the similarity of their climate and solar resource; as noted previously, Portland homes were simulated with a TOU rate structure (where the price per kWh charge depends on the season and time of day) and Seattle homes were simulated with a simple tiered block rate structure (where the price per kWh is only dependent on season and total consumption per day). The following figures provide a comparison of daily load profiles; Figure 6 shows January 8 load profiles for baseline PV0-B0 1,344 ft^2 prototypes in Seattle and Portland, while Figure 7 shows the load profiles for the homes with 15 kW PV and 12 kWh battery system controlled with the 1DA battery dispatch method. While the load profiles for the baseline (PV0-B0) prototypes are very similar in shape between the two locations, the shapes are very different when PV and battery storage are added. As can be seen in Figure 7, the Seattle home behaves as expected, flattening and reducing peak demand since energetic costs are the same throughout the day. The Portland home, however, has time-dependent pricing (also shown in Figure 7), which results the Portland home achieving more significant reductions during the peak period than the Seattle home. Future work investigating the impact of peak demand charges (not typical in the residential sector) on the load profiles would likely show that such a pricing scheme would reduce the peak demand even further.

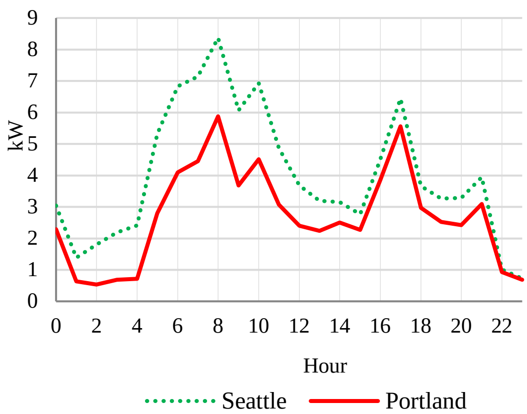

Figure 6: Comparison of 1,344 ft^2 Homes in Seattle and Portland with no PV or Battery Storage; January 8

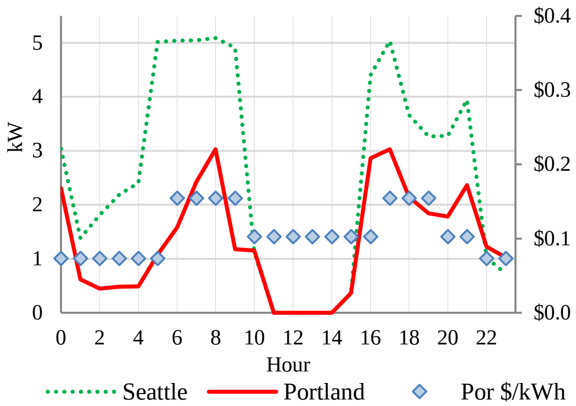

Figure 7: Comparison of 1,344 ft^2 Homes in Seattle and Portland with 15 kW of PV and 12 kWh of Battery Storage; January 8

Key Findings and General Considerations

The methods used in this study allowed for quick comparisons across different parameters. After further parsing of the data, the following observations were made:

1. *Comparison across dispatch methods provided insights into maximum average demand.* Of the dispatch methods studied, the probabilistic forecast method reduced maximum average demand during the peak hour (6 to 7 AM) the most. Out of 81 DER combinations, 14 combinations with PF dispatch methods reduced demand at 6 AM by 1 kW or more per household. While the most effective of these was the DER combination with 15 kW of PV and 12 kWh of battery storage (1.56 kW reduction per household) controlled with the PF method, even a system with no PV and a 12-kWh battery controlled with the PF method reduced demand more than other system configurations controlled with other dispatch methods.
2. *Comparison across dispatch methods provided insight into battery charging dynamics.* One further consequence that could be seen from the addition of battery storage was the additional battery charging from the grid during night-time hours. This effect was most evident in the probabilistic forecast cases, where the total night-time kWh consumption increased as the battery size increased (largest impact for the PF-Perfect and PF80 cases). This trend was much less pronounced in the 1DA, 1DB, and AGPT dispatch cases.
3. *Our overall approach provided insights into overall profile shape and variability.* The profiles were readily screened, and the sum of morning and evening ramp rates were considered a measure of the overall variability of the load. While lower PV capacities resulted in lower evening ramp rates (since PV reduces midday load the most), the addition of batteries and probabilistic forecast methods resulted in flatter (i.e. less variable) load shapes. Ramp rates for cases with no PV capacity are lower than ramp rates for homes with large PV capacities due to the

midday trough, but batteries and more intelligent control methods are able to alleviate this issue. Table 3 below depicts this trend based on aggregated data for the region.

