NOTICE

Economic Sizing of Batteries for the Smart Home

Xin Jin*, Jeff Maguire, Dane Christensen

Buildings and Thermal Sciences Center, National Renewable Energy Laboratory (NREL)
Golden, Colorado, USA
Xin.Jin@nrel.gov, Jeff.Maguire@nrel.gov, Dane.Christensen@nrel.gov

* Corresponding Author

ABSTRACT

This paper presents a methodology to economically size a home battery based on parametric analysis using home energy management system (HEMS) software to optimally dispatch the battery along with controllable loads under several use cases. We account for connected equipment, controls, renewable resources, and other factors such as building characteristics and utility tariffs. The paper defines an analytical pathway for such a sizing tool, develops initial sizing guidance, and clarifies technical and market opportunities for home batteries in the context of existing and emerging equipment and control technologies. A parametric analysis that included 132 scenarios has been performed based on different combinations of pertinent parameters. Results indicate that four variables dominate the decision-making process: application scenarios (new construction or retrofit), utility tariffs, existence of HEMS, and the anticipated payback time. Life-cycle cost analysis indicated that in the absence of utility incentives, batteries plus HEMS have a payback time of longer than 10 years for new construction under a time-of-use rate structure and feed-in tariff; larger batteries have a longer payback time but may provide more benefits to utilities on reducing power backfeed under certain circumstances.

1. INTRODUCTION

Energy storage is an emerging technology for enabling important capabilities in the modernized smart grid. Energy storage supports improved system operation by enabling variable generation resources through temporal disconnection of generation from consumption. Storage also provides additional means of saving money under time-varying utility tariffs or demand rates, as well as the ability to participate in incentive-based grid services such as demand response. In a future smart home, residential energy storage may comprise several elements:

1. Home battery—electrical energy storage in the form of batteries, such as today's lithium-ion products;
2. Thermal storage—thermal energy storage, such as water heater and heating, ventilation, and air conditioning (HVAC) systems coupled to thermal mass of the water tank and the building itself; and
3. Virtual storage—load flexibility that permits the shifting of energy consumption in time (Zhao, et al., 2017).

These energy storage elements are expected to be operated in a unified manner to achieve whole-building outcomes, so they should be sized and selected based on the whole-building opportunity. It is precisely this context that leads us to the operation-informed methodology presented in this paper.

Customer-sited batteries are marketed today with three primary value propositions. First, the home battery can make a home more resilient by providing backup power to the house during a grid outage. Second, the home battery can help a home become more sustainable by consuming its own photovoltaic (PV)-generated energy. Third, the home battery can provide financial benefits and help save its owner money under certain utility rate structures. All these potential uses have merit but would result in different optimal battery sizes. When sizing for resiliency, the optimal size will depend on how long a grid outage the battery supports, the weather conditions during the outage, and what critical loads are expected to remain operable. Sizing for sustainability depends on the PV array size, the solar resource, and how much energy the home uses throughout the day. Sizing for financial reasons depends on the utility tariff contract structure and the available incentives, both for batteries and participation in other events such as demand response. In all these sizing cases, constraints on first-cost versus operating revenue must also be considered.

No standard cross-industry methods exist to assist a homeowner or builder in sizing a home battery and estimating its benefits. Because the first cost is still very high (typically over $5,000), we endeavored to design an analytical method

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for assessing payback time under different use cases and focused on sizing for financial reasons. We evaluated the relative benefits and tradeoffs for homeowners and utilities between home batteries, home batteries in combination with controllable end-use equipment, and controllable end-use equipment alone, when each is operated with model predictive control (MPC) via a local home energy management system (HEMS) (Jin, Baker, Christensen, & Isley, 2017). Because equipment control could be used in some cases in lieu of charging or discharging the battery, it is expected that controllable load flexibility would result in different battery-cycling profiles and a smaller economically optimal battery size, compared with a battery alone.

Several tools currently exist for sizing home batteries. EPRI has developed StorageVET™, a web-based tool for techno-economic analysis of battery systems both at utility and homeowner scale (Electric Power Research Institute, 2016). The National Renewable Energy Laboratory has developed REopt, a techno-economic analysis tool that can be used to optimize energy systems—from individual buildings to microgrids—that includes the ability to model batteries, PV, and building loads (Cutler, et al., 2017). Some battery manufacturers also provide simple sizing tools that estimate battery size based on house size and the loads in a home (Tesla, 2018). Rules of thumb also exist for sizing batteries for on- and off-grid homes, but they are typically used when sizing battery systems for resiliency rather than financial reasons (Sanchez, 2017). However, none of these tools can fully account for controllable loads in the home and how their usage under MPC-driven HEMS can help maximize a smart home's cost-effectiveness using a package of connected loads and battery.

