THE EFFECTS OF BATTERY STORAGE AND LOAD MANAGEMENT ON PHOTOVOLTAIC SELF-CONSUMPTION

A Thesis
by
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Abstract

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Despite the rapid growth of the photovoltaic (PV) industry, most of the energy demand in the United States is supplied by fossil fuel power plants. One of the main reasons for this is that PV is non-dispatchable, meaning it is limited to times when the sun is shining. Because of this, utilities must maintain reliable grid infrastructure for times when PV is not available but there is still demand, such as in the evening when the sun has gone down but the electricity demand is greatest. This leads to electricity infrastructure going unutilized much of the time, wasting valuable resources while fossil fuel power plants are still harming the environment.

The non-dispatchable nature of PV limits the amount of PV that can be connected to the grid. One remedy for this limit is to add energy storage to PV systems, or to shift deferrable loads from times of peak electricity demand to times when the sun is shining. With storage, batteries can be charged when the sun is shining, and discharged when the electricity demand is highest. Energy storage and load shifting allow more loads to be met locally rather than importing energy from the grid, or exporting excess PV production to the grid. This process is known as self-consumption.

This study compares the levels of self-consumption in a PV self-consumption system with and without the use of battery-based energy storage. It also compares four different load shifting load profiles against a baseline load profile without load shifting.

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Thanks to my beautiful wife Annie, who has been the main breadwinner as I've been completing this degree. Your love and support means more than you know. I love you, and I can't wait for our next phase of life together. Also, In the words of Ray Sinclair, "it's easier to tell your mom you flunked out of school than your wife."

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Thanks to my parents, and in-laws, and siblings for all of your continued love and support. Dad, after much resistance, I finally got excited about research.

Thanks to Amy and Michael Darling for allowing me to log data from their breaker panel. As requested, I have not posted it on YouTube, but the findings are included in this thesis.

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CHAPTER 1: INTRODUCTION

Introduction

Despite continued growth in the renewable energy industry, the percentage of energy that we generate from fossil fuels in the United States remains high. The US Energy Information Administration (2016) reported that at the end of 2015, 66% of our electricity generation came from coal and natural gas, whereas renewable energy (including hydroelectric) provided only 13% of our electricity generation nationally with nuclear (20%) and petroleum (1%) making up the difference.

Various policies and incentives worldwide have been helpful in increasing the adoption of renewable energy systems. A few include net metering, feed-in tariffs, tax incentives, rebates and utility rate structures. For example, the United States has had a Federal Investment Tax Credit since 2006, which provides a 30% tax credit on the installation cost of renewables (Solar Energy Industries Association [SEIA], 2016a). This is slated to taper out over the next few years, as have many of the other incentives worldwide such as feed-in tariffs in Germany (Schwartz, 2016).

Although absolute renewable energy generation rates are low, the significant increase in renewable energy generation placed on the electrical grid has created challenges for utilities. Utility companies are mandated to provide consistent and reliable power for their customers. This is feasible because conventional generation of power is dispatchable, meaning it can be turned on and off to meet demand. Many renewable energy generation sources including solar and wind, however, are non-dispatchable. This prevents electric utilities from relying solely on renewables because utility customers utilize electricity when the sun is not shining and the wind is not blowing. A utility's generating portfolio must meet consumer demand all day and year round, which requires generating assets to meet baseline loads as well as ramping up production during times of peak demand.

To highlight the challenge utilities face in meeting peak demand, PJM data from 2012 will be used. PJM stands for Pennsylvania, Jersey, Maryland and is a regional transmission organization (RTO) that is responsible for wholesale electricity movement for thirteen states in the Eastern and Midwestern United States (Pennsylvania, Jersey, Maryland [PJM], 2016a). In Figure 1, the 8,760 individual hourly demands for the year 2012 are ordered from greatest demand to least demand in gigawatts (GW). Within the 50 hours of highest demand, the demand drops about 12,000GW (Pennsylvania, Jersey, Maryland [PJM], 2016b). One coal fired power plant provides about 1 GW of production. This means that the equivalent of 12 coal fired power plants are only being used for less than 50 out of 8,760 hours in a year. That is a large amount of capital investment that must be recovered, and a large outlaying of tax dollar subsidies for such limited public benefit. This data demonstrates how the need to meet peak demand can dramatically increase utility costs, leading to higher customer costs.

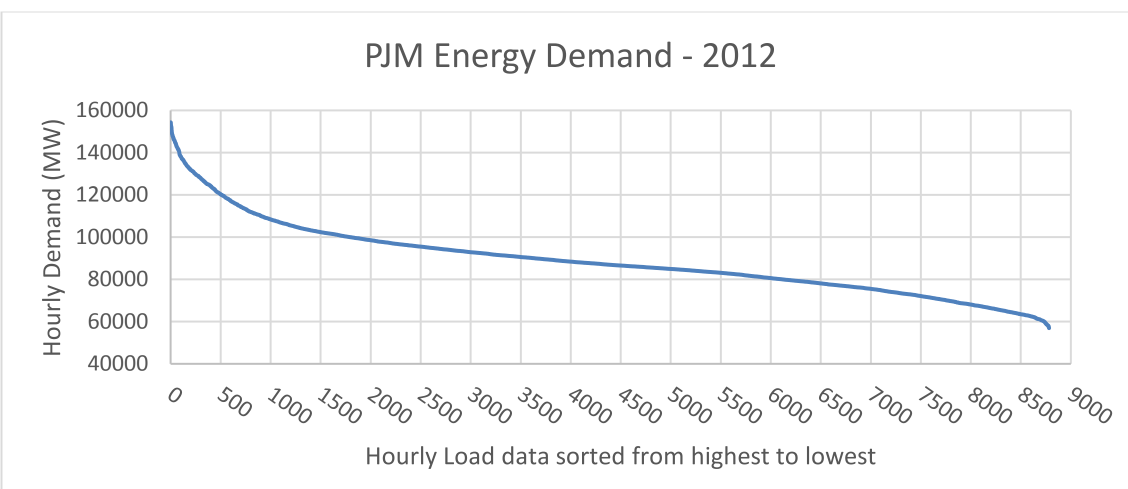

Figure 1. PJM energy demand 2013 (PJM, 1999-2016).

As the number of grid connected photovoltaic (PV) installations increase, utilities have more trouble maintaining grid integrity because of the variable availability of solar electricity. Many grid-tied systems are net metered, meaning the utility is expected to absorb (provide credits for) the excess energy produced by the PV system, while still providing electricity to the customer when the PV system is not producing (Schwartz, 2016). One solution to this challenge is to increase on site use of the energy produced by the PV system.

The ability of residential scale renewable energy generation systems to directly satisfy local loads is known as self-consumption (European Photovoltaic Industry Association [EPIA], 2012). Ideally, homeowners would use 100% of the solar electricity they generate on site for their specific load profile. However, self-consumption is limited by a temporal mismatch between generation and load, and the trend towards larger PV systems. Energy storage and load management provide two options to increase self-consumption of non-dispatchable generation without sacrificing reliability.

Using storage, excess solar energy generated during the day can be stored for use after the sun goes down, most importantly during late afternoon demand peaks.

There are several options for energy storage including battery, flywheel, compressed air, and hot water storage. All have potential to increase the grid penetration of renewable electricity sources the utility can accommodate. This project will specifically look at residential-scale battery storage and its potential to decrease residential imports and exports from the grid. If batteries charge while the PV modules are producing electricity during the day, and discharge during the peak utility demand that often occurs during late afternoon/early evening, then the number of fossil fuel generated power plants operating to meet the demand of the short daily peak could be decreased (B. Raichle, personal communication, February 15, 2016).

Another factor that could aid electric utilities in meeting peak demand is the concept of demand side management, or load shifting. Both terms refer to managing when and how much electricity a customer uses. There are two main categories of electric loads, deferrable and non-deferrable. Non-deferrable loads are needed immediately and cannot be shifted, such as lights or the microwave. Deferrable loads have the potential to be rescheduled to a later time, such as an electric water heater, the dishwasher, or washing machine. The strategy of programming these devices to operate during off-peak hours or hours when renewable generation occurs, rather than during peak demand hours, can be added to storage to enhance the effectiveness of renewable energy systems (Luthander, Widen, Nilsson, & Palm, 2014). The combination of battery-based storage and load shifting as described above have a high potential for increasing the local use of PV power, or self-consumption (Castillo-Cagigal, Gutiérrez, Monasterio-Huelin, Caamaño-Martín, Masa, & Jiménez-Leube, 2011a).

Statement of the Problem

The rising use of grid interconnected renewable energy production poses a problem for utility companies. Renewable energy production technologies such as solar and wind are variable, or nondispatchable in their capacity to generate electricity. Although these technologies can potentially produce large amounts of energy, the supply of renewable generation does not meet the demand at all times throughout the year (Denholm & Hand, 2011), and the utility grid can only accommodate certain levels of energy produced by renewables without disruptions. This makes renewables less desirable for a utility that is required to supply consistent and reliable power to its customers.

Self-consumption is the process where utility customers produce and consume their own electricity by way of a renewable energy system such as PV technology (EPIA, 2012). Self-consumption could potentially increase the level of renewables accommodated by the grid by using battery-based energy storage and load shifting (Luthander et al., 2014). Battery-based storage allows the production from PV generation to be discharged during peak hours for increased self-consumption (Fitzgerald, Mandel, Morris, & Touati, 2015). The time of use for deferrable loads can also be changed to run during times of peak PV production rather than peak demand (Luthander et al., 2014).

Figure 2 illustrates how a systems level of self-consumption could be increased through energy storage and load shifting. Loads are shifted to times of day when there is surplus PV production, and stored energy from batteries is discharged during times of day when there is a higher demand.

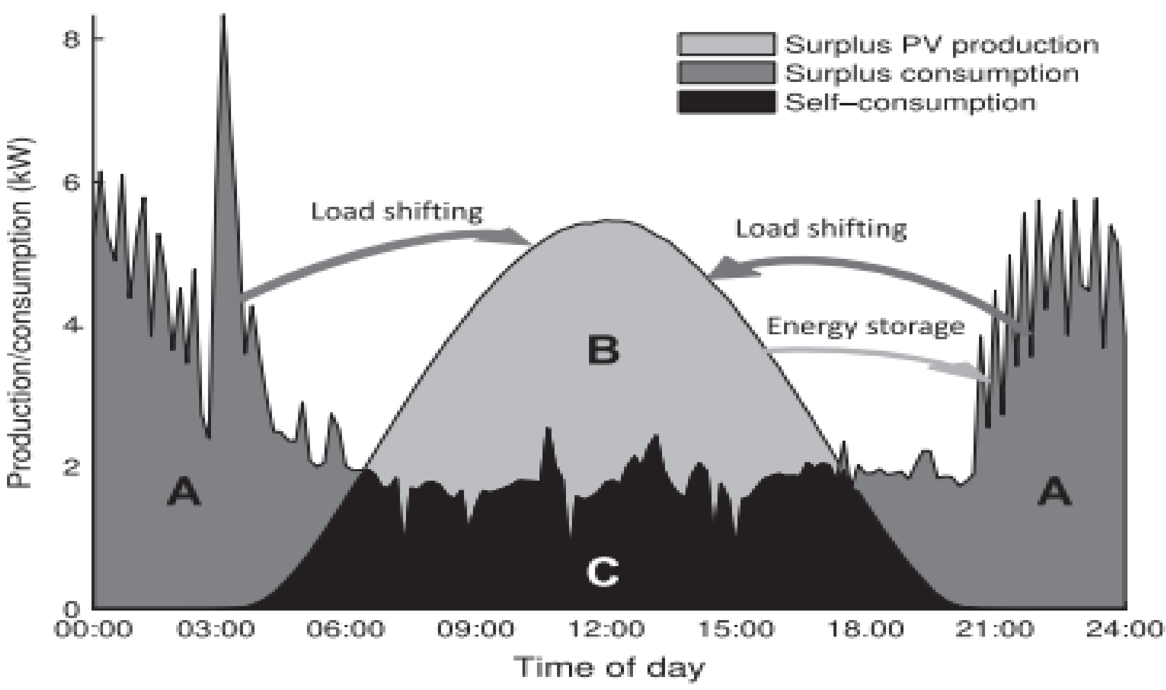

Figure 2. Storage and load shifting visual (Luthander et al., 2014, p. 82).

The widespread use of combined storage and load shifting has the potential to significantly increase the amount of renewable energy that can be used by the utility grid, therefore decreasing our reliance on fossil fuels. More research on the effectiveness of these technologies to increase self-consumption is needed to increase the distributed grid hosting capacity of renewables (Luthander et al., 2014). Also, with net metering policies on the decline in the United States (Schwartz, 2016), self-consumption research is needed to enable the continued growth of residential renewable energy.

Purpose of the Study

This study will examine how PV, battery-based storage, load shifting, and insolation affect self-consumption on a residential scale. Theoretically, increased self-consumption should increase the PV used on site while reducing the amounts of electricity needed from the grid, and therefore leveling grid imports and exports. A fabricated residential load profile based on local residential consumption data and a United States Department of Energy (DOE) typical residential load profile were the basis of our experimental loads. A combination of PV, battery-based storage, and load shifting experimental scenarios were conducted to see their potential effect on self-consumption compared to the baseline residential load profile. The goal of the study was to quantify the ability of these scenarios in leveling a home's grid imports and exports with battery-based PV self-consumption systems. This could lead to a greater adoption by utilities of distributed renewable energy on the electric grid, as well as inform customers as to the benefits of battery-based energy storage.

Research Questions

1. To what extent can adding storage to a PV system increase self-consumption?
2. To what extent can load shifting of typically deferrable residential loads increase self-consumption?

Assumptions

There are several assumptions that had to be made during the course of this study. The first was that the data collected only pertained to this specific system, which included a 3.36kW PV system, an 8.6kWh lithium-ion battery bank, and this particular load profile. Results would differ if any of these factors were changed. Testing those scenarios was beyond the scope of this thesis.

Another assumption included in this study was that algebra can be used to calculate control data such as load, PV, and PV +battery. For instance, since the load is the same every day and the PV values can be isolated, both "PV only" and "PV + battery" effects can be calculated from the same data set.

Limitations of the Study

This project incorporated a unique set of components to create a custom battery-based, PV self-consumption system. The odds of this system being replicated exactly are quite low, which could pose challenges for future researchers or homeowners. That being said, the components used have similar capabilities to other products currently on the market. Although other products may have slight variations, one advantage of a unique system like this is that a similar system could be created using a variety of products to maximize performance or cost effectiveness.

The fabricated load profile was from one house in Boone, North Carolina, which was then normalized to a DOE residential load profile for Asheville, North Carolina because a profile from Boone was not available. Although this house may not be typical of other residential loads or of houses in other locations, findings from this project will be applicable and customizable to other locations and their respective load profiles.

Battery degradation was not determined, nor was it considered in the analysis or results of this study.

Because of time constraints, data were collected from November 2016 to March 2017. These are the months with the fewest hours of insolation in Boone, North Carolina and data collected at a time of year with more insolation could show more dramatic results.

A final limitation of this study was that it did not analyze energy flow through the system. Although the system we used logs many parameters, there are several unknowns from a logging perspective for the energy flow. For instance, the "System Grid Input Power" includes power being imported from the grid, but the system cannot provide information as to where that power ends up (e.g. system loads, charging the battery bank). This issue will be further explained in Chapter Four.

Significance of the Study

The findings of this study are applicable to utility companies, renewable energy industry companies and professionals, and homeowners with current or future renewable energy production systems. Utilities will be interested in how the utilization of storage and load shifting can increase self-consumption, decrease peak demands, and increase the number of renewable energy generating technologies that can be accommodated by the grid without causing power disruptions. Renewable energy industry companies and professionals will be interested in how the findings may increase the desirability of their current products or lead to new product developments and business approaches. Finally, homeowners will be interested in this study because of its implications regarding the potential increase in effectiveness of their current renewable system, or the possible savings that could come from using a battery-based PV self-consumption system. Homeowners in areas with time-of-use (TOU) or demand based electricity rate schedules, whereby consumers are charged more for electricity during times of peak demand, will be interested in the potential savings energy storage and load shifting could provide.

This project will add to the current body of knowledge in the area of self-consumption within the renewable energy profession. Findings from this project could help lead to increased numbers of renewable energy systems that could be installed and tied to the grid without causing grid disruptions. Currently, this number is limited by the challenges previously described. One exciting possibility and direct application of this project is that we are using an Adara Power battery system. Adara Power is one of the leaders in the United States self-consumption industry (Schwartz, 2016) and the findings from this study have the potential to be incorporated into the company's business model.

CHAPTER 2: REVIEW OF LITERATURE

Self-consumption is a concept that has risen as a technological solution to utility grid, regulatory, and economic challenges, in which locally generated electricity is preferentially consumed locally. Technologies that make self-consumption unique include battery-based energy storage and load-shifting technologies. This chapter discusses the available literature and the basis for my self-consumption research.

Incentives and Regulations Affecting Renewable Energy Adoption

Various economic incentives have driven the growth of PV both domestically and internationally. Some of the major incentives include Feed-in-tariffs (FIT), Investment Tax Credits (ITC), Renewable Energy Portfolio Standards (RPS), and Net Metering (NEM) (Timilsina, Kurdgelashvili, & Narbel, 2012).

Feed-in-Tariffs

The Feed-in Tariff (FIT) incentive is one where the government pays producers for renewable technology energy production at a higher price per kWh than can be bought from the grid and is often guaranteed for a specific number of years. In 2010, FIT's were being used in more than 75 places worldwide. For example, Germany's FIT paid 0.43 Euros/kWh for rooftop solar arrays less than 30 kW in size, and could be locked in for 20 years. The FIT is thought of as a key driver for grid-connected PV, especially within the European Union (Timilsina et al., 2012).

Investment Tax Credits

An Investment Tax Credit (ITC) is a tax credit given to businesses and individuals who invest in renewable energy technologies. In the United States, a 30% ITC was enacted in 2006 and has given solar development in the United States significant leverage along with additional credits from various states. If the tax credit exceeds the taxes owed at the end of the year, the credits may be carried forward to subsequent years until the full credit is received (Timilsina et al., 2012). In 2016, the Federal ITC was granted a five-year extension. It will continue at 30% through 2019, and then decline gradually to 10% for businesses and 0% for homeowners after 2021. This will give the solar industry more time to reduce costs, making it more cost-competitive with other forms of energy production (Bebon, 2016).

Renewable Energy Portfolio Standards

Renewable Energy Portfolio Standards (REPS), known as Tradable Green Certificates in Europe, are grid penetration targets for renewable energy. They come in the form of a goal of a certain percentage of electricity generation from renewables by a specific year. For example, North Carolina adopted a REPS target of 12.5% of electricity made from renewable energy by the year 2021 (North Carolina Clean Energy Technology Center [NCCETC], 2016a). This has created a trading system where utilities can buy and sell renewably generated electricity from others to meet their goals. Thirty-one out of 50 states in the USA have committed to the RPS (Timilsina et al., 2012).

Net Metering

Net metering is a system where PV owners and other electricity producers are able to export excess generation to the grid. Typically, compensation is in the form of credits rather than actual payment at the same rate as consumption prices. Australia, Canada, the United States, and several European countries have implemented net metering (Timilsina et al., 2012).

In the United States, 41 states as of January, 2016 had mandatory net metering rules for utilities. (North Carolina Clean Energy Technology Center [NCCETC], 2016b). Net metering causes financial challenges for utilities because large solar customers can avoid paying for electricity through these credits. The question also arises as to who is responsible for paying for costs caused by the intermittent nature of PV systems (Lamontagne, Crawford, & Romano, 2016). Customer fixed costs including grid maintenance are also reduced by net metering because a utility's revenue is primarily generated by unit sales of electricity. (Clean Technia, 2016). As of 2015, 27 states had enacted legislation to revise or replace net metering rules. Hawaii, Nevada, and California have replaced net metering with buy-all, sell-all policies, which pay customers at the avoided cost rather than retail rate for PV generation. This decreases the value of PV systems to utility customers who have them, signaling the start of a trend away from net metering as a heavily customer-friendly rule (NCCETC, 2016b). Utilities have also begun charging PV customers high net-metering facilities charges that in some cases negate the benefit of having the PV in the first place (Blue Ridge Electric Membership Corporation [BREMCO], 2017).

A possible compromise between net metering and buy-all, sell-all could be to sell only solar PV not consumed on site back to the utility at the avoided cost, rather than all PV. This would essentially incentivize the adoption of storage on the grid by making self-consumption with battery-based storage a more economically feasible option. The economic proposition of a self-consumption system would be further enhanced if the adopter of the storage system was also compensated for the ancillary services the system is capable of providing (Fitzgerald et al., 2015). This is further discussed in a later section.

Renewables without Incentives

Many of these economic incentives for PV previously described are coming to an end Evidence of this includes decreased feed-in tariff rates in Germany, lowered net metering rates in Hawaii (Schwartz, 2016), and the German Renewable Energy Act of 2012 that limits the amount of PV power that can be exported to the grid by PV owners (EPIA, 2012). Increasingly, the burden of the intermittent nature of solar PV systems is being put back on the utility, which then must be recovered from the customer. With an aging grid infrastructure and the prospect of future carbon regulation, energy storage in the form of batteries can help customers and utilities to mitigate solar's intermittency and still make economic sense (Lamontagne et al., 2016).

Behind the Meter

As electricity flows from the grid to the consumer, or to the grid from a renewable system such as residential PV, the utility uses meters to track the flow of electricity to and from the grid. The concept of "behind-the-meter" (BTM) involves using energy storage to minimize electricity imports during peak demand or minimizing PV production exports by using it locally. BTM is the furthest "downstream" location where energy storage and production can be deployed, and also where it can provide the most ancillary services. This local use of PV production to minimize imports and exports in areas with unfavorable incentives for renewables is known as self-consumption (Fitzgerald et al., 2015).

Self-Consumption

According to the European Photovoltaic Industry Association (2012), although self-consumption technology could reduce governmental financial support for PV generation, it will enable continued PV industry operations to be financially feasible after these benefits expire completely. In a study done by Lang, Ammann, and Girod (2015), PV self-consumption potential was modeled using four different building types in three different European countries.

They concluded that self-consumption PV without battery storage can already be economically attractive in the absence of subsidies. Drivers of this feasibility include the total investment amount, PV production capacity, electrical demand of the building, and local electric prices. The model found that large multi-floor office buildings in areas with high local electric prices and low ratios of PV production to electric demand had the best results. Simply put, in buildings with high electrical demand that matches PV production, self-consumption rates increase. For this reason, they concluded that large office buildings have the most potential for self-consumption. Lang and colleagues (2015) noted that more research needs to be done with self-consumption economics as it relates to subsidies while employing electrical storage. From these results, it could be concluded that self-consumption using battery-based storage could make self-consumption more economically feasible on a smaller scale, even with peak energy loads that do not match peak PV production.

Self-consumption can aid in minimizing the mismatch of demand and production. Self-consumption can reduce spikes in solar production by reducing the amount of electricity exported to the grid during peak sun (EPIA, 2012). Also, decreased export-based incentives for direct grid-tied PV systems mean that self-consumption could increase a PV system's profits while simultaneously lowering stress on the utility grid (Luthander et al., 2014). Customers who do not get the advantage of exporting PV energy to the grid at a cost premium may find it cost-effective to store excess production so they can increase their self-consumption, especially as battery prices decrease (Merei, Moshovel, Mangor, & Sauer, 2016). The flexibility provided by energy storage could increase the rates of self-consumption compared to systems without storage, as described by Lang and colleagues (2015). Using generated PV locally will offset the higher cost of imported electricity rather than receiving credits or reimbursements at a lower rate (Schwartz, 2016). Battery-based storage can enable customers to increase their local use of generated electricity, along with providing ancillary services to the grid operator (Fitzgerald et al., 2015). Some of these services are outlined in the next section.