Table 3: Comparison of Combined Morning and Evening Ramp Rates for PV-Battery Pairs and Dispatch Methods, Aggregated Across Whole PNW Region

Battery Capacity	Battery Control Method	Combined Ramp Rate (MW/hr)	
		PV 0 kW	PV 15 kW
0 kWh	N/A	324	421
12 kWh	1DB	291	375
12 kWh	AGPT	258	323
12 kWh	1DA	237	321
12 kWh	PF95	257	309
12 kWh	PF80	190	256
12 kWh	PF	155	234

4. *Our overall approach provided insights about hourly and annual impacts.* Total home consumption (regardless of electricity source) tends to stay the same (with minimal differences idle loads from PV inverters and/or batteries), since changes in behaviour are not modelled. The electricity that a household obtained from the grid, however, was drastically changed by the addition of PV. The addition of batteries had a negligible effect on the grid-sourced load on an annual-averaged basis, since the battery merely changed the timing of grid-sourced energy use. However, the addition of PV and battery systems did result in significant hourly changes in grid-sourced loads. The most variation in hourly impacts is seen for households with larger PV and battery capacities, since the PV over-produces during the middle of the day and larger batteries can charge from the PV system instead of the grid. This is most evident for the PV15-B12 homes, where the coefficient of variation (CV) across discharge methods is 4.9%. The AGPT battery discharge method tended to result in the lowest annual grid-based consumption across all PV capacities studied. A home with 15 kW of PV and no battery was seen to consume 1,500 kWh/yr more grid energy than a home with a 15-kW solar array and 12 kWh battery operated with an AGPT battery dispatch method. The AGPT dispatch method with 6 and 12 kWh batteries also resulted in the greatest annual electricity bill savings for each level of PV capacity.

Summary and Conclusions

The building stock model approach described in this paper is an accessible method for assessing aggregate DER impacts across any region of interest. Prototypical building simulations can account for building physics and site-level insights, and ensure that the building stock is representative of the region. Building stock data can be used to develop appropriate weightings and to calibrate the prototype models to accurately represent particular building populations. Parametric variation of solar and battery capacity levels via further simulations then provide scenarios that can be aggregated across the building stock. The results from this approach allowed for the analysis of annual, daily, and hourly impacts across various levels of aggregation – from the home and system level to the region-wide population. The impact of different battery dispatch methods was also investigated and explained in the context of expected battery and building load behaviour. This paper's approach enabled further parsing of the results down to the highest-potential cases at particular locations where more sophisticated simulations and analysis may be warranted for program design, rate design, or other planning objectives.

The analysis described in this paper resulted in an uncalibrated maximum technical potential of a 4,290 GWh reduction in grid-sourced electricity consumption for electrically heated homes in the Pacific Northwest region (7% of regional residential electricity sales in 2015) and a maximum average peak reduction of 1.7 kW in distribution-level capacity per home. This approach was less costly, used accessible methods with freely available tools, and can be generalized for similar application to other regions. The accuracy of this approach and applicability to any region of interest does depend on the quality of prototype building data available and the representativeness of the building prototypes. However, the inputs can be tuned to match the desired accuracy of the output results and to match high-level planning objectives. As a screening tool only, inputs based on secondary data alone may suffice, while for regulated utility planning, the use of well-calibrated building models would be warranted to ensure ground-truth. Finally, although this paper focused solely on technical potential for various DER deployment scenarios, future analysis could accommodate additional economic inputs to examine economic potentials and rate-related impacts.

Nomenclature

1344C = Prototype with crawlspace and 1,344 ft^2 total conditioned area

1DA = Peak Shaving 1-Day Look Ahead battery dispatch method, from SAM

1DB = Peak Shaving 1-Day Look Behind battery dispatch method, from SAM

2200C = Prototype with crawlspace and 2,200 ft^2 total conditioned area

2688B = Prototype with basement and 2,688 ft^2 total conditioned area

AGPT = Automated Grid Power Target battery dispatch method, from SAM

ASHP = Air-source heat pump HVAC system

Average Daily Demand Reduction Potential = Annual-average of daily demand reduction during a pre-defined peak period (e.g. 6AM-7AM), based on the difference between a given DER deployment scenario (e.g. PV5-B6) and a baseline scenario (i.e. PV0-B0)

b_i = The derived regression coefficients for the probabilistic forecast model.

