CONSUMER SAVINGS AND PEAK REDUCTION POTENTIAL OF A SIMULATED RESIDENTIAL MICROGRID WITH DEMAND RESPONSE AND ELECTRIC VEHICLE DISCHARGE CAPABILITIES

A Thesis
Presented to
The Academic Faculty

By

Jamie Kono

In Partial Fulfillment
Of the Requirements for the Degree
Master of Science in Mechanical Engineering

Georgia Institute of Technology

December 2016

CONSUMER SAVINGS AND PEAK REDUCTION POTENTIAL OF A SIMULATED RESIDENTIAL MICROGRID WITH DEMAND RESPONSE AND ELECTRIC VEHICLE DISCHARGE CAPABILITIES

Dr. Bert Bras
School of Mechanical Engineering
Georgia Institute of Technology

Dr. Godfried Augenbroe
School of Architecture
Georgia Institute of Technology

Dr. Cassandra Telenko
School of Mechanical Engineering
Georgia Institute of Technology

Date Approved: December 1, 2016

ACKNOWLEDGEMENTS

I would like to thank Ford Motor Company who funded this work and Ford team members Jacob Mathews and Danny Boston for their valuable feedback on my work.

I would like to thank my advisor, Dr. Bert Bras, for his ideas and guidance through this process. I would like to thank Dr. Godfried Augenbroe and Dr. Cassandra Telenko for providing their help and feedback on my thesis.

I would like to especially thank Gustavo Carniero for his collaboration on this work and his excellent insight into building modeling and the proper use of the Energy Performance Standard Calculation Toolkit.

I would like to thank my family for their encouragement and support, with special thanks to my father, Jim Cummings, who taught me to understand and marvel at the mechanics of the world around me.

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NOMENCLATURE

DR	Demand Response: Building actions to reduce peak demand
EIA	Energy Information Administration
EPC	Energy Performance Calculation
EPSCT	Energy Performance Standard Calculation Toolkit
EV	Electric Vehicle
HVAC	Heating, Ventilating and Air Conditioning
kW	kilowatt
kWh	kilowatt-hour
kWh/hr	kilowatt-hour per hour: Hourly electrical demand
NREL	National Renewable Energy Laboratory
PR	Peak Reduction: Efforts to reduce peak demand from the centralized grid
PV	Photovoltaic
SLB	Second-Life Battery
V2G	Vehicle to Grid discharge

SUMMARY

Increased use of solar electricity generation, electric vehicles, and other distributed electricity resources pose a problem to the electrical grid. Microgrids may provide a solution to increased variability in electricity generation and demand while also allowing residential customers to more readily provide peak shaving services.

This thesis models the electricity use of a small residential microgrid implemented to observe peak demand reduction program events and to provide local power services during outage scenarios. An hourly reduced-order building model and separate battery model are used to create a 10-home microgrid which incorporates photovoltaic arrays, electric vehicle discharge to grid, stationary batteries, and building demand response as strategies to reduce peak consumption and provide energy services during outages.

A microgrid that implements demand response (DR) and vehicle to grid (V2G) strategies saved $75-320 annually on electricity bills under time of use and critical peak pricing tariffs with an additional $20-80 savings from connecting as a microgrid.

A neighborhood without microgrid connectivity was able to reduce peak electricity demand from the larger grid by up to 46% through demand response and vehicle to grid discharge. A neighborhood with microgrid connectivity was able to lower peak demand further to 62% through the same strategies. The marginal peak savings from microgrid connectivity increased as buildings implemented more severe demand response levels and allowed more electric vehicle battery to be discharged to grid.

A microgrid with a small shared stationary battery was shown to further reduce peak load and supplement microgrid resilience.

Many independent houses were able to provide basic electric loads through electric vehicle discharge during a four-hour outage but failed during longer outages. The microgrid was able to provide minimal loads and moderately reduced loads for most outages of 4, 24, and 72 hour lengths with the aid of a small number of community-owned stationary batteries.

While a neighborhood has little financial incentive to pursue adding or including microgrid capabilities, pooled electric resources in the form of a microgrid allow for greater peak reduction and energy security. The microgrid lays the foundation for the future energy landscape: a reliable, flexible grid connecting electric vehicles, rooftop solar, and other distributed resources.

INTRODUCTION

1.1 Summary

Microgrids are a collection of buildings and electricity resources that can connect to or operate independently from the larger, centralized grid. Microgrids frame the electrical grid of the future: where many localized grids are connected, providing more appropriate levels of interaction for coordinating peak reduction and electrical stability in a world with large numbers of electrical vehicles and distributed, variable generation. To examine the usefulness of microgrids in reducing peak demand to the grid at large, this thesis evaluates several research questions examining the value of a residential microgrid to consumers and utilities alike.

1.2 Microgrid Overview and Motivation

A microgrid, according to the US Department of Energy, is "a localized grouping of electricity sources and loads that normally operates connected to and synchronous with the traditional centralized grid (macrogrid), but can disconnect and function autonomously as physical and/or economic conditions dictate" ("About Microgrids,." 2016). Microgrids improve the energy security of a region and allow affected regions to power themselves during periods of disaster, infrastructure maintenance, or other outage situations. A microgrid can allow critical resources such as hospitals, police and fire stations, and communications facilities to keep serving the area during outages such as the Tohoku hospital during the three-day outage in Sendai, Japan after the 2011 tsunami (Hirose, Reilly, & Irie, 2013).

Beyond outage scenarios, microgrids can serve to create a more reliable electrical grid. Colson and Nehrir (2009) discuss the benefits of multi-agent system where localized grid controllers manage loads semi-independently to counter the impact of slow or disconnected smart grid communications. These more reliable control systems can better handle the increase in variable loads from increasing penetration of solar panels and electric vehicles.

Electric vehicles (EVs) are becoming a greater portion of the US vehicle stock. Cleary et al. (2010) estimate that between 250,000 and 500,000 new plug-in hybrid vehicles will be sold each year through 2020. While EVs have no driving emissions, their potential to decrease carbon and other emissions is only achieved by charging with low-emission electricity sources.

Electricity produced by residential rooftop solar is one such low-emission electricity source. As of July 2016, the estimated distributed (non-utility-owned) PV capacity was 11.8GW (US EIA, 2016). This generation peaks in mid-day and disappears in early evening to produce a diurnal "duck curve" which poses generation logistics issues and power quality issues at larger penetrations (Radhakrishnan & Reddy, 2015).

The special challenge of increasing levels of electric vehicle and photovoltaic penetration is balancing electrical loads. The United States peak electricity capacity has risen from 810GW in 2009 (Federal Energy Regulatory Commission, 2009) to over 1TW in 2016 (US EIA, 2016). Large numbers of EVs charging during peak hours would spell major problems for the US electrical grid. Solar generation helps to offset some peak loads, but as solar penetration increases, the grid's ability to handle the variable nature of the solar generation will come into question.

Treating a house, rooftop solar panels, and an electric vehicle as part of the same system is one approach to handling residential electrical needs. Integrating a neighborhood of such houses (see Figure 1) can allow the neighborhood to smooth electrical demand and supply before it sends power to grid. Such a decentralized strategy is proposed by smart grid technologies (San Diego Gas & Electric, 2013).

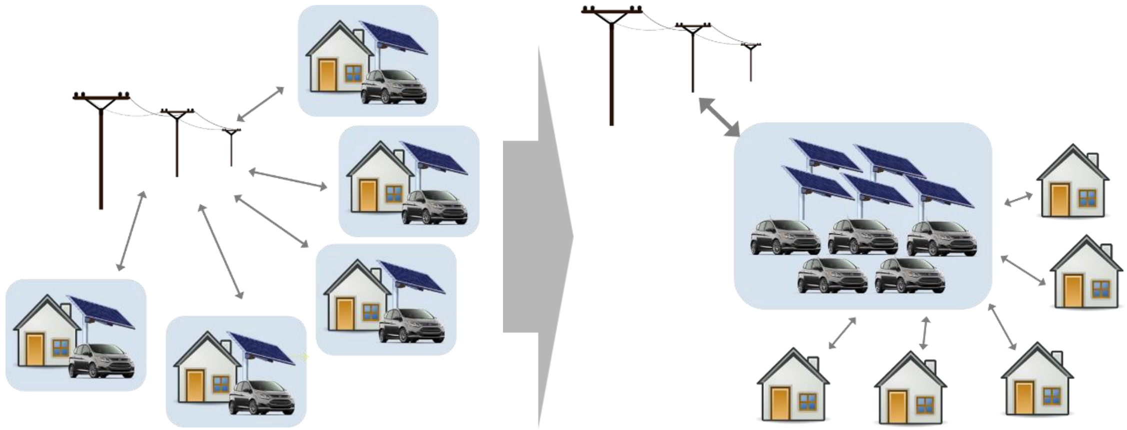

Figure 1. A neighborhood of homes that connect directly to the grid (left) and a neighborhood of homes that share electricity resources before connecting to the grid (right).

This thesis is created to examine one neighborhood operating as a microgrid whose goal is to provide peak shaving services to the grid. It creates a ten-home neighborhood where each house has solar panels, one electric vehicle driven by the main commuter, and simple demand response capabilities. The neighborhood is evaluated (1) as if all homes interacted directly with the grid and (2) as if all homes shared electrical resources as a microgrid before interacting with the larger grid. The microgrid scenario also implements a stationary battery shared by the community.

While demand response from a utility perspective means a wider array of actions to lower utility demand, this thesis refers to demand response (DR) as a building's efforts to lower usage by implementing thermostat setbacks, equipment shutoff and appliance delay. DR does not refer to electric vehicle or stationary battery discharge. The community's total effort to reduce demand from the grid during peak hours is referred to as peak reduction.

Several studies have demonstrated the benefits of demand response, PV arrays, electric vehicle discharge, and stationary battery discharge as means to reduce peak demand. This thesis will examine these four peak reduction and load smoothing strategies for a small residential neighborhood and evaluate their combined effectiveness as well as the effectiveness of managing the electrical power of the neighborhood before interacting with the grid. It will evaluate peak reduction potential on an hourly basis as well as potential consumer savings by applying several peak reduction tariff policies.

1.3 Research Questions

As the choice to install photovoltaic panels and drive electric vehicles lies with the consumer, the financial benefits of a microgrid for a homeowner are worth considering. Current electricity tariffs across the United States and in other countries are often designed to charge higher prices for peak usage and lower for off-peak usage. Load smoothing can decrease consumer electricity cost under time of use tariffs, which leads to the first research question:

How much of a financial benefit do microgrids pose to residential customers within current peak reduction infrastructure: static time-of-use utility rate structures and simple window-based peak demand reduction events?

The other side of microgrid implementation is the benefit to the utility. The peak reduction available to utilities through demand side management programs is a valuable commodity as it prevents utilities from having to install new peaker plants or purchase electricity at a premium from other electrical regions (Denholm, Diakov & Margolis, 2015). Microgrids are able to achieve this through coordinated peak reduction efforts. This thesis will consider four strategies within the microgrid setup: demand response such as thermostat setbacks or equipment use delay/reduction, solar energy generation, electric vehicle discharge, and stationary battery discharge. This is demonstrated in the second research question:

How much of a peak electricity reduction benefit can microgrids that use demand response, solar arrays, electric vehicle discharge, and stationary batteries provide to utilities?

Lastly, the benefits of microgrids extend beyond moderating peak usage. Microgrids provide consumers energy security in times of outage by islanding off of the grid. The thesis examines this idea briefly by testing several outage scenarios in which all peak reduction strategies are deployed. This strategy addresses the last research question:

How long can simple residential microgrids (with extreme demand response and vehicle to grid discharge capabilities) provide electricity to its houses during power outages?

1.4 Research Approach

The study simulates a residential microgrid by incorporating a reduced-order building model that can simulate commercial, industrial, and residential building types. It uses the Energy Performance Standard Calculation Toolkit (EPSCT) (Augenbroe, Kim & Lee, 2015) which uses the International Standards Organization (ISO) 13790:2008 Standard (ISO, 2008), which provides reasonable data on average building usage on an hourly level and also simulates PV panel output. The usage patterns for the home were informed by the Building America Simulation Protocol (Hendron & Engebrecht, 2010), which provide hourly schedules for hot water usage, appliance consumption, and lighting consumption.

The EPSCT is a macro-enabled Microsoft Excel spreadsheet. This thesis uses an additional worksheet appended to the model that simulates an electric vehicle battery. Ten instances of the combined battery-building model are created and connected to a master input spreadsheet with input parameters for all ten homes, including occupancy and usage schedules, building and battery characteristics, and demand response values.

Each model is run as if the buildings operated separately, with a final amount purchased from the grid representing the demand for each separate house. Additionally, each house's building demand (before battery discharge) and PV generation is exported to a centralized spreadsheet which simulates the microgrid scenario. In this configuration, the building demand and solar generation values are summed and ten battery models in the centralized spreadsheet provide discharge services to the aggregated community. This process produces two main outputs: (1) the total hourly electricity purchased from the grid for all houses with separated resources and (1) the hourly electricity purchased from the grid for the community with combined resources. From these values, electricity costs for the year and demand during peak periods can be calculated.

The study will consider two existing utility peak reduction programs: (1) a static time-of-use pricing scheme, which can include critical peak pricing, and (2) a number of utility-determined periods in which buildings are obligated to comply with peak reduction measures.

The first peak reduction program uses time-of-use electricity tariffs with three cost tiers inspired by Georgia Power's Electric Vehicle rate (Georgia Power, n. d.), shown in Figure 2. The lowest-cost tier, "super off-peak," runs from 11pm to 6am. The second tier, "off-peak," runs from 6am to 11pm, except for when "on-peak" hours are specified. The highest tier, "on-peak", runs 2-7pm, May-September only. The highest tier has much higher than average utility prices, while the super off-peak has much lower. An additional time of use tariff structure is considered, which adds a fourth tier, called a critical peak pricing rate, which has an extremely high price during utility-specified peak periods. Performance within the time-of-use tariff structure will be evaluated based on consumer cost savings.

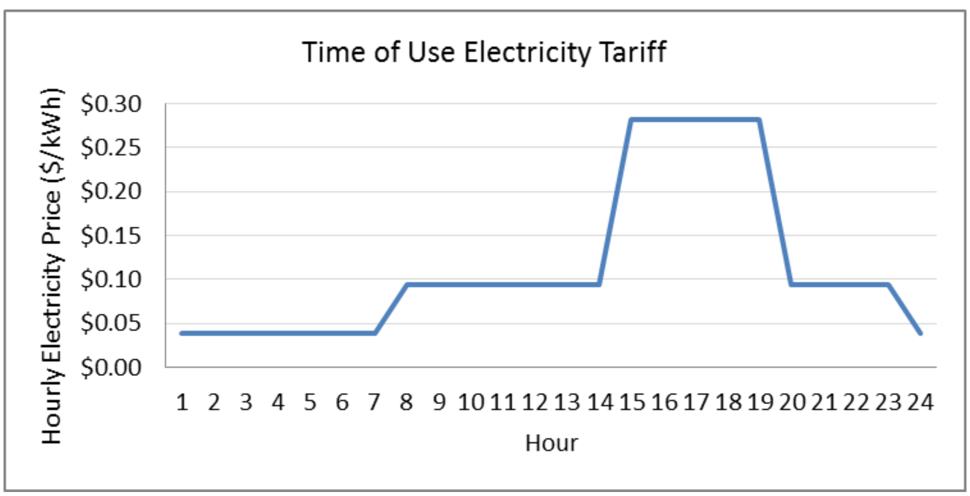

Figure 2. Example time of use electricity tariff.

The second peak reduction program mimics a demand-side management program used by many utilities or utility aggregators that requires customers to reduce their peak energy usage by shutting down equipment or lowering usage by a certain amount during selected peak days. The model used in this thesis is based on a program offered by PJM, a regional transmission organization that manages utility-customer interactions in thirteen states including Ohio, New Jersey and others. Residential customers are obligated to participate in peak reduction efforts 10 days of each summer. These events can last for up to six hours. The performance of this peak reduction strategy will be evaluated by the hourly peak reduction provided by the community.

The microgrid will be evaluated in a number of different configurations. The first will be a standard residential configuration with electric vehicle discharge available. Another configuration will involve consumer demand response, including turning off unneeded lights/appliances with controllable power strips, raising the thermostat, and delaying schedulable appliances. These two demand reduction strategies will also be evaluated in combination. Lastly, the neighborhood with shared electrical resources will be simulated with a community-owned stationary battery to further supplement peak reduction.

A final evaluation will involve the resiliency of the community. The neighborhood will be simulated to run with no available utility power during several representative periods throughout the year. The performance will be determined by the neighborhood's ability to provide electricity at various levels of service throughout the outage.

2 BACKGROUND

2.1 Summary

This section provides background information on microgrids, demand response programs, battery discharge, and building energy simulation.

Several studies have studied or simulated microgrids to achieve better grid stabilization and reliability. A number of microgrids currently exist, primarily on physical islands, where distributed resources such as hydroelectric, solar, diesel, and natural gas generators are used alongside battery storage, pumped storage, and demand control measures. Other studies evaluate the increased resiliency of a microgrid as penetrations of distributed energy resources (solar, electric vehicles, wind) increase.

Peak demand is a pressing and costly issue for United States utilities. As peak demand increases along with increased variable generation, peak reduction techniques become more attractive. These strategies include residential demand response, solar generation, and battery discharge. Building demand response (DR) in the form of thermostat setbacks and equipment shutoff are a commonly used demand reduction strategy and electric vehicle discharge to grid is gaining attention as another peak reduction resource. Peak reduction by stationary batteries has historically been uneconomical, but falling battery prices are making this strategy more viable.

Electric vehicle discharge is discussed in more depth as issues surrounding the extra use of vehicle batteries could cause increased consumer cost. In addition, effective discharge strategies are emerging as electric vehicles become of interest to the electricity sector.

Lastly, the section reviews building modeling softwares. A number of building simulation programs are considered, and it discusses previous simulations on electric vehicle-integrated homes performed by Ford Motor Company in the MyEnergi Lifestyle project.

2.2 Microgrids

2.2.1 Overview

Current state-of-the-art microgrids are usually found on physical islands, where providing reliable grid-scale power through a local microgrid is less expensive than running overseas connections. Many of these existing microgrids also utilize high proportions of renewable energies, since importing diesel or other fossil fuels are often cost-prohibitive.

The main components of a microgrid, as shown in Figure 3 are:

- Energy generation equipment, which creates the power,
- Power electronic converters, which convert electricity to usable forms and manage the quality of power in the system,
- Energy storage equipment, and
- Consumer loads.

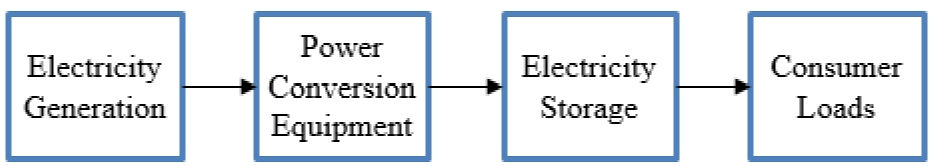

Figure 3. Main components of a microgrid.

The following sections describe several existing microgrids and a number of studies on microgrid or smart grid technologies.

2.2.2 Existing Microgrids

Table 1 outlines the main characteristics of several existing microgrids. Some are on physical islands and some are test microgrids that are joined to a larger grid.

Table 1. General characteristics of selected microgrids

	Borrego Springs, CA, USA	Sendai, Japan	Isle of Eigg, Scotland	Leaf House, Italy	El Hierro, Canary Islands
Pop. Served	3500	Hospital	96	6 apartments	10,000
Year Est.	2008	2004	2008	2008	2012
Islanding Realized?	9 hours, 2015	2 days, 2011	Always	Self-sufficient ~60% of hours	Always
Peak Reduction	15%	N/A	N/A	N/A	N/A
Costs of Upgrades	$8-13M	N/A	£1.6M	Not profitable with energy savings	$86.4M
Renewable Generation	26MW Solar	50kW PV CHP	30kW PV 112kW hydro 24kW wind	20kW PV Solar Thermal Geothermal HP	11.5MW wind
Other Generation	2x1800kW diesel	2x350kW gas	2x80kW diesel	None	12.7MW diesel
Storage	500kW/ 1500kWh Lithium	200kW Fuel Cell	200kWh Lead Acid	5.8kWh Lithium-ion, 1300L hot water storage	11MW hydro-reservoir
Power Management Strategy	Real-Time Pricing	Prioritized Buildings	5kW demand limit per house	Self-contained management software	None

2.2.2.1 Borrego Springs

San Diego Gas & Electric constructed a large microgrid in Borrego Springs, CA. Located in the southern California desert, the 5,000 person city was connected to the grid from one main cable. The goal of the microgrid is to provide more reliable power to the remote area, and to reduce peak demand to the utility. Borrego Springs uses a 26MW solar facility and two 1800kW diesel generators in conjunction with a residential real-time pricing system that allows homeowners to manage the energy use of various appliances (HVAC, pool pumps, electric vehicle chargers, etc.). The community has shown peak energy use reduction of more than 15 percent and in May 2015, the entire community functioned as an island for 9 hours during the day (San Diego Gas & Electric, 2013).

2.2.2.2 Tohoku Fukushi University, Sendai, Japan

A microgrid located at Tohoku Fukushi University in Sendai City, Japan made news during the Tohoku Earthquake in 2011. The microgrid powered a teaching hospital for two days during a power outage caused by the earthquake and tsunami. The system consisted of two 250kW gas generators, a 200kW phosphoric acid fuel cell, and a 50kW PV array. Waste heat from the gas generators was used to heat the building. The various parts of the hospital were prioritized differently, with the most critical areas receiving the highest priority (Hirose et al. 2013).

2.2.2.3 Leaf House, Italy

The Leaf House (shown in Figure 4) is a small residential microgrid in the form of a 6-unit apartment building in Italy. The building uses passive solar strategies, a 20 kW PV array, a 5.8kWh Lithium-ion battery, and geothermal and solar thermal systems to provide domestic hot water. The building stores up to 1300L of hot water for off-solar usage. The building is self-sufficient 60% of the time (Comodi et al., 2015).

Figure 4. A six-unit apartment microgrid with PV, geothermal, solar thermal, and battery and hot water energy storage (Comodi 2015).

2.2.2.4 Isle of Eigg, Scotland

The Isle of Eigg is a physical island 30km from mainland Scotland. Electricity provided to the 37 houses and 5 businesses on the island is provided by a microgrid established in 2008. It features 112kW of hydroelectric power, a 30kW PV array, 24kW of wind power, two 80kW backup diesel generators, and a 200kWh battery. Consumer load management is basic: houses have a 5kW demand limit, and if a house exceeds the limit they are disconnected from the grid and can be reconnected after paying a small fee. There are basic feedback alarms to warn residents approaching the limit. (“Renewable Energies,” 2012)

2.2.2.5 El Hierro (Canary Islands), Spain

El Hierro is located in the Canary Islands. It is powered by Gorona del Viento (Figure 5), a hydro-wind facility that uses 11.5MW of wind power to pump fresh water up the mountainside to a high-elevation reservoir. The water is released downward to a low-elevation reservoir as more electricity is needed. The water functions as a battery, and from full “charge” can allegedly power the island for two days (Plitt 2015).

Figure 5. El Hierro hydro-wind plant (Plitt 2015).

2.2.3 Other Microgrid Studies

2.2.3.1 <u>Department of Defense Energy Surety Microgrids</u>

Sandia National Laboratories evaluated the cost-effectiveness of a microgrid in achieving energy security at a US military installation. Critical buildings were already equipped with backup generators and uninterruptible power supplies (UPS) systems to keep power on during outages. The study recommended that three of five critical buildings already connected with medium voltage lines be connected as a microgrid. It also recommended installing energy storage devices for the systems to avoid short-term generator cycling and manage renewable energy penetration. While the study found a small microgrid worthwhile, it also found that no less fuel was consumed in a microgrid setup versus a separated generation setup (Stamp, Eddy, Jensen & Munoz-Ramos, 2015).

2.2.3.2 US Solar Decathlon

In 2013, the US Solar Decathlon, a contest to build cost-effective solar homes, operated all 19 contest homes as an islanded microgrid for one day. All houses had PV systems, with a 28% capacity penetration and 105% load penetration. The microgrid was supplemented with a 500kW diesel generator and 140kW of installed PV. The experiment showed no decrease in power quality, even with six EVs charging simultaneously (Kurnik et al., 2015).

2.2.4 Microgrid Resilience

The need for energy security during outage scenarios also drives interest in microgrids. In 2015, there were at least 46 reported outages effecting more than 50,000 customers in the US, shown in Table 2. More than half lasted longer than one day (Office of Electricity Delivery and Reliability, 2015).

Table 2. Outages in 2015 effecting more than 50,000 customers.

Outage Length	Number of Outages
Less than 4 hours	7
4-12 hours	5
12-24 hours	5
24-72 hours	24
More than 72 hours	5

New Jersey installed 100MW of combined heat and power systems after Hurricane Sandy (New Jersey Board of Public Utilities 2015). The New Jersey Master Energy Plan called for increased investment in microgrid technologies for disaster preparedness, citing 143 five-minute or longer outage events and 27 day-long outages in New Jersey between 1985 and 2013.

One method of planning for resilient microgrids is setting a minimum load to be serviced in outages. Lu, Bahramirad, Wang & Chen (2015) proposed a neighborhood microgrid that prioritizes pre-specified critical loads in outages. Any extra electricity will be used to power additional equipment. Additionally, interconnected microgrids can allow for greater grid stability. Chanda & Srivastava (2016) showed that several connected microgrids can effectively respond to unexpected maintenance or security-related outages.

2.3 Utility Demand Response Programs

2.3.1 United States Peak Demand Capacity

The United States peak demand capacity in 2009 was 810GW and was predicted to be 950GW by 2019 (FERC, 2009). As this peak demand capacity grows, demand response programs show potential to help reduce the need for additional peak generation capacity.

Areas with high air conditioning loads show greater potential for peak reduction through demand response programs. Air conditioning use is strongly related to the time of day and results in peak energy consumption during the afternoon in the summertime. These peaks times are often the drivers behind utility peak periods. Even in cooler climates, air conditioning tends to dominate the peak usage because space conditioning loads in the winter often draw on fuels other than electricity (FERC, 2009).

Many utilities already regulate peak demand through the use of dynamic electricity pricing and other more sophisticated infrastructure, but most of these programs are focused on larger buildings where a single infrastructure improvement can affect a larger amount of power consumption. For residential scenarios, dynamic pricing and advanced metering infrastructure requires infrastructure upgrades which may be more expensive than the demand response cost savings they produce (FERC, 2009).

In 2014, the US spent $647 million on residential demand response for a total demand reduction capacity of 50.2 GW, or $12.9 per kW of peak demand reduction on average. The peak reduction capacity and program cost in the ten states with the largest (by MW capacity) residential demand response programs are shown in Figure 6 and Figure 7.

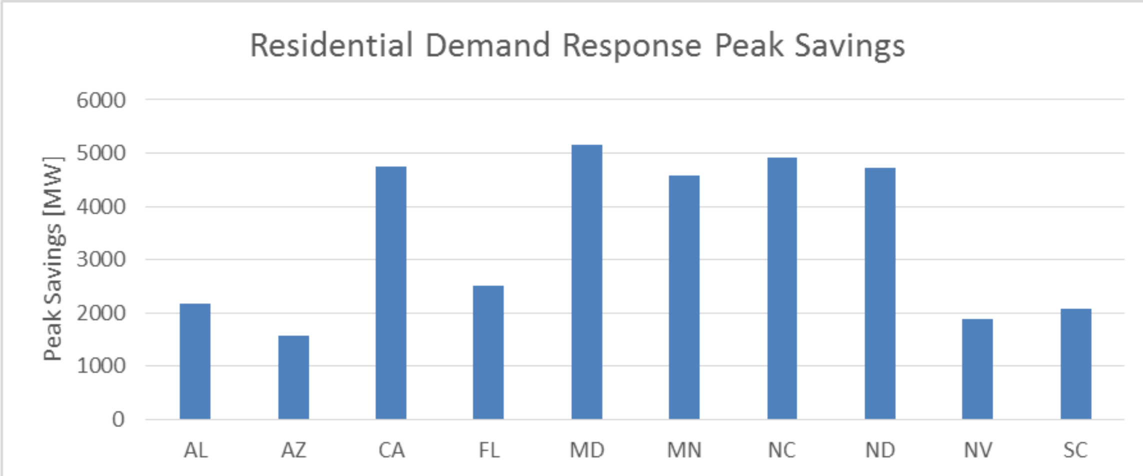

Figure 6. Residential peak reduction capacity for the top ten states (EIA, 2014).