Renewables and Electric Utilities

As the amount of grid connected PV increases in the United States, electric utilities have an increased challenge to maintain grid integrity (Schwartz, 2016). A combination of new energy efficiency standards and effects of the 2008 Great Recession have led to decreased sales for utilities while costs are increasing for maintaining a reliable utility grid. (Hledik, 2014). Increasing amounts of renewables being added the grid also add complications. The typical residential load profile of consumption does not match typical PV system production, which poses challenges that need to be solved in order for utilities to adopt higher levels of non-dispatchable renewable energy generation. A few of the challenges caused by the intermittent nature of PV production beyond the obvious difficulty of satisfying a non-controllable load with non-dispatchable generation include frequency regulation and protecting voltage limits (Luthander et al., 2014). If grid frequency is not within an acceptable range, grid instability such as system level frequency spikes or dips may occur. This is also true for grid voltage. Voltage must remain within a certain range so power production is matched with demand. (Fitzgerald et al., 2015). Even though residential PV systems are producing electricity, owners of these systems still need the grid when the sun is not shining. In order to meet this demand, the utility has to maintain a pre-PV generation infrastructure (Schwartz, 2016).

Utility Charges

Utility electricity generation costs vary depending on system load and the time of day, as shown in Chapter One through the PJM data. This being said, most utility customers pay the same price for electricity at all times, known as flat rate pricing (Newsham & Bowker, 2010). Flat rate pricing provides no incentive for customers to minimize peak energy use even though it costs more to produce electricity during peak hours. As peak demand grows, utilities have to build more generation assets with low run time whose cost cannot be recovered by the asset's energy production, therefore disproportionately increasing customer costs (Solar Energy Industries Association [SEIA], 2016b). Utilities have implemented varying rate schedules to better align customer revenue with underlying utility costs (Hledik, 2014). Fixed charges, minimum charges, demand charges and time-varying pricing are a few of these strategies described in the following sections.

Facilities charges.

One rate change some utilities are using to cover increasing grid costs is a monthly fixed facilities charge. This increases customers' existing facilities charge by a fixed amount per month (Mclaren, Davidson, Miller, & Bird, 2015). The solar industry has opposed high fixed charges arguing that they unfairly penalize customers who are investing in clean energy. This "tax on the sun" reduces the financial draw of solar investments by increasing charges that cannot be reduced by solar production (Hledick, 2014). This disproportionately affects small consumers because they still have to pay the fixed facilities charge, and furthermore does not encourage energy conservation.

Minimum charges.

A minimum charge allows utilities to achieve revenue requirements while not acting as a deterrent to solar customers or energy efficiency measures. For instance, if the minimum charge set by the utility was $50, and a solar customer only owed $30 for energy used that month because of their PV production, they would simply pay the extra $20 to make up the difference. With minimum charges, solar PV and energy efficiency gives utility customers more opportunity to decrease their overall bill than with fixed charges (McLaren et al., 2015), but for energy conscious customers, minimum charges could be a deterrent to PV if their energy costs are typically at the minimum charge level or lower.

Demand charges.

A demand charge is a billing component based on a customer's maximum demand for the month, or a set time period. Two methods for this are billing demand, which is based on the maximum demand across all hours, and coincident peak demand, which is based on the peak demand for certain hours of the day. In a study of nine utilities that include a demand charges, Hledik (2014) found that demand charges typically make up 25-60% of the utility customer's bill, which incentivizes smarter load management to decrease peak demand. While demand charges are common in commercial rate structures, residential demand charges have potential to better align the cost of electricity generation with the cost to deliver it to customers. In addition to cost recovery for utilities, demand charges simultaneously compensate solar customers for their renewable generation (Hledik, 2014). One challenge for demand charges is the added requirement of smart meters, which allow utilities to log and charge customers for energy consumed by the hour or by smaller time intervals.

Time-varying pricing.

Time-varying pricing is a rate schedule where customers are charged more for energy used during selected peak times. This more accurately reflects the true cost of generation at the time it is used (Newsham & Bowker, 2010). This also provides incentives to customers to decrease peak consumption, or to generate their own electricity through a renewable energy system if the production occurs during peak pricing (SEIA, 2016b). Since this rate schedule also requires smart metering to track customers' consumption during certain times, time-varying pricing could cause a failure in net metering as net metering has no mechanism to track which rate is in effect at the time of generation. (B. Raichle, personal communication, April 13, 2016).

One goal of time-varying pricing is to prevent grid instability while lowering overall costs by reducing the grid demand over a few critical hours. Newsham and Bowker (2010) studied the effectiveness of four common time-varying pricing systems in North America. These systems included:

- Time-Of-Use (TOU): Each day is divided into blocks with a different price per kWh for each block. More expensive blocks correspond to peak demand times.
- Critical Peak Pricing (CPP): Similar to TOU in that each day is divided into different priced blocks, but CPP only applies to specific days that forecast higher demand. These days are advertised in advance by the utility, and prices are higher than a normal TOU system. This can be done with or without the utilities having enabling technology, that automatically curtail loads on event days remotely.
- Real Time Pricing (RTP): No two days have the same rate as the kWh price is linked to real time energy market prices. Future pricing is unable to be forecasted far in advance, and spikes may be greater than with other time-varying pricing systems. This is only available in de-regulated energy markets.
- Peak Time Rebates (PTR): This addition to the CPP system provides customers rebates for not using power during peak periods.

Newsham and Bowker concluded that CPP with enabling technology was the most effective strategy at reducing peak consumption. This system of time-varying pricing reduced peak loads by up to 30% on those forecasted event days, whereas TOU alone without CPP could reduce daily peaks by up to 5%. The researchers also noted that although smart metering can be an expensive initial investment, it could be better financially than building more generation capacity to meet peak demand. Also, as smart meters get more prevalent in North

America, it will be easier to learn about the effects of additional time-varying systems (Newsham & Bowker, 2010).

Time-varying pricing encourages renewable generation such as PV that produces during times of day with high electricity rates, or energy storage to increase self-consumption by using the stored energy during peak hours with high rates rather than drawing from the grid. For example, in Australia, the country with the highest level of residential solar grid penetration, TOU rates between 3:00pm and 8:00pm are so high that storage used to increase self-consumption of solar energy and decrease energy required from the utility grid is cost effective (Schwartz, 2016). By reducing electricity purchases during peak TOU pricing periods, customers can use energy storage and PV to reduce their energy bills (Fitzgerald et al., 2015). This is an example of a behind-the-meter application, which was previously discussed.

Battery-based Storage

Why Battery Storage?

As more renewable energy sources come onto the utility grid, the intermittent and non-dispatchable nature of renewables is certainly a disadvantage. For this reason, energy storage is crucial to making these renewable energy sources more dispatchable (Hadjipaschalis, Poullikkas, & Efthimiou, 2008), which will in effect have the added benefit of reducing their intermittency and allow for greater grid penetration of renewables.

More specifically, battery-based energy storage enables these benefits in tangible ways through many ancillary services at all levels of electricity production, distribution, and consumption. According to a study done by Fitzgerald and colleagues at the Rocky Mountain Institute, (2015), battery-based storage can provide up to thirteen different services to the three main stakeholder groups as shown in Figure 3.

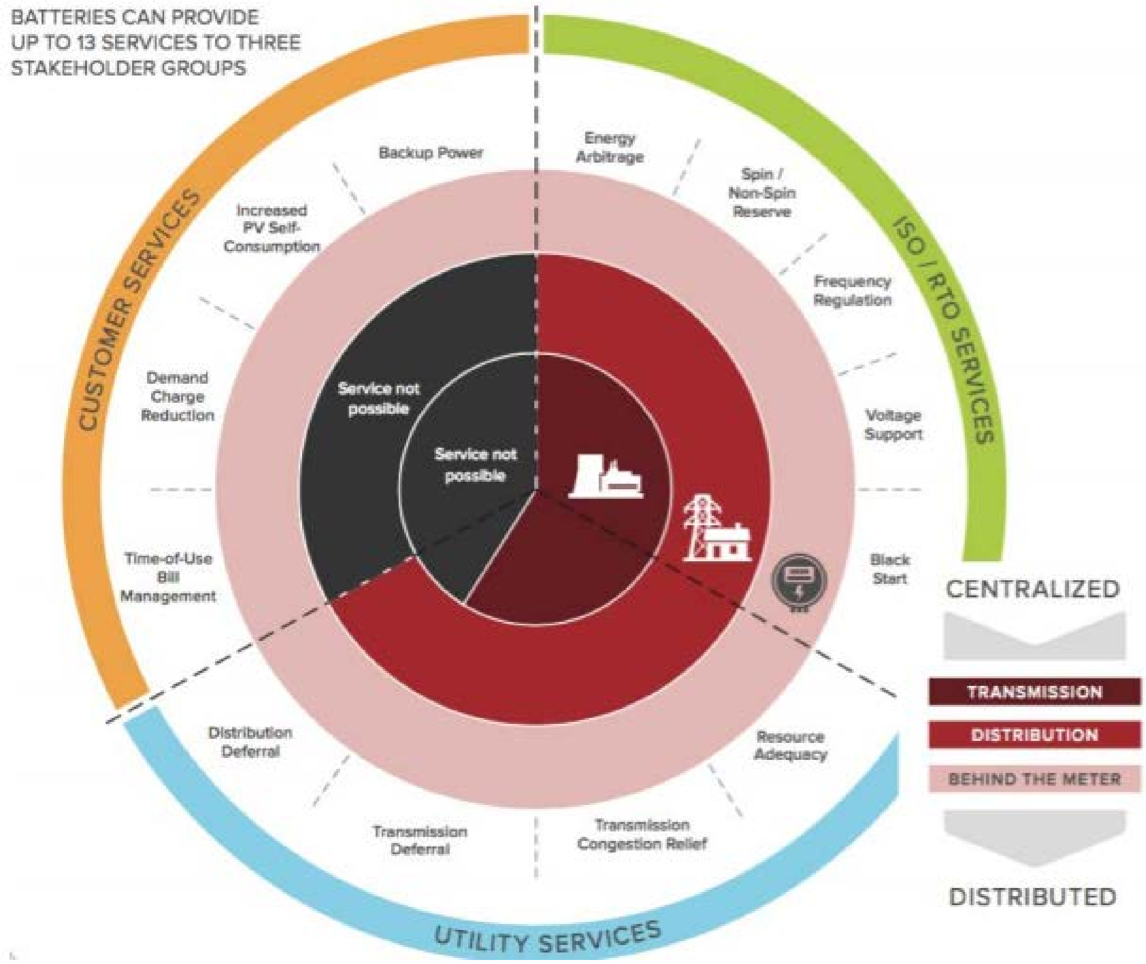

Figure 3. Battery ancillary services (Fitzgerald et al., 2015, p. 6)

These three groups are Regional Transmission Organizations (RTO's) and Independent System Operators (ISO's), utilities, and utility customers. RTO's and ISO's can benefit from frequency regulation and voltage support, because batteries can provide an immediate and automatic response to changes in demand. This helps prevent system-level frequency variation and ensures that power production is matched with demand at an acceptable voltage range (Fitzgerald et al., 2015).

On a utility level, battery storage can be used to meet generation requirements during peak demand hours and can reduce transmission congestion if deployed downstream of congested corridors and discharged during these peak times. These services reduce the need for investing in new fossil fuel power plants, which minimizes the risk of overinvestment in this area. Along these same lines, energy storage can help utilities delay, minimize, or avoid transmission and distribution system upgrades. This infrastructure is typically driven by a few peak events that occur each year, as well as by uncertain growth rates. Storage can help meet the demand during these events of limited timing and can help avoid oversizing transmission and distribution systems unnecessarily (Fitzgerald et al., 2015).

The scope of this project is focused more on the customer level, specifically residential level services that batteries can provide. As previously mentioned, batteries can provide more services the farther downstream they are located, and they provide the most potential value on the customer level when located behind the meter. There are four main services that battery storage can provide on the customer level including TOU bill management, increased self-consumption, demand charge reduction, and backup power (Krause & Brearley, 2016).

Time-of-use bill management.

As previously discussed, TOU bill management minimizes electricity purchases during expensive peak hours by using stored energy during those times. This energy can either be purchased from the grid during less expensive off-peak hours (Fitzgerald, et. al. 2015), or in the case of this study, charged from a renewable energy source such as PV. The main economic return for the TOU bill management service that battery storage can provide is based on the difference in pricing between on and off peak rates (Krause & Brearley, 2016).

Increased self-consumption.

Batteries can provide the service of increased self-consumption, which is the main focus of this thesis. Self-consumption minimizes the export of PV power that is generated behind the meter. This may improve the economic return of PV under most rate schedules because the locally generated energy is used directly rather than imported at a higher price and exported at a lower price, thereby increasing the avoided cost. This also enables customers to reduce their purchases during higher cost peak demand hours (Fitzgerald et al., 2015). A study by Johann and Madlener (2014), using the load profiles of ten different houses in Germany found that PV self-consumption could be increased by up to 20% through the addition of battery-based storage.

Demand charge reduction.

Demand charge reduction is another service that batteries can provide to utility customers. This is especially attractive in commercial applications, because demand charges can account for up to 50% of an energy bill (Krause & Brearley, 2016). Demand charges, like TOU billing incent customers to change their load profiles, in this case, to lower their peak demand. Batteries can enable customers to lower their demand charge by using stored energy to satisfy loads that would otherwise contribute to their peak demand (Fitzgerald et al., 2015).

Backup power.

A final service that battery-based energy storage can provide customers is backup power. This enables customers to still have power in the event of a grid failure. While it is hard for a residential customer to put a value on backup power in an economic sense, the security it provides is an attractive service to many (Fitzgerald et al., 2015).

Battery Technology

There are three main classifications of batteries that are typically used for renewable energy storage systems. These types are lead-acid, nickel-based, and lithium-based. Nickel-based batteries are split up into three types: nickel-cadmium (NiCd), nickel-metal hydride (NiMH), and nickel-zinc. Lithium-based batteries, like the nickel-based batteries, can be split into two subgroups: lithium-ion (Li-ion) and lithium-polymer (NiZn) (Hadjipaschalis, et. al, 2008).

Energy densities, roundtrip efficiencies, and lifespan for each type are depicted in Table 1. Additional notes are made in subsequent sections.

Table 1. *Battery Characteristics* (Hadjipaschalis et al., 2008; Nair & Garimella, 2010).

Battery Type	Energy Density	Efficiency	Lifespan
Deep Cycle Lead Acid	30Wh/kg	85-90%	1200-1800 cycles
Nickel-Cadmium	50Wh/kg	60-83%	1500-3000 cycles
Nickel-Metal Hydride	80Wh/kg	65-70%	1200-1800 cycles
Nickel-Zinc	60Wh/kg	80%	1200-1800 cycles
Lithium-Ion	80-150Wh/kg	90-100%	over 1500 cycles
Lithium-Polymer	100-150Wh/kg	90-100%	600 cycles

Lead-acid batteries.

Deep-cycle lead-acid batteries have been a great option for grid connected renewable energy systems. Their ability to discharge up to 80% of their energy over and over again makes them ideal for this application (Nair & Garimella, 2010). They are the oldest of the three types, are easy to install, have relatively low levels of maintenance, and are cheaper to install than other types of batteries. Their low self-discharge rate (about 2%) enables them to be used in long term storage applications (Hadjipaschalis, et. al, 2008).

A few drawbacks of lead-acid batteries include their decreased performance at extreme temperatures, limited lifespan, and the toxic materials used to produce them (Nair & Garimella, 2010).

Nickel-cadmium.

When compared with lead acid batteries, NiCd batteris have lower maintenance requirements. They are durable and good for operating in adverse conditions (Nair & Garimella, 2010). On the down side, NiCd batteries may be 10 times more expensive than lead acid batteries (Hadjipaschalis, et. al, 2008), suffer from severe self-discharge, and contain toxic, heavy metals (Nair & Garimella, 2010).

Nickel-metal hydride.

NiMH batteries, on the other hand do not contain toxic heavy metals making them more environmentally friendly. Similar to NiCd batteris, however, they suffer from self-discharge, so are not a good option for long-term storage (Nair & Garimella, 2010).

Lithium-based batteries.

Lithium batteries are the main choice for cell phones, laptop computers, and electric vehicles. A few advantages the lithium-based batteries have over their nickel counterparts are low self-discharge rates, and even lower maintenance requirements. Some improvements that need to be made include decreased costs, increased lifespan, and decreased flammability (Hadjipaschalis et al., 2008).

Lithium-ion.

Li-ion batteries have the greatest potential for success in the renewable energy sector because they provide stable voltage and quick response times. Although the market and investments are driving down costs significantly, high initial investment is the main drawback for Li-ion batteries (Nair & Garimella, 2010). Additional drawbacks include shortened lifespan at high temperatures or deep discharges and flammability issues (Hadjipaschalis et al., 2008).

Lithium-polymer.

These batteries tend to be lighter and less flammable than Li-ion batteries. Limited lifespan is their main drawback reaching only about 600 cycles (Hadjipaschalis, et. al, 2008).

Value of Battery-based Energy Storage

It is important to distinguish between the cost and value of battery-based storage. If only used for one service, such as backup power, a battery system may go unused for 50-95% of its useful life. Using batteries for multiple services, or for stacked services can significantly increase the value of a battery-based energy storage system. For example, a system primarily installed for increased self-consumption will not only aid a customer in reduced demand charges, but it can help the utility by being available to help with frequency regulation or voltage support (Fitzgerald et al., 2015).

The current economic landscape of high battery costs and low energy prices make battery-based energy storage difficult to justify economically for the customer. Installing battery-based storage with a PV system will perform many of the ancillary services previously described at some level, but many of these services are unaccounted for in the economics (Krause & Brearley, 2016). Residential customers will benefit from services that apply to their utility rate schedules such as demand charge reduction or time of use bill management, but currently customers do not benefit from the RTO/ISO and Utility services that residential storage can provide. In general, regulations have been slow to develop to put BTM storage on an equal playing field with electricity generators for all parties. For example, utilities in many states are not required to consider BTM storage as an alternative to normal infrastructure upgrades (Fitzgerald et al., 2015).

Self-Consumption

According to Castillo-Cagigal and colleagues (2011b), self-consumption is the most distributed form of energy generation. This is because it is consumed at the point of generation and reduces transport losses and grid energy demand. The two approaches that have been most commonly employed and that show the most potential for increased self-consumption are battery-based energy storage and load shifting, which is part of demand side management (Luthander et al., 2014). Research has shown that the combination of small-scale storage and load shifting can significantly increase self-consumption in residential homes (Castillo-Cagigal et al., 2011a). In a review done by Luthander and colleagues (2014), the researchers concluded that it is possible to increase the original rate of self-consumption by 13-24% through adding a battery system sized 0.5-1kWh per kW of PV, or separately with load shifting by 2-15% in contrast with the original self-consumption rates. With these baseline success numbers in mind, this section will discuss a few specific studies that have been done regarding battery storage and load shifting for increased PV self-consumption.

Self-Consumption with Battery Storage

Battery-based storage increases self-consumption because the excess PV generation can be stored in the batteries and used later, when PV production drops off (Merei et al., 2016). Batteries also provide added functionality such as customer energy savings during times of high utility rate schedules, backup power, and grid support (Braun, Budenbender, Mangor, & Jossen, 2009).

Braun and colleagues (2009) used lithium ion batteries paired with PV in their Sol-Ion system to study self-consumption. They were also studying the effects of the German Renewable Energy Sources Act that provided a new tariff for self-consumption. The system was modeled using 5kW of PV and various lithium-ion battery capacities in 2.3kWh increments. They concluded that with five of the 2.3kWh blocks, self-consumption of PV production could be increased by 82% for their specific load profile compared to the same system without batteries, while providing additional functionalities to the system, aiding in the return on investment.

There is a trend in the available research between the ratio of the size of battery to PV and the increase in self-consumption. As depicted in Figure 4, with a battery capacity of 0.5-1kWh per kW of PV, the increase in self-consumption has been shown to be 13-24% (Luthander, et. al, 2014).

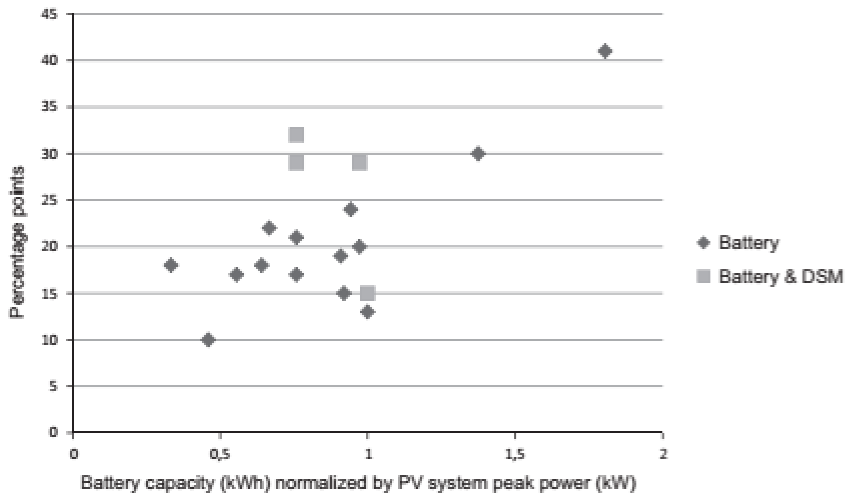

Figure 4. Battery capacity vs. self-sonsumption (Luthander et. al., 2014, p. 90).

A study by Hoppmann, Volland, Schmidt, and Hoffman (2014) explored this concept of battery to PV ratio further in their simulation of battery and PV sizing using residential load profiles in Germany over nine years (2013-2022) using projected energy prices. They simulated PV systems ranging from 0.4-14kW and storage systems ranging from 0kWh to 20kWh to see which combination would increase savings based on energy prices in Germany. According to the model, for their scenarios using medium retail and wholesale prices, the optimal PV system was 3-7kW with a battery capacity of 4.5-6.5kWh. The optimal size was very sensitive to energy prices.

More research is needed on the optimal ratio of sizes for storage and PV. Optimization is driven heavily by the economics of the initial investment and energy prices. The customer must balance the price of storage with the benefit it provides to the system as prices of technology and energy continue to evolve.

The studies previously mentioned focus on residential sized battery storage. Battery prices will have to come down for implementation of larger batteries on a larger scale. A study by Merei and colleagues (2016) concluded that it is not yet economically feasible to utilize battery storage in commercial applications. They studied PV self-consumption on commercial buildings in Germany with and without storage. They also concluded that for batteries to make economic sense, energy prices would need to be higher.

Self-Consumption with Load Shifting or Load Shifting and Battery Storage

One article that studied the effects of load shifting on self-consumption was by Widen (2014). He simulated load shifting for 200 single family houses in Sweden that had varying sized PV systems and no storage, monitored on a ten-minute time step. He used meteorological data and load data to simulate how the load shifting of washing machines, clothes dryers, and dishwashers influenced residential load profiles and self-consumption. Widen concluded that load shifting could potentially increase self-consumption by 200kWh/year for systems with 3-9kW of PV, which only corresponds to a few percent self-consumption increase (Widen, 2014).

Other research has found that adding both battery storage and load shifting has a higher potential to increase self-consumption compared to only load shifting. A pair of studies by Castillo-Cagigal and colleagues (2011a & 2011b) showed that electricity demand side management (EDSM) and active demand side management (ADSM), can increase self-consumption and decrease grid peak demands.

The first of these studies used EDSM in a solar house using a system consisting of 7.2kW of PV, 72 kWh of lead acid battery storage, and a gateway for EDSM that allowed a user to program times of use for eight loads. These loads could be moved to times of day that match energy production, therefore increasing self-consumption. Experiments were done using four different PV profiles and EDSM for three deferrable loads including a washing machine, dishwasher, and dryer for both weekday and weekend use. They found a weekday reduction of energy consumption from the grid of 1.2-2.2kWh per day, because typical residential peaks are in the evening. This caused both energy savings and peak demand reductions (Castillo-Cagigal et al., 2011a). Figure 5 shows a visual representation of the EDSM.