CDD = Cooling degree days; measure of building cooling requirements

eFAF = Electric forced-air furnace HVAC system

HDD = Heating degree days; measure of building heating requirements

HourlyIndicator = 23 variables indicating the hour of the day (h1 = 1:00 am, h2 = 2:00 am, etc.).

Irradiance = Power per unit area for solar radiation, provided in units of W/m^2

kW = The estimated building load, in kilowatts

MonthlyIndicator = 11 variables indicating the month (m1= January, m2 = February, etc.).

PF (or PF Perfect) = Probabilistic Forecast battery discharge method, perfect knowledge case

PF 80% = Probabilistic Forecast battery discharge method, 80% confidence case

PF 95% = Probabilistic Forecast battery discharge method, 95% confidence case

POR, SEA, BOI, SPO, KAL = Locational abbreviations for Portland, Seattle, Boise, Spokane, and Kalispell

PNW = Pacific Northwest region (covering the states of ID, OR, MT, and WA)

PV = Photovoltaic system

Ramp Rate = Difference between minimum and maximum kW divided by the time elapsed during a specified period of interest, in units of kW/hr

SAM = System Advisor Model, software developed by US DOE National Renewable Energy Laboratory

Temp = Outside dry-bulb temperature, in °F

ZONL = Zonal electric heat HVAC system

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References

Belenky, Alexander S. 2015. "A Game-Theoretic Approach to Optimizing the Scale of Incorporating Renewable Sources of Energy and Electricity Storing Systems in a Regional Electrical Grid." *Energy Systems* 6 (3): 389-415. doi:http://dx.doi.org/10.1007/s12667-015-0145-9.

DiOrio, N.; Dobos, A.; Janzou, S.; Nelson, A.; Lunstrom, B. (2015). Technoeconomic Modeling of Battery Energy Storage in SAM. 32 pp.; NREL/TP-6A20-64641

Duer, A. (2016). Battery Storage Optimization and Deployment. Applied Energy Group. Presented at the Biennial Meeting of the American Council for an Energy Efficient Economy (ACEEE). Pacific Grove, CA. http://aceee.org/files/proceedings/2016/data/papers/3_981.pdf

Ecotope Inc. (2012). 2011 Residential Building Stock Assessment: Single-Family Characteristics and Energy Use. Seattle, WA: Northwest Energy Efficiency Alliance. Retrieved from: http://neea.org/resource-center/regional-data-resources

EPRI (2015). Electric Power Resource Planning: EGEAS Software Overview. Retrieved from EPRI website: http://eea.epri.com/pdf/NG%20Planning_EPRI_EGEAS_Webcast_041615_Final.pdf

FERC (2016). Electric Storage Participation in Markets Operated by Regional Transmission Organizations and Independent System Operators. Retrieved from FERC website: https://www.ferc.gov/whats-new/comm-meet/2016/111716/E-1.pdf

Foliente, Greg and Seongwon Seo. 2012. "Modelling Building Stock Energy use and Carbon Emission Scenarios." *Smart and Sustainable Built Environment* 1 (2): 118-138. doi:http://dx.doi.org/10.1108/20466091211260578.

Kavgic, Ma, A. Mavrogianni, D. Mumovic, A. Summerfield, Z. Stevanovic, and M. Djurovic-Petrovic. "A review of bottom-up building stock models for energy consumption in the residential sector." *Building and environment* 45, no. 7 (2010): 1683-1697.

NARUC (2016). Distributed Energy Resources Rate Design and Compensation. Retreived from NARUC website: http://pubs.naruc.org/pub/19FDF48B-AA57-5160-DBA1-BE2E9C2F7EA0

NREL (2010). System Advisor Model (SAM): Performance Model Documentation. Retrieved from NREL website: https://sam.nrel.gov/performance

RTF (2016). Regional Technical Forum (RTF) Standard Information Workbook, Version 2.6. Northwest Power and Conservation Council. Retrieved from: https://rtf.nwcouncil.org/work-products/supporting-documents

Saif, Ahmed, R. Pandi, H.H. Zeineldin, and S. Kennedy. "Optimal allocation of distributed energy resources through simulation-based optimization." *Electric Power Systems Research* Vol. 104 (2013): 1-8. doi: http://dx.doi.org/10.1016/j.epsr.2013.05.019