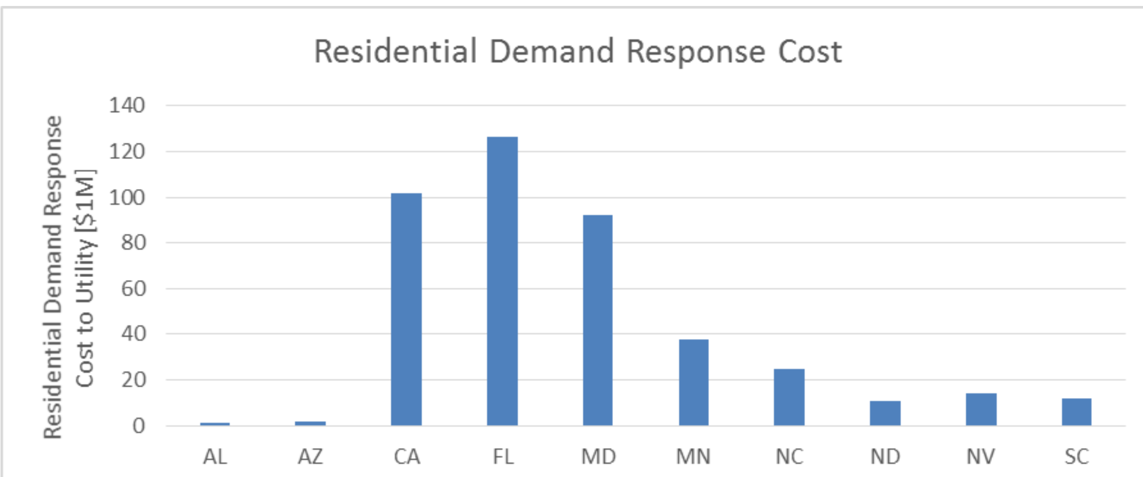

Figure 7. Residential demand response program cost for the top ten states (EIA, 2014).

2.3.1.1 Direct Load Management

Direct load management allows the utility to turn off a device for a period of time during peak hours. One example is the "On Call" program provided by Florida Power and Light. The service installs a device onto a homeowner's air conditioning unit, pool pump, or water heater that can disable the device for a short period of time. Participants get a monthly credit on their bill regardless of whether it is used ("On Call," 2016).

2.3.1.2 Static Time-of-Use Pricing

Time-of-use pricing is used to encourage residential users to shift loads from higher peak periods to lower peaks. Some utilities target these programs at electric vehicle users, as EVs are a large and controllable load. One example of such a system is offered by the Sawnee Electric Membership Corporation serving Cumming, GA. Table 3 shows the tariff rates, with a low rate for “off-peak” hours and a higher rate for weekday afternoons in the summer (Sawnee Electric Membership Corporation: “Plug-in,” 2011).

Table 3. Example time-of-use pricing scheme.

Tariff Schedule	Applicable Time Period	Cost per kWh
Off-Peak	All hours other than on-peak	\$0.0415
On-Peak	June-Aug, Weekdays, 2-8pm	\$0.280

2.3.1.3 Critical Peak Pricing

An expansion of time-of-use pricing is the critical peak pricing scheme. Critical peak pricing adds a higher priced tier that occurs during utility-specified critical peaks. This price is typically much higher than on-peak pricing. For example, Sawnee Electric Coop provides residential consumers with the following critical peak pricing scheme, described in Table 4 (Sawnee Electric Membership Corporation: “Critical Peak Pricing,” 2011).

Table 4. Example critical peak pricing scheme.

Tariff Schedule	Applicable Time Period	Cost per kWh
Off-Peak	All hours other than on-peak or critical peak	\$0.0415
On-Peak	June-Aug, Weekdays, 2-8pm, excluding critical peak hours	\$0.207
Critical Peak	Hours of utility load management system operation	\$0.950

2.3.1.4 Demand Charges

Another pricing scheme involves levying demand charges for maximum electricity demand. One paper analyzes the effects of winter peak demand charges in Norway. The proposed demand charges would be applied based on the maximum registered demand between 7am and 4pm on weekdays for three winter months (Stokke 2010).

2.3.1.5 Real-Time Pricing and Day-Ahead Pricing

More dynamic pricing schemes are also used to control peak demand, including real-time pricing and day-ahead pricing. (Ehsanfar, 2016). These use changing electricity tariffs to encourage users to shift loads as the utility needs. One real time pricing event observed in the Borrego Springs microgrid is shown in Figure 8. The price of electricity was raised during the RTP events and demand on the event day lowered as homes adjusted their usage to reduce costs.

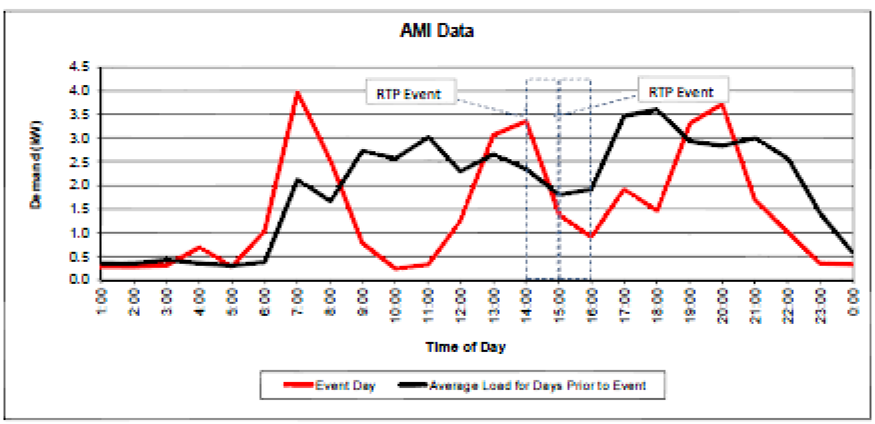

Figure 8. Building load reduction during a real time pricing (RTP) event at Borrego Springs, CA (SDG&E 2013).

Many studies have been conducted on the most effective implementation of real-time and day-ahead pricing schemes using game theory and other energy management processes (AlSkaif , Zapata, Bellalta & Nilsson, 2016; Bisschoff & Gouws, 2015).

This thesis examines the potential of neighborhoods to reduce consumption during utility peaks which may be used to accommodate real-time and day-ahead pricing schemes, but the interaction of residences and hourly pricing is outside the scope of this thesis and these pricing schemes will not be considered.

2.3.2 Complement of Vehicle Discharge, Solar Generation, and Demand Response

Consumer demand response, PV generation, and electric vehicle discharge to grid can be complementary in their usefulness for peak reduction and load smoothing. A 2016 study in South Aftrica showed 14% reduction in electricity consumption and 15% cost savings through time-of-use tariffs for combined demand response, PV, and V2G technologies (Setlhaolo & Xia, 2016).

Katz et al. (2015) shows that combined PV and battery systems can be effective tools for smoothing peak energy use. Figure 9 shows energy consumption for a strip mall with PV and battery load smoothing techniques employed.

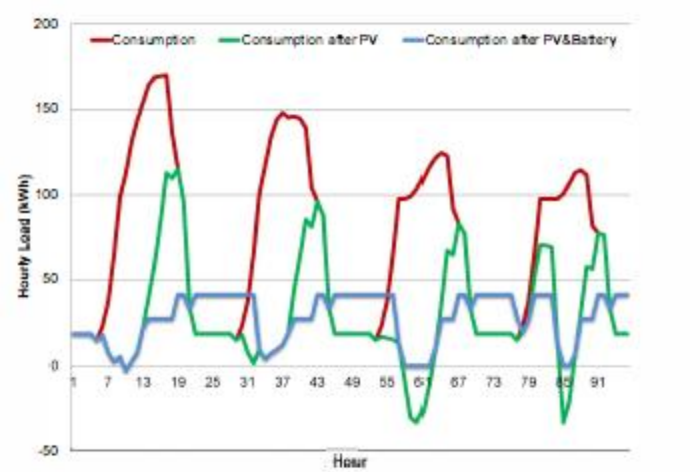

Figure 9. Peak shaving for a strip mall with PV and battery (Katz 2015).

Hale, Doebber and Jorgenson (2015) considered demand response with variable generation systems and found that as variable generation increases, demand response because increasingly valuable, especially at a utility scale. One study found that demand response and solar generation was complementary but lacking in total peak demand reduction (Vajjala & Jewell, 2015).

2.4 Vehicle to Grid Discharge

2.4.1 Vehicle to Grid Research

As variable levels of electricity generation increases, the need for quick-response electric services increase. EVs equipped with vehicle to grid (V2G) capabilities have the greatest potential for grid services in this realm (Yao, Gao, Momoh & Muljadi, 2015). These kind of services costs $12 billion each year in the United States, or 5-10% of total electric cost (Xiang, Xue, Sirouspour & Emadi, 2012). An NREL study in 2015 modeled the outputs of wind, solar, and V2G to show that plug-in hybrid vehicles equipped with V2G capabilities can be a quick-response electricity source for accommodating variable load and generation and for accommodating peak loads (Yao et al., 2015).

A number of studies has shown the potential for EVs to fill nighttime low demand periods (Ma, 2013) or grid-specified periods (Kundu, 2012). Gottwalt (2016) showed that EVs have significant potential for residential peak reduction within a microgrid.

2.4.2 Battery life

While electric vehicles provide an enticing source of “free” available battery space, the lifespan of EV batteries are a particularly concerning topic. A study using the Battery Lifetime Analysis and Simulation Tool for Vehicles (BLAST-V) model predicts that EV battery degradation is driven primarily by calendar effects: the effects of sources other than battery cycling, such as temperature or time (Neubauer, Smith, Wood & Pesaran, 2015). BLAST-V is a semi-empirical model that considers the effects of temperature, time, depth of discharge, and state of charge based on existing (albeit sparse) laboratory data. BLAST-V compares the effects of battery cycling and calendar effects separately, then considers the maximum effect of the two as the driving force behind battery degradation. Figure 10 shows simulated capacity loss from these two sources during a EV’s lifetime.

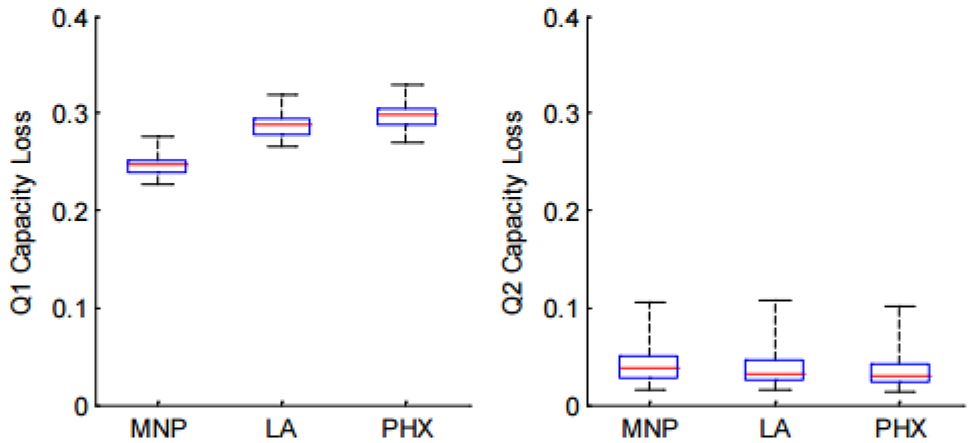

Figure 10. 22.1kWh Battery Electric Vehicle capacity degradation from calendar effects (Q1) and cycling effects (Q2) (Neubauer et al., 2015).

While the results of the study suggest that battery cycling has less impact on the health of an electric vehicle battery, the study also notes that depth of cycling may have a significant impact on battery health during second-life discharge. Due to these conflicting results, this thesis proceeds cautiously regarding the overuse of V2G.

2.4.3 Discharge Algorithms

In order to properly smooth peak loads, the rate of battery discharge is a topic worthy of investigation. The first and simplest method of discharging batteries is discharging as much as possible to reduce the current building demand (Quoilin et al., 2016). Maity and Rao (2010) evaluated battery discharge for load levelization. Figure 11 shows the results of a home with PV generation and battery storage configured to purchase a constant amount from the grid during each hour.

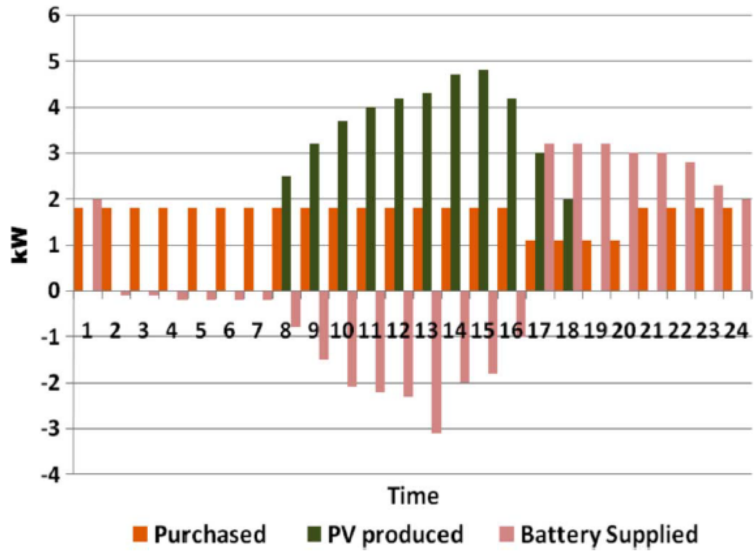

Figure 11. July average of hourly energy sources for load levelization (Maity 2010).

Several battery discharge algorithms have been created to deal with real-time or day-ahead pricing. Day-ahead pricing allows battery operators to discharge more power during high price periods. Kim and Lavrova (2013) developed an algorithm to schedule load shedding, battery discharge and purchasing from other agents using a fuzzy logic algorithm that optimized cost savings against a real-time pricing scheme. Mishra and Zhu (2012) determined battery discharge based on day-ahead pricing by creating a demand prediction algorithm based on nine different factors: outdoor temperature/humidity, day of week, previous day's power, etc.

2.5 Stationary Battery Discharge

While historically not economical, battery storage for microgrid resilience or peak reduction is slowly becoming more viable as the cost of batteries falls.

Denholm et al. (2013) discuss the value of battery energy storage in the context of solar and wind generation. While additional variable generation increases the value of battery storage, the study found that battery storage was still not close to economical due to the suppression of peak pricing and other factors. Another study examines EVs and second life batteries (SLBs) as a cost-effective alternative to additional generation sources to provide backup energy services during infrastructure maintenance or downtime (Denholm, Diakov & Margolis, 2015). A study by the National Renewable Energy Laboratory suggested the most economical application of second life batteries would be for utility use as peak shaving devices to replace peaker plants (Neubauer et al., 2015).

2.6 Residential Building Simulation Programs

In order to accurately model electricity use during peak times, a reasonable building model must be developed. Several models are discussed, along with an outline of the MyEnergi Lifestyles program which serves as the inspiration for this thesis.

2.6.1 My Energi Lifestyle

My Energi Lifestyle (MEL) is a project created by Ford Motor Company to further the incorporation of electric vehicles into an energy efficient home. The first generation of MEL, described in Figure 12, evaluated a single home combined with an electric vehicle and PV system to find 60% energy cost reduction and 50% CO_2 emission reduction.

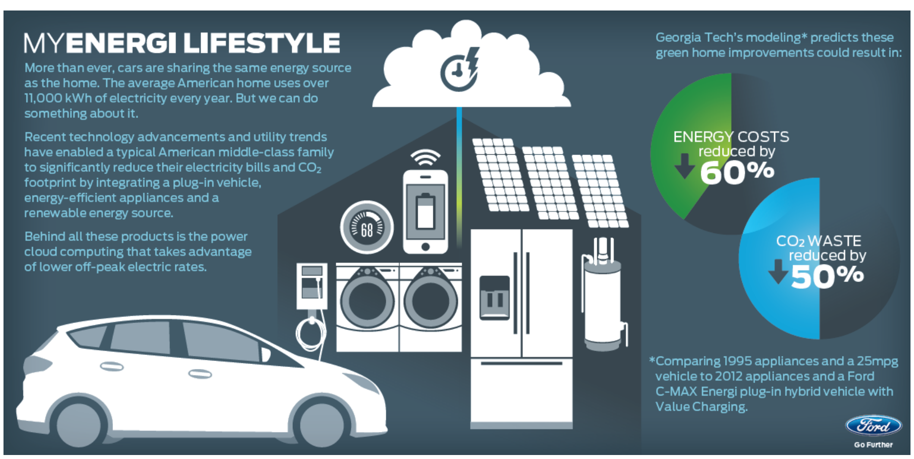

Figure 12. MyEnergi Lifestyle by Ford Motor Company: electric-vehicle integrated homes.

The second generation of MEL evaluated a home with a stationary battery included, and the third generation evaluated a more contemporary home with high efficiency appliances and building envelope. The program used a finite element model mesh to model heat transfer across the various parts of the building (Lee, Boston, Wang, Augenbroe, et al., 2013). The heat transfer was calculated in steady-state conditions with alterations to account for time-changing values.

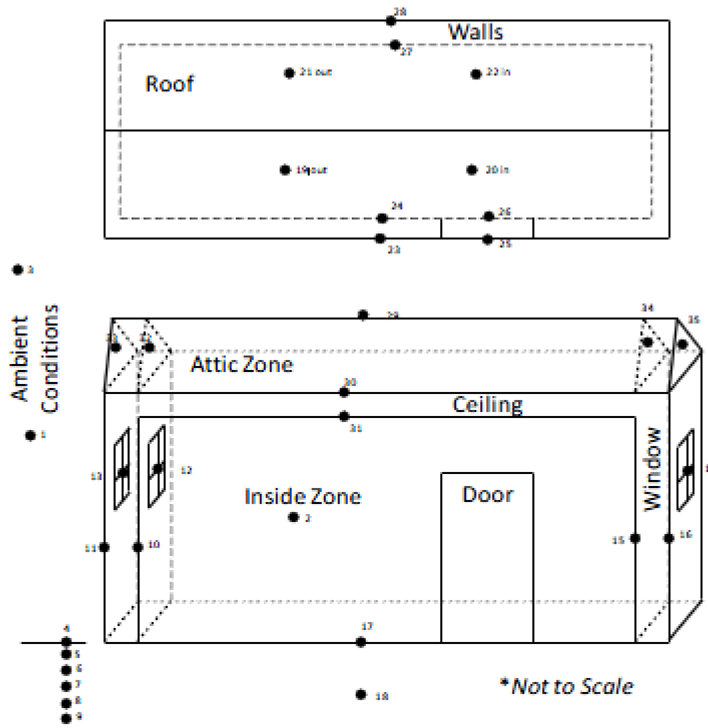

Figure 13. Finite Element Model Mesh for MyEnergi Lifestyle 1.0.

Later iterations of the MyEnergi Lifestyle program examined the implementation of energy efficiency improvements, scheduled appliances, and stationary batteries. The studies did not consider vehicle to grid discharge.

2.6.2 Energy Performance Standard Calculation Toolkit

This thesis used the Energy Performance Standard Calculation Toolkit (EPSCT) (Augenbroe, Kim & Lee, 2015), a modified version of the Energy Performance Coefficient (EPC) calculation to model each building in the microgrid. The EPC model performs an hourly heat balance calculation for the various parts of a building, according to supplied characteristics, such as wall insulation value, window solar heat gain coefficients, etc. The model is an implementation of the ISO 13790:2008 standard (ISO, 2008), which uses normative assumptions to create a building model from relatively few inputs.

The EPC model has been used in a cost optimization of energy reduction technologies (Simmons, Tan, Wu, Yu & Augenbroe, 2013) and a validation of the LEED Energy and Atmosphere score (Kim, Augenbroe & Suh, 2013).

The model is available as a spreadsheet calculation which allows for customized interactions at the hourly level. This enables multiple models to be coordinated into a microgrid model. The EPC model also requires lower computational resources, allowing a coordinated microgrid to be run without excessive computing power. The reduced-order model provides for relatively accurate results while not requiring large number of parameters to be specified. The model excels at comparing parametric changes rather than predicting real building loads. Its accuracy is especially high when considering buildings with high air conditioning requirements (Zhao, 2012).

2.6.3 Gridlab-D

Gridlab-D is a program developed by the US Department of Energy that models electrical distribution systems and buildings. It has been used to test real-time pricing demand response and peak reduction through efficiency improvements (Chassin, Fuller & Djilali, 2014). This model simulates buildings using the equivalent thermal parameters method which provides time and temperature solutions to a second-order ordinary differential equation which describes the building model (Chassin et al., 2014). This reduced-order model also provides the benefits of lighter computational requirements and fewer parameters inputs.

Gridlab-D was designed to model the electrical needs of multiple buildings for the purposes of distribution system modeling and has been used for demand response applications (Vajjala et al., 2015). Jewell et al. (2014) used Gridlab-D to evaluate the potential of efficiency improvements and thermostat setbacks to achieve peak reduction in Wichita, Kansas.

2.6.4 EnergyPlus

EnergyPlus (US Department of Energy, 2013) is a US Department of Energy program that performs a heat balance calculation for temperature and moisture content. It can simulate more advanced window and HVAC systems and can provide calculations at the seconds level. EnergyPlus provides a higher accuracy, finite element analysis with multiple zones and more sophisticated building component information. BEOpt was chosen as the utility to run EnergyPlus ("BEOpt," 2016).

3 METHODS

3.1 Summary

This thesis employs a reduced order building model and a battery model to simulate the electricity consumption of ten residential buildings that utilize various load smoothing and peak reduction strategies.

First, a synthetic neighborhood is created to reflect a realistic US community. The occupants and schedules are based on US Bureau of Labor Statistics data on employment and commute times and the Federal Highway Administration's travel distance data. General variability about mean characteristics are chosen to achieve an organic set of schedules.

Building schedules are formulated based on occupancy schedules and the US Building America Simulation Protocols. These schedules include major appliance usage, plug loads, lighting, hot water usage, and space conditioning set points. Once again, these values are varied slightly to account for variation in occupant behavior.

Electric vehicle availability and charge/discharge algorithms are developed. Several discharge algorithms are used to approximate predictive discharge algorithms used in real-world situations. With the appropriate discharge algorithm detected, the variability in battery availability is analyzed through a Monte Carlo simulation. A battery availability distribution close to mean performance is chosen.

Building demand response and V2G are evaluated under time of use tariffs and critical peak pricing. Electricity savings are compared to occupant discomfort and vehicle battery usage. The average peak reduction achieved during 20 utility-determined summertime peak periods is calculated.

Stationary batteries are considered next, with varying sizes available to achieve partial to complete peak reduction. EV and stationary battery discharge are combined with demand response to model a number of outage scenarios in a rudimentary resilience evaluation.

3.2 Building models

The neighborhood simulated in this thesis is made of ten homes modeled using the Energy Performance Standard Calculation Toolkit (EPSCT). Building characteristics are drawn heavily from MyEnergi Lifestyles, a project by Ford Motor Company that examined an electric vehicle-integrated home.

3.2.1 Location

Columbia, SC was selected as the location for study. Hourly TMY3 (Typical Meteorological Year) data for Columbia Metro Airport (TMY file 723100) was used to provide weather and solar irradiation data. Columbia, SC was chosen because it has an average insolation level for the United States as shown in Figure 14.

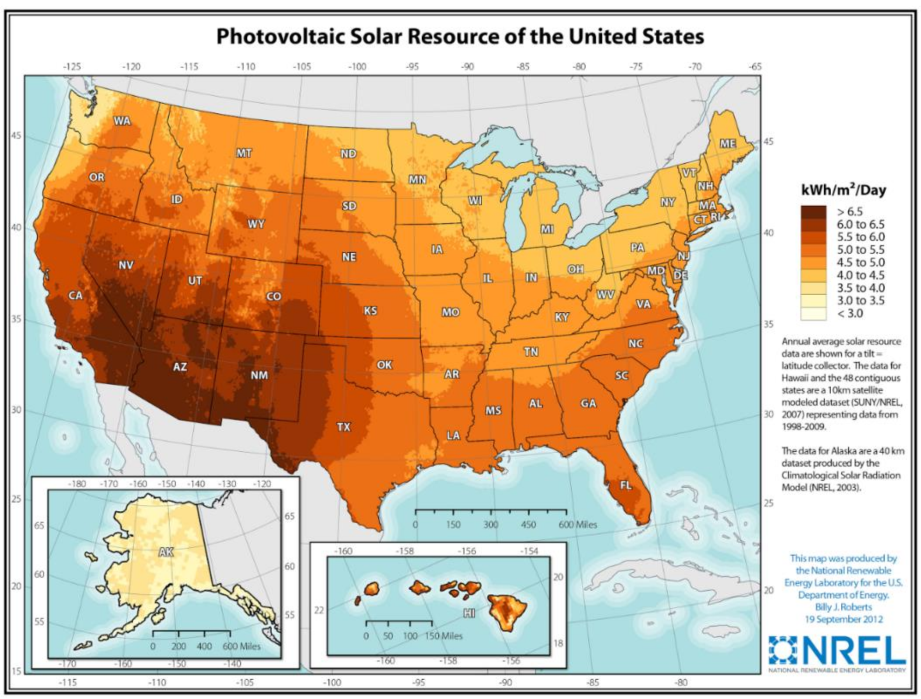

Figure 14. Solar generation potential for the United States (NREL, 2016).

3.2.2 Building Characteristics

Building characteristics, as shown in Table 5, were selected based on Building America Simulation Protocols (Wilson, Engebrecht Metzger, Horowitz & Hendron, 2014) and regional efficiency standards.

Table 5. Building characteristics for a 4-person home.

Location	Columbia, SC (3A)
Floor Area	$160m^2$
Wall Height	4m
N, S wall width	10m
E, W wall width	16m
Window area	$24m^2$ All dir.
Window/Floor area	0.15
A/C COP	4.01
Heating Type	Heat Pump
Heating Performance	HSPF 10, COP 2.93
PV system	$19.2m^2$ (4kW)
PV angle	30
PV orientation	S
Occupancy	1-5
Metabolic Rate	100 W/person
Daily Appliance Use:	
Refrigerator	3432Wh
Dishwasher	2191Wh
Clothes Washer	1831Wh
Clothes Dryer	2514Wh
Miscellaneous	7728Wh
Daily Lighting Use	4949Wh
Daily DHW Use	8663Wh
Wall Insulation	R-20
Roof Insulation	R-38
Floor Insulation	R-19
Window type	Double glazed
Thermostat Set point	70/75F

3.2.3 Community Composition

The initial neighborhood was manually assembled with the goal of creating a diverse set of house types that roughly represent US demographics. Table 6 describes the employment and schooling status of the houses. The 10-house neighborhood has 17 adults and 10 children. 65% of the adults in the community were full-time workers, 12% were part-time workers, and 24% did not work. The US statistics for these numbers are 51%, 11%, and 37%, respectively (Bureau of Labor Statistics, 2016). These numbers are summarized in Table 7.

Table 6. Employment and schooling status of the houses in the MEL community.

House Number	Occupant Description	Adults	Full-time workers	Part-time workers	Night-shift	Children	Children non-schooled	Children in after-school care
1	Single	1	1	0	0	0	0	0
2	Single, night-shift	1	1	0	1	0	0	0
3	Single parent	1	1	0	0	1	0	1
4	Senior couple	2	0	0	0	0	0	0
5	Couple, no kids	2	2	0	0	0	0	0
6	Parents with infant	2	1	1	0	1	1	0
7	Parents, child in school	2	2	0	0	1	0	0
8	Parents with children in school	2	1	1	0	2	0	0
9	Stay-at-home-parent and infant	2	1	0	0	2	1	0
10	Parents with children in school	2	1	0	0	3	0	0
	Total	17	11	2	1	10	2	1
	% of adults or children		65%	12%	6%		20%	10%

Table 7. Comparison between US demographics and MEL 4.0 community.

	Number of People	% of Adults or Children	US Statistics
Total Adults	17		
Full-time workers	11	65%	51%
Part-time workers	2	12%	11%
Non-working adults	4	24%	37%
Total Children	10		
Children in School	8	80%	
Children not in School	2	20%	

3.2.4 Schedule Construction

3.2.4.1 Occupancy

The occupant schedule was based on the number of adults, their work status, the number of children and their school status. Full-time dayshift workers were scheduled to leave and return from work on a normative basis, where the average departure time was 8am, average commute time was 20 minutes, and the average workday was 9 hours. One full-time worker worked a night shift. This data is based on data from the US Department of Labor (Bureau of Labor Statistics, 2005; Bureau of Labor Statistics, 2016).

3.2.4.2 Lighting

The total daily lighting use was based on calculations performed for previous iterations of MEL, which were informed by Building America Simulation protocols (Morris et al, 2014). The shape of the lighting schedule profile was based on Building America lighting schedules (Hendron and Engebrecht, 2010) with a normalized variation for each hour.

$$LightingUse(hour) = TotalLightingUse * BALightingFraction * VariationFactor$$

Where

$$VariationFactor = InverseNormal(Mean = 1, StandardDeviation = 0.2)$$

VariationFactor is the inverse cumulative distribution function for a normal curve with mean 1 and standard deviation 0.2.

