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Quantitative Evaluation of Residential Virtual Energy Storage in Comparison to Battery Energy Storage: A Cyber-Physical Systems

Chiedozie Franklin Ononuju
Bucknell University, cfo002@bucknell.edu

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QUANTITATIVE EVALUATION OF RESIDENTIAL VIRTUAL ENERGY
STORAGE IN COMPARISON TO BATTERY ENERGY STORAGE:
A CYBER-PHYSICAL SYSTEMS APPROACH

by

Chiedozie Franklin Ononuju

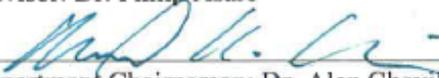
A Thesis

Presented to the Faculty of
Bucknell University
In Partial Fulfillment of the Requirements for the Degree of
Master of Science in Electrical Engineering

Approved:



Advisor: Dr. Philip Asare



Department Chairperson: Dr. Alan Cheville



Engineering Thesis Committee Member: Dr. Amal Kabalan



Engineering Thesis Committee Member: Dr. Peter Mark Jansson

(Date: May 2017)

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Abstract

Virtual energy storage (VES) refers to an indirect method of storing energy without using a battery. In a residential setting, VES uses the building structure interior appurtenances together with its physical properties as an energy storage device. It represents a methodology in energy storage mechanisms to help with load management in residential microgrids. It is an approach that is critical to the necessary paradigm shift from the less flexible and more costly “demand response” energy market of the present to the more flexible and potentially less costly “availability response” energy market of the future. This work quantifies VES monetary cost-savings potential for residential homes, as part of an effort to develop smart systems (using power sensors, and simple computation and control mechanisms) to assist individuals in making decisions about energy use that will save energy and, consequently, electricity costs.

The project also compares the cost-effectiveness of VES to that of battery energy storage (BES)—currently the more traditional and widely-advocated-for approach to energy storage for load management. In addition, this project devises a load management framework for a residential microgrid, where strategies that enable energy and cost savings for both utilities and consumers are tested.

To make a home act as its own storage device, we need to intelligently control its heating, ventilation, and air conditioning (HVAC) system. Through this control, we can harness the house’s thermal storage abilities by methods such as preheating or precooling

the house (with due consideration to user comfort) during periods when energy is less expensive so that this heat or coolness will be retained during higher-cost periods.

A well-insulated residential home equipped with sensing technology and intermittent generation resources will be utilized as a testbed for this project. Using a testbed is advantageous as it provides realistic results as well as a platform where behavior of the home can be learned. By combining modeling techniques with test results from a live testbed, cost-saving solutions can be simulated and later evaluated.

This work provides a means to determine how to reduce peak demand and save costs for both utilities and consumers by changing consumer behavior, while respecting consumer thermal comfort preferences. Additionally, by creating the aforementioned modeling framework, we provide the load management community with tools by which they can readily test their optimization algorithms. By so doing, more efficient algorithms can be developed (potentially leading to increased residential energy efficiency).

1 Introduction

In the United States, utilities practice a demand-response, centralized generation-dispatch model where the amount of energy generated at any instant is controlled to meet the customer load, and generation prices respond accordingly. At peak demand periods, there is an upswing in generation costs, leading to increased locational marginal prices (LMPs)—the price of electricity at any given node in the power transmission system. Locational marginal pricing is used by many regional transmission organizations (RTOs) to communicate the marginal cost of recently added capacity to the electricity market. The LMP is used to determine how much the RTOs pay generators and to establish the marginal price of electric energy sales in specific locations [1, 2].

In the electric power industry, load-serving entities (LSEs) employ various pricing schemes [3, 4] and implement special programs [4, 5, 6] aimed at changing the consumer’s load shape when such load shapes may not be beneficial to the utilities (i.e. if consumer load curves decrease utility profit, increase operating costs, or bring about new costs). Likewise, the consumer wanting to reduce electrical energy consumption and, consequently, monetary costs may engage in a myriad of strategies that help shape their¹

¹ “They” is used as the gender-neutral third-person-singular pronoun in this thesis. The derivative forms of “they” are used in a similar manner.

demand to match utility supply. These symbiotic interactions comprise what is known as load management².

1.1 Motivation³

The demand-following model employed by the power industry is less amenable to load management than a hypothetical supply-following model because utility generation is often less flexible than consumer consumption (especially when consumers employ intermittent distributed generation such as solar and wind).

We envision a future where the available generation capacity in the electricity market (including intermittent renewables) will drive consumer demand and thus guide consumer behavior rather than the other way around. With the growth of renewable generation—which is non-dispatchable—and with proper price signals from the utility to the consumer, this vision [7, 8, 9] can become a reality: load management can be preemptively employed to guide consumer demand in ways that result in cost savings for both consumer and utility and thus the power industry can be gradually transformed to a

² Load management is also known by other terms including: demand response, demand-side response, demand-side management, energy management, and energy demand management.

³ The motivation for this thesis was published in the Proceedings of the 2016 ACM Buildsys Conference: C. Ononuju, P. Asare and P. Jansson, "Preliminary Exploration of Virtual-Storage-Based Load Management," in *Proceedings of the 3rd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments*, Palo Alto, 2016.

supply-following system. Our goal is to create a framework and motivate a load-management environment that can turn this hypothetical supply-following model into reality.

1.2 Load Management Techniques

Various techniques enable a load-management environment and the literature classifies them into six: peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shape [10]. These techniques are illustrated in Figure 1.

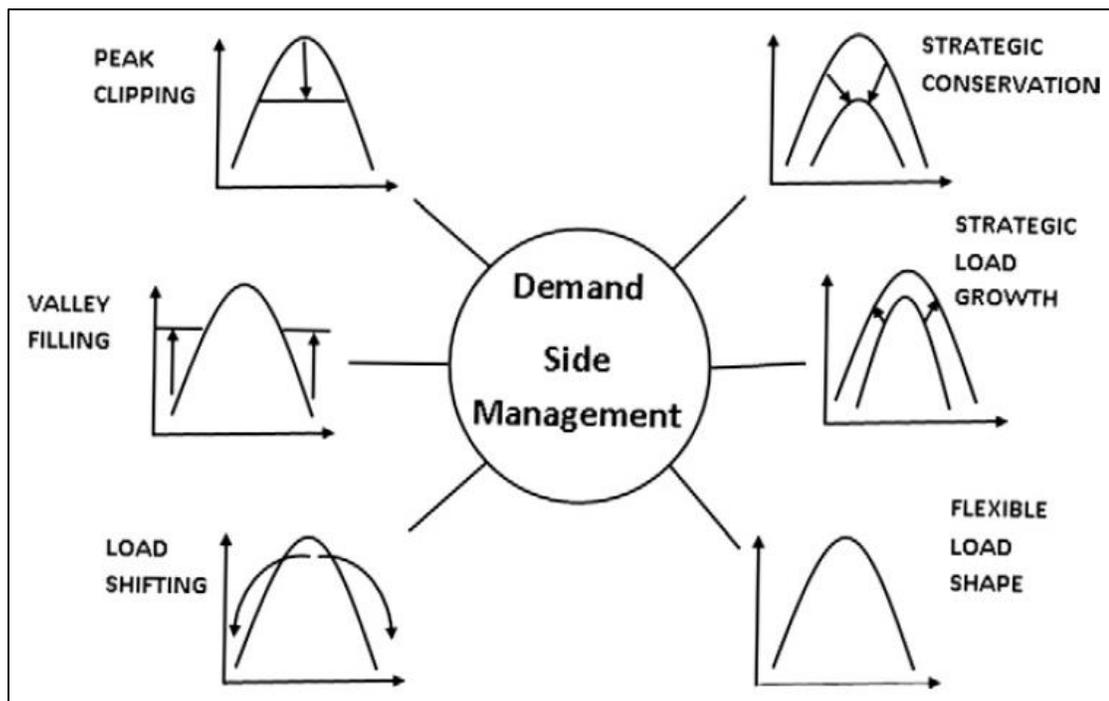


Figure 1. Load management techniques (reproduced as is from [11]).

Peak clipping refers to reduction of consumer load during peak periods. This can be done by turning off (or cycling) appliances during such periods. Valley filling, on the other hand, refers to increased energy use during off-peak periods (i.e. times of inexpensive generation) in order to meet utility-preferred minimum supply levels. Load shifting refers to reducing the amount of energy used when generation is expensive and using these loads during cheaper periods, making it essentially a combination of the previous two techniques.

Strategic conservation is a general decrease in the aggregate consumer demand resulting from special programs [4, 5, 6] that the utility implements. Strategic conservation measures can include home weatherization as well as promotion of more-efficient appliances: for instance, LED lightbulbs instead of incandescent lightbulbs. Essentially, strategic conservation refers to any load management strategy where either new appurtenances are installed or existing appurtenances are better utilized. In recent times, the term “strategic conservation” has been replaced with “energy efficiency” [6].

The opposite of strategic conservation is strategic load growth—a general rise in aggregate consumer load due to special programs that utilities promote. However, with today’s high levels of energy consumption both in the United States and around the globe [12], and with predicted increased global energy demand in the years to come [13], strategic load growth is seldom employed [6].

Finally, flexible load shape is a technique that applies to adaptable consumers. Such consumers may be willing to accept incentives from the utilities in order to decrease load,

though this approach can lead to non-optimal comfort levels for the customer—a tradeoff which the customer may accept to reap monetary benefits. In recent times, “flexible load shape” has been replaced with the term “dynamic energy management” [6]. This technique is usually carried out to ensure reliability of transmission and distribution networks as well as decrease stress on the grid [10, 14].

Each of the six load management techniques typically goes hand-in-hand with another of the aforementioned; they have been applied in a myriad of ways in both industrial and residential settings.

In this thesis, when we carry out residential load management, we are shifting load from peak periods to off-peak periods in a way that is expected to provide cost savings for both the consumer and the utility. Note, however, that to carry out residential load shifting (and thus peak clipping) in a controlled manner, without changing consumer preferences, some form energy storage is necessary. Such storage acts as a conduit between peak and off-peak loads.

We also assume for this project that the consumer is willing to receive, to some extent, incentives from the utility to carry out load management. These incentives, however, should not decrease the comfort level of the consumer we are considering. Therefore, our project employs load shifting, peak clipping, valley filling, and flexible load shape techniques in cost-effective ways.

1.3 Need for Energy Storage Systems

Load management techniques do not explicitly take into account that cycling some (or all) appliances during peak periods may cause the consumer significant discomfort. In addition, it is possible that the consumer strongly prefers to use certain appliances during peak periods—for instance air conditioners on hot summer days.

To carry out load management with these added considerations, the consumer needs a “buffer”—some form of electrical energy storage that will allow them to adequately shift energy consumption (as seen by the utility) in a manner that respects utility supply preferences. Consumers engage in such load shifting by storing energy when it is cheaper, while using the stored energy (in a manner that respects their personal thermal comfort and daily routines) when generation is expensive.

1.4 Types of Energy Storage Systems

There are various methods and systems by which energy, which is intended for subsequent conversion into electricity, can be stored. Luo et al. [15] and Chen et al. [16] give a comprehensive review of these technologies. They discuss their characteristics and applications while outlining current research and development being conducted on each of the technologies. They also inform the reader of the extent to which each technology is suitable for integration into the electrical power system. The technologies outlined (in great detail) by Luo et al. [15] and Chen et al. [16] include:

- i. Pumped Hydroelectric Storage
- ii. Compressed-Air Energy Storage
- iii. Flywheel Energy Storage
- iv. Capacitors and Supercapacitors
- v. Superconducting Magnetic Energy Storage
- vi. Solar Fuels
- vii. Hydrogen Storage and Fuel Cells
- viii. Battery Energy Storage
- ix. Thermal Energy Storage
- x. Any combinations of the above-listed (Hybrid Energy Storage)

Our project is focused on load management in a residential context. Usually, when energy storage is discussed in this context, rechargeable battery energy storage (BES) is the most prominent technique mentioned. BES implementations in residential load management typically involve load shifting where the battery is charged during cheaper off-peak periods so that the energy stored (in chemical form) can be harnessed during peak periods when electricity, as reflected by LMP, is expensive. However, BES systems are quite costly and their large capital cost may hinder some consumers from adopting them.

On the other hand, virtual energy storage—a kind of thermal energy storage⁴ (TES)—is a potentially advantageous alternative to BES. VES is a technique which makes intelligent use of the heating, ventilation, and air conditioning (HVAC) system—the largest residential energy consumer in the United States [17]. VES uses the physical properties of the house to harness thermal storage by methods such as preheating or precooling the house during off-peak periods so that this heat or coolness will be retained during peak periods. VES is characterized by minimal capital costs—the devices required are low-cost sensing and computation with the ability to interact with a relatively cheap and easy-to-install smart thermostat.

In order to better understand VES energy- and cost-savings potential in a residential setting, this project will explore VES load management in comparison to the more prevalent and widely-advocated BES approach. Thus we will conduct our analyses on a VES system as well as on a variety of batteries suited for residential use (see Table 3).

1.5 Thesis Objectives

Though virtual storage is typically used in commercial buildings, this storage approach has yet to see systematic use in residential buildings due to difference in scale,

⁴ Energy stored in the form of heat (or coolness).

requiring difference in approach. From our fairly substantial research, data on VES monetary cost-savings potential does not seem to exist. Therefore, it is the objective of this project to quantify this potential for a residential setting, perform cost-effectiveness analyses that compare VES relative to BES, and provide a modeling framework where various load management strategies (using either storage method) can be tested with cost quantification in mind. By doing all this, we can readily verify the relative advantages and disadvantages of either storage method and provide a means to evaluate the efficacy of various optimization strategies.

Our modeling framework will contribute to the field of load management as it will create a platform where researchers can test their optimization algorithms. The goal of this work, therefore, is not necessarily to determine the best optimization strategy but to create a model and provide the tools through which this determination can be made. It is our hope that our modeling framework will spur further research into VES in order to reduce monetary costs for both consumers and utility companies.

2 Background

2.1 Applications of Load Management Techniques

One of the most prominent applications of valley filling is in the charging of electric vehicles (EVs) during off-peak periods in order to decrease stress on the grid. Various optimization algorithms have been developed to facilitate this process. Gan et al. [18] proposed a decentralized protocol, and their protocol was shown to give optimal charging profiles. Karfopoulous and Hatziargyrou [19] propose a distributed, multi-agent method based on the Nash Certainty Equivalence Principle that considers network impacts. The approach of Karfopoulous and Hatziargyrou [19] is shown to efficiently allocate energy requirements during off-peak periods, thus achieving valley filling.

Ma et al. [20] formulate the problem of decentralized charging of large populations of EVs as a class of finite-horizon dynamic games. They come up with a valley-filling strategy that is nearly optimal. Zhang et al. [21] propose a decentralized valley-filling strategy for EV users in Beijing, China. In their research, they design a day-ahead pricing scheme by solving a minimum-cost optimization problem. Results of Zhang et al. [21] show that valley filling, through coordinated EV charging, leads to lower power generation costs compared to uncoordinated EV charging.

Research [22, 23, 24] has shown that peak clipping and load shifting can be applied in an industrial setting. Ashok [22] used integer programming to show how these

techniques can shave peak load and decrease monthly electricity bills in a steel plant. Middelberg et al. [23] obtain similar results for a colliery via an optimal control model. Babu and Ashok [24] employ mixed integer linear programming to show the possibility of reduced peak demand, and lower electricity bills, for electrolytic process industries. In general, peak clipping works in tandem with load shifting. In other words, load shifting is usually done to shave the peaks by moving peak load to other times in the day (which may or may not be valleys).

Supplementary to the peak clipping, valley filling, and load shifting techniques performed by the consumer, are a variety of special programs and/or pricing mechanisms implemented by the utility [3, 4, 5, 6] to stimulate strategic conservation (energy efficiency) as well as to incentivize adaptable customers (dynamic energy management) to decrease load in order to relieve the grid of stress.

2.2 Applications of BES Systems

BES systems are comprised of a number of electrochemical cells connected in series or parallel and producing electricity from chemical reactions [15, 16]. Each cell contains two electrodes—a positive anode and a negative cathode—as well as an electrolyte which may be in solid, liquid, or gel form [15, 16, 25]. The authors in [15] and [16] have presented in-depth analyses of various BES chemistries. In addition, they have outlined where such technologies are being deployed all over the world as well as progress

that has been achieved with different battery technologies and avenues for future exploration.

BES systems have been advocated by the electrical power as well as other industries because they provide fuel flexibility, decrease congestion in the transmission system, stabilize the transmission and distribution systems, improve power quality and reliability, enhance frequency regulation, and support the growth of intermittent renewable energy technologies [15, 16, 26]. BES technologies have also found applications in everyday areas of life where they provide power for a range of consumer items as well as for homes and vehicles. In this project, however, we are only concerned with battery technologies that can be used for home energy storage. Such battery chemistries can be found in Table 3.

BES technologies have been applied in load management in a variety of ways. Zhang et al. [27] explored BES in the data center of a commercial building which uses TOU⁵ pricing. They show that monetary savings is possible when energy stored in a UPS system during low-TOU periods is harnessed during high-TOU periods. However, Zhang et al. [27] used simulated data as opposed to data from a testbed.

⁵ Time-of-use pricing—a pricing mechanism where the day is divided into a few blocks with electricity in each block costing a price proportional to the demand for that block. This type of pricing mechanism is typically used for commercial and industrial customers. See: B. Spiller, "All Electricity is Not Priced Equally: Time-Variant Pricing 101," Environmental Defense Fund, 27 01 2015. [Online]. Available: <http://blogs.edf.org/energyexchange/2015/01/27/all-electricity-is-not-priced-equally-time-variant-pricing-101/>.

Similar to Zhang et al., Palasamudram et al. [28] employed batteries in a Content Delivery Network (CDN). The batteries were charged during off-peak periods and discharged during peak periods. Load data was obtained from Akamai's CDN. It was shown that the use of batteries increased power savings in the CDN.

BES research has also been carried out in residential settings. Nguyen and Le [29] tried to reduce electricity bills while considering user comfort. They provided a framework that incorporates a joint optimization model for an HVAC system as well as electric vehicles (EVs) in a home. The EVs are designated as battery storage devices for powering the HVAC systems during peak demand. Their scheme is shown to give considerable energy savings compared to a non-optimized house.

Similar to Nguyen and Le, Brush et al. [30] used EV batteries as storage devices in order to power a house during peak periods, from energy stored during off-peak periods. Unlike Nguyen and Le, however, Brush et al. use real load data from fifteen homes; their experiments show significant energy savings. Nevertheless, it is difficult to determine the kinds of savings that alternative approaches would have provided Brush et al.

2.3 Applications of VES Systems

What we define as virtual energy storage is a thermal-storage-based load-management technique that utilizes latent heat or coolness provided by a building's HVAC

system, in conjunction with the insulating properties of the building interior (and all appurtenances), to create what we call a “virtual battery”.

By intelligently controlling the HVAC system in a residence to precool (or preheat) the dwelling during off-peak hours so that the latent heat or coolness will be maintained during peak periods, energy and electricity costs can be saved. Leveraging the HVAC system—the largest energy consumer in a typical U.S. home [17]—in this way, makes it, in essence, an energy storage device. This is because the thermal energy to be utilized later is put into the house before intended use, by “charging” the house.

VES provides many of the same benefits for which BES systems are advocated. VES has strong value propositions for the future of the grid. ISO markets, system operators, and transmission and distribution companies can reap benefits from VES which include but are not limited to: regulation of power, provision of generation capacity, integration of renewables, reduction of congestion in transmission systems, and improvement in power quality and reliability [9]. Research into VES over the years has shown favorable results which encourage us to deploy this technology.

Zhang et al. [27] have used virtual storage in a datacenter by precooling the datacenter when energy was readily available (low TOU) and then allowing the servers to absorb heat when energy was relatively scarce (high TOU). A similar technique was used in our work, albeit for a residential setting [31].

Henze et al. [32], examined ice storage as well as virtual energy storage⁶ (by HVAC precooling) for a commercial building. They determined that the combined cost savings for both methods surpass the savings of each individual method. However, the combined cost savings for both methods is less than the sum of the savings from each individual method. This study is carried out for a commercial building, which uses TOU prices, rather than for a home. One disadvantage of this study is that actual utility rates are not used. Rather, a peak TOU of \$0.20/kWh is assumed and the off-peak TOU is presumed to be \$0.05/kWh.

Similar to Henze et al. [32], Braun [33] simulated the impact of dynamic adjustment of HVAC setpoints in a building. Braun found a reduction in peak electricity that varied from 10 – 35% compared to baseline levels.

Ellis et al. [34] approach VES in a unique way. Rather than preheating the house, they turn off the HVAC prior to the occupants' departure from the home. The rationale behind their technique is that the latent heat will keep the occupants warm for the period between when the HVAC is turned off and when they exit the building. Ellis et al. [34] used real data from two Cambridge, UK homes and three Seattle, USA homes to predict

⁶ Henze et al. use the term “thermal capacitance” which is a measure of how much heat an object can store. Thermal capacitance is sometimes referred to as “thermal mass”. See: E. Cheever, "Elements of Thermal Systems," Swarthmore College, Erik Cheever, [Online]. Available: <http://lpsa.swarthmore.edu/Systems/Thermal/SysThermalElem.html#Tcap>.

departure times for residents. Their analysis predicts a potential 1–8% of savings in gas use. However, the HVAC system for this thesis' testbed will be powered by electricity rather than gas.

In other work, Braun et al. [35] tested peak clipping and load shifting potential for the Iowa Energy Center. They used a simple precooling strategy and found that, cumulative peak loads in their test zones was reduced by 9%.

When examining work done in the area of VES, one important point to note is that climate plays a crucial part. Studies done by Kintner-Meyer and Emery [36] imply that VES is most effective in dry climates with a large temperature differential between day and night.

From our fairly significant research, we have not come across any work that quantifies residential VES monetary cost-savings potential to that of BES. However, as outlined above, there is a fair amount of research which evaluates the cost and energy savings of each individual mechanism. In this work, therefore, we will compare the monetary cost-savings potential of both mechanisms, relative to each other.