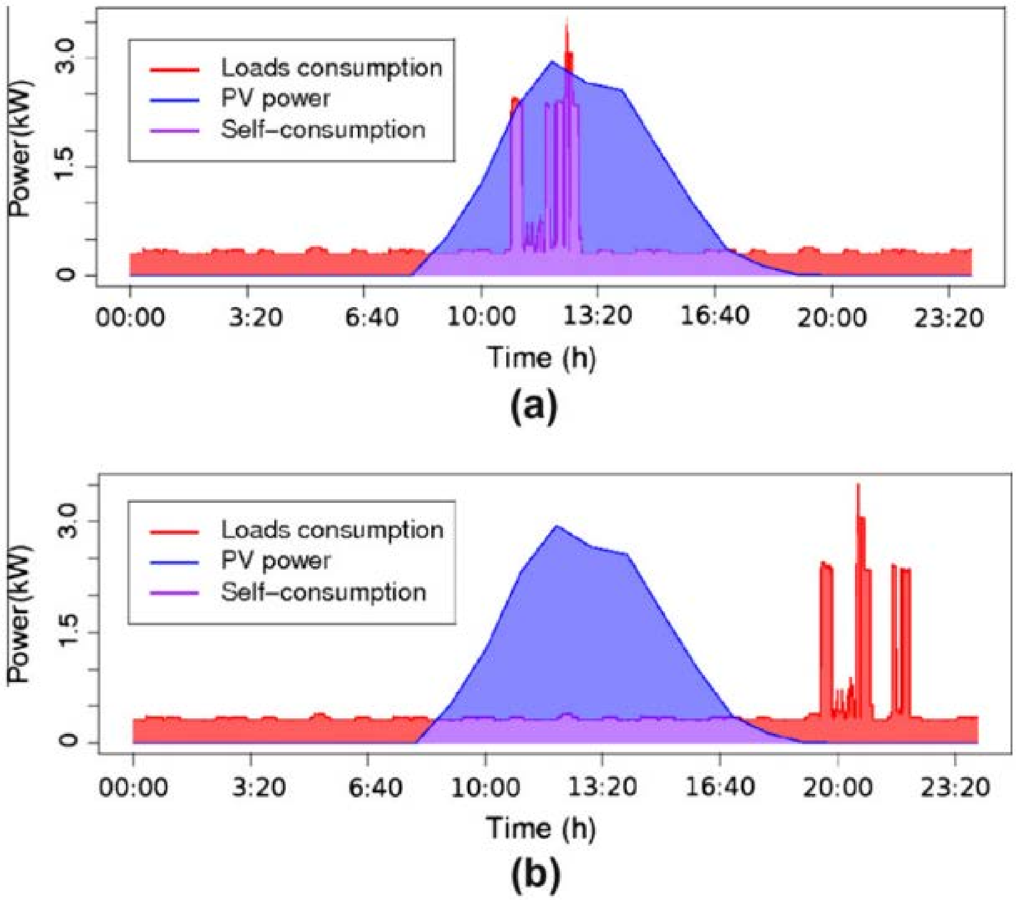

Figure 5. Load shifting vs. no load shifting profiles (Castillo-Cagigal et al., 2011a, p. 2664).

The second study used an updated version of the same system discussed in the previous article, now called the "Magic Box." Rather than EDSM, this system used ADSM, which is essentially EDSM with the addition of automatic controls of the magic box loads and smart meters that can log more complex energy flows. The magic box also differed from the previous article in that it had 5.55kW of PV and 36kWh of lead acid battery storage. The system had weather forecasting data from the State Meteorological Agency that the ADSM used in order to maximize self-consumption. The goal of this article was to look specifically at ADSM and storage capacity to maximize self-consumption. They conducted both simulated and real experiments to see the effects on self-consumption by modifying the battery capacity using both 0kWh and 5.4kWh capacity, and activating or deactivating the ADSM for one day and one week. With no battery storage and ADSM increased self-consumption by 26% over the course of a week. With 5.4kWh of battery storage and ADSM, self-consumption was increased by 76% over the course of a week. They also found that ADSM increases the self-consumption factor in systems with low storage capacity, but does not for systems with a high capacity of storage (5.4kWh). "The same effects produced by a system without ADSM can be obtained with ADSM reducing at the same time the batteries size" (Castillo-Cagigal et al., 2011b, p. 2347). ADSM can enable a smaller battery capacity by achieving the same results as a system without ADSM and a larger battery capacity. In general, the combination of small-scale storage and ADSM will increase self-consumption, and therefore increase the value of PV for the owner (Castillo-Cagigal et al., 2011b).

Previous Self-Consumption Research at Appalachian State

This thesis follows the thesis work of another Appalachian State University student, Pedro Franco (2016). Using a similar system (changes are described in the methodology section) and a fabricated load profile with a one-hour time step, Franco studied the effects on self-consumption rates of a system with 3.36kW of PV and an 8.6kWh lithium ion battery bank, and shifting of specific peak loads three and five hours earlier.

For load shifting, on days with similar insolation levels, Franco concluded that self-consumption rates increased as the load was shifted to times earlier than peak demand hours. For days with similar insolation levels around 6.26-6.46, self-consumption levels were 43.4% without load management, 47.9% with the 3-hours earlier load management condition, and

53.3% with the 5-hours earlier load management condition. This signifies an increase of self-consumption due to load management of 11-23%. In comparing the load profile in Figures 6 and 7, the load management of 5-hours earlier shifted loads to times where there was more insolation, leading to higher levels of self-consumption.

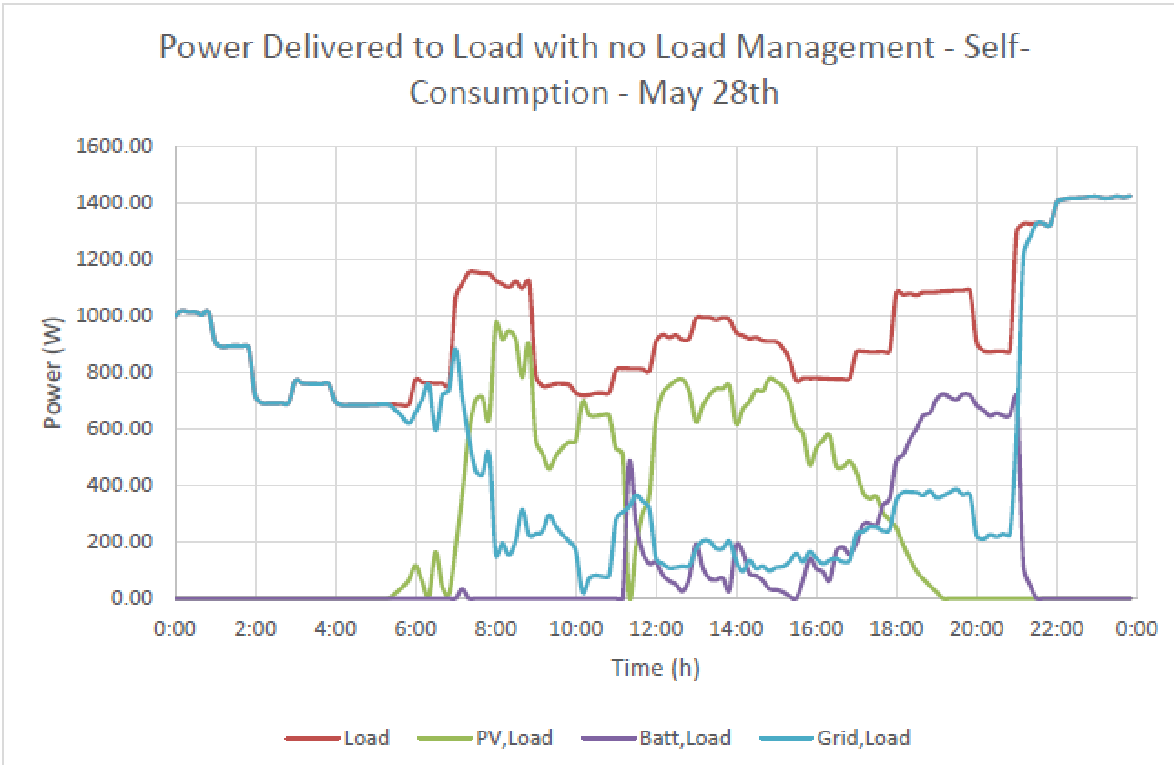

Figure 6. No load management (Franco, 2016, p. 55).

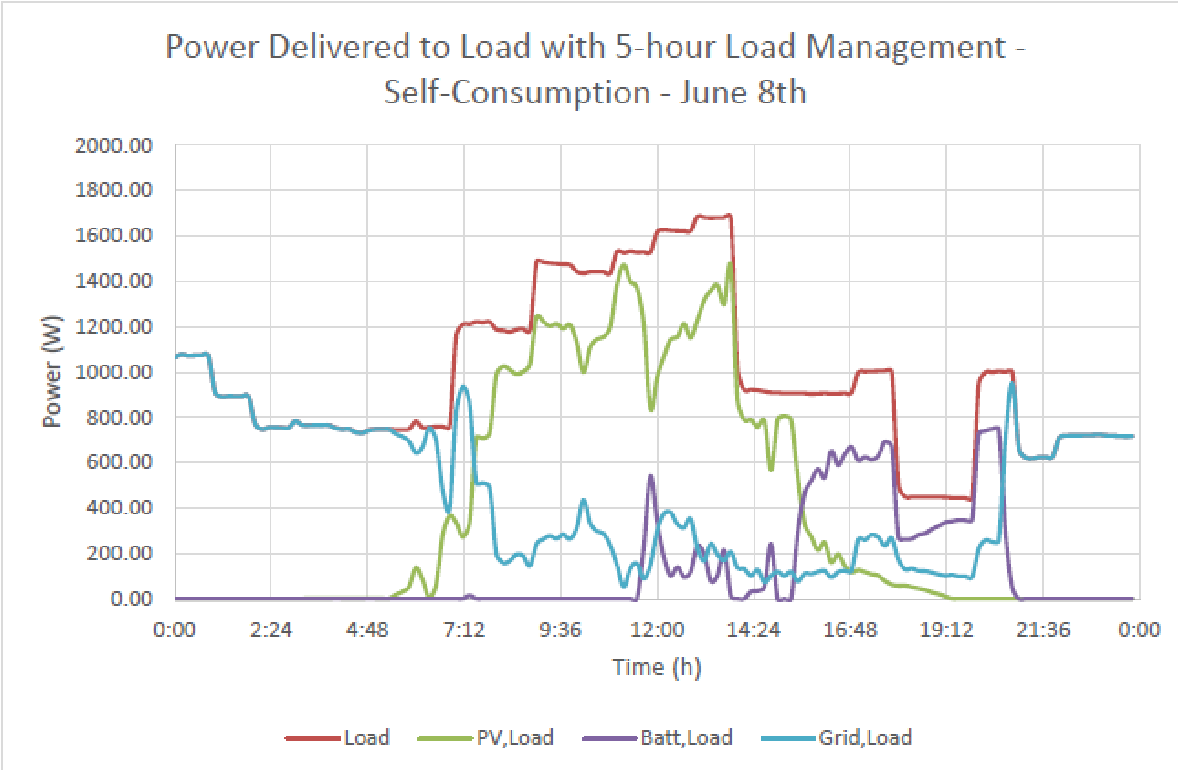

Figure 7. 5-hour load management (Franco, 2016, p. 55).

Franco also concluded that load management of 5-hours earlier decreased grid exports up to 68% from the condition with no load management, because more energy from the sun was used to supply loads during the day.

As for adding battery storage to the system, Franco concluded that although battery storage can increase self-consumption to a point compared to a system with no storage, as sun hours continue to increase the system reaches a point of saturation and begins to export more energy to the grid. This leads to a decrease in levels of self-consumption as seen in figure 8.

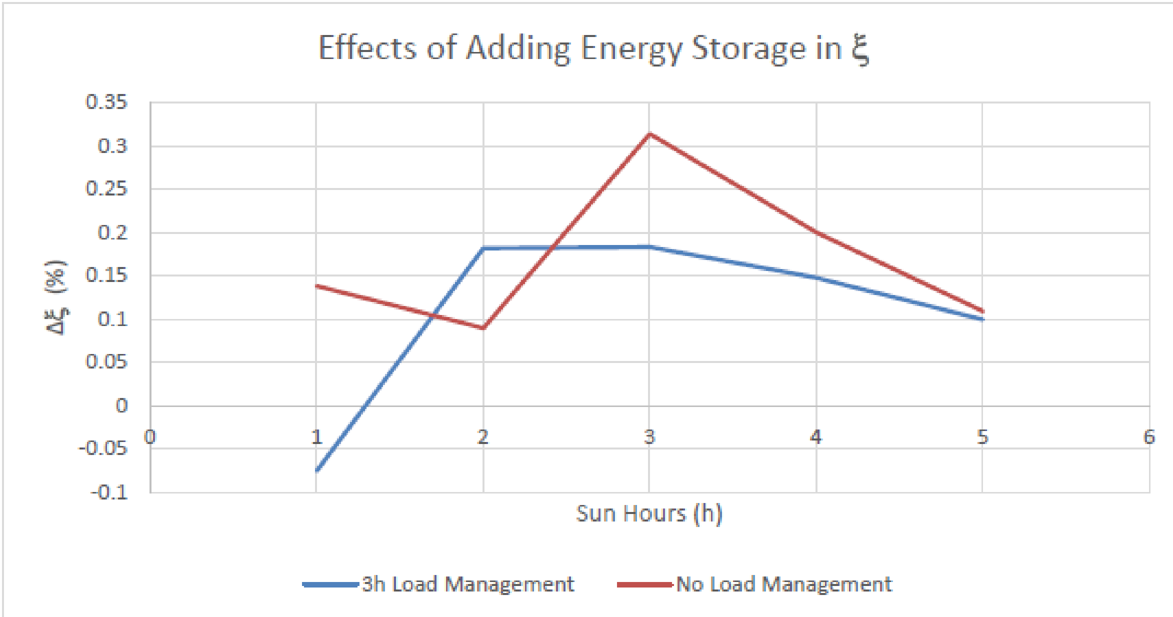

Figure 8. Effects of storage on self-consumption (Franco, 2016, p. 64).

Franco highlighted the importance of irradiance (instantaneous power from the sun) and insolation (total sun-hours for the day) in measuring self-consumption, because two days could have the same insolation, but very different irradiance profiles that affect loads and self-consumption levels differently. My thesis continues Franco's research with an updated system, 5-minute time step, and expanded load shifting experimentation.

Additional Research

Although research on the topic of self-consumption has increased over the past few years, it is limited. Most research articles are from Europe, although Asia is now the world's largest PV market. (Luthander et al., 2014). Luthander et al. (2014) also concluded that the field of self-consumption needs to be further researched. Topics of further research include grid impacts of self-consumption, self-consumption as a way to increase distribution grid hosting capacity, behavioral responses to PV self-consumption, and comparative studies for both battery-based storage and load shifting.

CHAPTER 3: METHODOLOGY

Background

This was an experimental research design using data collected from a battery-based PV system to study self-consumption under a variety of load profiles, including combinations of PV without batteries, PV with batteries, and PV with batteries and load shifting. The baseline load profile was from a residential load in Boone, North Carolina normalized to a United States Department of Energy (DOE) residential load profile from Asheville, North Carolina (Open Energy Information [OpenEI], 2013). Aspects that made this research unique from previous studies covered in the review of literature were the 5-minute time step, use of lithium-ion batteries, and collection of non-simulated data from real loads on a real self-consumption system.

Predecessor Thesis

Pedro Franco (2016) laid the foundation for this thesis with his previously mentioned work. A few changes were made to the system based on Franco's suggestions for future research to add to the body of knowledge he began.

In Franco's system (2016), the Midnite Solar Classic 200 charge controller was used. This worked to protect the battery system, but it could not communicate with the inverter and battery bank. For this reason, when the battery bank was full, PV output was curtailed because the charge controller sensed the battery at 100% state of charge (SOC). This was necessary to protect the battery bank from overvoltage in the event of no loads or grid. Another consequence of the inability of the charge controller to communicate to the inverter was that all power flows had to be monitored using a Campbell Scientific Data Logger with power, current, and voltage transducers. The Schneider Electric MPPT 80-600 charge controller used in this experiment communicated with the inverter, battery, and Combox. This avoided PV output curtailment and streamlines monitoring, but posed its own set of challenges as detailed in a later section.

Another change from Franco's thesis was the load profile used for this study. Franco had a one-hour time step load profile based on a profile from the DOE (OpenEI, 2013). One suggestion by Franco for further research was a shorter times step. This study used a 5-minute profile time step, which more closely reflects temporal variations in real loads.

Self-Consumption System

AC Coupled vs. DC Coupled

The self-consumption system used for this research project was a direct current (DC) coupled, battery-based, grid tied, PV system. A DC coupled system uses a DC bus to accept PV generated power via a charge controller, and uses an inverter/charger controller to send power to loads and import and export power from the grid. In contrast, an alternating current (AC) coupled system uses an AC bus to accept PV generated power via a PV inverter, and interacts with the battery bank via a battery inverter, that can also send power to a critical loads panel. DC coupled systems usually replace the batteryless inverter with the battery-based inverter-charger for a simpler battery-based backup in the case of a grid failure. AC coupled systems are often used for micro grids or for changing a direct grid tied system into one with battery backup (Sanchez & Mills, 2015). Figures 9 and 10 display system schematics for AC and DC coupled systems.

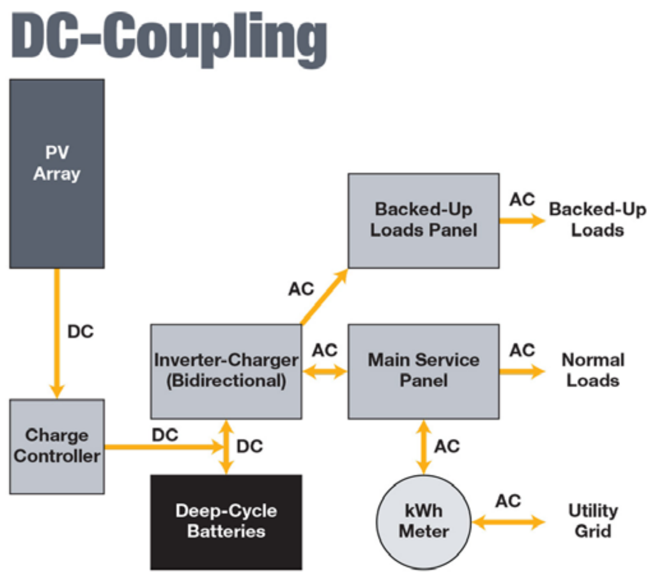

Figure 9. DC-coupling system (Sanchez & Mills, 2015, p. 1).

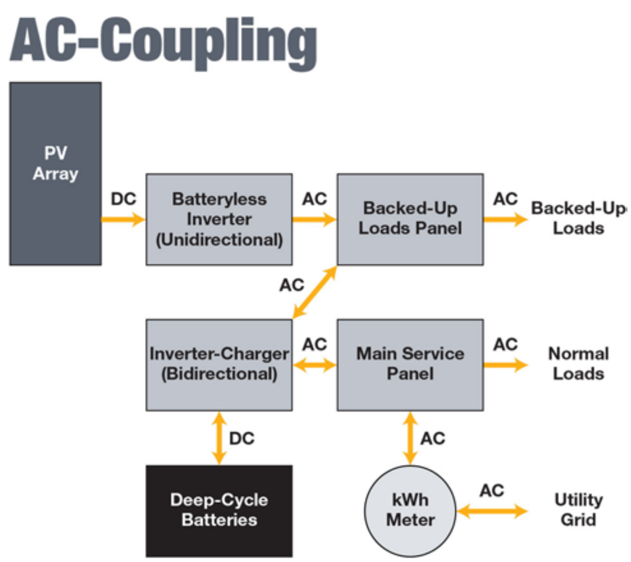

Figure 10. AC Coupling System (Sanchez & Mills, 2015, p. 2).

System Components

The system used in this research consisted of a 3.36 kW PV system made up of twelve 280W Solar World monocrystalline modules, an 8.6 kWh, lithium-ion battery bank by Adara

Power (formerly named Juicebox Solar), a Schneider Electric MPPT 80-600 Charge Controller, and a Schneider Electric Conext 5548 XW+ inverter, all connected through a Midnite Solar E-panel. These components, combined with the utility grid (AC in) and a fabricated load profile (AC out), provide the basis for the experimental system. Communication within the system is over Xanbus, and is controlled by the System Control Panel (SCP) and the Schneider Com-Box. The Com-Box also provides a web interface to assess system performance and set custom data logging parameters. See the basic system schematic in Figure 11, and pictures of the actual system at the Appalachian State University Solar Lab in Figures 12 and 13.

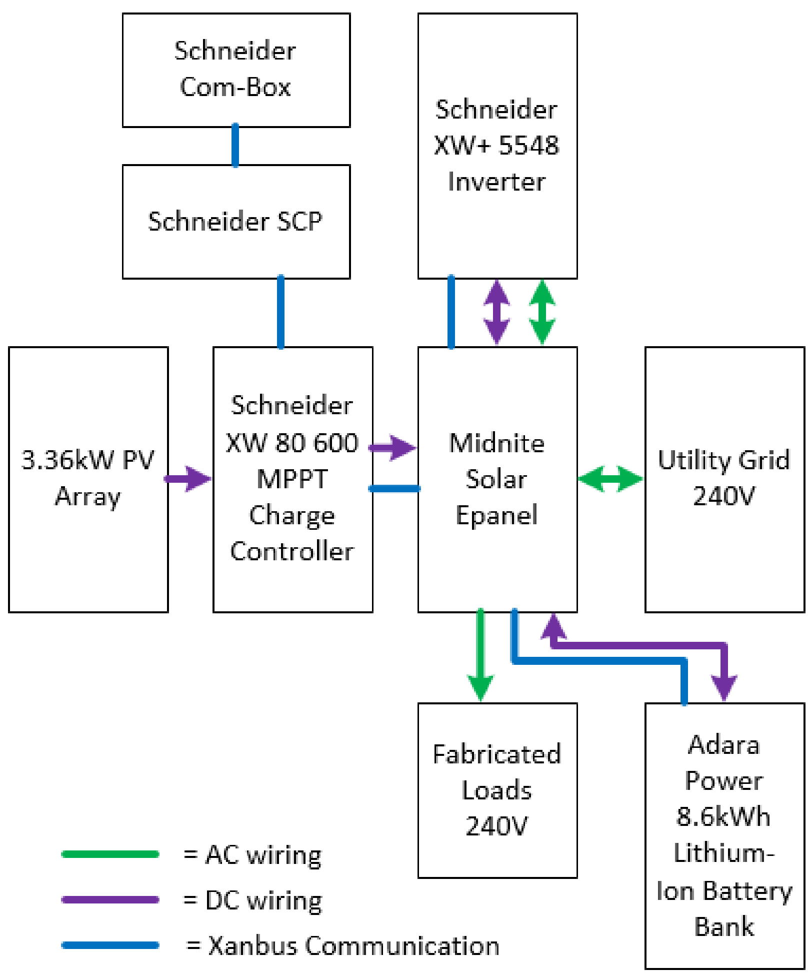

Figure 11. Self-consumption system schematic, Appalachian State Solar Lab.

Figure 12. 3.36 kW PV array, Appalachian State Solar Lab.

Figure 13. Self-Consumption system components, Appalachian State Solar Lab.

The red numbers in figure 13 represent the following devices:

1. Schneider Conext Com-Box

2. Schneider System Control Panel (SCP)

3. Schneider 80 600 MPPT Charge Controller

4. Fabricated Loads Sub-Panel

5. Solid State Relays for Fabricated Loads Controlled by Campbell Scientific CR1000

6. Resistive Loads

7. MidNite Solar E-Panel

8. Schneider XW+ 5548 Hybrid Inverter/Charger

9. Utility Grid Breaker Panel

10. Adara Power 8.6kWh Battery System

Fabricated Load Profile

One of the features of this project that made it unique is the fabricated load profile with a 5-minute time step. The DOE data only provide hourly data (OpenEI, 2013), but by monitoring a residential load in Boone, North Carolina on a one-minute time step, a 5-minute fabricated load profile normalized to the DOE hourly load was achieved. This load profile was fabricated using a multi-stage approach involving residential load monitoring, DOE residential load normalization, and load assignment using a Campbell Scientific controller.