3.2.4.3 Appliances

Appliances account for all equipment besides the HVAC equipment, lighting, and DHW equipment. Energy consumption and usage schedules are based on Building America simulation protocols (Hendron and Engebrecht, 2010).

The dishwasher, clothes washer, and clothes dryer energy use was considered individually in anticipation of delaying usage of this equipment to off-peak times. Although the BA protocol establishes that these three appliances are typically run less than once a day, for the simplicity of the model, we have assumed they run once each day, but with power consumption lessened such that the yearly consumption of each appliance is the same as the BA protocol.

All other equipment was modeled using the BA miscellaneous electric load profile. This includes other kitchen appliances such as the refrigerator and cooking appliances.

3.2.4.4 Water Heating

The water heating usage was initially calculated for each month, then scaled to each hour based on occupancy. Usage was later scaled to Building America DHW schedules (Hendron and Engebrecht, 2010), with adjustments made to account for differences in occupant commutes. Additionally, DHW usage associated with schedule appliances (dishwasher and clothes washer) is assigned in the same hour as the appliance is run.

3.2.5 Model Verification

To provide context to the EPSCT model, one building is also simulated in EnergyPlus and GridLab-D.

GridLab-D was run using a GLM file included in the Appendix. The file inputs the building geometry and thermal properties as well as specific schedules for DHW and equipment loads. Lighting was specified to the same levels as the Building America Simulation Protocols (Hendron 2014).

BEOpt, a high-level cost-optimization software was used to run EnergyPlus. BEOpt has fewer inputs available for user input and default schedules were left alone. The building geometry and heat transfer properties were entered along with annual equipment consumption values.

3.3 Electric Vehicle Battery Model

Once the building energy use is created, a battery model is used to determine the electricity charged to and discharged from the electric vehicle batteries. The battery available for discharge is based on vehicle presence at the home, the commute distance, and the participation level of the homeowner. This model is also configured to discharge in a way that smooths building loads.

3.3.1 Mobile Battery Model

The electric vehicle model is based on a 2016 Ford Focus Electric vehicle with a 23kWh lithium-ion battery and a 6.6kW 240V charger ("Ford Focus Electric," 2016). A full battery charge takes 3.6 hours. The efficiency was taken to be 300Wh/mile (KEMA, 2010), giving the 23kWh battery a range of 76.7 miles. Battery specifications and driving requirements are summarized in Table 8.

Table 8. Battery specifications and driving requirements

Battery Size	23kWh
Discharge buffer	20%
Average driving distance	30mi/day
Battery efficiency	0.3 kWh/mi
Battery losses (round-trip)	85%

The mobile battery is modeled in Excel. The model keeps track of the available battery stored, starting at 0 for hour 0. The model withdraws a certain amount from the battery if there is a signal to activate V2G. If there is a signal, the battery discharges to offset any building electricity deficit, limited by the stored amount in the battery and an hourly discharge limit of 6.6 kWh/hr. This logic is described in Figure 15.

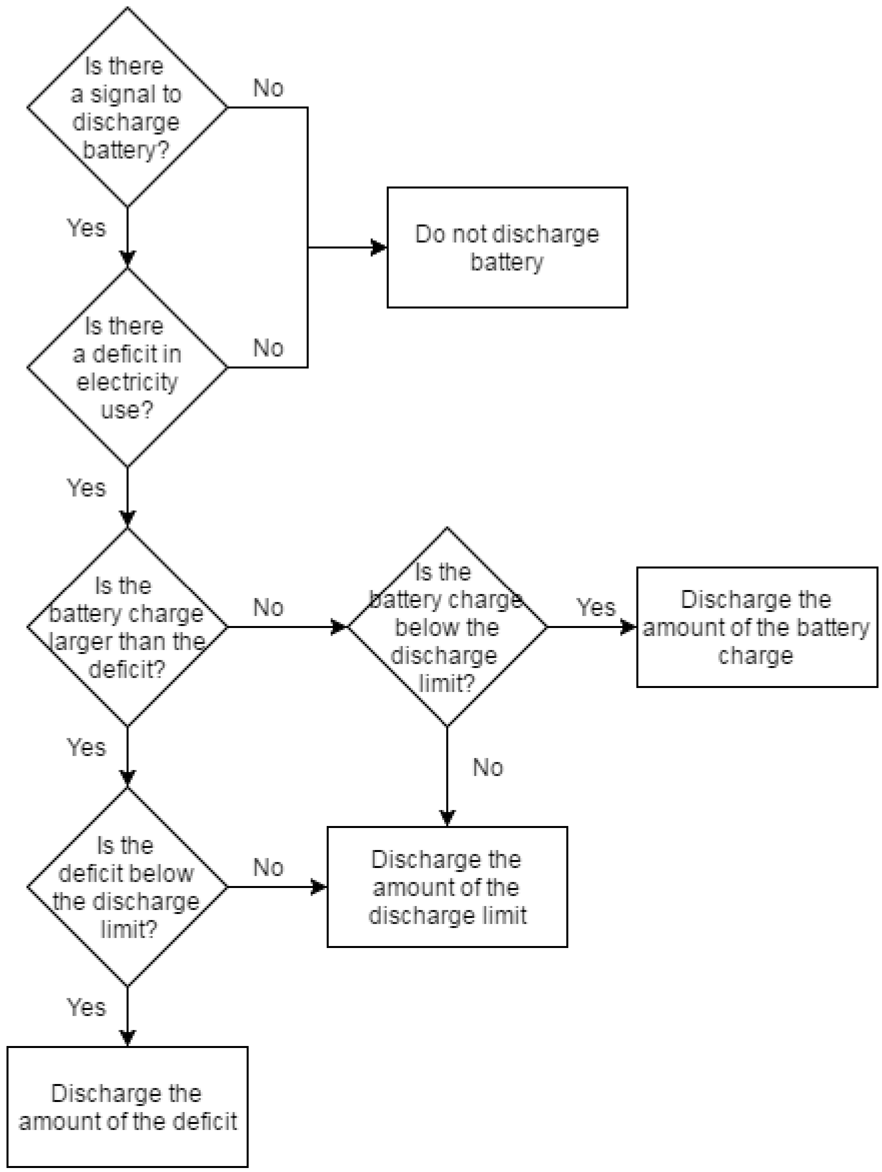

Figure 15. Basic electric vehicle battery discharge logic

3.3.2 Electric Vehicle Schedule

Electric vehicle charging and discharging is controlled by occupancy schedules and by peak periods. Figure 16 shows the EV charging schedule for 10 EVs (one per home).

EVs charging during the nighttime when super off-peak pricing is active. Two homes, homes 2 and 4, have vehicles present during the day and are reserved to be charged mostly from excess PV power generation.

ToU	hr	EV schedule									
		H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
S OFF	1	1	0	1	1	1	1	1	1	1	1
S OFF	2	1	0	1	1	1	1	1	1	1	1
S OFF	3	1	1	1	1	1	1	1	1	1	1
S OFF	4	1	1	1	1	1	1	1	1	1	1
S OFF	5	1	1	1	1	1	1	1	1	1	1
S OFF	6	1	1	1	1	1	0	0	1	1	1
S OFF	7	1	1	1	1	0	0	0	0	0	0
OFF	8	0	1	0	1	0	0	0	0	0	0
OFF	9	0	1	0	1	0	0	0	0	0	0
OFF	10	0	1	0	1	0	0	0	0	0	0
OFF	11	0	1	0	1	0	0	0	0	0	0
OFF	12	0	1	0	1	0	0	0	0	0	0
OFF	13	0	1	0	1	0	0	0	0	0	0
OFF	14	0	1	0	1	0	0	0	0	0	0
ON (sum.)	15	0	1	0	1	0	0	0	0	0	0
ON (sum.)	16	0	0	0	1	0	1	1	0	0	0
ON (sum.)	17	0	0	0	1	0	1	1	0	0	0
ON (sum.)	18	0	0	0	1	0	1	1	1	1	1
ON (sum.)	19	1	0	1	1	1	1	1	1	1	1
OFF	20	1	0	1	1	1	1	1	1	1	1
OFF	21	1	0	1	1	1	1	1	1	1	1
OFF	22	1	0	1	1	1	1	1	1	1	1
OFF	23	1	0	1	1	1	1	1	1	1	1
S OFF	24	1	0	1	1	1	1	1	1	1	1

	Range of charging hours for driving needs
	Extra charging from grid for volatile stock
	Extra charging from PV for volatile stock
	Start of daily commute
	Available for feed back (V2H)
	Feed back is delayed for later hours

Figure 16. EV charging and discharging schedule. One (1) corresponds to an EV present at the home and zero (0) corresponds to the EV absent from the home

3.3.3 Demographic Sensitivity

Since V2G is dependent on the availability of electric vehicle batteries, an additional two demographic makeups were considered. The first neighborhood consists of retirees or non-commuting professionals who are always home, making EV batteries available at all times. The second neighborhood was comprised of working professionals with longer workdays who were never home during the day, shown in Table 9. This neighborhood has very limited EV battery availability, and no EVs can collect excess PV generation.

Table 9. EV availability for the community of professionals with less EV presence (Shaded means EV is present).

Hour	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
1										
2										
3										
4										
5										
6										
7										
8										
9										
10										
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24										

3.3.4 Battery Capacity Availability

The available battery capacity also plays a large role in the effectiveness of V2G. Only a portion of the battery capacity is allocated for V2G. First, a portion is reserved to power the driver's daily commute. Second, a buffer amount is designated to prevent unhealthy levels of discharge. Lastly, the participant's willingness to discharge EV battery space influences the remaining space.

The total space available for V2G is calculated using the following equation:

$$\begin{matrix} Space\ available \\ for\ V2G \end{matrix} = \left(\begin{matrix} Battery \\ Capacity \end{matrix} - Buffer - \begin{matrix} Commute \\ Charge \end{matrix} \right) \times \begin{matrix} Participation \\ Level \end{matrix}$$

Three buffer levels of 10%, 20%, and 30% of the battery capacity are chosen. Daily commute distances for each house (shown in Figure 17) are created based on the average NHTSA daily car usage of 30 miles per driver per day (National Highway Administration, 2011). Variation among houses is determined at a 5 mi/day resolution with longer distances being applied to larger households.

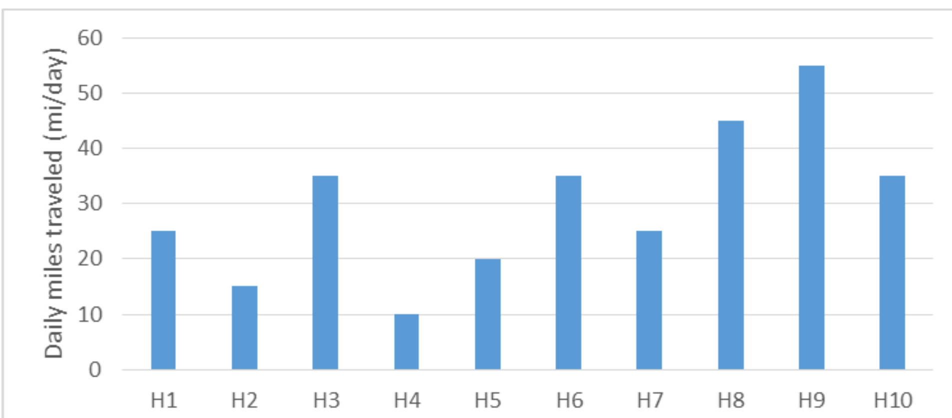

Figure 17. Daily commute distance for ten houses.

Participation level is the proportion of unreserved battery space that the homeowner allows to be used for V2G. The values for each home are based on a seed determined in the following section, and fitted to a normal distribution with a mean at the three specified average participation levels of 25%, 50%, and 75%. Figure 18 shows each house's participation level at the three different averages.

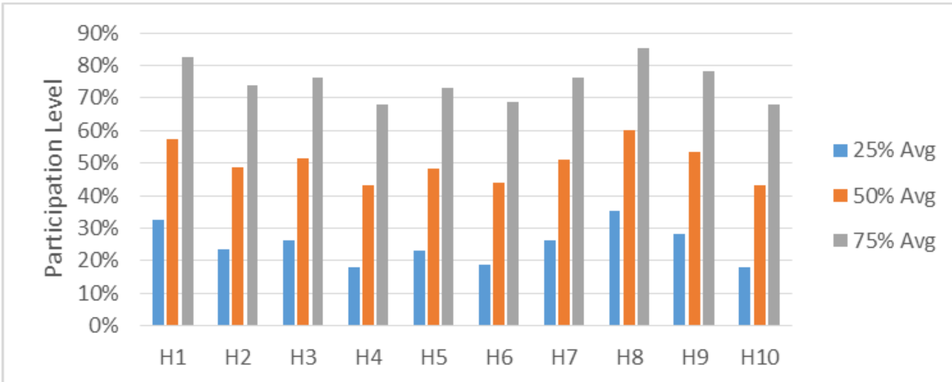

Figure 18. Example V2G participation level for ten houses at three different average levels of participation.

The battery space allowed for V2G in each home is calculated using the equation found above. The resulting battery availabilities are shown in Figure 19.

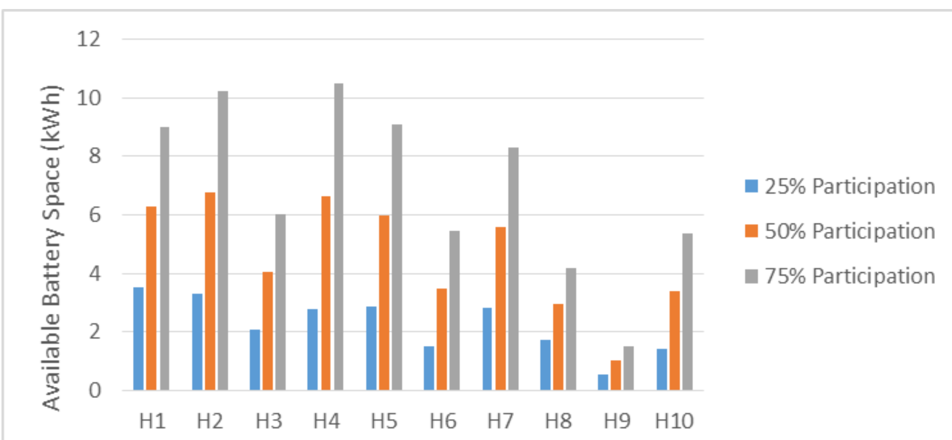

Figure 19. Example of battery space available for V2G at three different levels of participation.

3.3.5 Mobile Battery Stock Availability Sensitivity Analysis

The effectiveness of V2G discharge relies heavily on which each homeowner's relative willingness to use battery resources for V2G. Since V2G is limited to periods when the primary commuter is home, homes whose occupants are home during peak periods have more potential for V2G discharge.

To ensure that the model represents average behavior, a Monte Carlo simulation was created to evaluate microgrid performance with 500 different distributions of homeowner interest in V2G participation. 500 sets of 10 random numbers between 0 and 1 and with a mean of 0.5 were generated. Each set is one "scenario." These numbers serve as the percentiles when creating the level of participation for each house from a normal distribution. Figure 20 shows an example scenario.

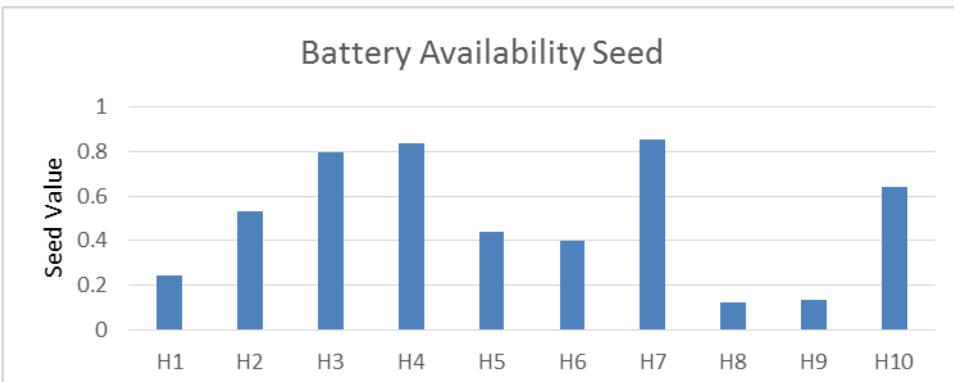

Figure 20. Example seed for battery availability sensitivity analysis.

Each seed is used to determine the V2G participation level of all ten houses by varying the participation level about a mean level (25%, 50%, or 75%). Each of the 10 numbers within the seed acts as the percentile of a normal distribution with a mean at the average level of participation (0.25, 0.50, or 0.75) and a standard deviation of 0.2. Figure 21 shows the level of participation for each house at a 50% average participation level using the seed shown in Figure 20.

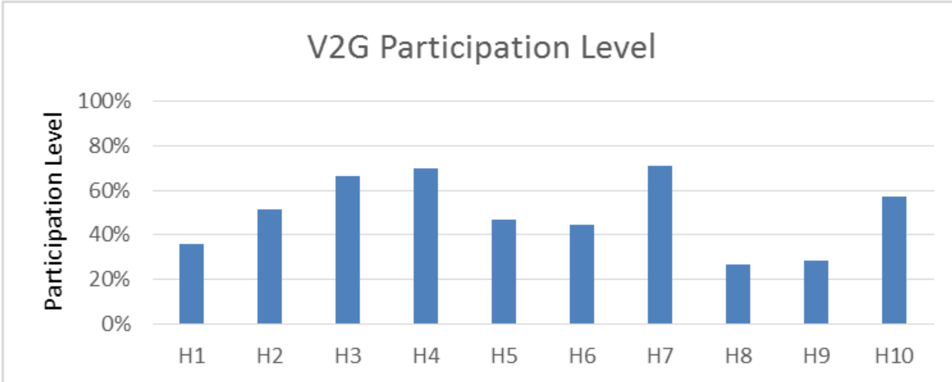

Figure 21. Example of the participation level for each house at 50% mean participation, generated from previous seed.

The space available for V2G is calculated from this participation level and one of three buffer amounts (10%, 20%, or 30%). This results in nine distributions of battery available for V2G.

The performance metric, mean peak consumption, was evaluated for all nine configurations of each seed. Mean peak consumption is calculated by evaluating the peak hourly consumption at each of the twenty peak days, and then taking the average of those twenty values.

The median of each of the resulting nine data sets (one for each buffer/average participation configuration) was evaluated. Using a least sum of squares method, the five scenarios whose results most closely matched all nine configurations were selected. The scenario that most closely matched the average seed values of those five was chosen as the representative distribution. This distribution is used for all V2G analysis.

3.4 Vehicle Discharge Algorithms

Since the goal of V2G is to smooth peak usage to a minimum level, a number of vehicle discharge algorithms were examined to approximate ideal discharge levels.

3.4.1 Demand Prediction

First, predicting building loads allows V2G discharge to anticipate the optimal discharge periods. For scenarios targeting load levelization during peak periods, it is important to distribute enough battery discharge across the hours such that all hours remain below a particular peak amount.

A simulation of each building without electric vehicle discharge was used as the "historical" usage data to inform demand prediction. The peak demand is characterized by examining usage in the 7 hottest days of each month. Pools of approximately equal numbers of high maximum daily temperatures and high average daily temperatures were selected and the days that fit into both pools were chosen as the hottest. Of those seven days, the hourly usage during each hour of the peak period is averaged to arrive with an average monthly peak period profile. An example is shown in Figure 22.

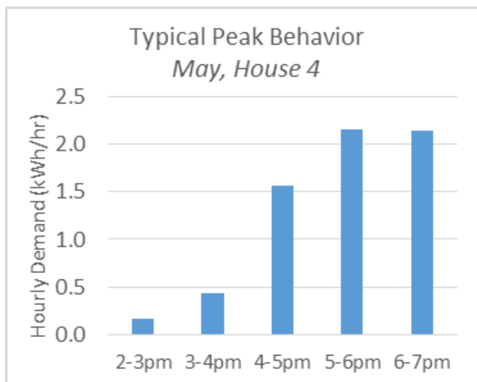

Figure 22. Peak usage in May for house 4 used for demand prediction.

3.4.2 Simple Discharge

The simplest discharge method discharges as much battery as possible until the battery runs out. Figure 23 shows simple battery discharge for an EV that is available for all five peak hours. Figure 24 shows simple battery discharge for an EV that is available from 5-7pm only.

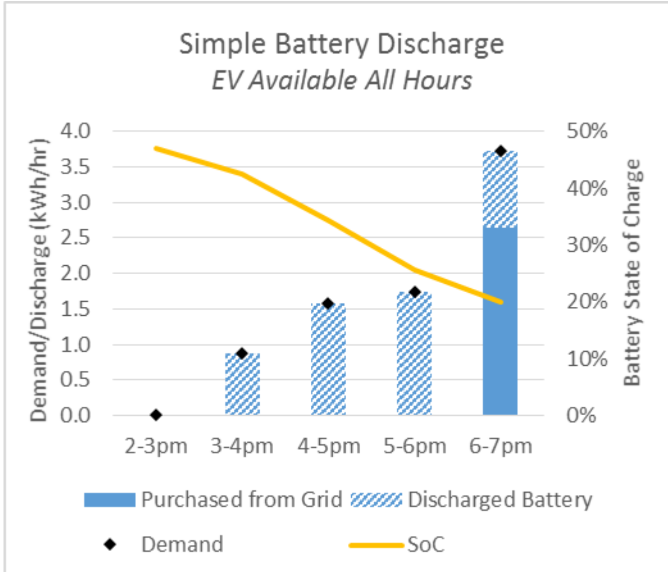

Figure 23. Example of simple battery discharge when EV is available during all peak hours.

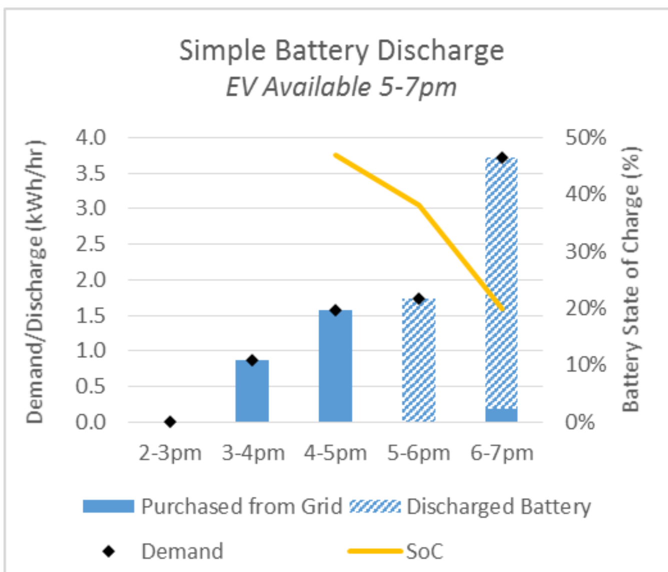

Figure 24. Example of simple battery discharge when EV is available 5-7pm.

An example of the ideally smoothed load is shown in Figure 25. Several discharge algorithms are considered this thesis in an attempt to achieve near ideal discharge.

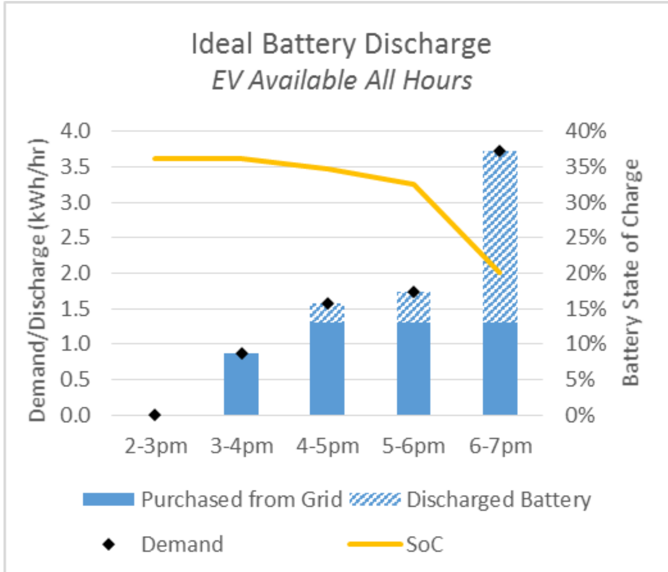

Figure 25. Ideal battery discharge performance.

3.4.3 Threshold Discharge

Threshold discharge prevents an EV from discharging all of its power during low-consuming hours by only discharging after the house or community has purchased a set amount from the grid. Figure 26 demonstrates a threshold of 0.6 kWh/hr. Any house consumption over 0.6kWh is offset by V2G discharge until the battery runs out of allocated charge.

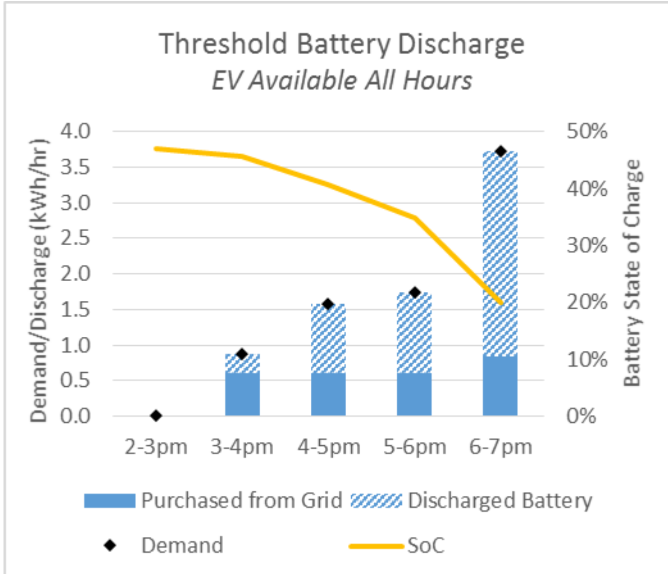

Figure 26. Example of threshold battery discharge when EV is available all peak hours.

The key drawback to this methodology is the importance of choosing an appropriate threshold. Figure 27 shows reduced performance from setting the threshold too high because the battery is underutilized and Figure 28 shows reduced performance from setting the threshold too low because the battery is used up before the final hour.

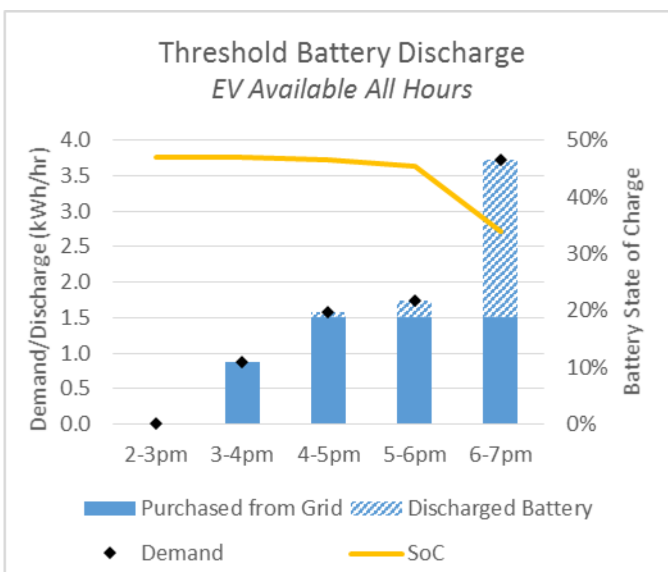

Figure 27. Example of threshold battery discharge when threshold is set too high (1.5 kWh/hr).

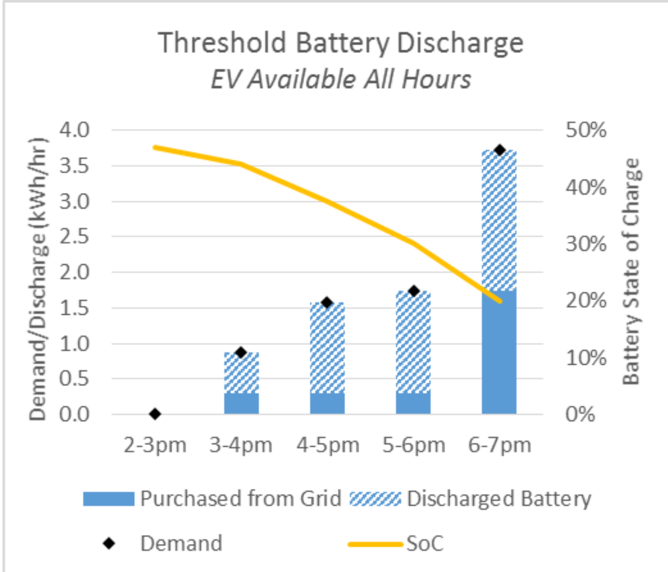

Figure 28. Example of threshold battery discharge when threshold is set too low (0.3 kWh/hr).

