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# Electricity storage in buildings for residential sector demand response: Control algorithms and economic viability evaluation

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Prepared for
*U.S. Department of Commerce*
*Engineering Laboratory*
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*Gaithersburg, MD 20899*

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## Abstract

"Smart grid"-enabled demand response (DR) provides significant opportunities to improve today's electricity grids' reliability, efficiency, affordability and security. In contrast to conventional DR, electricity storage in buildings (residential or commercial) can provide essential, flexible and reliable DR service without requiring consumers to operate their appliances on shifted or reduced schedules. With a number of DR tariffs and DR-enabling technologies available (e.g., storage technologies and two-way-inverters), one of the key current barriers for higher penetration of DR is consumers' understanding of the cost-benefit issue. To address this question, and focusing on the residential sector, we (i) devised an agent-based appliance-level stochastic model to simulate the electricity demand of an average U.S. household; (ii) developed control strategies to shift loads from the peak periods to the off-peak periods (i.e., loadshifting strategy) and to shed the peaks of the power demand loads (i.e., peak reduction strategy); (iii) suggested the potential profits for the consumers, i.e., the reduced electricity cost of the modified demand with realistic tariffs (Con Edison, New York) minus storage costs. We optimized DR operation for the above two DR strategies to maximize the profits for consumers and determined the economic viabilities for a range of traditional and advanced storage technologies. We concluded that annual profits range from $61 to $1365 per year per household by utilizing the loadshifting strategy and from $161 to $1058 per year per household by using the peak reduction strategy. These profits can be achieved without changing the actual consumption patterns of appliances. Of the two DR strategies, the peak reduction strategy can render more storage technologies economically viable.

**Keywords**

Demand response; Smartgrid; Electricity storage; Agent-based modeling; Arbitrage; Peak shedding

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**Glossary**

| | |
|---|---|
| ATUS | American Time Use Survey |
| CAES | Compressed Air Energy Storage |
| CF | Calibration factor |
| DADRP | Day Ahead Demand Reduction Program |
| DoD | Healthy depth of discharge |
| DOE | U.S. Department of Energy |
| DR | Demand response |
| DSASP | Demand Side Ancillary Service Program |
| EC | Effective capacity |
| EDRP | Emergency Demand Response Program |
| EPRI | Electric Power Research Institute |
| ES | Shifted electricity |
| FCR | Financing cost rate |
| FERC | Federal Energy Regulatory Commission |
| GHG | Green House Gas |
| MAC | Monthly Adjustment Clause |
| MFC | Merchant Function Charge |
| MSC | Market Supply Charge |
| NaS | Sodium Sulfur batteries |
| NiCd | Nickel Cadmium batteries |
| NiZn | Nickel Zinc batteries |
| NYISO | New York Independence System Operator |
| Pb-acid | Lead-acid batteries |
| PEV | Plug-in Electric Vehicle |
| PHS | Pumped Hydro Storage |
| RECS | Residential Energy Consumption Survey |
| RSEM | Relative standard deviation of the mean |
| SETIS | Strategic Energy Technology Information System |
| SMES | Superconducting Magnetic Energy Storage |
| SoC | State of charge |
| TOU | Time of use |
| UL | Upper limit |
| VRB | Vanadium Redox Batteries |
| ZEBRA | Sodium nickel chloride batteries |
| ZnBr | Znic Bromide batteries |
| $ZnMnO_2$ | Znic Manganese Dioxide batteries |

# 1 Introduction

## *1.1 Background*

Facing time-varying and overall increasing demand, today's electricity grid is struggling to balance supply and demand on a moment-to-moment basis reliably. Even in the relatively modern grid in the U.S., black-outs and brown-outs still occur and cost $500 per person per year [1]. Typical and traditional grids employ peak generating capacities, frequency regulation, and (some) grid-based storage [2-4] to follow a time-varying demand profile. Sitting idle during off-peak periods, peak generators typically increase overall cost as well as life cycle greenhouse gas(GHG) emissions per unit of consumed electricity [1, 5].

The novel "smart grid" provides significant opportunities for improving the grid's reliability, efficiency, affordability and security. One of the core characteristics of a "smart grid" is two-way flow of electricity and information between the supply side and the demand side [1]. In this context, rather than approaching the supply-demand mismatch from the supply side only, the demand side also plays an essential role in the future electricity grids. This set of solutions is broadly referred to as demand side management or simply demand response (DR). DR attempts to smoothen (in time) the electricity demand profiles themselves and thus enable the near-instantaneous balance of supply and demand at the device level. A large variety of DR approaches exist [6], which can be loosely categorized into incentive- or time-based schemes [7]. Potential benefits include reducing electricity prices, resolving transmission line congestion, and enhancing grid reliability [8]. Given appropriate incentives via DR tariffs, DR can also facilitate integrating higher percentages of intermittent capacity such as from solar and wind into the grid [9, 10]. A variety of DR programs are now available in different electricity markets to achieve the above benefits [11]. Two common ones are to shift load from peak periods to off peak periods (often referred to as loadshifting) [12, 13] and to reduce the peak power demand (often referred to as peak reduction) (e.g., [14]). Other DR approaches include loadfollowing in the real time market or the day-ahead market, providing regulation services or spinning reserves in the ancillary service market (e.g., [15]).

Conventional DR, typically employed in commercial/industrial buildings, involves temporally interrupting or delaying a building's various appliances to adjust their overall loads in response to incentive- or time-based DR signals. This however creates the challenge of having to balance DR benefits to the grid with a level of service commensurate with customer expectation [16]. If instead, buildings (whether commercial or residential) employ electricity storage, the demand side can provide DR vis-à-vis the grid without requiring a change in actual consumption patterns in the building.

## *1.2 Residential DR and residential demand profile modeling*

In contrast to commercial or grid based storage, DR via many, small residential consumers can be more manageable than via fewer, larger consumers because failure of a single consumer will not substantially disrupt the overall DR response. In addition, since residential consumers are typically more homogenously distributed spatially than industrial consumers, residential-based (as well as other geographically distributed) storage can respond to spatial contingencies more precisely [16]. Similarly, availability of residential-based storage would facilitate integration of building-based (rather than grid-based) decentralized renewables (not the focus of this study). Finally, residential storage schemes could also create synergies with plug-in electric vehicles (PEV). For example, Denholm and Short concluded that with proper charging schedules and coordination between PEVs, their batteries could improve the quality of electricity supply rather than burden it by imposing higher peak loads [17, 18]. However, a possible adoption barrier resulting from more frequent charging/discharging of the vehicles compared to driving alone and thus accelerated battery degradation would have to be carefully evaluated (e.g., [19]). Finally, in the US, about 38% of total electricity consumption is by residential consumers [20]. If a large portion of these were to engage in DR, this could smoothen the total load profiles substantially.

Since there are above benefits by installing storage devices in the residential sector, understanding residential load profiles will be required to conduct DR optimization work for the residential sector. Wright and Firth suggested measurements with 1 or 2 minute resolution in order to capture the peaks of individual households [21]. However, such appliance-level, high time resolution, measured residential demand data for individual households in the U.S. are largely unavailable. An exception is the recent data set made available by the Pecan Street Research Institute (www.pecanstreet.org). Bottom-up modeling was therefore proposed to complement the costly data collection process [22]. Such studies often use survey data of household activities (e.g., when do residential consumers cook, wash, watch television, etc.) [23, 24]. Richardson et al. then extended such mapping to a high-resolution stochastic model to simulate domestic demand profiles and compared the aggregated appliance demand profiles with measured residential sector demand profiles [25, 26].

### *1.3 Existing DR optimization research*

A large body of DR optimization research exists throughout the world. Alongside the growing body of research on pertinent tariffs (e.g., [27]), more DR programs have been offered in electricity markets [11]. When optimizing electricity cost under relatively straight forward time-of-use (TOU) tariffs (which typically provides different rates per kWh for different periods of the day), one key question in optimizing the overall system is how to size the storage so as to maximize the profits to consumers. And variations in consumption (from one day to the next or between seasons) make it more difficult to predict the optimal size of storage [28]. Another approach to DR is to reduce the peak power demand (in kW) specifically (rather than total kWh drawn during times of high kWh prices). This is relevant for tariffs, already available in the U.S. and other countries, that charge customers based on a combination of kW and kWh drawn from the grid [29, 30].

Other control schemes focus on arbitrage through real-time, day-ahead markets, or ancillary service markets (or combinations). For example, Byrne and Silva-Monroy estimated the maximum potential revenues in California via a linear programming approach [31]. Where linear programming was deemed too inflexible (e.g., because it typically does not capture the stochastic nature of load profiles), dynamic programming was deployed in order to capture uncertainties of electricity prices and load profiles [15, 32-34].

### *1.4 Motivations and objectives of present study*

Over the past decades, economics and operating performance of electricity storage technologies have improved [35-41]. However, in the U.S., today's existing DR programs represent less than 25% of the total market potential for DR [42, 43]and barriers to wider use of these technologies for DR in residential settings remain: For example, Mokrian and Stephen pointed out that storage technologies still lack practical control strategies and deeper understanding of cost-effectiveness [15]. Dunn et al. also raised the issue of economic viability [36]. Provided consumers will act based on economic criteria [44], the question arises whether the additional cost of installing storage (and the necessary inverters and controllers) in someone's house will be lower than the potential savings available via participating in DR-aimed tariffs. Analysis to answer this question is expected to lead to deeper understanding of cost-effectiveness and, where proven economically viable, wider adoption of storage-based DR.

Few of the above mentioned studies involve the use of storage, and fewer yet are applicable to storage-based DR schemes in the residential sector. However, recognizing the overall promise and possible benefits of such schemes, we set out to investigate whether consumers interested in such schemes could install DR systems that are both technologically feasible and economically viable under currently available tariffs. Here, we define economically viable specifically as meaning that the cost of battery and control systems, including financing, maintenance, and operating expenses, is smaller than electricity bill savings via arbitrage that the storage can enable over the lifetime of the storage system. And if such break-even can be achieved, which storage technology on one hand and dispatch strategy on the other hand (i.e., when and how to discharge/charge the storage) creates the lowest overall cost to the residential consumer?

To answer this question, we developed an agent-based stochastic demand model to randomly generate demand profiles for a single, representative household in the U.S. We developed two dispatch strategies for two currently available DR tariffs from Consolidated Edison Company of New York, Inc. (henceforth "Con Edison") respectively. We then evaluated the economic viability of various available storage technologies using a simulation-based approach. Finally, we further validated and understood the simulation results based on given load profiles.

### *1.5 DR scheme overview*

In the above context, a basic scheme to exercise DR is illustrated in Figure 1**.** As shown in the figure, the control unit supplies electricity to the appliances as required, however this electricity can be taken from the grid, the battery (discharging mode), or both. In addition, the unit passes electricity from the grid to the battery (charging mode). Note that although we only investigated two DR tariffs in this report, the term "tariff" in Figure 1 denotes tariffs more generally as other DR tariffs can be adopted within the scheme illustrated in Figure 1. We first explained the specific tariffs used in this work (Sec. 2), then overviewed electricity storage technologies, built up the framework of the cost model and scenarios (Sec. 3), followed by the agent-based stochastic bottom-up demand model (Sec. 0). Then in Sec. 5, we introduced the chosen dispatch strategy and rationale for the kWh tariff, explained how the model was used to determine optimal storage capacities and displayed results. In Sec. 6, the dispatch strategy and results based on the kW tariff were written. Finally, discussions and conclusions were addressed in Sec. 7 and Sec. 8 respectively.

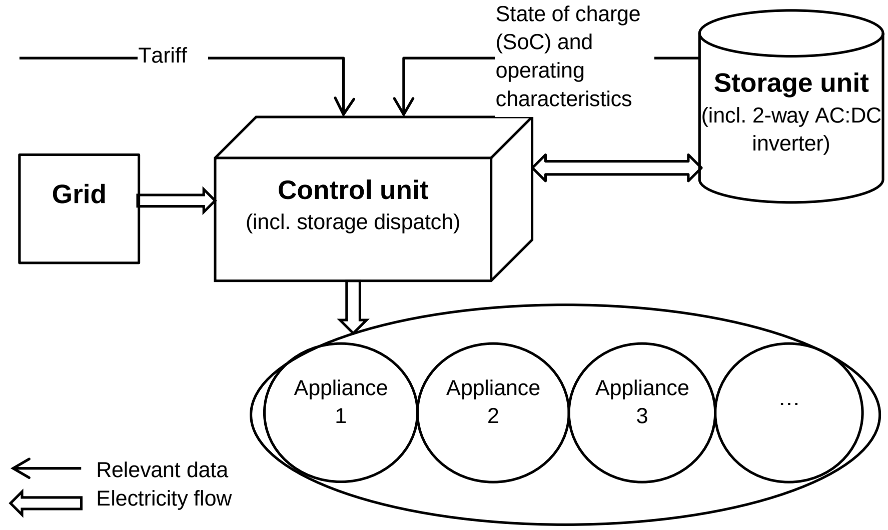


**Figure 1.** DR scheme and flows of relevant data and electricity.

## 2 DR tariffs

In contrast to other electricity storage analyses which are based on more general tariffs (e.g., [35]), we based our economic viability analysis on actual DR-relevant tariffs available from Con Edison. As typical in the U.S. electricity pricing, the monthly cost to residential consumers comprises (i) supply charges, (ii) delivery charges and (iii) taxes and other fees. Dependent on the specification class (SC), supply charges and delivery charges can charge in $ per kWh drawn from the grid (kWh tariff) or in both $ per monthly peak demand (maximum demand during one billing month) and $ per kWh drawn from the grid (kW tariff). The structure of the electric bill is illustrated in Figure 2.

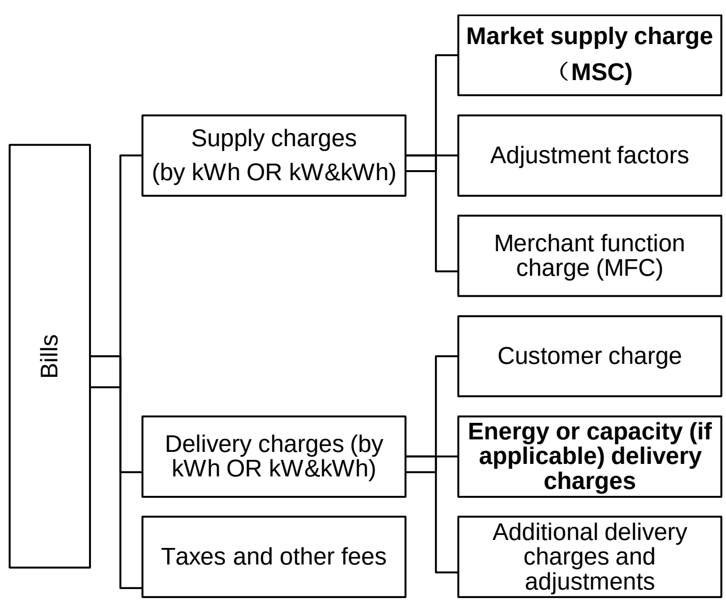


**Figure 2.** Con Edison rate structure (summarized from [45, 46])

A number of demand response tariffs are available from Con Edison. Among them, Emergency Demand Response Program (EDRP), Day Ahead Demand Reduction program (DADRP) and Demand Side Ancillary Service Program (DSASP) are incentivized by New York Independent System Operator (NYISO). Besides these programs, time-of-use tariffs (based on the kWh tariff or the kW tariff), distribution load relief program, commercial system relief program and curtailable electric service are also available for Con Edison's customers on a voluntary or mandatory basis. More information can be found on the NYISO website (http://www.nyiso.com) and Con Edison website (http://www.coned.com/). In this study, actual TOU tariffs available from Con Edison were investigated.

### *2.1 TOU kWh tariff*

For residential consumers with less than 10 kW peak demand monthly, SC1 is the specific classification assigned by Con Edison. Under SC1, both delivery charges and supply charges are charged in $ per kWh. Two rates are available for SC1 customers: Rate I (basic, Con Edison Rate I; Page 387-388 in [45]) and Rate II (TOU, Con Edison Rate II; Page 389 in [45]). The TOU kWh tariff charges differing rates for peak periods (Monday to Friday, 10 am-10 pm) and off-peak (all other hours). Rates further differ between summer (June to September) and other months. For comparison, the time-invariant "basic tariff", which charges the same $ per kWh rate irrespective of the time of day but varied by season, was also incorporated in the model.

Table 1 gives a full list of the charge items and the corresponding charge rates. Note that rates listed below don't reflect changes made by Con Edison after 02/25/2013. The relevant electric rate documents and definitions can be found on the Con Edison website: http://www.coned.com/rates/elec.asp. The market supply charge calculator (https://apps1.coned.com/csol/msc_cc.asp) was used to obtain historical market supply charge rates for each month. Charges for metering services are not included. Assume low-voltage services. MSC adjustment factor, MFC, Monthly Adjustment Clause (MAC) and MAC adjustment factor vary between months but variations are small. Therefore, for the sake of simplicity, average values over one year (02/2012-01/2013) was used for each charge rate mentioned above.

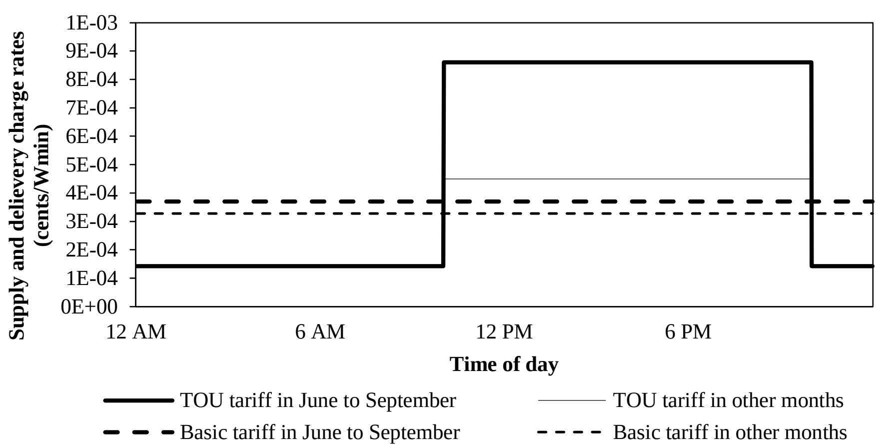


**Figure 3.** Daily electricity charge rates (supply and delivery, excluding monthly service fees).

Figure 3 depicts the values of charge rates for both TOU and basic kWh tariff. Solid lines represent rates under the TOU tariff while dashed lines represent rates under the basic tariff. Summer months (June to

September, heavy lines) are different from other months (light lines). Basic service charges ($15.76 per month for the basic tariff and $24.30 per month for the TOU kWh tariff) are only a small portion of the total electricity bill (Figure 15) and not plotted in Figure 3 .

During summer months, the TOU kWh tariff provides a lower charge rate during off peak hours while a much higher charge rate is observed during peak hours in comparison with the basic tariff. In other months, the charge rate increase during peak hours under the TOU kWh tariff, however is less than the charge rate decrease during off-peak hours. There is a slight increase in the charge rate under the basic tariff in summer months, but not significantly. Complete details are shown in Table 1.

**Table 1.** Electric rates for residential customers initial requirements less than 10 kW

| **SC1-Rate I (basic kWh tariff)** | | | | |
|---|---|---|---|---|
| **Supply charges** | MSC | See peak/off peak prices below | | |
| | MSC adjustment factor | -0.4341 | ¢/kWh | Averaged |
| | MFC | 0.5659 | ¢/kWh | Averaged |
| **Delivery charges** | Basic service charge (customer charge) | 15.76 | $ per month | |
| | Energy delivery charge | See peak/off peak prices below | | |
| | MAC | 1.7123 | ¢/kWh | Averaged |
| | Adjustment factor-MAC | 0.2013 | ¢/kWh | Averaged |
| | System benefits charge | 0.34 | ¢/kWh | |
| | Renewable portfolio standard program | 0.23 | ¢/kWh | |
| | Surcharge to collect PSL 18-a assessments | 0.4674 | ¢/kWh | |
| | Revenue decoupling mechanism adjustment | 0.2150 | ¢/kWh | |

**Summary (excl. basic service charge)**

| | | **Total** | | **Energy delivery charge** | | **MSC** | |
|---|---|---|---|---|---|---|---|
| **Jun-Sep** | First 250 kWh | 21.542 | ¢/kWh | 8.899 | ¢/kWh | 9.3455 | ¢/kWh |
| | Over 250 kWh | 22.867 | ¢/kWh | 10.224 | ¢/kWh | | |
| **Other months** | All kWh | 19.692 | ¢/kWh | 8.899 | ¢/kWh | 7.4948 | ¢/kWh |

| **SC1-Rate II Voluntary time-of-use (TOU kWh tariff)** | | | | |
|---|---|---|---|---|
| **Supply charges** | MSC | See peak/off peak prices below | | |
| | MSC adjustment factor | -0.4341 | ¢/kWh | Averaged |
| | MFC | 0.5659 | ¢/kWh | Averaged |
| **Delivery charges** | Basic service charge (customer charge) | 24.30 | $ per month | |
| | Energy delivery charge | See peak/off peak prices below | | |
| | MAC | 1.712 | ¢/kWh | Averaged |
| | Adjustment factor-MAC | 0.2013 | ¢/kWh | Averaged |
| | System benefits charge | 0.34 | ¢/kWh | |
| | Renewable portfolio standard program | 0.23 | ¢/kWh | |
| | Surcharge to collect PSL 18-a assessments | 0.4674 | ¢/kWh | |
| | Revenue decoupling mechanism adjustment | 0.2150 | ¢/kWh | |

**Summary (excl. basic service charge)**

| | | **Total** | | **MSC** | | **Energy delivery charge** | |
|---|---|---|---|---|---|---|---|
| **Jun-Sep** | Mon-Fri 10AM-10PM | 51.60 | ¢/kWh | 18.0313 | ¢/kWh | 30.27 | ¢/kWh |
| | All other hours | 8.52 | ¢/kWh | 4.0660 | ¢/kWh | 1.16 | ¢/kWh |
| **Other months** | Mon-Fri 10AM-10PM | 26.97 | ¢/kWh | 12.6878 | ¢/kWh | 10.98 | ¢/kWh |
| | All other hours | 8.74 | ¢/kWh | 4.2838 | ¢/kWh | 1.16 | ¢/kWh |

### *2.2 TOU kW tariff*

If residential customer's initial requirements[1] are expected to be in excess of 10 kW, SC8 will be assigned to these customers instead of SC1. Under SC8, delivery and supply charges are charged in both $ per kWh energy usage and $ per kW peak demand[2] (i.e. maximum demand during one billing period). Three rates are available for SC8 customers: Rate I (basic), Rate II (mandatory TOU) and Rate III (voluntary TOU). In this study, customers are assumed to select tariffs on a voluntary basis. Therefore, the mandatory TOU kW tariff is outside the scope of this study. In this kW tariff set, electricity bills consist of the cost of energy (charged in $ per kWh energy use) and the cost of demand (charged in $ per kW peak demand). For summer months, the TOU kW tariff records three maximum demands (i.e. three peaks) in three time periods: Monday to Friday, 8 am-6 pm; Monday to Friday, 8 am-10 pm; all hours of all days. For the remaining months, the tariff records only two peaks: Monday to Friday, 8 am-10 pm and all hours of all days. Different peaks are assessed different charge rates, and the monthly demand cost is the sum of these three (two) demand costs. The energy cost part charges differing rates for peak periods (Monday to Friday, 10 am-10 pm) and off-peak periods (all other hours). Both energy charge rates and demand charge rates further differ between summer months (June to September) and other months. In comparison, the time-invariant basic kW tariff charges the same $ per kWh rate and $ per kW rate, irrespective of the time of day but varied by season. One further difference between the basic kW tariff and the TOU one is that, according to [45] "the minimum charge for any monthly billing period shall be the charge for 10 kW of demand" under the basic kW tariff while there is no such "10 kW rule" embedded in the TOU one. The details of the charging rates are given by Table 2. The same sources and methods used to obtain kWh tariff details were used here too.