Residential load monitoring.

Loads were logged in a 1200ft^2 house with two occupants in Boone North Carolina. The house uses gas heat. The house had a load profile typical for this area (lower peak in the morning, higher peak in the evening). The residential load monitoring was completed using a Campbell Scientific data logger along with two 100 A current transducers. Current transducers were placed on each of the two 120 V lines in the main service panel of the house.

The data were logged over 23 summer days of normal operation on a one-minute time-step, so there were 1,440 individual data points for each day. The logged data were then exported to an Excel file. Weekday and weekend behaviors in terms of energy use varied significantly. This led to creation of different load profiles for weekends and week days. Since weekdays comprise the majority of energy use throughout the week, weekdays were isolated and weekend days were not used. A pivot table grouped by hour and minute was used to produce a graph of the one-minute weekday averages by hour. The daily electrical energy usage came out to 28.899 kWh. The graph of this load profile is shown in Figure 14.

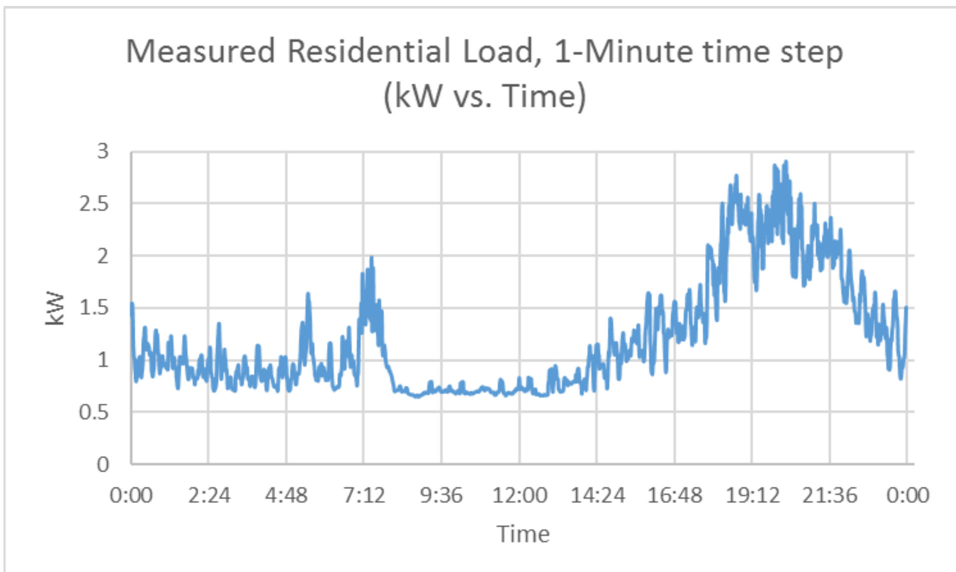

Figure 14. Measured residential load, 1-minute time step.

This load profile makes sense for summertime western North Carolina because of the smaller peak in the morning when the homeowners were getting ready for work, lower loads during the day while the homeowners were at work, and a larger peak in the evening when the homeowners were at home cooking dinner, preparing for the next day, watching TV, or running air conditioners.

Department of Energy residential load.

Hourly data from the DOE (OpenEI, 2013) depicting a typical residential load for Asheville was used to determine the daily energy consumption for a normal house in western North Carolina, the closest available option to Boone. The data represented for an entire year, with a total of 8760 hours. The Excel file included several subcategories of electric loads such as facilities, lighting, and appliances. It also included loads that were provided by gas such as heating and cooking. After isolating the electric-only loads for the entire house, a typical hourly electric load profile for a house in western, North Carolina that uses gas for heating and cooking was found. The total kWh daily electrical energy usage came out to 34.381 kWh. The graph of this hourly DOE load profile is shown in Figure 15.

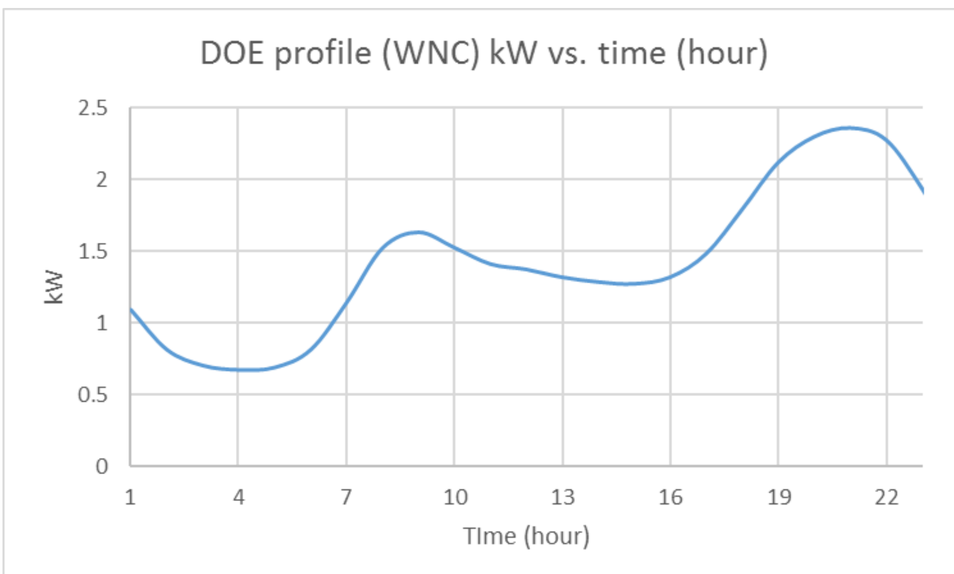

Figure 15. DOE hourly residential load profile for Asheville, North Carolina.

Residential load DOE normalized.

The one-minute Boone profile was normalized to the DOE load profile so the daily energy consumption of the logged data matched the daily total from the DOE load profile.

Normalizing the one-minute monitored load to the DOE loads made the findings of this research more applicable and generalizable to other homeowners, rather than just the house we monitored.

In order to normalize the one-minute load profile to the DOE load profile, a normalization factor was found that was then multiplied by the monitored load. The daily electrical energy usage for the DOE profile was 34.381kWh, whereas the daily electrical energy usage for the monitored one-minute load profile was 28.899 kWh. By dividing the DOE total by the monitored total (34.381kWh/28.899kWh), a normalization factor was found to be 1.189. Each value of the one minute monitored load profile was then multiplied by the normalization factor to arrive at the DOE normalized power for each minute of the monitored load. The DOE normalized monitored load is shown in Figure 16.

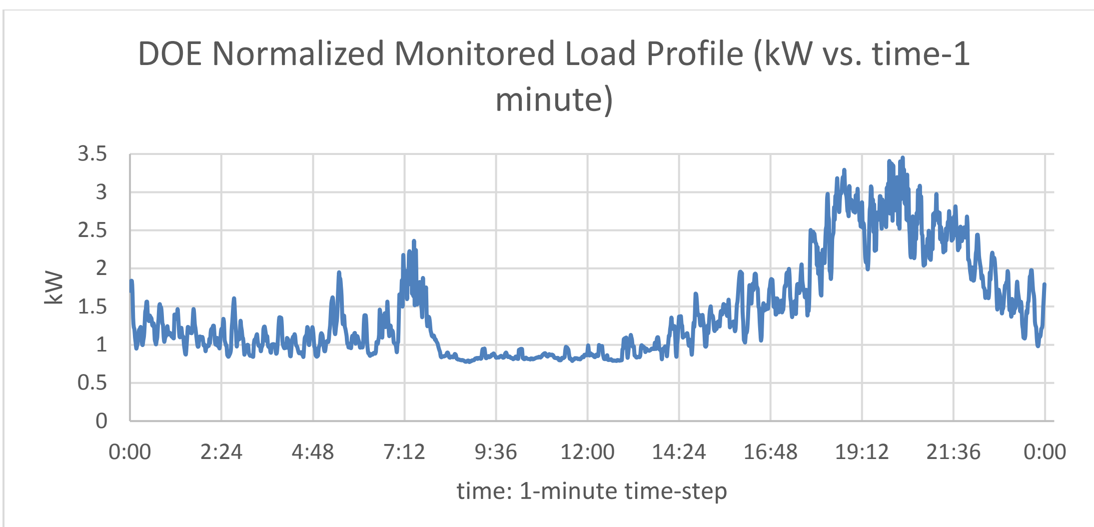

Figure 16. One minute DOE normalized monitored load profile in Boone, North Carolina.

The peak demand of the DOE normalized monitored load approached 3.5kW, as opposed to the monitored load, which approached 3 kW.

5-minute time step.

After analyzing the 1-minute normalized load profile, I determined that the majority of significant load events could be captured on a 5-minute time step rather than a 1-minute time step. This meant that averaging the 1-minute loads over five minutes did not limit the significance of the individual minute loads. The decision to go with a 5-minute time step also made load fabrication and Campbell Scientific programming less time intensive requiring 288 individual time steps rather than 1440 time steps, each containing eight different load values, as described in a later section. After finding the 5-minute averages, the 5-minute normalized load profile was found and is shown in Figure 17.

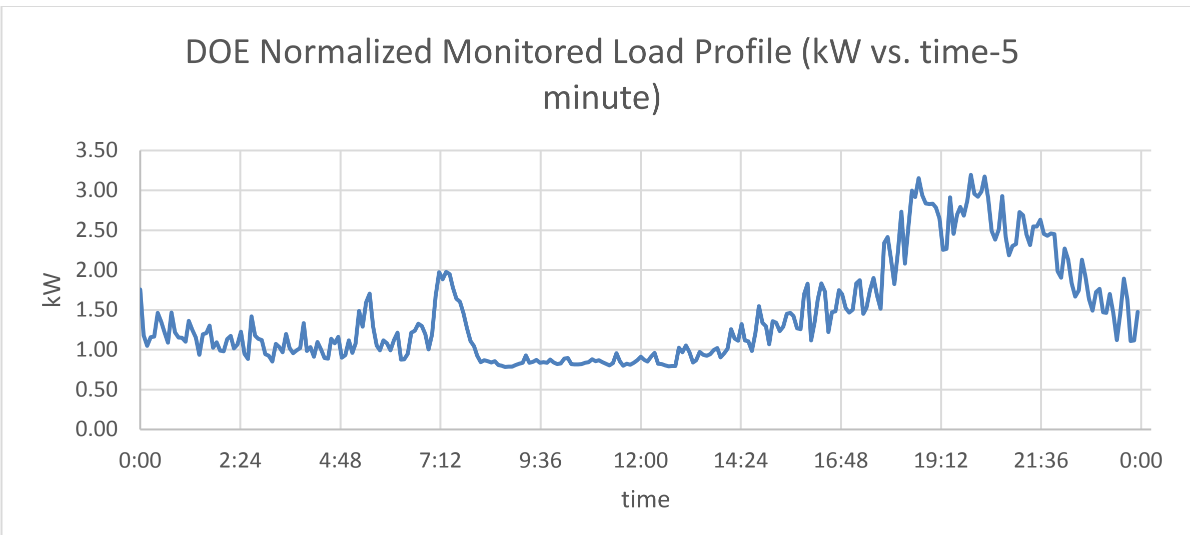

Figure 17. 5 Minute DOE normalized monitored load profile in Boone, North Carolina.

When compared to the 1-minute DOE normalized monitored load profile, it was clear that the 5-minute time step did, in fact, capture the majority of significant electrical load events for the 24-hour period.

Load assignment and optimization.

A Campbell Scientific CR-1000 data logger/controller was used to control eight solid-state relays controlling eight different resistive loads which were added together in a variety of ways to recreate the 5-minute DOE normalized monitored load profile.

To do this, power ratings were empirically chosen for each of the eight loads, and are shown in table 2. Then the combination of those loads was found for each time step that minimized the squared deviation for that time step.

Table 2. *Load Values for Fabricated Load Profile*

Load	Value (kW)
1	0.05
2	0.1
3	0.25
4	0.25
5	0.5
6	0.5
7	1
8	2

After minimizing the squared deviations for the actual DOE normalized load vs. the sum of selected fabricated load values, graphs of the normalized and fabricated profiles were generate, and are shown in Figures 18 (normalized) and 19 (fabricated). A difference of squares less than 0.005 for each time step was achieved.

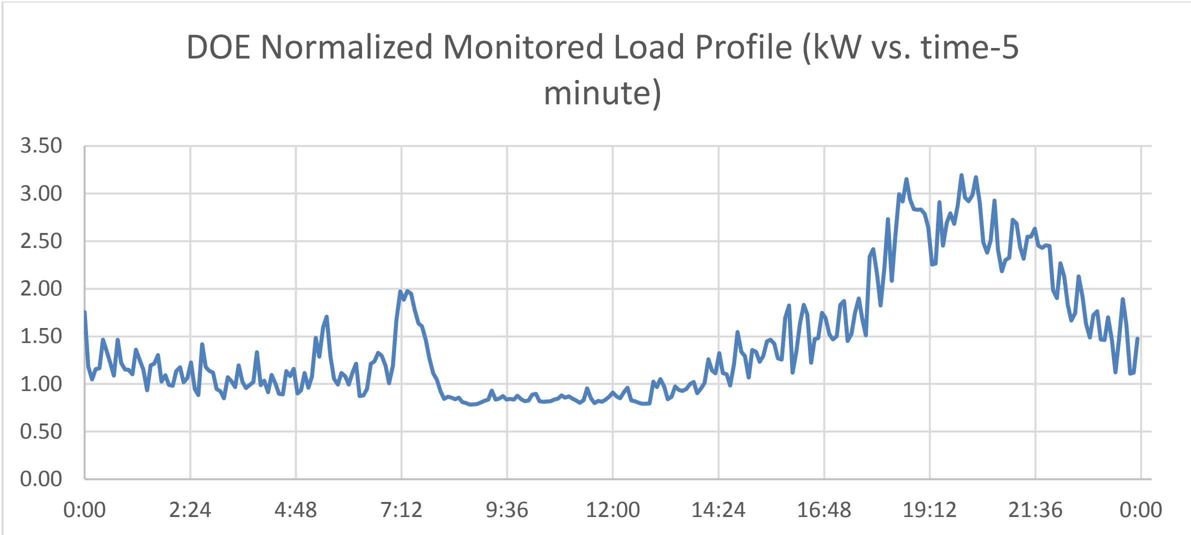

Figure 18. 5-minute DOE normalized monitored load profile.

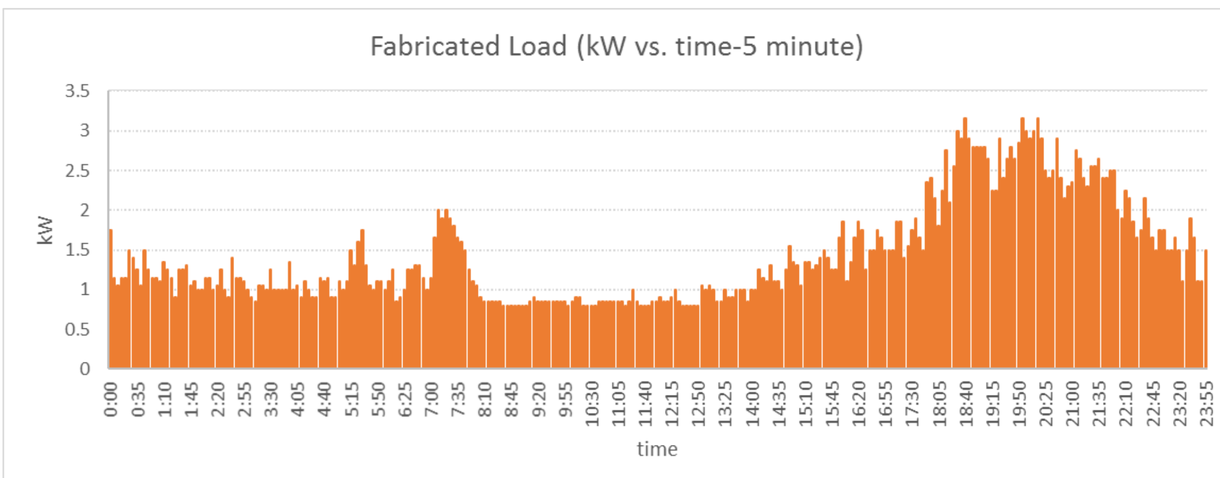

Figure 19. 5-minute fabricated load profile.

A program for the Campbell Scientific CR 1000 was then written to incorporate the eight loads at each of the 288, 5-minute time steps for a 24-hour period. The program turned on and off the eight different loads in varying combinations according to the fabricated load profile (see Appendix B). This load profile served as the baseline self-consumption load profile with no load shifting.

After the load profile was determined, it was necessary to actually create the eight different loads so they could be turned on and off by the CR 1000 using solid state relays. Commonly available resistive loads such as space heaters and incandescent light bulbs were used to closely approximate the target power values.

Table 3 shows the relay states, as controlled by the Campbell CR 1000, for each of the eight loads, for hour one of a 24-hour day. The far right difference of squares column indicates how close the resistive load was to the targeted normalized DOE load profile. Campbell Scientific programs for the experimental load shifting profiles were also created using this method.

Table 3. *Actual Load Values for Fabricated Load Profile*

Time	5 min loads	#	L1	L2	L3	L4	L5	L6	L7	L8	Resistive Load	Target Load (DOE Normalized)	Squared Deviations
0:00	1.76	1.00	0	0	1	0	1	0	1	0	1.754	1.75	0.00000
0:05	1.18	2.00	1	1	0	0	1	1	0	0	1.159	1.15	0.00056
0:10	1.05	3.00	1	0	0	0	0	0	1	0	1.053	1.05	0.00002
0:15	1.16	4.00	1	1	0	0	1	1	0	0	1.159	1.15	0.00000
0:20	1.17	5.00	1	1	0	0	0	0	1	0	1.152	1.15	0.00018
0:25	1.46	6.00	0	0	0	0	0	1	1	0	1.511	1.5	0.00221
0:30	1.35	7.00	1	1	1	0	0	0	1	0	1.404	1.4	0.00274
0:35	1.22	8.00	0	0	0	1	1	1	0	0	1.261	1.25	0.00167
0:40	1.09	9.00	1	0	0	0	0	0	1	0	1.053	1.05	0.00135
0:45	1.47	10.00	0	0	1	1	1	1	0	0	1.513	1.5	0.00223
0:50	1.22	11.00	0	0	1	0	0	0	1	0	1.254	1.25	0.00120
0:55	1.15	12.00	1	1	0	0	1	1	0	0	1.159	1.15	0.00006

Load Profiles

To determine how insolation and load shifting (demand side management) affects self-consumption, it was necessary to collect data from a variety of solar conditions, for a variety of load profiles. A baseline profile was used to determine self-consumption without load shifting, and four different additional load profiles were used to simulate load shifting for specific appliances.

Load Shifting Profiles

Four different load shifting profiles were created to compare the effect of load shifting on self-consumption to the baseline load profile. These profiles were determined by shifting the equivalent of typically deferrable loads from times of peak demand, to times when the solar resource is greatest. For example, the clothes washer was shifted from peak to very early morning and the clothes dryer was shifted to the middle of the day. This would allow the clothes to be moved from the washer to the dryer before the homeowner left for work, rather than both being shifted to the middle of the day when no one would be around to move them to the dryer. The equivalent deferrable loads that were shifted for the load profiles in this project were the dishwasher, clothes washer, clothes dryer, and water heater.

Experimental Load profiles

The load profiles of this thesis consisted of five different load profiles. One baseline or control load profile without load shifting, and four load shifting conditions of deferrable loads from the peak demand. After examining the logged profile normalized to the DOE data, I defined the peak as 6:00pm-10:00pm because this time period had the highest demand.

Baseline condition.

The baseline condition shown in Figure 20 was the 5-minute baseline DOE normalized Boone residential load profile described in a previous section.

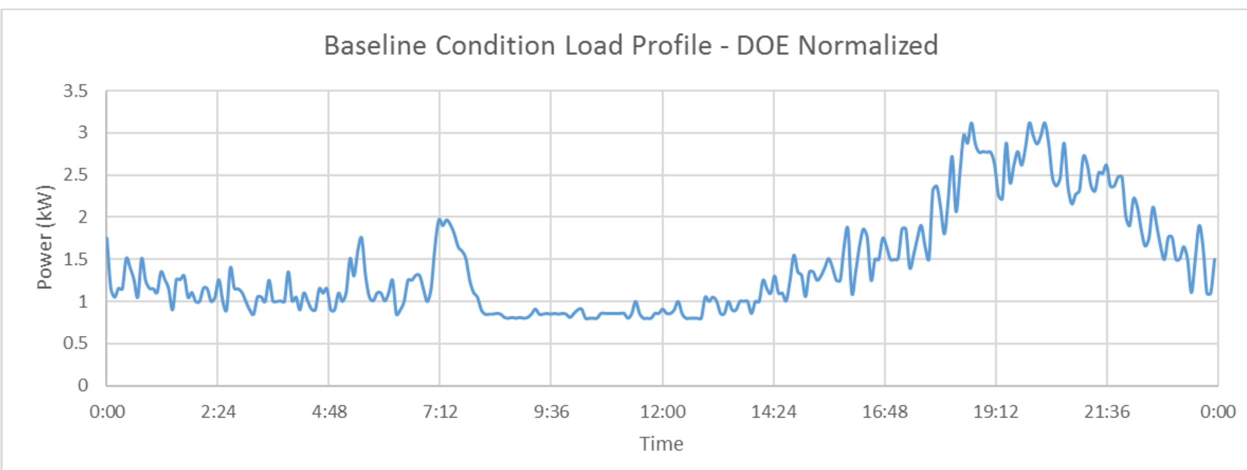

Figure 20. 5-minute fabricated load profile.

Dishwasher load shift.

The first load profile was shifting the 500W dishwasher for 60 minutes from the peak to the middle of the day when the sun was likely to be shining, and PV could potentially satisfy that load to increase self-consumption. Figure 21 shows the load profile and Table 4 indicates a summary the deferrable load, load power, amount of time shifted, original and shifted times, and shifted energy.

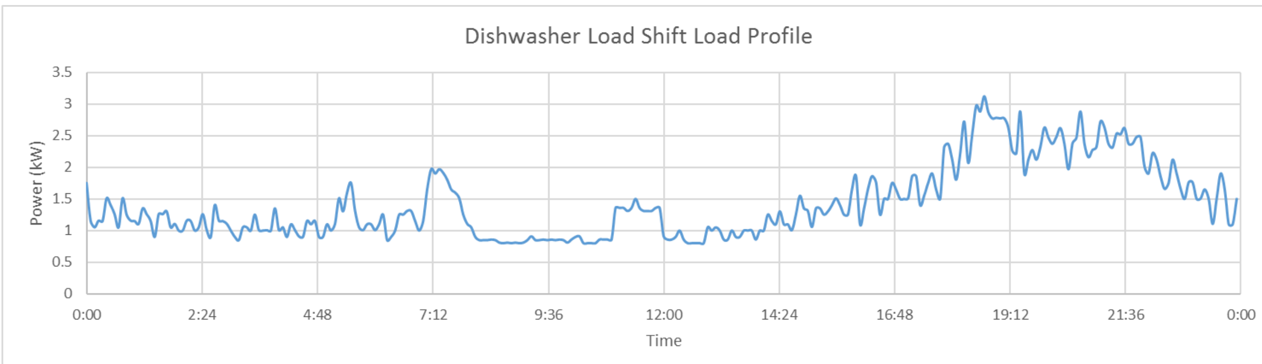

Figure 21. Dishwasher load shift profile.

Table 4. *Dishwasher Load Shift Summary*

Deferrable Load	Power (W)	Load Duration	Original Time	Shifted Time	Energy Shifted
Dishwasher	500	60 minutes	7:30pm-8:30pm	11am-12pm	0.5 kWh

Clothes washer and dryer load shift.