2.4 The Duck Curve

In 2013, the California Independent System Operator (CAISO) released net load data, corresponding to a typical spring day (March 31), for the years 2012 – 2020 [37, 38]. CAISO used actual net load data for 2012 and 2013 and projected what the net load would

look like on March 31 of 2014 through 2020. The results of their projections shown in Figure 2 is referred to as the “duck curve” [37, 39], due to its resemblance to the profile of a duck.

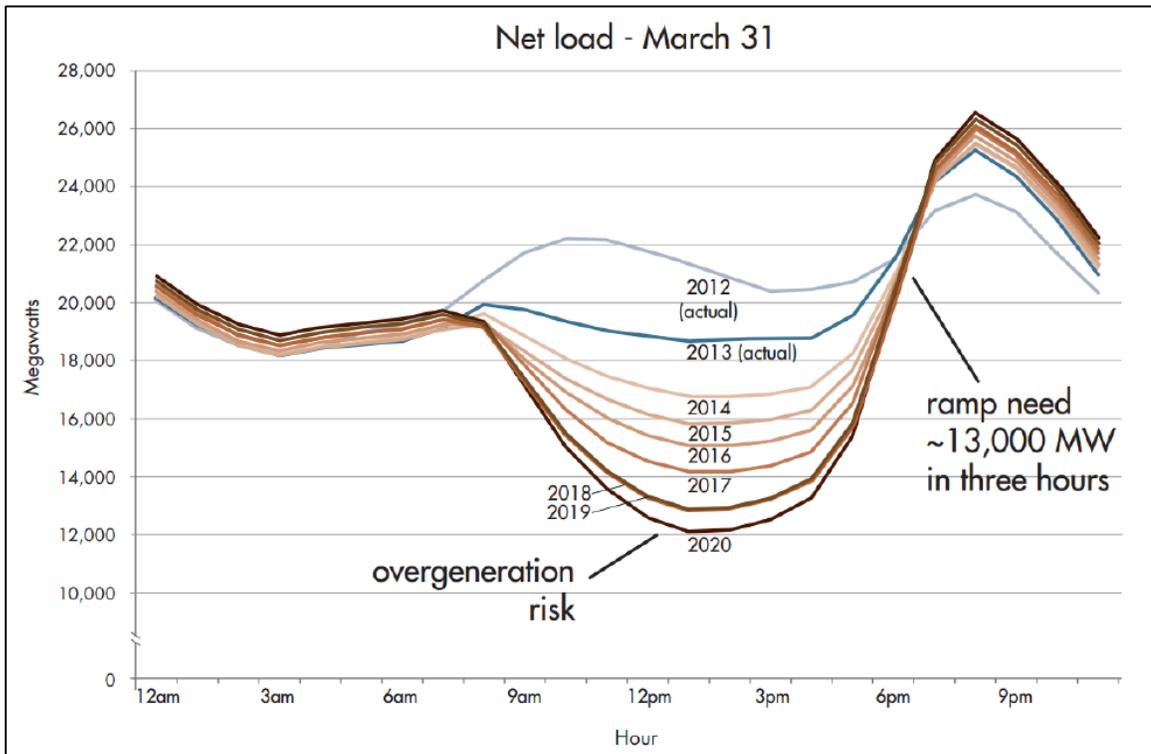


Figure 2. CAISO Duck Curve showing net load for a typical spring day, for 9 years (reproduced as is from [37]).

CAISO’s duck curve predicts a yearly decrease in net load from mid-morning to late afternoon—the belly of the duck. Further, there is a sharp rise in net load in the early evenings—the neck of the duck. The belly of the duck points to over-generation of

electricity [37]. Between the hours of 9 a.m. to about 3 p.m., solar PV⁷ is putting a lot of energy onto the grid. However, in the evening, when the sun goes down, solar generation is lost. During these times, people are getting back from work and turning on their HVAC systems and other appliances [40]. Consequently, there is a huge spike in demand between 4 p.m. and 7 p.m. which CAISO has to meet by quickly (and inefficiently) ramping up generation. Since California is expected to have about 33% of their generation comprised of renewable sources by 2020 [41], solutions to the duck curve phenomenon are needed.

Multiple strategies have been proffered [37, 40, 42] with load shifting and energy storage standing out as prominent answers [37, 40]. Jim Lazar, of the Regulatory Assistance Project, has listed ten strategies that will help flatten the duck curve [40, 42]. I will repeat Lazar's strategies verbatim here. They are:

Strategy 1: Target energy efficiency to the hours when load ramps up sharply.

Strategy 2: Orient fixed-axis solar panels to the west⁸.

⁷ It is important to note that the duck curve phenomenon is due to utility-scale solar and not residential PV. See Report: ScottMadden Management Consultants, "Revisiting the California Duck Curve: An Exploration of Its Existence, Impact and Migration Potential," ScottMadden Management Consultants, 2016.

⁸ Studies have shown that doing this increases solar PV output in the afternoon while decreasing output in the morning. See Report: Pecan Street, "South-Facing Solar Cut Peak Demand from Grid 54% – West-Facing Systems, 65%," Pecan Street, 18 November 2013. [Online]. Available: <http://www.pecanstreet.org/2013/11/report-residential-solar-systems-reduce-summer-peak-demand-by-over-50-in-texas-research-trial/>.

Strategy 3: Substitute solar thermal (with a few hours of thermal storage) in place of some projected solar PV generation.

Strategy 4: Implement service standards allowing the grid operator to manage electric water heating loads to shave peaks and optimize utilization of available resources.

Strategy 5: Require new air conditioners to include two hours of thermal storage capacity under grid operator control.

Strategy 6: Retire inflexible generating plants with high off-peak must-run requirements.

Strategy 7: Concentrate utility demand charges into the “ramping hours” to enable price-induced changes in load.

Strategy 8: Deploy electrical energy storage in targeted locations.

Strategy 9: Implement aggressive demand-response programs.

Strategy 10: Use inter-regional power exchanges to take advantage of diversity in loads and resources.

After all ten strategies are employed, Lazar illustrates the aggregate effect they have on the duck curve (see Figure 3). Figure 3 shows that the duck has been transformed into a flatter curve that is more manageable—from CAISO’s perspective.

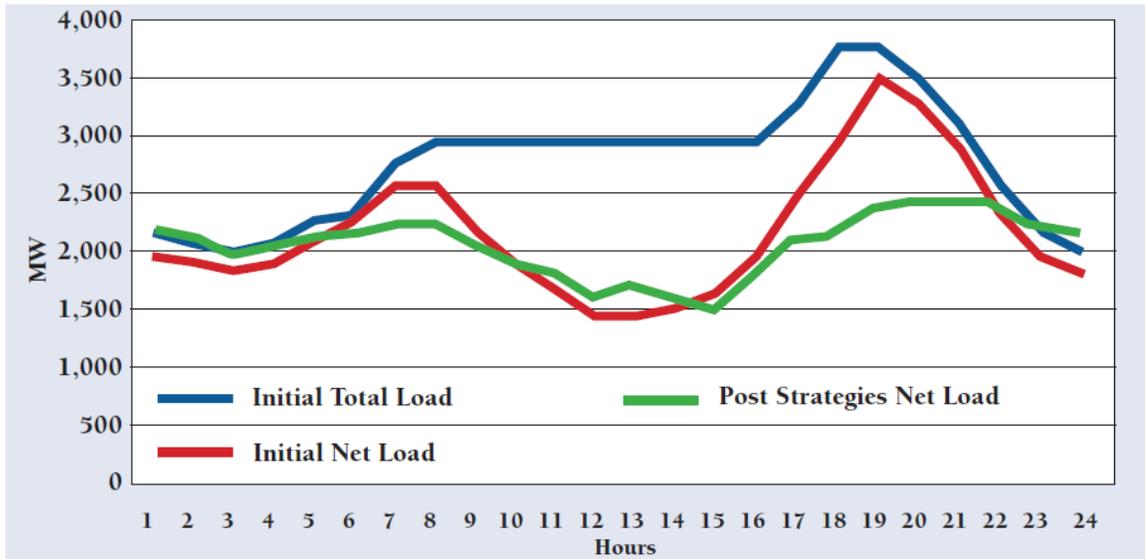


Figure 3. Effect of load management and incentive programs on the duck curve (reproduced as is from [40]).

We see our VES technique having important implications for Strategies 7 and 9. Strategy 7 can be used to incentivize VES—consumers could “virtually charge” the house by precooling (or preheating) prior to the high-priced ramping hours, so that they reduce the amount of money they have to pay during such periods.

In addition, concerning Strategy 9, if a large number of CAISO customers were precooling during off-peak hours, load would increase during such hours, pushing up the belly of the duck. Likewise, the latent coolness maintained in the house during the ramping hours would lower the neck of the duck as there would be less need to turn on the air-conditioning—a chief contributor to the evening ramp-up.

Third-party companies can aggregate these potential VES reductions. Assuming some fraction of the third-party earnings is transferred to the consumer, the consumer gains money while helping reduce stress on the grid. Similarly, CAISO benefits because they will not have to inefficiently ramp up generators. This will reduce their general operation costs.

VES is one of the multiple demand-side strategies [6, 10] that can help deal with the California duck curve phenomenon. A similar line of reasoning holds for Hawaii, where the “Nessie curve” [43] has been observed, as well as other states that are increasing their solar PV resources. Such states include: Arizona, Georgia, Nevada, North Carolina, and Texas [38, 37].

3 Methodology: Cyber-Physical Systems

Approach

A cyber-physical system is any system that integrates intelligence into the physical world using computational algorithms and sensing devices [44, 45]. The focus is on tight coupling between the computational algorithms and the physical world where the algorithms affect physical processes and are in turn affected by these physical processes. Traditional examples of products that are either considered cyber-physical systems or providers of opportunities for cyber-physical systems application include: cars, aircraft, manufacturing plants, and the electrical grid [46].

The problem of load management lends itself to a cyber-physical systems solution. Nowadays, humans conduct load management by manually reducing their demand during peak periods (although some devices are used to aid the process [47]). As mentioned previously, physical resources like batteries have been proposed to help with load management [15, 16, 26]. Nevertheless, with computer algorithms that can sense physical data, load can be managed more optimally and adaptively, and the added intelligence may greatly reduce the need for significant investments in physical resources such as batteries.

The advantage of cyber-physical systems methods is that they require low-cost physical resources like embedded computers [48], appropriate sensors and actuators, and networking technologies. With these, the major work is in developing the required

intelligence to manage the physical resources to achieve our specific goals (managing energy consumption in our case).

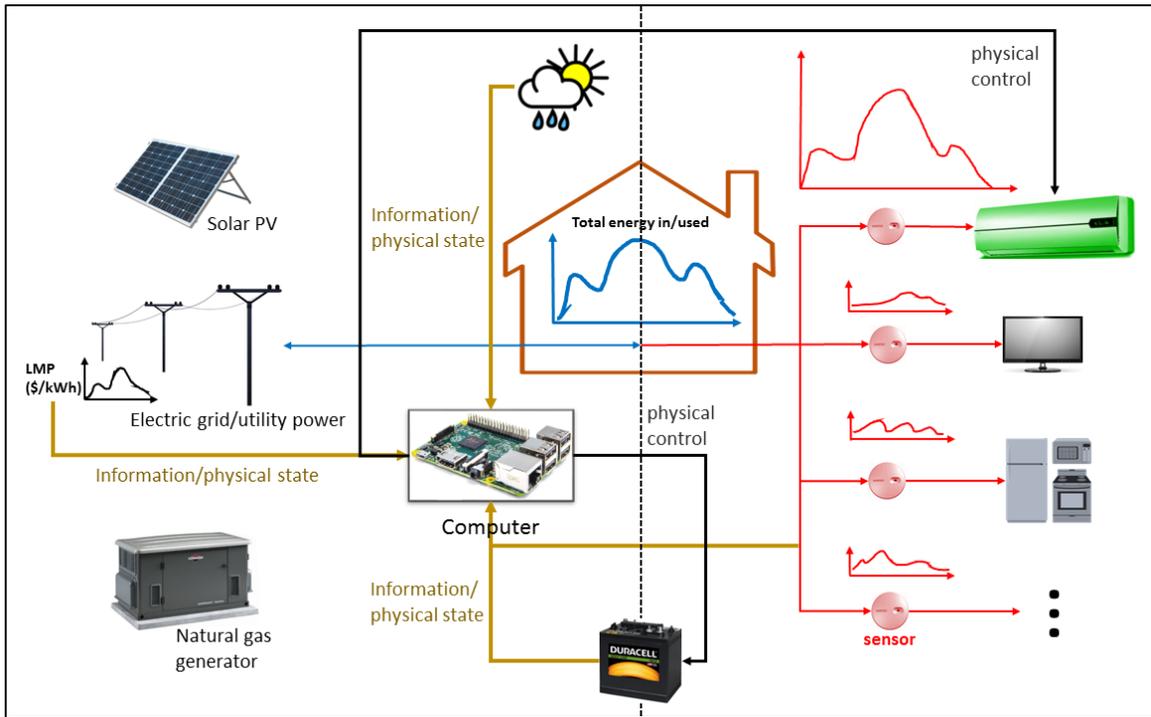


Figure 4. Smart residential microgrid from a cyber-physical systems perspective.

Figure 4 illustrates the general concept of load management from a cyber-physical systems perspective. The computer collects information about weather conditions, energy prices, condition of energy resources like the battery as well as consumption behavior of appliances. Based on such data as well as the (potentially) learned preferences of the residents, the computer controls the HVAC system, the battery, and possibly other resources in the home so that occupants get optimal use out of energy-consuming resources. The algorithms on the computer could also be designed to take the

environmental effects of energy consumption choices into account as it acts to shape the house load to reduce stress on the grid.

A major advantage of cyber-physical systems approaches is the ability to model complex systems to gain insights into their behavior before implementation, possibly following a model-based design approach [49] in doing so. Our work focuses on this modeling, but not yet with the intention of following a model-based approach to implementation.

Our VES approach requires information from the physical world (temperature data and some knowledge of the house's physical response to temperature). With this information from the physical world, as well as the electricity cost information, decisions that will control the house in such a way that it becomes its own virtual battery [9] can be made. The successful implementation of this virtual battery requires that we sense as well as control the HVAC behavior, based on the physical temperature data both inside and outside the house, since the HVAC system is highly dependent on temperature.

Our work provides support for the development of a cyber-physical system that will intelligently optimize energy and cost savings in a home. Therefore, though this work does not develop a residential-load-management cyber-physical system, it lays the groundwork and provides tools for researchers who will develop such systems to build upon.

3.1 The Testbed

To meet our objective of creating and validating a practical framework for residential load management, we use real data from a residential microgrid. A well-insulated home equipped with sensing technology and intermittent generation resources is used as our testbed. Despite the high quality of insulation in this testbed, modeling techniques used on it are transferable to homes with various grades of insulation. The testbed [50, 51, 52, 53] is a single-family home in Lewisburg, Pennsylvania, USA. The distribution company which supplies power to the home is Citizens’ Electric, a node located within the PPL zone of PJM—a regional transmission organization (RTO) in northeastern USA. Citizens’ Electric has a pricing scheme that is a fixed rate for half of the year. After Citizen’s Electric evaluates the electricity market for the first half of the year, they adjust their rate for the second half [54]. Consequently, it might appear that load management has no effect on the short-term nominal cost of electricity for a Citizens’ Electric customer. Nevertheless, load management, if properly carried out, will help reduce long-term nominal electricity prices for such customers.

It is important to note, however, that we do not use Citizens’ Electric’s fixed electricity rate in this project. Rather, we use PJM’s dynamic locational marginal prices (LMPs) as the “local utility electricity rate”. This is because the LMP, which changes hourly, reflects the actual cost of energy generation. Since we want to respect utility supply preferences, it is necessary to use a model that achieves this aim.

A simplified layout of the testbed showing generators, loads, and relationships between energy produced and energy consumed is illustrated in Figure 5.

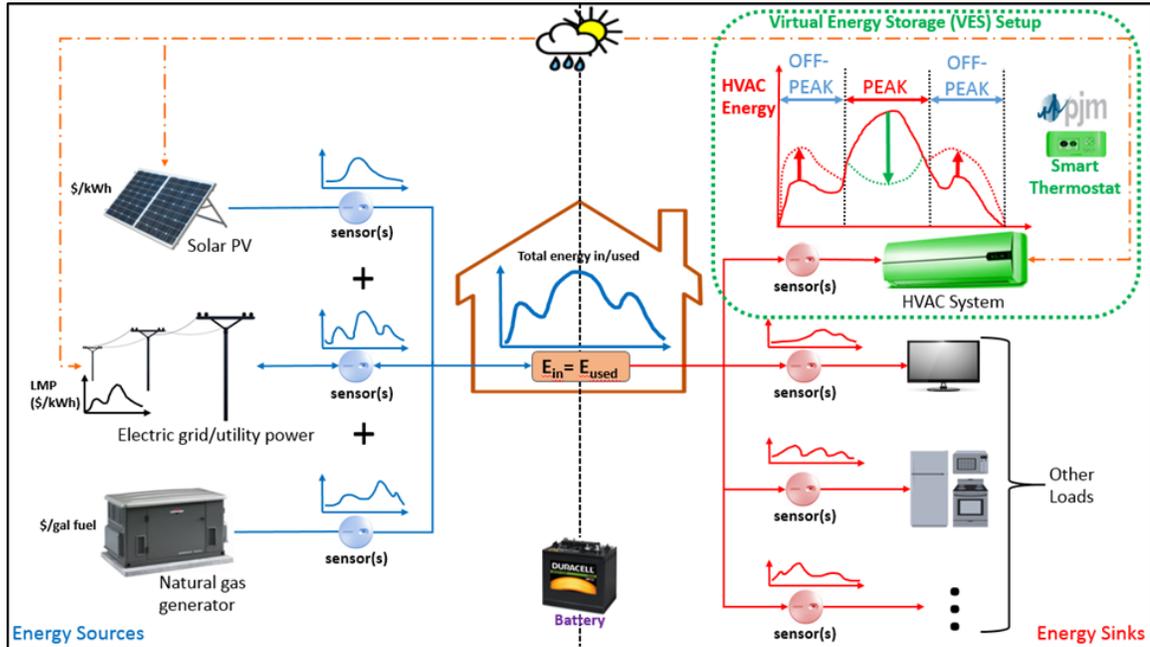


Figure 5. Residential microgrid testbed setup.

Previous researchers [50, 51, 52, 53] have equipped the home with a solar photovoltaic (PV) array—fitted out with net metering—and a natural gas generator. The PV system takes precedence of generation in the sense that it is always put to use whenever there is solar power available [51]. In other words, the two modes of power generation are either: grid-tied coupled with solar or natural gas generation coupled with solar. The natural gas generator is only used (in island mode) when its generation price is less than the local distribution company’s electricity rate. Nevertheless, such a situation hardly ever occurs for our testbed. So this scenario can, in some sense, be viewed as hypothetical.

The testbed, depicted in Figure 5, is divided (hypothetically) into two main functional parts: an area for energy sources and one for energy sinks (loads). Previous researchers have connected power sensors to some of these loads [51, 53]. In addition to the power sensors, the researchers in [50, 51, 52, 53] also installed a smart thermostat—Ecobee Smart-Si—in the testbed.

The mechanisms which comprise virtual energy storage (VES) are marked out by the green rounded rectangle in Figure 5. Within this rounded rectangle, we define VES in general: the process of increasing the HVAC energy during off-peak periods by cooling or heating the house so that the latent heat that is generated will lead to decreased HVAC energy use during peak periods.

For VES to make sense, the decreased HVAC energy usage in peak should correspond to decreased overall HVAC use. In other words, the virtual “charging” by preheating (or precooling) should not take up more energy than it displaces in peak. This thesis will quantify these peak and off-peak energy use dynamics.

Within the green rounded rectangle, it is implied that the smart thermostat and the price signals from PJM play important roles in our load management framework. The data obtained from this smart thermostat, combined with price signals we obtain from PJM, allows us to employ the HVAC system—the largest consumer of energy in the home [17]—as an energy storage device.

Typically, the way people try to mitigate the large HVAC energy use is by purchasing a battery⁹ and then charging it during off-peak LMP hours which usually coincide with the times when the HVAC is being used the least. They then use the battery¹⁰ to supply power to the HVAC system when electricity is most expensive—that is, during peak LMP hours. The problem with home batteries, however, is that they are expensive, costing anywhere from \$1500 to \$23000 (see Table 3 [55]).

In this project, we will try to see whether a smart thermostat which only costs a few hundred dollars can achieve cost and energy savings comparable to those achieved by home batteries. (For our experiments, we use the Ecobee Smart Si thermostat which costs about \$349, including installation [56, 57]).

3.2 Energy and Cost Quantification¹¹

We are interested in cost savings from the consumer perspective for reasons detailed in Section 1.1. In particular, we consider the scenario where the only available

⁹ Our testbed is not equipped with a battery. However, in order to compare cost-effectiveness of VES to BES, we only need to know the ideal capabilities of batteries currently on the market. Such information is publicly available online (See Table 3).

¹⁰ The battery shown in Figure 5 is placed on the (hypothetical) demarcation of the testbed because it takes on a dual role: it is a source when supplying energy to other appliances and a sink when it is being charged.

¹¹ Some of the work presented in this Section was published in the Proceedings of the 2017 IEEE Sensors Applications Symposium: P. Asare, C. Ononuju and P. M. Jansson, "Preliminary Quantitative Evaluation of Residential Virtual Energy Storage Using Power Sensing," in *Sensors Applications Symposium*, Glassboro, 2017. A few items, however, have been updated since the Symposium.

generation source is the grid. This is because any local (residential) generation sources such as PV, wind, and storage mechanisms essentially act to shift load from the grid, thereby lowering the customer's cost of grid use. Our developments will focus on using storage mechanisms to shift load from the grid, though translation to approaches like local intermittent generation should not be difficult.

We focus exclusively on storage mechanisms because, even though intermittent generation sources can augment power supply to storage mechanisms, explicitly considering these generators would only lead to increasing the cost of equipment, by the same amount, for both BES and VES. As such, considering local intermittent generation does not influence the relative comparison of VES cost-effectiveness to that of BES.

We will mostly consider energy consumed by the HVAC system since this is the largest consumer of energy in the residential home [17] and is the one we would like to control energy usage on. However, much of our developments can be broadly applied to overall energy consumption or other subsets thereof.