Recent research on home batteries has focused on scheduling flexible loads to provide grid services or increase self-consumption of PV. Several studies have been performed looking at improving the integration of PV with the grid through forecasting and demand-side management for homes without batteries (Masa-Bote, et al., 2014; Widén, 2014; Castillo-Cagigal, et al., 2011). Other studies have included additional energy sources, including micro combined heating and power and micro-wind turbines (Molderink, Bakker, Bosman, Hurink, & Smit, 2010; Cao, Hassan, & Siren, 2013). The HEMS used in this paper has previously been used to manage building loads to improve energy efficiency or respond to demand-response events while maintaining thermal comfort for homes with PV and battery; but it only considered one size for the battery and PV (Jin, Baker, Christensen, & Isley, 2017).

This paper focuses on financial metrics in specifying the battery capacity for homes with PV, under different use cases that in the future could include a utility self-supply tariff. Thus, the analytical method described supports two of the three messages described above. Sizing for resiliency is often driven by homeowner preference rather than economics and is not included here, although some recent work has tried to determine the economic benefit of resiliency for commercial buildings (Laws et al., 2018). It can also help quantify the gap in cost-effectiveness that a utility may compensate with an incentive, or that a manufacturer could target for product cost reductions, to achieve higher penetration of energy storage assets.

2. PARAMETRIC APPROACH FOR OPTIMAL BATTERY SIZING

We propose a parametric approach to determine the optimal battery size based on the information pertinent to all aspects of the building where the battery will be deployed, such as connected equipment, controls, renewable resources, climates, building characteristics, and utility rate structures.

Unlike other sizing tools and algorithms that model battery size as an optimization variable, the proposed methodology uses a parametric approach to explore combinations of pertinent parameters, perform annual energy simulation for each combination, and make recommendations on the optimal battery size based on the analysis results of the simulation data. The unique advantage of the proposed approach is that the decision-making process is powered by a rich set of data generated from representative scenarios, making the results easier to understand and validate. Traditional sizing approaches usually require a modest amount of user input and recommend a product configuration without revealing how the decision was made.

As shown in Figure 1, the parametric analysis starts with parameter selection, where combinations of different parameters are chosen from the parameter space. These are used to generate data from EnergyPlus for buildings that operate under different combinations of the parameters. Inverse gray-box building models are then created from the EnergyPlus data to explore the potential benefits of adopting HEMS-controlled smart appliances and/or home battery systems (HBSs) in the building. EnergyPlus is not directly used in this process because it lacks interfaces with MPC; instead we calibrate a gray-box model using EnergyPlus data and use it as the prediction model inside MPC. Techno-

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economic analysis is performed to identify the parameters that dominate the selection of battery sizes, narrow down the parameter space for additional simulations, and identify the decision criteria for selecting the optimal batteries sizes. The end goal of the study is to develop a set of criteria for selecting an HBS, which can then be quickly and simply used by end-users (e.g., homeowners, builders) to select the optimal battery sizes with a minimum set of inputs.
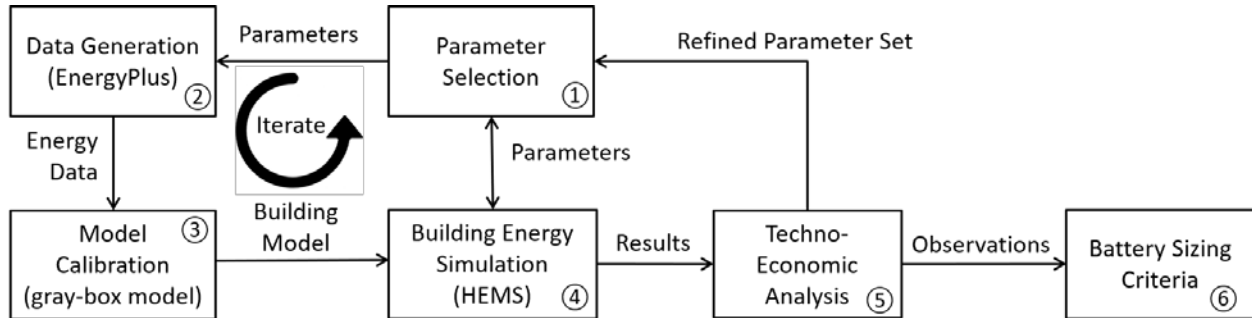

Figure 1: A block diagram of the parametric approach for optimal sizing of batteries.