The second load profile shifted the 500W clothes washer from peak to early morning hours, and the 2000W clothes dryer from peak to the middle of the day to simulate a realistic shift of these loads. Figure 22 shows the load profile and Table 5 summarizes the load shift.

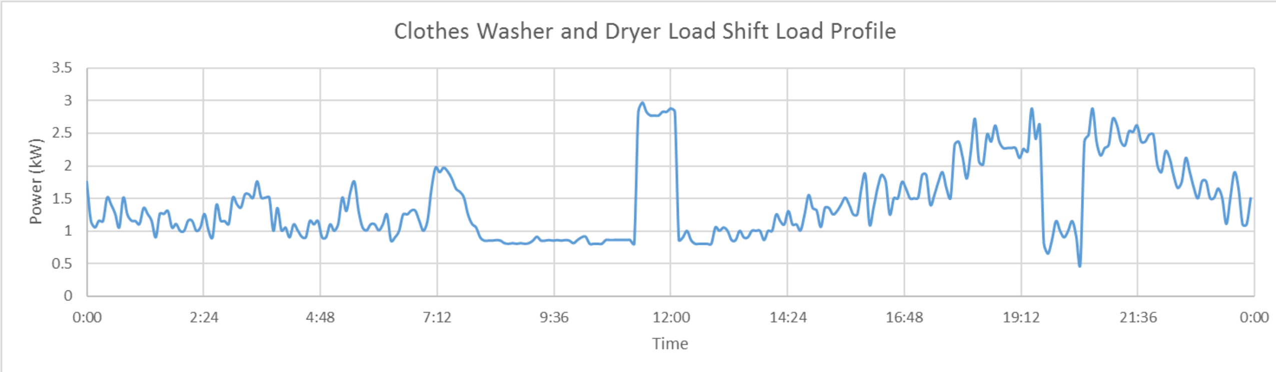

Figure 22. Clothes washer and dryer load shift profile.

Table 5. *Clothes Washer and Dryer Load Shift Summary*

Deferrable Load	Power (W)	Load Duration	Original Time	Shifted Time	Energy Shifted
Clothes Washer	500	50 minutes	6:25pm-7:15pm	3:00am-3:50am	0.417 Wh
Clothes Dryer	2000	50 minutes	7:40pm-8:30pm	11:20am-12:10pm	1.67 kWh

Water heater load shift.

The third load profile shifted a 2250W water heater for two periods of 45 minutes each (1.5 hours total) from peak to earlier in the day. Figure 23 shows the load profile and Table 6 summarizes the load shift.

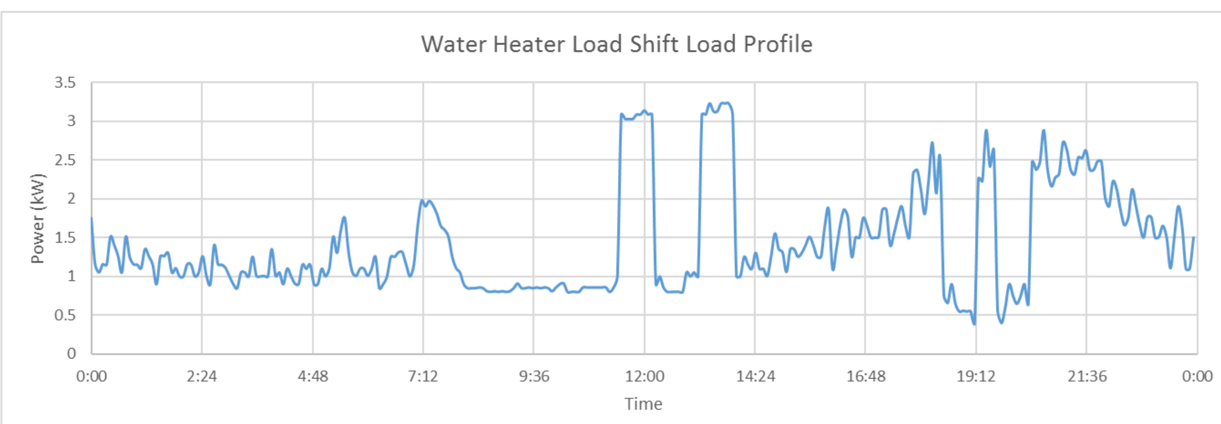

Figure 23. Water heater load shift profile.

Table 6. *Water HeaterLoad Shift Summary*

Deferrable Load	Power (W)	Load Duration	Original Time	Shifted Time	Energy Shifted
Water Heater	2250	45 minutes	6:30pm-7:15pm	11:30am-12:15pm	1.69 kWh
Water Heater	2250	45 minutes	7:40pm-8:25pm	1:15pm-2:00pm	1.69 kWh

All loads shifted.

The fourth load profile combined all of the load shifts for maximum reduction in peak and for potential maximum effects on self-consumption. Figure 24 shows the load profile and Table 7 summarizes the load shift. Shift times had to be changed from individual load shifts for this condition so all the shifts could target the peak.

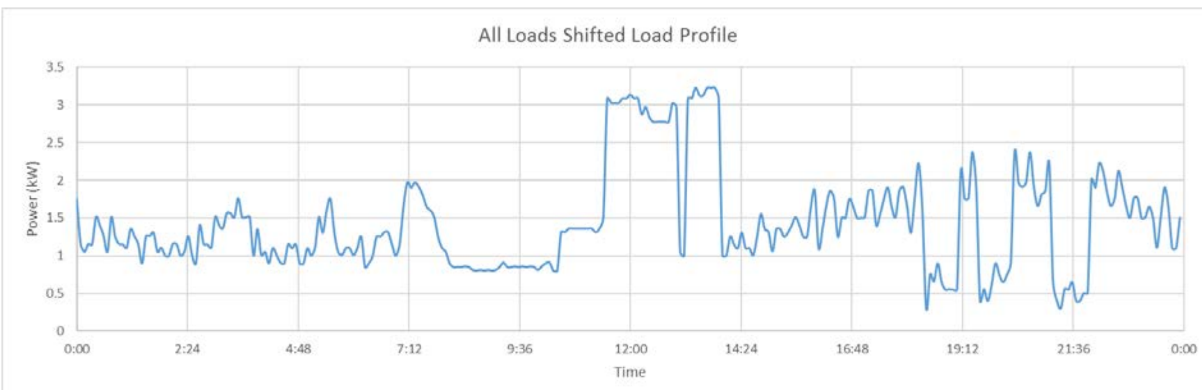

Figure 24. All loads load shift profile.

Table 7. *All Loads Shifted Load Shift Summary*

Deferrable Load	Power (W)	Load Duration	Original Time	Shifted Time	Energy Shifted
Dishwasher	500	60 minutes	5:50-6:25pm and 7:10pm-7:35pm	10:30am-11:30am	0.5 kWh
Clothes Washer	500	50 minutes	8:20pm-9:10pm	3:00am-3:50am	0.417 kWh
Clothes Dryer	2000	50 minutes	9:10pm-10:00pm	12:15pm-1:05pm	1.67 kWh
Water Heater	2250	45 minutes	6:25pm-7:10pm	11:30am-12:15pm	1.69 kWh
Water Heater	2250	45 minutes	7:35pm-8:20pm	1:15pm-2pm	1.69 kWh

The baseline and load shifting load profiles were run for a number of days in attempts to get a variety of insolation values for each condition to see the how insolation affected self-consumption across the conditions.

Instrumentation and Data Logging

The Schneider Combox interface provided a Custom Data Logging option to customize which parameters were logged on a specific time interval, which in this case was every five minutes. A CSV file for the desired time period could easily be downloaded and saved as an Excel file. Through the Com-Box custom data logging interface, it was possible to log over 90 different parameters. Of the parameters available, the ones used for this thesis were as follows:

1. Date/Time
2. System DC Charging Power – power going into the battery
3. System DC Inverting Power – power coming out of the battery
4. System Grid Input Power – power imported from the utility grid
5. System Grid Output Power – power exported to the utility grid
6. System Load Power – power to the fabricated load profile
7. System Total PV Power – power generated by the PV system
8. System Battery Voltage – current voltage of the battery bank

One parameter that needed to be calculated was the minimum between loads and PV. To determine this value, the 'Min' Excel function was used.

$$Min(System\ PV\ Total\ Power * 0.94, System\ Load\ Power) \tag{1}$$

This function took the minimum between the PV power multiplied by 0.94 to account for average inverter efficiency (Schneider Electric, 2015) and the fabricated load for each of the 288 time steps for the day. The result of this function was used in one of the self-consumption equations, explained in Chapter Four.

The only data set needed that was not logged by the ComBox was irradiance, which allowed us to calculate insolation, or sun hours per day. In order to get this information, irradiance data was downloaded from the NASA Aeronet website (National Aeronautics and Space Administration [NASA], 2016), which uses a pyranometer to log irradiance on a 1-minute time step from a building on Appalachian State University's campus located just over a mile from the PV array as the crow flies.

CHAPTER 4: RESULTS

Raw Data

Data were collected over a four month period from November 2016 to March 2017. Table 9 summarizes the collection period and indicates which load profile was collected on each day along with the insolation value for each day. Table 8 provides a key for Table 9.

With the five different load profiles combined, a total of 57 days of usable data were collected. Days that were not utilized either had inconsistent loads, no available insolation data, or the load profile was changed so a full days' worth of data was not available. Inconsistent loads were caused by lightbulbs burning out, or space heaters being out of commission. Due to load availability, the actual load profiles used in this experiment were well quantified and consistent, but slightly smaller than the fabricated loads described in the methodology.

Data Validation: Energy Balance

To ensure the data logged by the custom data logging setup through the Com-Box interface was correct, a check was needed. For this check, the system inputs should be equal to the system outputs, with some adjustment for efficiency losses.

For this balance check, October 26, 2016 data was used. With the system parameter inputs being System Total PV Power and System Grid input power, the total inputs for this day were 37.650 kWh. The raw data graphs are shown in Figures 25 and 26 for System Total PV Power and System Grid Input Power, and the daily energy input totals are in Table 10.

Table 8. *Key for Raw Data Summary*

Key:	
Number Values	Hours of Insolation
	Baseline Profile
	Dishwasher Load Shift
	Clothes Washer & Dryer Load Shift
	Water Hear Load Shift
	All Loads Load Shift
No Color or N/A	Inconsistent loads, load profile change day, or no insolation data

Table 9. *Raw Data Summary*

	November-16	December-16	January-17	February-17	March-17
1	2.8	3.5	1.3	2.1	2.5
2	3.9	N/A	1.0	2.6	5.8
3	3.3	1.5	1.2	1.4	5.4
4	4.1	0.3	1.0	4.5	5.5
5	4.3	1.9	1.0	2.4	5.5
6	4.0	0.6	1.0	4.2	1.4
7	4.1	3.3	2.2	2.6	1.2
8	2.3	N/A	N/A	1.5	5.8
9	2.4	N/A	2.1	N/A	5.9
10	4.0	N/A	2.1	N/A	4.1
11	3.2	N/A	1.4	N/A	5.2
12	3.3	N/A	2.6	N/A	6.2
13	3.7	N/A	0.8	N/A	3.6
14	2.6	1.0	1.5	N/A	1.4
15	3.7	3.1	0.8	2.4	6.3
16	3.4	0.9	2.5	4.8	6.6
17	3.6	1.1	0.8	N/A	2.6
18	3.6	0.2	3.3	2.3	3.9
19	1.1	2.6	3.0	1.8	5.5
20	3.7	3.2	2.4	4.3	5.0
21	3.6	3.1	0.9	2.8	
22	3.1	3.1	1.6	0.7	
23	2.2	2.1	0.9	3.1	
24	1.7	0.7	2.3	4.9	
25	2.7	0.4	3.8	4.1	
26	3.3	0.9	2.1	5.5	
27	3.4	0.4	0.9	N/A	
28	0.7	3.2	4.0	2.4	
29	2.1	2.3	1.0		
30	0.5	2.3	4.1		
31		1.1	3.7		

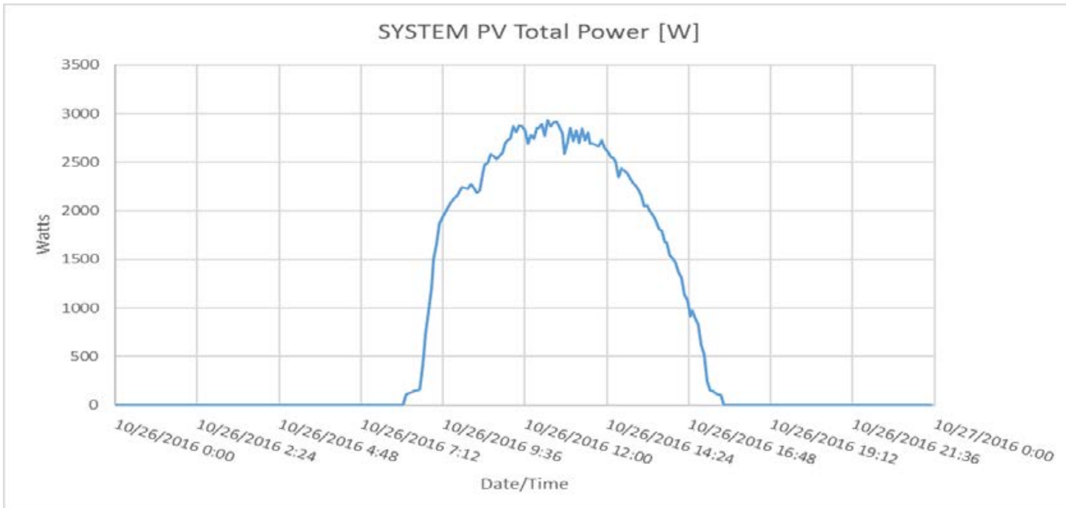

Figure 25. October 26, 2016 system PV total power (W).

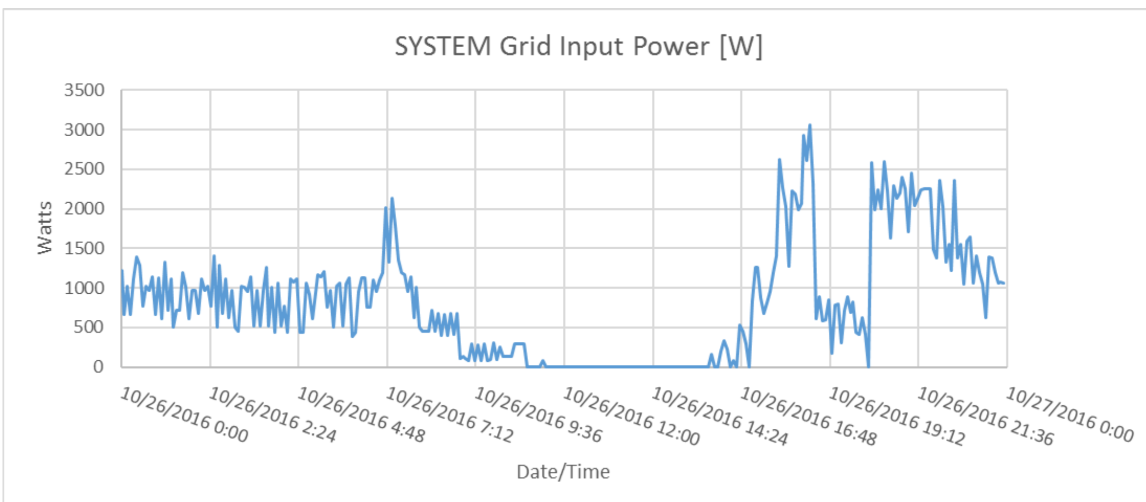

Figure 26. October 26, 2016 system grid input power (W).

Table 10. *October 26, 2016 System Inputs*

System Inputs	Daily Input Sum Value (watt-5 minutes)	Daily inputs in kWh
SYST PV Total Power	222557	18.546
SYST Grid Input Power	229238	19.103
Total	451795	37.650

The system parameter outputs included System Grid Output Power and System Load Power. Battery efficiency of 98% [System DC Charging Power*0.02] (Adara Power, 2016) and average inverter efficiency of 94% [System DC Inverting Power*0.06] (Schneider Electric, 2015), also were accounted for. A parasitic loss, which consisted of powering the inverter, SCP, and Com-Box at an empirically estimated 35 watts resulted in a loss of 0.84 kWh per day. This is shown in the raw data graphs in Figures 27 and 28 for System Grid Output Power and System Load Power, and the daily energy output totals in Table 11.

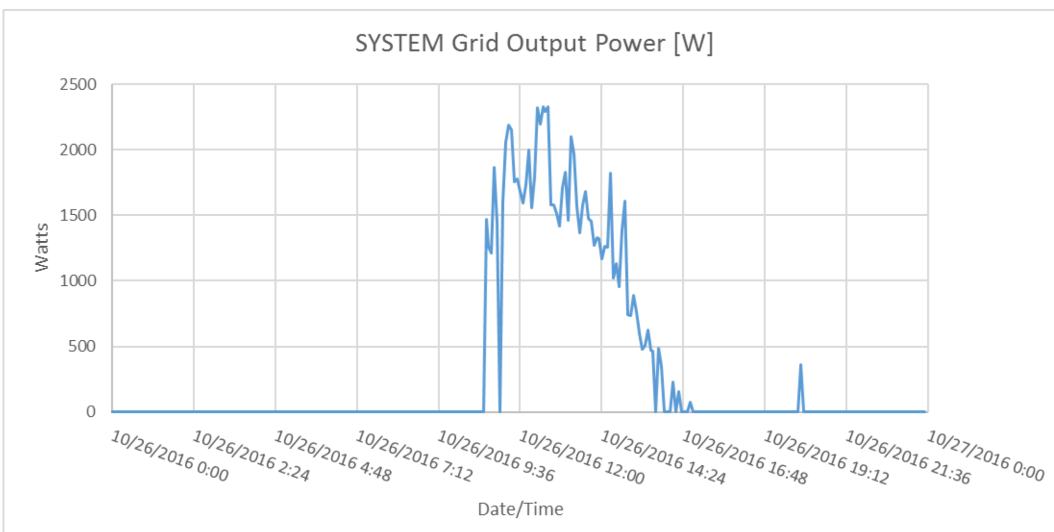

Figure 27. October 26, 2016 system grid output power (W).

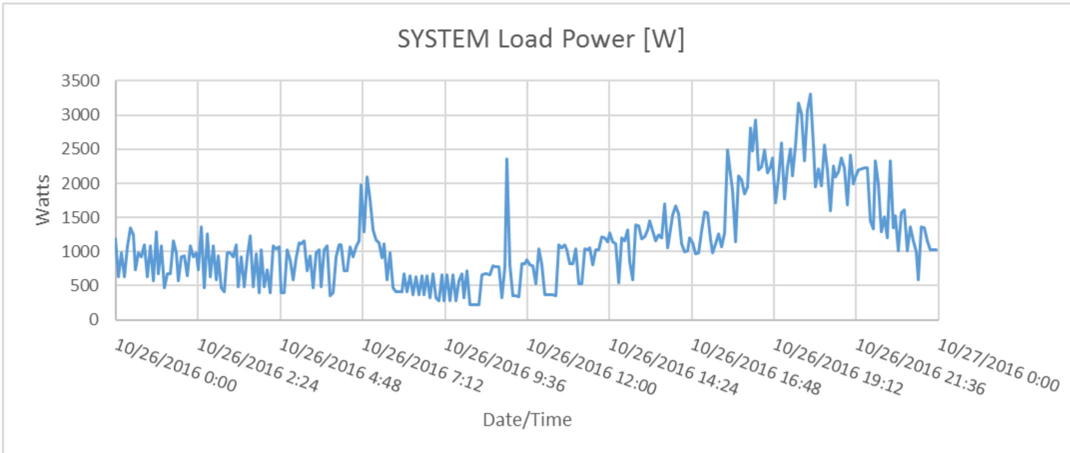

Figure 28. October 26, 2016 system load power (W).

Table 11. *October 26, 2016 System Outputs*

System Outputs	Daily Output Sum Value (watt-5 minutes)	Daily outputs in kWh
SYST Grid Output Power	88365	7.364
SYST Load Power	333615	27.801
Battery Loss	4492.88	0.374
Inverter Loss	14648.4	1.221
Parasitic Loss	10080	0.840
Total	451201.28	37.600

After comparing the inputs with the outputs, the percent difference was calculated between the inputs and outputs using the formula:

$$\frac{(37.650\text{ kWh} - 37.600\text{ kWh})}{\frac{(37.650\text{ kWh} + 37.600\text{ kWh})}{2}} * 100 = 0.133\%\text{ difference} \qquad (2)$$

With a percent difference of less than one percent between the system inputs and outputs, I was confident that this energy balance was correct.

Definitions of Self-Consumption

Self-consumption for this thesis was divided into two categories. The first category quantifies the percentage of the load profile satisfied by local generation. This category had two measures of self-consumption, one of PV only self-consumption, and another of PV+Battery self-consumption. The other category quantified the percentage of the PV generation that was self-consumed by the loads. There was only one measure of self-consumption in this category, as there was only one generator. If this was a hybrid system with a wind turbine, another measure would be added.

Using the parameters described in the methodology, three self-consumption factors were calculated to determine the measures of self-consumption for the load profiles.

PV Only Self-Consumption

The PV Only self-consumption factor indicates the percentage of the fabricated load that would have been satisfied by using PV Only, without battery storage. The equation for this factor, represented by ξ, was inspired by research from by Castillo-Cagigal and colleagues (2011b):

$$\xi = \frac{\text{Energy to loads from PV}}{\text{Energy consumed by loads}} \tag{3}$$

For this thesis, a PV Only self-consumption factor was calculated, with slight alterations to the equation used by Castillo-Cagigal. Using the smaller value of either the PV multiplied by the inverter efficiency or the load power (as described previously using the 'Min' Excel function) ensured that the value of loads the PV was meeting at that moment was used. Without this, if the PV was greater than the loads for a given moment, self-consumption levels would appear higher than they actually were because power would be exported. Dividing the minimum parameter by the system load power and multiplying it by 100 gave the percentage of the system load power that was accounted for directly by the PV. The equation used for the percentage of the load profile that self-consumed PV Only in this thesis was as follows:

$$\text{PV Only} = \frac{\text{Min(System PV Power}*0.94\text{,System Load Power)}}{\text{System Load Power}} x100\% \tag{4}$$

It should be noted that PV self-consumption was a modeled quantity based on measured PV output. It assumed that all available PV power went to satisfying loads (up to 100%). PV Only data was not separately collected.

PV+Battery Self-Consumption

The PV+Battery self-consumption factor indicated the percentage of the fabricated load that was satisfied using both PV directly and via battery storage. This factor accounted for the power going to the loads, but did not include power from the grid. It was essentially power from PV utilizing batteries, divided by the fabricated loads.

$$\text{PV} + \text{Battery} = \frac{\text{(System Load Power} - \text{System Grid Input Power)}}{\text{System Load Power}} x100\% \tag{5}$$

Generation Self-Consumption

The Generation self-consumption factor indicated the percentage of the PV generation that was consumed locally by the fabricated load or used to charge the battery. In other words, it told what fraction of the PV generation was going to the loads rather than being exported to the grid, taking into account inverter efficiency.

$$\text{Generation} = 1 - \frac{\text{System Grid Output Power}}{\text{System DC Inverting Power}*0.94} x100\% \tag{6}$$

This factor was important because of its ability to show how much of the generation was self-consumed locally by the loads, rather than how much of the loads were met through self-consumption. This factor could be important in future studies that compare varying sizes of battery banks or PV systems, and the economics of each. Without this factor, the PV system or battery could be oversized to produce high load self-consumption levels with no practical regard to economics, or how much of the energy generated by the system was being exported to the grid.

Self-Consumption Preliminary Results

In this section, raw data of self-consumption levels are shown in graphical form to show preliminary trends. All analysis is daily and each day represents one data point for each self-consumption factor. The trends and levels will be further discussed in the next chapter.