Simplified Energy Enthalpy Model (SEEM) (2016). Residential Single Family Existing HVAC and Weatherization – February 2016. Regional Technical

Forum. Northwest Power and Conservation Council. Retrieved from: https://rtf.nwcouncil.org/work-products/supporting-documents

Trabish, H.K. (2017, February 27). *How California's utilities are mapping their grids for distributed resources*. Retrieved from http://www.utilitydive.com/news/how-californias-utilities-are-mapping-their-grids-for-distributed-resource/436899

Wilson, E. et. al. (2014). 2014 Building America House Simulation Protocols. National Renewable Energy Laboratory. U.S. Department of Energy.

U.S. DOE (2016). United States Department of Energy, Energy Information Administration. OpenEI U.S. Utility Rate Database. Retrieved from: http://en.openei.org/wiki/Utility_Rate_Database

Table 4: Weighted Average Daily Demand Reduction Potential at 6 AM in MW, by PV Capacity, Battery Capacity, Battery Dispatch Method, and Location, Aggregated across the Pacific Northwest Region

City	Battery Control Method	PV 0	PV 0	PV 0	PV 5	PV 5	PV 5	PV 5	PV 10	PV 10	PV 10	PV 10	PV 15	PV 15	PV 15	PV 15
		B3	B6	B12	B0	B3	B6	B12	B0	B3	B6	B12	B0	B3	B6	B12
POR	1DA	8	18	37	13	22	34	58	23	32	43	69	33	42	53	79
POR	1DB	2	11	32	13	14	24	43	23	24	33	51	33	35	41	57
POR	AGPT	34	40	28	13	32	51	54	23	36	49	64	33	40	52	71
POR	PF95	10	24	47	13	25	43	70	23	36	54	83	33	46	65	93
POR	PF80	23	47	72	13	39	65	93	23	50	77	106	33	61	87	118
POR	PF	31	57	82	13	47	75	102	23	57	85	114	33	68	96	124
SEA	1DA	22	52	118	33	57	92	169	59	84	119	196	89	113	149	226
SEA	1DB	8	36	99	33	38	65	123	59	64	88	140	89	94	114	160
SEA	AGPT	88	113	81	33	81	128	142	59	89	124	160	89	109	136	176
SEA	PF95	27	61	117	33	66	109	177	59	93	140	209	89	124	170	242
SEA	PF80	58	119	185	33	99	172	244	59	126	200	278	89	155	227	312
SEA	PF	81	149	214	33	122	194	264	59	149	223	294	89	175	250	325
BOI	1DA	8	19	40	4	14	27	55	8	18	32	62	13	24	38	70
BOI	1DB	1	11	31	4	5	15	37	8	10	19	40	13	15	23	43
BOI	AGPT	21	23	17	4	11	23	39	8	13	23	42	13	17	26	45
BOI	PF95	10	22	46	4	16	33	62	8	20	39	71	13	26	45	78
BOI	PF80	21	44	72	4	28	54	87	8	33	60	95	13	38	65	103
BOI	PF	29	55	81	4	36	65	95	8	41	71	101	13	47	77	109
SPO	1DA	17	38	81	38	58	80	130	64	82	106	156	93	110	133	182
SPO	1DB	3	21	60	38	37	53	90	64	64	76	108	93	95	104	129
SPO	AGPT	33	42	32	38	49	68	86	64	68	79	102	93	95	100	121
SPO	PF95	21	47	95	38	64	99	154	64	91	128	185	93	121	154	214
SPO	PF80	44	94	154	38	89	143	210	64	115	169	239	93	142	193	265
SPO	PF	66	122	180	38	107	166	231	64	129	190	257	93	154	213	285
KAL	1DA	4	7	15	3	7	11	22	5	9	14	26	8	12	18	29
KAL	1DB	1	4	11	3	3	7	14	5	5	8	16	8	8	11	18
KAL	AGPT	5	8	7	3	5	9	14	5	7	10	16	8	9	12	18
KAL	PF95	4	8	18	3	7	14	26	5	10	17	31	8	13	21	35
KAL	PF80	8	17	30	3	12	23	38	5	15	26	43	8	18	29	48
KAL	PF	13	24	38	3	17	30	45	5	20	33	49	8	23	37	53