3.4.4 Proportional Discharge

Proportional discharge uses a prediction of the demand for each hour to divide the available battery among the three most consuming hours. Characteristic peak consumption described in section 3.4.1 is used to determine the three most consuming hours. The consumption from those three hours is scaled to percentages. The algorithm then multiplies the available battery at the start of the peak period by each proportion, to distribute the battery in a manner reflective of typical use. Figure 29 shows an example of proportional battery discharge.

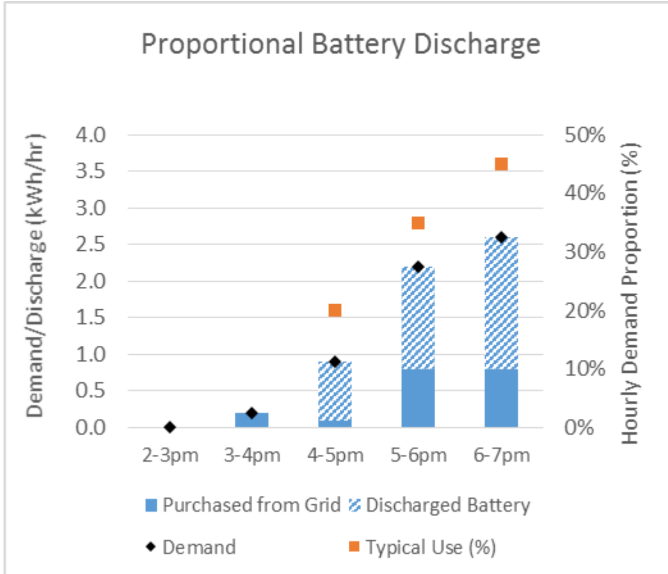

Figure 29. Example of proportional battery discharge performance.

3.4.5 Enhanced Proportional Discharge

When proportional discharge estimates that the amount of discharge needed for an early hour is more than the actual demand of that hour, it ignores that unused battery space until the last hour. To explore whether this phenomenon was making a difference in performance, the algorithm was changed to allow any extra battery amount to be used in the hour directly following the hour in which it was unused. Figure 30 and Figure 31 demonstrate the potential advantages to such a system. Hour 4-5pm has lower than anticipated demand and 0.2 kWh is not used. In the proportional discharge algorithm, the extra space would be discharged in the last hour if needed. However, in the enhanced proportional discharge algorithm, the extra space would be discharged in the next hour if needed.

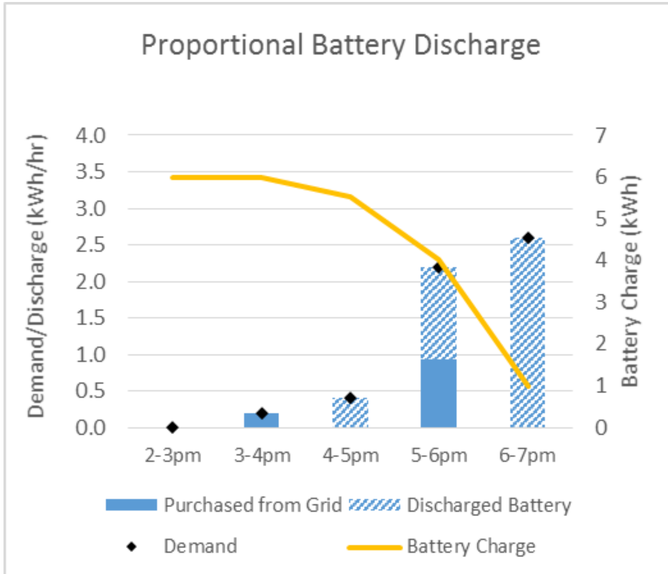

Figure 30. Example of proportional battery discharge with less-than-optimal discharge.

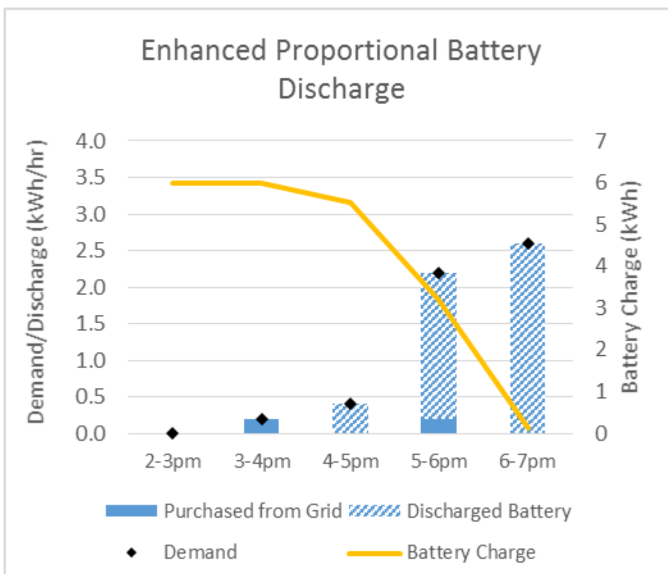

Figure 31. Example of enhanced proportional battery discharge that improves upon proportional discharge.

3.5 Peak Reduction

Two utility peak reduction programs are considered to gauge consumer cost savings. Building demand response, V2G, and stationary battery discharge are used to comply with these programs and to evaluate peak reduction potential of the neighborhood.

3.5.1 Variable Electricity Tariffs

This thesis two main utility peak reduction programs. First is a static time-of-use model which features increased "on-peak" pricing during summer afternoon/evening from 2-7pm. A more severe version of this pricing scheme is critical peak pricing, where during specific utility-determined periods, the customer pays an inflated critical price per kWh to encourage extreme usage cut backs. Table 10 shows the tariffs used for both variable tariff pricing schemes below.

Table 10. Time of use and critical peak pricing electricity tariffs.

	Time of Effect	Time-of-Use Rate ($/kWh)	Critical Peak Pricing Rate ($/kWh)
Super Off-Peak	11pm-6am	0.0384	0.0384
Off-Peak	All hours not on-peak	0.0938	0.0938
On-Peak	May-Sep weekdays, 2-7pm	0.2819	0.200
Critical Peak	2-7pm, 20 peak days	--	0.950

3.5.2 Demand Side Management Events

The second utility peak reduction programs is based on specific peak demand events that the consumer agrees to respond to. Usually these types of programs provide a static monetary incentive for participation, such as a monthly bill credit. The program used for this study was based on PJM, a utility aggregator in the northeast. Their "limited DR" program requires that the customer lower their demand during 10 days in the summer, for up to six hours at a time (PJM, 2016).

Since this ten-home microgrid will have a negligible effect on the overall utility demand, peak days are not directly based on building demand. Instead, since utility peak events are often driven by increased air conditioning usage (i.e. higher outdoor temperature) and other unknown events (such as generation facility maintenance), the peak demand events were chosen by creating a pool of 32 days whose average TMY3 outdoor temperature was greater than 26C (52 candidates) and whose maximum hourly temperature was greater than 32C (66 candidates). Twenty of these 32 candidates were selected at random to account for unknown utility demand events. From these twenty days, each house is assigned 10 random days to observe a peak demand event. Table 11 shows the 20 peak days and each house's compliance for that day.

Table 11. Utility peak event dates and individual house compliance.

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	Total
2-Jun											3
5-Jun											3
9-Jun											6
11-Jul											6
13-Jul											7
14-Jul											7
17-Jul											5
18-Jul											5
20-Jul											7
24-Jul											7
25-Jul											5
28-Jul											5
31-Jul											6
7-Aug											6
9-Aug											4
11-Aug											4
17-Aug											3
23-Aug											3
11-Sep											4
18-Sep											4

3.5.3 Demand Response

Demand response (DR) makes up the vast majority of residential peak reduction programs, mostly in the form of direct appliance shut off. This thesis uses three DR strategies.

The first DR strategy delays major appliances from peak periods to off-peak periods. If the dishwasher, washer, or dryer is scheduled to run during the peak period, it is delayed to the 10-midnight period. The hot water usage associated with these appliances is also delayed.

The second DR strategy is a thermostat setback. The thermostat is increased during the peak period, then set back to 75^{o}F at the end.

The third strategy lowers lighting and appliance use. Physically, this means activating circuits that turn off power to unnecessary plug loads, such as set-top boxes, laptop computers, and entertainment equipment.

The thesis considers three levels of DR severity as shown in Table 12. The first, Mild, only delays appliances. The second, Moderate, delays appliances, increases the thermostat by 4^{o}F, and reduces equipment and lighting by 25%. The third, Severe, delays appliances, increases the thermostat by 10^{o}F, and reduces equipment and lighting by 50%.

Table 12. Building demand response levels.

Demand Response Level	Appliance Delay	Thermostat Setback (from 75^{o}F)	Lighting and Equipment Reduction
Mild	Yes	None	0%
Moderate	Yes	4^{o}F	25%
Severe	Yes	10^{o}F	50%

3.6 Stationary Battery

A neighborhood with pooled electricity resources could also pool the costs and benefits of a stationary battery. A stationary battery is incorporated into the microgrid model. For peak reduction applications, it discharges using either a simple discharge or proportional discharge algorithm as created for V2G discharge. The proportional discharge algorithm discharges for the highest consuming hours within each month's proportions for smaller batteries and all five hours for larger batteries. Outage scenarios use the simple discharge method only. Large batteries also use the simple discharge in peak reduction scenarios.

Two battery types were considered: a second-life Ford Focus battery at 70% maximum charge, and the Tesla Powerwall 2. A summary of the batteries is shown in Table 13.

Table 13. Three batteries used in stationary battery configurations.

	Capacity (kWh)	Maximum Discharge Rate (kW)	Estimated Cost ($)
Tesla Powerwall	13.5	5	$6500
Second-life Ford Focus Battery	16.1	6.6	$4065

The second-life Ford Focus battery is a 23 kWh capacity battery that can hold only 70% nominal charge, for a real capacity of 16.1 kWh. The maximum discharge rate is assumed to be the same as the typical charging rate, 6.6kW. The price was estimated to be $250/kWh which is within a large range presented by NREL (Neubauer 2015).

The Tesla Powerwall 2 is a battery meant for home installation, with a capacity of 13.5 kWh and sustained discharge rate of 5kW (Tesla Powerwall 2 2016). Tesla sells the Powerwall 2 for $5,500 and estimates installation costs at $1,000 or higher.

Table 14 shows nine combinations of battery packs that were considered. Stationary battery capacities ranged from 27 kWh to 128.8 kWh.

Table 14. Five battery configurations use in the stationary battery analysis.

	Number of Batteries	Capacity (kWh)	Discharge Rate (kW)
2xPowerwall	2	27	10
2xSecond-Life	2	32.2	13.2
4xPowerwall	4	54	20
4xSecond-Life	4	64.4	26.4
6xPowerwall	6	81	30
6xSecond-Life	6	96.6	39.6
8xPowerwall	8	108	40
8xSecond-Life	8	128.8	52.8

3.7 Resilience Study

The final study incorporates V2G and stationary battery discharge in the microgrid to evaluate the microgrid's resiliency compared to independently operating homes. Three outage lengths in three seasons will be investigated: four hours (5-9pm), 24 hours, and 72 hours in: winter, spring, and summer (non-peak). The usage schedules of each building will be adjusted to two levels as described in Table 15 and Table 16. The first meets basic electrical needs and the second greatly reduces the electricity use of the house but provides more comforts than just the basic electrical needs. Power values for small appliances described in Table 16 are taken from the Building America Simulation Protocols (Wilson et al. 2014).

Table 15. Building end uses for outage scenarios.

	Minimal Loads	Moderately Reduced Loads
Thermostat Setting	85	82
Hot Water	No	Yes, no appliance draws
Lighting	1 CFL, 12hrs/day	Half of normal load
Refrigerator	Yes	Yes
Dishwasher, Clothes washer, Dryer	No	No

Table 16. Small appliance use during outage scenarios.

	Minimal Loads		Moderately Reduced Loads	
	Powered	kWh/day	Powered	kWh/day
Fan (ceiling)		0	X	168.2
Home security system	X	61.3	X	61.3
Garage door opener	X	35	X	35
Carbon monoxide detector	X	17.5	X	17.5
Smoke detectors	X	3.5	X	3.5
First color TV		0	X	309.7
Cable box		0	X	134.1
Microwave		0	X	131.2
Coffee maker		0	X	61.2
Toaster		0	X	45.9
Laptop PC (Plugged In)		0	X	72.1
Desktop PC w/Speakers		0	X	234
PC monitor		0	X	85.1
DSL/cable modem		0	X	52.6
Cell phone charger	X	3.5	X	3.5
Baby monitor	X	22.8	X	22.8

The four hour and 24 hour outages operate with the same restrictions as V2G discharge for peak reduction. The 72 hour outage is treated as a “crisis” outage where EVs stay home after the first day and all of their battery space (minus a 20% buffer) is allocated for V2G discharge.

4 RESULTS AND DISCUSSION

4.1 Preliminary Analysis

A number of preliminary analyses were conducted to verify and decide on an appropriate model. The first examines the validity of using the EPC model for building energy use. The second determines mean behavior when considering varied resident participation in V2G. The last analysis considers neighborhoods with more extreme schedules.

4.1.1 Model Verification

One building was simulated using GridLab-D and EnergyPlus to verify that results were in reasonable bounds. The results of the simulations are shown in Table 17 and Figure 32. EPC and EnergyPlus agree closely on all end uses besides HVAC. HVAC is modeled as lower in EnergyPlus. EV usage is not calculated within the EnergyPlus model, so EV usage is considered the same as the battery model added to the EPC model. EPC and GridLab-D have similar appliance, DHW, and EV usage. Lighting usage is slightly lower in GridLab-D and HVAC use is higher. EPC results are reasonably close to both simulations and closer to the more reliable EnergyPlus model. This outcome supports the claim that the EPC model is reasonable to simulate building use for this study.

Table 17. Annual energy use (kWh/yr) by end use for three simulation models.

	EPC	Gridlab-D	EnergyPlus
HVAC	5692	7444	4959
Lighting	1472	1306	1477
Appliances	6531	6428	6964
DHW	3162	3162	2482
EV	1877	1866	1877
Total	18734	20206	17759

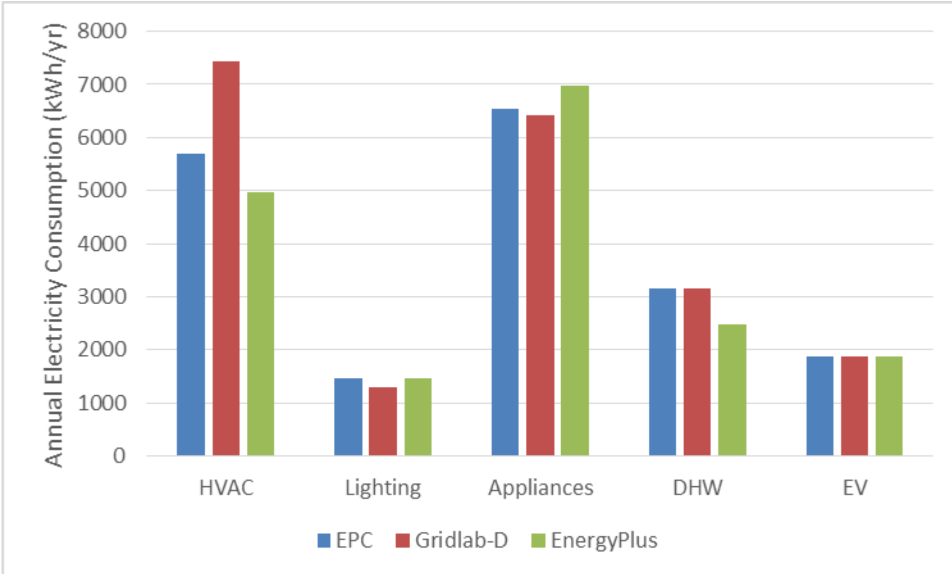

Figure 32. Electricity end uses for EPC, Gridlab-D, and EnergyPlus simulations.

4.1.2 Battery Availability Sensitivity Analysis

Before V2G is simulated, the availability of electric vehicle batteries is determined by conducting a Monte Carlo simulation of resident participation in a V2G system. The mean behavior determined by these results is used for all V2G simulations in this thesis.

The Monte Carlo simulation produced nine distributions for each of the average participation levels and buffers, shown below in Figure 33. Configurations with an average of 75% participation had lower peak consumption and a smaller spread. Configurations with a higher buffer showed a similar distribution shape but higher peak consumption, as less battery is available for peak shaving.

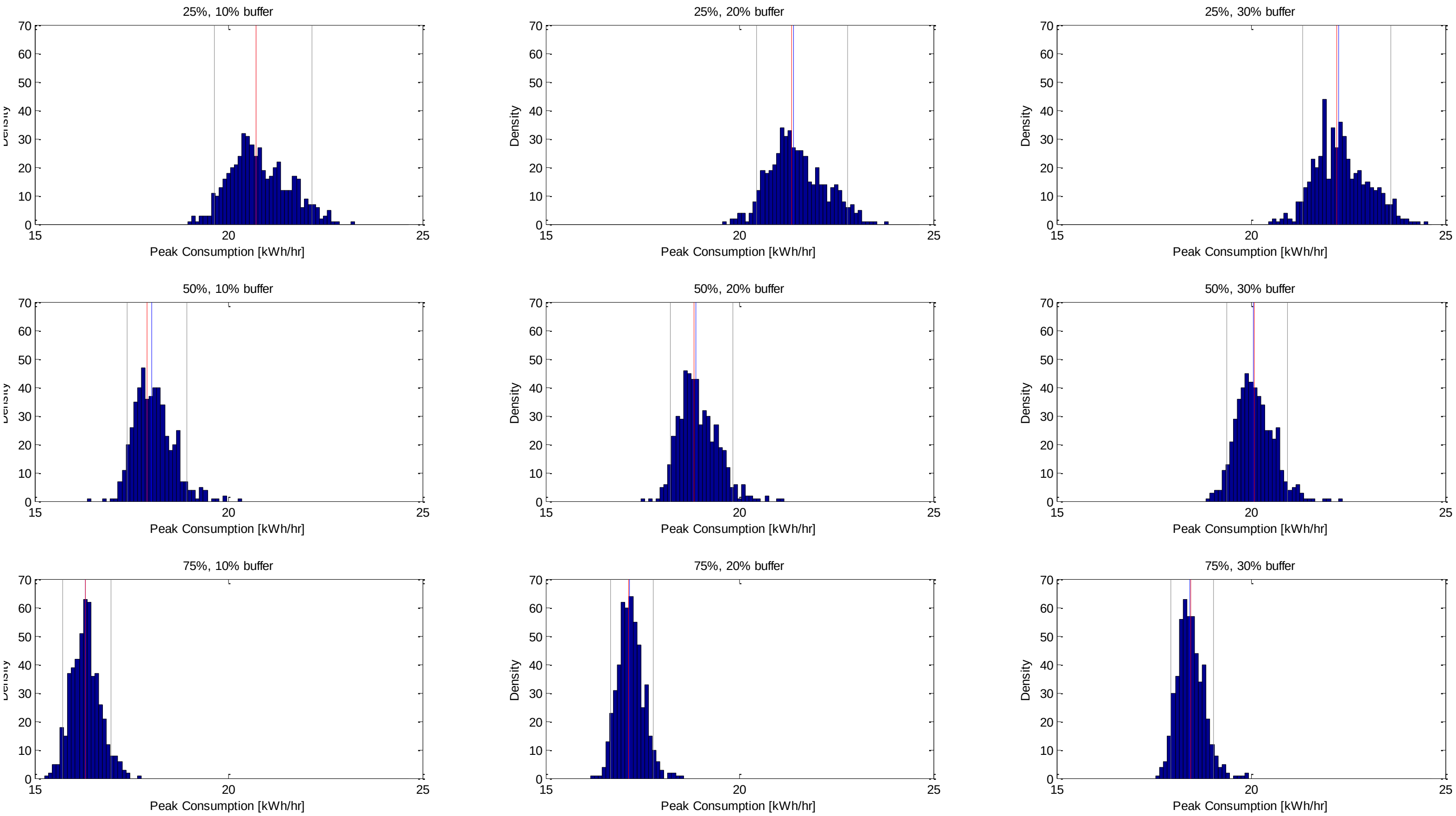

Figure 33. Monte Carlo simulations for varied V2G participation at three buffer levels and three average levels of participation.

Figure 34 shows the percentiles of each curve and highlights the more and less favorable cases. An item to highlight is that performance at a high buffer but high participation (75% Participation, 30% Buffer) shows comparable results to a 50% participation rate with a low buffer. While this model is only simulated, the potential for assuring customers that their battery is protected with a hard 30% buffer and requiring higher participation can be as effective as allowing a low buffer with less participation.

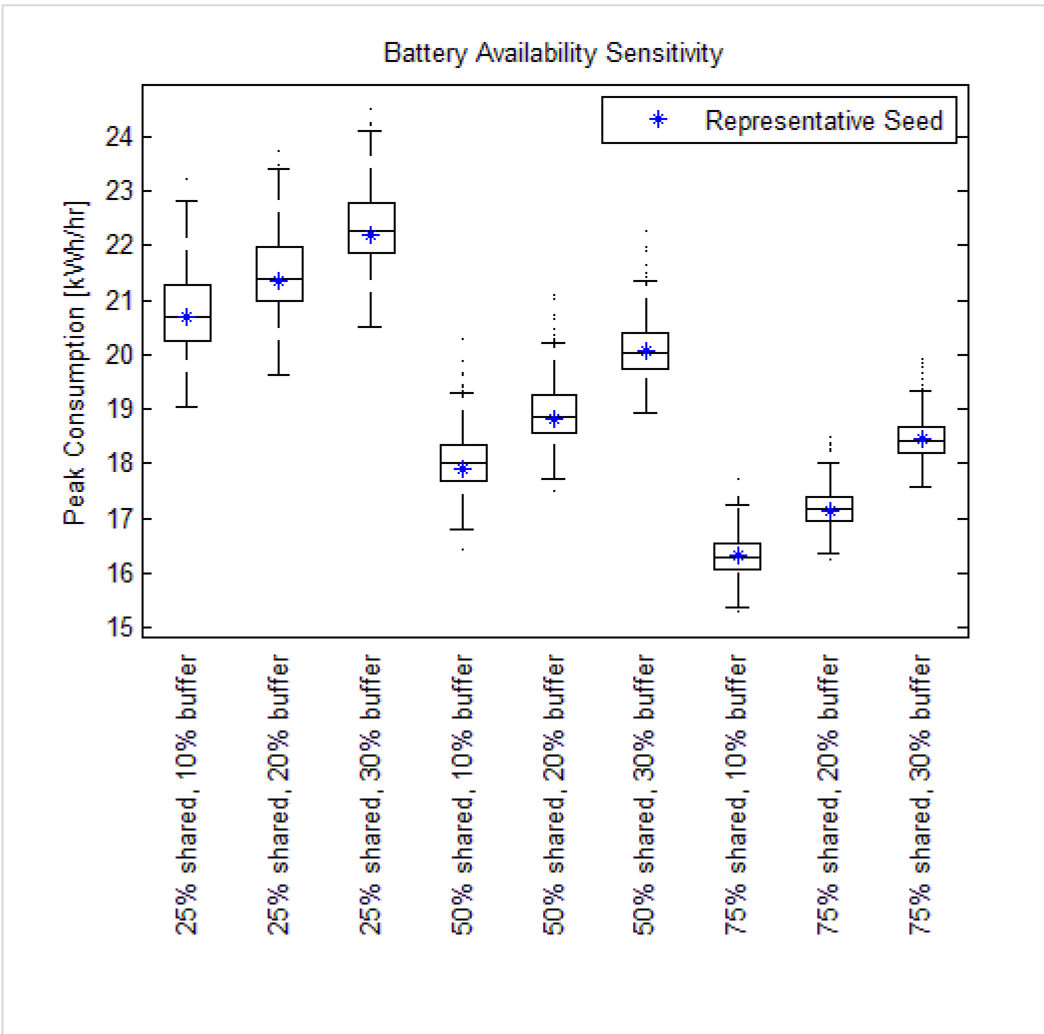

Figure 34. Spread of nine Monte Carlo simulations at different buffer levels and participation levels.

Figure 35 shows the V2G participation level with an average of 50% for the five scenarios whose results most closely matched the mean behavior of all nine configurations. Many of the houses show participation around the mean of 50%.

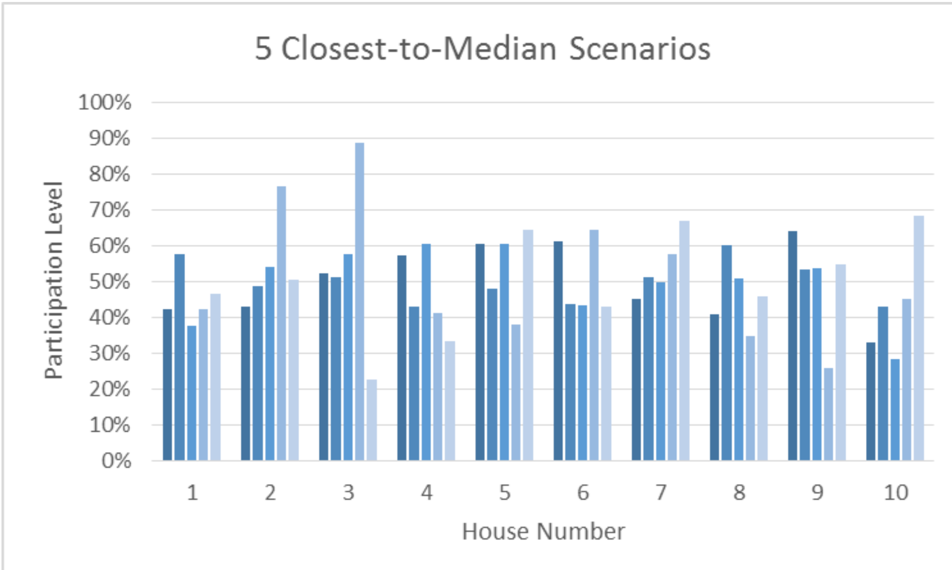

Figure 35. Participation level for the five scenarios that most closely matched the median behavior from the Monte Carlo simulation.

Figure 36 shows the five scenarios at either end of the distribution: five producing the highest peak consumption and five producing the lowest peak consumption. These results the fact that house 2’s EV is not available for V2G at any point during peak consumption, due to working a night shift. House 4, whose EV is available during the entire peak period, has a significant contribution to the effective battery space, as a low V2G participation appears in the highest consumption scenarios and high V2G participation in the lowest consumption scenarios. House 9, whose commute leaves only 1.9 kWh or 8% of the battery available for discharge (as shown in Figure 37), shows a similar pattern to house 2, as its willingness to participate has little effect on the effective battery space.

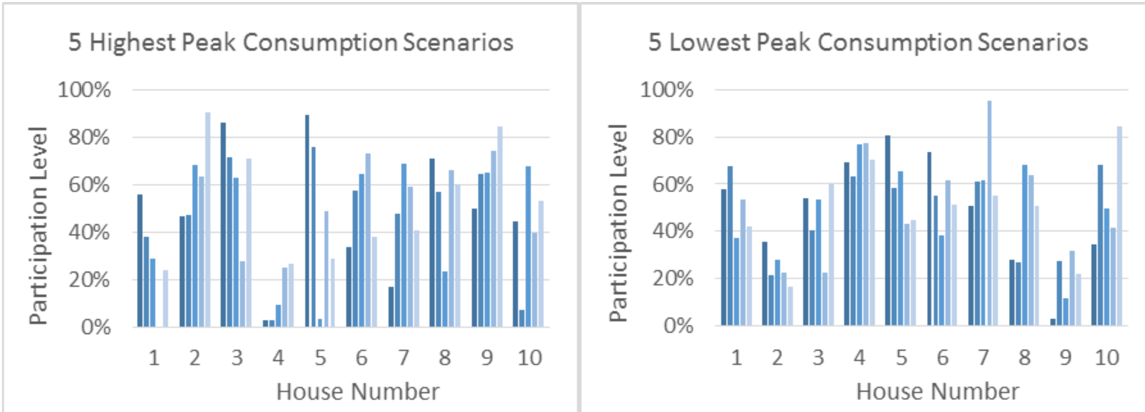

Figure 36. Participation level for the five scenarios that resulted in the highest and lowest peak consumption.