Insolation Bins

In research, it is important to control all variables besides the one being studied. The scientific method requires this so researchers may be able to confidently conclude that their results were indeed caused by the independent variable they are manipulating. Research that takes place outside, however, makes it impossible to control all the variables. In this thesis the variable being manipulated was the load profile, detailed in the load profiles section of the methodology chapter. Since the PV system was outdoors, the main variable that could not be controlled was insolation, or sun hours. One day could be very sunny (5+ sun hours) or very cloudy (under 1 sun hour), which would be expected to have significant influence on self-consumption levels regardless of load profile. This posed a challenge for data analysis because uncontrolled variables were in play. For this reason, the data in this thesis were grouped into insolation bins to better aggregate self-consumption factors under similar conditions. In Table 12, the counts of the number of days of data for each insolation bin for each load profile are detailed. Self-consumption factor values were found for each day of data, and then averaged for each load profile and for each insolation bin to show preliminary trends. A total of 57 days of data were collected, and the numbers in the colored cells are the numbers of days of data per insolation bin, per load profile. Each cell will henceforth be referred to as an "experimental condition." For example, the baseline profile at insolation bin 0-1 represents one experimental condition.

Table 12. *Count of Load Profile Data for Each Insolation Bin*

Count of Days at Each Load Profile for each Insolation Bin					
Insolation Bins (sun hours)	Baselin e	Dishwashe r	Washer/Drye r	Water Heater	All Loads Shifted
0-1	3		1	3	3
1-2	2	1	1	4	1
2-3	4	2	2	2	2
3-4	2		2	2	2
4-5	1	1	4		1
5-6			3	4	1
6-7			1		2
Totals:	**12**	**4**	**14**	**15**	**12**
Total Count:	**57**				

Self-Consumption Factors Under Varying Load Profiles

The preliminary graphs later in this section show similar trends in self-consumption levels for each load profile. Note the general trend of self-consumption percentage decreasing for the Generation self-consumption factor as insolation increased, and of PV Only and PV+Battery self-consumption percentages increasing as insolation levels increased. It should also be noted that the PV Only self-consumption levels were consistently higher than the PV+Battery self-consumption levels. These trends will be further discussed in the next chapter. For Figures 29-33, each load profile shows each self-consumption factor averaged by insolation bin.

Baseline load profile.

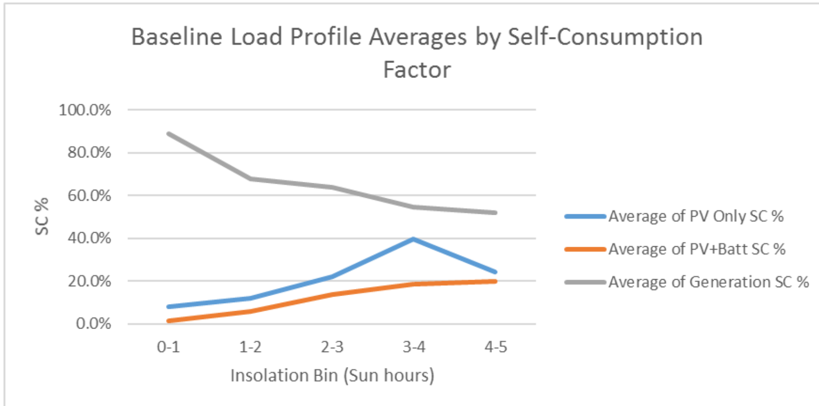

Figure 29. Baseline load profile self-consumption averages.

Dishwasher load shift.

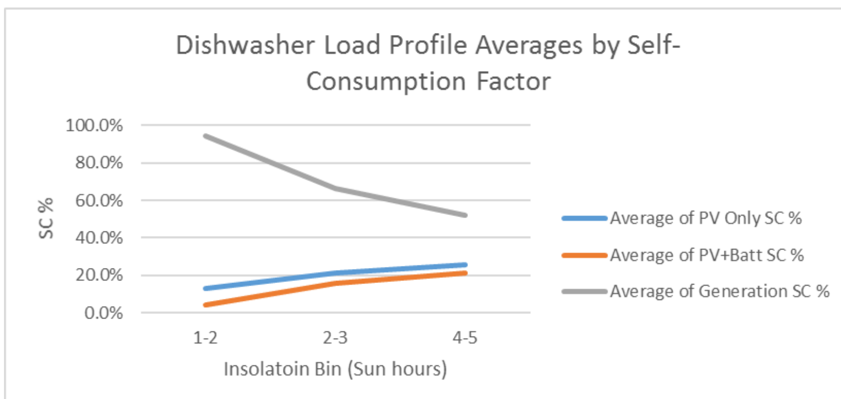

Figure 30. Dishwasher load profile condition self-consumption averages.

Clothes washer and dryer load shift.

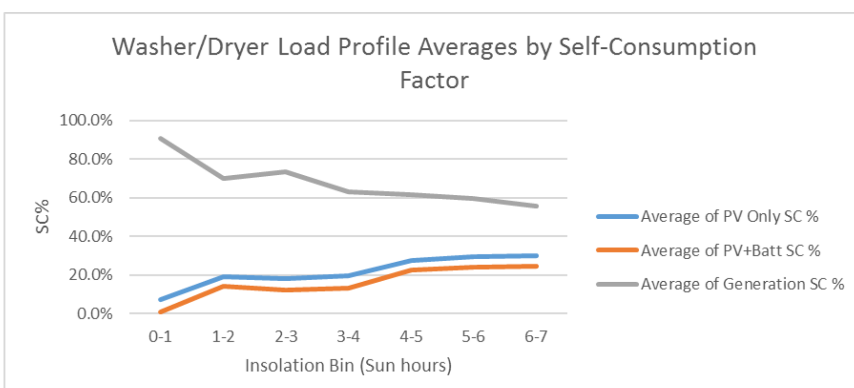

Figure 31. Washer/dryer load profile self-consumption averages.

Water heater load shift.

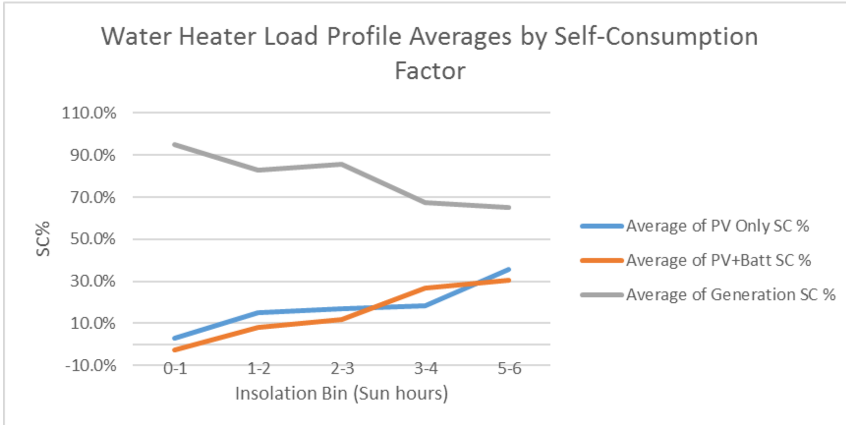

Figure 32. Water heater load profile self-consumption averages.

All loads shifted.

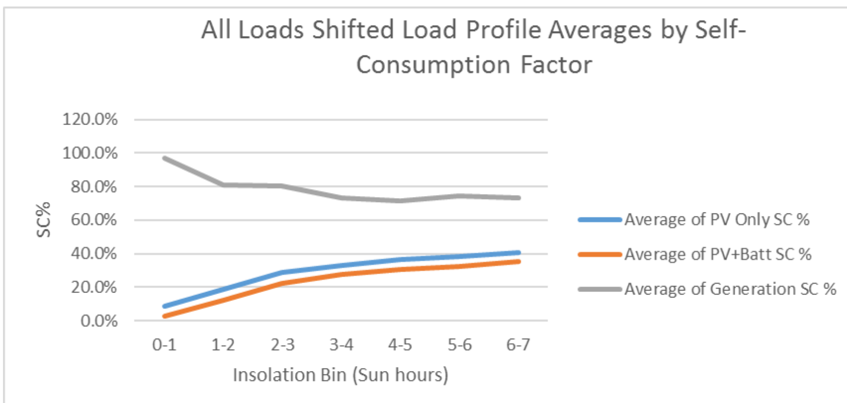

Figure 33. All loads shifted load profile self-consumption averages.

Effects of Load Shifting on Self-Consumption Factors

Load shifting seemed to generally increases self-consumption levels. As seen in Figures 34, 35, and 36, the All Loads Shifted load profile consistently had the highest percentages of self-consumption for the PV Only and PV+Battery self-consumption factors. For most of the load profiles the Generation self-consumption factors were close to 100% with low insolation. This makes sense because low insolation means limited PV production, so more of it will be consumed by the loads rather than exported to the grid. As insolation increased, the All Loads

Shifted load profile decreased the least, suggesting that load shifting drives down exports to the grid, and thereby increases self-consumption. These graphs will also be discussed and analyzed further in the next chapter.

PV Only self-consumption factor.

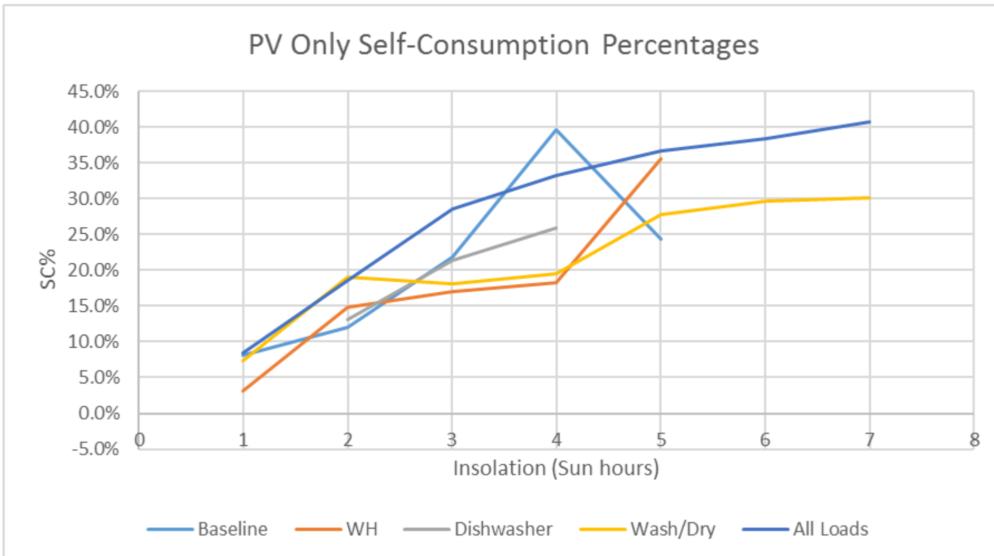

Figure 34. PV Only self-consumption percentages by load profile.

PV+Battery self-consumption factor.

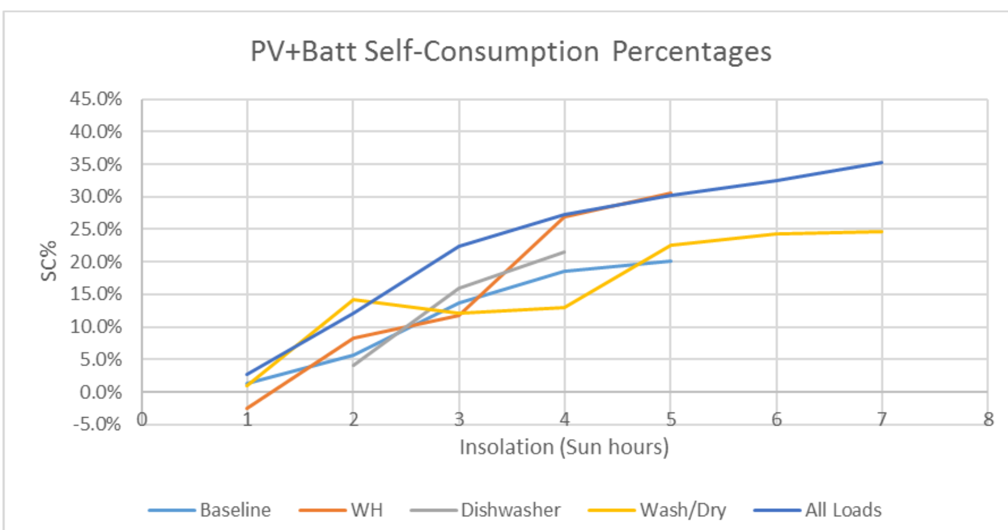

Figure 35. PV+Battery self-consumption percentages by load profile.

Generation self-consumption factor.

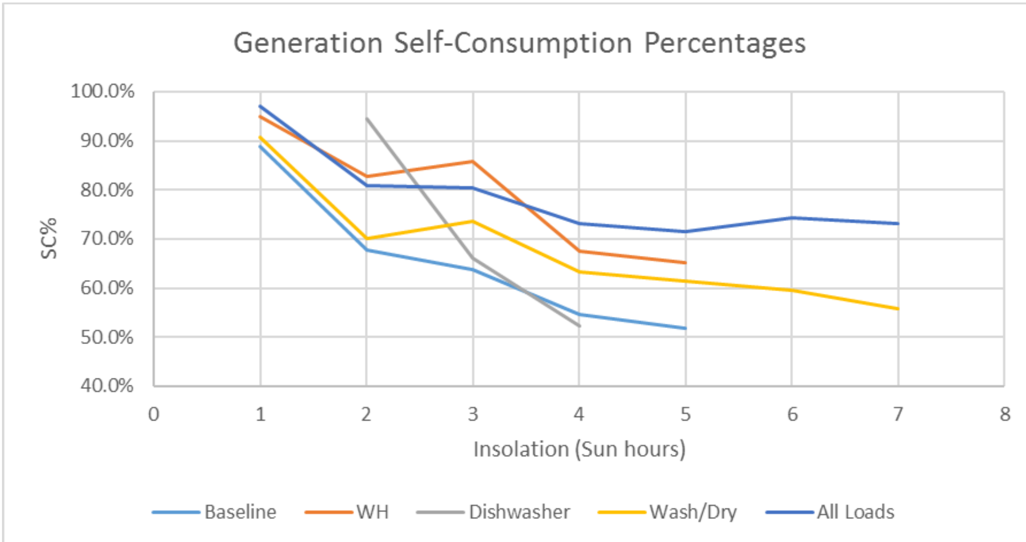

Figure 36. Generation self-consumption percentages by load profile.

CHAPTER 5: ANALYSIS AND CONCLUSIONS

Uncertainty and Data Spread

For each load profile, between four and 15 days of consistent data were collected. Even with a maximum of 15 days, that is hardly an acceptable number for a statistical analysis. Through using the entire data set of 57 days and the method of binning described in Chapter Four, a probability distribution of the deviations from the mean of the data points from the experimental conditions shown in Table 12 was made. The deviations for each experimental condition are shown in Appendix B.

The data represented by the normal distribution in Figure 37 has a standard deviation of 3% and a mean of zero. This shows the probability distribution of the deviations from the mean for each experimental condition. The histogram represents the data collected, and the line represents the model of a normal distribution. This means that each data point has an uncertainty of 3%.

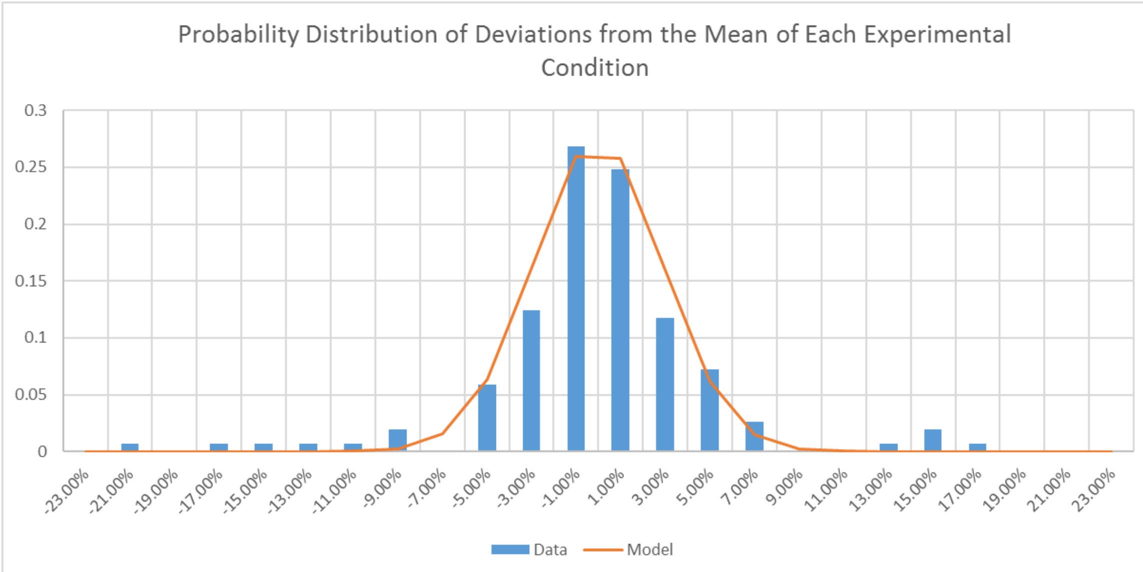

Figure 37. Probability distribution of deviation from the mean for each experimental condition.

Because the distribution of deviations closely follows a normal distribution as seen in figure 37, it is assumed that statistical errors dominate, and the uncertainty in the mean of each experimental condition is given by counting statistics:

$$\text{Error in the mean} \;=\; \text{Standard Deviation}/(\sqrt{N}) \tag{7}$$

In this case with a standard deviation of 3%, the uncertainty in each mean as a function of N is shown in Table 13.

Table 13. *Uncertainty in each mean as a function of the number of days in each experimental condition*

Uncertainty in Each Mean as a Function of Days in Each Experimental Condition	
N=1	3.0%
N=2	2.1%
N=3	1.7%
N=4	1.5%
N=5	1.3%
N=6	1.2%

Since most experimental conditions had four or fewer days, an average uncertainty of 2% was assigned to the mean self-consumption factor for each experimental condition, as shown in Figures 38-42.

Previous Day Influence

A reasonable question concerning this data would be whether or not the previous day influenced self-consumption levels for the day in question. It appeared that a high level of insolation the day before increased self-consumption levels for the following day, or that low levels of insolation the day before decreased self-consumption levels for the following day. This result could have been caused by a higher or initial lower battery state of charge for the day. If the battery state of charge was higher at the beginning of the day, it could be argued that it has more opportunity to discharge and therefore to increase self-consumption whereas it would not be able to discharge as much when starting the day with a lower state of charge.

To investigate this question, the battery voltage at the beginning of the day (midnight) was analyzed to see if the previous day did indeed influence the following day. If the battery voltage at midnight was lower when the previous day had low insolation levels, then it could be concluded that the previous day did influence self-consumption levels for the following day. If the battery voltage at midnight was the same or similar regardless of the previous day's insolation levels, it can be concluded that each day functioned as an independent unit, not influenced by the previous days state of charge.

Data from February 3-5, 2017 was analyzed to see the influence of the previous day on the following day (Table 14). If the previous day influenced the following day, the 12:00am battery voltage for February 4th would be lower than the 12:00am battery voltage for February 5th because the previous day's insolation levels were much different. Since the voltages were the same, the battery state of charge was the same at the beginning of each day. For this reason, I concluded that the previous day did not influence the following day, and therefore that each day can be analyzed as an independent unit.

Table 14. *Standard Deviation and Uncertainty by Self-Consumption Factor*

Date	Previous Day's Insolation	12am Battery Voltage
3-Feb-17	2.6	56.1
4-Feb-17	1.4	56.1
5-Feb-17	4.5	56.1

Self-Consumption Trends

Self-Consumption by Load Profile

In Chapter Four, trends in self-consumption levels for each load profile were presented. To recap, the five load profiles for this thesis included the following:

1. Baseline Load Profile(no load shifting)
2. Dishwasher Shifted Load Profile
3. Clothes Washer and Dryer Shifted Load Profile
4. Water Heater Shifted Load Profile
5. All Loads Shifted Load Profile

For the load profiles, the PV Only and PV+Battery self-consumption levels showed a strong relationship as illustrated previously in Figures 29-33. Upon further investigation of this relationship, it was interesting to find that data from one day in each of the Baseline and Water Heater load profiles weakened the relationship. For the Baseline load profile, the outlier of the PV Only self-consumption percentage on January 25, 2017 seemed to weaken the relationship. For the water heater condition, the outlier of the PV Only self-consumption percentage on

December 1, 2016 seemed to weaken the relationship (Tables 15 and 16). The reason for these outliers was investigated, but no logical explanation was determined.

Table 15. *Water Heater Self-Consumption Outlier*

Load Profile	Date	Sun Hrs	PV Only SC %	PV+Batt SC %
Water Heater	4-Dec-16	0.3	3.2%	-2.9%
Water Heater	30-Nov-16	0.5	2.1%	-2.8%
Water Heater	6-Dec-16	0.6	4.1%	-1.9%
Water Heater	7-Mar-17	1.2	10.4%	2.6%
Water Heater	6-Mar-17	1.4	14.7%	6.8%
Water Heater	3-Dec-16	1.5	14.5%	8.2%
Water Heater	5-Dec-16	1.9	19.9%	15.4%
Water Heater	28-Feb-17	2.4	18.5%	11.6%
Water Heater	1-Mar-17	2.5	15.5%	11.9%
Water Heater	7-Dec-16	3.3	31.3%	26.8%
Water Heater	1-Dec-16	3.5	5.4%	27.1%
Water Heater	3-Mar-17	5.4	34.6%	29.7%
Water Heater	5-Mar-17	5.5	35.6%	30.3%
Water Heater	4-Mar-17	5.5	35.8%	30.4%
Water Heater	2-Mar-17	5.8	36.1%	31.5%

Table 1. *Baseline Self-Consumption Outlier*

Load Profile	Date	Sun Hrs	PV Only SC %	PV+Batt SC %	Generation SC %
Baseline	21-Jan-17	0.9	7.8%	0.7%	83.0%
Baseline	23-Jan-17	0.9	8.0%	1.0%	95.0%
Baseline	29-Jan-17	1.0	8.5%	2.1%	88.6%
Baseline	3-Feb-17	1.4	14.4%	7.8%	80.9%
Baseline	22-Jan-17	1.6	9.8%	3.6%	54.4%
Baseline	1-Feb-17	2.1	18.2%	11.6%	78.5%
Baseline	24-Jan-17	2.3	29.3%	12.0%	67.3%
Baseline	5-Feb-17	2.4	23.1%	19.1%	54.4%
Baseline	20-Jan-17	2.4	16.8%	11.9%	54.7%
Baseline	31-Jan-17	3.7	22.9%	18.8%	56.2%
Baseline	25-Jan-17	3.8	56.3%	18.3%	52.9%
Baseline	4-Feb-17	4.5	24.3%	20.1%	51.9%

Based on the consistency of the other data points, we determined that the two outlier days should not be included in the analysis. With the removal of these outliers, the relationship became quite strong, as seen in Figures 38 and 39. The consistency is quite good despite the small number of data points.

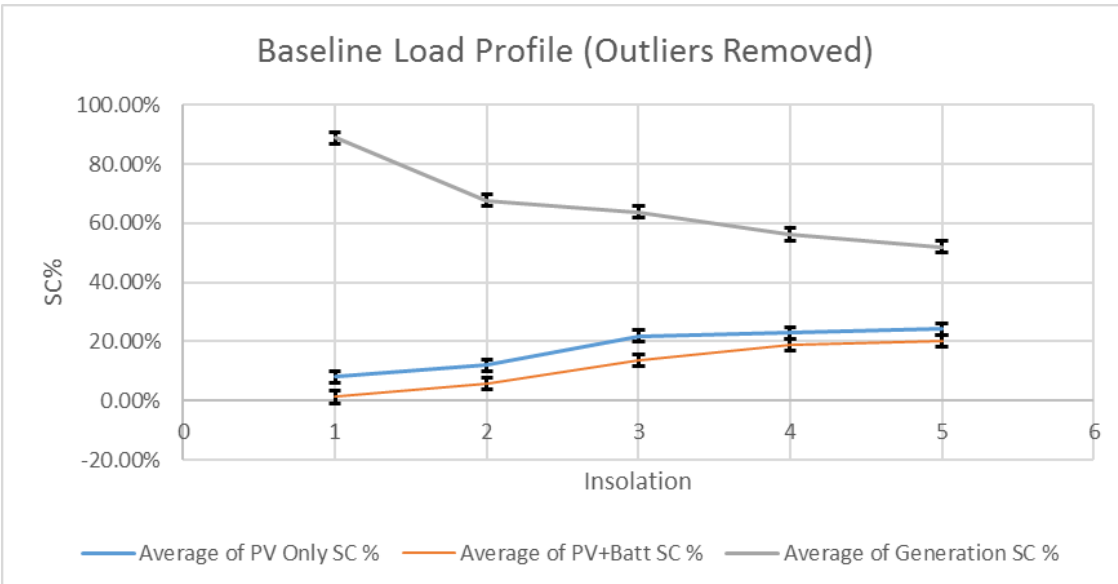

Figure 38. Baseline load profile self-consumption averages by self-consumption factor.