To illustrate how the TOU kW tariff works, one household whose maximum demand in June is 15 kW occurring at 12 am was employed as an example. By using the rates in Table 2, the demand cost charged by the TOU kW tariff would be:

$$15 \times 7.58 + 15 \times 17.92 + 15 \times 24.84 = \$755.1$$

If the consumer could wait till 9 pm to use appliances with high power ratings, the maximum demand (or peak demand) would be reduced to 9 kW during 8 am – 6 pm and 15 kW during 8 am -10 pm. The demand cost would be:

$$9 \times 7.58 + 15 \times 17.92 + 15 \times 24.84 = \$709.62$$

If the peak demand could be further postponed to occur after 10 pm, the peaks could be: 9 kW during 8 am-6 pm, 10 kW during 8 am -10 pm and 15 kW during all the hours. In other word, the peak of 15 kW occurs before 8 am or after 10 pm. The demand cost could be further decreased to:

$$9 \times 7.58 + 10 \times 17.92 + 15 \times 24.84 = \$620.02$$

From the above simple example, one's bill can be reduced by postponing the usage of high power rated appliances to off-peak periods under the TOU kW tariff. Alternatively, one can reduce the peaks (e.g., not

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[1] According to personal communications with representatives from Con Edison, the initial requirements are determined by installing demand meters.
[2] Demand charges are measured and billed according to 30-minute increments according to Con Edison.

using high power rated appliances simultaneously) or smooth his/her demand profile to achieve a lower electricity bill under either the basic kW tariff or the TOU kW tariff.

**Table 2.** Electric rates for residential customers with initial requirements in excess of 10 kW

| **SC8-Rate I (basic kW tariff)** | | | | |
|---|---|---|---|---|
| **Supply charges** | MSC | | | |
| | Demand supply charge(capacity) | 8.33 | $/kW | |
| | MSC adjustment factor | -0.4341 | ¢/kWh | Averaged |
| | MFC | 0.1626 | ¢/kWh | Averaged |
| **Delivery charges** | Demand delivery charge | See prices below. | | |
| | Energy delivery charge | 1.76 | ¢/kWh | |
| | MAC | 1.7123 | ¢/kWh | Averaged |
| | Adjustment factor-MAC | 0.2013 | ¢/kWh | Averaged |
| | System benefits charge | 0.34 | ¢/kWh | |
| | Charge for renewable portfolio standard program | 0.23 | ¢/kWh | |
| | Surcharge to collect PSL 18-a assessments | 0.3304 | ¢/kWh | |
| | Revenue decoupling mechanism adjustment | -0.7920 | ¢/kWh | |

**Summary**

| | **Demand delivery charge** | | **Subtotal (demand charges)** | | **MSC** | | **Subtotal (energy charges)** | |
|---|---|---|---|---|---|---|---|---|
| **Jun-Sep** | 27.14 | $/kW | 35.47 | $/kW | 5.010 | ¢/kWh | 8.52 | ¢/kWh |
| **Other months** | 20.98 | $/kW | 29.31 | $/kW | 4.901 | ¢/kWh | 8.41 | ¢/kWh |

Minimum charge: The minimum delivery charge for any monthly billing period shall be the charge for 10 kW of demand**.**

| **SC8-Rate III Voluntary time-of-use (TOU kW tariff)** | | | | |
|---|---|---|---|---|
| **Supply charges** | MSC | See peak/off peak prices below | | |
| | Demand supply charge(capacity) | 8.33 | $/kW | |
| | MSC adjustment factor | -0.4341 | ¢/kWh | Averaged |
| | MFC | 0.1626 | ¢/kWh | Averaged |
| **Delivery charges** | Demand delivery charge | See peak/off peak prices below | | |
| | Energy delivery charge | 0.82 | ¢/kWh | |
| | MAC | 1.7123 | ¢/kWh | Averaged |
| | Adjustment factor-MAC | 0.2013 | ¢/kWh | Averaged |
| | System benefits charge | 0.34 | ¢/kWh | |
| | Charge for renewable portfolio standard program | 0.23 | ¢/kWh | |
| | Surcharge to collect PSL 18-a assessments | 0.3304 | ¢/kWh | |
| | Revenue decoupling mechanism adjustment | -0.7920 | ¢/kWh | |

***Summary***

| | | **Demand delivery charge** | | **Subtotal($/kW)** | | **MSC(excl. demand supply charge)** | | **Subtotal(excl. demand charges)** | |
|---|---|---|---|---|---|---|---|---|---|
| **Jun-Sep** | Mon-Fri 8AM-6PM | 7.58 | $/kW | 7.58 | $/kW | 6.3976 | ¢/kWh | 8.9682 | ¢/kWh |
| | Mon-Fri 8AM-10PM | 17.92 | $/kW | 17.92 | $/kW | | | | |
| | All hours of all days | 16.51 | $/kW | 24.84 | $/kW | 3.93 | ¢/kWh | 6.5006 | ¢/kWh |
| **Other months** | Mon-Fri 8AM-10PM | 13.27 | $/kW | 13.27 | $/kW | 5.6230 | ¢/kWh | 8.1936 | ¢/kWh |
| | All hours of all days | 5.33 | $/kW | 13.66 | $/kW | 4.2249 | ¢/kWh | 6.7954 | ¢/kWh |

## 3 Electricity storage technologies, framework of storage cost model and scenarios

A variety of currently available technologies were investigated in this study, ranging from the conventional ones, e.g., Lead-acid (Pb-acid) batteries to relatively advanced ones, e.g., the novel Zinc Manganese dioxide ($ZnMnO_2$) batteries developed by City College of New York (CUNY). Some operating parameters and cost parameters are essential to perform a detailed comparison of the storage options and to incorporate the storage devices in the model. The general definitions are available in the following cost model. The main sources used here include the Electric Power Research Institute (EPRI) report [35], reports from Sandia National Laboratories [37, 38], European Commission's Strategic Energy Technologies Information System (SETIS) report [47], and study by Chen et al. [40]. The complete list of the operating characteristics, cost estimations of storage options are detailed in Table A.1. Note that technical properties and cost estimations of the devices can be different from one source to another and also depends on the specific applications and the angle of the analysis. The uncertainties of the data will be addressed in the financing model. Additionally, two scenarios were analyzed to address the inherent data uncertainties.

### *3.1 Electricity flow model and definitions*

Figure 4 illustrated the electricity flow starting from the grid to the storage and finally being discharged to appliance(s) along with losses during power conversion (PCS1 and PCS2, involving inverter and/or converter) and charging/discharging processes (CH1 and CH2).

Some definitions of the operating parameters are also useful in the model:

- $Eff_{\mathrm{G\ to\ S}}$ is defined as the ratio of electricity stored to electricity drawn from the grid, reflecting both loss through the first power conversion unit (PS1 in Figure 4**)** and charging process.
- $Eff_{\mathrm{S\ to\ A}}$ is defined as the efficiency of energy stored to electricity consumption by appliances, reflecting discharging loss and loss through the second power conversion unit (PS2 in Figure 4). In our model, $Eff_{\mathrm{G\ to\ S}}$ and $Eff_{\mathrm{S\ to\ A}}$ are equal in value.
- *DoD* is healthy depth of discharge.

The concept "power density" (kW/kWh) was used when the data collected from literature were converted to specific parameters used in the model (detailed values are listed in Table A.1). Power density is the maximum continuous (dis)charging power for a storage module of one kWh nominal capacity. In this report, sometimes, another similar term is used: "charging at, e.g., 1C", meaning, 1 kW per kWh nominal capacity. Certain storage can withstand pulse discharging, i.e. discharging at as several times the power of its nominal power rating. In this study, only the continuous (dis)charging power (i.e. nominal power rating at the normal (dis)charging mode) was considered in the model.

Figure 4 illustrates the concept of "effective capacity" (*EC*) as used throughout our analysis: *EC* reflects the maximum amount of electricity stored that can be withdrawn and used by appliances after discharging (CH2) and power conversion loss (PC2). We thus used cost for a given kWh effective capacity (per year) to provide a useful metric to levelize the costs of technologies of different lifespans and/or dis(charging) efficiencies:

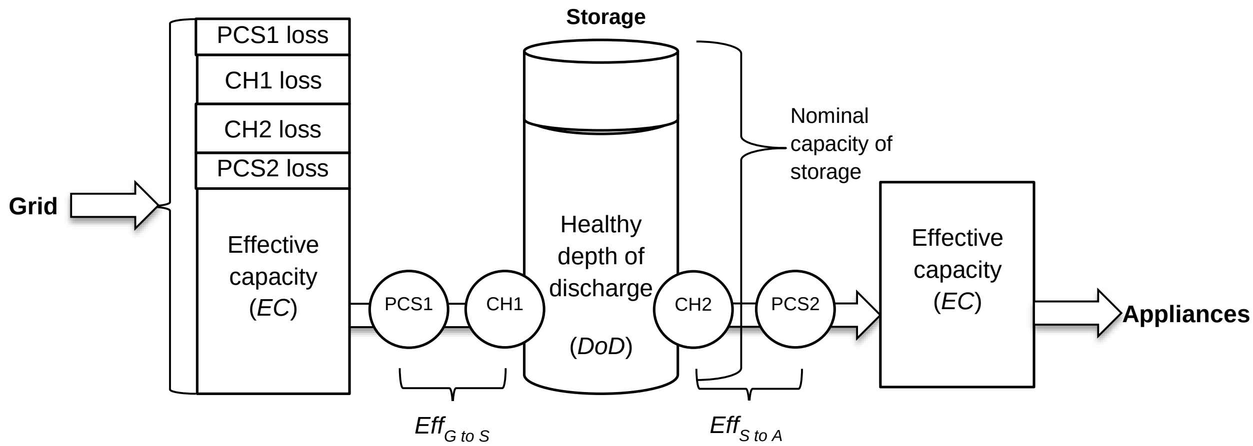



**Figure 4.** Illustration of the electricity flow

### *3.2 Uncertainties, financing cost model and scenarios*

Financing costs, here referring to the principal and 10% interest payments for the storage and control unit combined over their lifetime, were broken down into two parts: One part scales proportional to the storage capacity (kWh). The other, a one-time home installation fee, is (approximately) independent of the storage size (here assumed to be $2,000). To account for price variations by vendor as well as possible future price reductions and/or improvements in storage life time, we used ranges (low, high) of financing costs. Some uncertainties in storage cost and lifetime are due to their level of technological maturity. For example, the limited operational field experience for newer storage technologies, such as flow batteries and Li-ion batteries, make it difficult to obtain accurate cost values from current literature. In contrast, cost uncertainties for e.g., Pb-acid batteries and sodium sulfur (NaS) batteries, both more proven technologies [48], are smaller. Because of the inherent uncertainties in financing costs, relatively smaller operational and maintenance costs were not treated separately, but rather considered already included in the financing costs.

$$Cost = \left( PC \cdot \frac{EC}{Eff_{\mathrm{S\ to\ A}} \cdot DoD} + IC \right) \cdot FCR \tag{1}$$

Where *PC* denotes the purchase cost of storage per kWh nominal capacity (excl. installation),
*EC* denotes the effective capacity of storage,
*IC* denotes the installation fee (assumed to be $2,000),
*FCR* denotes the annual finance cost rate (principal repayment plus 10% interest, see Table 3).

Financing cost (interest rate and principal repayment) over the lifespan of the storage equipment (storage unit (costs incl. control unit) and installation cost) was calculated with an assumption of 10% interest rate. For the sake of simplicity, storage technologies were roughly categorized into four lifespans: The average lifespans of each storage technology were rounded to generally 5, 10, 15, or 20 years by assuming one cycle per day (one cycle includes charging and discharging storage once).

Example cashflows for equipment of 5-year life time and an initial $1,000 investment are listed in Table 3. Financing cost rates (*FCR*s) for any given interest rate and lifetime are given by equation 2 and the specific values used in the model are listed in Table 4.

$$FCR = \frac{r(1+r)^k}{(1+r)^k - 1} \quad (2)$$

Where $r$ denotes the interest rate,
$k$ denotes the number of *annual payments* (e.g., for a life time of 5 years, k=5).

**Table 3.** Cashflows [$] for a $1,000 upfront for equipment with a life time of 5 years

| Year ("stock" values are end of year) | 0 | 1 | 2 | 3 | 4 | 5 |
|---:|---:|---:|---:|---:|---:|---:|
| Interest | | -100 | -84 | -66 | -46 | -24 |
| Repayment of principal[a] | | -164 | -180 | -198 | -218 | -240 |
| Total financing cost | | 264 | 264 | 264 | 264 | 264 |
| Annual *FCR* (% of upfront) | | 26.4% | 26.4% | 26.4% | 26.4% | 26.4% |
| **Remaining debt** | -1000 | -836 | -656 | -458 | -240 | 0 |

[a] Repayment of principal = -Initial investment*FCR-Accumulated interest. *FCR* is solved by setting zero remaining debt at the end of the fifth year.

**Table 4.** List of *FCRs* (10% interest rate) used in the study

| ***FCR* [% of upfront cost]** | **per year** | **per day** |
|---:|---:|---:|
| 5 years | 26.4% | 0.072% |
| 10 years | 16.3% | 0.045% |
| 15 years | 13.1% | 0.036% |
| 20 years | 11.7% | 0.032% |

**Table 5.** Parameters of storage operating characteristics and purchase cost

| | | **Purchase cost of storage ($/kWh-capacity)** | | ***DoD*** | **Round-trip efficiency[a]** | **Life time (cycles)** | | **Power conversion system efficiency** | |
|---|---|---:|---:|---:|---:|---:|---:|---:|---:|
| | | **Best-case scenario** | **Average** (geometric mean) | **Average** (arithmetic mean) | **Average** (arithmetic mean) | **Average** (arithmetic mean) | (year) | PS1 | PS2 |
| Flywheel | | 1,000 | 2236 | 88% | 90% | 30,000 | 20 | 95% | 95% |
| Conventional batteries | Metal air battery | 10 | 40 | 100% | 45% | 800 | 5 | | |
| | Lead-acid (Pb-acid) | 106 | 489 | 75% | 78% | 2,350 | 10 | | |
| | Nickel-cadmium (NiCd) | 600 | 949 | 75% | 76% | 2,000 | 10 | | |
| Advanced batteries | Lithium-ion (Li-ion) | 500 | 1342 | 80% | 88% | 5,500 | 15 | | |
| | Sodium sulfur (NaS) | 250 | 826 | 80% | 81% | 3,250 | 10 | | |
| | NaNiCl ZEBRA | 100 | 141 | 80% | 90% | 2,500 | 10 | | |
| Flow batteries | Zinc bromine (ZnBr) | 150 | 541 | 100% | 68% | 6,000 | 15 | | |
| | Vanadium redox (VRB) | 150 | 433 | 100% | 75% | 10,000 | 20 | | |
| | Nickel zinc | 700 | 700 | 90% | 80% | 7,000 | 15 | | |
| | $ZnMnO_2$ | 100 | 141 | 90% | 80% | 4,000 | 15 | | |
| Super capacitor | | 500 | 707 | 100% | 95% | 5E+07 | 20 | | |
| CAES | | 2 | 29 | 70% | 55% | 12,500 | 20 | | |
| PHS | | 5 | 22 | 100% | 80% | 35,000 | 20 | | |
| SMES | | 1,000 | 3162 | 100% | 95% | 55,000 | 20 | | |

[a] The round-trip efficiency takes into account the charging loss through CH1 and the discharging loss through CH2.

Recognizing above parameter ranges, we analyzed economic viability under two scenarios: 1) Best-case; and 2) average-case. The best-case scenario uses the lowest cost cited in the literature for a specific storage technology. The average-case uses the average (geometric mean) of lowest and highest costs in the literature. For all other parameters such as lifetime (here specifically number of daily cycles), (dis)charging efficiencies, and *DoD*, we used arithmetic means of low and high literature values (same in both scenarios). Scenarios with low storage cost and long lifetime were not considered. Since cost often correlates with performance-related parameters such as lifetime or efficiency, such scenarios are much less realistic. The operating characteristics and cost estimations for storage options under two scenarios are summarized in Table 5.

# 4 Agent-based stochastic residential demand model

An agent-based, appliance-level demand model to randomly generate demand profiles (1 minute time resolution) for a typical household in the U.S. was devised based on the scheme illustrated in Figure 5.

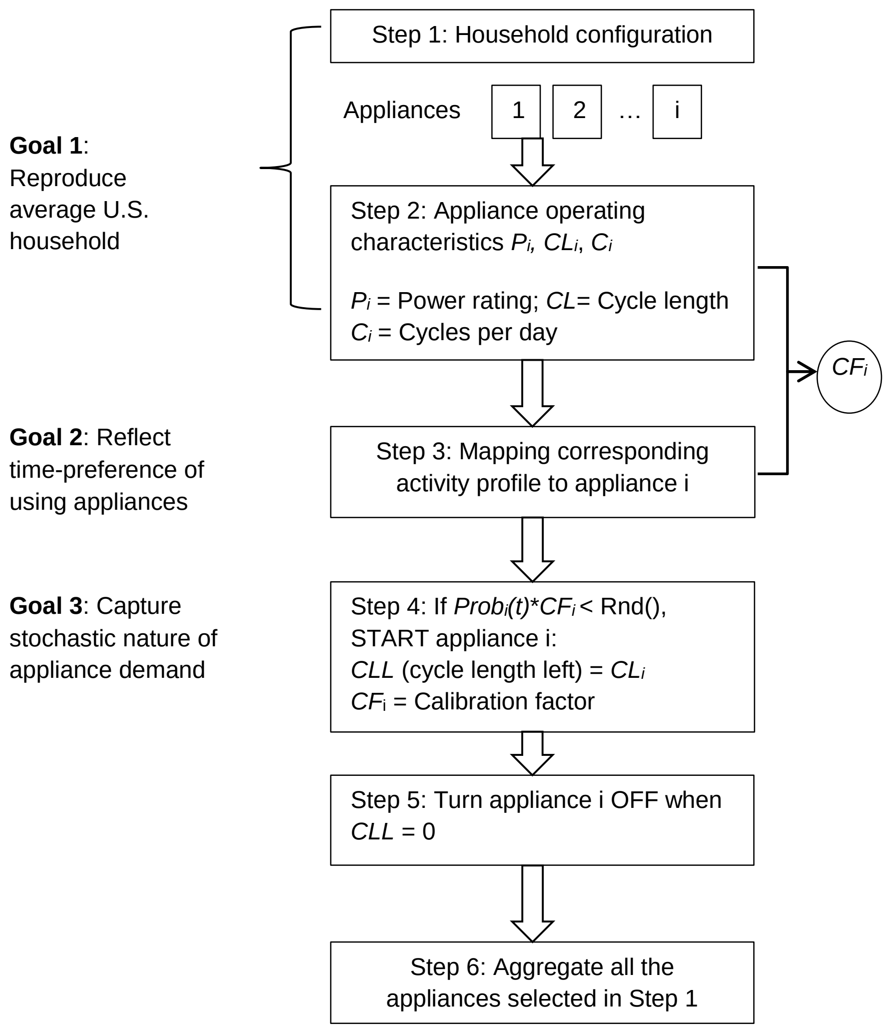



**Figure 5.** Illustration of the stochastic demand profile model.

Simulating one year of minute-by-minute demand, storage dispatch, and resulting electricity cost takes about 8 minutes on a laptop computer with 2.5 GHz Intel Core i5-2520M CPU and 4 GB RAM). The model generally follows the approach introduced by Widén [24]. The strategy of mapping time-use data of activities to corresponding appliances was explained and validated by Capasso et al. [22]. The simulated demand profiles, of each appliance individually as well as the household in aggregate, were subjected to various tests to confirm the fidelity of the model.

### *4.1 Presentation of data and steps to build up the demand model*

**Step 1: Household configuration and Step 2: Appliance operating characteristics**

We selected appliances according to two rules: 1) Match the total electricity consumption (in kWh) and demand profile (in kW) of a typical U.S. household; 2) match the consumption make-up from various appliance types (e.g., air conditioning vs. lights vs. heating, etc.).