We have developed a general energy-cost model that defines how cost savings can be computed from our physical experimental data. We detail the general energy-cost model in Section 3.2.1 and we examine how this energy-cost model relates to BES (in Subsection 3.2.2) and VES (in Subsection 3.2.3).

3.2.1 General Energy-Cost Model

Figure 6 shows energy use from the grid in a baseline case and with load shifting using a storage mechanism. The motivation for load shifting is that the period of high energy usage tends to coincide with when energy generation is most expensive (as reflected by LMP). This period is termed the peak period (T_p). We explain how this is defined in the Chapter 4 where we describe our experiments. But for the purposes of the rest of this discussion, simply knowing that T_p is some well-defined time interval suffices. We save costs by reducing the energy used from the grid (however, intermittent sources may also provide some energy) during this period.

Storage mechanisms help by shifting the HVAC peak load from the grid to elsewhere in space and in time. This load shifting means less energy is being used during the peak period (from the grid perspective) and hence the utility charges the consumer less during that period for the lesser energy demanded.

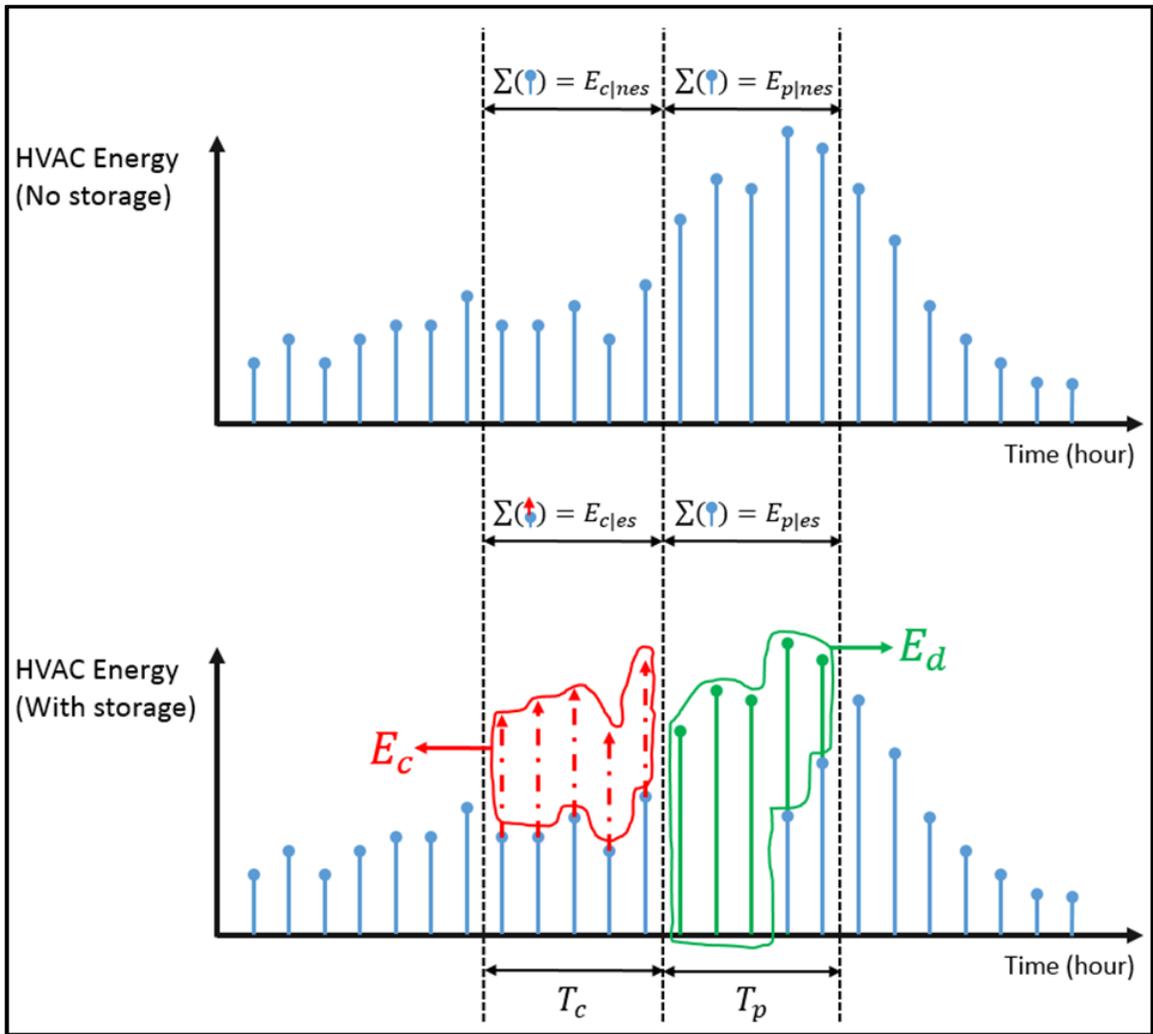


Figure 6. Energy model for general storage based on HVAC grid energy consumption.

The top graph shows HVAC consumption without storage and the bottom graph shows how storage affects HVAC consumption.

The difference between energy used in the non-storage case and in the storage case, during the peak period, is called the displaced energy (E_d)

$$E_d = E_{p|nes} - E_{p|es} \quad (1)$$

In Equation (1), $E_{p|es}$ indicates the energy storage case, $E_{p|nes}$ indicates the case where no energy is used, and the energies reference the peak period because this is the period in which we focus on saving energy. The term “displaced” is used instead of “discharged” because, for comparison of storage mechanisms, it is difficult to delineate how much of this difference in energy use was directly from the storage mechanism itself and how much was due to other factors such as favorable weather conditions, especially since we are focusing on the HVAC—a load that is highly dependent on weather.

Storage comes at a cost because we must put energy into the storage mechanism earlier in order to be able to use the energy stored at a later time. During the charging period (T_c), more energy is used than would be used otherwise. This extra energy factors into the cost of using the storage mechanism. The extra energy is called the charge energy (E_c), defined by

$$E_c = E_{c|es} - E_{c|nes} \quad (2)$$

The cost of energy in the LMP-based approach varies hourly, hence to get the monetary equivalent (cost) of any of the energies E_d or E_c , we would have to look at the energy each hour over the periods when those aggregate energy values are obtained. The cost of either E_d or E_c would then be

$$C(E_*) = \sum_{t_k \in T_*} E_{*|t_k} \cdot LMP_{t_k} \quad (3)$$

where T_* is the period under consideration, LMP_{t_k} is the LMP value for the hour t_k in that period, and $E_{*|t_k}$ is the corresponding charge or displaced energy in that hour. Equation (3) can be visualized more clearly using Figure 7.

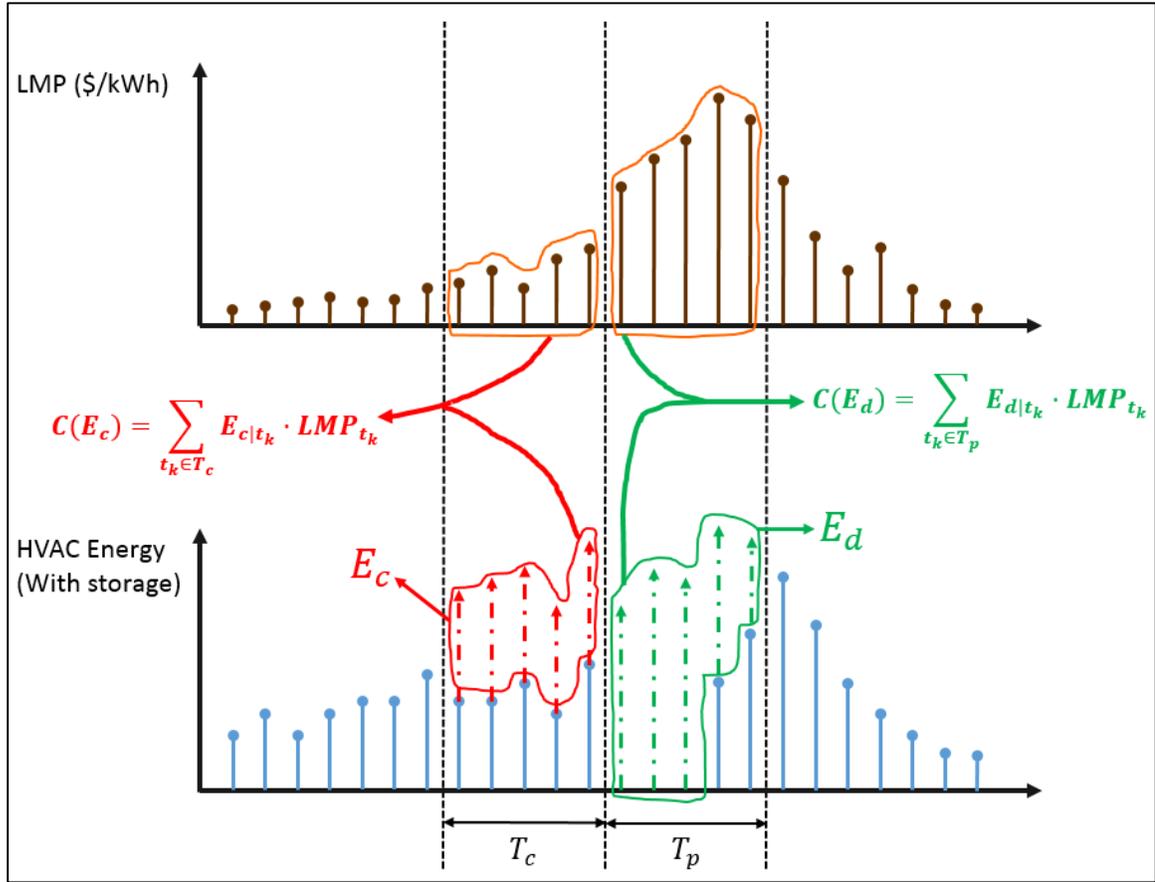


Figure 7. Visualization of cost equation (Equation (3)).

Equation (3) is compatible with our modeling framework (details in Chapter 5) wherein we simulate the HVAC energy use for VES and BES based on the thermal model of our home. However, when we conduct virtual storage tests in a physical experimental

fashion (procedure detailed in Chapter 4), computing hourly versions of E_d and E_c becomes cumbersome. This is because, to calculate E_d and E_c for VES experimental days, we need to identify baseline days that have temperature profiles similar to those of the VES days. Consequently, the charge periods and peak periods for VES days may not necessarily line up with those of their corresponding baseline days. We can remedy this issue by modifying the cost equation (i.e. Equation (3)) to use the average LMP in the period being considered.

$$C(E_*) = \overline{LMP}_* \cdot \sum_{t_k \in T_*} E_{*|t_k} \quad (4)$$

The resulting cost in Equation (4) is not exactly the same as using the hourly LMP values, but is a close enough approximation.

The amount saved by using a particular storage approach is represented by cost of E_d . This savings comes at a cost. One part of that cost is the operational cost of running the storage mechanism (i.e. the cost of the energy one must store to use later— E_c). The other part is the daily capital cost, which is the total cost of purchase and installation of necessary equipment and materials (including possible modifications to the house) for the particular storage mechanism amortized yearly over its expected lifetime, given by

$$C(\text{equipment}) = \frac{C(\text{purchase} + \text{installation})}{\overline{\text{Lifetime}}} \quad (5)$$

The daily effective savings, $C(ES)$, from using storage is the difference between the savings due to energy displaced and the total cost of using the mechanism.

$$C(ES) = C(E_d) - (C(E_c) + C(\text{equipment})) \quad (6)$$

A positive $C(ES)$ value indicates a cost-effective mechanism (i.e. overall savings for the customer despite the investment and operational costs). A zero value is still cost-effective since load shifting has benefits for utilities and generators which, in the long run, can reduce per unit cost for the consumer and hence lower total cost. Some negative values may be cost-effective in the long term for the same reason. We can use this model to compare the relative cost-effectiveness of any two storage approaches.

3.2.2 BES Special Considerations

In this case, the HVAC uses the same amount of energy as it would have used in the case where no energy storage was employed (i.e. it behaves the same way). The extra energy drawn from the grid during T_c is due to the energy needed to charge the battery, and the lower energy drawn from the grid during T_p is because part of the HVAC energy is supplied by the battery in the peak period.

In practice, we can measure E_c and E_d for the battery directly by instrumenting it with power sensors. The battery is used (at least in our scenario) to offset power that would otherwise be used from the grid by the HVAC. Thus, using the battery does not change the HVAC behavior. This is partly why E_c and E_d are directly measurable. The other reason is that the battery is a physically-separate storage device that takes in and discharges energy in electrical form which we can directly measure.

For BES, E_d is still considered the displaced energy because the HVAC energy usage during the peak period is partly dictated by other physical conditions (weather,

insulation, etc.). Hence, even though energy may be readily available in the battery, whether that energy is used or not depends on whether the HVAC needs to cool or heat the house in the peak period.

3.2.3 VES Special Considerations

In this case, the storage is achieved by modulating the behavior of the HVAC. This means the energy used by the HVAC under VES is different from what would be used in the case where no energy storage is employed. The extra energy drawn from the grid during the charge period, T_c , is due to the energy needed to precool or preheat the house, and the lower energy drawn from the grid during the peak period, T_p , is due to the greater periods of inactivity of the HVAC since temperature is partly maintained by the latent heat or coolness of the house due to precooling or preheating.

Since VES requires changes in behavior of the HVAC itself, and is not a separate physical storage device, E_c and E_d cannot be measured directly. In practice, we would have to actually measure $E_{c|nes}$, $E_{p|nes}$, $E_{c|ves}$, and $E_{p|ves}$ to compute E_c and E_d . Only one set of $E_{c|*}$ and $E_{p|*}$ can be measured for a given day. This means for any day on which VES is used, an equivalent day (with similar physical conditions such as outdoor temperature) needs to be found for purposes of computing these values if this is done in physical experimental fashion. An alternative would be to use simulation, which would be capable of providing a much better equivalent day.

Therefore, in order to generate more accurate VES data that will guarantee repeatable experiments and accommodate changing parameters, while allowing us perform a myriad of analyses on different days, we need to develop a model of the home.

3.3 Related Work

In 1991, Kenneth Wacks laid out a visionary plan for load management by home automation [58]. One could say that through this paper [58], Wacks motivated residential cyber-physical systems, though the devices to enable this vision did not exist at the time.

According to Wacks, for any distributed load control to be effective, there needs to be: real-time access to information from the utility, computer intelligence that can both interpret utility data and determine consumer preferences while communicating with appliances in the home [58]. Similar to Wacks, Marchiori et al. [59] voice the need for adaptive and intelligent approaches for using residential energy more efficiently.

Cyber-physical systems have been employed in a variety of ways in residential settings. Many optimization algorithms have been developed by researchers who approach the load management problem from different viewpoints. Researchers have looked at occupancy sensing as a means of load management—the basic premise being saving energy when rooms are unoccupied. In addition to occupancy sensing, model predictive control (MPC) and other control methods have been examined.

Occupancy sensing has been explored by Lu et al. [60] who use sensing technology to detect occupancy and sleep patterns in a dwelling to determine how these patterns save energy. They obtain a 28% savings through their approach, compared to a baseline scenario. Lu et al. [60] posit that energy conservation could be increased by automatically creating a thermostat setback plan for a home by studying historic user occupancy data. Their technique does not change the setback temperature of the user, rather it decides when a predetermined setting should come into effect [60].

Whitehouse et al. [61] advocate for re-conceptualizing the way buildings are designed in order to make them more suitable for occupancy sensing. Erickson et al. [62], use occupancy data collected via camera sensor networks to predict a 14% energy savings on a university building.

Beltran and Cerpa [63] use MPC and a blended Markov chain (BMC) model to estimate the thermal load and occupancy of a university building in order to better control the HVAC system; they simulated 15.5% expected savings in the winter with 9.4% in the summer.

Occupancy sensing is a popular technique in the load management optimization process. However, its major drawback is variability of human behavior. Due to this unpredictability, unoccupied periods may not necessarily occur during peak demand; and thus may not coincide with the opportunity to reduce costs. For instance, if children are at home all day during the summer or winter holidays, the HVAC system that relies on

occupancy sensing is always on and the utility requirements are not met. Thus, occupancy sensing alone is not enough. It needs to be coupled with different schemes to meet the utility-required demand during both peak and non-peak periods. By so doing, the user can become more energy-responsible to themselves and the utility.

Jia et al. [64] evaluate home energy management from the lens of a multi-time scale and multi-stage stochastic optimization framework for control of: an HVAC system, an electric vehicle, and deferrable loads i.e. loads whose time of use can be moved. The underlying principle for this work is MPC. In their work, Jia et al. reduced the large optimization problem into smaller, tractable sub-problems. Unlike many load management research projects, the work of Jia et al. [64] considers the trade-off between comfort and energy savings. One drawback of their work, however, is that data was not collected from a live house but rather simulated.

4 Physical Experiments, Analyses, and Results¹²

Our residential microgrid consistently collects data on power usage in the home using a variety of current transformers coupled to a central device.

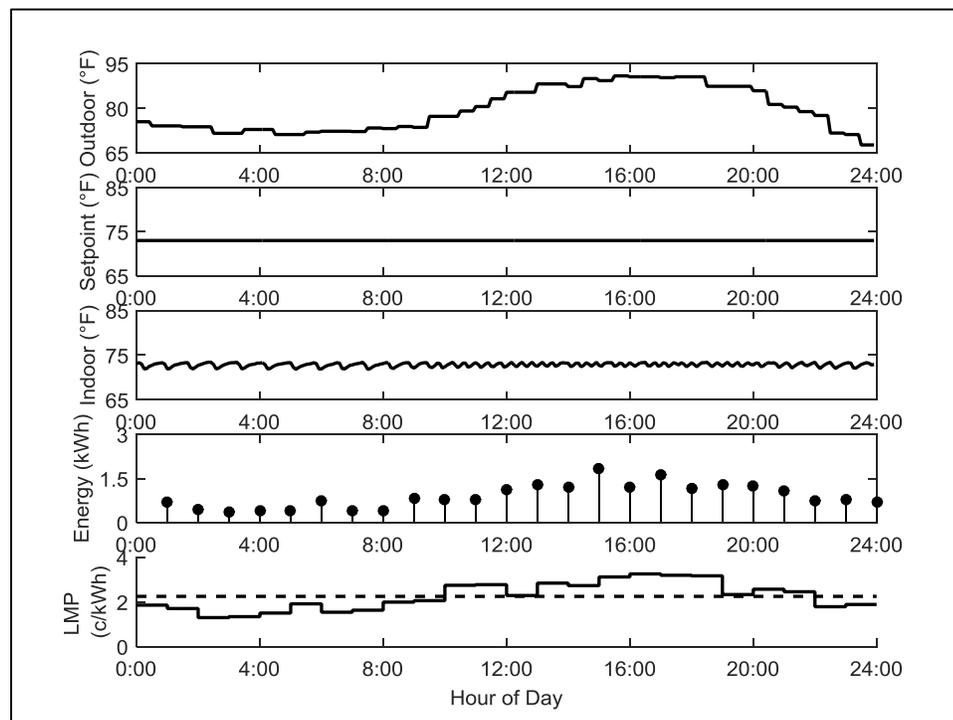


Figure 8. Data from microgrid for example day when no energy storage was used.

¹² The work presented in this Chapter was published in the Proceedings of the 2017 IEEE Sensors Applications Symposium: P. Asare, C. Ononuju and P. M. Jansson, "Preliminary Quantitative Evaluation of Residential Virtual Energy Storage Using Power Sensing," in *Sensors Applications Symposium*, Glassboro, 2017.

More details on this system can be found in [53]. The HVAC system is usually set to a consistent setpoint and no energy savings strategy is typically employed by the residents. Data from an example day without any virtual energy storage employed is shown in Figure 8.

4.1 VES Experiments

In summer 2016, we ran a number of virtual energy storage experiments on 8 different days. Each experiment involved precooling the house by setting the setpoint of the HVAC to about 68 °F (this is within the comfort preferences of the residents) for a period of time outside the anticipated peak LMP period, and then returning the setpoint back to the normal temperature of 73 °F. Data for an example day on which a virtual energy storage experiment was conducted is shown in Figure 9. Temperature data is collected using the Ecobee Smart Si thermostat, equipped with an online portal from where data is downloaded. The HVAC energy data is collected from power sensors, and the real-time LMP data is obtained from PJM’s website [65].

We used a simple approach when precooling—we manually observed expected temperatures and picked times where LMPs were typically out of peak for precooling. More sophisticated precooling is possible as we elaborate upon in Section 7.1. Since this was a preliminary evaluation conducted to give us a sense of direction for building our model, and the realities of physical experiments of this type is that we have no control over

the conditions, we had to go with a simple rule of thumb approach to obtain some data that would still provide us with insights on virtual energy storage.

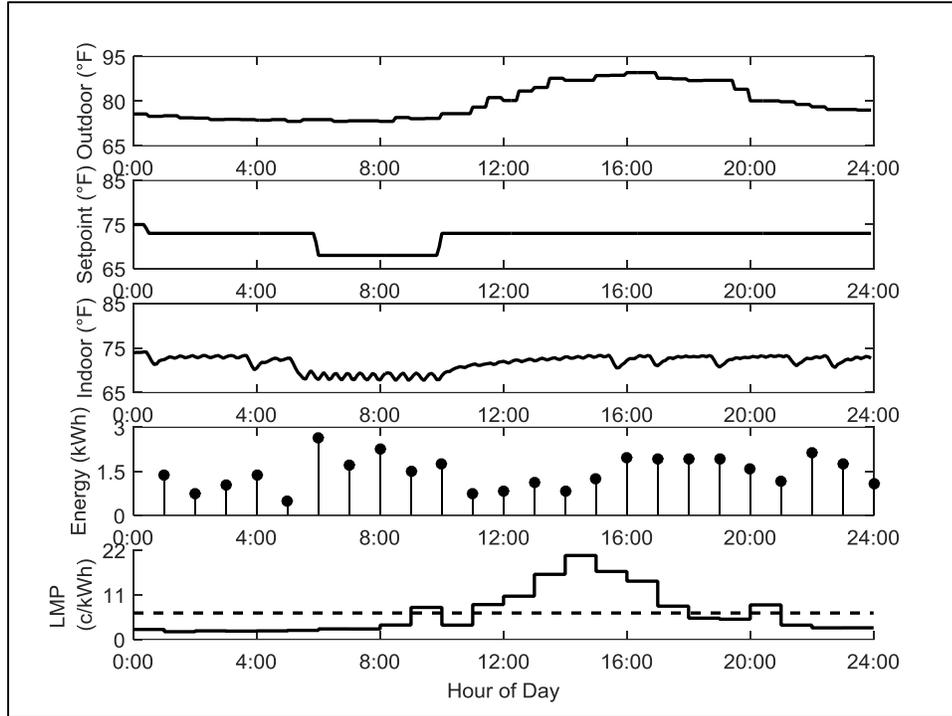


Figure 9. Data from microgrid for example day when virtual energy storage was used.