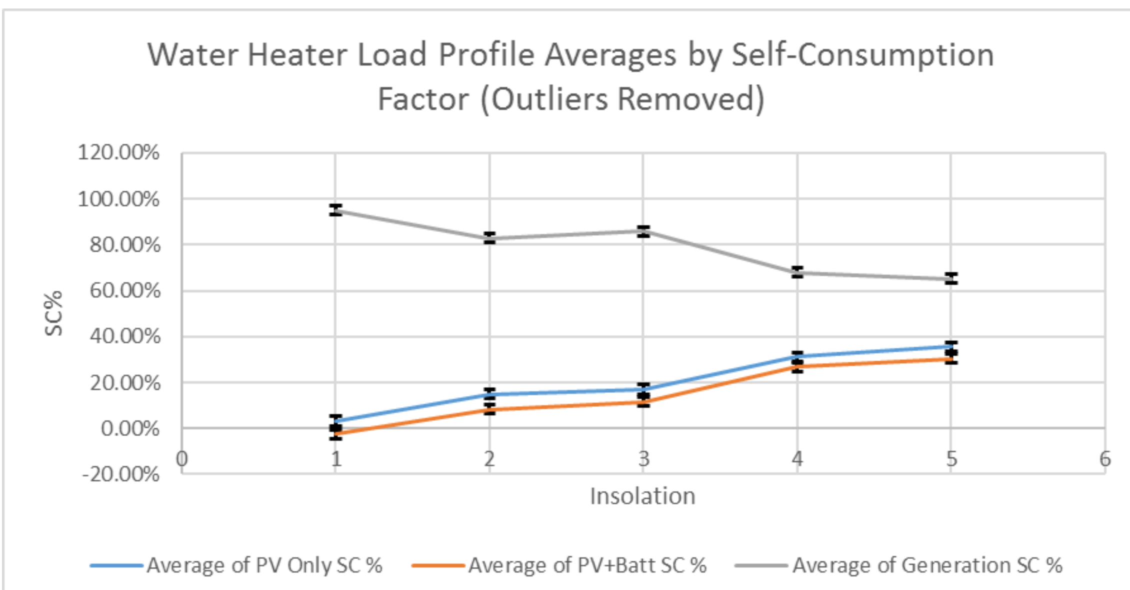

Figure 39. Water heater load profile self-consumption averages by self-consumption factor.

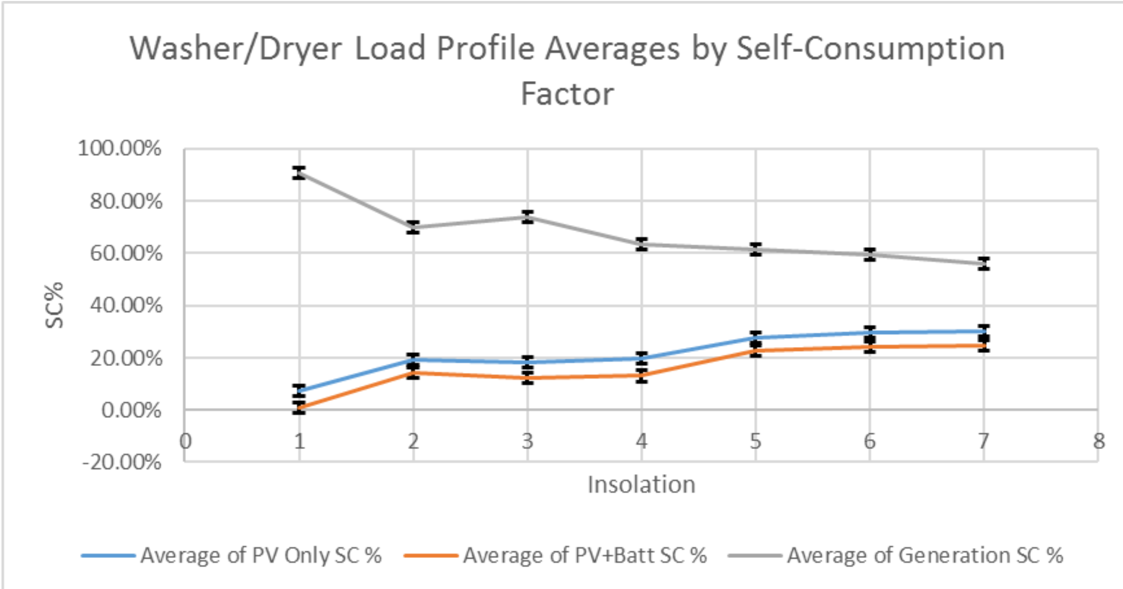

Figure 40. Washer/dryer load profile self-consumption averages by self-consumption factor.

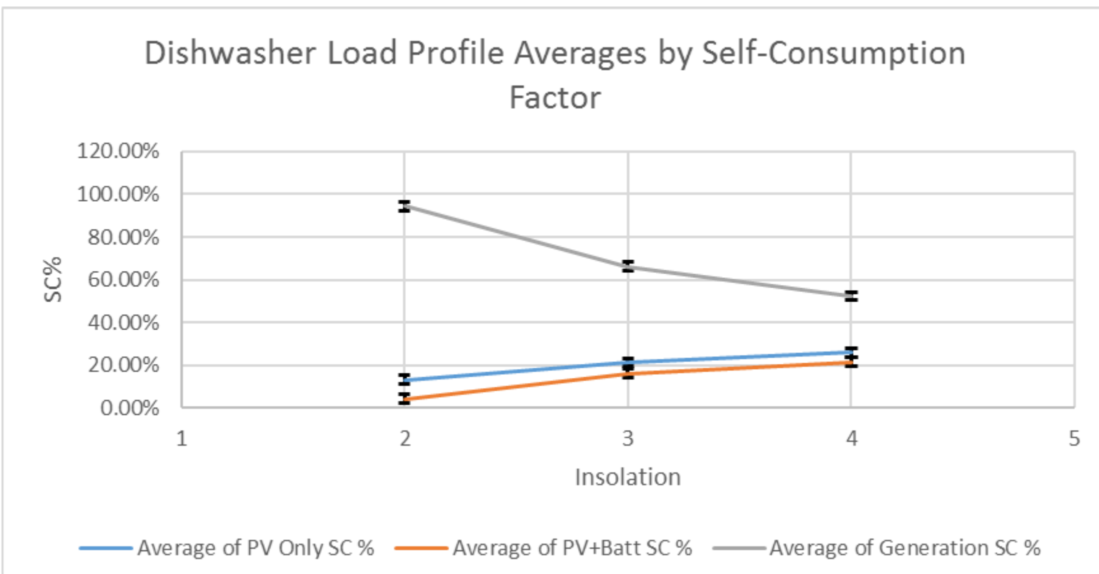

Figure 41. Dishwasher load profile self-consumption averages by self-consumption factor.

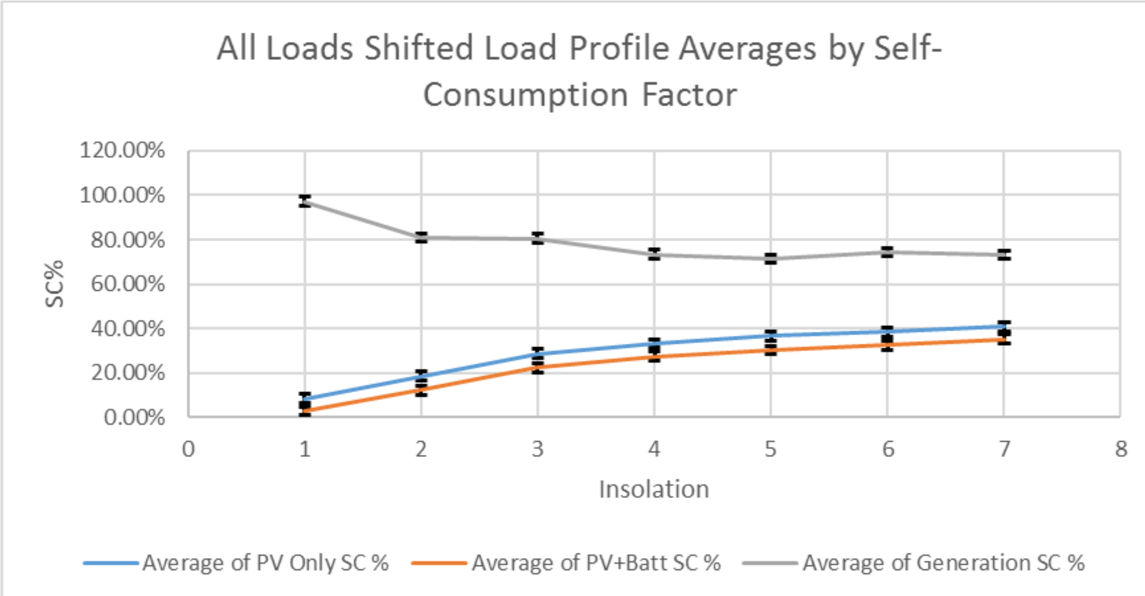

Figure 42. All loads shifted load profile self-consumption averages by self-consumption factor.

As seen in each of the load profiles, there was a consistent upward trend of PV Only and PV+Battery self-consumption rates as insolation increased. This makes sense because as there is more sun available, more of it can go towards meeting the load profile demands for the system. For the Generation self-consumption factor, there was a consistent decreasing trend as insolation increased. This is also logical, because as more sun results in more energy generation, which in turn means that the energy produced is more likely to be greater than the demand and therefore to be exported rather than self-consumed. Considering the low levels of uncertainty in each experimental condition (3% or less), these trends are statistically significant.

Effects of Load Shifting by Self-Consumption Factor

Another way to look at the data is by comparing the load profiles. This essentially reveals the effects of load shifting on self-consumption levels for the system. The graphs in this section were also created with the outliers of December 1, 2016 and January 25, 2017 removed, as mentioned in the previous section. For preliminary data graphs, readers can refer to the Self-Consumption Initial Results section in Chapter Four.

PV Only self-consumption.

For the PV Only self-consumption factor, the overall trend was that self-consumption percentages increased across all conditions as insolation increased, as shown in Figure 45.

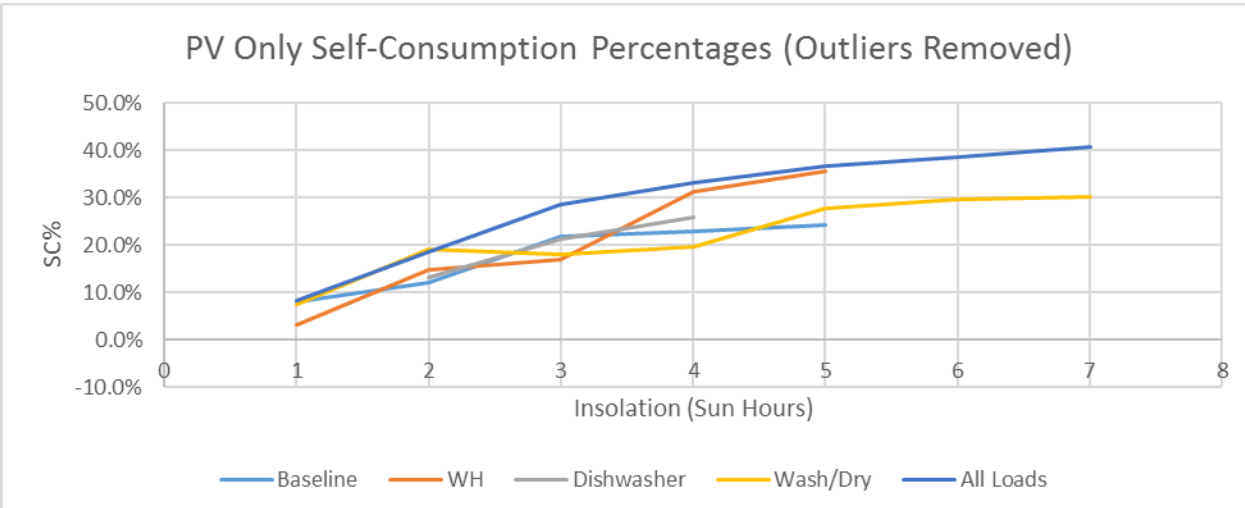

Figure 43. PV Only self-consumption percentages (outliers removed).

The most notable conclusion that can be drawn from this graph is that the All Loads Shifted load profile showed the highest magnitude and largest increases in PV Only self-consumption over the insolation bins. It makes sense that the load profile with the most load shifting resulted in the most increase in self-consumption.

Castillo-Cagigal and colleagues (2011b) found that load shifting through ADSM could increase PV Only self-consumption levels by 26% over the course of a week. Luthander and colleagues (2014) concluded from their review of self-consumption literature that PV Only self-consumption levels could be increased by 2-15% with load shifting. Although the All Loads Shifted load profile falls within this range for most of the insolation bins, more data are needed to quantify a specific percentage of self-consumption increase for each of the load profiles over the Baseline load profile and to draw more definitive conclusions.

Generation self-consumption.

The Generation self-consumption factor calculated in this thesis looks at the amount of the PV generation that was self-consumed by the load profile demand. Figure 44 shows the percentages for each load profile for the collected data. As mentioned in Chapter Four, it makes sense that Generation self-consumption percentages were close to 100% in the 0-1 sun hour insolation bin. With minimal PV production, most of the PV generation at that level would be used to satisfy load profile demands. It also makes sense for the self-consumption levels to decrease as insolation increases because with excess PV production, more PV generation would be exported rather than consumed locally if the loads were already met and the battery was fully charged.

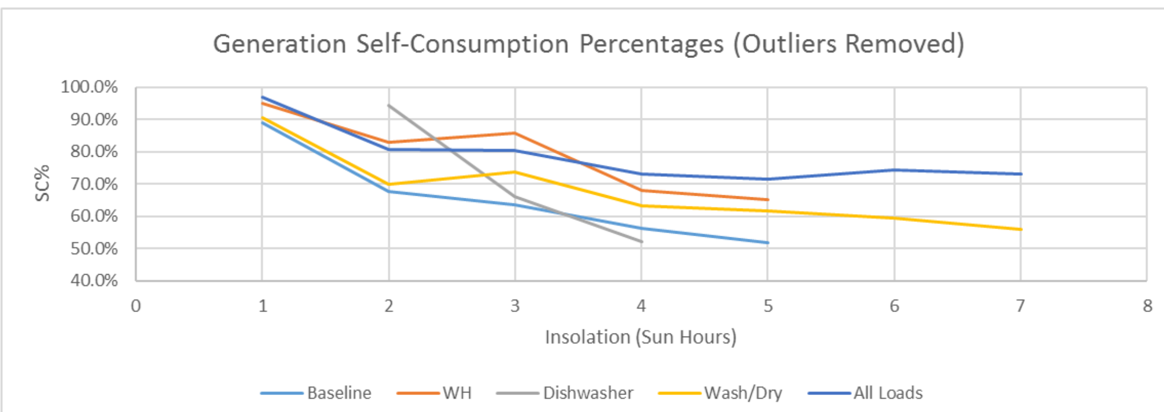

Figure 44. Generation self-consumption percentages (outliers removed).

It should be noted that load shifting seemed to increase Generation self-consumption levels in every load profile except possibly the Dishwasher condition, which is logical considering this load profile had the fewest kWh shifted. It also makes sense that the All Loads shifted load profile was the most consistently higher than the baseline load profile because it had the most kWh shifted. Again, more data are needed to calculate specific percentages for increases in self-consumption for each load profile.

Generation export percentages.

Another way to look at Generation self-consumption is the percentage of the PV generation that was exported. Higher exports means lower Generation self-consumption percentages because it is the inverse of the Generation self-consumption factor. Figure 45 shows the Generation export percentages for each load profile.

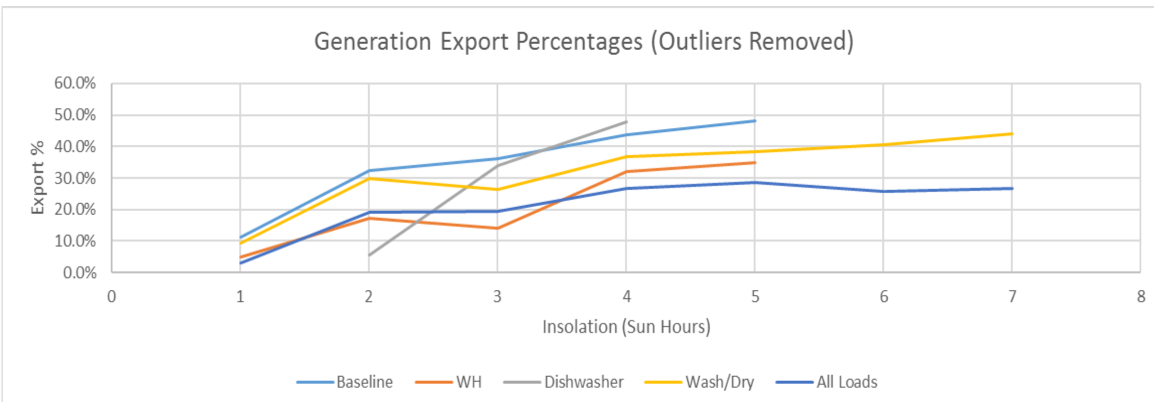

Figure 45. Generation export percentages for each load profile (outliers removed).

From this perspective, it makes sense that the Baseline condition exports were the highest because they did not have any load shifting. It is also logical that Generation exports for the other load profiles were lower because more of the PV generation would be consumed locally by the load profile demands rather than exported to the grid.

PV Only versus PV+Battery Self-Consumption Levels

The most puzzling result of this experiment lay in the fact that the levels of self-consumption for the PV Only self-consumption factor were consistently higher than those of the PV+Battery self-consumption. For this reason, self-consumption levels for this self-consumption factor were not analyzed in the previous section. According to the literature, and expected results of this thesis, self-consumption levels should have been higher through the addition of a battery, not lower. The battery should be able to store excess solar energy during the day, and discharge it in the evening, thereby increasing self-consumption levels.

To investigate this conundrum, I looked at self-consumption trends across the months of data collected. The data analyzed for this thesis came from the date range of November 30, 2016 through March 20, 2017. Although data were being collected before these dates, these were the dates when loads were consistent and I was able to get reliable data from the system. A look at days before this range helped to solve the mystery of the self-consumption levels.

Leading up to November 25, 2016, PV+Battery self-consumption levels were consistently higher than PV Only self-consumption levels as expected as seen in Figure 46. After November 25th, 2016 something changed making PV Only self-consumption levels consistently higher than PV+Battery self-consumption levels as seen in Figure 47.

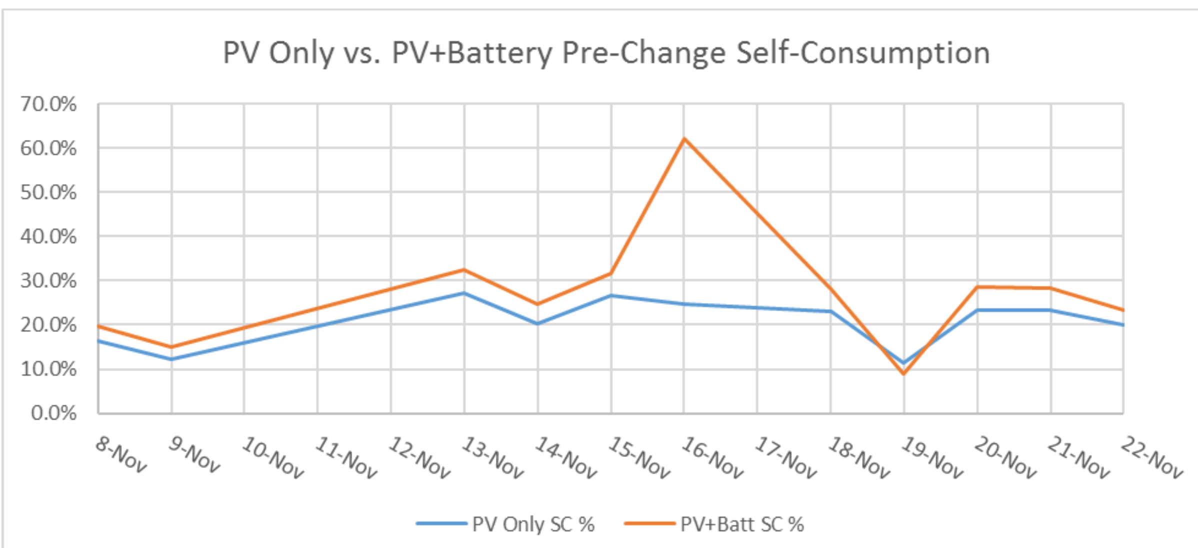

Figure 46. Pre-change PV Only vs. PV+Battery self-consumption levels.

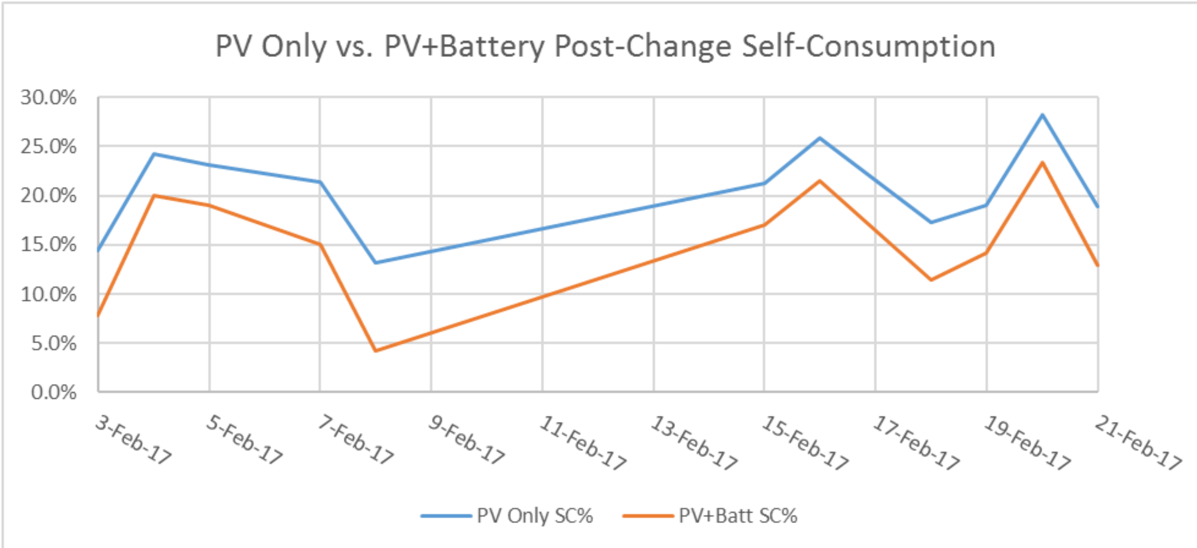

Figure 47. Post-change PV Only vs. PV+Battery self-consumption levels.