For each appliance, typical power rating, cycle length, and cycles per year were selected and slightly adjusted simultaneously within ranges cited in the literature (mostly from the Department of Energy (DOE) 2011 Building Energy Data Book, Table 2.1.16 [49] and the DOE Energy Saver [50], see Table 6 for details) so as to render the corresponding annual usage (in kWh) consistent with literature sources (mostly from the Residential Energy Consumption Survey (RECS) , see Table 6 for details).

**Table 6.** Operating characteristics of typical electric appliances in the residential sector in the U.S.

| Appliance | Power draw | Electricity consumption per cycle per household | Annual usage per household (calculated | Annual usage per household (lookup) | ON time | Cycles | Calibration factor (CF) | Activity code[a] | Sources |
|---|---|---|---|---|---|---|---|---|---|
| | (W) | (kWh) | (kWh) | (kWh) | (min) | (n/year) | ($min^{-1}$) | | |
| Dishwasher[b] | 1,457 | 0.69 | 253 | 120-512 | 54 | 365 | 4.12547 | 020203 | [24, 49-52] |
| Microwave oven | 1,500 | 0.15 | 170 | 131-209 | 6 | 1133 | 3.71951 | 020201 | [49-52] |
| Toaster oven | 1,400 | 0.47 | 52 | 50-54 | 20 | 111 | 0.36182 | 020201 | [49-51, 53] |
| Refrigerator | 250 | 0.08 | 1007 | 660-1359 | 20 | 12089[c] | 0.04085 | | [49, 50, 52, 54-56] |
| Freezer | 155 | 0.05 | 1120 | 470-1150 | 20 | 21681 | 0.19075 | | [49, 51, 52, 56] |
| Lighting-Bathroom | 317 | 0.16 | 162 | 940 | 31 | 989 | 2.23461 | 010201 | [51, 57, 58] |
| Lighting-Bedroom | 200 | 0.20 | 124 | | 60 | 621 | 0.74326 | TEWHERE=1 | [51, 58] |
| Lighting-Living Room | 256 | 0.26 | 215 | | 60 | 840 | 1.03289 | TEWHERE=1 | [51, 58] |
| Lighting-Dining Room | 235 | 0.12 | 163 | | 30 | 1387 | 3.07522 | 110101 | [51, 57, 58] |
| Lighting-Hallways | 207 | 0.05 | 91 | | 15 | 1752 | 2.04803 | TEWHERE=1 | [51, 58] |
| Lighting-Kitchen | 250 | 0.13 | 228 | | 32 | 1711 | 6.17806 | 020201 | [51, 57, 58] |
| Clothes dryer | 2895 | 2.90 | 1039 | 1000-1079 | 60 | 359 | 3.33162 | 020102 | [24, 49-52] |
| Clothes washer[d] | 2150 | 0.77 | 303 | 110-420 | 48 | 392 | 3.61809 | 020102 | [24, 49-52] |
| Television | 185 | 0.35 | 267 | 222-313 | 115 | 752 | 1.85108 | 120303 | [24, 49-52, 57] |
| Air conditioning | 3500 | 0.58 | 3220 | 2822 | 10 | 5520[e] | 96 | | [50, 54] |
| Space heater | 1,447 | 1.45 | 2136 | 2136 | 60 | 1476 | 0.01639 | | [49, 50, 54] |
| Vacuum | 1,440 | 0.84 | 53 | 55 | 35 | 63 | 0.56724 | 020101 | [24, 49, 50, 57] |
| Computers and others | 100 | 2.4 | 876 | 810 | 1440 | 365 | 1 | | [49] |

[a] Activity code in the above table is coded by 2011 American Time Use Survey 2011 [57]. Descriptions can be found in the coding document. http://www.bls.gov/tus/lexicons.htm

[b] Dishwasher operated in 4 stages: $P_1$=1457 W, $P_2$=220 W, $P_3$=1457 W, $P_4$=220 W; $T_1$=18 min, $T_2$=18 min, $T_3$=6 min, $T_4$=12 min.

[c] All 14 and 16 cu. ft. (TBX/CTX models vs. TBF models of past) will have an average run time of between 40 and 52% as do compact models,(TA2,4,6). Chest & Upright freezers run 75% to 90% of the time [56].

[d] Clothes washer is operated on three stages: $P_1$=2150 W, $P_2$=210 W, $P_3$=450 W; $T_1$=18 min, $T_2$=24 min, $T_3$=6 min.

[e] Assume space heater runs 12 hours per day and mean cycle length is 60 minutes. In use during the winter, i.e. in November, December, January and February.

**Step 3: Mapping corresponding activity profiles to appliances**

For activity profiles, we used 2011 American Time Use Survey (ATUS) data reported by 13,260 respondents [57]. Each appliance was linked to a corresponding activity with an activity code in Table 6. The column of activity codes were obtained from the ATUS. The full lexicons can be found in http://www.bls.gov/tus/lexicons.htm. Those with blank activity codes are discussed below. Activity probability profiles are displayed in

Figure 8-11. To smooth out artificial spikes, a rolling window of 11 minutes was applied.

### *4.1.1 Approach to air conditioning*

No suitable ATUS activity profile could be found for air-conditioning. Instead, a starting probability profile of air-conditioning was reproduced from Reddy, T. A., Figure.1 [59]. Note that the reproduced profile is not a starting probability profile but rather an in-use probability profile (while for all the other appliances, starting probability profiles are available from ATUS). Without time-varying air-conditioning demand profile, the aggregated demand profile for one whole household would have two (Figure 13(a)) instead of one (Figure 13(b)) peak over the course of one day. In other words, we cannot map a flat starting probability profile to air-conditioning because the time-variance of using air-conditioning is significant. Therefore, the in-use probability profile reproduced from Ref. [59] was assigned to air-conditioning as an approximation.

### *4.1.2 Approach to lighting*

A similar difficulty occurs with respect to lighting for which finding a directly related ATUS activity is difficult. Addressing lighting in bedroom, living room and hallways, the starting probability profile of occupancy being at home and awake (coded as TEWHERE =1) was used as an approximation. Unlike air-conditioning, the underlying assumption is that the load demanded by lighting will not contribute to shaping the demand profile of one whole household to a large degree.

### *4.1.3 Other appliances*

Uniform probability profiles were assigned to refrigerator, freezer and space heater under the assumption that using these three appliances is not occupancy related. They do however stochastically turn on and off, adding significant noise to the aggregate household profile (see Figure 7). Since power ratings of computer and some other rechargeable electronic devices such as mobile phone chargers are all relatively low, they will not contribute to a peak during the day but only contribute some base-load 24 hours a day. Therefore, in this model, computer and other typical electronic devices were grouped into a single appliance. The minimum ON time was set to 1440 minutes making it a base load without ever turning off.

**Step 4 & Step 5: Calibration and programming**

### *4.1.4 Calibration (all appliances)*

Since parameters where drawn from multiple sources, it is necessary to calibrate (or normalize) the on probability profiles to render the total starting probabilities over one year consistent with typical total annual cycle times for each appliance. Average number of cycles per day and duration of each cycle, for each appliance separately, were calibrated to follow data from the Buildings Energy Data Book (Table 2.1.16; [49]) and the RECS report [51].

$$Starting\ Prob_i(t) = \frac{N_{i,home}(t)}{13260} \tag{3}$$

$$In - use\ Prob_i(t) = \frac{M_{i,home}(t)}{13260} \tag{4}$$

Where $N_{i,\mathrm{home}}(t)$ denotes #respondents to START activity $i$ (at home/yard) at time step $t$,
$M_{i,\mathrm{home}}(t)$ denotes #respondents to DO activity $i$ (at home/yard) at time step $t$,
13260 is the total number of participants in the survey.

$$CF_i = \frac{CYC_i}{\frac{1440-(CL_i-1)\times CYC_i}{1440}\sum_{t=1}^{t=1440} Starting\ Prob_i(t)} \tag{5}$$

Where $CF_i$ denotes the calibration factor of appliance $i$,
$CYC_i$ denotes reference cycles per day for appliance $i$,
$CL_i$ denotes the cycle length of appliance $i$.

The flow chart in Figure 6 is used to illustrate the agent-based logic to randomly generate a demand profile for one household.

This publication is available free of charge from: http://dx.doi.org/10.6028/NIST.GCR.14-978

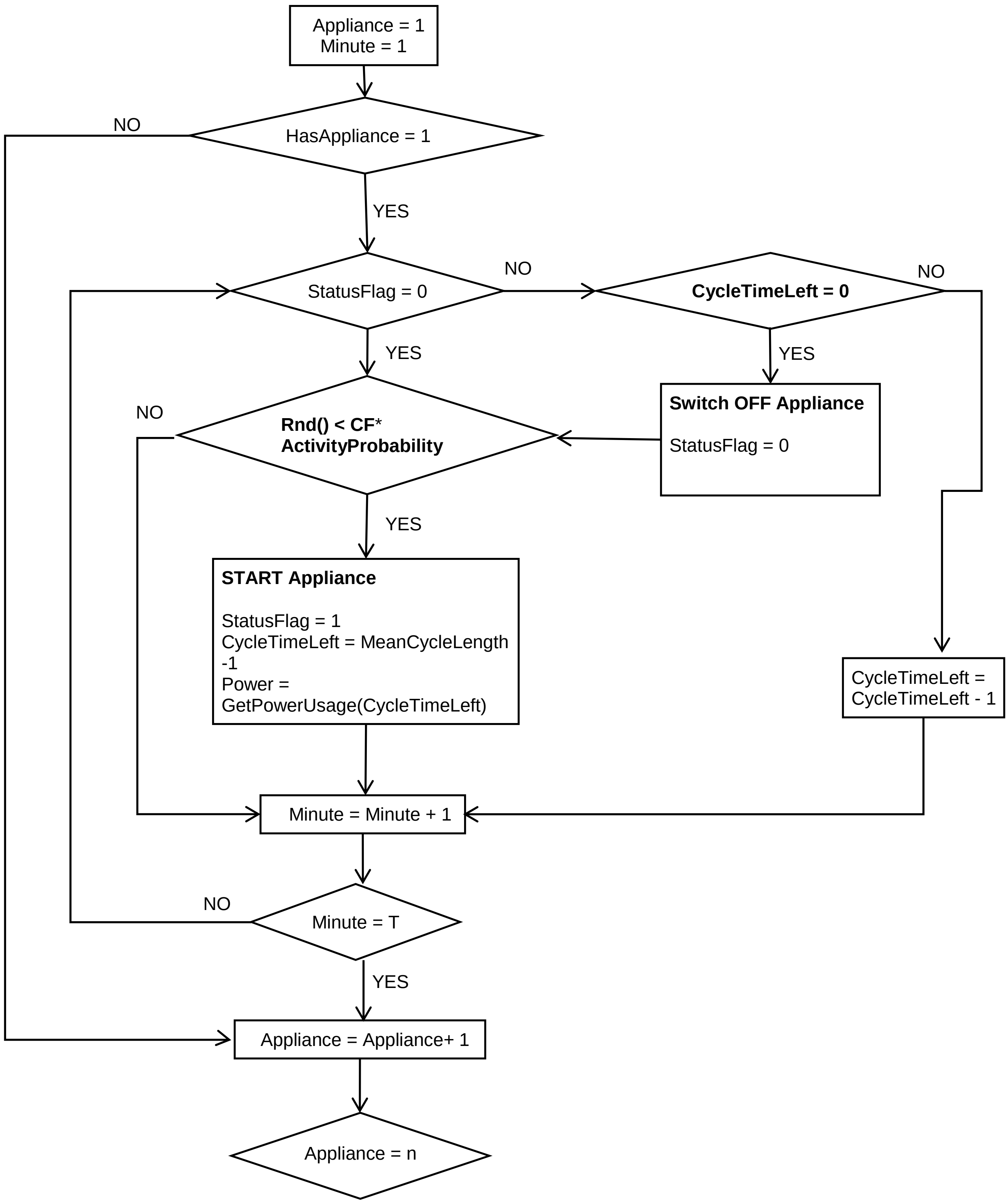



**Figure 6**[3]. Flow chart of agent-based logic in the appliance demand profile model.

[3] Continues until the total set time T (e.g., 525,600 minutes for one year or 1440 minutes for one day) is reached.

**Step 6: Aggregate appliances demand profiles to form household demand profiles**

Figure 7 shows an example how appliances demand profiles are aggregated to form the demand profile for one typical household in the U.S. in one random summer day.

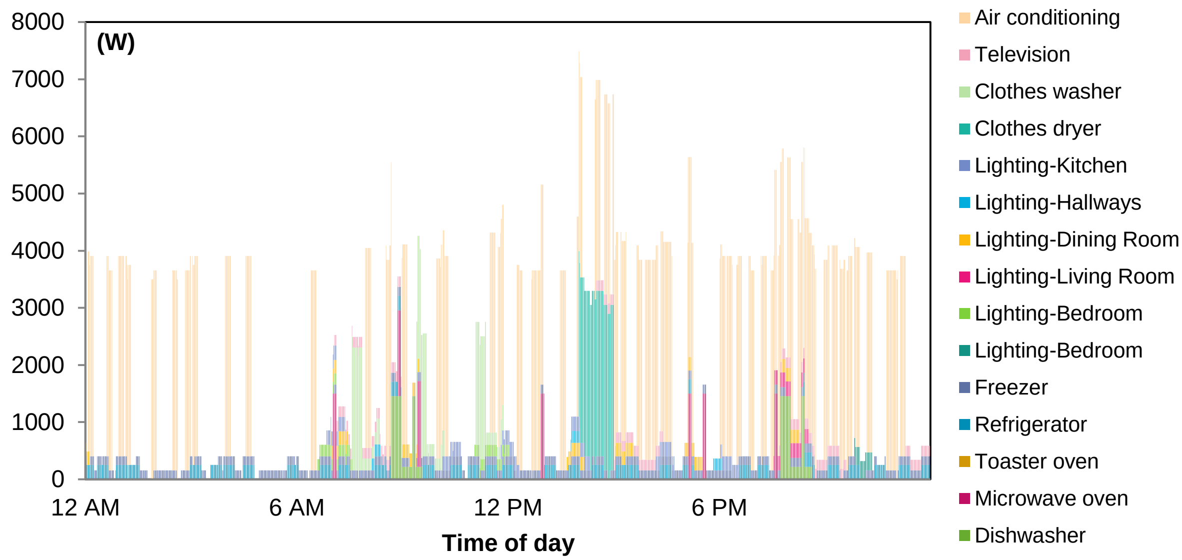



**Figure 7.** An example of one household demand profile generated by aggregating appliances demand profiles

## *4.2 Testing*

For individual appliances, we tested (i) on/off cycling; (ii) power and electricity draw, cycles per year, and total electricity consumption per year; and (iii) the average daily demand time profile. For the household aggregate demand, we tested (iv) average demand time profile (differentiated by season); (v) total kWh draw per year; and (vi) % contribution of appliance types to total annual kWh consumption (air conditioning vs. lighting vs. heating, etc.). The model was found to capture above features (i)-(vi) adequately.

Three groups of tests were performed. (1) On individual appliance level (Sec. 4.2.1), simulations for a large number of days should yield, for each appliance, the same average cycles per year and the average daily electricity consumption as the input parameters listed in Table 6. In addition, the average daily load profiles for each appliance were compared with the corresponding in-use probability profiles from ATUS (

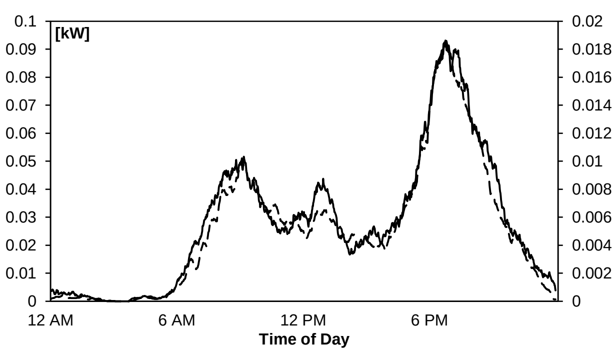
Figure **8**-11). (2) On household level (Sec. 4.2.2), the simulated average daily electricity usage profile (simulated over hundreds of days and thus reflecting the aggregate profiles of hundreds of households on a single day) was compared to RECS [54] (Figure 12) as well as sector-level daily demand profiles reproduced from EMET Consultants Pty Ltd, Figure 4.1 and Figure 4.2 [60] (Figure 13). (3) Finally, cycle lengths observed for a subset of appliances available from the Pecan Street Research Institute [61] were compared with the corresponding simulated cycle lengths. The comparison results confirmed that the simulated cycle lengths are within the measured ranges (not shown).

### *4.2.1 Individual appliance level and model convergence*

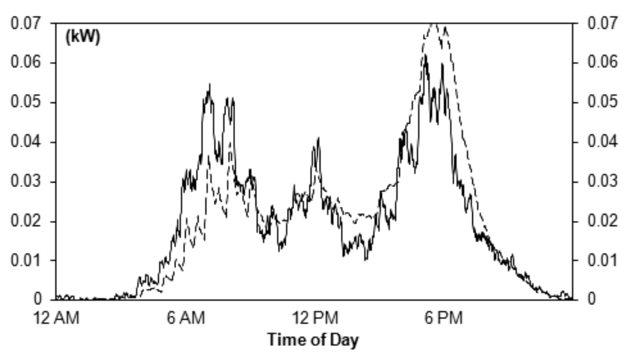
As shown in Table B.1 individual appliance demand loads were averaged over a large number of days to yield the results on a “converged” day. For each minute individually, the relative standard deviation of the mean (RSEM) power draw is less than 5%. Generally, the shapes of modeled mean curve loads for each appliance are in agreement with the shapes of in-use probability profiles from ATUS (

Figure **8**). Peaks are reproduced well. Figure 9 for air-conditioning is of particular interest here. Instead of the starting probability profile, in-use probability profile was used as an approximation. The simulated mean load curve displays a slight right-shift in comparison to its in-use probability profile. Still, the overall time-preference is captured well. One methodological source of the small mismatches visible e.g., in Figure 10 is the CF. The current way to calculates CFs involves an approximation made for available minutes in Eq.(5). However, instead incorporating accurate minute-by-minute CFs would be too time-consuming computationally. Lastly, the resulting mean load curves for lighting in the bedroom, living room, and hallways were compared to the probability profile reflecting when occupants were at home and awake. Due to the mismatch between appliance cycle lengths (no more than 1 hour for these three appliances, see Table 6 and the activity (being at home and awake) lengths (commonly more than 1 hour), the simulated curves and the comparison curves display mismatches in Figure 11. This mismatch however does not substantially affect our results and conclusions because the kW draw of lighting appliances is small in comparison to overall power demand.

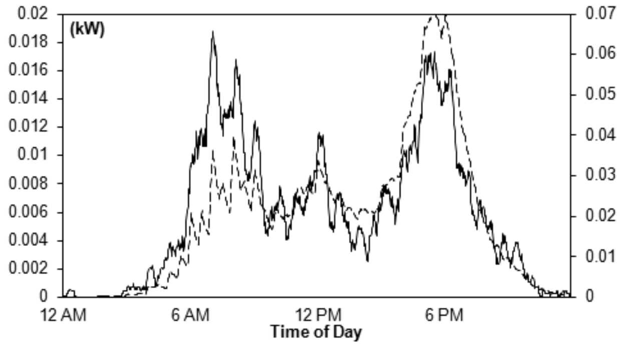
In summary, the model is able to capture the time-preferences well and the daily electricity consumption value from literatures (see Table B.1) is reproduced well. Possible future refinement lies in the improvement of starting probability profiles. Other sources of starting probability profiles for air-conditioning and lightings are desirable. A model to generate lighting load curve based on the indoor luminance may be included in the model in the future.