2.1 Parameter Selection

Table 1 lists the parameters that we consider in our parametric analysis. Each parameter has several levels within the typical range of the parameter. Five types of parameters are considered here: the first type is about the battery system, including the battery size and battery inverter size; the other four types include building characteristics, building equipment, building operation, and utility tariffs. Each unique combination of the parameters in Table 1 makes up a scenario. We explore the levels marked in bold for this paper.

2.1.1 Battery Size

A set of uniformly spaced battery sizes between 0 kWh and 9 kWh with a 3-kWh increment is considered in the study. A 0-kWh battery means the baseline case without battery. Two levels of battery inverter are also considered. Not all combinations of these two parameters are deemed reasonable; a 3-kW inverter is only paired with the 3-kWh battery packs, and a 6-kW inverter is paired with larger battery packs.

2.1.2 Building Characteristics

Application types, home size, envelope efficiency, and location are the parameters considered under the building characteristics category. Application types include new construction and retrofit, which result in large cost differences in purchasing and installing some equipment. Typical home sizes and two climate zones are considered in the study.

2.1.3 Building Equipment

For space heating, space cooling, and water heating, two types of technologies are considered for each equipment type: one is traditional technology with wider adoption, and the other is emerging technology with higher efficiency. Four levels of PV systems are considered.

2.1.4 Building Operation

Heating setpoint, cooling setpoint, and occupancy levels all have three values. Different combinations of controllable loads, namely, HVAC and water heater, are considered under this category. Possible combinations include none (i.e., traditional HVAC and water heater without smart controls), HVAC only, water heater only, and both equipment.

2.1.5 Utility Tariffs

A set of representative utility rate structures and tariffs are chosen for the parametric study. Two rate structures are studied: a flat rate (constant cost per kWh of energy consumption for every hour of the year) and a time-of-use (TOU) rate—where cost per kWh varies in steps throughout each day. We use a typical TOU rate structure as shown in Section 4.1. In each case study, we also apply net-metering (energy export is purchased by the utility at the current consumption rate) or feed-in tariff (FIT), where exported energy is credited at a lower rate than the homeowner is charged for consumption. The ratio between the energy export credit and the energy import cost for the FIT case may influence the control decision, which is a topic of future research.

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Table 1: Parameter space for the parametric analysis

Category	Parameter	# Levels	Level(s)
Battery Size	Battery Size	4	0, 3, 6, 9 kWh
Building Characteristics	Application Type	2	New Construction, Retrofit
	Home Size	1	2000
	Envelope Efficiency	1	IECC 2009
	Location	2	Cold, Hot-Dry
Building Equipment	Heating System	1	Electric Resistance
	Cooling System	1	Central AC
	Water Heater	1	Electric Resistance
	PV System	3	0, 3, 6 kW
Building Operation	Heating Setpoint Temp	1	71
	Cooling Setpoint Temp	1	76
	Occupancy Levels	1	Medium
	Controllable Loads	2	None, both HVAC and Water Heater
Utility Tariffs	Electricity Rate	2	Flat, TOU
	Feed-In Tariff	2	Net Metering, FIT
	Demand Charge	1	No

Key to acronyms: AC (air conditioner), ASHP (air-source heat pump), BA (Building America), FIT (feed-in tariff), HPWH (heat pump water heater), IECC (International Energy Conservation Code), TOU (time-of-use).

2.2 Data Generation

EnergyPlus models were created to simulate buildings, occupants, and appliances based on the parameters in Table 1. Annual building simulations were performed in EnergyPlus to generate training data for calibrating the gray-box building models in MPC. In the annual simulation, step changes in the heating and cooling setpoints were repeatedly imposed to excite the building such that the resultant building model can better capture the building dynamics. The calibrated model serves HEMS, HEMS + battery, and battery-alone studies in all parametric studies using that house.