4.2 Data Analysis and Cost-Savings Computations

For each of the 8 days, we obtained E_c and E_d by identifying an equivalent day where no energy storage was used—based on the outside temperature profiles for both days—and computing $E_{c|nes}$, $E_{p|nes}$, $E_{c|ves}$, and $E_{p|ves}$ from the HVAC power data. T_p (essential to finding $E_{p|nes}$ and $E_{p|ves}$) was defined as the time when the LMP was above

the peak threshold. The peak threshold (dotted lines in LMP plots of Figure 8 and Figure 9) is the value of the LMP that is one-half a standard deviation greater than the average LMP computed from only the positive LMP values for that day

$$LMP_{threshold} = Avg(LMP) + \frac{1}{2} Stdev(LMP), \quad (7)$$

where $LMP_i \in LMP \mid LMP_i > 0$

The monetary costs for E_c and E_d are computed using the average LMP method in Equation (4).

For the computations, we use the average LMP of the virtual storage day because that is the day for which we are actually carrying out the energy savings strategy. Although the baseline day has its own LMP value, this baseline day is only used as a reference in order to enable us compute E_c and E_d .

The capital cost for VES is based on the estimated cost of purchase and installation of about \$349 for the Ecobee smart thermostat system [56, 57]—which we use to monitor and control the HVAC—and an expected lifetime of 3 years based on its warranty [56]. This VES cost is inexpensive compared to the estimated purchase and installation costs of the BES systems which we compare it to. These BES systems cost between \$6500 and \$7700 (See Table 1)¹³.

¹³ We used the batteries in Table 1 for our physical experiments but, for our simulations, we updated our battery selection as depicted in Table 2.

For our experiments, the house’s quality of insulation was maintained i.e. we used the testbed as is—without modifying the house any more than the researchers in [3, 4] had. For this reason, insulation costs are not considered capital costs in our specific case. In other cases, such consideration may be necessary and insulation would have to be factored in. We even see the potential for insulation with active VES to be its own approach to improving load management since the passive VES we mention in our insights into virtual storage (Section 7.1) can be augmented by this insulation. In general we do not view these mechanisms (VES, BES, insulation, etc.) as mutually exclusive. Any combination of them can be considered in the model and applied as a strategy if that combination is found to be cost-effective.

As mentioned earlier, a key part of this work is comparing the cost-effectiveness of VES to the more traditional and widely-advocated BES. To do this, for each day, we looked for a battery (either grid-synchronous or island-mode-only) that had a capacity as close as possible to the E_d achieved by VES. With this, we then computed the cost savings for that battery using the following simplifying assumptions: the battery is used to displace an equal amount of energy as the VES mechanism i.e. $E_{d|bes} = E_{d|ves}$; T_c is the same for BES and VES allowing us to use the same average LMP for both mechanisms; and $E_c = E_d$, implying a 100% efficient battery and also implying that any energy used from the battery during T_p was previously put into the battery during T_c . In other words, that the battery was charged just the right amount of time such that $E_{c|bes}$ would equal $E_{d|bes}$. We computed

$C(\text{equipment})$ for the battery based on its estimated purchase and installation cost, as well as its expected lifetime based on its warranty.

4.3 Results

Figure 10 (obtained from data in Table 1) shows the results of the cost savings for 6 out of the 8 virtual storage days.

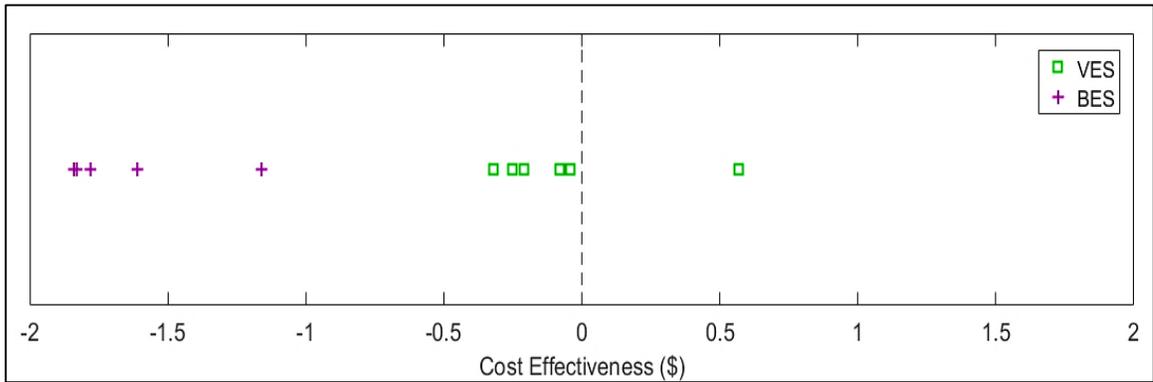


Figure 10. Results from VES experiments and cost-effectiveness¹⁴ comparison to equivalent BES for days in summer 2016.

Figure 10 does not show 2 of the virtual storage days because, for those days, we actually had increased energy use in T_p , resulting in negative E_d which is undesirable. These negative E_d values occurred because on those days, we precooled too late, causing us to

¹⁴ Cost-effectiveness here is per day. However, in our simulations (Chapter 6), the cost-effectiveness is computed on a yearly basis.

charge the house during some parts of the peak period. This meant a greater energy use than on their comparable baseline days—an unwanted scenario.

We learned from these negative E_d values the importance of precooling right before peak—not too early so that energy is not dissipated before its intended time of use (i.e. the peak period), and not during the peak period.

Table 1. Results from VES Experiments and Cost-Effectiveness Comparison to Equivalent BES for Days in Summer 2016.

VES Day	Eqv. NES Day	E_d kWh	E_c kWh	Equivalent BES	BES Capacity kWh	BES Expected Lifetime (years)	BES Equip. Cost (\$)	$C(BES)$ (\$)	$C(VES)$ (\$)
8/10	8/14	10.9	1.7	Tesla Powerwall 2 [66]	13.5	10	6500	-1.16	0.57
8/11	8/14	3.4	3.5	Sonnen-batterie Eco-compact [67]	4.0	10	7700	-1.83	-0.04
8/31	8/30	8.1	4.9	Tesla Powerwall 2	13.5	10	6500	-1.61	-0.08
9/1	8/30	5.1	5.4	LG Chem RESU 6.4EX [68, 69, 70]	6.4	10	6750	-1.84	-0.32
9/2	9/3	9.1	3.5	Tesla Powerwall 2	13.5	10	6500	-1.78	-0.21
9/5	9/6	4.1	3.8	LG Chem RESU 6.4EX	6.4	10	6750	-1.78	-0.25

Overall, we found that VES tends to be more cost-effective than BES and in some cases by an order of magnitude. Except in one VES case, both approaches had negative cost-effectiveness. For the VES case, this is due to the short expected lifetime of the Ecobee system as well as its inexpensive purchase and installation cost. These preliminary results

give us added motivation for building a model to simulate the house behavior. This model will help in further studies of storage mechanisms and their implications for residential load management.

We expect that with such a model, we can develop better load management strategies based on VES, gain better insights into its cost-effectiveness compared to BES, and provide tools that can help with reducing cost of these technologies to make them more cost-effective, or that will inform policy discussions around incentivizing investment in these technologies for the benefit of the entire energy industry.

5 Modeling the Cyber-Physical Home

The testbed described in Chapter 3 can be used in two major ways:

- i. As a data collection platform
- ii. As an adaptive cyber-physical system

For us to use it as an adaptive cyber-physical system, we need the ability to explore various load management strategies. As seen from Chapter 4, physical experiments make it difficult to compare multiple strategies, in an “apples-to-apples” fashion for the same day. Remember that for each of the 8 days in the physical experiments (Section 4.3) we obtained E_c and E_d by identifying an equivalent day where no energy storage was used. We then computed the virtual storage charge and displaced energies by comparing the virtual storage day to the somewhat equivalent baseline day.

In a physical experiment, once virtual storage was conducted on the house, and we collected the data, that was the end of the experimental process—we had no idea what might have happened if we had tried to precool in a different way. Thus, we find it necessary to build a simulation framework—for modeling a house that can potentially act as a cyber-physical system. As discussed in Chapter 3, our approach is a cyber-physical systems one because it uses data obtained from wireless sensing technology to adapt to changing environmental conditions as well as energy prices [45]. Figure 11 illustrates the basic idea behind this operation of the home.

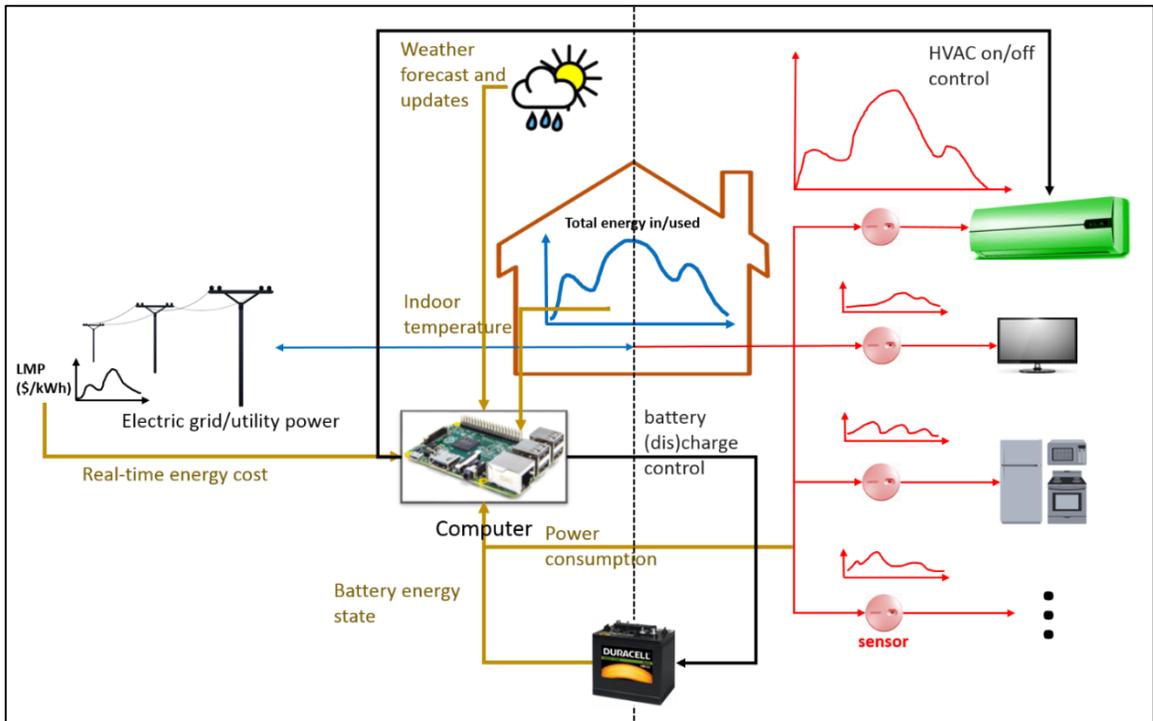


Figure 11. Testbed as a cyber-physical system with information flow and control indicated.

5.1 General Modeling Framework

The aim of our model is to help quantify VES in both energy and monetary terms, test and validate home energy optimization strategies of varying complexities, compare the energy and cost savings of VES to those of BES, and motivate further research and other applications while doing all these in a scalable fashion. The goal of this work is not necessarily to determine the best VES and/or BES algorithm but to create a platform

through which this determination can be made. Consequently, our model serves as a research tool.

We build our modeling framework in MATLAB and Simulink and we employ a modular approach comprising of the four black boxes outlined in Figure 12. Each black box performs specific functions which we detail in Sections 5.2 to 5.5.

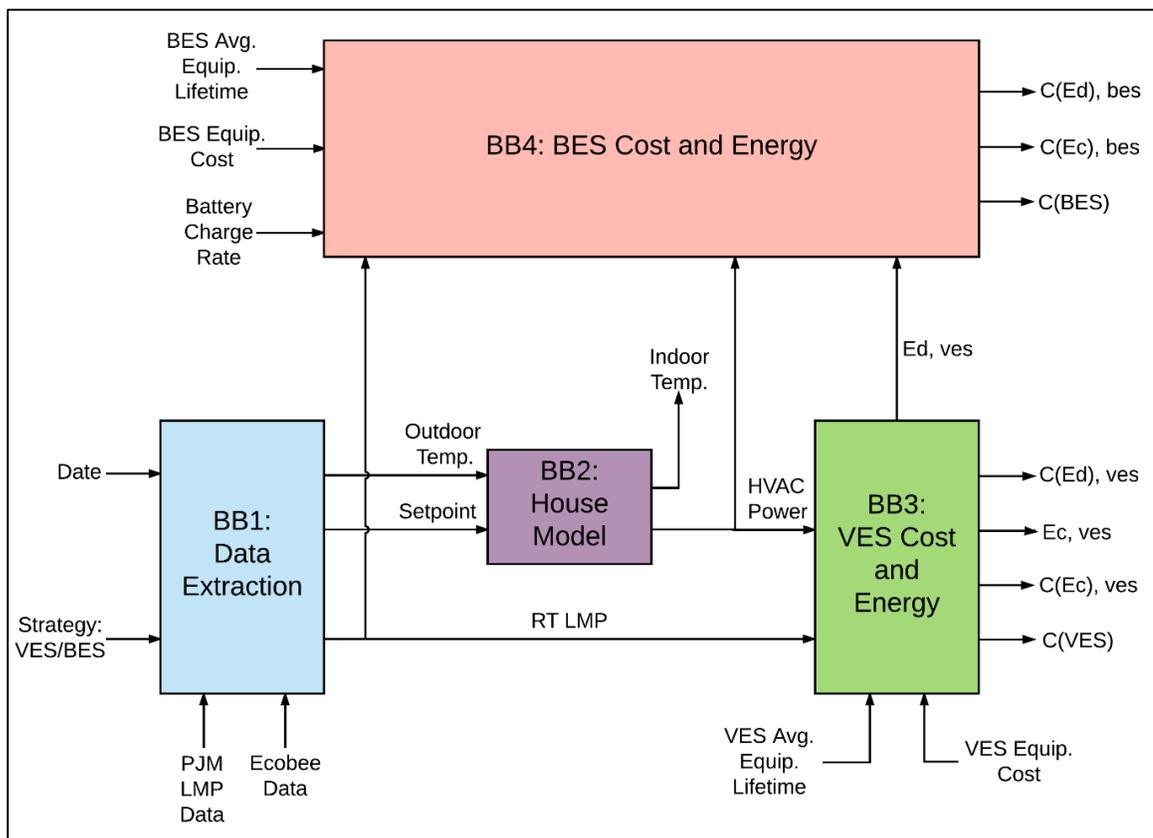


Figure 12. General load management framework.

5.2 Black Box 1: Data Extraction

Simulations in our model run on the recorded actual outdoor temperature for previous days of interest as well the recorded real-time LMP data for such days. BB1 takes in the archived/recorded real-time LMP and Ecobee Smart Si data files from our testbed. The user specifies the date¹⁵ and the type of storage being employed—either VES or BES—and the black box returns the outdoor temperature recorded by the Ecobee Smart Si thermostat, the HVAC temperature setpoint profile for that day (which it generates automatically based on the strategy chosen), and the hourly LMP data for the Citizens’ Electric node, in the PPL zone, of PJM’s network.

The residential testbed is divided into two levels: upstairs and downstairs. For ease of analysis, we only use the data from the downstairs thermostat in this our proof-of-concept framework. In the future, the framework may be expanded to include the upstairs section of the house in order to get a more detailed and holistic understanding of our specific testbed. Nevertheless, to acquire a fundamental understanding that lets us grasp the implications of virtual energy storage on individual as well as global levels, we do not

¹⁵ Our analysis is focused on spring and summer days in 2016, specifically: June 1, 2016 to August 31, 2016. On these days, the HVAC was programmed to cool the house. It is assumed that similar analyses can be carried out on days when the HVAC is set to heat the house.

need to include both sections of the house. It is our understanding that the implications of virtual energy storage will be the same for both sections of the house.

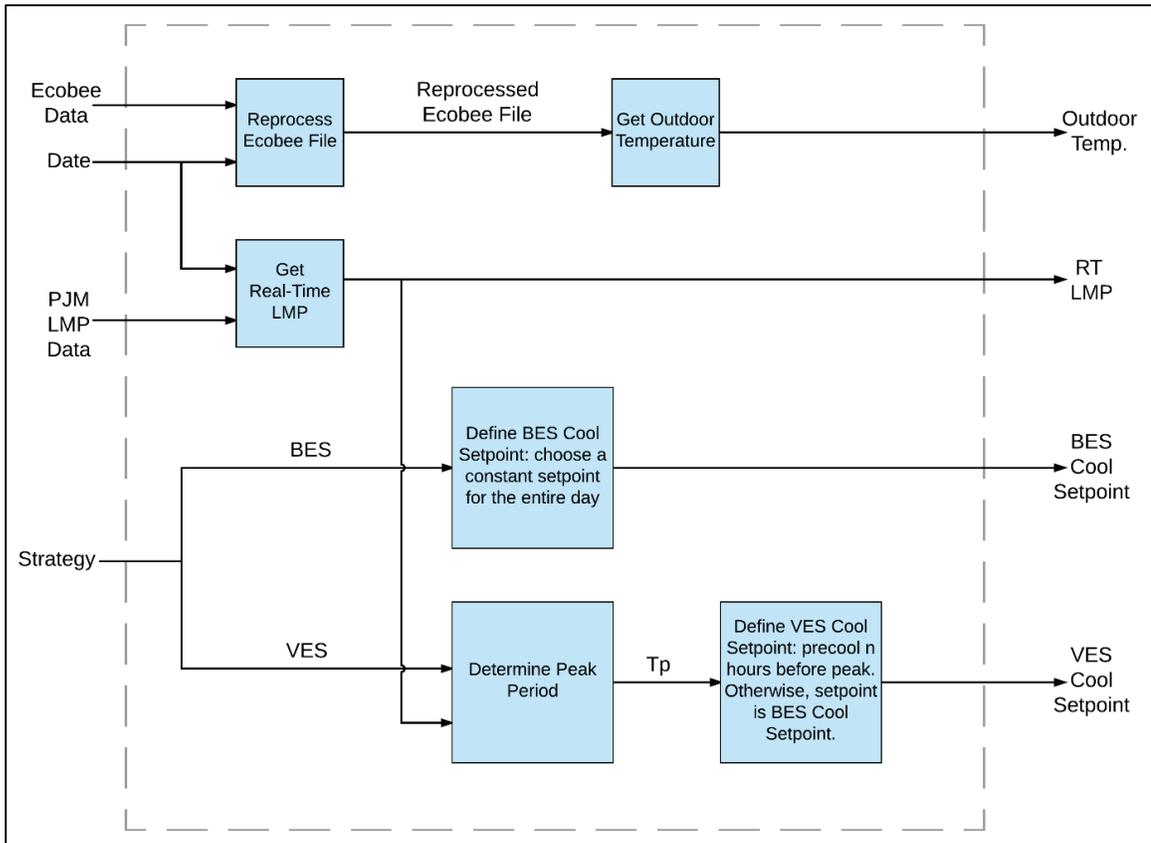


Figure 13. BB1: Data Extraction (detailed).

The “Data Extraction” black box is expressed in more detail in Figure 13. In this black box, the strategy chosen will determine the setpoint. If BES is selected, then a constant setpoint is maintained throughout the day. This is because the battery does not change the HVAC behavior; the battery’s purpose is to reduce the amount of energy drawn

from the grid during peak periods. Thus, for BES, the HVAC behaves the same as it would in the NES case i.e. the case where no energy storage strategy is employed.

On the other hand, if VES is selected, the setpoint is kept at a temperature lower than the NES (baseline) temperature, for a certain amount of time before peak. This amount of time is what we call the charge period—the period when we charge the house by precooling. Outside the charge period, the temperature is set at the regular baseline temperature.

Therefore, the thermostat settings for BES are kept the same as in the NES case. It is only when conducting VES that the framework needs to actively manipulate the thermostat settings.

5.3 Black Box 2: House Model

This black box captures (approximately) the thermal behavior of the house. It is currently implemented as a Simulink model. There are two parts to this model. The first is the natural thermal model of the house that takes the HVAC behavior into consideration. The second part is a model of the HVAC behavior which includes calculations of the power used by the HVAC (based on its behavior).

5.3.1 Thermal Model (with HVAC) and Model Validation

Our model of the house is of the form:

$$\frac{dT_{in}(t)}{dt} = \alpha_1(T_{out}(t) - T_{in}(t)) + \alpha_2\frac{dT_{out}(t)}{dt} + \alpha_3\beta_{HVAC}(t) \quad (8)$$

The terms associated with α_1 and α_2 capture the behavior of the indoor temperature of the house when the HVAC is off (where it only reacts to the outdoor temperature). The coefficients, α_1 and α_2 , are proxies for the insulation as well as temperature response properties of the house. The value α_3 represents the effect of the HVAC on the indoor temperature and $\beta_{HVAC}(t)$ is a Boolean variable that indicates whether the HVAC is on or off at a particular point in time.