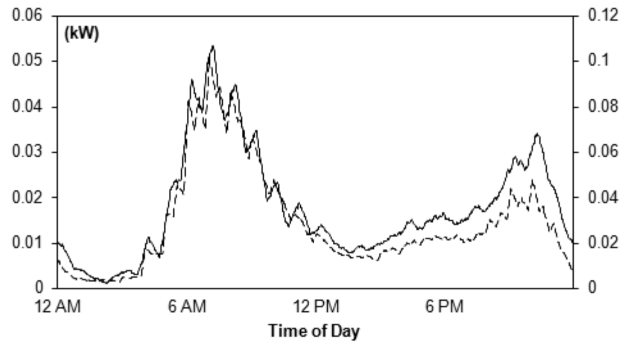

(a) Dishwasher



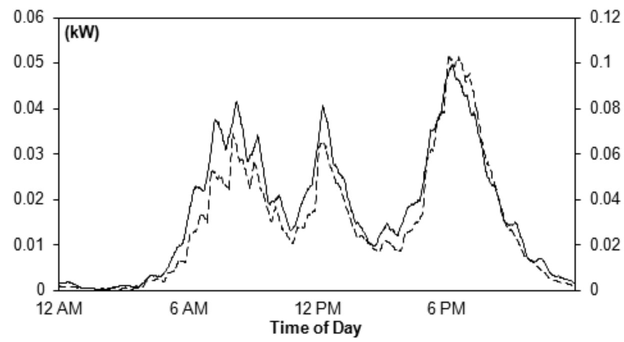

(b) Microwave oven



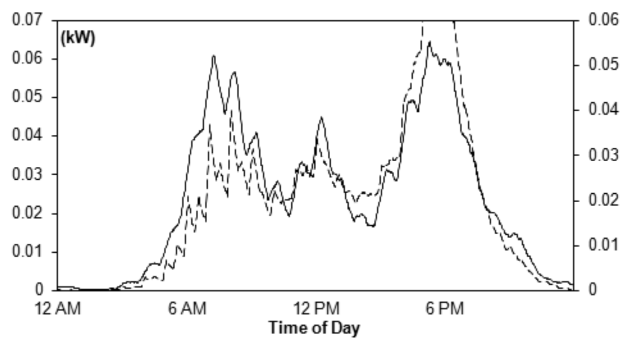

(c) Toaster



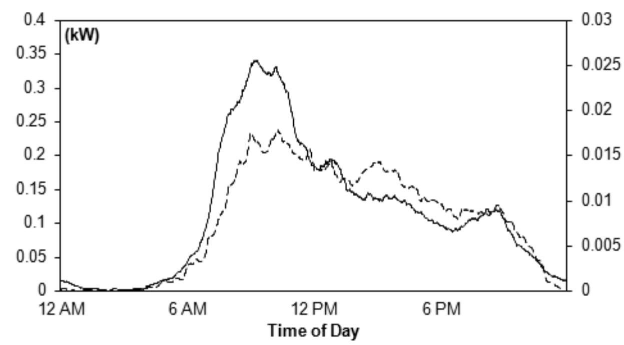

(d) Lighting in the bathroom



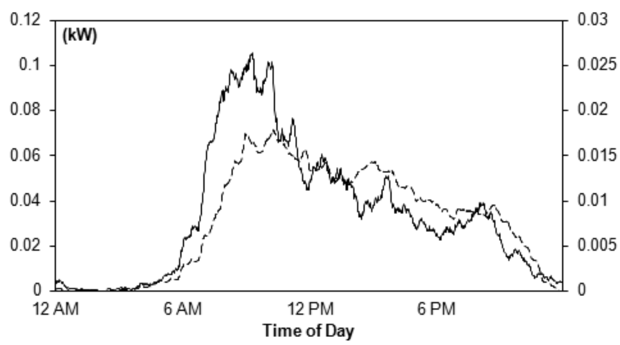

(e) Lighting in the diningroom



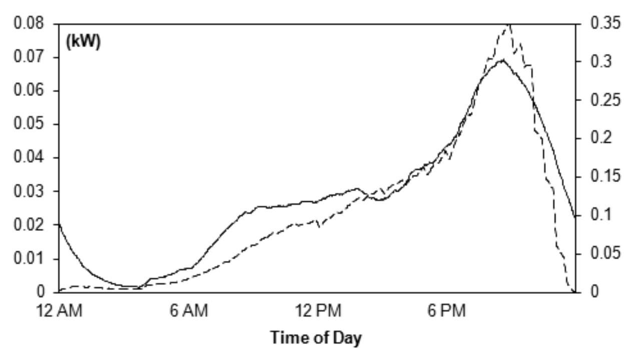

(f) Lighting in the kitchen



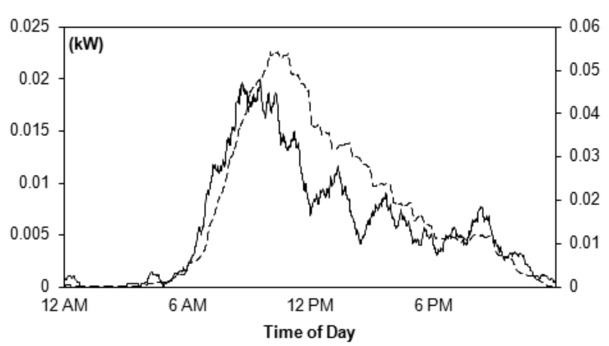

(g) Clothes washer




(h) Clothes dryer




(i) Television




(j) Vacuum cleaner

**Figure 8[4].** Mean load curve from simulations and in-use probability profile from ATUS [57].

[4] The probability profiles are plotted on the secondary axis. The solid lines represent the mean load curves from simulations while the long-dashed lines represent the in-use probabilities.

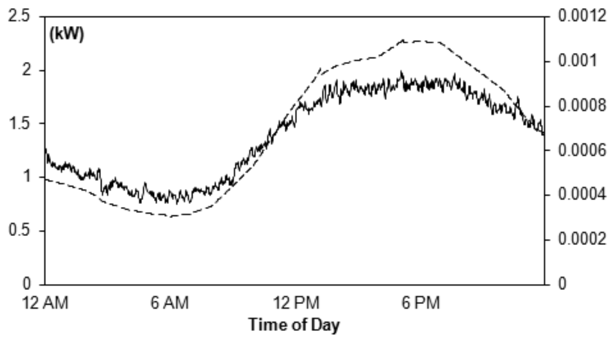
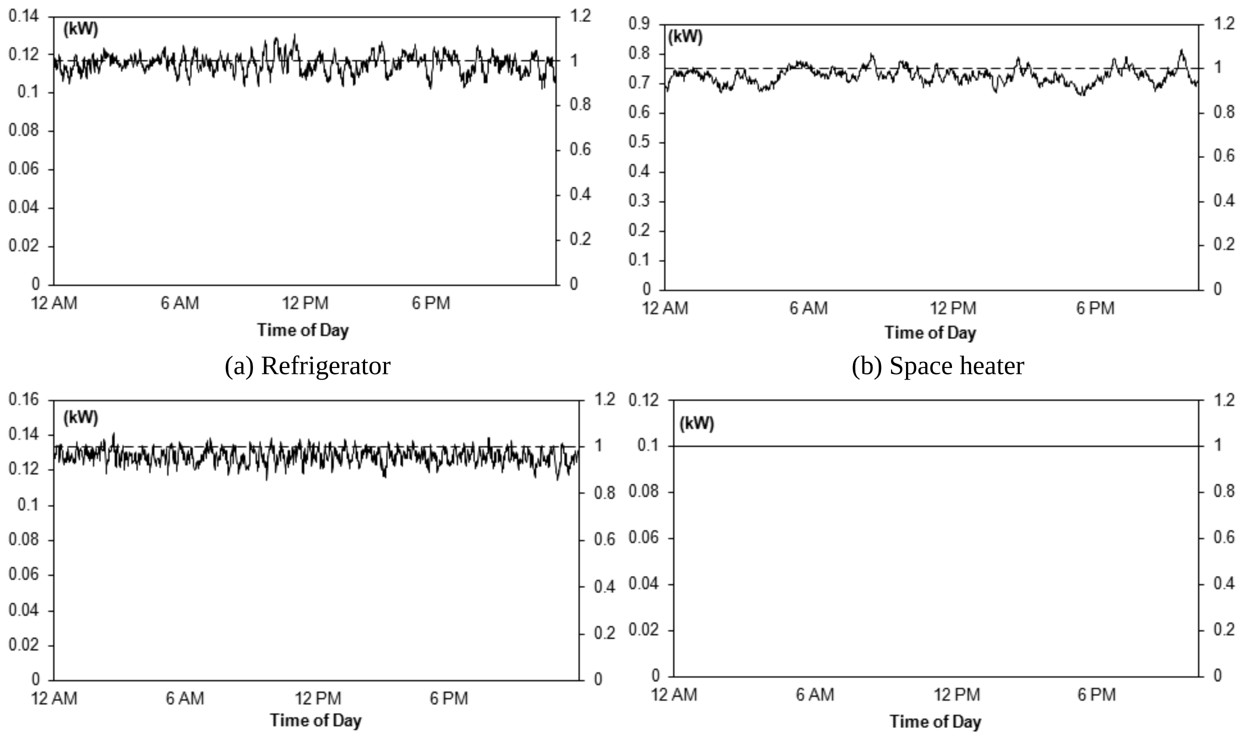



**Figure 9[5].** Mean load curve from simulations and in-use probability profile for air-conditioning.



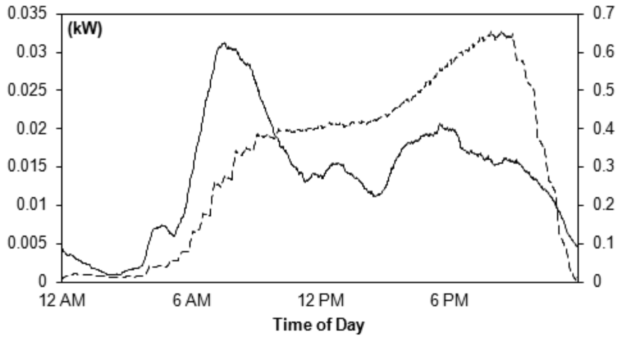

(a) Refrigerator (b) Space heater

(c) Freezer (d) Computers and other rechargable electronic devices

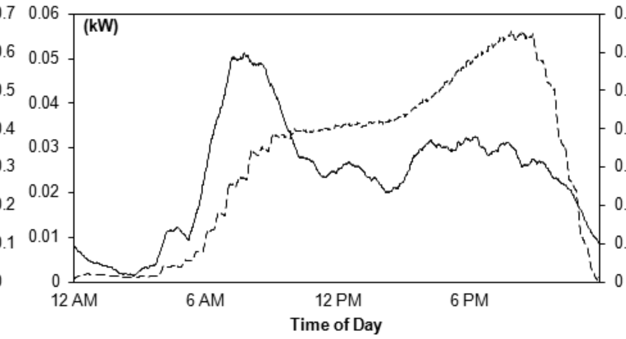
**Figure 10[6].** Mean load curve from simulations and flat in-use probability profile

[5] The in-use probability profile was reproduced from Reddy, T. A., Figure 1 [59] Reddy TA. Statistical analyses of electricity use during the hottest and coolest days of summer for groups of residences with and without air-conditioning. Energy. 1990;15:45-61.

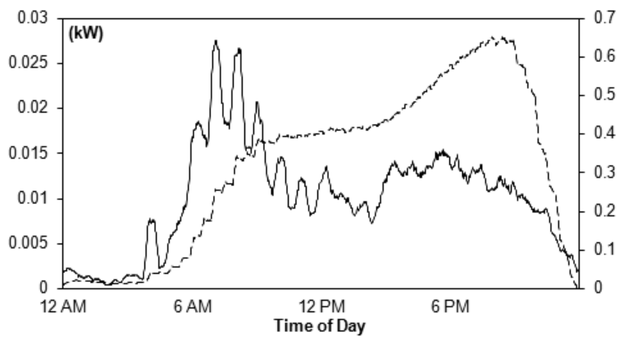
[6] No ATUS [57] US Bureau of Labor Statistics. 2012 American Time Use Survey. United Department of Labor; 2013. data are available for the appliances in Figure 8. Therefore, flat starting probability profiles were created. For these appliances, the in-use probability profile is also flat. For an average demand profile, the impact from these appliances are small because demands from them are not time-variant and thus will not change the shape of the demand profile a lot. For one single day, these appliances compromise a large portion of the single household daily electricity consumption.




(a) Lighting in the bedroom




(b) Lighting in the livingroom



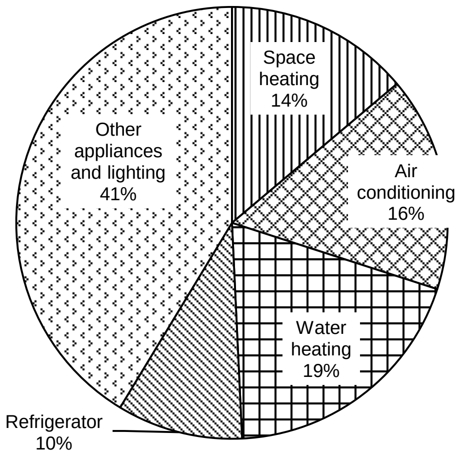

(c) Lighting in the hallways

**Figure 11[7].** Mean load curve from simulations and respondents being at home and awake probability profile.

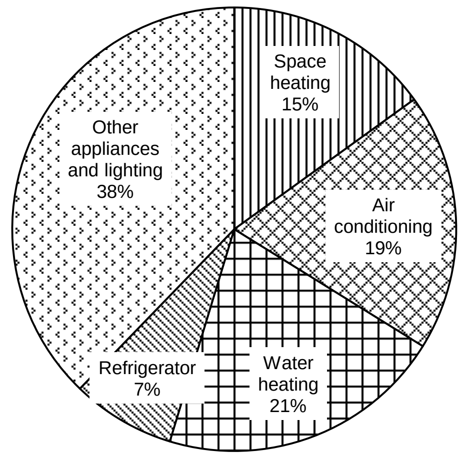
### *4.2.2 Household level*

The main purpose here was to test the aggregate appliance demand profiles in comparison with the RECS data for per average household in U.S. (Table CE 2.1 [62]). From Table B.1, the average daily electricity consumption per household is 30.6 kWh which is only 1% less than data given by 2009 RECS data (31 kWh). The pie chart in Figure 12 also displays a good agreement between 2005 RECS results (Table US14 [54]) and simulation results from the model. Numbers are portions of total annual electricity consumption in the residential sector. 2009 RECS data were only partly available in 2012 when the comparison was conducted. Therefore 2005 RECS data were used instead where 2009 RECS data were not available.

[7] No ATUS data are available. Here, probability profiles simply reflects the likelihood of respondents being at home and awake. Mismatches exist but lighting only compromise a small portion of the daily electricity consumption per household (see Table 6).



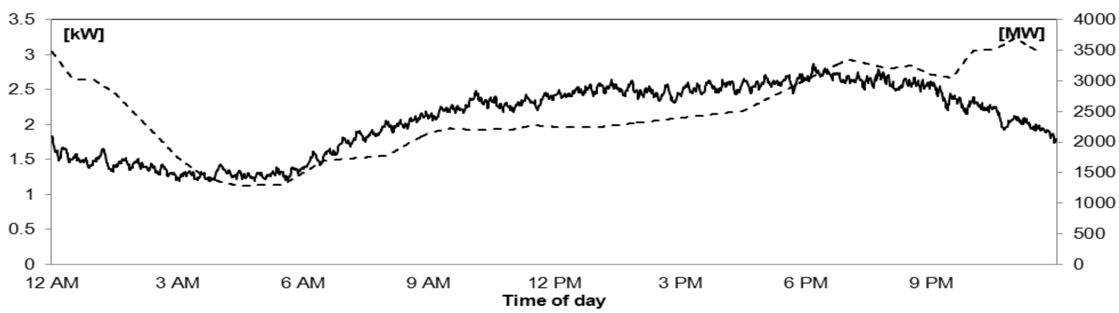

(a) RECS 2005



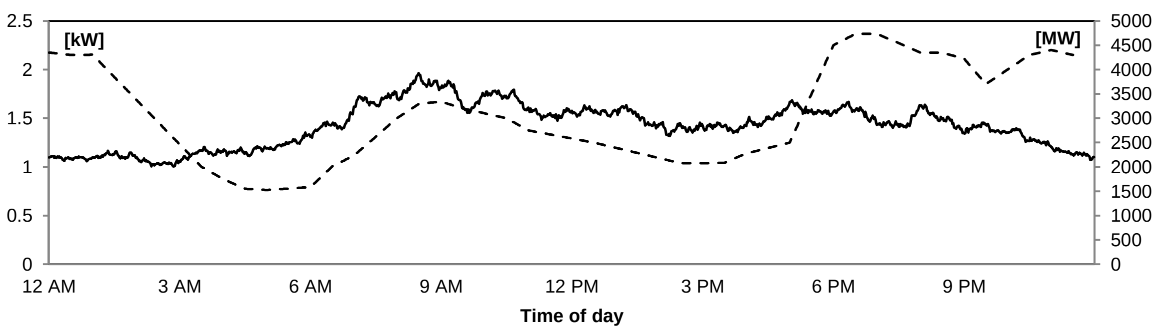

(b) Simulation results

**Figure 12.** Pie chart comparison between RECS 2005 data and simulation results

In Figure 13, average demand profile from simulations are plotted vis-à-vis with EMET reported aggregated demand curves [60] for summer days and winter days, respectively. Note that the simulation model correctly predicts two demand peaks per day during non-summer months (Figure 13 (b)) while the additional air conditioning during the summer results in only one obvious peak (Figure 13 (a)).




(a) Summer




(b) Winter

**Figure 13.**[8] Mean load curve from simulations versus aggregated demand curves reproduced from EMET[60].

[8] Solid lines represent the yielded mean load curves while the long-dashed lines represent the reference demand curves.

# 5 Storage dispatch strategy, operating optimization and economic viability evaluation results (loadshifting)[9]

*5.1 Storage dispatch strategy (loadshifting strategy)*

Figure 14 shows examples (example for Li-ion battery with 15kWh *EC*, 80% *DoD)* of simulated data traces for two randomly chosen days. Solid lines represent a random spring summer day while dashed lines represent a random spring day. Dotted lines in Figure 14 (b) indicate max. (dis)charging rate (1C for Li-ion battery). Implementing a straight forward arbitrage strategy, storage charging commences at 10pm (indicated by "A" in Figure 14; all letter markers are for solid lines), at the lowest possible charge rate such that storage reaches full capacity by 10am (see B) without however causing unnecessary burden on the grid (Eq.(2)). From 10am onwards, any appliance – e.g., demand at 12 pm (see C ) reflects the aggregate demand of the air conditioning, freezer, and clothes washer (other appliances are off) – is first supplied by discharging storage (see D), thus minimizing purchase of costlier electricity from the grid. Whenever the maximum discharge rate (1C, i.e. 1kW per kWh nominal capacity) is reached (not in Figure 14) or the storage's state of charge (*SoC*, Eq. (3)) reaches *DoD* (see E), the control unit supplements electricity from the grid (see F). Breaching either maximum discharge rates or *DoD* have been demonstrated to lead to early degradation (e.g., [63]) and are thus avoided.

$$Charge\ rate = \frac{\frac{EC}{Eff_{\text{S to A}} \cdot Eff_{\text{A to S}}}}{12} \tag{6}$$

$$SoC(t) = SoC(t-1) - \frac{\frac{DischE(t)}{Eff_{\text{S to A}}}}{EC} \geq DoD \tag{7}$$

Where *EC* denotes the effective capacity of storage (see section 3.1),
$Eff_{\text{G to S}}$ denotes the ratio of electricity stored versus drawn from grid,
$Eff_{\text{S to A}}$ denotes the efficiency of energy stored to consumption by appliances,
*DoD* denotes the healthy depth of discharge,
*SoC(t)* denotes the state of charge of storage at time step *t*,
*DischE(t)* denotes the amount of electricity discharged at time step *t*.

[9] In Sec.5, the basic and TOU tariff mentioned are both kWh tariff if not stated otherwise.

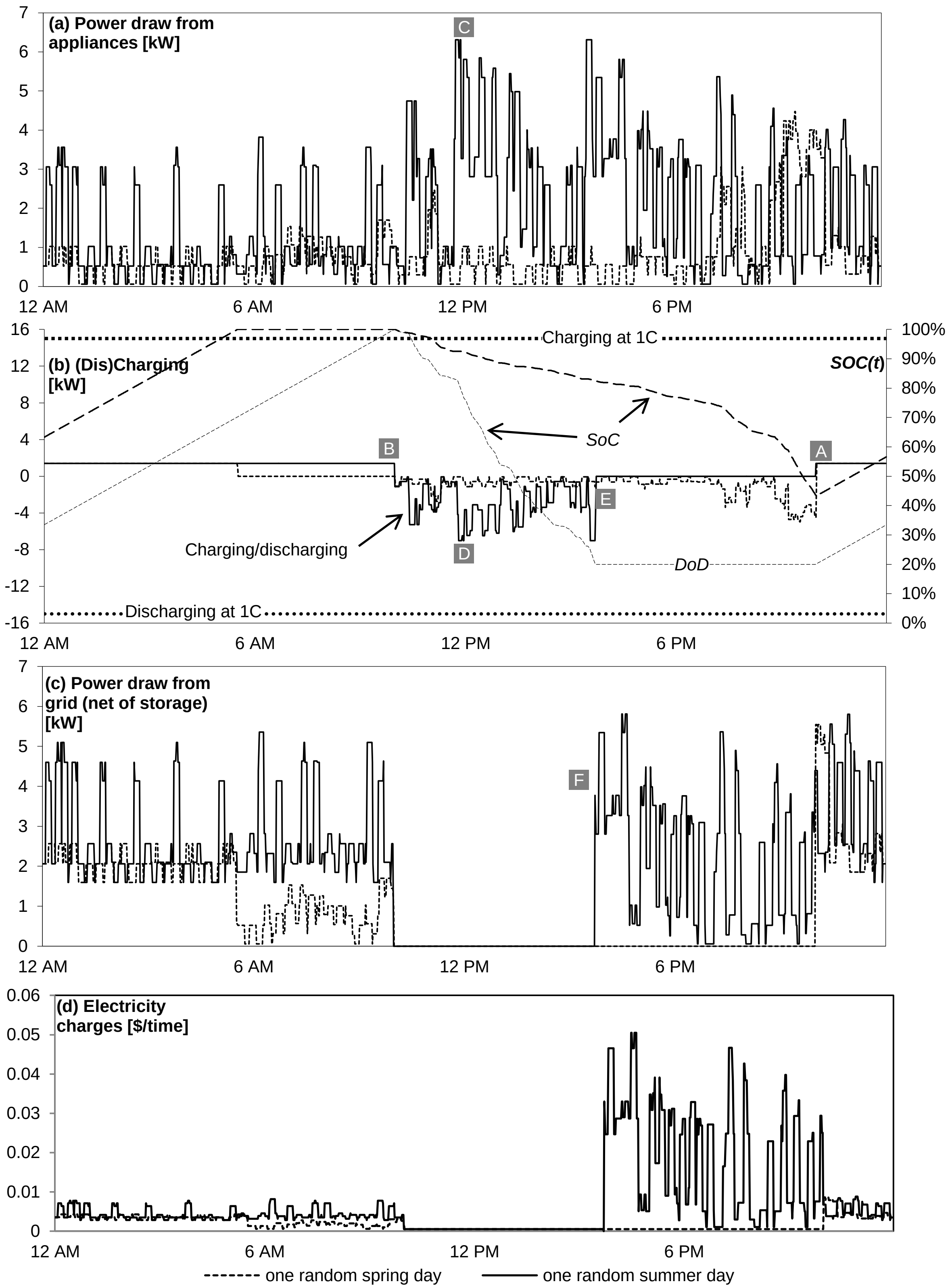



**Figure 14.** Data traces generated by the loadshifting strategy

### 5.1 Operation optimization and economic viability evaluation model

Using the above model, the storage capacity was varied to maximize profit to the consumer:

$$\text{Max}\, profit = \ Electricity\ bill_{\text{basic w/o S}} - (Cost + Electricity\ bill_{\text{DR with S}}) \tag{8}$$

Where *Electricity bill*$_{\text{DR tariff with S}}$ denotes electricity bill for 1 year under the DR tariff (with storage), *Electricity bill*$_{\text{basic w/o S}}$ denotes electricity bill for 1 year under the basic tariff (without storage), *Cost* denotes the financing costs of storage (see Sec. 3.1).