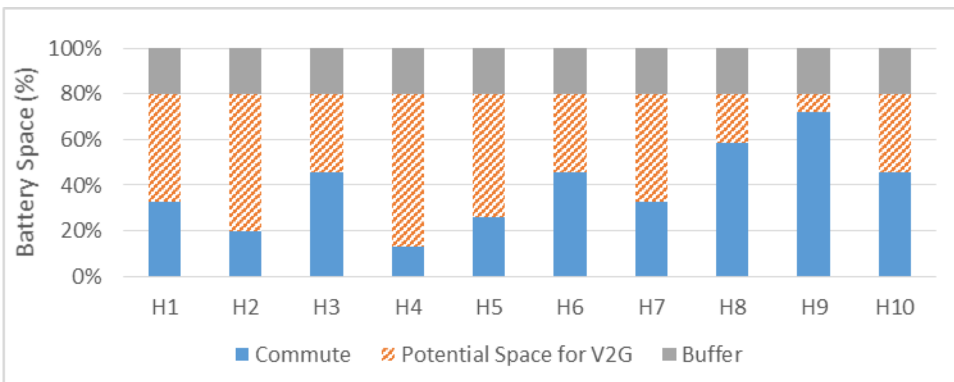

Figure 37. Battery space allocation for a 20% buffer scenario before homeowner participation is determined.

Figure 38 shows the resulting participation levels at the three different participation levels. Figure 39 demonstrates the chosen scenario for a 50% average participation with a 20% buffer.

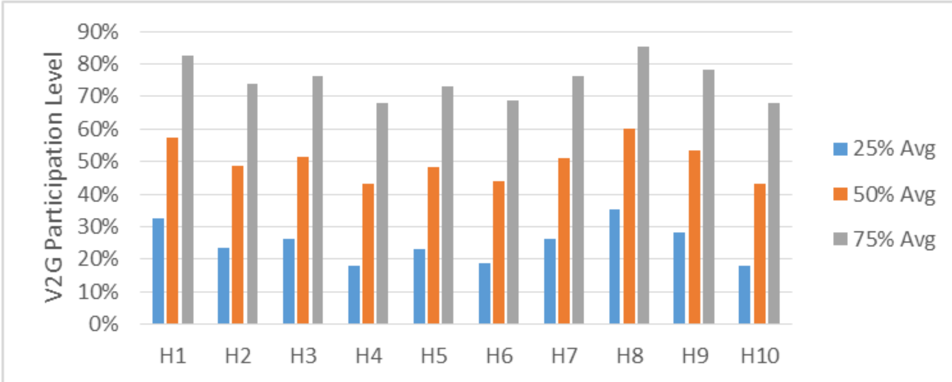

Figure 38. V2G participation at three average levels.

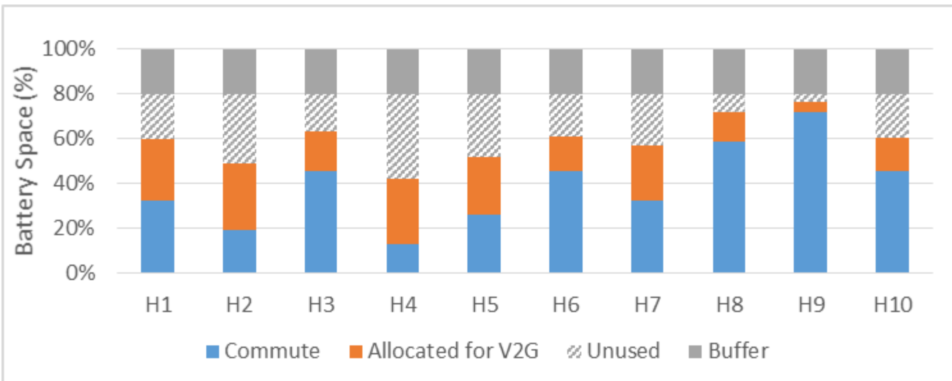

Figure 39. Battery space allocation in a 50% average participation, 20% buffer configuration

The resulting seed is used to inform battery availability for all V2G analysis. While the impact of varying participation is still an important factor in the effectiveness of a microgrid, the seed chosen here will represent average performance.

4.1.3 Demographic Sensitivity Analysis

One last preliminary analysis examines two other neighborhoods with extreme schedules. One neighborhood is home all day, while the other neighborhood is never home during the day. Table 18 and Figure 40 show the peak consumption of the three communities. Note that the All Home community has lower peak consumption due to the lack of thermostat setbacks during periods of no occupancy which drive up peak consumption when occupants arrive home. The addition of DR changes All Home and None Home community performance similarly to the original community.

Table 18. Peak consumption (kWh/hr) of three different community types.

	None Home		All Home		Original	
	Shared	Separate	Shared	Separate	Shared	Separate
Regular	38.1	38.1	34.2	34.2	38.1	38.1
DR	28.4	28.4	25.1	25.1	28.2	28.2
V2G	31.4	31.4	26.6	32.1	28.8	29.3
V2G & DR	22.5	23.6	17.2	23.8	20.1	21.8

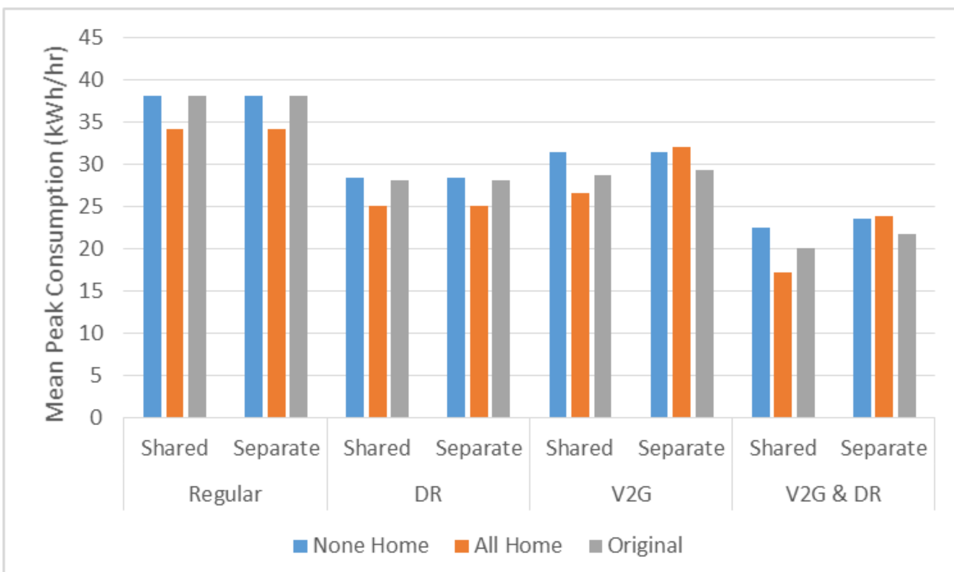

Figure 40. Peak consumption of three different community types.

Figure 41 shows the peak reduction from adding V2G capabilities to each community with and without DR. The None Home community shows less peak reduction from V2G due to the lower electric vehicle availability. The All Home community shows almost no benefits from V2G when resources are separate, but modest benefits from V2G for shared resources, as there is still extra EV battery available after individual homes are supplemented.

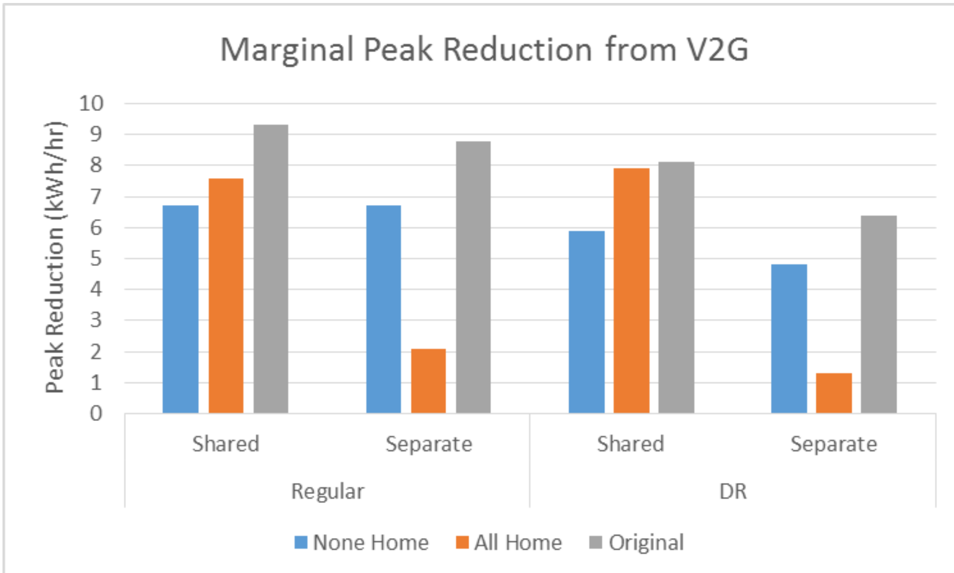

Figure 41. Marginal peak reduction from vehicle to grid discharge.

In general, the results from different community performance supports the idea that the more homogeneous the community in terms of battery availability, the less it gains from sharing electricity resources locally.

4.2 Variable Electricity Tariffs

With the model complete, the consumer savings from peak reduction techniques are examined. This section evaluates the electricity cost savings from EV discharge and demand response during peak time of use electricity tariffs. Four pricing schemes were considered: time of use with and without excess electricity sell-back allowed, and critical peak pricing with and without excess electricity sell-back allowed. Figure 42 shows the electricity costs from all four pricing schemes. V2G and DR increasingly reduce electricity costs with a small cost savings for shared resources over separate resources in each scenario.

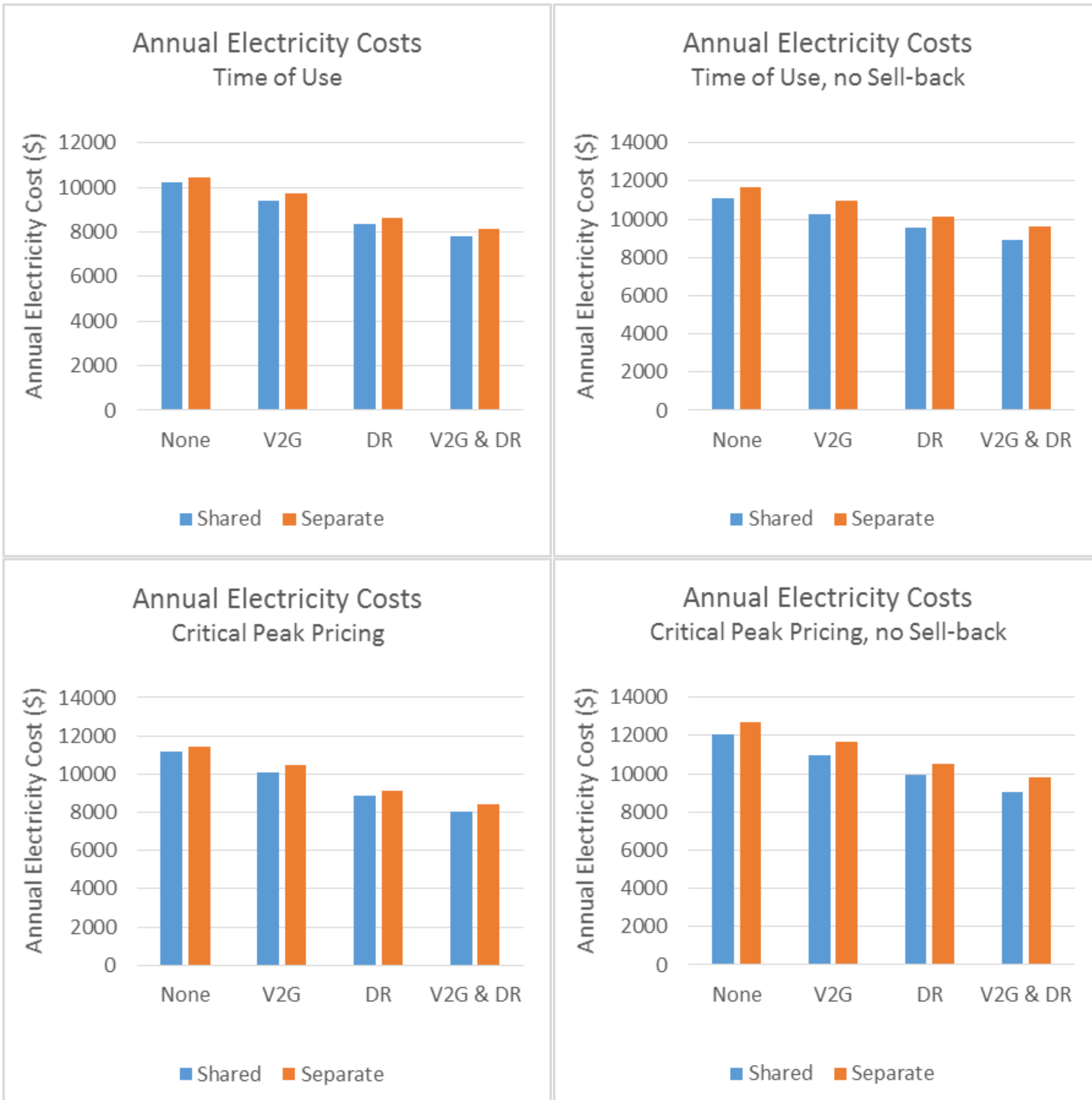

Figure 42. Annual electricity costs with V2G and DR strategies under four variable pricing schemes.

4.2.1 Cost Savings from Shared Resources

Table 19 and Figure 43 show the cost savings from sharing electricity resources versus having separate resources. The regular operation, which has no V2G or building demand response, derives its savings from sharing excess electricity from solar arrays among houses during the early hours of the peak periods. V2G shows increased savings from sharing as electric vehicles can discharge excess battery space to other houses. Moderate DR shows slightly less savings than no DR because lower building energy consumption from DR lowers the amount of PV that buildings can share in the early peak period where solar generation produces more than the total neighborhood energy consumption.

Table 19. Annual neighborhood electricity cost savings of shared vs. separate resources.

	Regular Operation	V2G	Moderate DR	V2G & Moderate DR
Time of Use	$229	$307	$225	$339
Time of Use no sell-back	$590	$662	$567	$676
Critical Peak Pricing	$264	$356	$249	$399
Critical Peak Pricing no sell-back	$608	$698	$580	$731

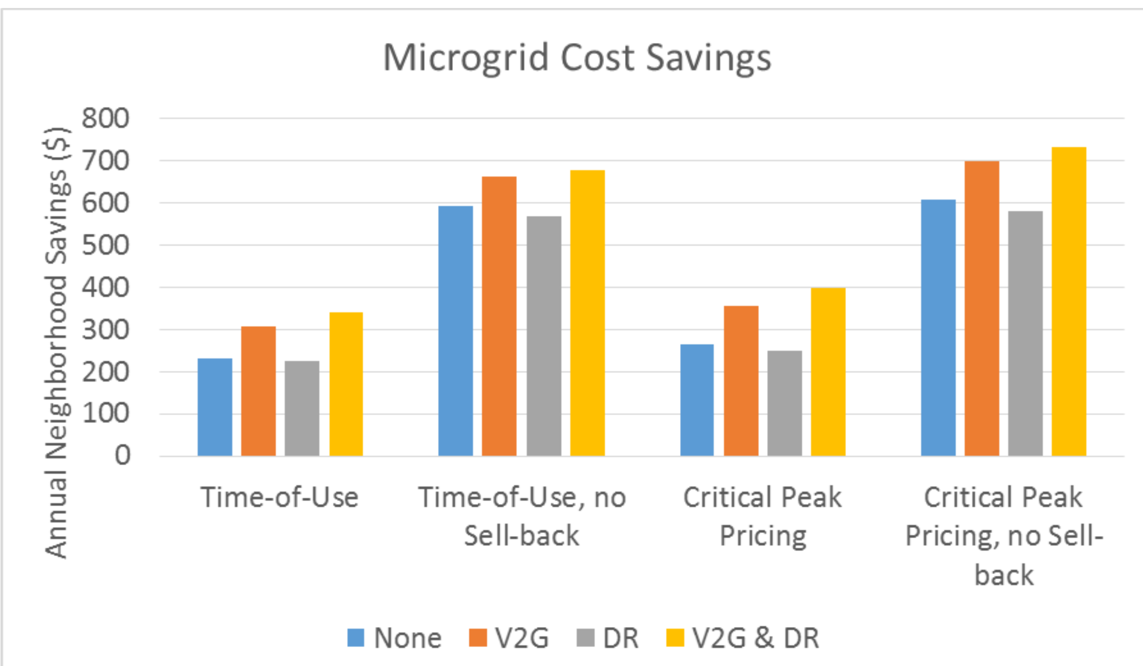

Figure 43. Annual electricity cost savings from sharing electricity resources.

Even the highest savings values provide only modest savings across the neighborhood. $731 saved per year translates to a $73 per household savings per year, which provides homeowners little financial incentive to join a microgrid.

4.2.2 Cost Savings from Vehicle to Grid Discharge and Demand Response

V2G and DR add additional cost savings under time of use and critical peak pricing electricity pricing schemes. The cost savings from these two strategies under time of use pricing and critical peak pricing are shown in Table 20 and Table 21, respectively.

Table 20. Annual electricity cost savings of V2G and DR under time of use pricing schemes.

	Time-of-Use		Time-of-Use, no Sell-back	
	Shared	Separate	Shared	Separate
V2G	$801	$724	$836	$765
Moderate DR	$1815	$1820	$1552	$1575
V2G & Moderate DR	$2403	$2293	$2174	$2088

Table 21. Annual electricity cost savings of V2G and DR strategies under critical peak pricing schemes.

	Critical Peak Pricing		Critical Peak Pricing, no Sell-back	
	Shared	Separate	Shared	Separate
V2G	$1076	$985	$1112	$1022
Moderate DR	$2299	$2315	$2126	$2154
V2G & Moderate DR	$3139	$3004	$2999	$2876

V2G produces the smallest cost savings as shown in Figure 44, with moderate DR producing around twice the cost savings. Combined, V2G and moderate DR produce less than the sum of their separate cost savings.

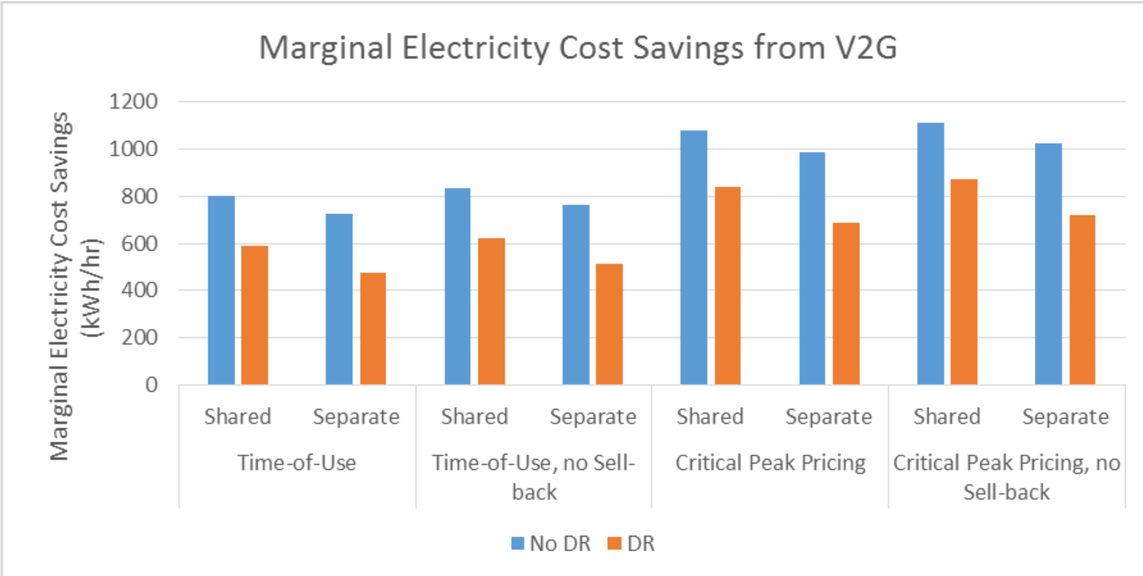

Figure 44. Annual electricity cost savings from V2G and demand response.

Figure 45 provides insight into the lack of synergy for the two peak reduction strategies. V2G has the most potential for variable tariff savings at the 6-7pm hour because almost all of the electric vehicles are present for this hour. V2G is limited in this last hour as hourly electricity demand goes to zero. No more gains can be achieved by V2G as the neighborhood building consumption is too low.

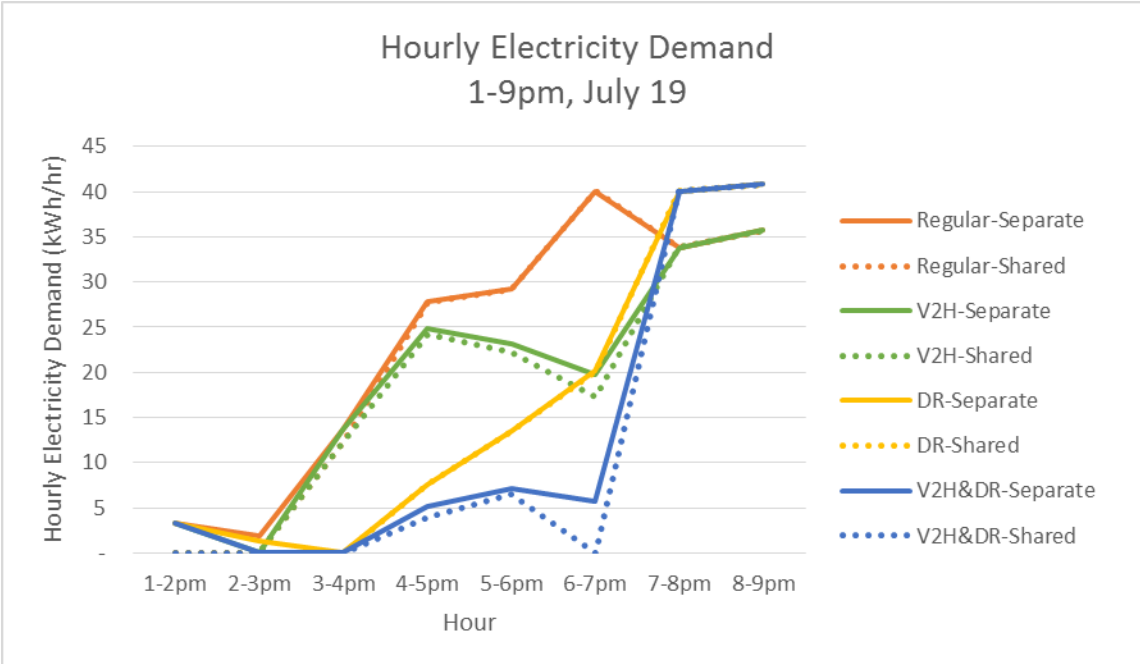

Figure 45. Hourly Electricity Demand for critical peak day: July 16 from 1 to 9pm.

Also in Figure 45 note that the demand after the peak period rises for the scenarios with DR as the thermostat returns to its typical setting and requires more cooling energy during that period. While outside of the scope of this thesis, the effects of subhourly spikes in power consumption right after peak demand periods are worthwhile considerations.

Periods that fall under the peak time of use pricing but not critical peak pricing, such as August 16 in Figure 46 where average demand is 5 kWh/hr lower than July 16 shown in Figure 45 have a different effect on marginal savings from V2G discharge. On these days, DR has less of an impact as there is less air conditioning energy to be reduced through thermostat setbacks and there is less energy to be displaced by V2G discharge. V2G still reaches a floor in the last hour of the peak period and thus shows similar losses in marginal savings.

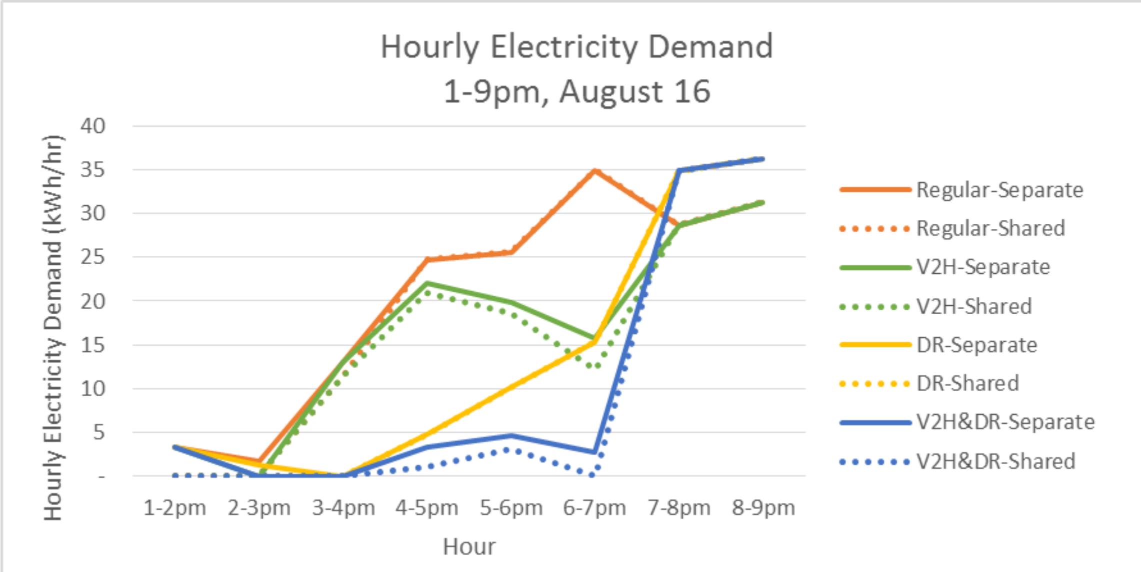

Figure 46. Hourly Electricity Demand for (non-critical) peak day: August 16 from 1 to 9pm.

DR and V2G provide higher cost savings for consumers, up to $314 per year savings. However, the savings comes at a high cost to consumer comfort and requires daily V2G which could degrade battery quality over time.

4.3 Building Demand Response

While consumers see little cost savings for participating in peak reduction programs or for joining a microgrid within current systems, utilities may see a larger benefit. Each of the ten homes now observe building demand response on 10 of 20 specified peak days to evaluate how much peak reduction potential is achievable.

Peak consumption was recorded for three different demand response severities. Peak consumption did not vary between separate and shared electricity resources for any level of DR. Table 22 shows that DR reduces average peak consumption by 10-31%.

Table 22. Peak consumption and reduction with DR.

	Mean Peak Consumption (kWh/hr)		Peak Reduction (kWh/hr)		% Peak Reduction	
	Shared	Separate	Shared	Separate	Shared	Separate
No DR	38.1	38.1	--	--	--	--
Mild DR	34.2	34.2	3.9	3.9	10%	10%
Moderate DR	28.2	28.2	9.9	9.9	26%	26%
Severe DR	26.3	26.3	11.8	11.8	31%	31%

DR performance shows no difference between shared and separate resources because the only potential for peak reduction through sharing is sharing PV. Figure 47 shows that the peak consumption usually happens in the later half of the peak period, where solar electricity generation is greatly reduced or zero, meaning that no excess electricity is being produced by any house.

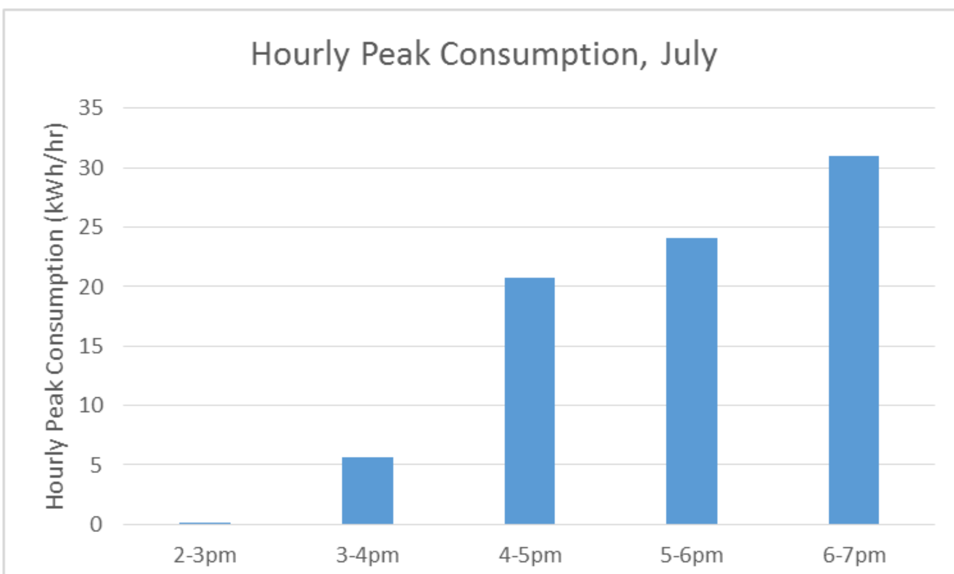

Figure 47. Average neighborhood hourly peak consumption for the hottest seven days in July.

4.4 Vehicle to Grid Discharge

In addition to DR, the community can trigger V2G during peak periods. This section examines the effects of V2G alone during these periods. It considers several different levels of homeowner participation and different battery buffers reserved to preserve a healthy charge. Additionally, it considers a number of battery discharge algorithms for optimal peak smoothing.