2.3 Model Calibration

Table 2: Validation results of the gray-box models against EnergyPlus models

Building Locations	Models	Water Heating Load (kWh)	HVAC Load (kWh)	Total Controllable Loads (kWh)
Phoenix	EnergyPlus	2,099	9,404	11,503
	Gray-Box Models	1,950	9,932	11,882
	Difference	-7.10%	5.61%	**3.29%**
Chicago	EnergyPlus	3,676	21,494	25,170
	Gray-Box Models	3,623	21,426	25,049
	Difference	-1.44%	-0.32%	**-0.48%**

We did not use EnergyPlus to implement MPC but instead used two weeks of EnergyPlus output data to train appropriate control models on a rolling basis. A gray-box building model (Jin et al, 2017) was calibrated using the training data following the optimization-based method described by Braun and Chaturvedi (2002). The calibrated model was validated against EnergyPlus by using another year's weather profile that was different from the one used in the training stage. Annual simulations were performed in both EnergyPlus and MATLAB to comparatively evaluate the energy consumption. Two locations were considered in the initial study to evaluate the impact of climate on battery sizing. Phoenix and Chicago were selected due to their distinct weather conditions. As shown in Table 2, the annual HVAC and water heating energy differences were 3.29% for a home in Phoenix and -0.48% for a home in Chicago.

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3.4 Building Energy Simulation

The building energy simulation module loads the parameters for a specific scenario and performs annual simulations using a HEMS-based building energy simulation software (Jin et al., 2017) with the calibrated gray-box building model and other information exported from EnergyPlus. Annual building energy simulation is performed to evaluate the impact a HEMS/HBS technology on energy consumption, customer comfort, and interaction with the grid. As depicted in Figure 2, the HEMS-based simulation software comprises three main modules: an MPC module performing high-level planning, a real-time dispatch controller for implementing the decision from MPC, and building energy simulation models for simulating the responses of building equipment to the real-time control signals. The software operates at two epochs: the MPC implements at slow timescale for long-term planning, and the dispatch controller implements the MPC decisions in real time to control the simulated building equipment. The software plays a crucial role in the parametric simulation framework, and its inputs and outputs are specified in Figure 2 for interfacing with other modules in the framework.
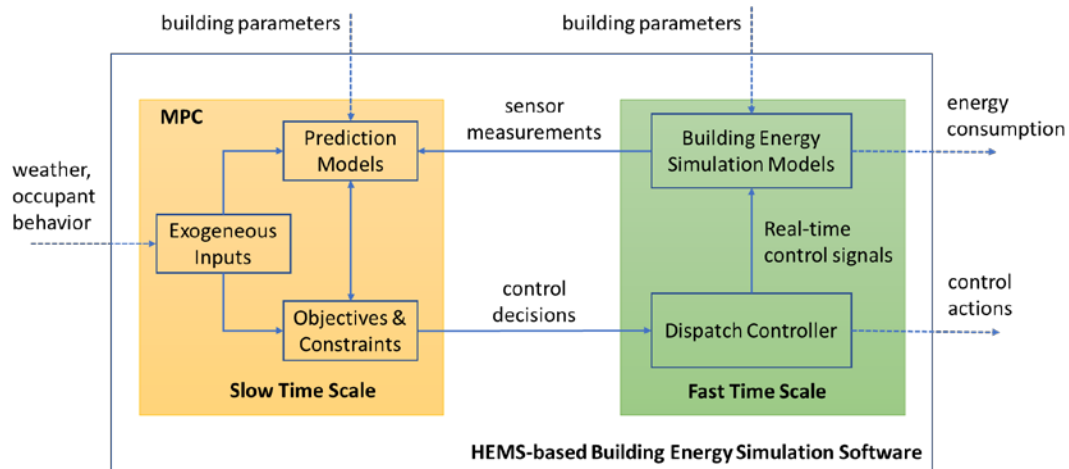

Figure 2: A block diagram of the building energy simulation software.

The MPC aims to minimize the energy cost and thermal discomfort in air and water simultaneously. In this study, the HEMS was not explicitly designed to minimize exported power, although it may be provided as a side benefit under certain rate structures. The MPC's prediction time step was set to 30 minutes and the receding prediction horizon was set to 16 prediction time steps, or 8 hours. Both the prediction time step and the horizon can be adjusted. CVX, a software for disciplined convex optimization, is used as the optimization engine (Grant & Boyd, 2013).