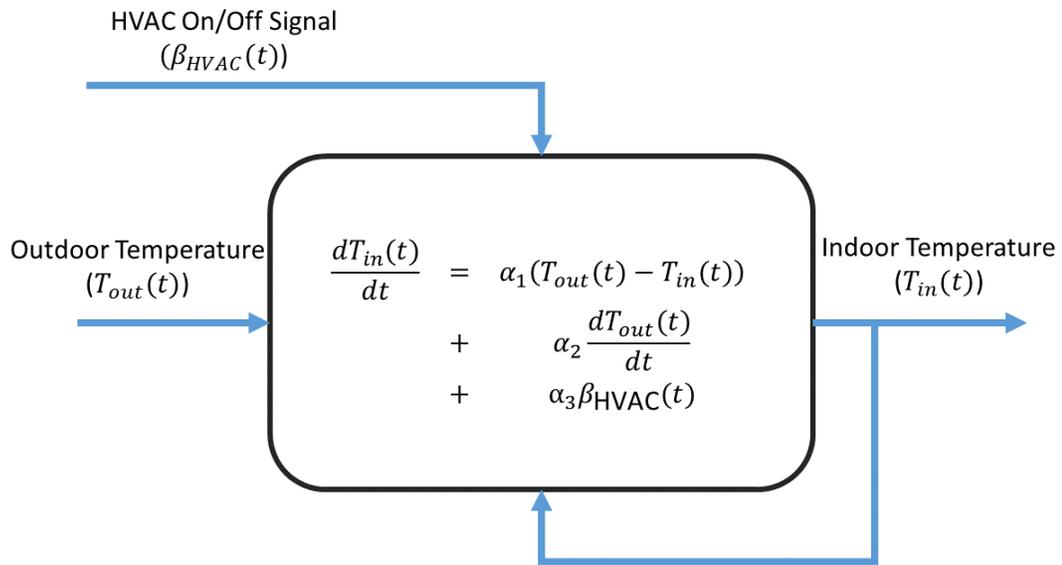


Figure 14. Visual representation of the house thermal model.

The model can be represented visually as shown in Figure 14, where the house model takes in the outdoor temperature as well as the HVAC on/off signal and produces the corresponding indoor temperature over time (which is fed back into to the model for the model to work).

The model parameters $(\alpha_1, \alpha_2, \alpha_3)$ were determined from data collected on the testbed (in spring and summer 2016 for months of June, July, and August) through a combination of multiple regressions followed by manual tweaks to the values to ensure a better fit.

To determine α_1 and α_2 , we looked at contiguous data when the HVAC was off. There were days in June, July, and August 2016 where we could have set up the house to run the “HVAC-off” scenario as the premises was unoccupied for a few days, but since we could only get access to control the house later in that period, we had to rely on previously collected data and extract as many samples of contiguous data as we could.

To determine α_3 , we looked at periods where the HVAC was off for a brief interval that was followed by the HVAC being turned on. α_3 roughly captures the slope representing the change in indoor temperature due to HVAC action. The values we arrived at were: $\alpha_1 = 2 \times 10^{-5}$, $\alpha_2 = 0.9$, and $\alpha_3 = -7.5 \times 10^{-4}$.

To validate our thermal model, we ran the archived outdoor temperature and HVAC setpoint data through it. We then compared the indoor temperature that the model produced to the archived indoor temperature for that day. We computed the root mean-squared error

(RMSE) of these indoor temperature data for each day we ran (we ran all the days in June, July, and August (92 days)). The RMSEs for different combinations of test data are shown in Figure 15.

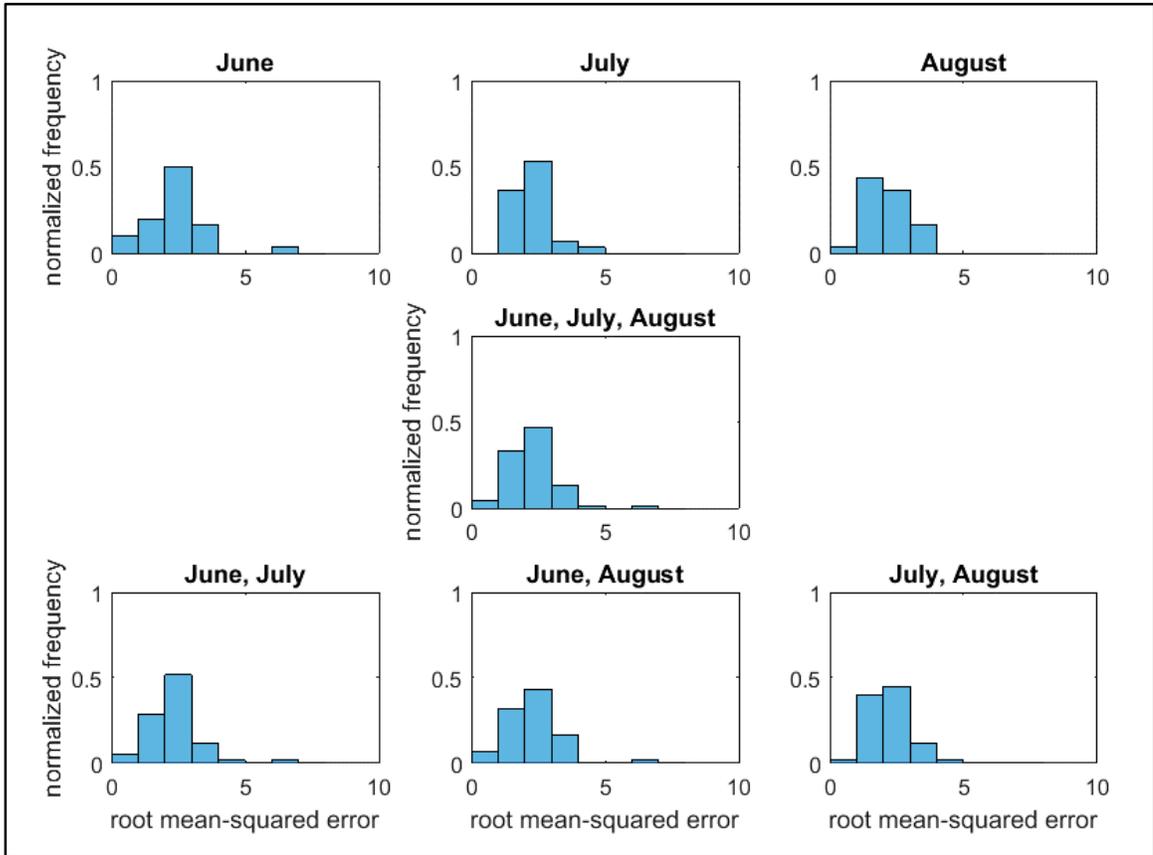


Figure 15. Root mean-squared error of model output to recorded data.

Overall, the RMSE is centered between 2 and 3 °F with some variation between the days. We found this to be good enough for our purposes since our aim was to compare VES and BES on the same set of conditions, which this model gives us, though the realism with respect how accurately it models our particular testbed is limited.

5.3.2 HVAC Behavior and Power Model

The model of the HVAC system reacts to both the HVAC setpoint and the indoor temperature to determine whether or not to turn on the HVAC cooling mechanism. We modeled a simple thermostat with hysteresis where cooling is carried out if the indoor temperature gets higher than some threshold above the HVAC setpoint. Similarly, the HVAC is turned off if the indoor temperature gets lower than a threshold below the HVAC setpoint. More complex models can easily be provided in future projects that leverage our work.

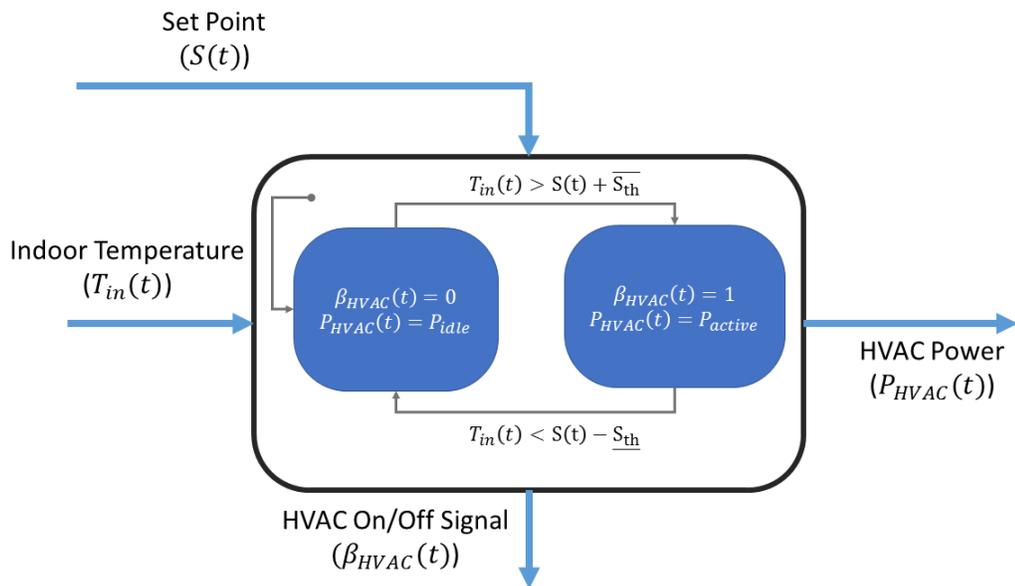


Figure 16. Hybrid system model of HVAC behavior and power consumption.

Also, since we are interested in the power consumption of the HVAC, the model also outputs the HVAC power in each state. When we say the HVAC is “off”, we actually

mean it is in some idle state drawing idle power. This HVAC behavior and power can be captured in the simple hybrid system model [71, 72] shown in Figure 16. We determined the values for P_{idle} and P_{active} from analysis of the HVAC power data recorded by the testbed and found P_{idle} to be around 0.1 kW and P_{active} to be around 4 kW.

5.3.3 Overall Model

The overall model combines the house thermal model with the HVAC behavior model. It reacts to the given setpoint data (control input), the outdoor temperature (environment), and initial indoor temperature to produce the indoor temperature profile and the HVAC power consumption.

A part of the “cyber” in the cyber-physical systems model is in the behavior of the HVAC itself. The other parts of this “cyber” are actually outside the overall house model that is illustrated in Figure 17 and Figure 18. These other “cyber” parts are seen in Black Box 1 where we have an algorithm that defines the VES strategy, and in Black Box 4 where we have an algorithm that we can apply to find out how to utilize the battery in the most cost-effective ways.

Note that the HVAC reacts to the setpoint so it can be controlled, to some extent, by this variable. In fact, this is how we model VES algorithms in our framework: by providing the HVAC with a setpoint that forces it to cool the house down during non-peak LMP periods.

The overall model of the house can be viewed in two ways. We can look at it simply as connecting the HVAC behavior model to the house thermal model as shown in Figure 17. This provides an explicit separation of the HVAC behavior and thermal response and also helps with implementation.

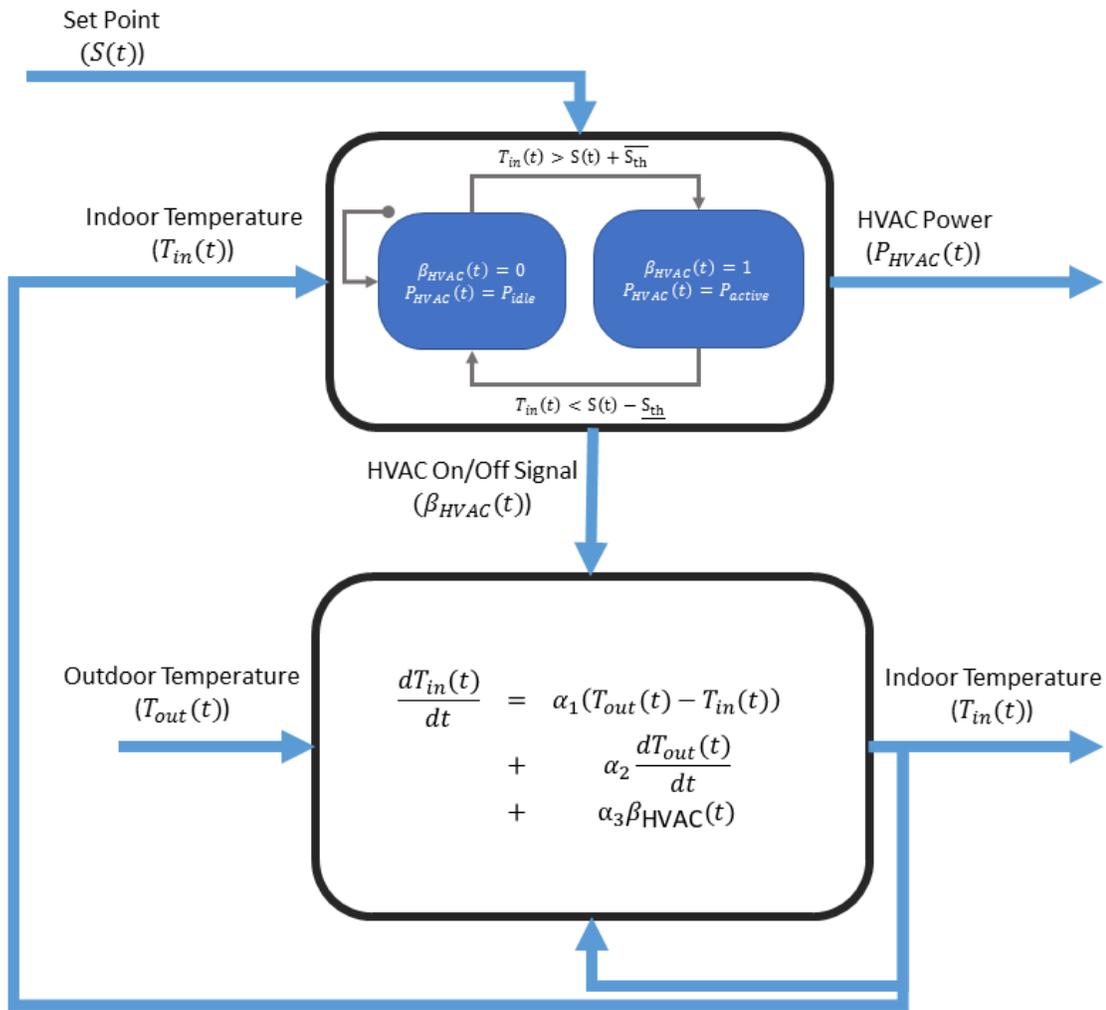


Figure 17. Overall model of the house: HVAC behavior model connected to house thermal model.

The second way to view this model is as a combined hybrid system, as in Figure 18, where the behavior of the HVAC is not explicitly shown. This viewpoint provides a more compact mathematical representation and can help with developing optimization algorithms as well as for performing formal verification [73] on the model and algorithm to ensure they behave as expected.

Nevertheless, our focus is more on simulation to compare VES to BES and less on system development and verification. Despite this focus on simulation, system development and verification considerations are still important to keep in mind.

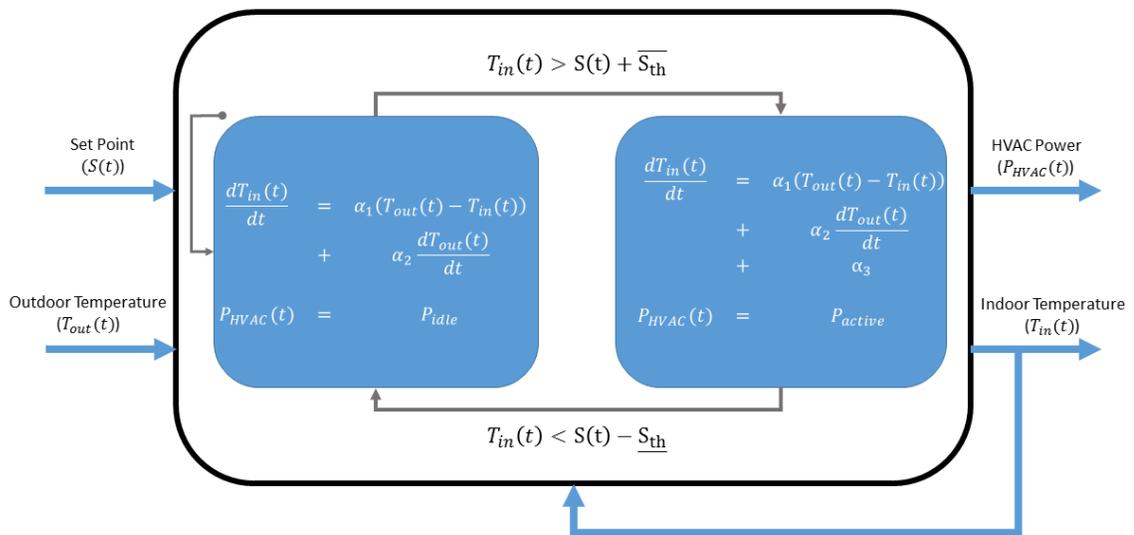


Figure 18. Overall model of the house: viewed as a combined hybrid system.

5.4 Black Box 3: VES Cost and Energy

This black box, detailed in Figure 19, takes in as input the simulated HVAC power, the real-time LMPs for the Citizens' Electric node on PJM's network, the total purchase and installation cost of VES equipment and the average expected lifetime of this equipment.

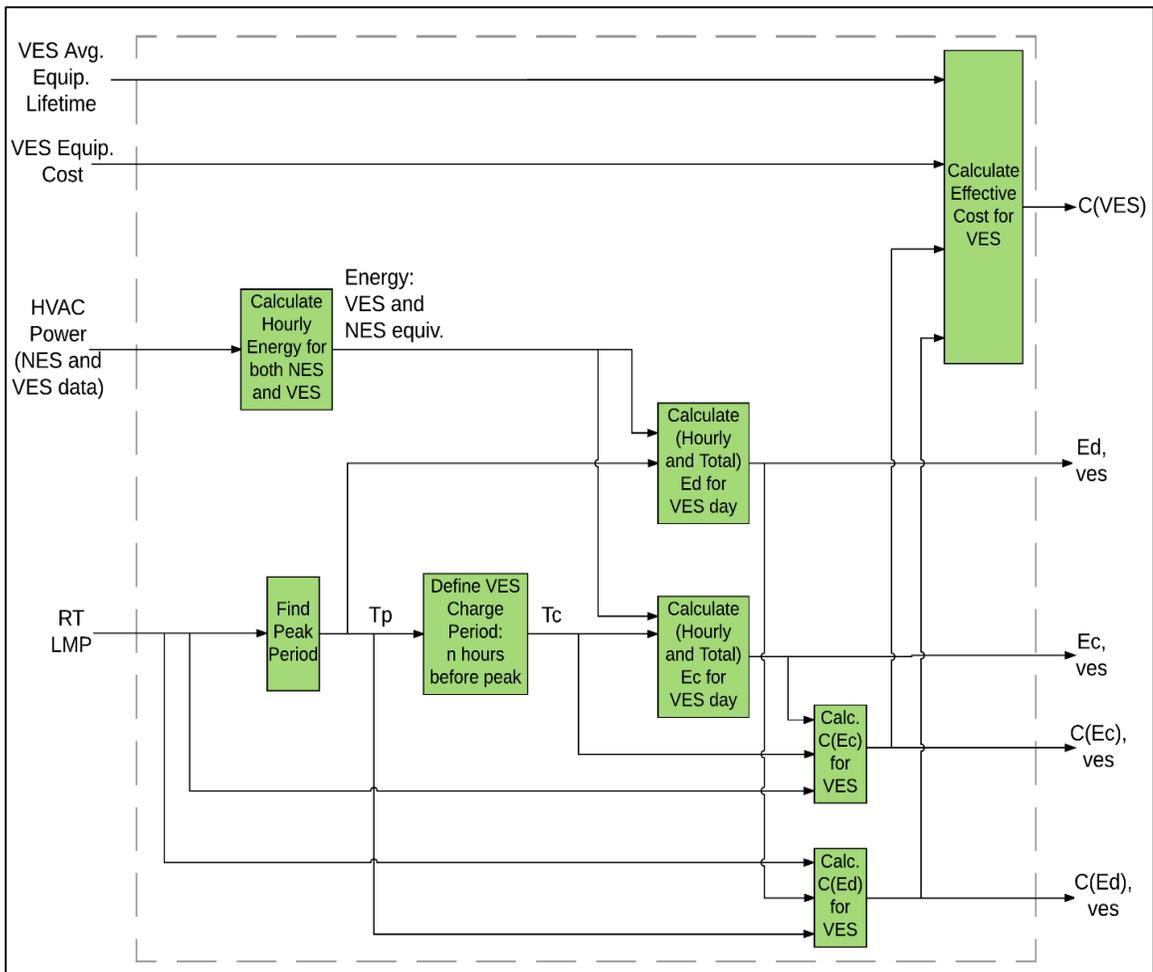


Figure 19. BB3: VES Cost and Energy (detailed).

The black box outputs the energy used to virtually “charge” the home as well as the energy displaced by this storage mechanism, together with their respective costs. This black box also returns the effective amount of money the consumer saves (taking into consideration yearly-amortized equipment costs) by deploying virtual storage, $C(VES)$.

For a given day, we can simulate the HVAC power consumption if VES were employed as well as if there was no energy storage (NES) carried out. The difference between these two scenarios is simply the definition of the cool setpoint in BB1. The NES cool setpoint (same as the BES cool setpoint for reasons detailed in Section 5.2) will be a predetermined constant temperature for the entire day. The VES cool setpoint, however, will involve precooling a certain number of hours prior to peak.

Since, with regards to any day for which virtual storage is simulated, we will need to compute E_d and E_c (as these are not directly measurable without a point of reference), we will have to simulate the same day in the NES mode to provide this baseline reference with which we can calculate the VES charge and displacement energies.

BB3, presented in Figure 19, makes this requirement clearer by stipulating that the HVAC input power for any given day is taken as two data streams: one for VES and the other for the exact same day in NES mode. By doing this, we can calculate hourly versions of E_d and E_c for VES, whereas this was difficult to do when we conducted VES tests in a physical experimental fashion.

This hourly E_d and E_c data, together with the real-time LMP (also given hourly) can be used to calculate $C(E_d)$ and $C(E_c)$ values for VES by using Equation (3) repeated here.

$$C(E_*) = \sum_{t_k \in T_*} E_{*|t_k} \cdot LMP_{t_k}$$

where T_* (T_p or T_c) is the period under consideration, LMP_{t_k} is the LMP value for a given hour, t_k , in either of the two specified periods, and $E_{*|t_k}$ is the corresponding displaced or charge energy for the given hours which comprise T_p or T_c .