4.4.1 Battery Availability

Different levels of homeowner participation in a vehicle to grid program can have significant effects on its usefulness. Balancing a healthy charge level in the vehicle batteries with the economic benefits of peak reduction through vehicle to grid is a significant concern.

The stochastic nature of homeowner behavior is evaluated through a Monte Carlo simulation. Three different levels of battery availability were investigated with three different battery discharge buffer levels for a total of nine battery configurations. The inputs are described in Figure 48.

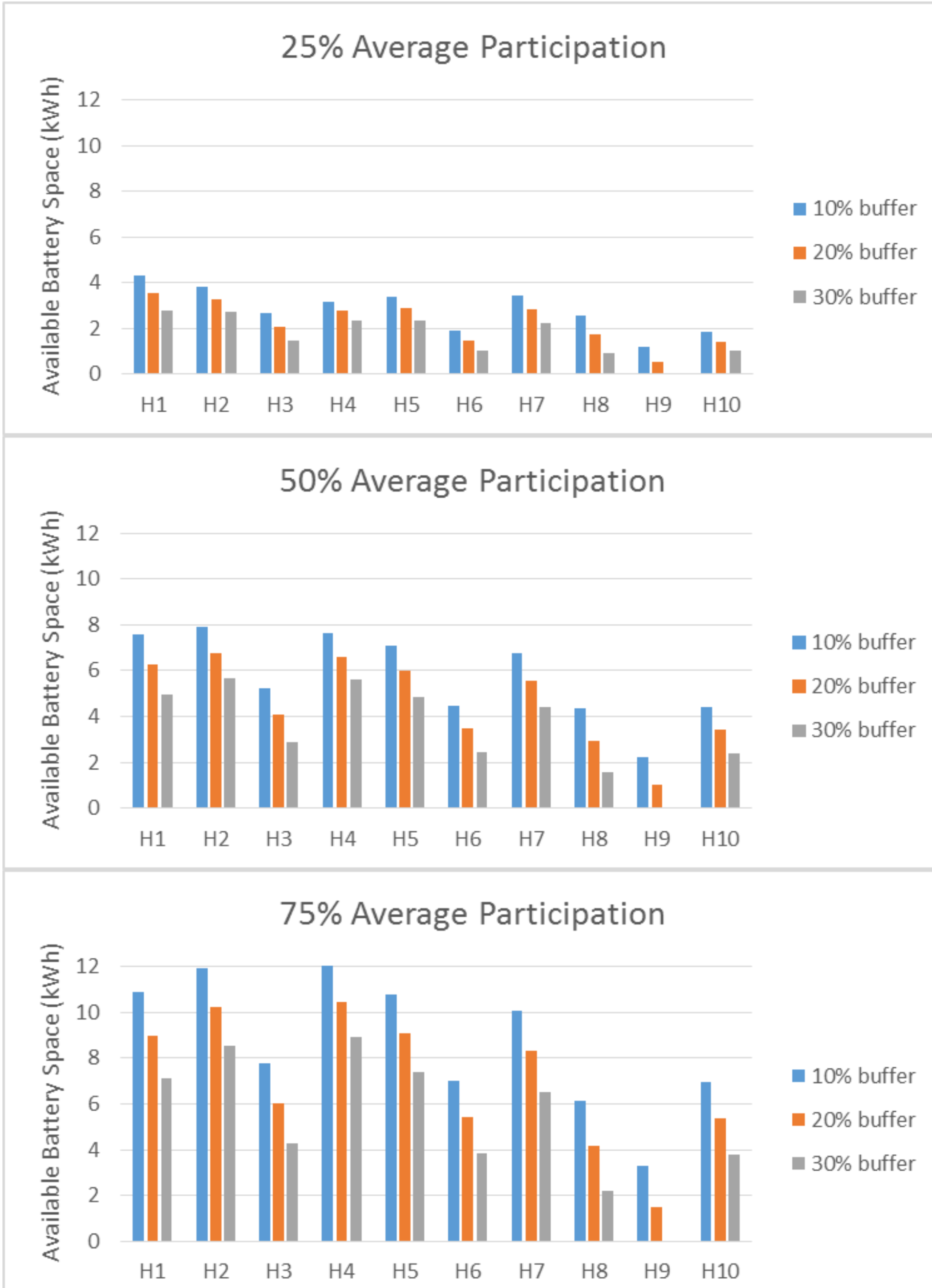

Figure 48. Available battery space for all nine battery configurations.

Peak reduction from V2G varied as shown in Figure 49 and Table 23. 25% shared resources resulted in 11-18% peak reduction with almost no differences between shared and separate performance. 50% shared resources resulted in 19-28%, with a difference of

0.8, 1.4, and 2.2% difference between shared and separate resources. 75% shared resources yielded 23.7-32.7% savings with differences between shared and separate ranging from 2.1% to 3.7%. The 10% buffer configuration showed the largest difference between shared and separate resources.

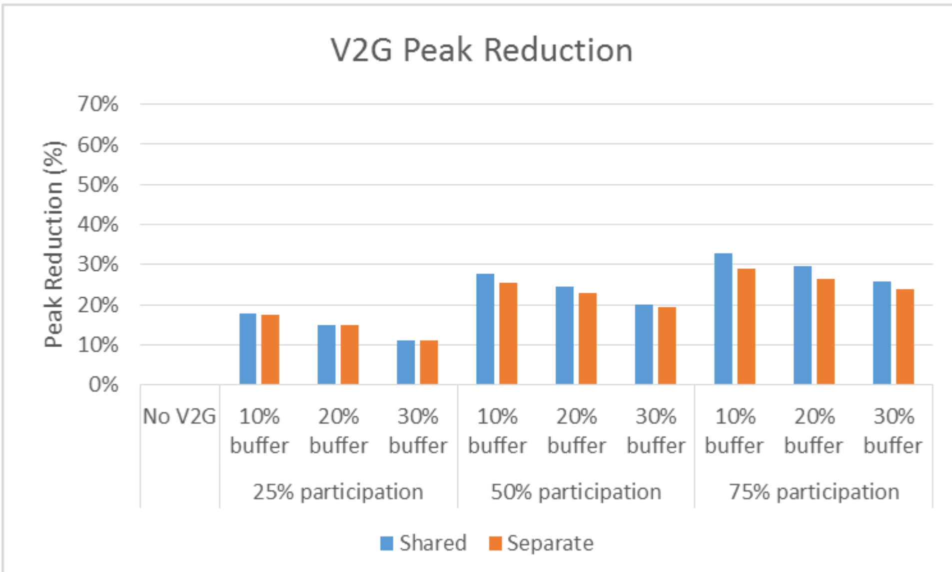

Figure 49. Peak reduction from V2G with shared and separate energy resources.

Table 23. Peak reduction from vehicle to grid discharge.

		Shared	Separate
No V2G		0.0%	0.0%
25% V2G participation	10% buffer	17.8%	17.6%
	20% buffer	14.8%	14.8%
	30% buffer	11.1%	11.1%
50% V2G participation	10% buffer	27.6%	25.3%
	20% buffer	24.4%	23.0%
	30% buffer	20.0%	19.3%
75% V2G participation	10% buffer	32.7%	29.1%
	20% buffer	29.6%	26.5%
	30% buffer	25.8%	23.7%

Figure 50 demonstrates the dependence of peak consumption on available battery space. As the available battery space increases, the peak consumption decreases. Both curves become shallower with more battery availability, possibly due to inefficient discharge, lack of availability at the proper times, or a limited discharge rate. At lower levels of battery availability, there is almost no difference between shared and separate resources, as each battery is discharged fully to its own house during peak periods and little inter-house sharing occurs.

As the available battery capacity rises, separated battery resources have no means to discharge additional energy to other houses and is effectively wasted for the purposes of peak demand discharge. This curve suggests that as battery space increases beyond that considered in this study, shared electricity resources would produce even higher peak reduction than separated resources.

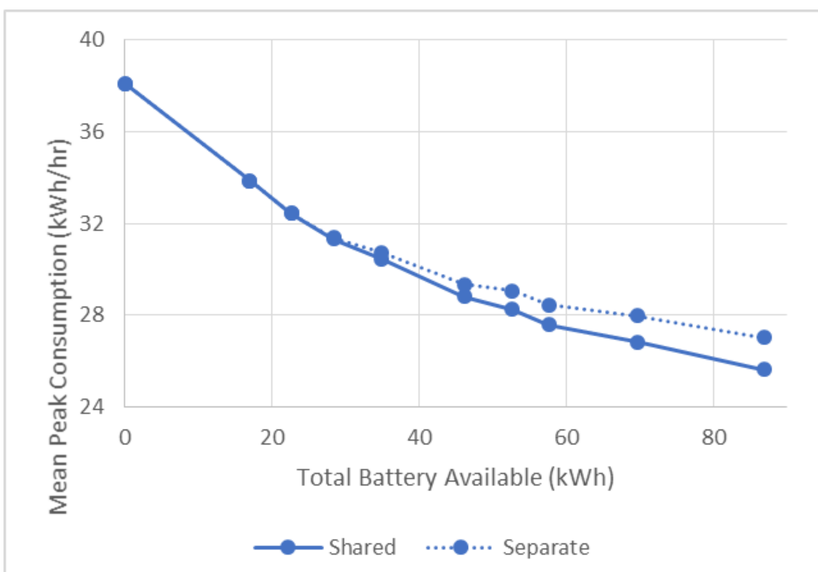

Figure 50. Peak consumption compared to total battery space available for V2G.

4.4.2 Battery Discharge Algorithms

The ability to appropriately discharge the electric vehicle batteries is important to effective peak smoothing. Table 24 and Figure 51 show the mean peak consumption of the neighborhood at four levels of demand response and with the three discharge algorithms evaluated. The threshold provides the least reduction and the proportional and enhanced proportional are nearly the same. For some scenarios, peak performance decreases with the enhanced proportional discharge, and for others, it increases.

Threshold discharge only competed with proportional discharge for one scenario: mild DR, shared resources. The reason for this is that the threshold used for the analysis was 22 kWh/hr and 2 kWh/hr for individual houses. 22 kWh/hr was determined based on a brief optimization with the mild shared scenario. This suggests that threshold calculations could mirror the performance of proportional algorithms, but only with more sophisticated refinements.

Table 24. Mean peak consumption (kWh/hr) with three different V2G algorithms.

		No V2G	Proportional	Threshold	Enhanced Proportional
No DR	Shared	38.1	28.8	30.6	28.8
	Separate	38.1	29.3	32.6	29.4
Mild DR	Shared	34.2	25.2	25	24.7
	Separate	34.2	26.0	29.3	26.0
Moderate DR	Shared	28.2	20.1	22.4	20.1
	Separate	28.2	21.8	27.9	21.8
Severe DR	Shared	26.3	17.5	22.2	17.5
	Separate	26.3	21.3	24.9	21.6

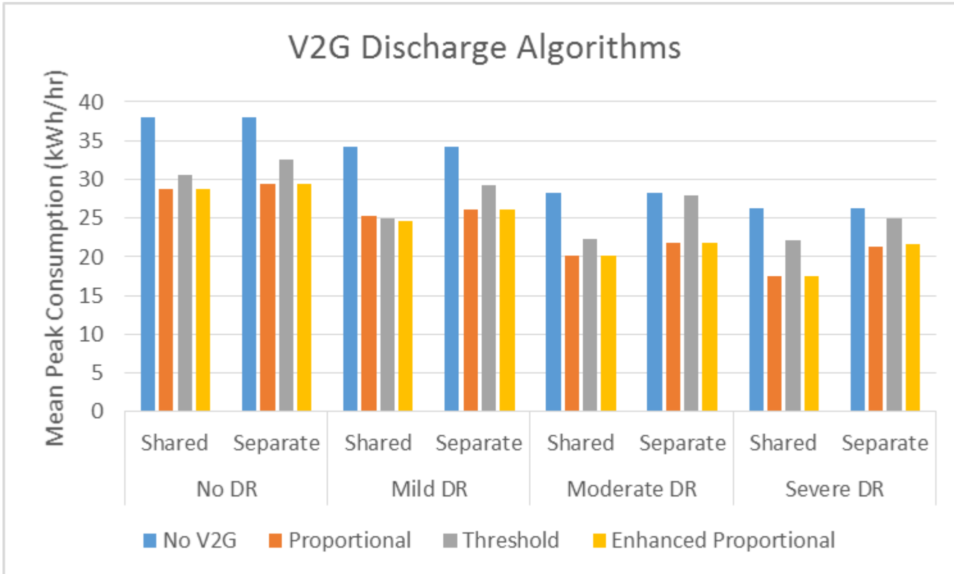

Figure 51. Peak performance with three different vehicle to grid discharge algorithms.

Due to the more consistent performance of proportional discharge, and the inconclusive benefit of the enhanced proportional discharge, studies using V2G in this thesis use the proportional discharge algorithm.

4.5 Demand Response and Vehicle to Grid Discharge

While DR during peak periods have the potential to reduce peak consumption by up to 30%, V2G capabilities have the ability to complement building DR by providing additional load offset during evening hours when residential consumption is high but solar generation is low or nonexistent.

DR showed a 10 to 31% reduction in peak electricity consumption and V2G showed an 11 to 33% reduction in peak electricity consumption. DR showed no difference between shared and separate resources and V2G showed 0-3.7% peak reduction differences between shared and separate resources.

Three demand response scenarios were coupled with nine V2G discharge scenarios to examine the interaction between the two peak reduction strategies.

V2G increased the mild DR peak reduction from 10% to between 21% and 43%, as shown in Figure 52. Higher battery availabilities showed greater peak reduction with larger gains from the shared resources configuration.

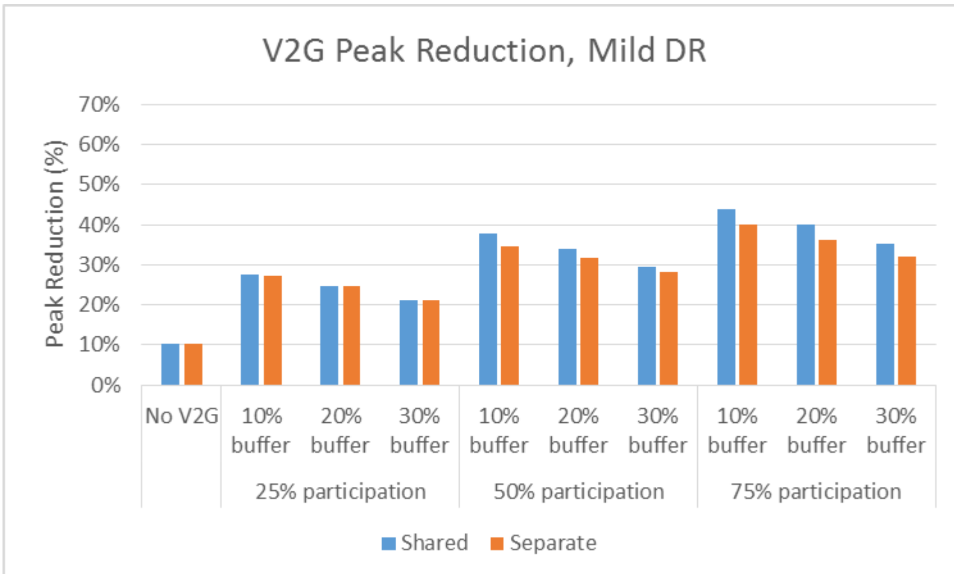

Figure 52. Peak reduction from V2G with mild DR.

V2G increased moderate DR peak reduction from 26% to between 36% and 58% as shown in Figure 53. Once again, higher battery availabilities produced larger peak reductions, with even higher gains at the 75% availability level. Separated resources at the 50% and 75% level differ by 1.1-2.2% while shared resources increase by 5.3-6.1%.

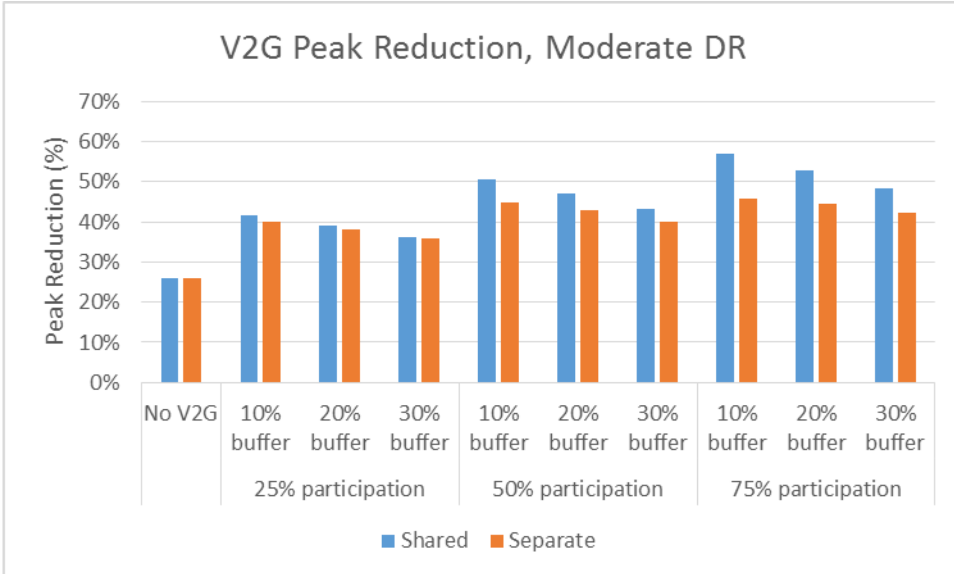

Figure 53. V2G peak reduction with moderate DR.

V2G increased severe DR peak reduction from 31% to 39-63% as shown in Figure 54. Separate resources saw almost no increase in peak reduction as battery size increased, but instead stayed at 39-45%.

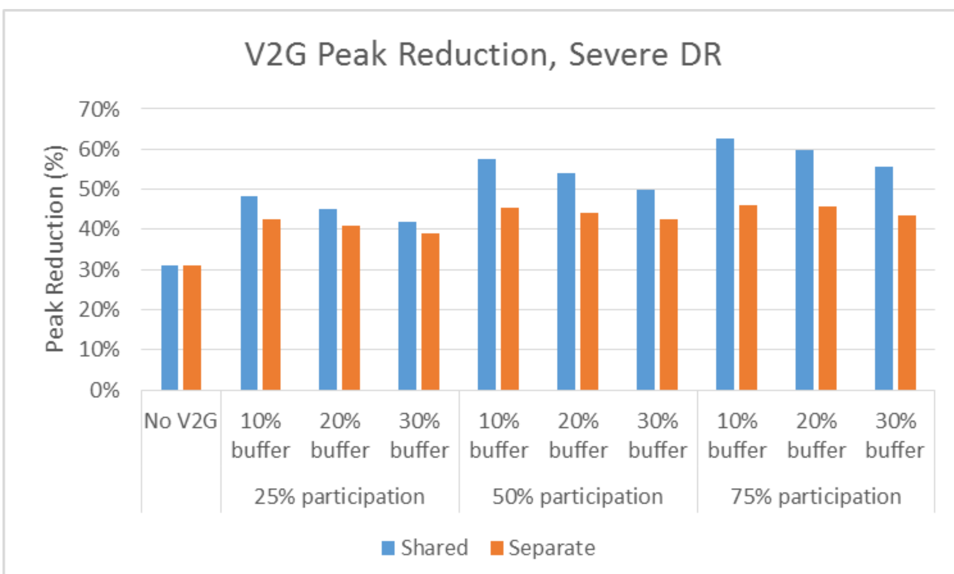

Figure 54. V2G peak reduction with severe DR.

The effectiveness of increased demand response severity rises more with microgrid connectivity. Figure 55 and Figure 56 show the marginal peak reduction from increasing DR severity for all V2G cases with shared resources and separate resources, respectively. The no DR and mild DR case shows little difference between shared and separate resources, but gains from moderate DR diminish slightly and gains from severe DR are very small.

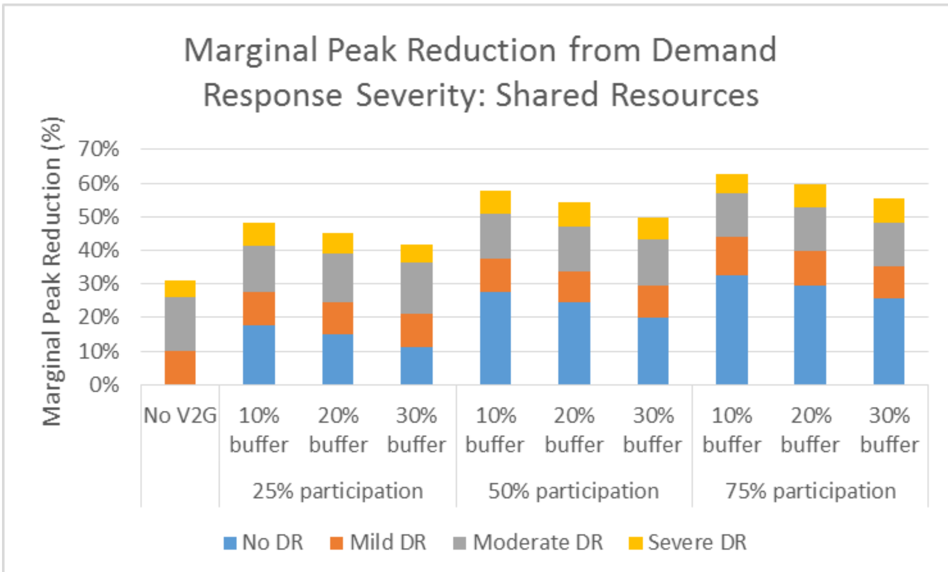

Figure 55. Marginal peak reduction from increasing DR severity with shared resources.

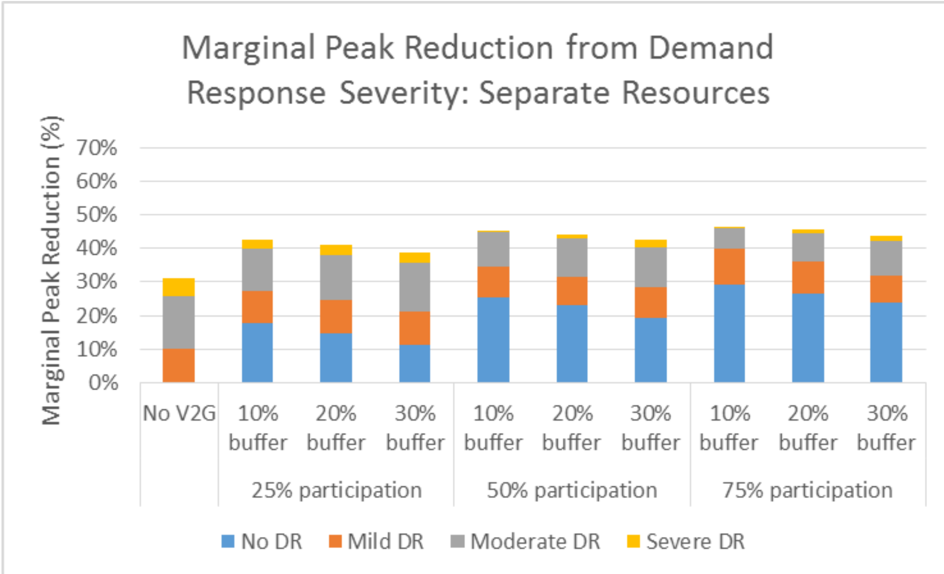

Figure 56. Marginal peak reduction from increasing DR severity with separate resources.

Figure 57 compares the peak reduction performance of the system as battery availability increases. Once again, peak consumption is heavily influenced by the total battery availability of the system. As the availability increases, peak reduction stagnates. For the two higher DR levels, the usefulness of increased battery availability ends around 50-60kWh of battery space. As the homes decrease their energy use through building DR, the complementary nature of V2G and DR disappears when resources are not shared. When resources are shared, the marginal benefits of increased battery availability decline, but do not level off like the separate resources configuration.

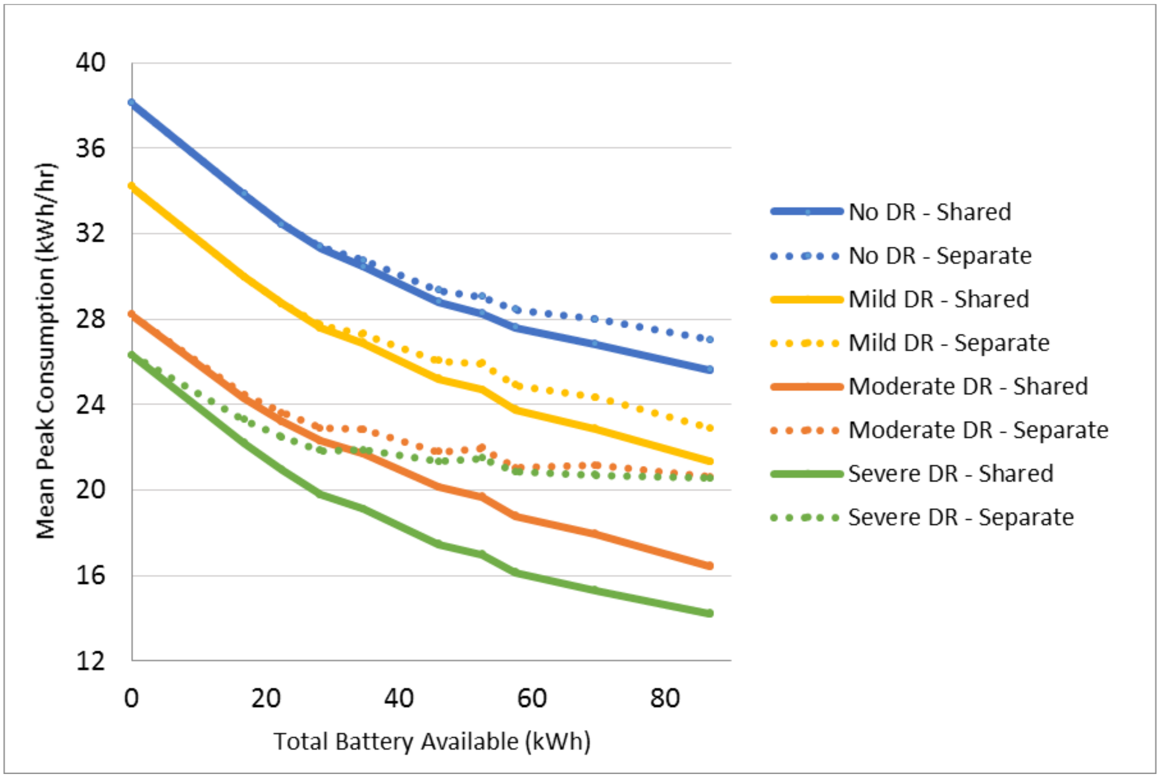

Figure 57. Peak consumption compared to V2G battery space at four different DR levels.

Figure 58 reiterates the large difference in performance between the shared and separate resources configurations, especially at severe DR levels. As battery increases and as building demand decreases, separate resources provide dwindling peak reduction returns while shared resources remain useful.

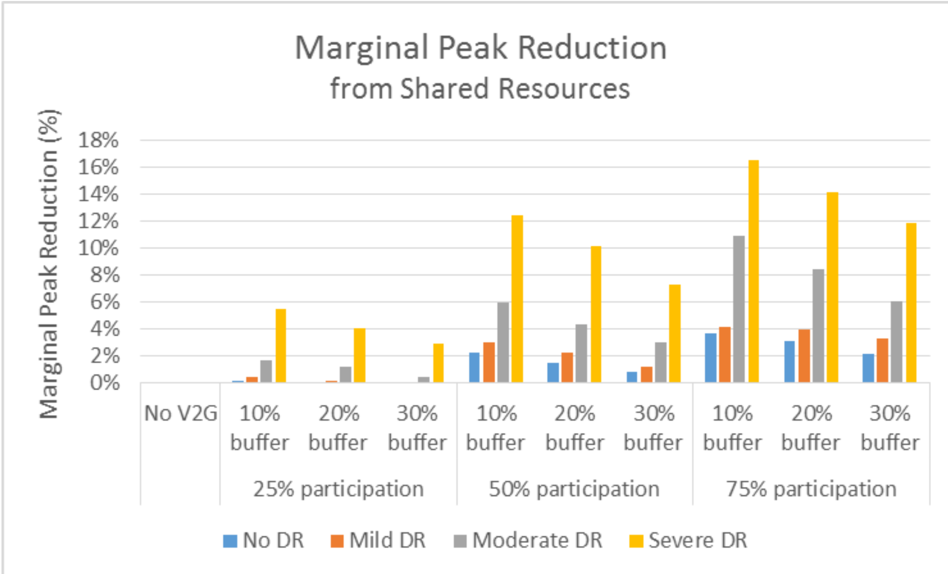

Figure 58. Marginal peak reduction from shared resources over separate resources.