The dispatch controller translates the fractional decisions (i.e., between 0 and 1) from MPC to control the equipment at fast timescale, subject to the physical constraints of the equipment. The CVX engine in MPC outputs run-time fractions that can be interpreted as duty-cycle signals, whereas most major equipment such as HVAC and water heaters use on/off control. Therefore, we used the dispatch controller to bridge the gap between MPC and real-time control of building equipment. The building energy models implement the control signals and provide updated status to MPC as sensor measurements. Both dispatch controller and building energy models were implemented at 1-min time intervals in this study. The calibrated gray-box models were used as the prediction models in MPC. The same models were also used as the building energy simulation models in the initial study and in the future will be replaced by more sophisticated building models to better capture the dynamics of the actual building equipment. In hardware-in-the-loop experiments or field deployment, the building energy simulation models will be replaced by actual building equipment. For use cases without HEMS, we simply bypass the MPC module and implement deadband-based control strategies in the dispatch controller to mimic the behavior of traditional appliances.

3. METRICS FOR TECHNO-ECONOMIC ANALYSIS

Larger HBSs may provide more flexibility and operating cost savings, but these benefits come with higher upfront cost. Thermal storage and virtual storage controlled by HEMS can also serve as a battery and has the potential to reduce the size of the HBS. This section describes four metrics for evaluating the cost-effectiveness of the HEMS/HBS: annual operating cost savings, net present cost/benefit, battery degradation reduction, and backfeed reduction. The first three metrics are from the homeowner's perspective, and the last one is from the utility's perspective.

3.1 Annual Operating Cost Savings

Annual operating cost savings (AOCS) is the difference between the operating cost on an annual basis before and after an HBS and/or a HEMS is deployed in a home. AOCS directly indicates the cost-effectiveness of a system during operation, but it does not consider the upfront cost such as hardware cost and installation cost. AOCS is also used in the internal rate of return and breakeven cost calculations.

3.2 Net Present Cost/Benefit

The cost-benefit analysis of a HEMS/HBS can be performed by comparing the net present cost (NPC) of the system and the net present benefit (NPB) to its owner (Maguire, 2013). If the NPB is higher than the NPC, then installing the HEMS/HBS would be cost effective over the evaluated period.

The NPC is the cumulative discounted cost of the system—including initial cost, financing, tax impacts, incentives, and operations and maintenance (O&M)—equal to the sum of the cost in each year multiplied by the discount factor in that year. The NPC is:

$$NPC = IC + \sum_{n=0}^{N}(MC_n - I_n)\, DF_n \tag{1}$$

where IC is the system's net installed cost, N is the study length, MC_n is the O&M cost in year n, I_n is the incentive in year n, and DF_n is the discount factor in year n. DF_n is defined as $\frac{1}{(1+d)^n}$, where d is the discount rate (5%).

The NPB is the discounted cumulative benefits of operating cost savings over the evaluated period and is defined as:

$$NPB = \sum_{n=0}^{N}(AOCS_n \cdot DF_n \cdot FEF_n) \tag{2}$$

where FEF_n is the fuel escalation factor in year n: $FEF_n = (1 + e)^n$, and e is the fuel escalation rate (0.5%). To calculate the breakeven cost of an HBS or HEMS, Equations (1) and (2) are combined and solved for IC, the breakeven cost.

3.3 Battery Degradation Reduction

Battery degradation can be modeled by calendar fade and cycling fade (Smith *et al*, 2013). Calendar fade represents solid electrolyte interphase growth and loss of cyclable lithium over time. Cycling fade accounts for active material structure degradation and mechanical fracture. Contributing factors of battery degradation include energy throughput, temperature, depth of discharge, resting state of charge, and discharge rates. Energy throughput is the dominating factor of cycling fade and is used in this paper to quantify the battery degradation under different operation strategies.

3.4 Backfeed Reduction

Power backfeed, or energy export, due to excessive PV generation or battery discharging in areas with high PV penetration has posed great challenges to utilities because the backfeed may cause overvoltage in the distribution feeder. Therefore, the amount of reduction in power backfeed provided by an HBS or HEMS is evaluated to quantify the benefits to utilities. This reduction may allow the utilities to support more PV on a given feeder.

4. RESULTS AND DISCUSSION

Following the procedures shown in Figure 1, some 132 annual simulations were implemented in MATLAB, one for each unique combination of parameters. HEMS operates at 30-minute intervals in applicable scenarios to control the HBS and building loads such as the HVAC and water heater, and load dispatch into the building energy simulation was performed at 1-minute intervals. This section summarizes the initial results and performs a techno-economic analysis to identify the parameters that dominate the optimal sizing of the HBS.