We compute total $C(E_d)$ and $C(E_c)$ for the period we considered (spring and summer 2016, assuming this duration to represent a typical year of storage use). We also computed the $C(VES)$ for the year.

5.5 Black Box 4: BES Cost and Energy

This black box details how $C(E_d)$, $C(E_c)$, and $C(BES)$ are calculated for the BES case, using the following inputs: the average expected lifetime of the BES equipment, the BES equipment cost, HVAC power, $E_{d|ves}$, real-time LMP, and the charge rate of the battery.

Since we want to compare virtual energy storage to the more widely-advocated battery energy storage in an “apples-to-apples” fashion, we assume (as in Section 4.2) that the batteries are used to displace an amount of energy equal to that displaced by VES,

leading us to set $E_{d|bes} = E_{d|ves}$ (this will give a conservative estimate that can be used as a point of reference to consider other possibilities).

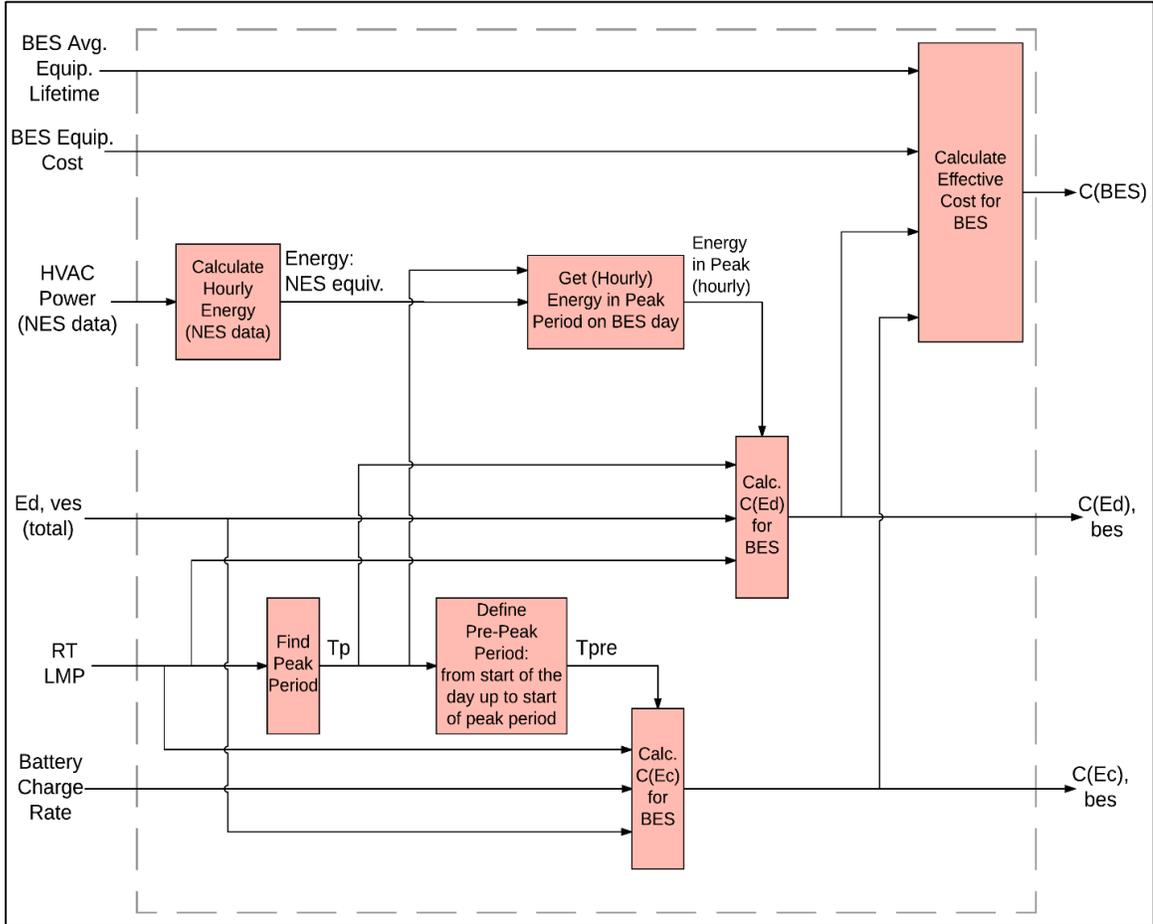


Figure 20. BB4: BES Cost and Energy (detailed).

To ensure we achieved this specification, we found batteries that are able to supply the maximum value of $E_{d|ves}$ that was obtained during the period we considered (spring and summer 2016, assuming this duration to represent a typical year of storage use). We want these batteries to be able to supply this maximum $E_{d|ves}$ over their lifetime, even after the

degradation of capacity to 80% of the original which is commonly marked as the end of life [74]. The batteries also have to be able to support the active power demand of the HVAC system (roughly 4 kW)¹⁶ regardless of their capacity. Of the larger list of batteries in Table 3, we ended up with 10 batteries that meet these criteria.

In addition to the case where we set $E_{d|bes} = E_{d|ves}$, we considered a second case where the battery supplied energy (up to its dischargeable¹⁷ capacity) to the HVAC system, during the peak period. This scenario is a best-case one. In these best-case scenarios, we typically have $E_{d|bes} > E_{d|ves}$. There are two options for the battery discharging its dischargeable capacity in peak:

- i. The battery's dischargeable capacity is greater than the HVAC peak period demand.
- ii. The battery's dischargeable capacity is less than the HVAC peak period demand, thus the battery depletes all its dischargeable capacity during T_p but still is unable to meet the entire peak demand.

In BB4 (expressed in Figure 20), we see that the total HVAC energy used, on any day when the BES mechanism is deployed, will be equal to that used if the NES scenario

¹⁶ We specify 4.15 kW in our algorithm that selects the battery in order to give us some "buffer".

¹⁷ We define dischargeable capacity here to mean:

$$\text{Dischargeable Capacity} = \text{Usable Capacity} \times \text{Round-Trip Efficiency (RTE)}$$

were employed for the entire day. The reason for this is that we are not modulating the HVAC behavior on BES days. Rather, we are simply changing the sources that supply energy to the HVAC in the peak period (grid for the entire $T_{p|nes}$; battery for all or part of $T_{p|bes}$).

Since we want to obtain maximum savings, we discharge the battery during the hours of T_p that will give us the maximum $C(E_{d|bes})$. Likewise, we find the minimum amount of money it would cost us to charge the battery in the hours leading up to the peak period¹⁸ i.e. we find the minimum possible $C(E_{c|bes})$. Note that $E_{c|bes}$ is determined using the round-trip efficiency (RTE) of the battery:

$$E_{c|bes} = \frac{E_{d|bes}}{RTE} \quad (9)$$

Finally, similar to Black Box 3 (Section 5.4), we compute yearly $C(E_{d|bes})$, $C(E_{c|bes})$, and $C(BES)$ for both scenarios ($E_{d|bes} = E_{d|ves}$ and best-case).

¹⁸ We denote the hours leading up to the peak period by T_{pre} and we define this duration as the hours from the start of the day to the peak period. Theoretically, we could also charge the battery the night before BES is to be carried out, if LMP prices are more favorable during those hours than on the storage day. However, we leave the addition of this level of complexity to future work and we strictly focus on pre-peak hours that belong to the BES day.

6 Simulation Experiments, Analyses, and Results

Using our model developed in Chapter 5 and programmed in MATLAB and Simulink, we run BES and VES simulations for 92 days (June 1, 2016 to August 31, 2016) that typically have high temperatures and thus would necessitate cooling of the testbed.

Table 2. Batteries for Comparison to VES.

Battery	Chemistry	Usable Capacity (kWh)	Charge Rate (kW)	Round-trip Efficiency	Cost ¹⁹ (USD)	Cycle Life (Cycles)
LG Chem Resu 10	LiNiMnCoO ₂	8.8	5.00	0.95	6512	3200
LG Chem RESU 6.5	LiNiMnCoO ₂	5.9	4.20	0.95	4884	3200
Akasol neeoQube	LiFePO ₄	5.0	5.00	0.98	8880	7000
DCS PV 10.0	LiFePO ₄	10.0	5.12	0.98	7399	5000
BMZ ESS3.0	LiNiMnCoO ₂	5.4	8.00	0.97	5929	5000
Magellan HESS	LiNiMnCoO ₂	11.5	5.00	0.97	15244	4000
GridEdge Quantum	Na-NiCl ₂	7.7	4.50	0.95	14800	3500
Ampetus Energy Pod	LiFePO ₄	11.5	5.00	0.97	8425	4400
Sunverge SIS	LiFePO ₄	9.9	5.00	0.96	19240	7000
Alpha-ESS ECO S5	LiFePO ₄	13.0	5.00	0.95	9158	6000

¹⁹ Cost values were originally given in Australian dollars. We converted the values to U.S. dollars. Conversion was done based on the currency-market rate on May 10, 2017.

We selected the batteries for our simulation from a choice of 27 batteries taken from a well-documented dataset maintained by SolarQuotes [55]. The batteries are listed in Table 3 (which is found in Section 10.1 of the Appendix). We picked batteries that would meet the HVAC active demand of 4 kW at their steady discharge rate and that had enough capacity to offset as much energy as the best possible VES day in the period we considered. This gave us 10 batteries (listed in Table 2) for comparison.

6.1 Energy Behavior and Savings Margins

6.1.1 Energy Behavior

The first comparison we performed was in the energy behavior of both VES and BES. We wanted to model VES in terms of a battery as much as possible so we considered both the capacity and round trip efficiency values as shown in Figure 21.

In Figure 21, we can see the cyber-physical nature of VES manifesting itself with the variation in both capacity and roundtrip efficiency shown by the error bars. Since VES depends on an algorithm reacting to physical conditions to produce the effect of being a battery, the behavioral strategy is unfortunately at the mercy of these physical conditions. In fact, it is possible for VES (based on the way we defined the displaced energy and charge energy—relative to a baseline day) to exhibit roundtrip efficiencies greater than 100% and also to have negative displaced energy. For Figure 21, however, we only considered days

that would give physically meaningful roundtrip efficiencies (i.e. between 0 and 100%) as well as displaced energies that implied positive capacity.

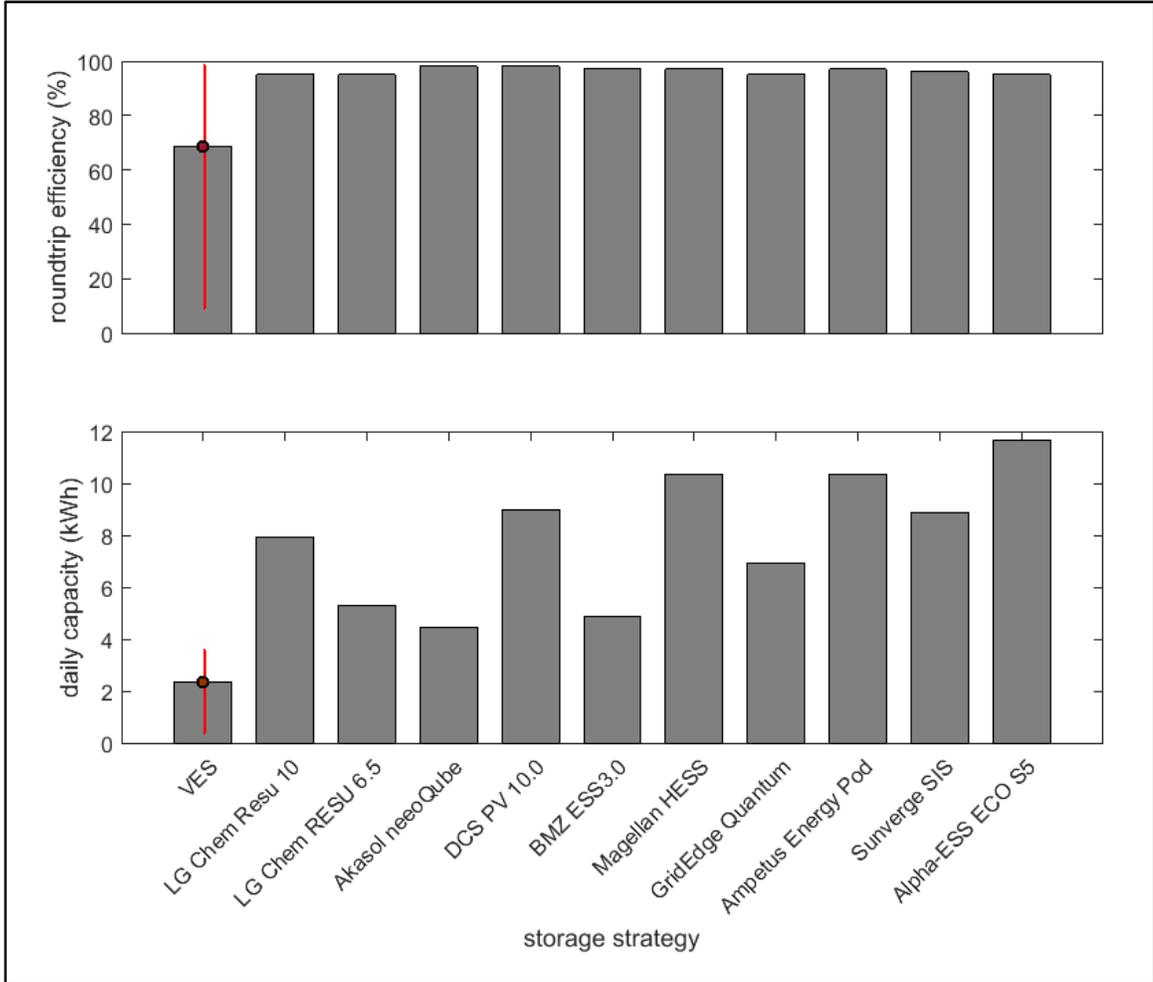


Figure 21. Round-trip efficiency and daily kWh-capacity of storage mechanisms.

6.1.2 Savings Margins

Based on the energy used to charge and discharge both VES and BES, we computed the daily savings margins i.e. $(C(E_{d|es}) - C(E_{c|es}))$ where “es” denotes the storage

mechanism—either VES or BES. For the batteries, we looked at two cases. The first was assuming that the battery offset as much energy as VES did that day and the second was assuming that the battery offset as much of the HVAC peak period energy as it could, given its capacity.

For both cases, we assume the battery was charged during the period that would produce the lowest possible charge cost and was used within the period where cost would have been greatest had that energy been consumed from the grid. The rest of our analysis considers these two assumptions about BES use. The summary of daily margins is shown in Figure 22.

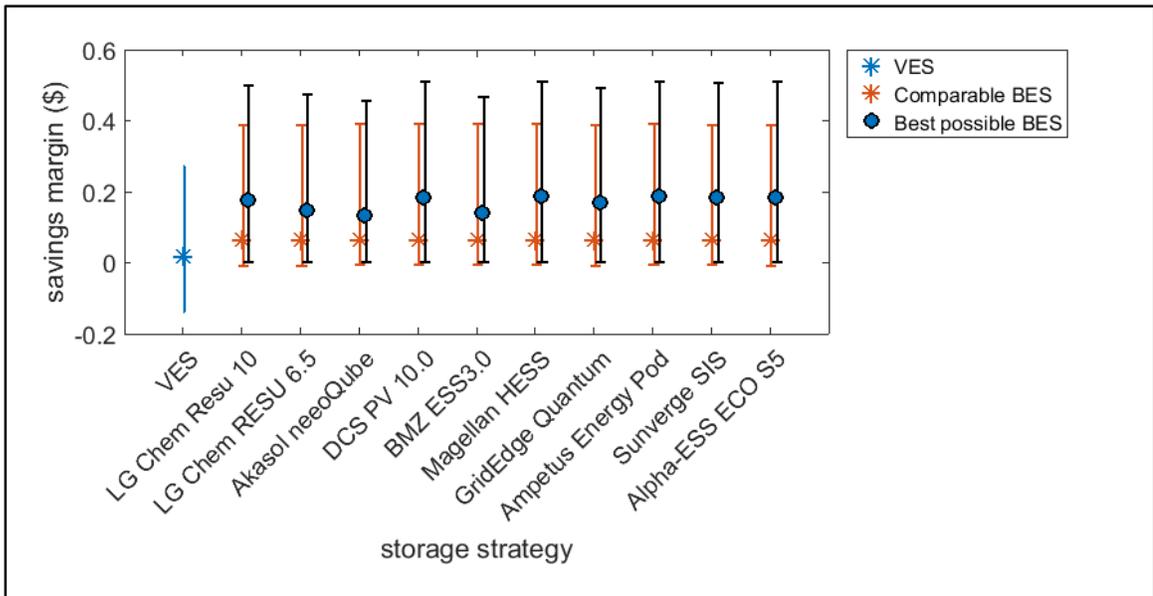


Figure 22. Summary of daily savings margins of storage mechanisms.

The batteries always have positive margins and have higher margins compared to VES (which also has some positive margins but also some negative ones). This is because we can more easily control when we charge and discharge batteries to ensure we get the best possible savings. We are limited, however, in how far ahead of peak we can “charge” with VES since charging comes at cost and the house starts to leak energy (even if slowly) the moment the HVAC is turned off.

6.1.3 Insights into Margins

We briefly explored factors that might contribute to the daily margin fluctuations for VES as well as for the batteries. Figure 23 – Figure 25 show the margins for each day in the months of June, July, and August with corresponding profiles of the outdoor temperature during the peak and pre-peak hours.

Overall, on days where temperatures are higher in the peak period and there is less temperature overlap between the peak and pre-peak periods, we see more savings in both the VES and BES cases. Further analysis of these relationships could help in the development of optimal VES algorithms.

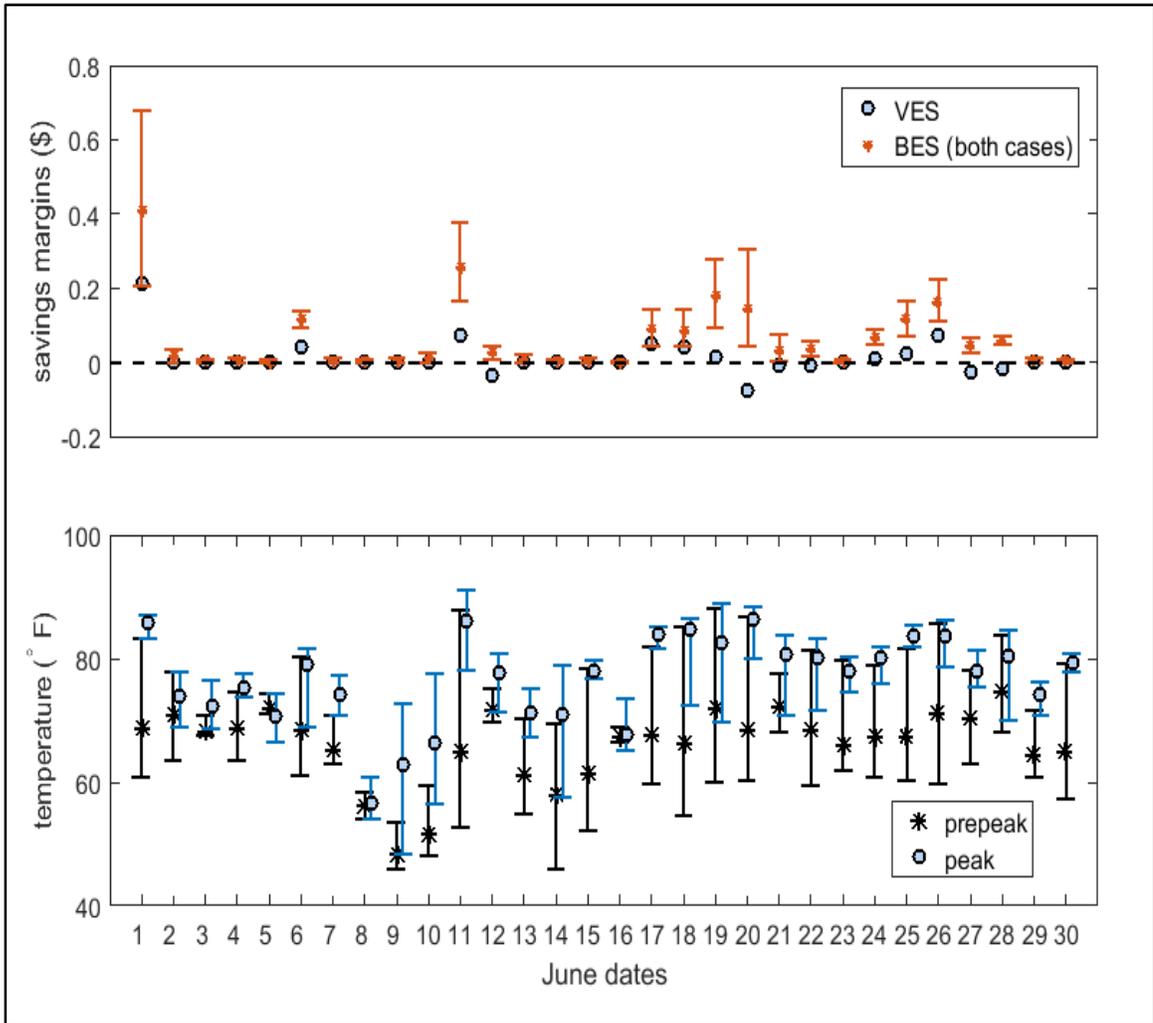


Figure 23. Margin-temperature relationship (June).