4.6 Community-Shared Stationary Battery

DR and V2G combined produce significant peak demand reduction. A stationary battery, made more viable when shared among a number of homes, allows for further peak reduction.

Several different levels of stationary battery capacity were evaluated within the microgrid and evaluated for peak performance. Table 25 and Figure 59 show the peak consumptions of the neighborhood with shared resources and different stationary batteries installed.

As battery availability approaches the total needs of the community during peak periods, the effectiveness of the proportional discharge method wanes due to limited discharge to the three most consuming hours. As a result, the discharge algorithm was changed to 5hr proportional for larger batteries (green cells in Table 25) and simple discharge for the larger batteries when observing severe DR (yellow cells).

Table 25. Microgrid performance with stationary batteries at different DR levels.

Battery	System Capacity (kWh)	Mean Peak Consumption (kWh/hr)			
		None	Mild	Moderate	Severe
None	0	27.6	23.8	18.8	16.1
2xPowerwall	27	21.8	18.2	13.2	10.8
2xSecond-Life	32.2	20.6	16.9	12.0	9.7
4xPowerwall	54	16.8	12.9	7.7	6.4
4xSecond-Life	64.4	16.1	11.7	6.6	5.9
6xPowerwall	81	11.5	7.9	3.5	2.0
6xSecond-Life	96.6	9.3	5.7	1.9	0.8
8xPowerwall	108	8.0	4.5	1.3	0.4
8xSecond-Life	128.8	6.1	2.9	0.7	0.0

Blue: 3hr proportional discharge, Green: 5hr proportional discharge, Yellow: simple discharge

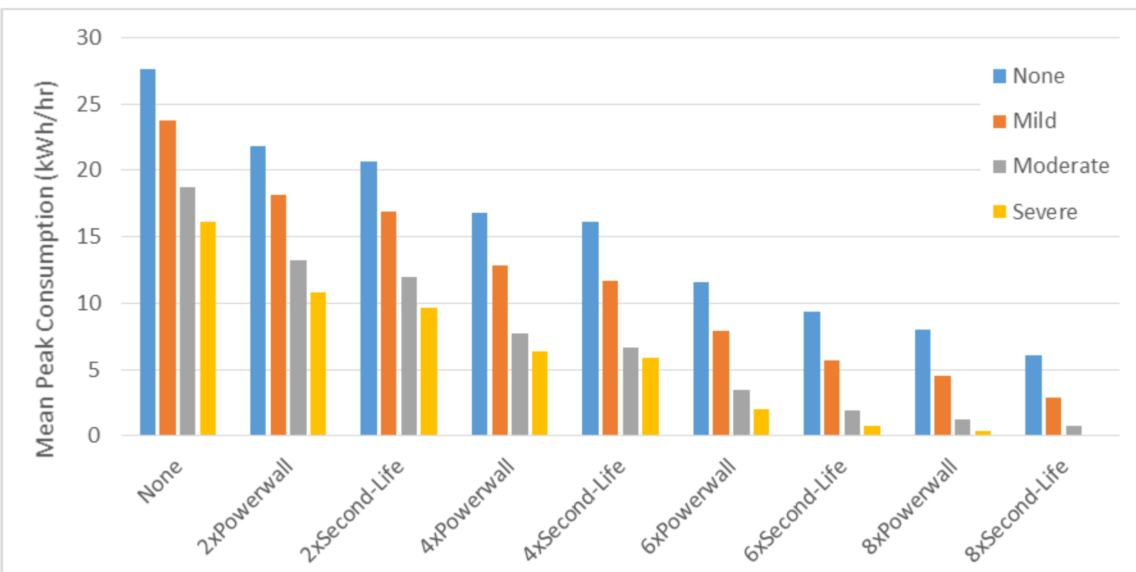

Figure 59. Peak consumption of microgrid equipped with stationary batteries.

Figure 60 compares the system performance to the installed stationary battery capacity. The decrease in peak consumption varies relatively linearly with the battery capacity until batteries with capacities around 60kWh. This is the area at which the two hours with lesser peak consumption which are ignored by the proportional discharge begin to limit the peak reduction. For batteries 81kWh and larger, the 5-hour proportional discharge removes this barrier.

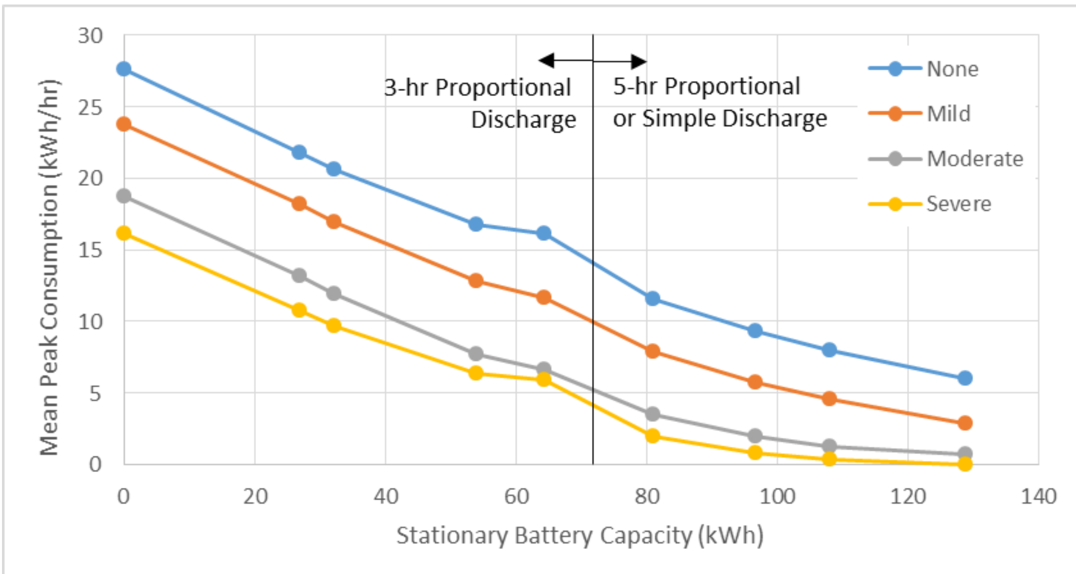

Figure 60. Peak consumption of microgrid equipped with stationary batteries compared to battery capacity.

Peak consumption declines as the battery capacity increases, with somewhat smaller marginal gains at higher battery capacities. This occurs because the other peak reduction techniques narrow the peak as well as lower it, so that less energy is required to reduce the peak further.

Figure 61 shows the effect of six Powerwall batteries for moderate DR under a proportional discharge algorithm. Solar generation offsets all peak consumption for hour 15 and part of peak consumption for hour 16. The demand not met by PV in the last three hours is met fully by the EV and stationary batteries. For this situation, the maximum demand during this period is limited purely by the second hour, where battery discharge is not activated. While the three-hour proportional discharge algorithm is successful for smaller batteries, larger batteries see a decline in effectivity.

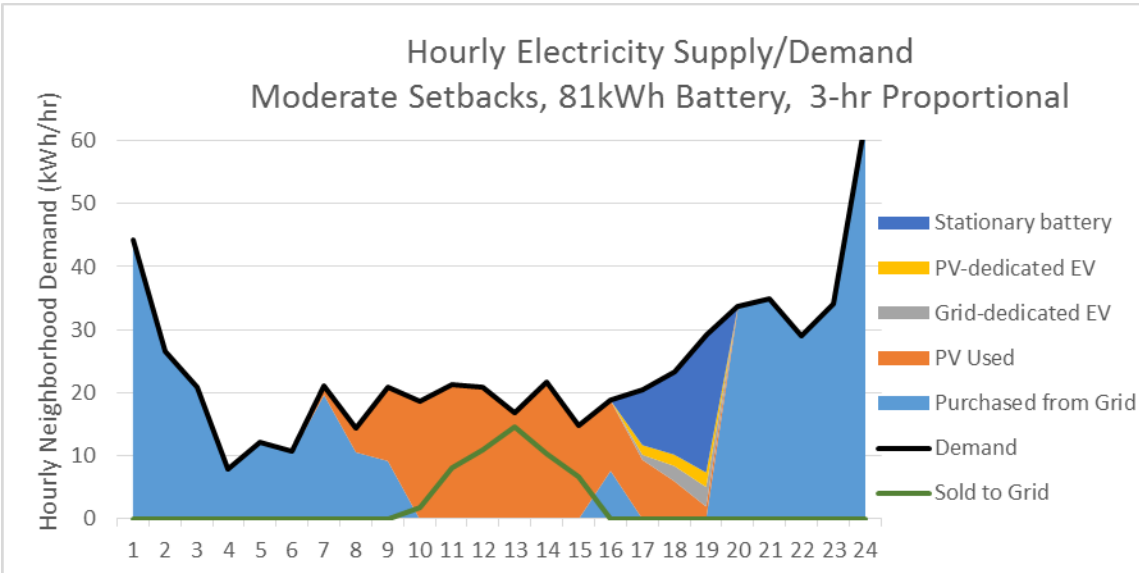

Figure 61. Hourly demand for an 81kWh battery with 3-hour proportional discharge.

Figure 62 shows the same battery and severe DR with a five-hour proportional discharge amount. The battery discharges significantly during the second hour and lowers the community maximum usage in a more equitable manner. Ultimately, however, such a large battery meets all of the peak demand for this day and simple discharge provides the optimal discharge, as shown in Figure 63.

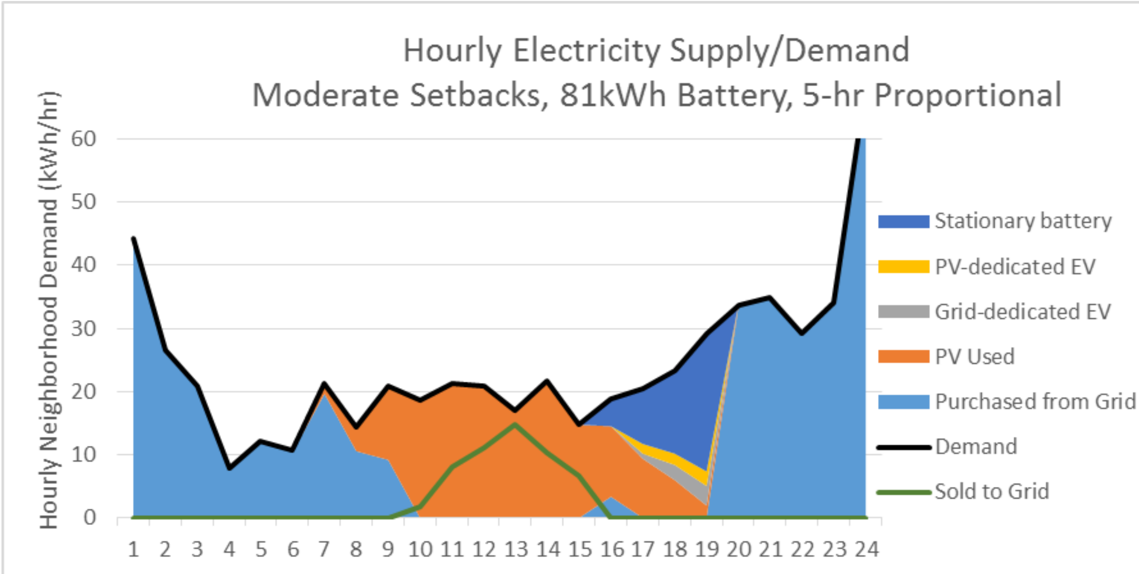

Figure 62. Hourly demand for an 81kWh battery with 5-hour proportional discharge.

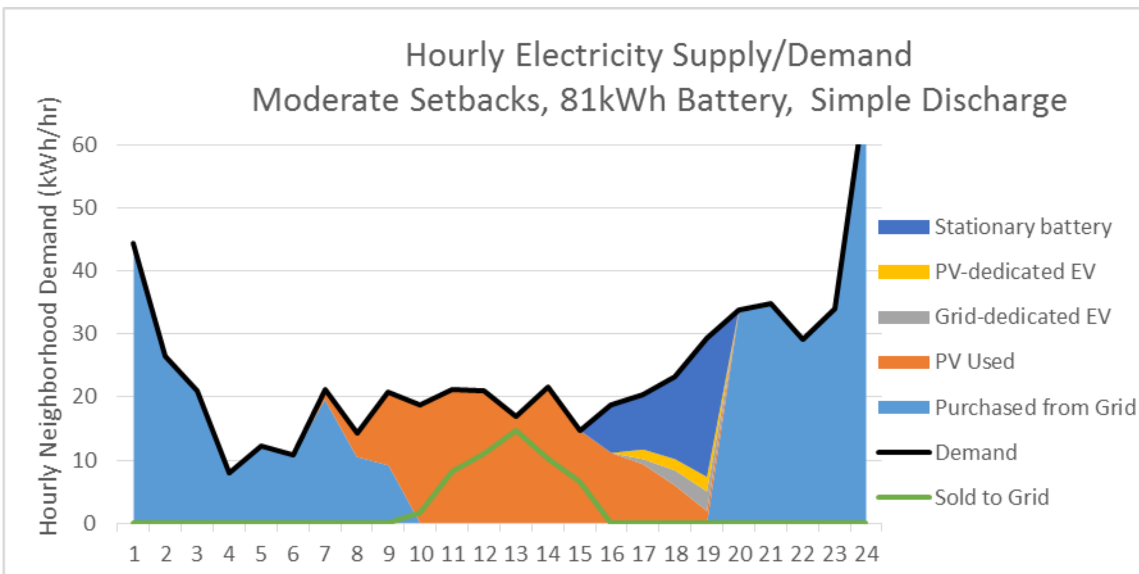

Figure 63. Hourly demand for an 81kWh battery with simple discharge.

Stationary batteries provide a means for peak reduction beyond that achievable by V2G or DR. While the shared cost of a community-owned battery may be less of a burden to individual homeowners, the economics of such a peak reduction strategy is worth investigating in future studies.

4.7 Resilience Study

The last facet of a microgrid considered in this thesis is the potential for a microgrid to operate independently of the grid. While a consumer receives little financial motivation for joining a microgrid, consumers will benefit from a more secure electricity supply.

The neighborhood was simulated with and without shared electricity resources in an outage situation. The neighborhood with shared resources also includes a community-owned stationary battery.

4.7.1 Four-Hour Outage

A four hour outage represents the most common, short-term outages. This outage is modeled from 5-9pm, which might imitate a short outage from a thunderstorm or minor system damage.

The neighborhood is modeled with lower electricity loads, as a form of extreme demand response. The lower level provides for minimum loads, such as a refrigerator and home alarms. The higher level provides for moderately reduced loads, which allow for more appliances, water heating, and a more comfortable temperature. The microgrid and independent homes are judged on their ability to provide these loads with PV, V2G, and batteries only.

4.7.1.1 Minimal Loads

First, a scenario where only the most basic loads are met is considered. Table 26 shows the hours of unmet demand in each house for a four-hour outage from 5-9pm in three different seasons. For separate houses, only house 2 has unmet demand in spring and summer. EV discharge and PV generation is enough to cover the entire period. In winter (shown in Figure 64), PV generation does not cover the usage from 5-6pm in houses 1, 3, and 5 whose EVs arrive home at 6pm. Sharing resources results in no unmet demand using V2G only.

Table 26. Hours of unmet demand for minimal loads during four-hour outages.

	Houses with separate resources										Houses with shared resources	
	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	V2G only	V2G & Batteries
Winter	1	3	1	0	1	0	0	0	0	0	0	0
Spring	0	3	0	0	0	0	0	0	0	0	0	0
Summer	0	2	0	0	0	0	0	0	0	0	0	0

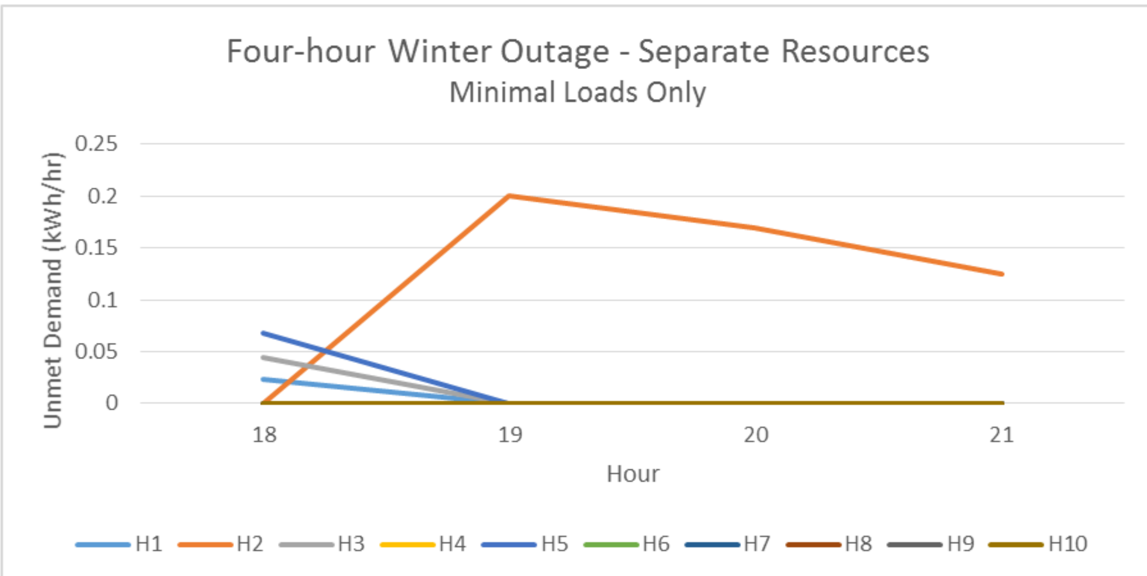

Figure 64. Unmet demand for minimal loads in separate houses during a four hour winter outage.

4.7.1.2 <u>Moderately Reduced Loads</u>

Next, moderately reduced loads provide a greater level of comfort for residents: a more comfortable thermostat set point, hot water and reduced plug load and lighting levels.

Table 27 shows the hours of unmet demand during each outage. For separated electricity resources, only homes 4 and 7 meet their electrical needs throughout the outage. Figure 65 and Figure 66 show the unmet demand for winter and summer, respectively. Homes whose EV arrives at 6pm are not able to offset all of their loads with PV generation and have unmet demand for the first hour of the outage. Homes with EVs present during the entire outage are able to provide power for the beginning of the outage, but run out of charge toward the end. The summer outage results in less unmet demand because solar generation is higher and can cover more load in the first two hours of the outage.

Table 27. Hours of unmet demand for moderately reduced loads during four-hour outages.

	Houses with separate resources										Houses with shared resources	
	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	V2G only	V2G & Batteries
Winter	1	4	1	0	1	1	0	2	3	2	0	0
Spring	1	4	1	0	1	1	0	2	3	2	0	0
Summer	1	4	1	0	1	0	0	1	3	1	0	0

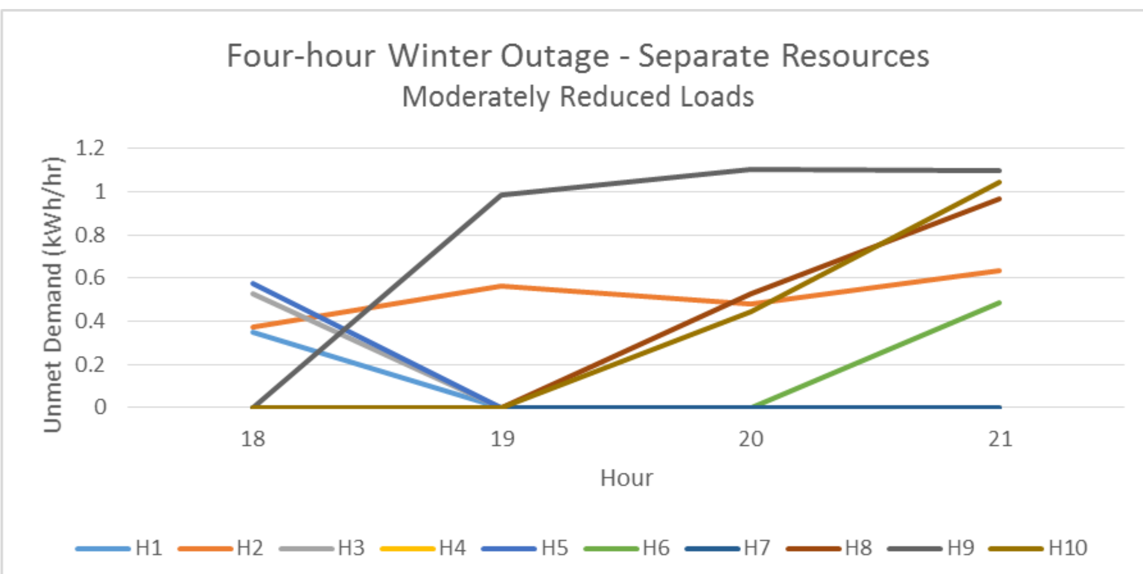

Figure 65. Unmet demand for moderately reduced loads in separate houses during a four hour winter outage.

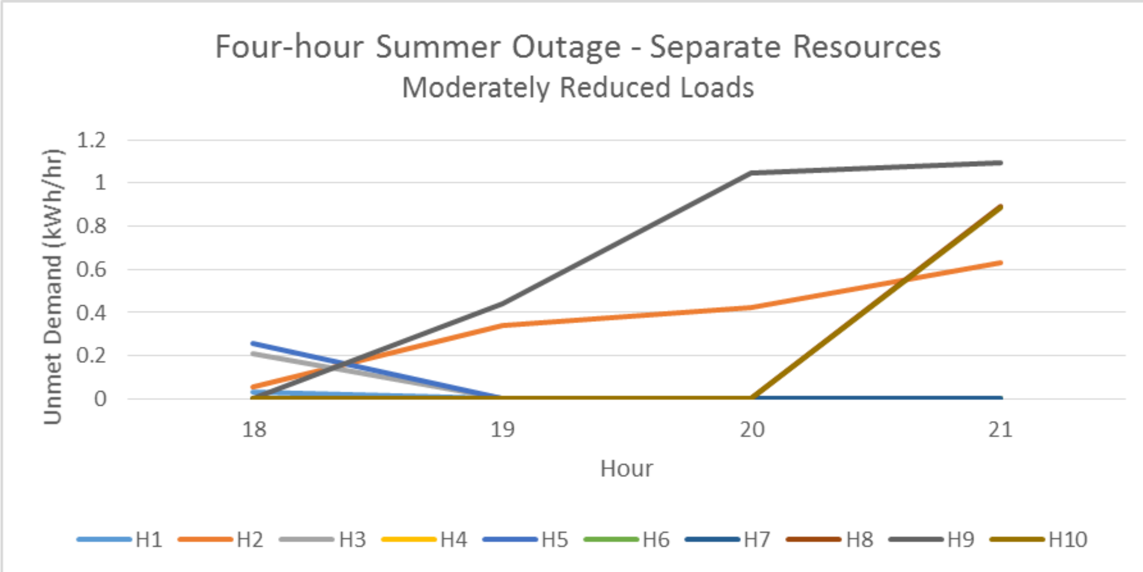

Figure 66. Unmet demand for moderately reduced loads in separate houses during a four hour summer outage.

4.7.2 24-Hour Outage

A 24-hour outage represents a more significant outage, running from midnight to midnight. This outage judges the longer-term resilience of the microgrid and independent homes.

4.7.2.1 Minimal Loads

Minimal loads in a 24-hour outage provide more strain on the independent homes. Table 28 shows the unmet demand for minimal loads. Figure 67 and Figure 68 show hourly unmet demand for the winter outage which is similar to the spring and summer outages. All houses but house 4 has unmet loads. Some houses, such as house 1, 5 and 7 only have a few hours of unmet due to a gap in between EV arrival/departure and PV generation. Others run out of charge before the end of the outage. In Figure 68 the community with shared resources has one hour in the morning where it relies on stationary batteries, as most EVs have left for work but PV generation isn't large enough yet. Additionally, the community uses stationary batteries starting at 10pm after the vehicle batteries are drained. One 13.5kWh stationary battery (a $6,500 cost) would meet the community's electricity needs for the three 24-hour outages.

Table 28. Hours of unmet demand for minimal loads during 24-hour outages.

	Houses with separate resources										Houses with shared resources	
	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	V2G only	V2G & Batteries
Winter	3	10	7	0	3	5	2	7	11	7	4	0
Spring	2	10	5	0	2	3	1	6	10	5	3	0
Summer	2	9	5	0	2	2	1	6	10	5	2	0

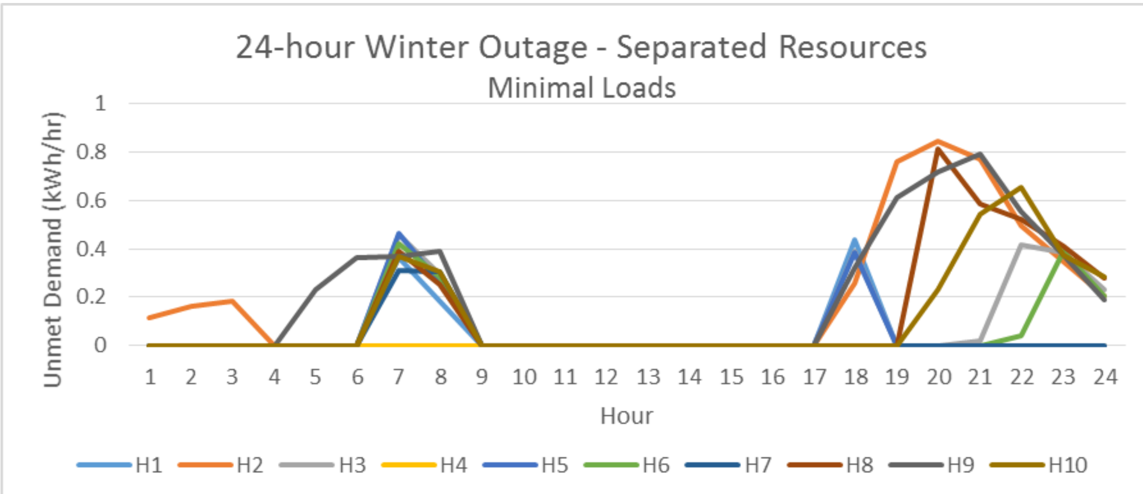

Figure 67. Unmet demand for minimal loads in separate houses during a 24-hour winter outage.

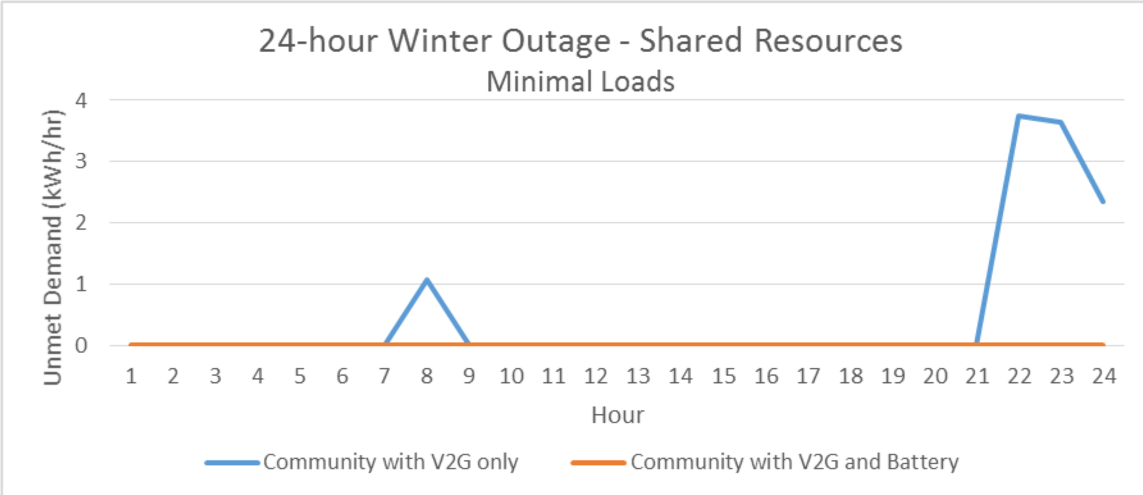

Figure 68. Unmet demand for minimal loads in a microgrid during a 24-hour winter outage.

4.7.2.2 Moderately Reduced Loads

Table 29 shows the unmet demand for moderately reduced loads. Results are similar to those with minimal loads except that houses experience more hours of unmet demand. Figure 69 and Figure 70 demonstrate the hourly unmet demands for the winter and summer outages, respectively. More houses run out of battery charge before the end of the outage and houses experience greater magnitude of unmet demand.

Table 29. Hours of unmet demand for moderately reduced loads during 24-hour outages.