4.1 HEMS/HBS Cost and Utility Tariffs

It is critical to define the upfront cost of an HBS or HEMS because the cost directly impacts the NPC. The upfront installed cost and incentives of a HEMS and an HBS are listed in Table 3. It is assumed that the HEMS can be easily installed by homeowners or builders and therefore does not incur any installation cost. The hardware cost and installation cost of an HBS is different for retrofit (O'Shaughnessy, 2017) and new construction, so the upfront installed cost of these two solutions are listed separately. The new construction cost estimate is based on the price quote from a battery manufacturer plus $500 builder installation cost. A $400/kWh incentive is assumed for HBS (Self-Generation Incentive Program, 2017). We assume that the smart thermostat cost is $250 and there is a $75 incentive provided by the utility (Xcel, 2017). The connected water heater system consists of an electric water heater (A.O. Smith, 2017) and an add-on communication module (Lowes, 2017).

Table 3: Cost and incentive assumptions for HBS, HEMS, and connected devices

		Cost		Incentive
		Retrofit	New Construction	
HBS Upfront Installed Cost	Inverter	$1,271/kW	$630/kW	$0/kW
	Battery	$1,060/kWh	$338/kWh	$400/kWh
	Base cost	$0	$500	$0
HEMS Hardware Cost	HEMS	$100		$0
	Sensors	$250		$0
	Smart thermostat	$250		$75
	Connected water heater	$575 (water heater) + $40 (controller)		$0

Three utility tariffs were used in the simulation analysis based on a recent utility rate sheet (Southern California Edison, 2017):

- TOU + FIT: TOU rates for energy import, and $0.03/kWh for energy export
- TOU + Net Metering: Same TOU rates for energy import and export
- Flat Rate + FIT: $0.16/kWh for energy import, and $0.03/kWh for energy export

where the TOU rates are defined as:

- Winter: $0.13/kWh (off-peak), $0.27/kWh (mid-peak), and $0.34/kWh (on-peak)
- Summer: $0.13/kWh (off-peak), $0.28/kWh (mid-peak), and $0.45/kWh (on-peak)
- Weekends: On-peak is at mid-peak costs

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4.2 Techno-Economic Analysis of the Simulation Data
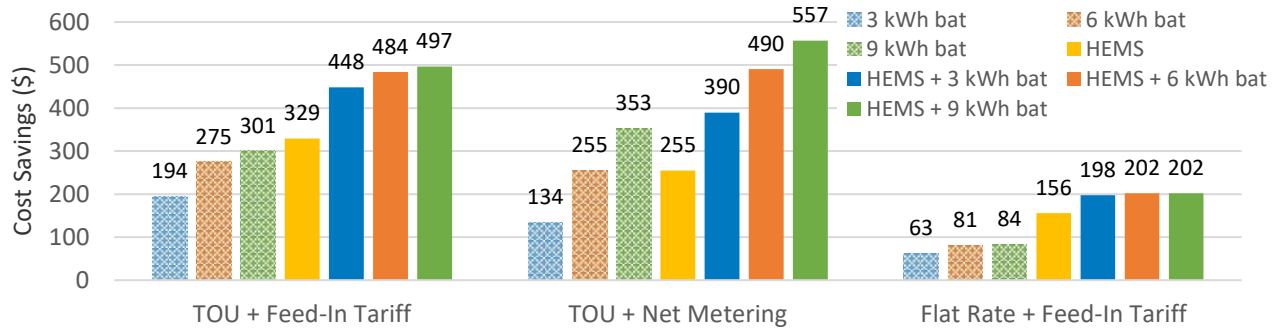
4.2.1 Annual Operating Cost Savings

Figure 3: Annual operating cost savings for the Phoenix home under different HEMS and HBS combinations.

Figure 3 summarizes the AOCS for the Phoenix home under different combinations of connected loads and HBS. The following observations can be made from Figure 3:

- For homes with batteries only, increasing the battery size does not significantly improve the annual operating cost savings in the presence of FIT.
- For homes with HEMS, adding a small battery improves annual operating cost savings, but adding larger batteries is less cost-effective without net metering.
- Utility tariffs have significant impact on annual operating cost savings. The same solution has more cost savings under TOU and little cost savings under flat rate.