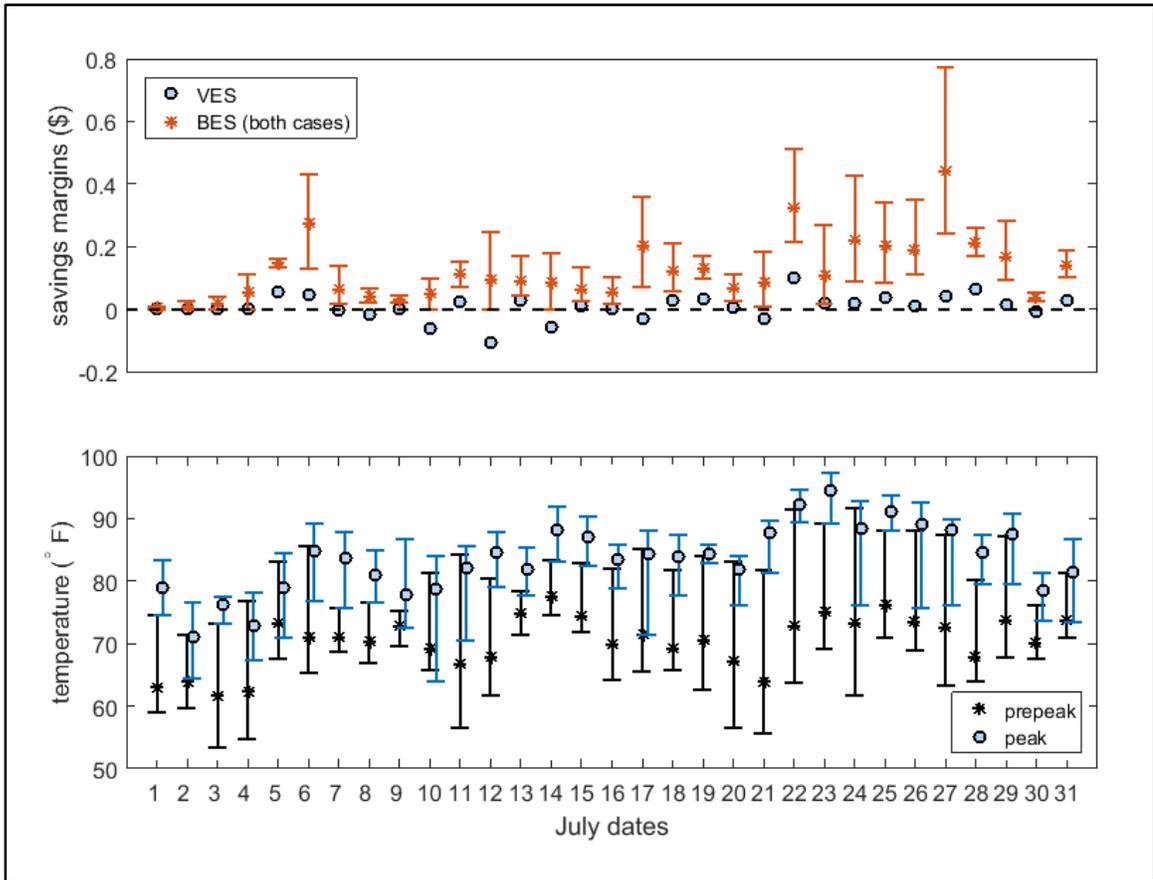


Figure 24. Margin-temperature relationship (July).

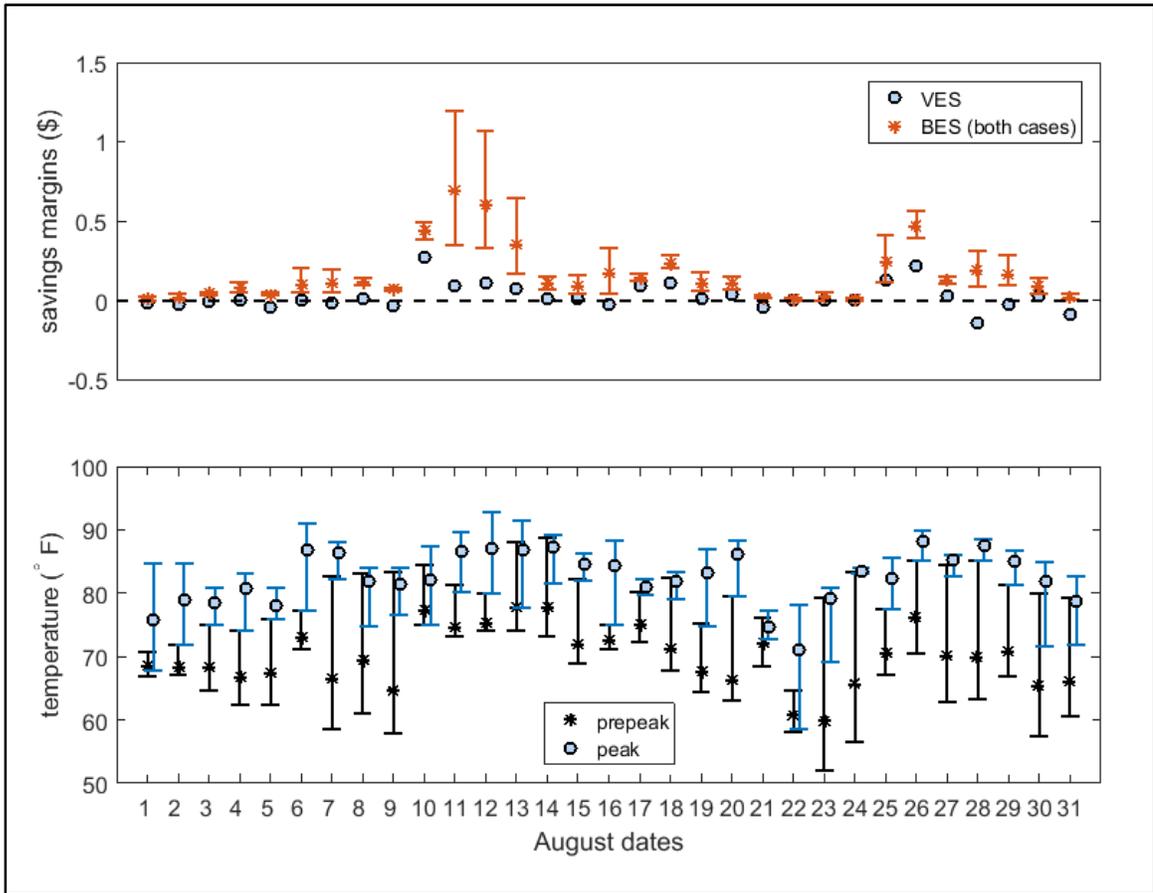


Figure 25. Margin-temperature relationship (August).

6.2 Overall Cost-Effectiveness with No External Incentives

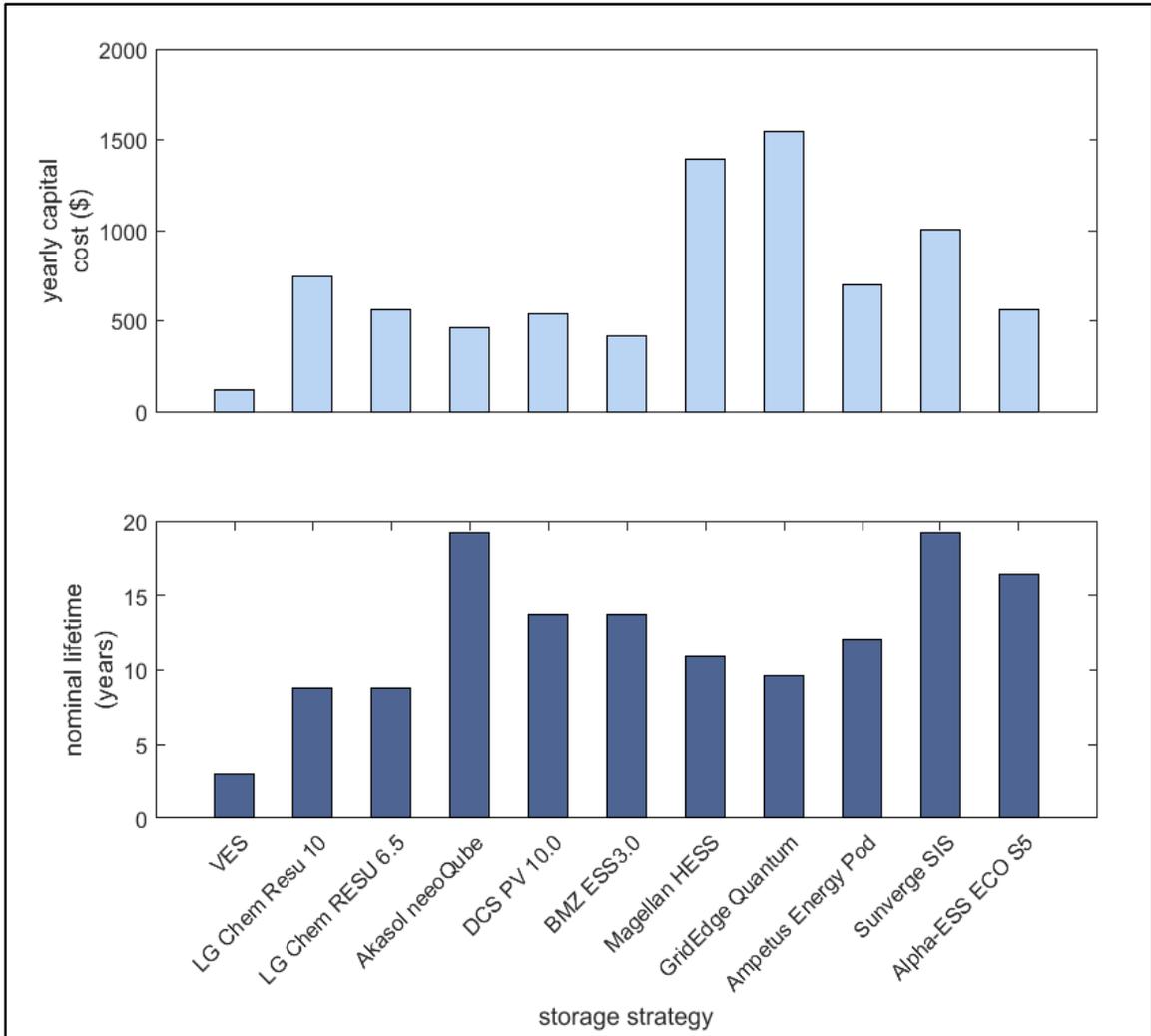


Figure 26. Yearly capital cost and nominal lifetime of storage equipment.

To consider the overall cost-effectiveness as mentioned in Section 3.2, we have to account for the cost and lifetime of the equipment that allows us to get the savings margins

shown previously. The costs and lifetimes²⁰ for the BES mechanisms we considered as well as for VES are shown in Figure 26. We look at the equipment cost yearly since it gives the consumer a sense of what their typical overall costs will be.

Since we only looked at data from three months in the year in spring and summer, the implicit assumption is that the consumer is mainly interested in employing storage strategies during these three months. However, we note that since the consumer must purchase the equipment, they must bear the losses resulting from not employing the mechanisms year-round.

We also assume that 2016 is a representative year since it is the 2016 savings margins we use in our overall cost-effectiveness assessments. To get overall cost-effectiveness, we combine capital costs with the savings margins as shown in Figure 27.

Notice that no VES or BES strategy is cost effective (i.e. they all fail to show positive values). This is because even though we get some daily savings by employing these strategies, the capital costs dominate and thus make the overall cost-effectiveness negative. Therefore, VES is attractive because its capital cost is smaller than those of BES and it appears (assuming our model matches some house perfectly) to be more cost-effective than all the batteries.

²⁰ These we obtained by dividing the cycle life in Table 2 by 365.25 days in a year—assuming the battery were to be used daily. This is a simplifying assumption, but it gives lifetime values that are reasonable enough for us to achieve our aim—to understand the implications of BES and VES relative to each other.

Results shown in Figure 27 allude to the point that there has to be some incentive for a residential customer to either purchase a battery or VES equipment, else there is no rational economic reason for carrying out these strategies, from a customer's perspective [75]. The next section discusses some of such incentives.

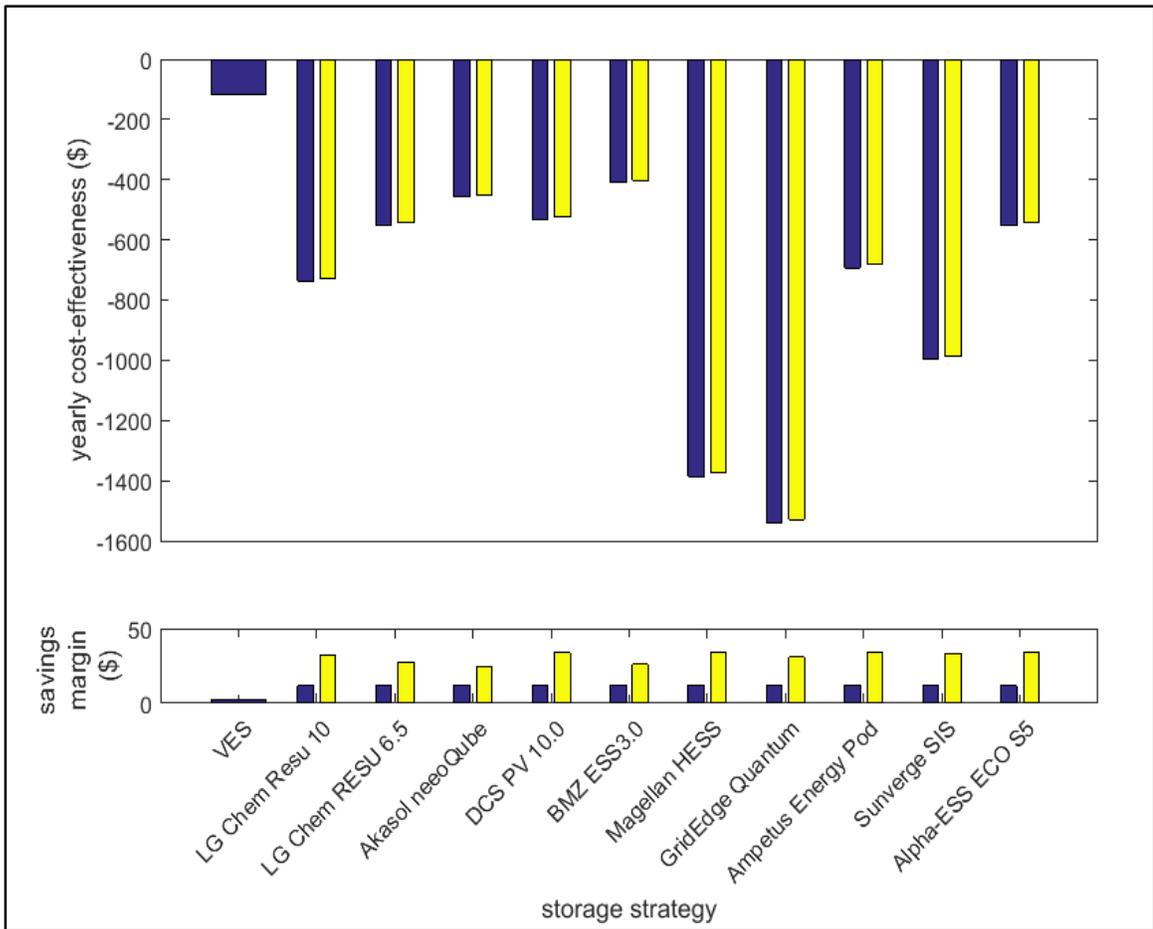


Figure 27. Overall yearly cost-effectiveness without external incentives. For the batteries: the blue bars represent the case where $E_{d|bes} = E_{d|ves}$ and the yellow bars represent the best-case scenario.

6.3 Overall Cost-Effectiveness with PJM Capacity Credit

Incentives

In order for PJM to make sure that there is enough energy supply to meet future demand, it operates a capacity market [76, 77]. In this market, generators bid to supply energy if called upon at some point in the future. Generators whose bids are accepted are expected to have enough capacity so that whenever they are called upon, they will supply their capacity obligation.

At PJM capacity auctions, traditional power plants as well as demand-side and efficiency resources can bid for capacity. In other words, there is no distinction between a 1-MWh capacity obligation from a coal-fired power plant and a 1-MWh of capacity obligation from load management techniques [78]. The power plants and demand-side companies who have their bids accepted get paid the agreed capacity rate, regardless of whether or not they are later called upon by PJM to supply (or cut down, in the case of load management) power [75].

Based on this information about PJM's capacity market, we looked at the case where a consumer works to be involved in the capacity market as a generator (probably through a third-party demand-response aggregator).

For the BES case, we reasoned that the capacity provided would be the average capacity over the battery's lifetime since battery capacities degrade over time. We also

assumed an 80% capacity at end of life [74] and linear capacity degradation throughout the battery's lifetime.

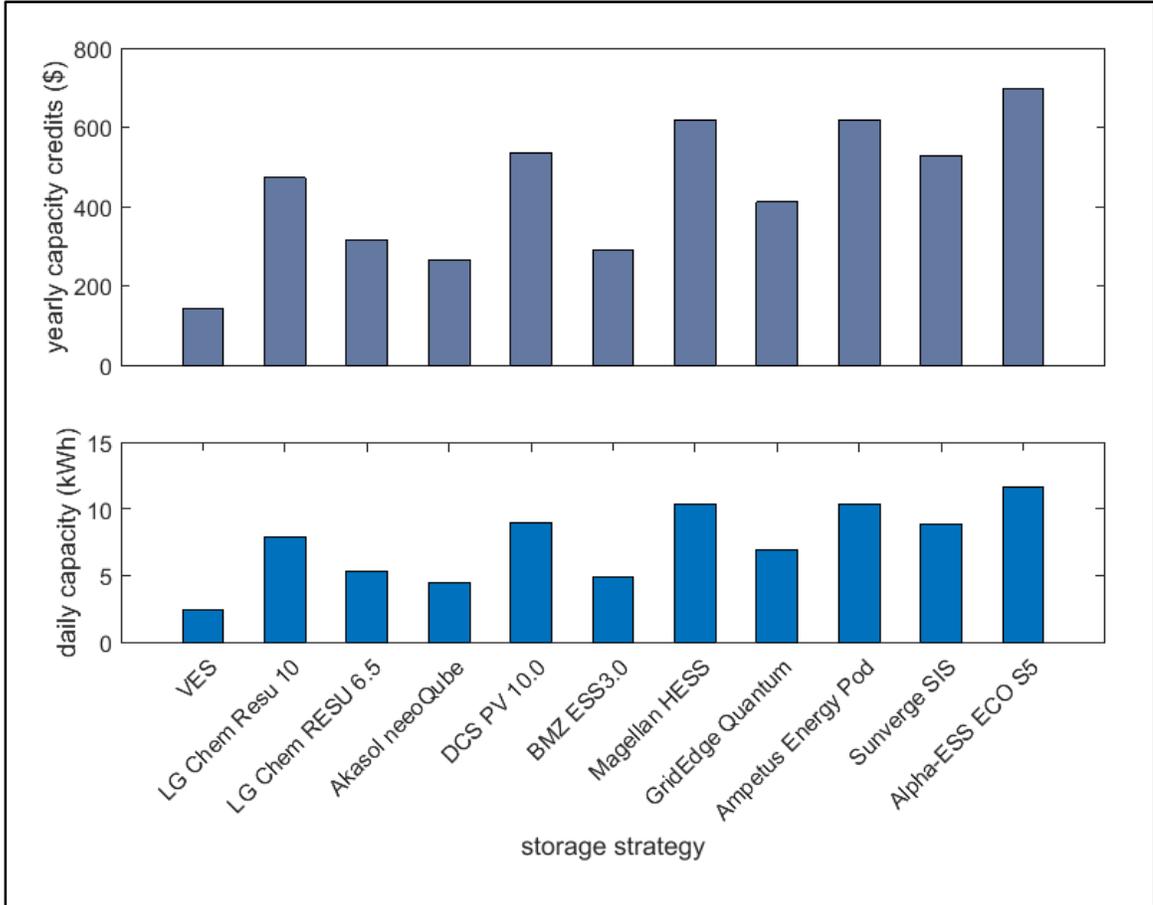


Figure 28. Yearly capacity credits for the storage mechanisms.

For the VES case, we used the average displaced energy ($\overline{E_{d|ves}}$) in 2016 as its capacity. Based on PJM's capacity agreement with generators in the PPL zone (where our testbed is situated) for \$163.27/MW-day [77], we estimated the capacity payments that

each strategy would receive yearly if residential customers could bid²¹ into PJM's capacity market. (Again, we are assuming 2016 to be the typical year). Results are shown in Figure 28.

We recomputed the overall cost-effectiveness assuming the customer also receives the total²² capacity payment for being a generator in the capacity market. These results are displayed in Figure 29.

From the results in Figure 29, we see that the capacity payment makes VES become cost effective (within the assumptions of our modeling). The Alpha-ESS ECO S5 and the DCS PV 10.0 batteries also become cost-effective.

These results make sense for VES because the capital cost for VES is fairly small so a small incentive is all that is needed in order to cross into positive cost-effectiveness. In the case of the two cost-effective batteries, their yearly capital costs are lower than many of the other batteries we considered. Also, they have relatively high kWh capacity compared to the other batteries.

²¹ If this situation were to occur in reality, it is more likely that a third-party demand-response/load-management aggregator would be in charge of this entire bidding process. In addition, the capacity contributions of an individual consumer may not be passed down, in its entire monetary equivalent, from the third party to the consumer.

²² This situation is unlikely—for the same reason in the previous footnote.