The maximum *profit* was determined simply by stepwise increasing the effective storage capacity from zero to two times the average electricity consumption during peak periods ($E_{\text{peak}}$). At each increase (10% of $E_{\text{peak}}$), *annual payment* (=storage cost plus electricity bill) was recorded by the model. Two baselines (i.e., cost without storage) were used: (a) Electricity bill for one whole year under the basic tariff before installing storage (*Electricity bill*$_{\text{basic w/o S}}$, shown in Eq.(8)); (b) electricity bill for one whole year under the TOU tariff (also without storage) (*Electricity bill*$_{\text{DR w/o S}}$, not shown in Eq.(8)).The rationale for considering two baselines is the fact that consumers, even before installing storage, could be on either the basic tariff or the TOU tariff. Under certain circumstances such as the specific appliance configuration in our model, simply switching from the basic to the TOU tariff (before installing storage) can significantly increase the electricity bill (in our case due to much higher day time electricity use from using air conditioning in the summer months, see Figure 15). One could argue that for such circumstances the savings from arbitrage must be high enough to offset not only the installation and cost of storage but also the electricity bill increase that results from switching to the TOU tariff that enables the arbitrage savings in the first place. We therefore present economic viability results for both baselines.

### 5.2 Results

The "typical residential household" devised in our model consumes 11,164 kWh electricity per year, with an average daily consumption (all seasons over one year) of 31 kWh (50 kWh/day during summer months). We first investigated the cost composition for the two baselines, then optimized the size of storage, followed by evaluating the economic viabilities of different storage options. Finally, an analytic approach was developed to identify the optimal capacity size and analytic results were compared with the empirical results.

#### 5.2.1 Base case (no storage): Composition of electricity bill and seasonal effects

We first broke down annual electricity bill into eight parts: 1) Cost during peak periods in summer; 2) off-peak periods in summer; 3) peak periods in winter; 4) off-peak periods in winter; 5) peak periods in other months (no space heater or air-conditioning is used); 6) off-peak periods in other months; 7) basic monthly service charges; and finally 8) financing costs of storage system (including installation).

Figure 15 uses the example of $ZnMnO_2$ battery with 30kWh *EC*, average-case scenario) to show annual payments without storage (the first and second columns); the third column shows payments when buying and operating storage. Figure 15 shows a net increase of ~\$650 in *annual payments* (from \$2,523, or 26%) when switching from basic to TOU tariff (no storage yet installed). The increase is mostly due to raised electricity bills for peak periods in the summer. For other months, there is no significant increase or decrease in the electricity bill under the two tariffs. In the summer, peak consumption under TOU is ~\$800 higher than those charged under the basic tariff while the less expensive off peak consumption under TOU only results in a ~\$250 decrease. Higher basic service charges for TOU contribute the remaining \$100 to the net \$650. Generally, basic service charges contribute only a small portion to total electricity cost; therefore consumption and load shifting patterns and the supply and delivery portions of each tariff are crucial drivers of overall cost and potential arbitrage savings.

Figure 15 also shows a TOU cost structure when using (profit optimized) 30 kWh *EC* of $ZnMnO_2$ batteries that can supply the entire daily electricity consumption during peak hours in non-summer months (and a portion during summer months). This leads to annual arbitrage savings of ~\$700 compared to the TOU base case (\$20 for the basic tariff base case). Since during summer months only a portion of peak-consumption can be loadshifted to off-peak times, installing more *EC* than 30 kWh would decrease the annual electricity cost. However, since such additional capacity would essentially remain idle during non-summer months (no return on investment), annual profit would decrease. Therefore, 30 kWh *EC*, for this particular battery technology, (dis)charging losses and *DoD*, is the optimal size. This is illustrated further in Sec. 5.2.2.

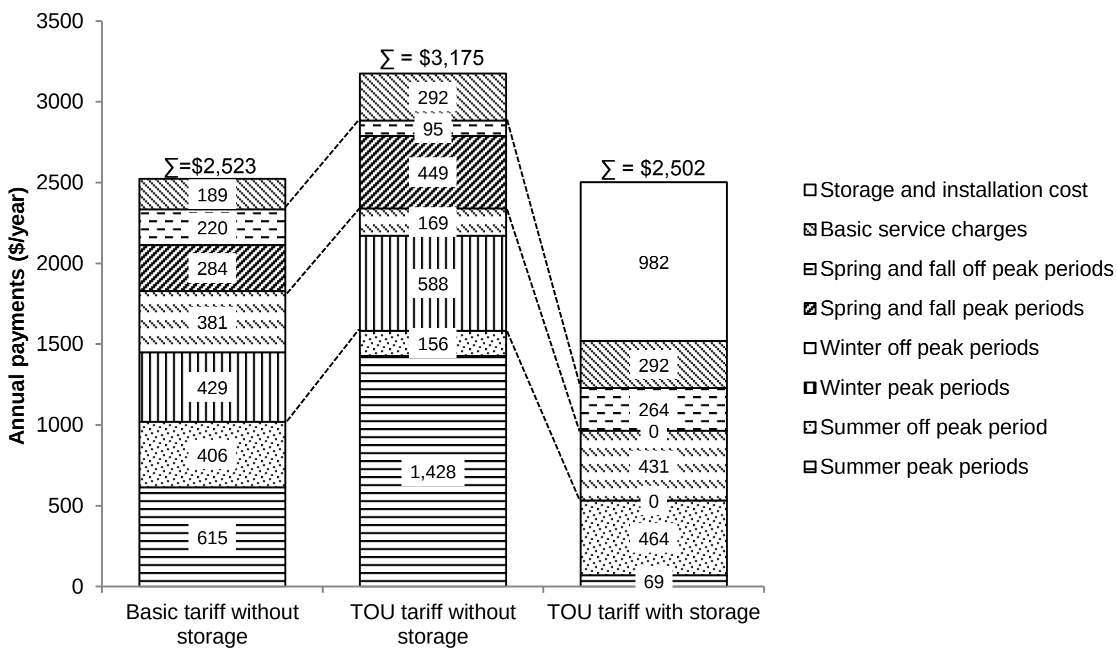



**Figure 15.** *Annual payments* breakdowns (under the kWh tariff)

### *5.2.2 Optimal effective storage size*

Figure 16 shows the impact of increasing *EC* on *annual payments* (best-case scenario) for a selection of storage technologies. Payments include financing for storage purchase (best-case scenario) and installation as well as electricity bills. Error bars indicate residual uncertainty of the stochastic simulation (standard error of the mean). See Sec. 5.2.3 for other storage technologies not displayed in the figure.

Li-ion batteries exhibit a continuous increase in *annual payments* while NaS batteries, after a step-increase in *annual payments* (due to installation costs), exhibit a small decrease, followed again by an increase. For ZnBr, ZEBRA (NaNiCl batteries), Metal air and $ZnMnO_2$ batteries, significant decreases in *annual payments* can be achieved. NiCd batteries, flywheel, Superconducting Magnetic Energy Storage (SMES) and NiZn batteries (not shown in Figure 16) exhibit payments higher than Li-ion batteries. The super capacitor option shows trends similar to NaS batteries. Payments simulated for Pb-acid batteries are almost identical to those for ZnBr batteries. For Compressed Air Energy Storage (CAES), see Sec.7.4.

Figure 16 suggests three broad classes of storage technologies when determining the optimal storage size to achieve lowest costs: (1) Li-ion or NaS batteries do not provide any economic benefits (even in the best case scenario). (2) For Pumped Hydro Storage (PHS) and Metal air batteries, the exact size is not crucial: As seen in Figure 16, an increase in *EC* from 30 kWh to 50 kWh leads to only minor increases in *annual payments* (see explanation in Sec. 5.3). (3) For the remaining storage technologies, sizing should be conducted accurately. For example, increasing *EC* of ZnBr batteries from 30 kWh to 50 kWh would cause ~$800 additional *annual payments*.

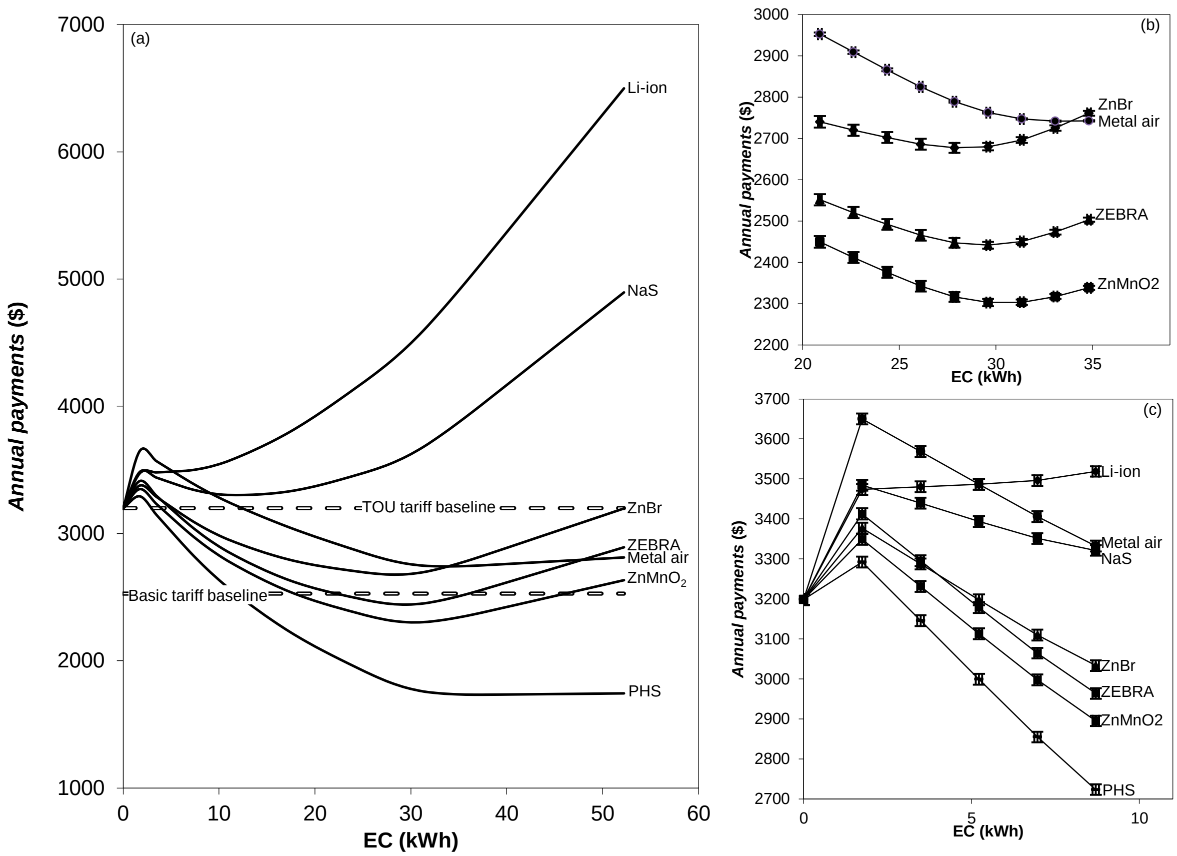



**Figure 16.** *Annual payments* for various storage technologies and capacities (loadshifting). Error bars represent one standard deviation above and below the mean.

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### *5.2.3 Economic viability*

Table 7 summarizes the optimization results for best-case and average-case scenarios for all storage technologies. *Profits* from arbitrage savings versus the basic tariff and the TOU tariff baselines are also shown. Optimal effective storage capacity span a wide range depending on the storage technology, 12 kWh~37 kWh in the best-case scenario and 7~35 kWh in the average-case scenario. For economically viable technologies, *annual profits* range from as low as $8 for the super capacitor (0.3% of annual electricity cost without storage, TOU baseline) to $1,465 for PHS (46%). Because of the additional cost increase when first switching from the basic to the TOU tariff (before installing storage, Sec. 5.2.1), more technology options are economically viable when assuming the TOU baseline versus the basic tariff baseline. Only PHS and CAES are economically viable in both scenarios and both baselines. This raises the question of their technological viability for residential settings (see Sec. 7.5). Finally, flywheel, SMES, NiZn, NiCd, NaS and Li-ion batteries are not economically viable for either scenario or baseline, and the aforementioned $8 profit for super capacitors is below the accuracy of the stochastic simulation (see Figure 16). We thus concluded that – for the average U.S. household consumption profile and Con Edison tariffs used in this study – short-term storage technologies (flywheel, super capacitor, and SMES) as well as some emerging batteries are not economically viable.

**Table 7.** Optimal effective capacity and maximum profits for two scenarios (loadshifting)

| | **Best-case scenario[a]** | | | | **Average-case scenario[b]** | | | |
|---|---|---|---|---|---|---|---|---|
| | Optimal capacity[c] (kWh) | *Annual payment* ($/year) | *Profit[d]* ($/year) | *Profit[e]* ($/year) | Optimal capacity[c] (kWh) | *Annual payment* ($/year) | *Profit[d]* ($/year) | *Profit[e]* ($/year) |
| **Flywheel** | - | 3542 | -1013 | -344 | - | 3847 | -1315 | -664 |
| ***Conventional batteries*** | | | | | | | | |
| Metal air | 33 | 2742 | -213 | ***456*** | 30 | 3121 | -590 | ***61*** |
| Lead-acid (Pb-acid) | 28 | 2690 | -161 | ***509*** | - | 3590 | -1058 | -407 |
| Nickel-cadmium (NiCd) | - | 3661 | -1132 | -462 | - | 3805 | -1273 | -622 |
| ***Advanced batteries*** | | | | | | | | |
| Lithium-ion (Li-ion) | - | 3474 | -945 | -275 | - | 3729 | -1198 | -546 |
| Sodium sulfur (NaS) | 12 | 3302 | -774 | -104 | - | 3707 | -1176 | -525 |
| Sodium nickel chloride (NaNiCl ZEBRA) | 30 | 2442 | ***87*** | ***757*** | 28 | 2704 | -172 | ***479*** |
| ***Flow batteries*** | | | | | | | | |
| Zinc bromine (ZnBr) | 28 | 2677 | -149 | ***521*** | - | 3476 | -945 | -294 |
| Vanadium redox (VRB) | 30 | 2450 | ***79*** | ***749*** | 10 | 3261 | -729 | -78 |
| Nickel zinc (NiZn) | - | 3529 | -1000 | -330 | - | 3513 | -982 | -330 |
| Zinc manganese dioxide (ZnMnO2) | 30 | 2303 | ***226*** | ***896*** | 30 | 2510 | ***22*** | ***673*** |
| **Super capacitor** | 12 | 3191 | -662 | ***8*** | 7 | 3412 | -880 | -229 |
| **CAES** | 37 | 2073 | ***456*** | ***1126*** | 33 | 2292 | ***239*** | ***890*** |
| **PHS** | 37 | 1733 | ***796*** | ***1465*** | 35 | 1818 | ***713*** | ***1365*** |
| **SMES** | - | 3500 | -971 | -302 | - | 3974 | -1442 | -791 |

[a] The best-case scenario uses the lowest cost available in the literature.

[b] The average-case scenario uses the average (geometric mean) of lowest and highest costs in the literature.

[c] '-'indicates optimal storage is zero because any storage would only increase overall cost. Optimal storage size above zero but negative profits indicate cases where larger storage means lower cost, however not low enough to offset cost from change in tariff and installation.

[d] Compared with the payment charged by the basic tariff without installing storage. Positive values of profit indicate the evaluated storage option is economically viable and vice versa.

[e] Compared with the payment charged by the TOU tariff without installing storage.

## *5.3 Analytic approach to optimal size of storage*

The above model determines the economic viability and optimal *EC* via a trial-and-error approach. To understand the underlying effects more fundamentally we derived an analytical formula that can predict optimal *EC* directly, based on statistical parameters obtained from simulating only the demand profile (without also simulating storage dispatch and electricity cost).

Within the above scheme, the number of kWh shifted (*ES*), which drive cost savings via arbitrage, cannot exceed the effective capacity (*EC*), which drives financing costs for storage. Therefore, optimal *EC* can be expected to be approximately equal to the daily-average consumption during peak times $E_{\text{peak}}$ (~30kWh, see Table 1). Crucially, however, $E_{\text{peak}}$ varies stochastically from one day to the next and systematically between seasons. Optimal *EC*, therefore, is driven by the trade-off between gaining more arbitrage savings during days with relatively high $E_{\text{peak}}$ and wasting idle capacity during days with low $E_{\text{peak}}$. Now assume a set *E* comprised of *N* days' $E_{\text{peak}}$ (across all seasons) and let yet-to-be-determined optimal *EC* be denoted by $E^m_{\text{peak}}$. *m* indicates the *m*-th $E_{peak}$ in the set when sorted from smallest to largest. This means that for *m* days of the set, *EC* can shift 100% of the $E_{\text{peak}}$ to off-peak hours. For the remaining *(N-m)* days, only a portion of $E_{\text{peak}}$ can be shifted. If *EC* is increased to $E^m_{\text{peak}}+\Delta E$, then additional *(N-m)* days in the set can shift an additional portion of their $E_{\text{peak}}$, namely $\Delta E$, from peak to off-peak hours. Resulting incremental arbitrage savings are $(N\text{-}m)\cdot S^*\cdot\Delta E$. Resulting incremental storage costs are $N\cdot C^*\cdot\Delta E$, where $S^*$ and $C^*$, both in $/kWh, are given by:

$$S^* = P_{\text{peak}} - \frac{P_{\text{off-peak}}}{Eff_{\text{S to A}} \cdot Eff_{\text{G to S}}} \tag{9}$$

$$C^* = \frac{PC \ \cdot FCR}{Eff_{\text{S to A}} \cdot DoD} \tag{10}$$

Where $P_{\text{peak}}$ and $P_{\text{off-peak}}$ denote the costs per kWh during peak and off-peak hours, respectively,
$Eff_{\text{G to S}}$ denotes the ratio of the amount of electricity stored over the amount of electricity drawn from the grid (see Figure 4 for more details),
$Eff_{\text{S to A}}$ denotes the efficiency of converting energy from storage to appliances,
*DoD* denotes the healthy depth of discharge,
*PC* denotes the purchase cost of storage per kWh nominal capacity (excl. installation),
*FCR* denotes the annual finance cost rate (principal repayment plus 10% interest, see Sec. 3.2).

Now recognizing that *profit* can be increased so long as additional arbitrage savings for any incremental $\Delta E$ are higher than additional storage costs, we find the optimal *EC* by requiring:

$$\mathrm{F}\left(E^m_{\text{peak}}\right) = 1 - \frac{C^*}{S^*} \tag{11}$$

Where F(*E*) denotes the portion of $E_{\text{peak}}$ in set *E* that are smaller than $E^m_{\text{peak}}$.

$E^m_{\text{peak}}$ can be solved by referring to the *m*-th $E_{\text{peak}}$ in the sample ranking from smallest to largest when

$$m = N \cdot \left(1 - \frac{C^*}{S^*}\right) \tag{12}$$

The value of $C^*$ varies substantially across storage technologies, due to varying costs and operating characteristics. In contrast, $S^*$ does not vary much across storage technologies. For example, Metal air batteries ($C^*$= 0.011 in best-case scenario) and PHS ($C^*$ = 0.002) exhibit nearly flat cost after *EC* reaches

30 kWh (Figure 16). For comparison, $C^*$ for ZnBr batteries is 0.069 (best-case scenario), leading to a marked rise in *annual payments* once *EC* is increased beyond the optimal capacity (Figure 16). Generally, higher ratios of $C^*$ to $S^*$ will lead to smaller optimal *EC* (Eq.(11)). Note that storage size is optimized across one year. Tradeoffs occur between different seasons because demand profiles and tariffs are different. For NaS batteries for example, optimal *EC* in the summer is 31 kWh (in best-case scenario). But in other seasons $S^*$ is smaller and therefore any *EC* increase in seasons other than summer will lead to smaller profits. As a result of this tradeoff, the optimal *EC* for NaS batteries, across the full year, is 12 kWh (Table 7).

In summary, optimal *EC* can be determined as a function of the histogram of $E_{peak}$, the operating characteristics and cost of storage, and the peak versus off-peak kWh charges. In contrast, installation cost and fixed monthly electricity fees affect the achievable profit (Eq.(8)) but not optimal *EC*.

# 6 Storage dispatch strategy, operating optimization and economic viability evaluation results (peak reduction)[10]

## *6.1 Storage dispatch strategy (peak reduction strategy)*

Figure 17 illustrates the storage dispatch strategy for the kW tariff (example for $ZnMnO_2$ battery with 10 kWh *EC*, 90% *DoD*, the upper limit (*UL)* is set as 2.5 kW) The long dashed line in Figure 17(a) indicates the *UL*. In Figure 17(b), the short dashed lines indicate max. (dis)charging (1C for $ZnMnO_2$ battery. In Figure 17(c), the dotted line is measured on the basis of 1 minute while the solid line is averaged on the basis of 30 minutes.

The goal is to reduce the peak demands for each month to the pre-assigned *UL* by utilizing storage. When the aggregate demand from the appliances exceeds the *UL* (e.g., at $\boxed{\text{A}}$ in In Figure 17; all letter markers are for solid lines), the grid only supplies it with the power equaling the *UL* (see $\boxed{\text{C}}$); the remaining demand is supplied by discharging storage (see $\boxed{\text{B}}$). On the contrary, when the aggregate demand from appliances is below the *UL* (e.g., at $\boxed{\text{D}}$), storage (if not full) is charged at the dynamically calculated charging rate (see $\boxed{\text{E}}$): The combined power draw from the storage charging and the appliances demands could not exceed the *UL* (see $\boxed{\text{F}}$). Whenever the maximum discharge rate (1C i.e. 1 kW per kWh nominal capacity) is reached (not in Figure 17) or the storage's state of charge reaches *DoD* (see $\boxed{\text{G}}$), the control unit supplements electricity from the grid. In the end, the measured synthetic demand from appliances and storage is averaged over a 30-minute window as specified by Con Edison (see $\boxed{\text{H}}$; the dashed line is the minute-by-minute demand profile while the solid line the averaged demand profile).