Location has a minor influence on the annual operating cost savings. The Chicago home has a very similar AOCS except that it has slightly more cost savings under TOU + FIT and less cost savings under Flat Rate + FIT.

4.2.2 Cost-Benefit Analysis: NPB vs. NPC

Figure 4 compares the NPBs of different solutions to the NPC for new construction with and without the $400/kWh incentive for batteries. The $75 incentive for a smart thermostat was still applied. Results from Figure 4 indicate:

- Without incentives, the NPC of the HEMS-only solution is lower than the 5-year NPB, whereas the NPCs of battery-only solutions are higher than the corresponding 20-year NPBs.
- With incentives, the NPCs of battery-only solutions become lower than the 20-year NPBs, but they are still much higher than the 10-year NPBs in all three cases. The 9-kWh battery has a lower NPC than the 6-kWh battery because the inverter cost is the same whereas the incremental cost for increasing the battery size is negative for new construction (i.e., $338/kWh cost - $400/kWh incentive).
- With incentives, the NPCs of the HEMS + HBS solutions are lower than the corresponding 15-year NPBs in all three cases. HEMS + 3-kWh battery becomes cost-effective between 5 years and 10 years; HEMS + 6 kWh/9kWh battery breaks even between 10 and 15 years.

For retrofit solutions, due to the high upfront installed cost for inverter and battery, HEMS is the only cost-effective solutions under the TOU + FIT rate structure. The payback periods for new construction and retrofit applications of the Chicago home are even longer than those of the Phoenix home.

This information can be used by utilities to determine the appropriate amount of incentives for encouraging behind-the-meter battery-storage deployment in areas with high-penetration PV. Equipment manufacturers can also use this information to set the target for price reduction.
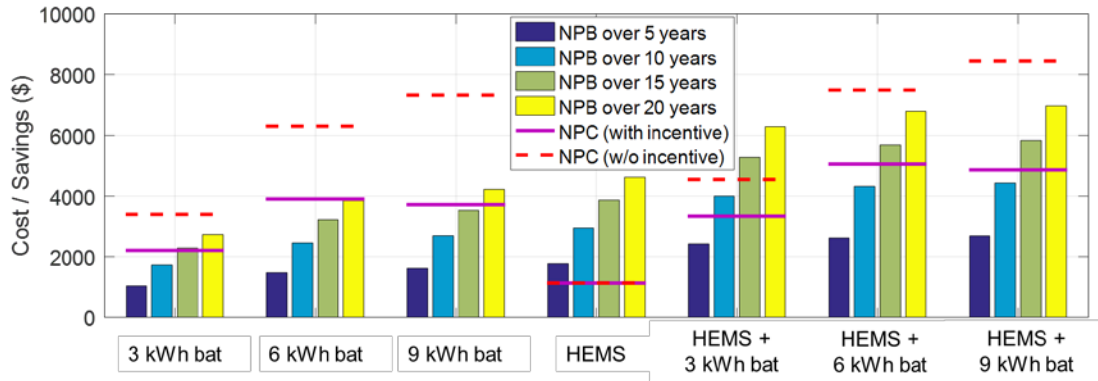
Figure 4: Comparison of NPC and NPB for the Phoenix home (new construction) under TOU and FIT.
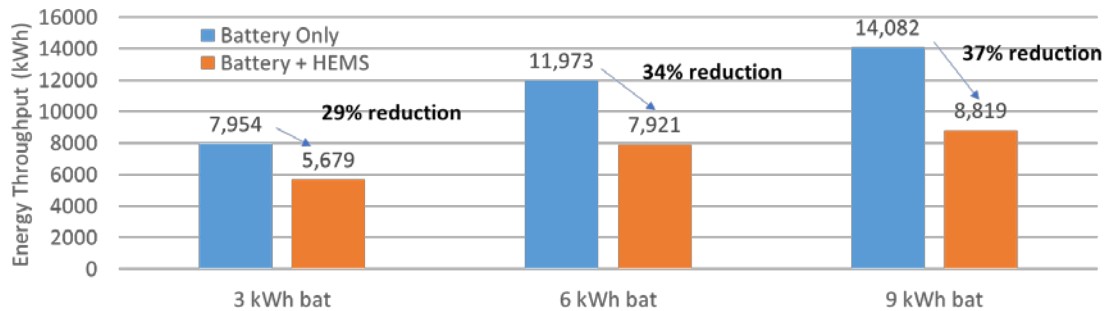
4.2.3 Battery Degradation

Figure 5: Annual battery energy throughput for HBS in the Phoenix home under TOU and FIT.