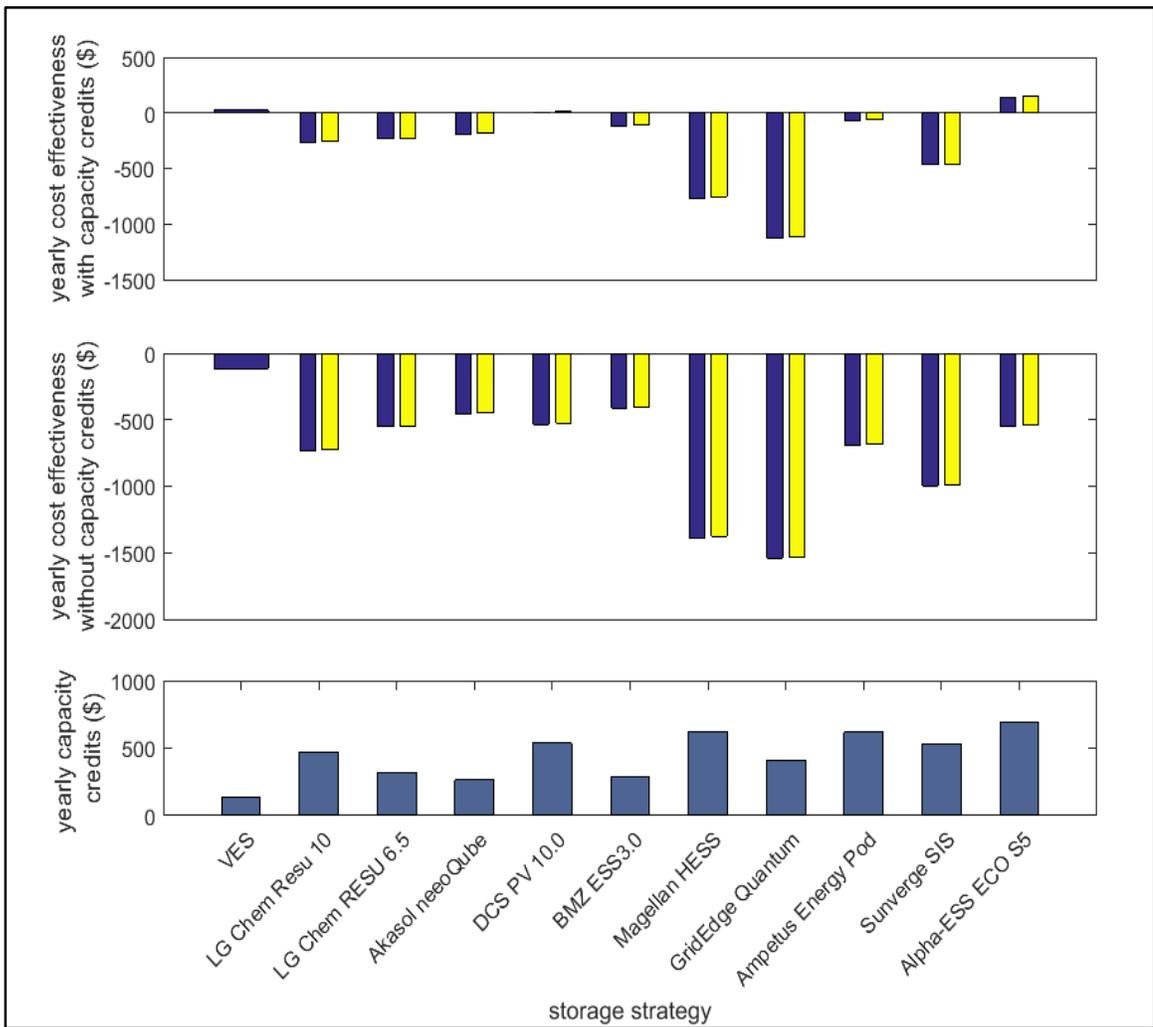


Figure 29. Overall yearly cost-effectiveness with PJM capacity credits as an external incentive. For the batteries: the blue bars represent the case where $E_{d|bes} = E_{d|ves}$ and the yellow bars represent the best-case scenario.

With respect to capacity, therefore, we see the ratio of yearly capital cost to kWh-capacity as the deciding factor for whether or not a storage mechanism will be cost-

effective in a year. In fact, the three mechanisms that give positive cost-effectiveness have the three lowest ratios of yearly capital cost to kWh-capacity as illustrated in Figure 30.

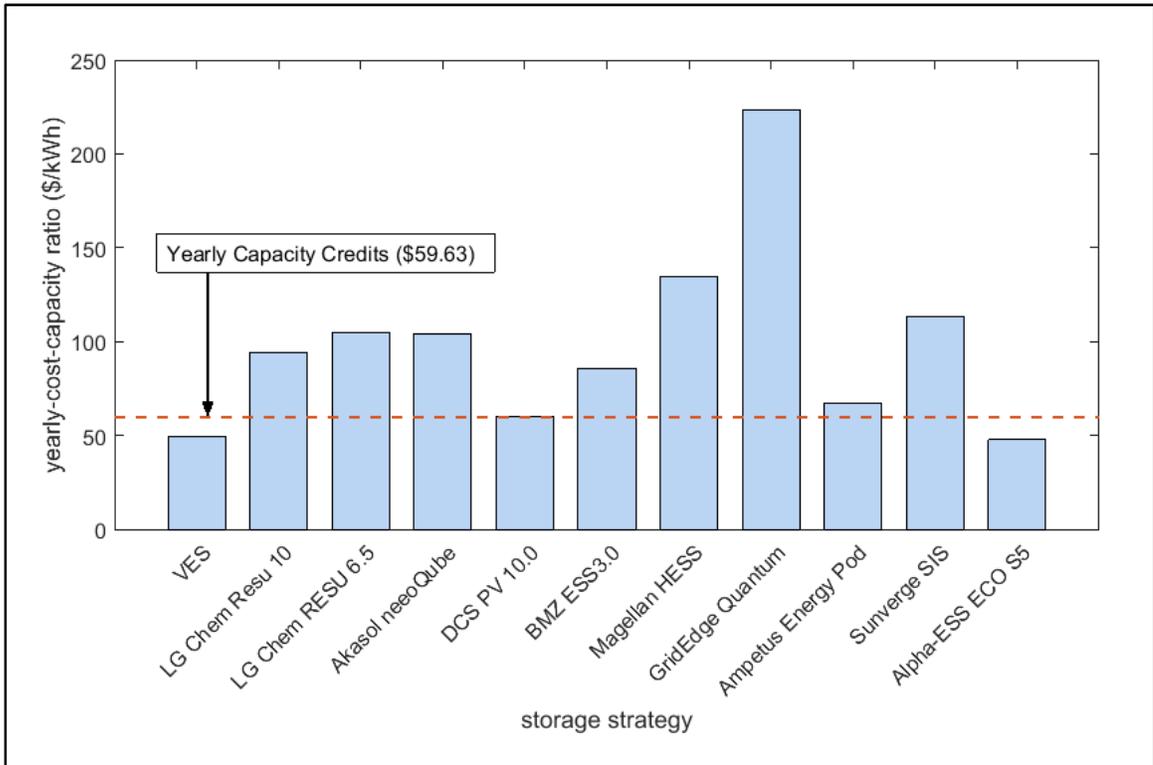


Figure 30. Ratio of yearly capital cost to kWh-capacity of the storage mechanisms. The PJM capacity credit for the typical year considered (2016) is \$59.63/kW-yr.

In general, the lower the ratio of capital cost to kWh-capacity, the likelier it is that PJM capacity credits will offset a consumer’s investments (also factoring in what it costs to charge the storage mechanism).

These results highlight the need for incentives to make storage mechanisms worthwhile for the customer, given the current costs and lifetimes of these technologies.

Nevertheless, general improvements in the technologies (reduced costs or longer lifetimes) would make them more cost effective and reduce the need for incentives.

On the issue of incentives, we know that rooftop (residential) solar panels are affordable because the incentives received in the form of Solar Renewable Energy Certificates (SRECs) [79, 80] make their residential deployment more economically viable than standalone BES or VES.

It is also important to note that, from an incentives perspective, VES is the easiest mechanism to incentivize (at least according to our modeling) because it is the closest to positive cost effectiveness. On the other hand, the cost-effectiveness of batteries vary widely from battery to battery.

7 Discussions and Conclusion²³

7.1 Insights into Virtual Energy Storage

The first key insight is that virtual energy storage is always going on in a house. This phenomenon is governed by the outside temperature (which puts energy into the house or draws energy out of it) and the behavior of the HVAC (which, like the outside temperature, also puts energy into the house or draws energy from it). In essence, the user wanting to maintain a set temperature range in the house is analogous to keeping a “virtual battery” within a certain charge. We can call this process passive virtual energy storage. On the other hand, the approach we have employed here is what one could call active virtual energy storage. In this case, by using sensors and other information sources to understand environmental conditions and energy prices, we can improve the cost of active energy needed to maintain temperature (or virtual charge) within a certain range of temperatures known to be still acceptable to the user. In our data collections, power sensors were critical to determining the overall effects of this phenomenon. In a system that takes advantage of VES, these sensors and additional information sources would combine to form a virtual sensor that the system uses to manage energy use.

²³ Majority of this Chapter was published in the Proceedings of the 2017 IEEE Sensors Applications Symposium: P. Asare, C. Ononuju and P. M. Jansson, "Preliminary Quantitative Evaluation of Residential Virtual Energy Storage Using Power Sensing," in *Sensors Applications Symposium*, Glassboro, 2017.

There are a few key insights about the behavior of virtual energy storage based on our explorations that can improve on the simple approach used in this work. First is the fact that we are partially in control of “charging” this energy source. For example, if we precool the house to about 68°F and then stop active precooling, the outside temperature may act to keep the temperature close to this value without any further intervention on our part. In this case, one can say that the outside temperature is also “charging” the house. This process is something we do not control, but it is something we can anticipate (based on weather forecasts) in order to “charge” more intelligently and reduce the amount of active energy required. Conversely, the outside temperature may act to “leak” stored energy before our desired time of energy use. In traditional BES, we have control over when energy goes in and when energy is discharged from the battery, and batteries are designed to leak as little energy as possible between charge and use. In VES, however, we do not have that luxury of perpetual storage. This means, for example, it is usually better to “charge” the house (precool or preheat) closer to when the energy is most needed, accounting for the effects (both positive and negative) of the outside temperature as well as the monetary cost of the energy needed to “charge” the house. How much “charging” needs to be done is also dictated by the outside temperature at the time one intends to “charge” and what the final intended temperature after “charge” is.

However, it is necessary that we precool or preheat early enough (and outside the peak period) for VES. If we precool or preheat too late, we run the risk of putting energy

into the house in a manner that results in a VES day having a greater energy usage during its peak period than a similar non-energy-storage day. Such a situation is of no benefit to the consumer.

Another important insight is that VES varies by climate and thus location [36]. Therefore, one can expect that in a hotter climate, for instance in Arizona, the summer VES savings would be greater than the savings achieved in Pennsylvania because, presumably, the air conditioner would be utilized more in Arizona than in Pennsylvania.

Lastly, it is important to note that cost-effectiveness analysis of VES is best done when a simulation model of the house is available. This allows for data acquisition of a full day of non-energy-storage and a full day of VES—both based on the same outside temperature—to perform a more accurate comparison. It also allows for a hybrid approach where one of these scenarios is collected from the testbed and the other is generated in simulation. This overcomes the limitation of a purely experimental approach where no two days are exactly alike in terms of outside temperature.

7.2 Conclusion

Virtual energy storage represents an interesting opportunity for residential load management in an effort to make the energy market more flexible and potentially less costly for all involved. Our explorations revealed interesting insights into this phenomenon

that will help the future work of developing systems that harness its full benefits while keeping costs low.

Our cost-savings model revealed some insights into overall cost-effectiveness of storage-based approaches to load management and the potential policy implications. Our modeling framework makes it possible for us to generate no-energy-storage days for testing and evaluation. In addition, this framework allows for the testing of optimization strategies, with modifications for each unique case.

It is our hope that other researchers leverage our work to further explore VES by testing their home energy optimization strategies, developing better load management strategies based on VES, gaining better insights into the cost-effectiveness of VES as compared to BES, creating other tools that can help with reducing cost of these technologies, informing policy discussions around incentivizing investment in these technologies, and a myriad of other applications that will improve the cost-effectiveness of residential energy storage to benefit the entire energy industry.

8 Future Explorations

Future researchers can apply our work as well as improve on it in a myriad of ways. We have thought about a few paths for these explorations and improvements and have outlined them below.

8.1 Model Accuracy

Since this work was carried out to provide a general proof-of-concept framework, there were a number of approximations made and conditions assumed. To improve upon the model accuracy, some of these approximations and assumptions may need to be reconsidered to give way to a more refined and streamlined model. Nevertheless, this proof-of-concept framework is highly useful as it illustrates all the analyses available to us, while conveying the benefits (and bottlenecks) associated with storage mechanisms.

Additionally, in our work, we did not have enough days where we intentionally controlled the HVAC behavior (or even turned it off) to see how the indoor temperature naturally responds to the outdoor temperature. Fortunately, we were able to obtain a few days of this natural thermal data to give us a house model where the predicted indoor temperature follows the measured indoor temperature in a general-trends fashion. However, availability of more of natural thermal data in the model-building process would

have made our model even more robust. Nevertheless, we were still able to demonstrate the possibility of energy and cost savings, despite our uncontrolled data.

Another avenue for model improvement is the consideration of other factors, besides the outdoor temperature, that may have an effect on the indoor temperature. Literature tells us that solar radiation affects the indoor temperature [81]. Considering this factor and others could potentially improve the accuracy of our model.

Also, in our model, we assumed thermal comfort levels had to be fixed for an entire day. This is not always true. Future researchers can try to account for situations where the user's comfort preferences might change over the course of a day.

We could also consider the effects of the consumer's HVAC settings (especially when they are away for extended periods) on pets and/or plants. And another area of potential interest for future researchers could be load management for networked neighborhoods. The studies in [29, 82, 83] serve as a good starting point for this neighborhood-oriented work.

Finally, there is the important issue of model validation. Future work should involve conducting the strategies performed on the model in the live testbed to check whether model results agree with reality.

8.2 Model Optimization

Although we noted that our project was not aimed at developing the best optimization strategy, this is an interesting avenue for future exploration. There is potential for our framework to be leveraged in a more predictive fashion. A good feature of this prediction would be the ability of the model to obtain the forecasted outdoor temperature from weather websites. This forecasted temperature, although not always spot-on, gives a good sense of direction in terms of general expectations for the day and also informs the strategies to be carried out.

We see the framework in Figure 12 being enhanced in such a way that, given only the date as input, the model can determine a valid HVAC use strategy as well as specifics of battery storage. In other words, the model could tell us how much pre-heating/cooling and how big of a battery is required, while doing all of this adaptively. The model would also give the corresponding costs for a chosen storage strategy. These optimizations would relieve the user of the task of having to explicitly program the model with the strategy to use.

8.3 Renewable Energy Sources

We intentionally considered only storage mechanisms (and not renewable energy sources) in this project despite the testbed being equipped with on-site solar and natural gas generation. The reason was because, for our comparison, such generators would

contribute the same cost to both VES and BES and hence would not count as unique costs. Omitting these generators from our analysis allowed us focus on the costs that were exclusive to either storage mechanism. This enabled us carry out simple “apples-to-apples” comparisons of VES relative to BES.

However, future work could take into consideration solar and wind, accounting for the credits associated with carrying out these techniques.

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10 Appendix

10.1 Battery Data

Table 3. A Selection of Batteries Currently Available on the Market (Data Obtained from SolarQuotes [55]).

Battery	Chemistry	Usable Capacity (kWh)	Charge Rate (kW)	Round-trip Efficiency	Cost ²⁴ (USD)	Cycle Life (Cycles)
LG Chem Resu 10	LiNiMnCoO ₂	8.8	5.00	0.95	6512	3200
LG Chem RESU 6.5	LiNiMnCoO ₂	5.9	4.20	0.95	4884	3200
Redflow Zcell	ZnBr (flow)	10.0	3.00	0.80	9324	3650
SimpliPhi PHI3.4 Smart-Tech battery	LiFePO ₄	2.8	3.10	0.98	3811	10000
Leclanche Apollion Cube	LiNiMnCoO ₂	5.4	3.30	0.97	6808	6000
GCL E-KwBe 5.6	LiNiMnCoO ₂	5.6	3.00	0.95	2701	2555
Delta Hybrid E5	Lithium-Ion	4.8	3.00	0.90	4884	6000
ELMOFO E-Cells ALB52-106	Lithium Ion	4.4	5.00	0.96	6061	8000
Akasol neoQube	LiFePO ₄	5.0	5.00	0.98	8880	7000
Ampetus "Super" Lithium	LiFePO ₄	2.7	1.50	0.95	1702	10000

²⁴ Cost values were originally given in Australian dollars. We converted the values to U.S. dollars. Conversion was done based on the currency-market rate on May 10, 2017.

Fronius Solar Battery	LiFePO ₄	9.6	4.00	0.90	11507	8000
DCS PV 5.0	LiFePO ₄	5.1	5.12	0.98	4366	5000
DCS PV 10.0	LiFePO ₄	10.0	5.12	0.98	7399	5000
BMZ ESS3.0	LiNiMnCoO ₂	5.4	8.00	0.97	5929	5000
Aquion Aspen 48S-2.2	Aqueous Hybrid Ion [84]	2.2	0.68	0.90	1628	3000
Hybrid "Home" Plus	Lead Crystal [85]	8.2	3.00	0.92	8140	2400
SolaX Lead Carbon	Pb-C	4.5	4.60	0.88	5173	2000
Enphase AC Battery	LiFePO ₄	1.1	0.26	0.96	1480	7300
Magellan HESS	LiNiMnCoO ₂	11.5	5.00	0.97	15244	4000
GridEdge Quantum	Na-NiCl ₂	7.7	4.50	0.95	14800	3500
SENEC.home Li 10.0	LiNiMnCoO ₂	10.0	2.50	0.95	13838	12000
Sonnenbatterie	LiFePO ₄	16.0	3.00	0.95	22570	10000
SolaX BOX	LiFePO ₄	11.5	4.60	0.97	10434	4000
Ampetus Energy Pod	LiFePO ₄	11.5	5.00	0.97	8425	4400
Sunverge SIS	LiFePO ₄	9.9	5.00	0.96	19240	7000
Alpha-ESS ECO S5	LiFePO ₄	13.0	5.00	0.95	9158	6000
Fusion Power Systems Titan-3	Aqueous Hybrid Ion	8.0	3.50	0.94	10175	4000

10.2 Electricity Pricing

Utilities use pricing schemes to communicate their preferences to consumers. One such scheme is real-time pricing (RTP) where electricity prices vary throughout the day, usually hourly. Such a scheme is more amenable to large commercial customers than residential customers. Nevertheless, some companies such as Commonwealth Edison and Ameren Illinois [86, 87] engage in RTP schemes for residential customers.

Another pricing mechanism is known as time-of use (TOU) pricing where the day is divided into two or three peak and non-peak periods, each period with its own price of electricity [3]. This method encourages customers to move their demand away from periods when electricity is expensive and use energy when electricity is cheap. However, this mechanism does not incentivize customers to reduce energy during such critical times as heat wave periods. TOU schemes are mostly used by commercial and industrial customers. According to the Environmental Defense Fund [11], most utilities in the United States have some form of TOU scheme available to residential customers, however, adoption has been low.

Variable peak pricing (VPP) is a type of TOU pricing where the peak TOU price changes from day to day [88] and thus encourages customers to reduce energy use during critical peak periods.

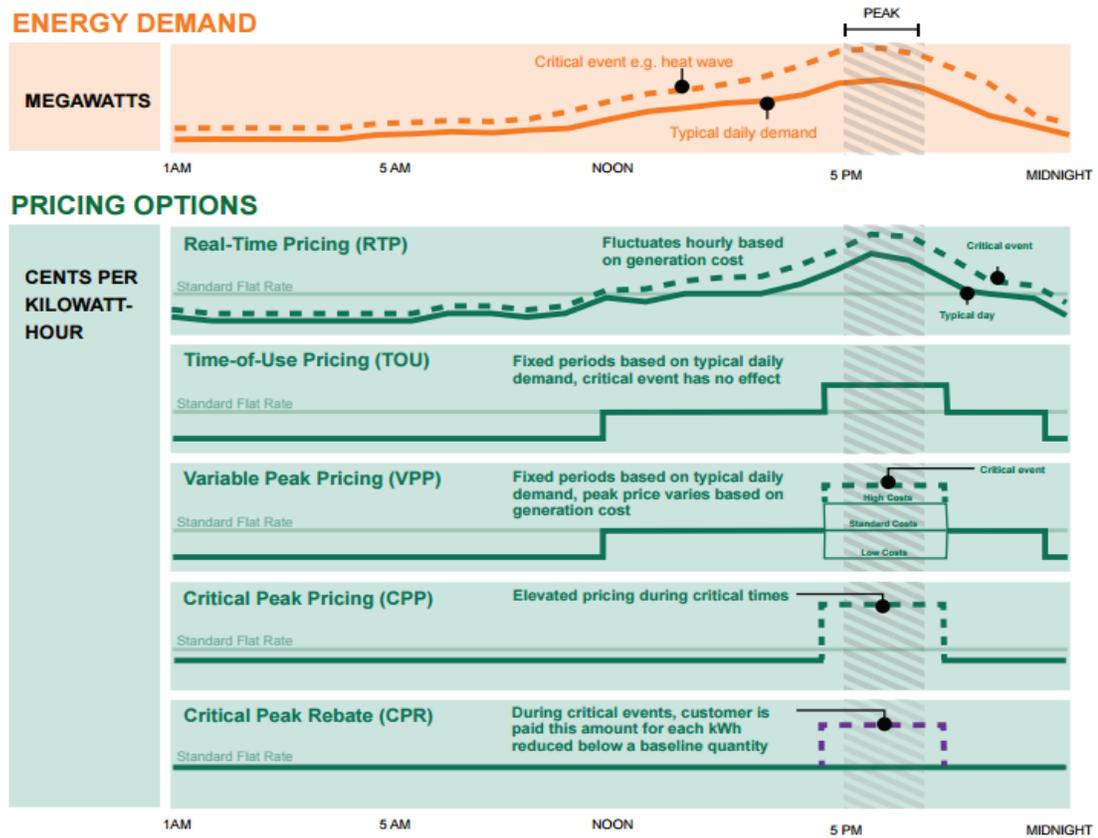


Figure 31. RTP, TOU, VPP, CPP, and CPR pricing mechanisms (reproduced as is from [88]).

In addition to the aforementioned pricing mechanisms, there is another scheme known as critical peak pricing (CPP) where customers pay a flat rate daily but are sent a warning notification in advance of a drastic price increase [3]. This enables them to react appropriately to reduce demand during such events. A variation on CPP is the critical peak rebate (CPR) where customers are compensated for every kWh they reduce during critical peak periods [3].

Figure 31 illustrates the different pricing schemes for a generic energy demand curve. Our project uses LMP (a form of RTP) as pricing scheme. Although our testbed operates under Citizens' Electric fixed rate, we use the LMP because it is more reflective of actual utility behavior.

10.3 Computer Code

To obtain our MATLAB code, please follow this link:

philip.asare.net/research/energy

In the event that the link is moved, a notice will be displayed on the webpage.