[10] In Sec. 6, both the basic and the TOU tariff are kW tariff, unless stated otherwise.

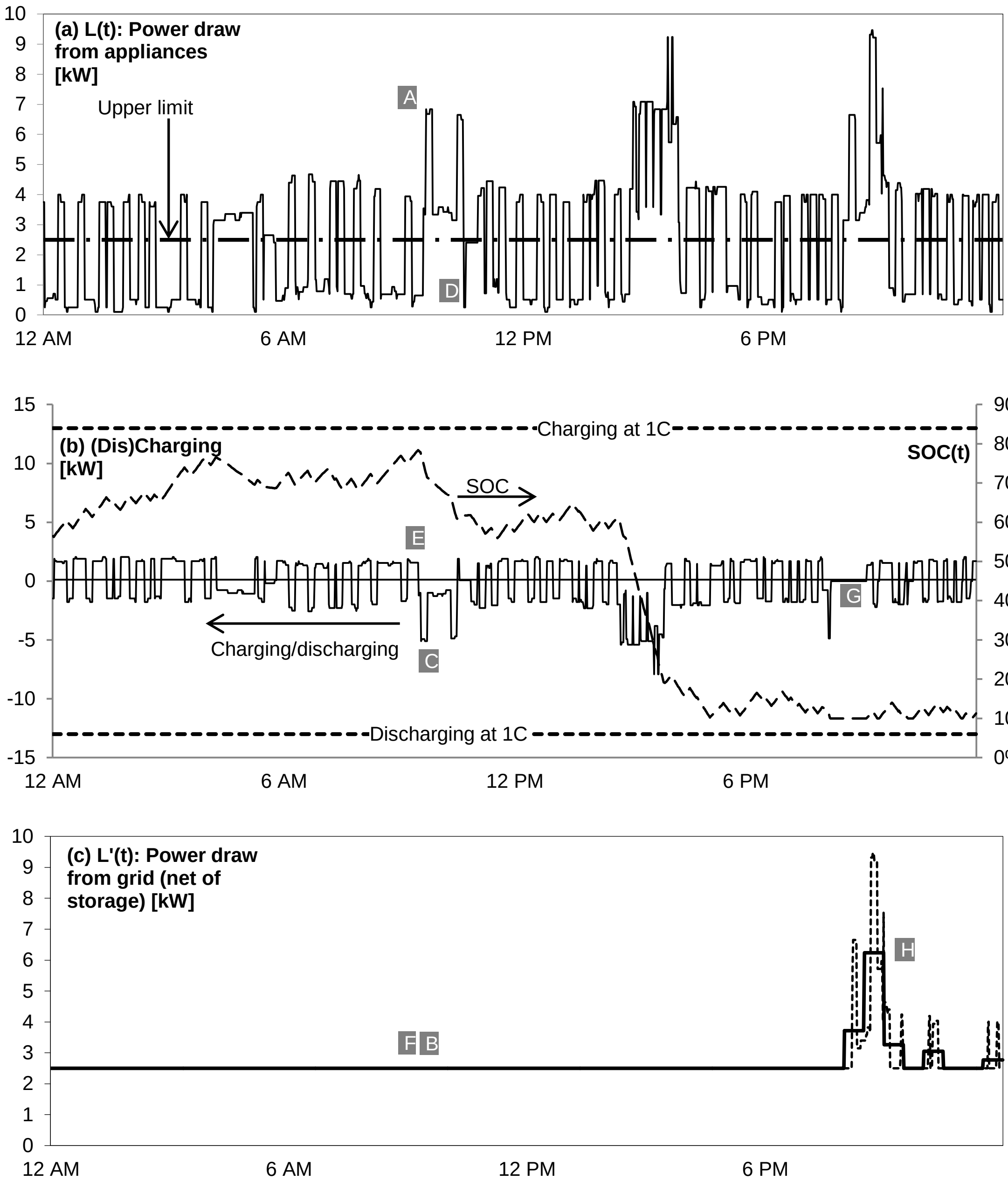


**Figure 17.** Data traces generated by the peak reduction strategy.

### *6.2 Operating optimization and economic viability evaluation model*

In contrast to the loadshifting control strategy which works only in the context of the TOU tariff, this specific peak reduction control strategy is not time-of-use constrained and can possibly reduce the peak demands, thus reducing the electricity bills under both the TOU tariff and the basic tariff. However, note that there is the "10 kW rule" specified by the basic tariff: The minimum peak demand during the billing period is 10 kW. Consider that monthly peak demands (averaged every 30 minutes) simulated by our model are less than 10 kW. The peak demand reduction will not lead to a reduction in the electricity bill charged under the basic kW tariff, still charged for 10 kW. On the contrary, since there is no such "10 kW rule" in the TOU tariff, for a typical U.S. household as modeled in this study, the peak reduction control strategy is used under the TOU tariff only.

Using the above agent-based demand model and control strategy, the storage *EC* and the operating *UL* were varied separately to maximize *profit* (Eq. (8)) to the consumer under the TOU tariff. The maximum *profit* was determined by stepwise increasing the effective storage capacity geometrically from zero to the average daily electricity consumption (20% increase at each step) and adjusting the *UL* geometrically from 2 kW to 6.3 kW (10% increase at each step) for each *EC*. The steps were selected based on the preliminary results. For each case, *annual payments* were recorded and compared with two baselines: (a) The electricity bill for one whole year under the basic tariff before installing storage (b) the electricity bill for one whole year under the TOU tariff before installing storage.

### *6.3 Results*

The "typical residential household" devised in our model consumes 11,164 kWh electricity per year, with the average peak demand (averaged over 30 minutes) of 6.5[11] kW (during summer months) and 5.7 kW (during the remaining months). We first investigated the cost composition for the two baselines, then optimized the size of storage and the operating *UL*, followed by evaluating the economic viabilities of different storage options.

#### *6.3.1 Base case (no storage): Composition of electricity bill and seasonal effects*

Similar to what we have done for the loadshifting model, we broke down two baselines into seven parts to investigate their cost composition: 1) Demand cost in summer; 2) energy cost in summer; 3) demand cost in winter; 4) energy cost in winter; 5) demand cost in other months; 6) energy cost in other months; 7) financing costs of storage system (incl. installation cost).

In Figure 18, the first and second column show payments without storage. The third column shows *annual payments* when buying and operating storage under the TOU tariff (by using peak reduction strategy described in Sec. 6.1). Figure 18 shows a decrease of ~$1,500 when one switches from the basic tariff to the TOU tariff with no storage installed. The difference mainly comes from the ~$560 decrease in the demand cost in winter and the ~$800 decrease in the demand cost in spring and fall months. This big difference may be partly due to the "10 kW rule" embedded in the basic tariff. Rather than seeing a decrease under the TOU tariff, the summer demand costs remain almost unchanged. For summer months, the average peak demand is still less than 10 kW (averaged over the course of 30 minutes), indicating that that the 10 kW rule's impact should still remain but be offset by the costlier summer TOU tariff, without storage being installed or the consumer's electricity consumption habits being altered.

Unlike the TOU kWh tariff, which incurs an increase in the *annual payments* when a consumer switches from the basic kWh tariff and no storage is installed, the TOU kW tariff costs less in terms of energy cost throughout the year. Nevertheless, the reduction in the annual energy consumption cost is only $81 in total for one whole year.

[11] Although the simulated peak demand for one household is less than 10 kW, SC 8 is still considered to be available for the modeled household because two or more households can choose to hold one single account, which is possibly eligible to use SC 8.

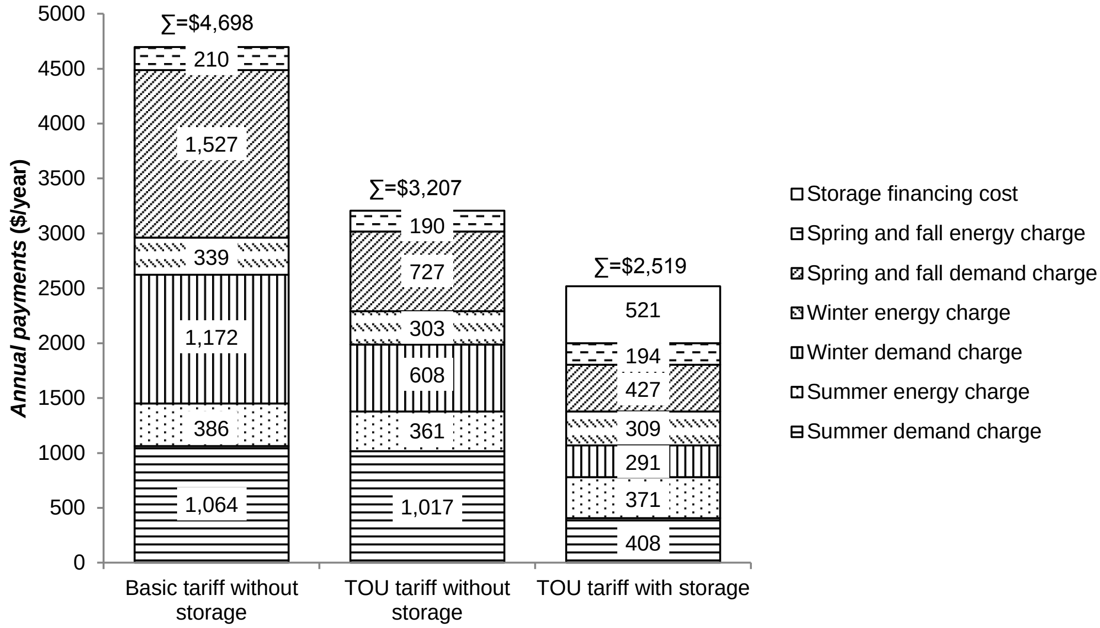


**Figure 18.** *Annual payments* breakdowns (under the kW tariff).

The third column in Figure 18 is based on the $ZnMnO_2$ battery of 10 kWh *EC* with an *UL* of 2.5 kW. By utilizing this storage and the control algorithm elaborated above, we expect a ~$700 reduction in the *annual payments* per year: The summer demand cost is expected to be reduced by ~$600 and followed by a ~$320 reduction for winter months, then a $300 reduction for spring/fall months. Energy charges are slightly increased ($20) compared with those charged under the TOU tariff before storage is used.

### *6.3.2 Optimal effective storage size and optimal operating upper limit*

The surface plot of Figure 19 shows an example of the varying *annual payments* by installing $ZnMnO_2$ batteries with varying *EC* and *UL*. The *EC* geometrically increases from 0.1 kWh to 34 kWh at 20% increase at each step. The *UL* geometrically increases from 2 kW to 6.5 kW at 10% increase at each step. The optimal *EC* and the optimal operating *UL* were identified by the lowest point on the surface. Figure 20 plots a selection of lines (obtained from Figure 19) at controlled *EC*s or controlled *UL*s.

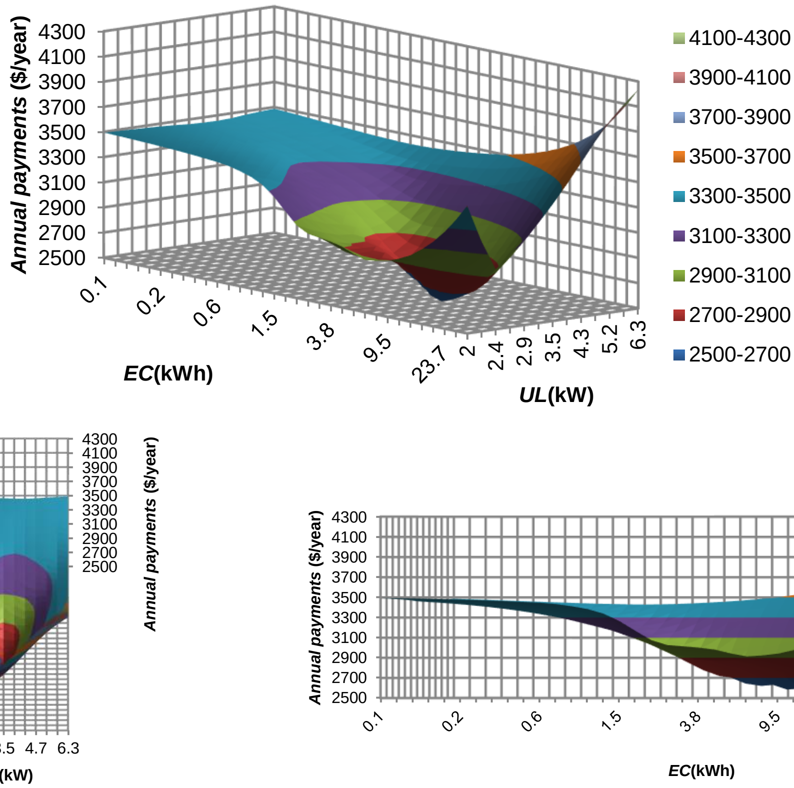


**Figure 19.** Surface plot of annual payments with varying *ECs* and varying *ULs* (peak reduction).

Figure 20(a) shows how the *annual payments* change with the *UL* on the horizontal axis. In the figure, each line represents one case with one specific *EC*. A general trend can be found that the *annual payments* first decrease, followed by increases when the *UL* increases gradually from 2 kW to 6.5 kW. This can be explained by looking into how the demand profiles would respond by implementing different *UL*s (Figure 21and Figure 22).

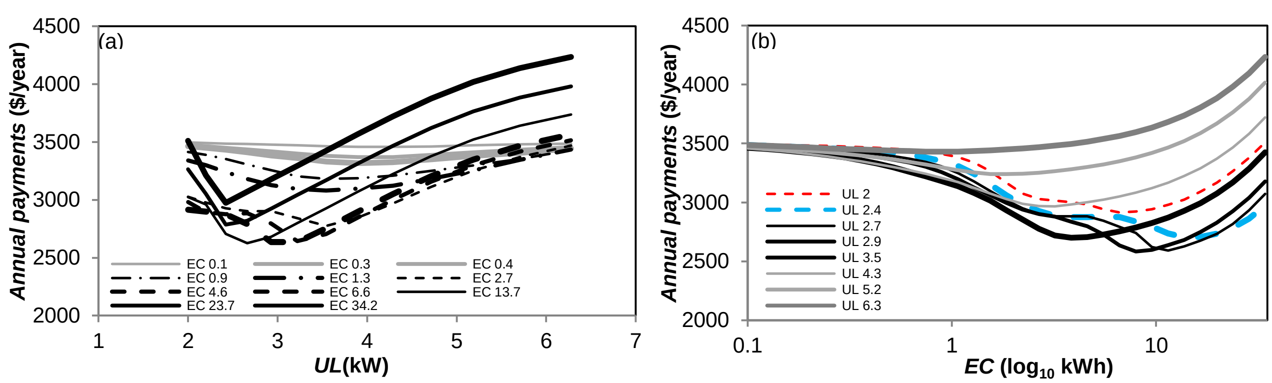


**Figure 20.** *Annual payments* variations at controlled *ECs* or controlled *ULs* (peak reduction)

When ECs are small (e.g., EC = 0.3 or 0.4 kWh in Figure 20(a)), the annual payments are reduced by installing small size storage operated at the *UL* around 4 kW. When *EC* is moderate (e.g., *EC* = 2.7, 4.6, 6.6 kWh in Figure 20 (a)), on certain days, lower *UL* (e.g., 2 kW) may lead to lower peaks during the day, but the capacity constraint prevents it from lowering the peaks for other days during the month: The monthly peak demand to be charged will still remain the same. For example, Figure 21displays the measured loads by using $ZnMnO_2$ battery sized at the *EC* equaling 4.6 kWh but implementing different *UL*s (2 kW, 3.2 kW and 6.3 kW). For the purpose of comparison, the original minute-by-minute aggregate appliances demand profile (solid grey line) and the averaged one (dashed black line) without using storage are also plotted. Around 5 PM – 6 PM, however, the 2 kW *UL* results in a demand of 4 kW due to the insufficient available capacity of storage. In contrast, with batteries that have not yet been dumped, the case with the *UL* of 3.2 kW successfully reduces the peak to 3.2 kW. In this case, the higher *UL* results in lower peaks in comparison to those that result from a lower *UL*. However, when the *UL* is higher than the optimal one, the ruled demand is higher (e.g., when *UL* is 6.3 kW (green line) in Figure 21 (a)), thus the electricity bills increase.

Note that instead of reducing the daily peak demands, a high *UL* (e.g., 6.3 kW) may result in a load higher than the original load without using storage (see the green line in Figure 21(a)), when the original load is below the *UL*. During that time slot (30 minutes before 12 AM in Figure 21(a)), the grid refills the storage which had been discharged previously. In addition, some extra electricity goes into losses during the (dis)charging processes.

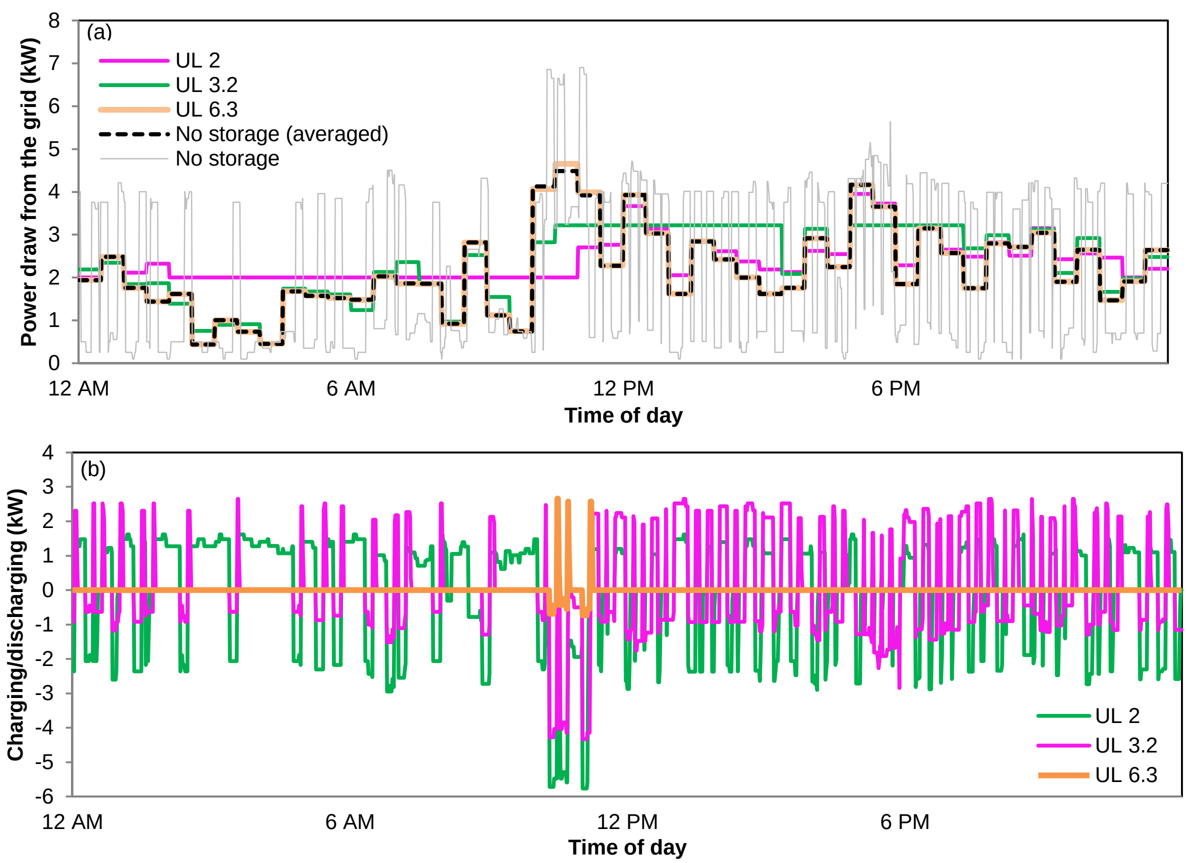


**Figure 21.** Demand profile simulations and storage (dis) charging patterns by implementing different operating *UL*s (*EC* = 4.6 kWh).

When the *EC* is higher (e.g., *EC* = 23.7, 34.2 kWh in Figure 22), the optimal *UL*s are reduced with increased *EC*s. However, although the *EC* is as high as 23.7 kWh, the 2 kW *UL* target is not yet fulfilled (see Figure 22). In both Figure 21 and Figure 22, the demand loads are equaling or above 2 kW most of the time in both cases, indicating that when the *UL* is as low as 2 kW, the storage has taken every chance to get charged. Further reducing the loads requires a much higher capacity which stays idle for most of time because no available time slots can be found to re-charge this amount of capacity.