	Houses with separate resources										Houses with shared resources	
	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	V2G only	V2G & Batteries
Winter	3	10	7	0	4	6	4	10	13	9	6	0
Spring	2	10	6	0	3	5	1	8	12	8	5	0
Summer	2	10	7	0	3	6	4	10	13	9	6	0

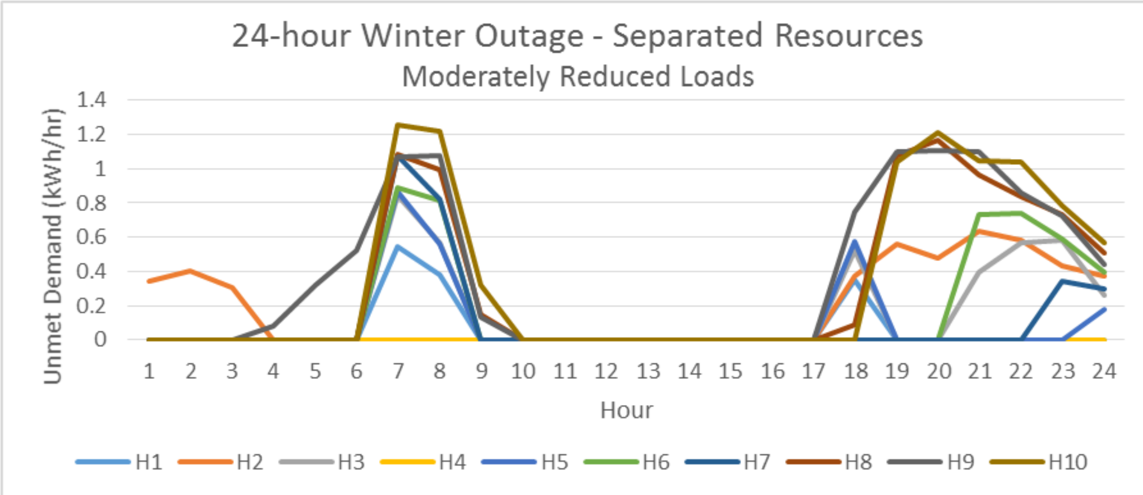

Figure 69. Unmet demand for moderately reduced loads in separate houses during a 24-hour winter outage.

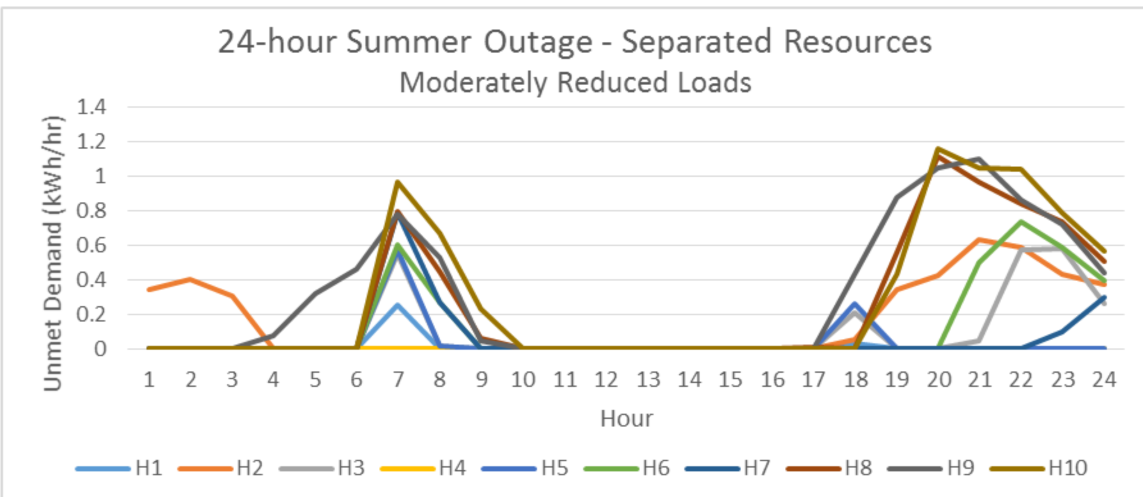

Figure 70. Unmet demand for moderately reduced loads in separate houses during a 24-hour summer outage.

Figure 71 shows the hourly unmet demand for the microgrid configuration. V2G fails to meet a large portion of morning winter usage as the few vehicles remaining at the neighborhood at 7-9am are depleted. Vehicles run out of charge around 9pm and rely on stationary batteries. Three 13.5kWh batteries are required to provide electricity at moderately reduced loads for the entire 24 hour outage at each season.

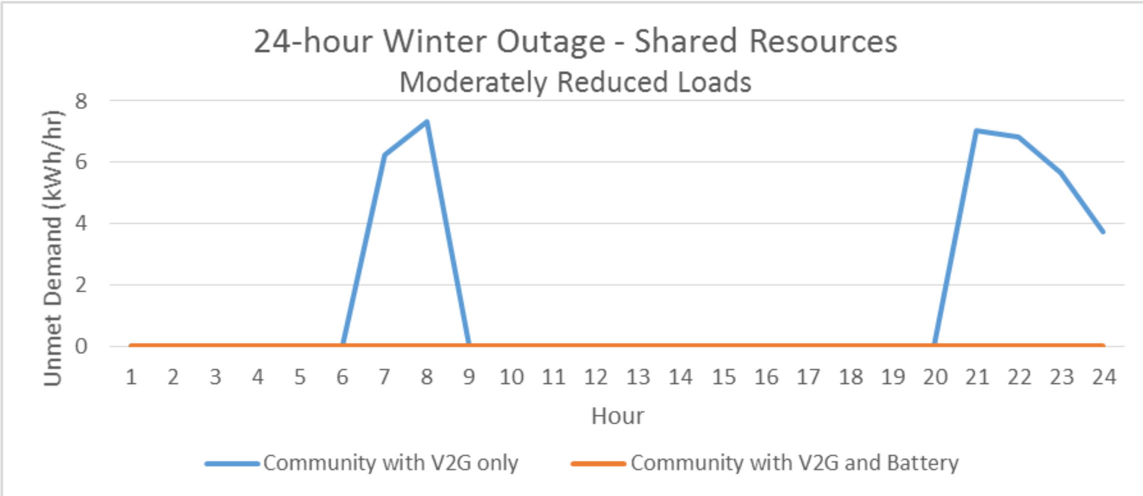

Figure 71. Unmet demand for moderately reduced loads in a microgrid during a 24-hour winter outage.

4.7.3 72-Hour Outage

Lastly, a 72-hour outage represents a more severe event, such as a winter storm or a hurricane outage. For this scenario, commuters only commute on the first day and the batteries are allowed to discharge fully after the commuters arrive home the first day. The additional battery capacity allows for more utilization of solar on the following days.

4.7.3.1 <u>Minimal Loads</u>

Table 30 shows the hours of unmet demand for the 72-hour outage. Results for the first 24 hours are very different from the 24 hour outage because the 72-hour outage is classified as a "crisis" outage where users expect the power to be out longer than normal and allow a deeper discharge of the battery.

Table 30. Hours of unmet demand for minimal loads during 72-hour outages.

	Houses with separate resources										Houses with shared resources	
	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	V2G only	V2G & Batteries
Winter	3	13	6	0	3	2	2	20	25	7	0	0
Spring	2	13	2	0	2	1	1	8	14	1	0	0
Summer	2	12	2	0	2	1	1	6	13	1	0	0

Figure 72 shows the hourly unmet demand for the summer outage which acts similarly to the spring outage. Gaps similar to those in the 24-hour outage appear around the morning and afternoon due to lack of PV and EV overlap. House 2 still experiences unmet demand during their night-shift when no EV is available for discharge. Houses 8 and 10 run out of charge during the night since a large portion of their charge was used for the day's commute. Once workers stop commuting, their EVs are able to capture enough PV to power their homes continuously in both spring and summer outages.

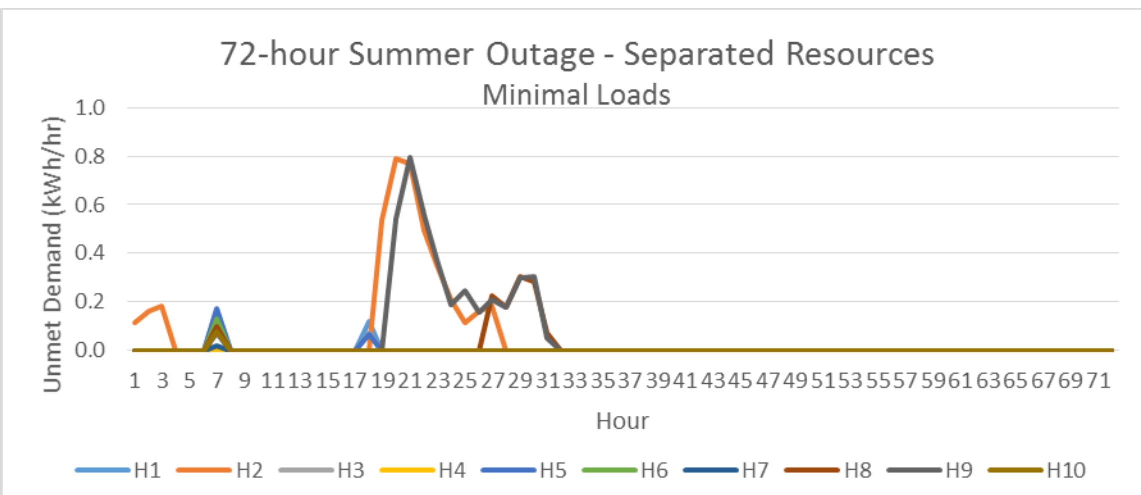

Figure 72. Unmet demand for minimal loads in separate houses during a 72-hour summer outage.

Figure 73 describes unmet demand in the winter outage. The winter outage shows similar behavior to the spring and summer outages in the first 36 hours. The difference for the winter outage is that PV generation is not enough to sustain some houses throughout the day. As houses run out of battery charge in the second night/third morning, they experience unmet demand.

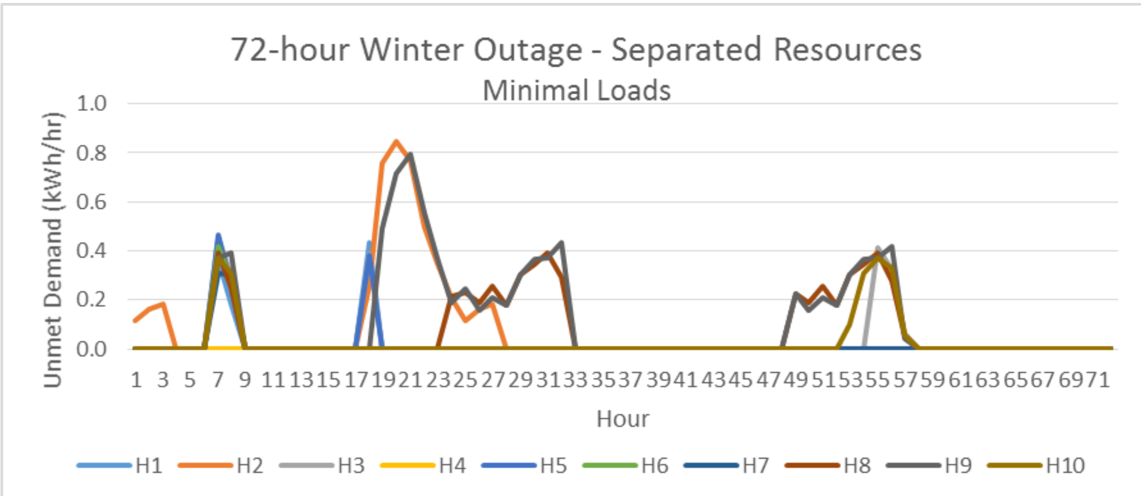

Figure 73. Unmet demand for minimal loads in separate houses during a 72-hour winter outage.

4.7.3.2 Moderately Reduced Loads

Table 31 shows unmet demand for moderately reduced loads. Most houses experience a larger number of hours of unmet demand in the winter. More houses run out of battery in spring and summer, as well. Figure 74 shows that beyond the first night/second morning lack of battery charge due to commute, houses are able to provide electricity for themselves from PV stored in EVs with the exception of house 10 which runs out of charge two hours before PV generation resumes on the last morning. Figure 75 shows unmet demand during winter. Only three homes (1, 4, and 5) are able to generate enough PV electricity to sustain their loads.

Table 31. Hours of unmet demand for moderately reduced loads during 72-hour outages.

	Houses with separate resources										Houses with shared resources	
	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	V2G only	V2G & Batteries
Winter	5	13	18	0	6	20	16	32	36	32	14	0
Spring	2	13	2	0	2	1	1	13	17	11	0	0
Summer	2	13	3	0	3	2	2	17	19	16	0	0

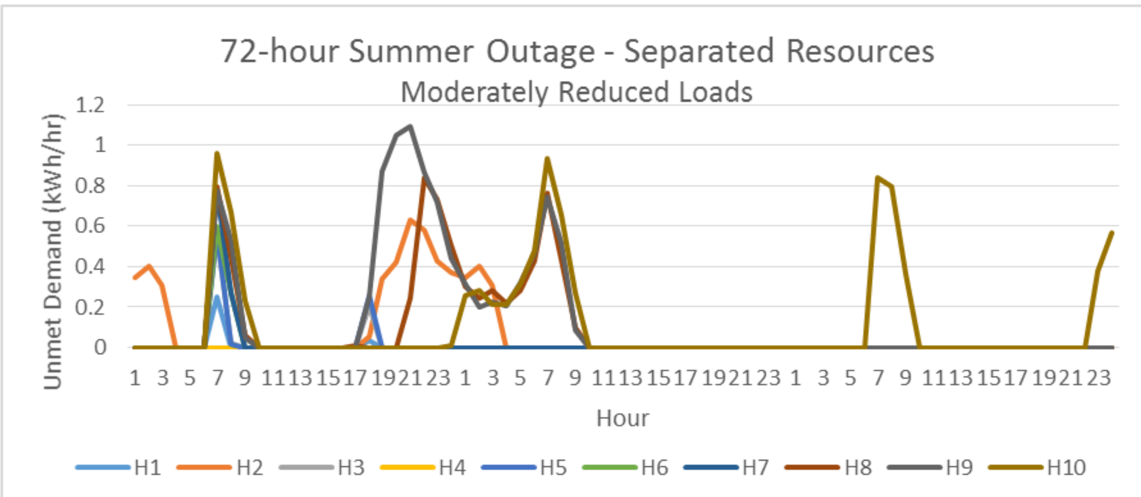

Figure 74. Unmet demand for moderately reduced loads in separate houses during a 72-hour summer outage.

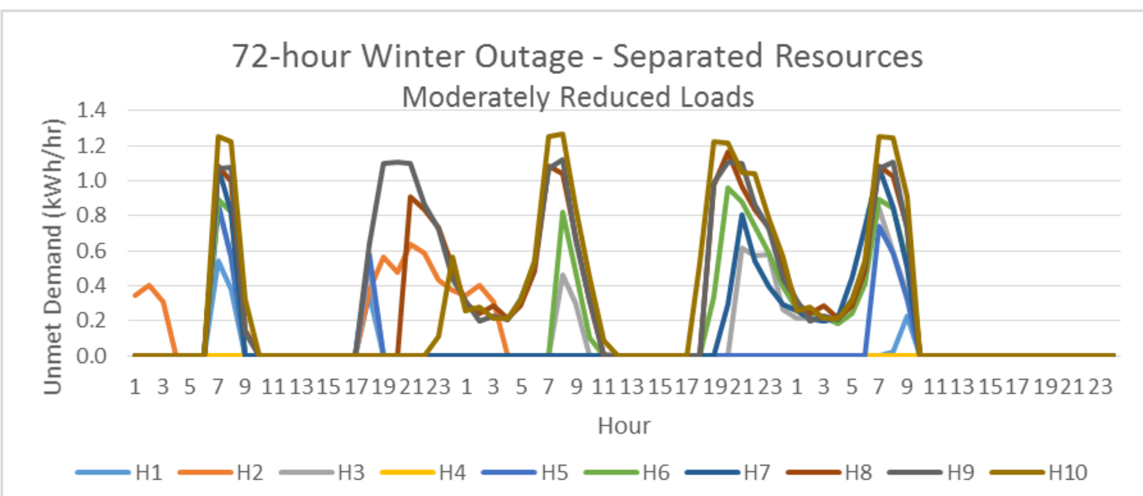

Figure 75. Unmet demand for moderately reduced loads in separate houses during a 72-hour summer outage.

Shared resources, shown in Figure 76, show that while the interconnectivity of the microgrid allows for all demand to be met with V2G for the first 45 hours, PV generation is not enough to sustain the moderately reduced loads over a long period of time. For the winter outage, seven 13.5kWh batteries are required to provide electricity during the entire period. Spring and summer outages do not require any stationary battery discharge from the community.

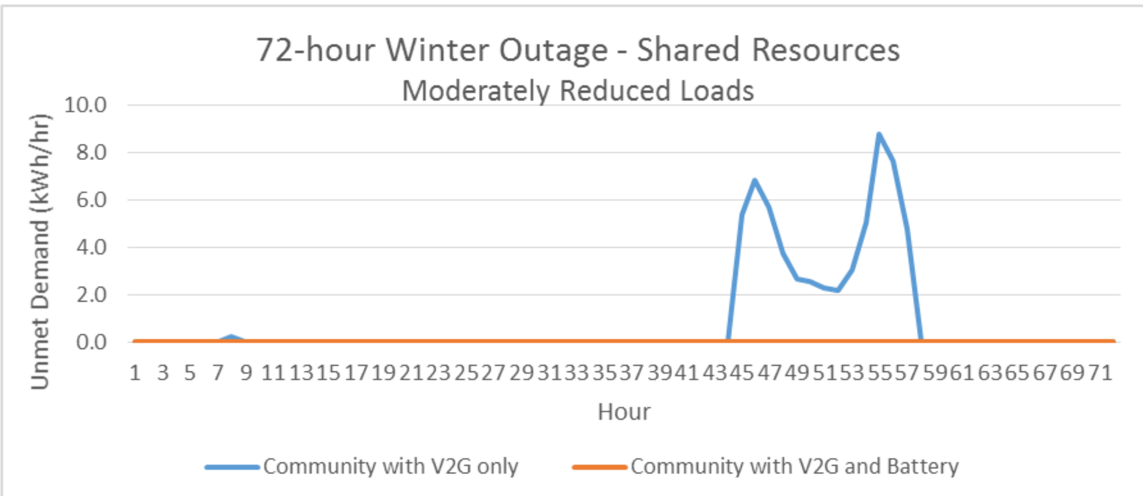

Figure 76. Unmet demand for moderately reduced loads in a microgrid during a 24-hour winter outage.

4.8 Discussion

A financial evaluation showed that demand response and vehicle to grid discharge provide only small financial benefits to consumers observing variable electricity tariffs. Homes saved $75-$320 annually, but at the cost of significant EV battery usage and occupant discomfort. Shared resources increased the savings by $20-$80 annually which allows for more savings at the same level of investment/discomfort, but does not provide a financial justification for infrastructure upgrades to create a microgrid.

From the utility perspective, however, residential buildings have a large potential for peak reduction. DR provided 10-31% of peak reduction, with no difference in performance for shared electrical resource and separate electrical resources.

V2G discharge provided 11-29% peak reduction with an additional reduction up to 3.6% from sharing electrical resources. The small amount of peak reduction from sharing electrical resources is caused by the sharing of extra battery discharge potential for homes whose battery availability is higher than their consumption.

Coupling V2G discharge and DR provided 10-46% peak reduction, with up to an additional 16% reduction from shared resources. The large contribution of shared resources captures the inter-house transfer of V2G discharge as houses decrease their individual demand and allow for discharge to other houses that need electricity during that hour. The reduced electricity demand also allows EV batteries that are available during more hours of the peak period to retain battery space for hours of greater demand later in the period.

DR and V2G showed up to a 23 kWh/hr peak demand reduction from the 10-home neighborhood, or 2.3kWh/hr demand reduction per residence. Stationary batteries incorporated into a neighborhood of shared electrical resources allowed for additional peak reduction for hours when electric vehicles are not available for V2G and solar generation is low. An 81kWh community-owned stationary battery system was able to reduce the community's peak usage by an additional 14-16kWh/hr at all levels of demand response.

The neighborhood with shared resources showed much greater resiliency to power outages. Many independent homes were unable to provide electricity during outages of 4, 24, and 72 hours. Homes failed to self-power in the time period when EVs are not present but PV generation has not begun. Some houses with less allocated battery space were not able to sustain power during the 24-hour period.

The microgrid provided power to all houses during the 24-hour outage but relied on stationary batteries. One 13.5kWh battery (a cost of $6,500) was required to provide all homes with minimal power, and three 13.5kWh batteries (a cost of $19,500) were required to provide all homes with moderately reduced power.

72-hour crisis outages showed significant black outs in wintertime for all homes except for the one house with an EV present all day. Many homes failed to meet a large portion of demand during the outage. The microgrid was able to provide power to all homes through V2G only during spring and summer outages but required seven batteries to provide the last day of power. Larger solar capacity might reduce the need for more batteries and make longer wintertime outages manageable, however, the conditions that caused the outage (such as winter precipitation) may reduce or remove solar generation altogether. Overall, V2G within a community microgrid greatly increased the homes' ability to provide basic power services during outages of several lengths. A small number of stationary batteries allowed the community to provide moderately reduced loads for all outage scenarios.

5 CONCLUSIONS AND FUTURE WORK

5.1 Summary

This thesis examined the potential impacts of sharing electrical resources among members of a small neighborhood. It found that consumer cost savings under current electrical tariffs are not sufficient motivation to participate in a microgrid, however it found significant benefits to the utility in the form of peak reduction and benefits to the homeowner in terms of resiliency. As utilities pursue more peak reduction programs, new tariffs incentivizing load smoothing in residences will increase the value to the consumer.

Consumer cost savings from time of use and critical peak pricing schemes range from $75-$320 annually but require the discomfort of building demand response and the additional use of their electric vehicle battery. Savings from a microgrid configuration range from $20-$80 and provide little financial incentive for consumers to join a microgrid. If utilities keep the same electric rate structures, the increased peak reduction potential of microgrids and DR/V2G will be unreachable as it requires consumer participation.

While consumer cost savings was low, the same strategies applied to twenty peak demand days showed significant peak demand reduction.

Building demand response resulted in 10-30% peak reduction, with no improvement from implementing a microgrid. V2G showed 11-29% peak reduction, with a microgrid lowering peak consumption an additional 0-3.6% due to V2G discharge between houses. Together, DR and V2G reduced peak demand by 10-46% with an additionally 0-16% reduction from a microgrid configuration.

As the severity of demand response and the availability of V2G increased, the microgrid allowed additional peak demand reduction that independent homes could not achieve.

Such peak reduction strategies result in limited home occupant discomfort levels and limited electric vehicle discharge but provide significant peak demand reduction potential, with microgrid connectivity allowing for greater realization of peak reduction at higher levels of effort. A utility seeking large levels of demand response from residences would benefit from the synergy between V2G and DR without coordinating a large-scale V2G system.

Most independent homes were not able to meet electrical loads for the outage scenarios considered. Even when EVs were made more available for V2G discharge in a crisis scenario, some homes were unable to support basic electrical loads from PV generation and V2G discharge alone. In comparison, a microgrid using V2G was able to provide minimal electricity services during all outages. A microgrid with seven 13.5 kWh Tesla Powerwall batteries and V2G was able to accommodate moderately reduced electrical loads in all outages scenarios that provides residents with a more comfortable home during an outage.

A stationary battery can provide resilience to a residential microgrid, but can also contribute to peak demand reduction. Six 13.5 kWh Tesla Powerwall batteries were able to reduce peak demand by an additional 14-16 kWh/hr with V2G and DR enabled. Cost savings to the consumer from peak reduction incentives allow a community to offset the cost of the batteries.

Ultimately, this thesis shows that microgrids allow consumers to more effectively combine peak demand reactions while also providing energy security in the case of an outage. While current time-of-use electricity tariffs do not motivate customers to use DR and V2G for peak demand reduction, DR and V2G were highly effective in reducing peak loads during a set number of peak demand events. This demand reduction resource increases the flexibility and resilience of the greater grid. Residential microgrids enable the grid to handle an influx of electric vehicles and distributed renewable electricity generation in a future tending toward low-carbon, renewable energies.

5.2 Future Work

This thesis examined building demand response, vehicle to grid discharge, and stationary batteries as strategies to reduce peak consumption and smooth electrical demand from the larger grid. This research could be expanded by considering additional strategies to adjust building loads, implementing other electricity generation sources, and including different communities within the microgrid.

Adjusting building loads through increased building efficiency is a logical addition to this work. As building consumption decreases, battery discharge and solar generation are more able to offset peak demand. Additionally, increased efficiency may take the place of demand response measures, which would allow consumers to reduce peak usage while maintaining normal levels of comfort.

Another study could leverage the thermal mass of a building or water heater to shift peak loads to morning and early afternoon periods or late evening periods when solar resources or electric vehicle battery availabilities are higher. Such a study would be more involved, as many building simulation models do not consider a robust thermal mass calculation. Several studies consider nighttime wind-driven heating of high thermal mass buildings (Dréau & Heiselberg, 2016), cold storage methods (Xydis & Mihet-Popa, 2016), and ice battery storage (Monsef & Yari, 2016).

The addition of other distributed energy resources, such as wind generators, geothermal heat pumps, and microturbines with combined heat and power would provide more insight into microgrid performance as distributed energy resources increase.

Beyond adjusting loads or sources of electricity, expanding the scope of the microgrid to neighborhoods of homes with different vintages, retrofit levels, and renewable energy/electric vehicle participation may provide new insights into microgrid functionality. The increased electrical diversity of these communities may provide vastly different impacts of combined solar generation, DR, and stationary and mobile battery discharge.

Expanding further to a larger number of homes or a distribution of building types may show different results. A larger number of homes may yield more confident or more extensive impacts of EV discharge for peak reduction. Additionally, combining neighborhoods with commercial or industrial buildings may allow for more complementary behavior, since the different building types have different EV availabilities and different daily electrical load profiles.

APPENDIX: GRIDLAB-D CODE

```
#include "MEL_schedules.glm"
clock {
  timezone EST+5EDT;
  starttime '2000-01-01 00:00:00';
  stoptime '2001-01-01 00:00:00';
}
module climate;
object climate {
  tmyfile "SC-Columbia.tmy2";
}
module residential {
  implicit_enduses NONE;
};
module tape;
module powerflow;

schedule daily_use {
     * * * * * 0.00;
}

schedule dishwasher1 {
      * 20-18 * * * 0.00;
      * 19 * * * * 1;
}
schedule clotheswasher1 {
      * 15-13 * * * 0.00;
      * 14 * * * * 1;
}
schedule dryer1 {
      * 16-14 * * * 0.00;
      * 15 * * * * 1;
}
schedule evtowork1 {
      * 8 * * 1-5 1;
      * 9-7 * * 1-5 0;
      * * * * 6-0 0;
}
schedule evtohome1 {
      * 18 * * 1-5 1;
```

```
      * 19-17 * * 1-5 0;
      * * * * 6-0 0;
}
object triplex_meter {
  name Meter1;
  nominal_voltage 120V;
  phases AS;
  object recorder {
    property measured_real_energy;
    file aggEnergy.csv;
    interval 31536000;
  };
}

object house {
  name House1;
  parent Meter1;
  floor_area 160 m^2;
  ceiling_height 4 m;
  aspect_ratio 1.6;
  window_wall_ratio 0.12;
  number_of_doors 2;
  number_of_stories 1;
  Rroof 38;
  Rwall 19;
  Rwindows 2.87;
  window_exterior_transmission_coefficient 0.69;
  heating_setpoint 70 degF;
  cooling_setpoint 75 degF;
  heating_COP 2.93;
  cooling_COP 4.01;


     object ZIPload {
          name l1;
          heat_fraction 1.0;
          base_power lighting1*4.149;
     };

     object occupantload {
          name o1;
          number_of_occupants 1;
          occupancy_fraction occupancy1;
          heatgain_per_person 341;
     };
```

```
	object ZIPload {
		name e1;
		heat_fraction 0.95;
		base_power MEL1*17.695;

	};

	object evcharger_det {
		name ev1;
		travel_distance 13.333;
		battery_capacity 23;
		charging_efficiency 0.85;
		arrival_at_work 800;
		duration_at_work 9.5 h;
		arrival_at_home 1800;
		duration_at_home 13.5 h;
		work_charging_available false;
		mileage_efficiency 3.333;
	};

	object ZIPload {
		name dhw1;
		heat_fraction 0.16;
		base_power occupancy1*0.606;
	};
}
object multi_recorder {
		file "multi.csv";
		property
House1:air_temperature,o1:occupancy_fraction,House1:panel.p
ower,House1:hvac_load,l1:actual_power.real,e1:actual_power.
real,dhw1:power.real,dhw1:energy.real,ev1:battery_SOC,ev1:c
harge_rate,ev1:vehicle_location,ev1:energy.real,ev1:power.r
eal;
		interval 3600;
};
```

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