As shown in Figure 5, combining battery with HEMS significantly extends the battery lifetime by reducing the battery energy throughput. The larger battery has a higher percentage reduction of energy throughput. Future research includes incorporating a battery life model to quantify the battery degradation in terms of capacity loss.

4.2.4 Annual Backfeed Reduction

Reducing power backfeed helps mitigate the issues of feeder overvoltage and voltage variation, and thus, it maintains grid reliability for areas with high levels of PV penetration. Backfeed reduction was evaluated over 30-minute intervals for the entire simulation period. As shown in Figure 6, the following are found under TOU and FIT:

- The 3-kWh battery, HEMS, and their combinations are the most cost-effective solutions for backfeed reduction.
- Increasing the battery size from 3 kWh to 6 kWh provides modest incremental contribution to backfeed reduction, whereas batteries larger than 6 kWh has little or no incremental contribution to backfeed reduction.
- Backfeed reduction depends more on location than other metrics. The Phoenix home has more backfeed reduction because Phoenix has better solar resources, and thus, higher probabilities of backfeed.

Utility tariffs dominate the backfeed reduction. Feed-in tariffs reduce power backfeed whereas net metering encourages backfeed. Under TOU and net-metering rate structure, all solutions perform energy arbitrage for the economic gain, thus losing backfeed reduction benefits.
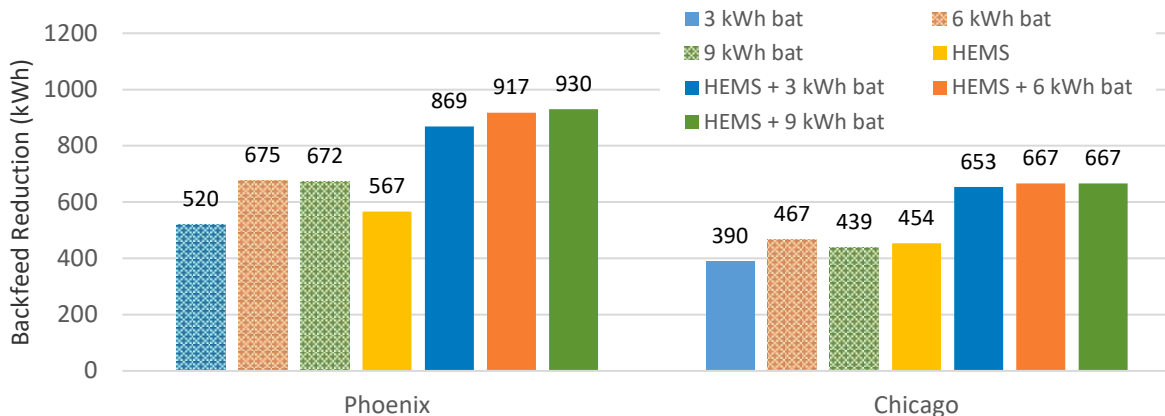
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Figure 6: Annual backfeed reduction under TOU and FIT for different combinations of HBS and HEMS.

5. CONCLUSIONS

This paper presents a novel methodology for economic sizing of home batteries and performs a parametric analysis on five types of parameters that have a potential impact on the optimal battery size for a home. Techno-economic analysis of the simulation results from 132 scenarios suggests that four variables have the largest direct impact on the battery sizing: application scenario (retrofit or new construction), utility rate structure, existence of a HEMS, and desired payback time. It is revealed that without incentives for batteries, HEMS and HEMS + 3-kWh battery are the only cost-effective solutions for new construction and the payback times are about 3 years and 13 years, respectively. Retrofit solutions are not economical in the absence of incentives due to higher hardware and installation cost. In general, the cases of smaller battery or no battery (i.e., HEMS only) have shorter payback times whereas larger batteries provide slightly better backfeed reduction under certain circumstances.

In future studies, we plan to 1) expand the parametric study to a larger parameter space while using design of experiments and/or a design-day approach to reduce the runtime; 2) study how to optimize the battery inverter size as an independent variable to match the battery size; 3) explore how the ratio between the energy export credit and energy import cost for the FIT case may influence the battery sizing results; and 4) incorporate a battery-life model to quantify the battery degradation in terms of capacity loss.

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