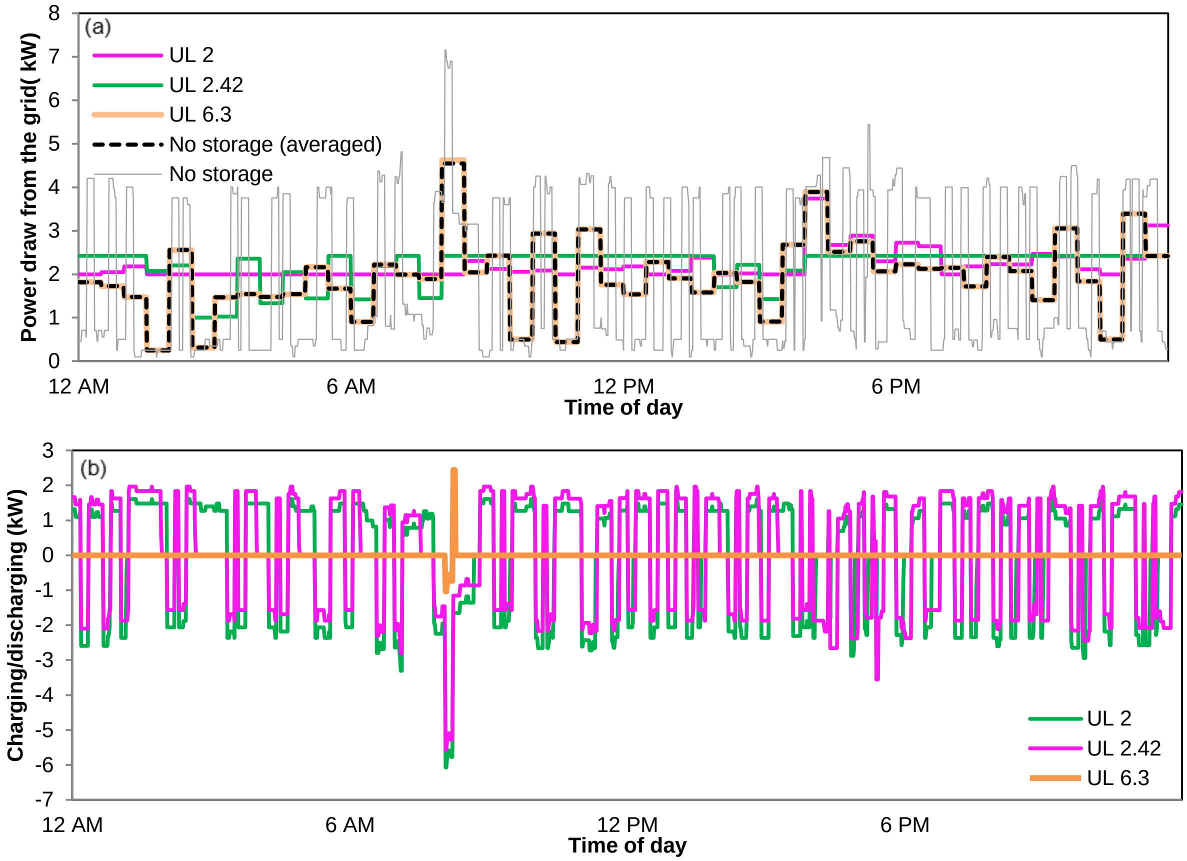


**Figure 22.** Demand profile simulations and storage (dis)charging patterns by implementing different operating *UL*s (*EC* = 23.7 kWh)

Looking into the plots with the axis of *EC* (Figure 20(b)), each line represents a case with a certain *UL*. The *annual payments* first decrease, then increase. As discussed above, the higher capacity can effectively reduce the peaks during days and months, thus resulting in lower peaks, which comes with a penalty of the higher storage cost. Note that although in Figure 20(a), optimal *UL* generally decreases with higher *EC*, optimal *EC* does not always increase with lower *UL* (see Figure 20(b), blue versus red trace). As explained above, in order to further reduce the loads to remain below 2 kW from 2.42 kW, possibly much more capacity is needed. By weighing the largely incurred financing cost of storage against the relatively small potential electricity bill reduction, the model determines that a smaller capacity which is insufficient to get the loads below or closer to the *UL* is the optimal solution.

In the end, the energy cost can decrease or increase the *annual payments* in two ways: It can 1) increase the *annual payments* due to the additional cost for the energy losses during the storage charging/discharging processes, or 2) possibly decrease the annual payments due to the arbitrage savings from loadshifting. For the latter, the peak reduction control algorithm possibly reduces the loads and the electricity consumption during peak periods simultaneously. However, the potential of the arbitrage savings is limited: Under the TOU kW tariff, the difference between the peak energy charge rate and the off peak charge rate is only 2.5 cents per kWh shifted electricity in summer months, and 1.4 cents per kWh shifted electricity in other months (Table 2). Assuming storage of 30 kWh *EC*, the maximum potential for arbitrage savings under the TOU kW tariff is:

$$2.5 \times 30 \times 92 + 1.4 \times 18 \times 120 + 1.4 \times 9 \times 153 = 11851.8\ cents/year = \$118.5/year$$[12]

$118.5 per year is considerably smaller than the *annual payments* (more than $2000 per year). In terms of energy losses, the energy cost is between 6 to 8 cents per kWh electricity consumption (Table 2), which should be paid attention to when the storage has low efficiencies. Seen from Figure 21(b), when the *EC* is 4.6 kWh the lower *UL* tends to result in more frequent charging/discharging, thus more energy losses. However, when the *EC* is 23.7 kWh in Figure 22(b), the optimal *UL* (2.42 kW) leads to higher energy losses in comparison with the *UL* of 2 kW. Besides, by comparing Figure 21(b) and Figure 22(b), more energy losses occur when *EC* is larger.

In summary, with higher storage *EC*, the loads can be smoothed effectively with lower optimal *UL*. However, to further reduce the loads, the *EC* should be increased exponentially. Otherwise, given an insufficient storage capacity (e.g., Figure 22), lowering the *UL* would result in higher loads after the storage reaches its *DoD* in comparison with loads measured by implementing a higher *UL*. The optimal *EC* and the optimal *UL* are thus determined by weighing the reduced electricity bills coming with higher *EC* and potentially lower optimal *UL* against the increased financing cost of storage. The *optimal annual payments* are thus a function of the charging/discharging efficiencies, the financing cost of storage (Eq. (1)) and the demand profiles. Table 8 and Table 9 summarize the optimal *EC*, the optimal *UL* and the minimum *annual payments* for a variety of storage options in the average-case scenario (Table 8**)** and in the best-case scenario (Table 9), respectively.

Figure 23 shows the impact of the rising financing cost on the corresponding optimal *EC* for various storage options (average-case scenario). Each marker represents one storage option. Detailed financing costs are given in Table 5. An exponential reduction trend can be seen in that decreasing financing costs leads to increasing optimal *EC*s. When the financing costs are less than $50 per kWh per year, the optimal *EC*s are more than 5 kWh. With small financing costs, CAES and PHS are optimized at *EC*s of more than 20 kWh. The exponential trend observed can be explained that with low financing costs, the model determines that the marginal savings from lowering *UL* and enlarging *EC* exceed the marginal financing cost of storage. Above, we have explained that in order to get down to a low optimal *UL*, e.g., 2 kW, the increase in *EC* is remarkable and exponential. On the other hand, after the financing costs grow into more than $50 kWh per year, the variations of the optimal *EC*s with increasing financing costs become less obvious.

[12] According to the testing results of our agent-based demand profile model (see Table B.1), the average electricity consumption during peak periods (i.e. the maximum amount of electricity that can be shifted for the purpose of arbitrage savings) is 30 kWh for summer days (92 days out of one year), 18 kWh for winter days (120 days out of one year) and 9 kWh for the remaining days.

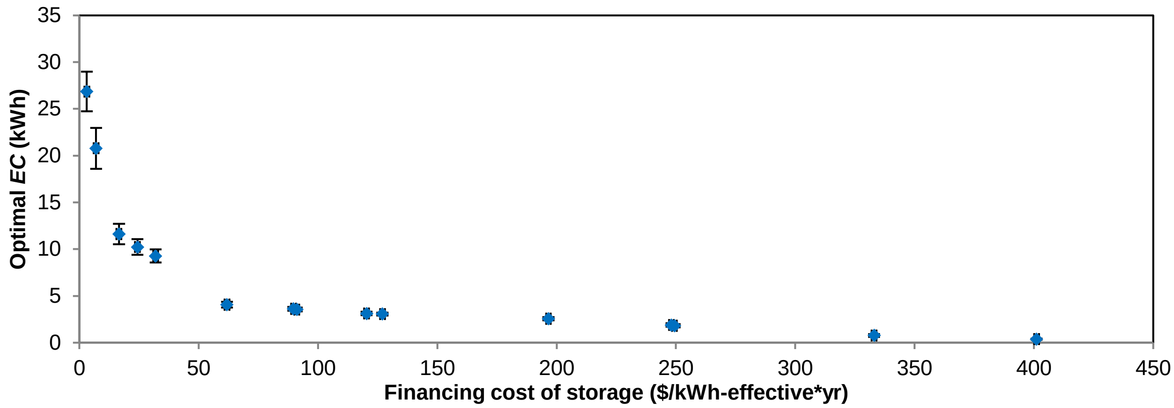


**Figure 23.** Optimal *EC*s for a variety of storage costs in the average-case scenario (peak reduction). Error bars represent one standard deviation above and below the mean.

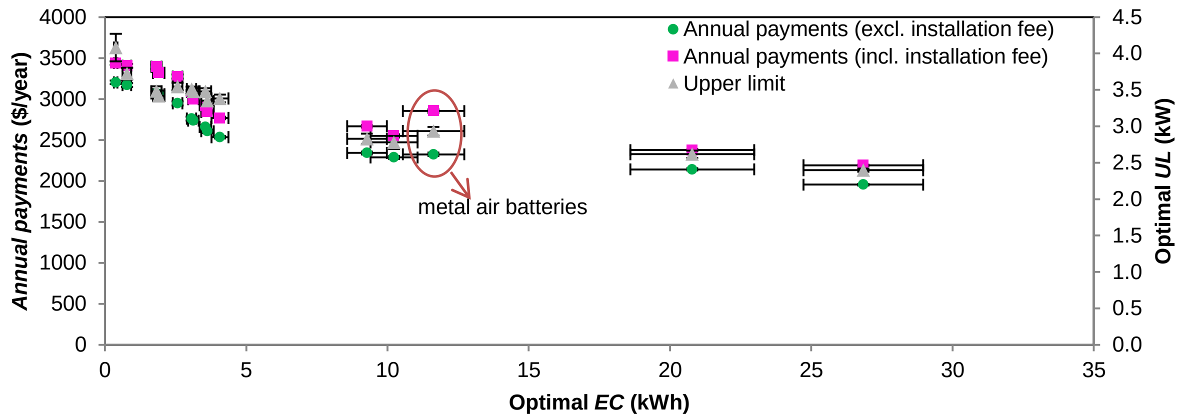


**Figure 24.** *Annual payments* and optimal *UL*s for a variety of storage options in the average case scenario (peak reduction). Error bars represent one standard deviation above and below the mean.

Figure 24 shows the impact of increasing *EC* on the corresponding optimal operating *UL*s and the *annual payments* (average-case scenario) yielded by installing a variety of storage options. As discussed above, generally, the higher optimal *EC* comes with a lower *UL*, except for metal air batteries (circled points in Figure 24). Note that according to Table 5, the round-trip efficiency of metal air batteries is 45%, the lowest one on the list. It is shown above that when the optimal *EC* is of a moderate amount, a higher *UL* would lead to less electricity getting into/out of storage, and thus also to fewer (dis)charging losses. In this sense, the model determines a higher *UL* for metal air batteries to reduce the energy losses in comparison to the expected *UL* following the trend.

The minimal *annual payments* also exhibit a decreasing trend with higher optimal *EC*s in Figure 24, except for the point representing metal air batteries. It is possibly due to the low lifetime of metal air batteries (5 years, see Table 5). The low lifetime would result in the high annualized installation fee, which makes the *annual payments* of metal air batteries become higher than the points on the left side. When the annualized installation fee is subtracted from the annual payments, the *annual payments* of metal air batteries drop remarkably.

In summary, the decreasing financing cost of storage leads to the optimal *EC* increasing. When the financing cost is less than $50 per effective kWh per year, the optimal *EC* increases exponentially. Generally, for the optimal *UL*, a larger optimal *EC* comes with a lower optimal *UL*, but exceptions exist due to the impact of interactions between energy losses and the operating *UL*. In the end, the lower annual payments can be approached by the lower financing cost of storage (thus the higher optimal *EC*) and the lower optimal *UL*.

### *6.3.3 Economic viability*

Table 8 summarizes the optimization results for the average-case scenario for all storage technologies. Optimal *EC*s span a wide range depending on the storage technology, 0.38 kWh – 26.84 kWh in the average-case scenario. The optimal *UL*s range from 2.4 to 4.1 kW in the average-case scenario. As shown in Figure 18, the TOU kW tariff costs less compared to the basic kW tariff for the typical consumer modeled in this study. Assume that the SC8 consumers would select the kW tariff, which costs less, as their base tariff. The modeled minimal *annual payments* therefore are compared against the TOU kW tariff baseline: Storage yielding negative *profit* against the TOU kW tariff baseline is determined as "not economically viable". Table 8 shows that for economically viable technologies, annual *profits* (also determined by using the TOU kW tariff baseline) range from $161 for the Pb-acid batteries (5% of annual electricity cost without storage ,TOU baseline) to $1058 for PHS (33%). Flywheel, SMES, NiCd, Li-ion and NaS batteries, all sized at small *EC*s (0.38 kWh – 2.6 kWh), are not economically viable in the average-case scenario. Nevertheless, the gaps are all below $200/year. In the end, though PHS and CAES are determined as economically viable storage options, their technological viabilities for residential settings are discussed in Sec. 7.

**Table 8.** Optimal *EC*, optimal *UL* and maximum *profits* for the average-case scenario (peak reduction)

| | | ***Annual payments* ($/year)** | **SEM[a]** | **Optimal *EC* (kWh)** | **SEM** | **Optimal *UL* (kW)** | **SEM** | **Basic w/o storage** | **SEM** | ***Profit*[b] ($/year)** | **TOU w/o storage** | **SEM** | ***Profit*[c] ($/year)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Flywheel** | | 3406 | 23.16 | 0.778 | 0.15 | 3.724 | 0.08 | 4692 | 2.54 | *1287* | 3248 | 17.30 | -158 |
| **Conventional batteries** | Metal air battery | 2852 | 20.94 | 11.63 | 1.09 | 2.934 | 0.06 | 4692 | 2.54 | *1840* | 3248 | 17.30 | *396* |
| | Pb-acid | 3087 | 23.64 | 3.065 | 0.17 | 3.511 | 0.03 | 4692 | 2.54 | *1606* | 3248 | 17.30 | *161* |
| | NiCd | 3394 | 26.10 | 1.819 | 0.18 | 3.482 | 0.07 | 4692 | 2.54 | *1299* | 3248 | 17.30 | -146 |
| **Advanced batteries** | Li-ion | 3320 | 26.67 | 1.900 | 0.20 | 3.418 | 0.07 | 4692 | 2.54 | *1372* | 3248 | 17.30 | -72 |
| | NaS | 3273 | 25.87 | 2.571 | 0.17 | 3.546 | 0.05 | 4692 | 2.54 | *1419* | 3248 | 17.30 | -25 |
| | ZEBRA | 2666 | 16.66 | 9.271 | 0.70 | 2.827 | 0.07 | 4692 | 2.54 | *2026* | 3248 | 17.30 | *582* |
| **Flow batteries** | ZnBr | 2922 | 20.10 | 3.550 | 0.21 | 3.479 | 0.04 | 4692 | 2.54 | *1770* | 3248 | 17.30 | *326* |
| | VRB | 2769 | 16.17 | 4.069 | 0.30 | 3.382 | 0.05 | 4692 | 2.54 | *1924* | 3248 | 17.30 | *479* |
| | ZnNi | 2999 | 22.36 | 3.129 | 0.18 | 3.479 | 0.04 | 4692 | 2.54 | *1694* | 3248 | 17.30 | *249* |
| | ZnMnO2 | 2550 | 18.20 | 10.23 | 0.83 | 2.779 | 0.09 | 4692 | 2.54 | *2142* | 3248 | 17.30 | *698* |
| **Super capacitor** | | 2842 | 20.43 | 3.625 | 0.22 | 3.350 | 0.05 | 4692 | 2.54 | *1850* | 3248 | 17.30 | *406* |
| **CAES** | | 2376 | 13.75 | 20.79 | 2.19 | 2.616 | 0.05 | 4692 | 2.54 | *2316* | 3248 | 17.30 | *872* |
| **PHS** | | 2190 | 9.18 | 26.84 | 2.12 | 2.398 | 0.02 | 4692 | 2.54 | *2502* | 3248 | 17.30 | *1058* |
| **SMES** | | 3438 | 21.19 | 0.380 | 0.06 | 4.082 | 0.19 | 4692 | 2.54 | *1255* | 3248 | 17.30 | -190 |

[a] Standard deviation of the mean.

[b] Compared with the payment charged by the basic kW tariff without installing storage.

[c] Compared with the payment charged by the TOU kW tariff without installing storage. Positive values of profit indicate the evaluated storage option is economically viable and vice versa.

In the best-case scenario, all storage technologies are economically viable (see Table 9). The optimal *EC*s range from 2.636 kWh to 27.744 kWh depending on the storage technology in the best-case scenario. The optimal *UL*s range from 2.4 to 3.6 kW, which are generally lower than the corresponding ones in the average-case scenario. In the best-case scenario, annual *profit*s range from $63 for NiCd to $1,119 for PHS (TOU baseline).

**Table 9.** Optimal *EC*, optimal *UL* and maximum *profits* for the best-case scenario (peak reduction)

| | | ***Annual payments* ($/year)** | **SEM[a]** | **Optimal *EC* (kWh)** | **SEM** | **Optimal *UL* (kW)** | **SEM** | **Basic w/o storage** | **SEM** | ***Profit*[b] ($/year)** | **TOU w/o storage** | **SEM** | ***Profit*[c] ($/year)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Flywheel** | | 3052 | 29.13 | 2.968 | 0.18 | 3.450 | 0.07 | 4692 | 2.54 | ***1641*** | 3248 | 17.30 | ***197*** |
| **Conventional batteries** | Metal air battery | 2663 | 11.35 | 23.494 | 2.23 | 2.662 | 0.00 | 4692 | 2.54 | ***2029*** | 3248 | 17.30 | ***585*** |
| | Pb-acid | 2670 | 22.14 | 9.520 | 0.80 | 2.885 | 0.09 | 4692 | 2.54 | ***2022*** | 3248 | 17.30 | ***578*** |
| | NiCd | 3185 | 28.34 | 2.636 | 0.11 | 3.582 | 0.06 | 4692 | 2.54 | ***1507*** | 3248 | 17.30 | ***63*** |
| **Advanced batteries** | Li-ion | 2903 | 27.32 | 3.525 | 0.14 | 3.382 | 0.05 | 4692 | 2.54 | ***1789*** | 3248 | 17.30 | ***345*** |
| | NaS | 2850 | 24.28 | 4.356 | 0.29 | 3.318 | 0.05 | 4692 | 2.54 | ***1842*** | 3248 | 17.30 | ***398*** |
| | ZEBRA | 2588 | 22.87 | 11.791 | 0.58 | 2.693 | 0.06 | 4692 | 2.54 | ***2104*** | 3248 | 17.30 | ***660*** |
| **Flow batteries** | ZnBr | 2607 | 22.06 | 9.689 | 0.82 | 2.907 | 0.06 | 4692 | 2.54 | ***2085*** | 3248 | 17.30 | ***641*** |
| | VRB | 2523 | 21.93 | 11.594 | 0.59 | 2.776 | 0.08 | 4692 | 2.54 | ***2170*** | 3248 | 17.30 | ***725*** |
| | ZnNi | 3011 | 27.49 | 3.012 | 0.17 | 3.514 | 0.06 | 4692 | 2.54 | ***1681*** | 3248 | 17.30 | ***237*** |
| | ZnMnO2 | 2485 | 23.18 | 12.760 | 0.79 | 2.693 | 0.06 | 4692 | 2.54 | ***2208*** | 3248 | 17.30 | ***763*** |
| **Super capacitor** | | 2753 | 25.82 | 4.230 | 0.34 | 3.288 | 0.06 | 4692 | 2.54 | ***1940*** | 3248 | 17.30 | ***495*** |
| **CAES** | | 2227 | 15.07 | 24.655 | 2.17 | 2.565 | 0.04 | 4692 | 2.54 | ***2466*** | 3248 | 17.30 | ***1021*** |
| **PHS** | | 2129 | 8.93 | 27.744 | 2.08 | 2.398 | 0.02 | 4692 | 2.54 | ***2563*** | 3248 | 17.30 | ***1119*** |
| **SMES** | | 2979 | 27.92 | 3.227 | 0.15 | 3.382 | 0.05 | 4692 | 2.54 | ***1713*** | 3248 | 17.30 | ***269*** |

[a] Standard deviation of the mean.

[b] Compared with the payment charged by the basic kW tariff without installing storage.

[c] Compared with the payment charged by the TOU kW tariff without installing storage. Positive values of profit indicate the evaluated storage option is economically viable and vice versa.

## 7 Discussion

In this section, we first compare results from two DR strategies devised in this study: Loadshifting strategy and peak reduction strategy (Sec. 7.1). The a variety of options were discussed that could render DR via residential storage (even) more economically attractive, gain wider adoption, and thus provide more benefits to the grid as a whole (Sec. 7.2-7.4). Finally, the technological viabilities of installing PHS and CAES in residential buildings are addressed in Sec. 7.5.

### *7.1 Demand tariffs versus energy tariffs*

The Con Edison tariff used in our analyses charge both the delivery and the supply portion of monthly electricity bills according to the kWh drawn from the grid (Sec. 2.1). For residential customers with at least 10kW peak demand (over any 30min window, at least once a month), Con Edison offers another TOU kW tariff (SC8-Rate II; see Sec. 2.2) that charges both by demand (kW) and by energy consumption (kWh). The results for these two tariffs (and two strategies) are compared in Table 10 in terms of economic viabilities of storage options.

As seen in Table 10, the TOU kW tariff can render more storage technologies economically viable: Not economically viable under the TOU kWh tariff and by using the loadshifting strategy (see Sec. 5.1), a number of batteries, incl. metal air, Pb-acid, ZEBRA, ZnBr, VRB and ZnNi batteries, and super capacitor become economically viable by implementing the peak reduction strategy (see Sec. 6.1) in the average-case scenario.  However, "short term" technologies such as flywheels and SMES are not economically viable (average-case scenario); their cost per kWh capacity is simply too high. In the best-case scenario, all the storage technologies can generate positive profits by using the peak reduction strategy while only five storage technologies are economically viable by using the loadshifting strategy.

Another tariff model, participating in the frequency regulation market (likely via aggregating multiple residences into a single contractor), may generate alternative or additional savings also (future work, not in this study) [15, 18].

**Table 10.** Economic evaluation results comparison between two strategies

| | | TOU kWh tariff[a] | | TOU kW tariff[b] | |
|---|---|---|---|---|---|
| | | Average-case scenario | Best-case scenario | Average-case scenario | Best-case scenario |
| **Flywheel** | | NO | NO | NO | ***YES*** |
| **Conventional batteries** | Metal air battery | NO | ***YES*** | ***YES*** | ***YES*** |
| | Pb-acid | NO | NO | ***YES*** | ***YES*** |
| | NiCd | NO | NO | NO | ***YES*** |
| **Advanced batteries** | Li-ion | NO | NO | NO | ***YES*** |
| | NaS | NO | NO | NO | ***YES*** |
| | ZEBRA | NO | ***YES*** | ***YES*** | ***YES*** |
| **Flow batteries** | ZnBr | NO | NO | ***YES*** | ***YES*** |
| | VRB | NO | NO | ***YES*** | ***YES*** |
| | ZnNi | NO | NO | ***YES*** | ***YES*** |
| | ZnMnO2 | ***YES*** | ***YES*** | ***YES*** | ***YES*** |
| **Super capacitor** | | NO | NO | ***YES*** | ***YES*** |
| **CAES** | | ***YES*** | ***YES*** | ***YES*** | ***YES*** |
| **PHS** | | ***YES*** | ***YES*** | ***YES*** | ***YES*** |
| **SMES** | | NO | NO | NO | ***YES*** |

[a] Determined by comparing the minimum annual payments by implementing the loadshifting strategy (see Sec.5.1) to the basic kWh tariff baseline (see Table 7).

[b] Determined by comparing the minimum annual payments by implementing the peak reduction strategy (see Sec. 6.1) to the TOU kW tariff baseline (see Table 8).

### *7.2 Technological improvement and storage cost reduction*

Roundtrip efficiencies reported in various literature on metal-air batteries, ZnBr batteries and Vanadium Redox Batteries (VRB) are relatively low (45% for metal-air, 60%-75% for ZnBr, 65%-85% for VRB, see Table 5). However, research is underway to improve efficiencies of metal-air and flow batteries [41, 64].This would significantly increase achievable profits for residential customers. For example for metal-air batteries, assuming a doubling of roundtrip efficiency from 45% to 90% (achievable in the future [65]), *annual profits* could be increased by 22% (average-case scenario, loadshifting strategy).

In contrast, the efficiencies of flywheel storage and SMES are already high (see Table 5). With high power rating but low energy capacity (and thus short discharge duration), device costs of flywheel and SMES are expensive (per kWh capacity). For these devices, potential cost reductions to consumers would result from manufacturing cost reductions rather than efficiency increases.

For not yet fully matured battery technologies, future manufacturing cost reduction (and/or life time improvement) may be achieved in the coming years due to the modularity and scalability of battery systems and technology breakthroughs, for example the use of less costly Na as an alternative to Li in Li-ion batteries [36]. In contrast, Pb-acid batteries have been cost-competitive in the market for a long time. Instead of manufacturing cost, the main limiting factor for Pb-acid batteries is the relatively limited lifetime (number of cycles). Another common disadvantage of Pb-acid batteries, their low-energy density

[48], will likely not constitute material issue for residential use. For Pb-acid batteries sized at 45 kWh (optimal nominal capacity for Pb-acid (best-case scenario, loadshifting strategy) in this study), the required volume is 0.38-0.9 $m^3$ (energy density of 50-120 Wh/l, Table A.1). Even when including additional space for the control unit, this can be easily fit into a single family home.

### *7.3 Lowering installation costs*

Besides the storage manufacturing cost (Sec. 4.2), lowering the fixed one-time home installation costs also has potential to improve economic viability. Some storage technologies and scenarios, while not economically viable in our model, are so close to break-even that a reduction in installation costs would render them economically viable. For example, as can be seen from Table 7, the best-case scenario for super capacitors has a gap to break-even of only $149 per year (loadshifting strategy). With assumed installation cost reduction of 50%, the super capacitor would become economically viable. Still, by using the loadshifting strategy, for flywheel, Li-ion batteries, NiCd batteries, NiZn batteries, and SMES, storage manufacturing costs and/or (dis)charging losses are so high that gaps to provide profit are more than $900 per year, i.e. higher than the savings possible from lowered installation costs. In the contrast, the break-even gaps yielded by utilizing the peak reduction strategy are all below $190 per year (Table 8, average-case scenario), indicating that they are likely to become economically viable or get closer to be break-even if the assumed installation cost would be reduced by 50%.

### *7.4 Impact of interest rates*

Considering 5% instead of 10% interest rate would result in 27% lower total financing costs of the storage system (interest and principal repayments). Conversely, a more conservative 15% instead of 10% would increase financing costs by 50% (for examples for 15 years lifetime). However, considering average instead of best case storage costs leads to much higher cost increases (between 41% (super capacitor) and 362% (Pb-acid batteries)). In other words, the sensitivity of economic viability to the exact interest rate is low compared to the large uncertainty in storage manufacturing costs themselves. Varying interest rates are therefore not further considered in this study.

### *7.5 Technological viability of PHS and CAES*

With regards to economic viability, PHS and CAES show the highest possible profit (Table 1). However, from a practical perspective, applications of PHS and CAES will be limited by site conditions. Although emerging PHS and CAES technologies have been proposed or demonstrated to work as compact systems [66], their low energy density still poses obstacles: For PHS, the optimal *EC* of 12kWh (average-case scenario, loadshifting strategy) would require 488$m^3$ (~500 tons) of water stored in two separate tanks at 10m altitude difference. This will be possible only for select residential buildings and specific architecture. For CAES, however, recent commercially available systems have been shown to be suitable for installation e.g., in the basement of single-family homes [66].

## 8 Conclusions and future work

We found that, when choosing suitable storage technologies and carefully sizing capacity, typical U.S. households can achieve considerable profits when load-shifting their electricity consumption or reduce their peak power demands. The annual profits range from $61 to $1365 per year per household by utilizing the load-shifting strategy and from $161 to $1058 per year per household by using the peak reduction strategy. These profits can be achieved without changing the actual consumption patterns of appliances. The peak reduction strategy can render more storage technologies economically viable than the loadshifting strategy. Note that the demand model represents the U.S. average household (see test results in Sec. 4.2). For other households – with different appliance configuration (e.g., a second television or air conditioning unit) or tariffs other than the specific *Con Edison* tariff used here – profits may change.

An important further investigation into the benefits of DR would be a quantification of possible greenhouse gas emissions savings (on a lifecycle bases, [67-70]). Further optimized or new dispatch strategies may be found by analyzing patterns of demand profiles in the frequency rather than the time domain [71].

**Acknowledgements**

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# Appendix A. Operating characteristics of storage technologies and cost estimations

**Table A. 1.** Characteristics of storage technologies and cost estimations, incl. data sources

| | **Description** | **Power density (kW/kWh)** [1] | | **Healthy depth of discharge (%)** | **Round-trip efficiency (%)** | **Energy density** | | **Operating temperature** | **Self-discharge (%/day)** | **Cost** | **Life time (cycles)** | **Commercial availability** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Continuously discharging power** | **Pulse power** | | | **(Wh/kg)** | **(Wh/l)** | | | **Capital cost ($ /kWh)** | | |
| **Conventional batteries** | | | | | | | | | | | | |
| Metal air | Anode: Metals with high energy density like Al or Zn<br>Cathode: A porous carbon structure or a metal mesh covered with proper catalysts<br>Electrolytes: Good OH-ion conductor | 0-10[2] | NA | 100[3] | 40-50[4] | 110-420[5] | 200[3] | NA | small | 10-60[2]<br>160[3] | 100-300[2]<br>~1,500[3] | Mature in conventional generation Demo to increase lifetime and efficiency |
| Lead acid (Pb-acid)[6] | Anode: Pb+SO4$^{2-}$↔PbSO4+2e-<br>Cathode: PbO2+SO4$^{2-}$+4H$^+$+2e- ↔PbSO4+2H2O | 0.05-3.4 | 11.2-15 | 70-80 | 75-80 | 30-50 | 50-120[7] | (-20) - 50℃[7] | 0.1-0.3 | 106-400<br>950-2260 for advanced batteries | 200-1000<br>4500 for advanced batteries | Mature |
| Nickel cadmium (NiCd)[8] | 2NiO(OH)+Cd+2H2O↔2Ni(OH)2+Cd(OH)2 | 0.05-2.77 | 30 | NA | 60-91 | 40-75 | 171.6 | NA | 0.2-0.6 | 600-1500 | 1000-3000 | Mature |
| **Advanced batteries** | | | | | | | | | | | | |
| Lithium-ion (Li-ion)[9] | | 0.12-6.17 | 0.3-15.64 | 80[10] | 75-100 | 50-200 | 100-500 | -20-+45/60℃ | 0.1-0.3 | 500-3600 | 1000-6000<br>>10,000[11] | Mature portable market |
| Sodium sulfur (NaS)[12] | 2Na+4S↔Na2S4 | 0.03-0.14 | NA | NA | 70-92 | 150-240 | 150-370 | 300-350℃ | 20 | 250-555<br>1100-2730[13] | 2000-4500 | Mature in Japan; Demo in USA |
| Sodium nickel chloride (NaNiCl ZEBRA)[14] | 2NaCl+Ni↔NiCl2+2Na | NA | NA | NA | 90 | 100-120 | 150-180 | -40-+70℃ | 15 | 100-200 | 2500 | Demo and trial |
| **Flow batteries** (additional electrolyte is stored externally, which is usually pumped through the cell (or cells) of the reactor) | | | | | | | | | | | | |
| Zinc bromine (ZnBr)[15] | Positive electrode: 2Br$^-$↔ Br2(aq)+2e$^-$<br>Negative electrode: Zn2$^+$ +2e$^-$ ↔ Zn | 0.2-0.5 | NA | 100 | 60-75 | 30-85 | 30-60 | -30 -+50℃ | 1 | 150-1000<br>725-1950 | 2000<br>5000<br>10,000 | Mature? |
| Vanadium redox (VRB)[16] | Negative electrode: V2+/V3+<br>Positive electrode: V4+/V5+<br>Electrolyte: Mild sulphuric acid solutions | 0.25-0.33 | NA | 100 | 65-85 | 4-33 | 10-30 | Ambient conditions | Small | 150-1250 | 10,000+ | Immature, a few examples worldwide |
| Nickel zinc[17] | Water-based flow-assisted batteries. | 2.78 | NA | 90 | 80 | 31.49 | 28.6 | | Low | 700 | 5000 | |
| Zinc manganese dioxide[17] | | | | 90 | 80 | | | | Low | 100-200 | 3000-5000 | |

**Table A.1.** (continued) Characteristics of storage technologies and cost estimations, incl. data sources

| | Description | Power density (kW/kWh) | | Healthy depth of discharge (%) | Round-trip efficiency (%) | Energy density | | Operating temperature | Self-discharge (%/day) | Cost | Life time (cycles) | Commercial availability |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Continuously discharging power | Pulse power | | | (Wh/kg) | (Wh/l) | | | Capital cost ($ /kWh) | | |
| **Flywheel**[18] | To store energy mechanically in the form of kinetic energy by rotating a mass around an axis. In charging periods, the mass speeds up by electricity transformed by the motor. When discharging, the flywheel slows down. | 4<br>56-160[19] | 117 | 75-100[20] | 85-95 | 3-30[21] | 10-80[21] | -20 ~ +40℃ | 20-100 | 1000-5000[22] | 10,000-25,000 | Demo, few plants under construction |
| **Super capacitor**[23] | Make use of high surface area actived carbons as electrolyte solutions between two solid conductors | 70-220 | 1524-2454 | 100 | 95 | 0.05-15 | 2-10 | -40~+85℃ | 2-40 | 500-1000<br>30,000 | 10E4-10E8 | Developing in transport applications |
| **Compressed air energy storage (CAES)**[24] | The energy is stored as the compressed air in tanks or underground geologic formations. When the demand turns to peak, the compressed air is released into a gas-fired turbine generator system. | 0.002-1 | - | 70 | 42-54<br>65-95[25] | 30-60 | 3-6 | - | 0 | 2-430[26] | 5,000~20,000 | Mature in conventional generation demo to increase efficiency and decrease size |
| **Pumped hydro storage (PHS)**[27] | To store energy by means of two reservoirs located at different elevations | | | | 75-85 | 0.5-1.5 | 0.5-1.5 | - | 0 | 5-100 | 20,000-50,000 | Mature |
| **Superconducting magnetic energy storage (SMES)** [27] | Energy is to be stored in the magnetic field created by injecting a DC electric current into a superconducting coil | | | | 95 | 0.5-5 | 0.2-2.5 | 1.8-4.1K | 10-15 | 1,000-10,000 | 10,000-100,000 | Immature, few power quality applications |

[1] Certain storage technologies can withstand so called pulse discharge modes at peak discharging power which is considerably higher than its normal (dis)charging power. Continuous discharging power here refers to the maximum continuously discharging power.
[2] Taken from Chen, et al. [1].

[3] Taken from EOS Energy Storage [2].

[4] Taken from Edberg and Naish [3].

[5] Usually referred to the weight at the charged state (oxygen included). Taken from Naish, et al. [4].

[6] Summarized from Chen, et al. [1,5-8], unless stated otherwise.

[7] Taken from Naish, et al. [4].

[8] Summarized from Chen, et al. [1, 5, 7, 9], unless stated otherwise.

[9] Summarized from Chen, et al. [1, 5-7, 9-12], unless stated otherwise.

[10] Available sources indicate that the healthy DoD is 80% for Li-ion batteries with one exception of 60%.

[11] The enlarged life cycles are achieved at 50% DoD and by strictly controlling (dis)charging processes.

[12] Summarized from Chen, et al. [1, 5-7, 12, 13], unless stated otherwise.

[13] $1100-2700/kWh is indicated by the NGK company. According to the NAS battery cost projection by NGK, the cost is expected to be reduced to $140/kWh if massively produced (1600 MWh/year).

[14] Summarized from Chen, et al. [1, 5].

[15] Summarized from Chen, et al. [1, 5-7, 14, 15].

[16] Summarized from Chen, et al. [1, 4-7, 12, 16, 17].

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[19] The range reflects different flywheel models. The latest generation of flywheels using magnetic bearings and the ring, which increases the energy capacity of flywheel thus reduces the relative power density (kW/kWh). On the other hand, the model of the high power rating and the low energy capacity reflects the first generation of flywheels, which can be applied in the power quality regulation market.

[20] Conventional flywheels are limited to drop 59% of the maximum rator speed due to the industrial "fail-safe" standard, while the new generation can dump 100% of the maximum rator speed [22].

[21] The high end in the range takes into account the integrated power conversion system, cooling system and pumped vacuum system while the low end reflects the energy density of the rator only.

[22] A high speed flywheel costs as high as five times the manufacturing cost of a low speed flywheel.

[23] Summarized from Chen, et al. [1, 5, 7, 23].

[24] Summarized from Chen, et al. [1, 5, 7, 24].

[25] The round-trip efficiencies of CAES from literatures vary due to the different definitions used for the CAES round-trip efficiency. On the condition that the waste energy utilization is taken into account, the round-trip efficiency of CAES could be increased. The emerging CAES technology is claimed to be able to increase the efficiency from 40% to 70%. According to Ref. [24], the advanced CAES could be materialized by 2015.

[26] The costs of CAES system varies with different scales or kW capacities.

[27] Summarized from Chen, et al. [1, 5].

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# Appendix B. Demand profile model testing results

**Table B.1.** Testing results of the appliance demand profile model

| | | Single day | | | | | Converged day | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Operating parameters | | | | RSEM[28] | Duty cycles per year | | | Daily electricity consumption | | | | | | RSEM[29] | Power draw on first/last minute | | | Overall shape of the demand profile |
| | | Max. power (W) | Min. power (W) | Cycle length (min) | | | From simulations | Expected | Relative error | From simulations (Wh) | Expected (Wh) | Relative error | $E_{peak}$ (Wh) | $E_{off\ peak}$ (Wh) | $E_{peak}/E_{off\ peak}$ | | P(1) (W) | P(1440) (W) | Relative error | |
| Individual appliance | Dishwasher | 1457 | 0 | 54 | OK | 5% | 344 | 365 | -5.81% | 653 | 692.8 | -5.81% | 497 | 156 | 3.20 | 12% | 5.5 | 6.6 | -17.86% | OK |
| | Microwave oven | 1500 | 0 | 6 | OK | 5% | 1171 | 1133 | 3.30% | 481 | 466 | 3.30% | 314 | 168 | 1.87 | 50% | 0.3 | 0.5 | -42.86% | OK |
| | Toaster oven | 1400 | 0 | 20 | OK | 5% | 112 | 111 | 1.16% | 144 | 142 | 1.16% | 90 | 54 | 1.67 | 100% | 0.1 | 0.1 | 0% | OK |
| | Refrigerator | 250 | 0 | 20 | OK | 2% | 12087 | 12089 | -0.02% | 2760 | 2760 | -0.01% | 1393 | 1367 | 1.02 | 5% | 115 | 108 | 6% | OK |
| | Freezer | 155 | 0 | 20 | OK | 0% | 21699 | 21681 | 0.08% | 3072 | 3069 | 0.09% | 1538 | 1534 | 1.00 | 5% | 122 | 129 | -5% | OK |
| | Lighting-Bathroom | 317 | 0 | 31 | OK | 5% | 920 | 989 | -7.00% | 413 | 444 | -7.00% | 185 | 227 | 0.81 | 6% | 10.1 | 10.5 | -4% | OK |
| | Lighting-Bedroom | 200 | 0 | 60 | OK | 5% | 623 | 621 | 0.35% | 341 | 340 | 0.35% | 190 | 151 | 1.26 | 7% | 4.5 | 4.5 | -1% | NOT YET |
| | Lighting-Living room | 256 | 0 | 60 | OK | 5% | 816 | 840 | -2.75% | 573 | 589 | -2.75% | 328 | 244 | 1.35 | 5% | 8.4 | 8.5 | -1% | NOT YET |
| | Lighting-Dining room | 235 | 0 | 30 | OK | 5% | 1336 | 1387 | -3.68% | 430 | 447 | -3.68% | 295 | 135 | 2.18 | 12% | 1.7 | 1.7 | 1% | OK |
| | Lighting-Hallways | 207 | 0 | 15 | OK | 5% | 1705 | 1752 | -2.71% | 242 | 248 | -2.71% | 136 | 105 | 1.30 | 11% | 1.8 | 1.8 | 0% | NOT YET |
| | Lighting-Kitchen | 250 | 0 | 32 | OK | 5% | 1650 | 1711 | -3.57% | 603 | 625 | -3.57% | 391 | 211 | 1.85 | 14% | 1.3 | 1.3 | -2% | OK |
| | Clothes dryer | 2895 | 0 | 60 | OK | 5% | 353 | 359 | -1.60% | 2802 | 2847 | -1.60% | 1775 | 1026 | 1.73 | 13% | 16.2 | 16.5 | -2% | OK |
| | Clothes washer | 2150 | 0 | 48 | OK | 5% | 388 | 392 | -1.09% | 822 | 831 | -1.09% | 500 | 322 | 1.55 | 21% | 4.1 | 4.5 | -9% | OK |
| | Television | 185 | 0 | 115 | OK | 5% | 704 | 752 | -6.30% | 684 | 730 | -6.30% | 489 | 195 | 2.51 | 5% | 21.9 | 22.3 | -2% | OK |
| | Air conditioning | 3500 | 0 | 10 | OK | 1% | 5270 | 5520 | -4.53% | 33414 | 30667 | 8.96% | 20879 | 12535 | 1.67 | 5% | 1335 | 1405 | -5% | OK? |
| | Space heater | 1447 | 0 | 60 | OK | 2% | 1465 | 1476 | -0.71% | 17432 | 17364 | 0.39% | 8757 | 8676 | 1.01 | 5% | 683 | 677 | 1% | OK |
| | Vacuum | 1440 | 0 | 35 | OK | 5% | 63 | 63 | -0.12% | 146 | 146 | -0.12% | 89 | 57 | 1.55 | 19% | 1.3 | 0.6 | 132% | OK |
| | Computers and other rechargeable electronic devices | 100 | 100 | 1440 | OK | 0% | 365 | 365 | 0.00% | 2400 | 2400 | 0.00% | 1200 | 1200 | 1.00 | 0% | 100 | 100 | 0% | OK |
| Whole household | Summer | 12207 | 100 | - | OK | 2% | - | | | 50306 | 57392[30] | | 30235 | 20071 | 1.51 | 5% | 1829 | 1797 | 2% | |
| | Winter | 9003 | 100 | - | OK | 2% | - | | | 33705 | - | | 17862 | 15843 | 1.13 | 5% | 1111 | 1115 | 0% | |
| | Spring or fall | 8242 | 100 | - | OK | 3% | - | | | 16259 | - | | 9348 | 6911 | 1.35 | 5% | 419 | 420 | 0% | NA |
| | Average day | | | | | | - | | | 30586 | 31011[31] | -1% | 17408 | | | | | | | |

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[28] RSEM denotes the relative standard deviation of the mean. Here, the RSEM is the maximum RSEM among RESMs of fully cycles per year, daily electricity consumption, electricity consumption during peak hours and electricity consumption during off-peak hours.

[29] Here, RSEM is the larger one between RSEM of the power draw at the first minute of the day and RSEM of the power draw at the last minute of the day.

[30] The average daily electricity consumption for summer days is obtained from Pecan Street Research Institute, http://www.pecanstreet.org/. [accessed 5/13/2013].

[31] The average daily electricity consumption per household in U.S. is obtained from U.S. Energy Information Administration, 2009 Residential Energy Consumption Survey (RECS) Data Table CE2.1 Fuel Consumption Totals and Averages, U.S. Homes, U.S. Energy Information Administration. http://www.eia.gov/consumption/residential/data/2009/index.cfm?view=consumption#fuel-consumption. [accessed 1/22/2014].