Upon further investigation, it seemed as though the minimum battery voltage, or battery recharge voltage set point was changed in the system. This was confusing because no changes were made on our end, leading me to believe that it could have been a change by Adara Power since they have control over the battery remotely. Looking at the battery voltages before and after November 25, 2016 reinforced this hypothesis as shown in Figure 48. November 25, the battery was regularly discharging down to just below 52 volts whereas after November 25, the battery only discharged down to just below 56 volts. This trend continued forward from that date. This change in effect limited the size of the battery, therefore decreasing its ability to discharge excess PV energy to increase self-consumption levels. After contacting Adara Power regarding the change, one of their engineers suggested that the “sell-block” setting may have been changed to prevent selling to the grid from 7:00pm-10:00am. This would prevent battery exports during most of the peak demand from 6:00pm-10:00pm, severely limiting the ability of the battery to increase self-consumption levels. It is unclear why this change would have been made, because we did not make any changes from this end.

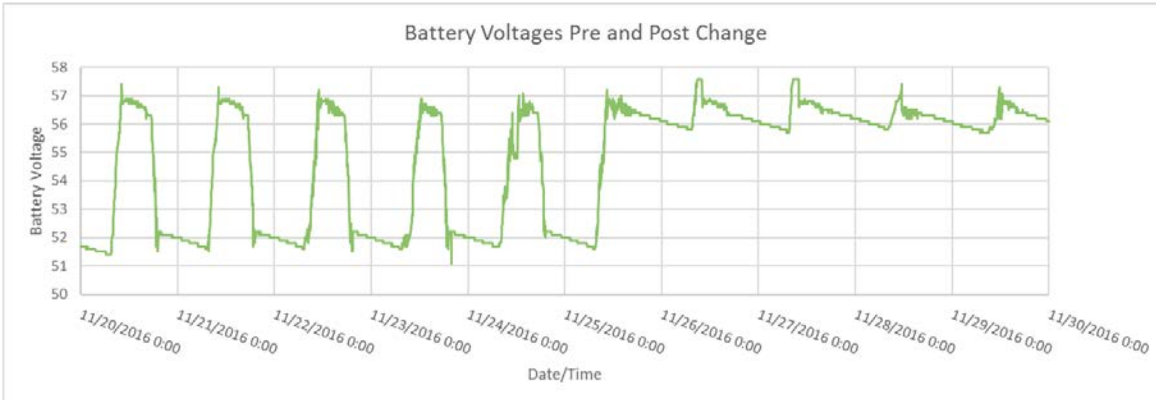

Figure 48. Pre and post-change battery voltages.

To determine the effective battery capacity resulting from the "sell block" setting, I determined total energy delivered to the battery from PV during six days from January 20 to January 25. Charging energy varied from 0.57 kWh to 1.26 kWh. From time-ordered charts of battery voltage, it appears as if on most days some of this energy was used to satisfy loads. However, on one day, January 25, it appears that all of the energy delivered to the battery, 0.66 kWh, was used to charge, as evidenced by a rapid and monotonic increase in battery voltage from 7:55am to 8:45am shown in Figure 49. Also at 3.8 sun hours of insolation, this day had a more than sufficient solar resource to fully charge the battery. These factors suggest that the effective battery capacity was around 0.66 kWh, or around 8% of the rated capacity. This is consistent with the observed lack of increase in self-consumption with the addition of storage.

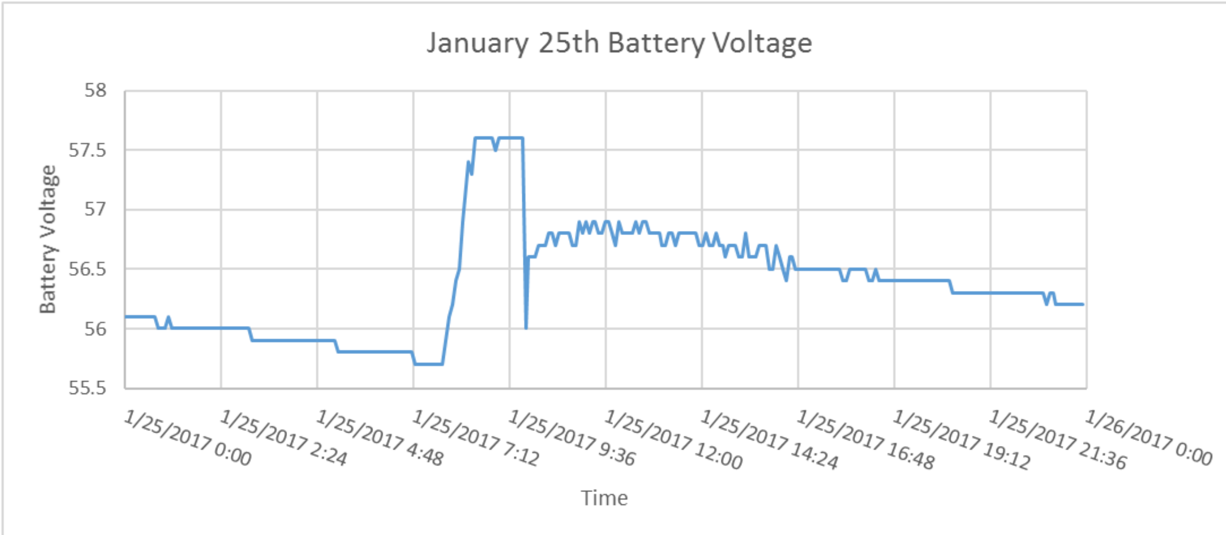

Figure 49. January 25 battery voltage.

Johann and Madlener (2014), in their study of ten houses in Germany, found that PV self-consumption levels could be increased by up to 20% by adding storage. Also, Luthander and colleagues (2014) concluded from their review of the self-consumption literature that PV self-consumption could be increased by 13-24% by adding a battery bank of 0.5-1kWh per kW of PV. For eleven of the days prior to the voltage set point change in this study, there was an average of 6.7% increase in self-consumption with the addition of batteries from PV Only self-consumption levels. From the days used for the graph in Figure 47, an average decrease of 5.5% in self-consumption levels occurred with the addition of batteries.

Based on this analysis, I cannot conclude anything about the effect of adding storage on self-consumption levels. Simply put, I was not utilizing the battery bank and that resulted in the failure of the self-consumption levels to increase with the addition of storage.

The reason for the decrease in self-consumption with the addition of the battery bank should be explored further. Although there is not a clear reason for this behavior, I hypothesize that the decrease in self-consumption was caused by the round trip energy loss of a portion of the PV going to charge the battery rather than satisfying loads, and then not being able to discharge enough to increase self-consumption.

Recommendations for Adoption

One goal of this thesis was to aid in driving the practical application of load shifting and battery-based energy storage to increase residential PV self-consumption levels. This, in turn can help the utility and can create savings for the homeowner, as discussed in Chapters One and Two.

On the most basic level, I would suggest a behavior change to increase self-consumption for the homeowner, and it would not cost anything. This behavior change could include doing laundry during the middle of the day and using the dishwasher only during off-peak times. If those or other appliances have built-in timers, they can be set to start during the middle of the day when PV production is potentially the greatest.

One step up from that would be to install load management infrastructure on major appliances in your home. This would prevent deferrable appliances with a high demand from operating during peak times, and allow them to increase PV self-consumption by operating when the PV production is greatest. Appliances I would suggest for load management infrastructure include deferrable loads such as the water heater, clothes dryer, clothes washer, and dishwasher. If the house has electric heating or cooling, pre and post peak heating and cooling would be advised to limit the use of those appliances during peak hours.

Finally, the addition of batteries can potentially aid in increasing self-consumption. Although the findings on the effects of adding batteries on self-consumption in this thesis were inconclusive, batteries of the appropriate size with the proper inverter settings have been shown in the literature to increase self-consumption rates. As learned in this thesis, two of these settings would be enabling battery exports during peak hours, and using the maximum depth of discharge setting that does not harm the batteries.

Suggestions for Future Research

I have several suggestions to make this project better in the future if it was to be recreated, but also for future research going forward.

Load Reliability

Lightbulbs proved to be an unreliable load source for the fabricated load profile. Cycling on and off potentially every five minutes proved to be a challenge for the bulbs, especially in cold temperatures. Bulbs burned out frequently, especially the bulbs of high wattage. Even with checking the bulbs several times a week, there were many days in which data could not be collected because of a burned out bulb that changed the load totals for the day significantly. My suggestion to mitigate this challenge would be to only use reliable loads such as heaters or resistors of a specific wattage.

Expanded Data Collection Timeframe

Because of time constraints, the data for this project were collected from October 2016 to March 2017. These are the months of the year with the least amount of insolation. Logging data in the future from March to November could show increased levels of self-consumption and and increased effects of load shifting on self-consumption due to higher levels of insolation. Logging data for an entire year could also be an interesting option.

Also on the subject of time, another option for future research would be to see if defining a day differently would change results or reduce scatter. For example, if a day was from 5:00am-5:00am rather than midnight to midnight.

Finally, changing the data and load profile from a daily pattern to weekly or monthly profiles could show differences in the effects of load shifting and battery-based storage on both weekend and weekday schedules for greater impacts.

System Flow of Energy

With the custom data logging setup, there was the potential to log over 90 different parameters (20 at a time) through the Combox. A trial and error system of logging, analysis, and repeat was used to narrow down the parameters to those needed to visualize the flow of energy throughout the self-consumption system. After much analysis, we determined that there were energy flows in the system that could not be broken down into useful amounts of information. Several energy flow forks in the system proved unobtainable. For example, the energy coming into the system from the grid (System Grid Input Power) could go either to the loads (System Load Power) or to charging the battery (System DC Charge), but the breakdown between the two could not be determined with the custom parameters from the Combox. None of the documentation from Schneider Electric clarified these energy flows, and a conversation with a Schneider representative did not give me the answers I was looking for. Figure 50 shows in detail the complexity of the system with the different parameters that could be logged. It would be good to figure out the detailed system energy flows.

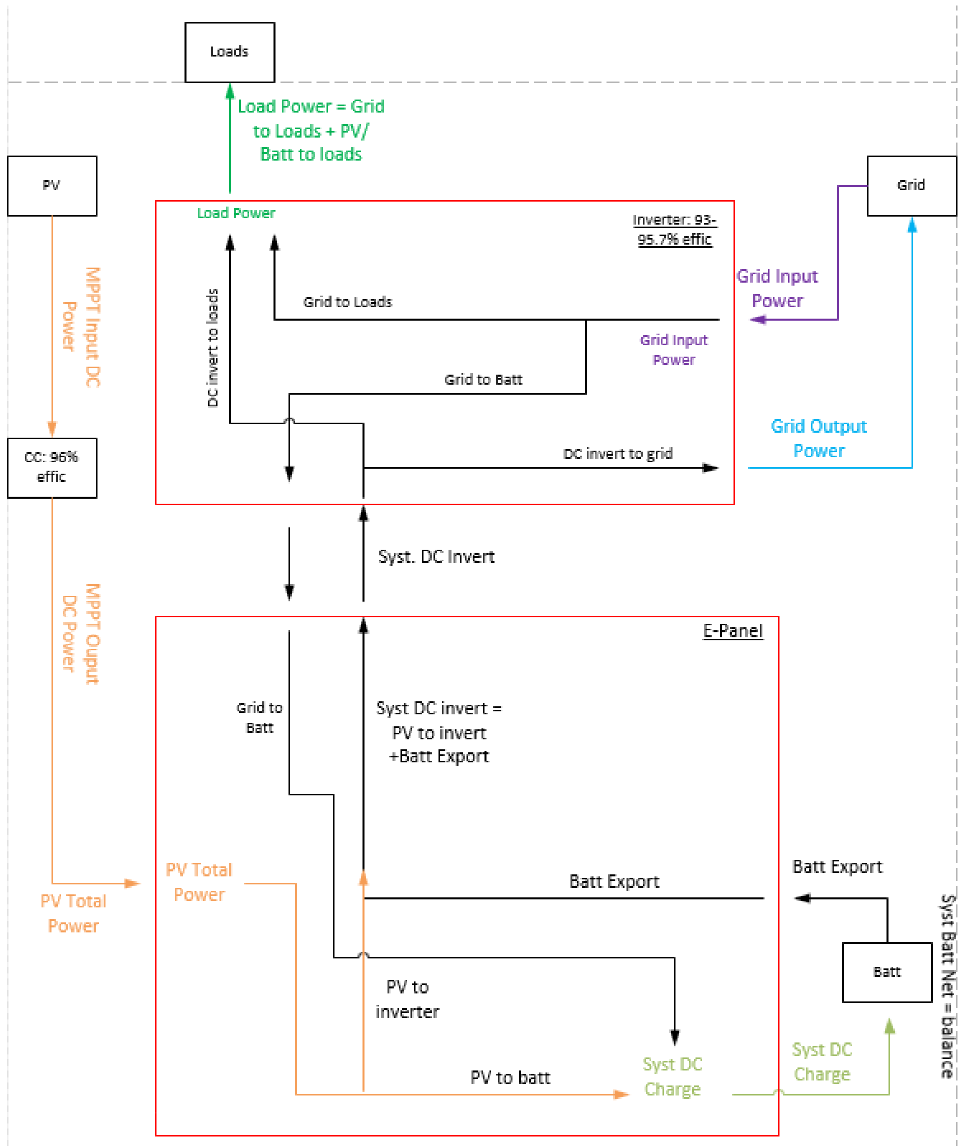

Figure 50. System energy flows and parameters.

Inverter Settings

The research and data for this thesis only used one combination of inverter settings. Future research could be done to see how different inverter settings could be used to help increase self-consumption.

The inverter settings should also be set so the battery can discharge during peak hours if that aids in what is being studied. More communication regarding inverter settings and changes should be had with Adara Power to ensure that settings are not changed remotely creating unexpected results.

PV Array and Battery Bank Sizing

As discussed earlier in this chapter, how the availability of battery depth of discharge affects self-consumption could be studied working with Adara Power.

Furthermore, this system could be used to see how different sized battery banks or PV systems affect self-consumption. This could potentially be achieved by working with Adara Power and unplugging one or more battery packs out of the four that make up the 8.6kWh battery bank. Restringing the PV to achieve varying sized PV arrays could also be interesting. This would add to the available research on self-consumption system sizing optimization.

Weather Forecasting

The effects of load shifting in response to weather forecasting would also be an interesting extension of this research. This would call for more automation and technology, but could make load shifting more effective because it would be planned for a specific time when the sun is forecasted to actually be out rather than simply times of day when the sun is typically more likely to be shining.

Economics of System Performance

A final suggestion for further research using this self-consumption system would be to look at the economics of the system performance across varying utilities. Comparing and contrasting utilities that have varying compensation plans, rate schedules, charges, and levels of state tax incentives would be interesting.

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APPENDIX A: INVERTER CONFIGURATION

<u>Appalach+A1:C36ian State University Settings</u>
Configuration is DC-coupled system.

Schneider Inverter Settings

Setting Name	Setting	Comments
Type	XW5548+	Not an actual setting. Information provided for reference only. Record model #, serial # and firware revision, available under System Settings -> View Device Info Example: Model #: 865-5548-01 Serial #: 000018465944 F/W Rev.: 2.01.00 BN21
Inverter	Enabled	
Search Mode	Disabled	
Grid Support	Enabled	
Charger	Enabled	
Mode	Standby	***NOTE: Make changes to settings while in Standby Mode. Return to Operating Mode once complete.***
Inverter Settings		
LBCO	46V	Represents 3.14V/cell.
LBCO Hyst	1V	
LBCO Delay	10 sec	
HBCO	70V	Represents 4.20V/cell. Maximum recommended battery voltage from Samsung for charge.
HBCO Hyst	2V	This setting is not configurable with the Connext SCP programming tool. This is the default setting.
Search Watts	50W	Search mode not enabled. Setting provided for reference only.
Search Delay	2 sec	Search mode not enabled. Setting provided for reference only.
Charger Settings		

Battery Type	Custom	
Custom Settings		
Equalize Voltage	57.4V	Represents 4.10V/cell (90% SoC per Samsung for 18650-22P cell). *NOTE: Equalize voltage is not used for LiIon battery pack and is not used when Equalize Support is disabled on the XW+ inverter, but it should be set in case the Equalize mode is inadvertantlyy enabled.*
Equalize Support	Disabled	
Bulk Voltage	57.4V	Represents 4.10V/cell.
Absorb Voltage	57.4V	Represents 4.10V/cell.
Float Voltage	57.4V	Represents 4.10V/cell. *NOTE: Float voltage is not used in 2 Stage, No Float charging mode, but Float Voltage should be set in case charge mode is inadvertantly changed to a mode which includes the float stage.*
Batt Temp Comp	-108mV/C	
Batt Capacity	172Ah	
Max Charge Rate	39%	Percentage is of Continuous Current Rating of inverter (140A on XW6448, 110A on XW5548). 39% on XW5548 yields 42.9A (which is approximately 1/4C for four 14S20P Nexcon battery packs: (2150mA / 4) x 20 x 4 = 43,000mA = 43A). ***NOTE:*** *this setting is NOT tied to the Max Bulk Current setting.*
Charge Cycle	2StgNoFloat	Two stage, no float charge type.
Default Battery Temp	Warm	
Recharge Voltage	51.3V	Represents 3.66V/cell. No charge occurs above this setting *from the grid, but charging from the PV system is not affected by this setting.* Voltage must drop to this level before charging from AC1 (IN) will start. *NOTE: In an AC-coupled system, the solar inverter output is tied to AC-LOAD, not AC1 (IN).*
Absorption Time	60 min	
Charge Block Start	10:00AM	Charge Block Start and Stop may be customer/region specific settings and subject to change based on local regulations.
Charge Block Stop	9:00PM	
AC Settings		
AC Priority	AC1	

AC1 Breaker Rating	60A	This setting is tied directly to the breaker used in the inverter and MUST be changed if the physical breaker is changed to a lower/higher value.
AC1 Min Volt	106V	
AC1 Max Volt	132V	
AC1 Min Freq	55Hz	
AC1 Max Freq	65Hz	
AC2 Breaker Rating	60A	*NOTE(S):* *Typically no generator is attached to AC2 - review settings if installation includes a generator.* *This setting is tied directly to the breaker used in the inverter and MUST be changed if the physical breaker is changed to a lower/higher value.*
AC2 Min Volt	80V	*NOTE: Typically no generator is attached to AC2 - review settings if installation includes a generator.*
AC2 Max Volt	138V	*NOTE: Typically no generator is attached to AC2 - review settings if installation includes a generator.*
AC2 Min Freq	55Hz	*NOTE: Typically no generator is attached to AC2 - review settings if installation includes a generator.*
AC2 Max Freq	65Hz	*NOTE: Typically no generator is attached to AC2 - review settings if installation includes a generator.*
Grid Support Settings		
Grid Support Voltage	64.0V	Represents 3.6V/cell. Grid Support is the level to which the batteries will discharge to sell to the grid (if this feature is enabled). Ideally this setting should be at or below the Recharge Voltage setting if the system is expected to charge cycle based on grid discharge.
Sell	Enabled	This setting is dependent on customer preference and/or local/regional regulatory requirements.
Max Sell Amps	16.0A	Typically this setting is set based on maximum available PV output. Unless Enhanced Grid Support is enabled, inverter will try to meet the Max Sell Amps setting by making up any shortfall from battery storage. ***NOTE:*** *Max Sell Amps is an AC setting (per AC line), not a DC setting. For example: if Vbat = 55V and Max Sell Amps = 5A (per AC leg, at two legs = 10A total), then (AC) 10A x 120V = 1200VA; thus (DC) 1200VA / 55V = ~21.8A (drawn from DC/battery).*
Load Shave	Disabled	
Load Shave Amps	0.0A	Load Shave disabled. Setting provided for reference only.

Load Shave Start	12:00AM	Load Shave disabled. Setting provided for reference only.
Load Shave Stop	12:00AM	Load Shave disabled. Setting provided for reference only.
Sell Block Start	7:00PM	
Sell Block Stop	10:00AM	
Generator Settings		
Gen Supp Mode	Disabled	
Gen Supp Amps	48.0A	*NOTE: This setting will be set based on the support generator if implemented. Typical installations have not included generator support.*
Aux Settings		
Manual Aux	ManualOff	*NOTE: Future JuiceBox control firmware may toggle this under its control to manually control a relay to control the output from an AC-coupled solar inverter.*
Active Level	ActiveHigh	
Advanced Features		
RPO	Disabled	*NOTE: Future JuiceBox control firmware may toggle this under its control to manually control Remote Power Output.*
Power Save	Disabled	
Sell Delay 40s	Disabled	
Gen Support Plus	Disabled	
AC_Coupling	Disabled	
Batt_Balance	Disabled	
Peak Load Shave Delay 2 Hours	Disabled	NOTE: Enabling this setting will allow the MPPT solar charge controller (in DC-coupled systems) to charge the batteries first, then (after two hours expires), Peak Load Shave mode (if enabled) would be entered for AC Load Support.
Miscellaneous (not settable with SCP)		
Max Bulk Current	80.0A	
Discharge Imax	150%	There is a mismatch between CommBox and SCP. One shows as Amps (CommBox) the other as percent (SCP). Changing the parameter on either side shows the SAME value (in native unit) on the other device when read. For example setting 60A will read as 60%, setting 140% will read as 140Amps.

Discharge Time	10 sec	

System Module Identification Information

System	Unit Info	Description/Comment
Schneider XW+ Inverter	Model	Example: 865-5548-01 ***Record actual in this box***
Schneider XW+ Inverter	Serial No.	Example: 000018465944 ***Record actual in this box***
Schneider XW+ Inverter	Firmware	Example: 2.01.00 BN21 ***Record actual in this box***

APPENDIX B: LOAD PROFILES

Five Minute Load Profiles in kW					
Time	Baseline Load Profile	Dishwasher	Clothes Washer & Dryer	Water Heater	All Loads
0:00	1.754	1.754	1.754	1.754	1.754
0:05	1.159	1.159	1.159	1.159	1.159
0:10	1.053	1.053	1.053	1.053	1.053
0:15	1.159	1.159	1.159	1.159	1.159
0:20	1.152	1.152	1.152	1.152	1.152
0:25	1.511	1.511	1.511	1.511	1.511
0:30	1.404	1.404	1.404	1.404	1.404
0:35	1.261	1.261	1.261	1.261	1.261
0:40	1.053	1.053	1.053	1.053	1.053
0:45	1.513	1.513	1.513	1.513	1.513
0:50	1.254	1.254	1.254	1.254	1.254
0:55	1.159	1.159	1.159	1.159	1.159
1:00	1.152	1.152	1.152	1.152	1.152
1:05	1.108	1.108	1.108	1.108	1.108
1:10	1.353	1.353	1.353	1.353	1.353
1:15	1.261	1.261	1.261	1.261	1.261
1:20	1.152	1.152	1.152	1.152	1.152
1:25	0.902	0.902	0.902	0.902	0.902
1:30	1.261	1.261	1.261	1.261	1.261
1:35	1.261	1.261	1.261	1.261	1.261
1:40	1.305	1.305	1.305	1.305	1.305
1:45	1.053	1.053	1.053	1.053	1.053
1:50	1.108	1.108	1.108	1.108	1.108
1:55	1.002	1.002	1.002	1.002	1.002
2:00	1.002	1.002	1.002	1.002	1.002
2:05	1.159	1.159	1.159	1.159	1.159
2:10	1.152	1.152	1.152	1.152	1.152
2:15	1.002	1.002	1.002	1.002	1.002
2:20	1.053	1.053	1.053	1.053	1.053
2:25	1.261	1.261	1.261	1.261	1.261
2:30	1.009	1.009	1.009	1.009	1.009

2:35	0.902	0.902	0.902	0.902	0.902
2:40	1.404	1.404	1.404	1.404	1.404
2:45	1.159	1.159	1.159	1.159	1.159
2:50	1.152	1.152	1.152	1.152	1.152
2:55	1.108	1.108	1.108	1.108	1.108
3:00	1.002	1.002	1.511	1.002	1.511
3:05	0.902	0.902	1.411	0.902	1.411
3:10	0.851	0.851	1.36	0.851	1.36
3:15	1.053	1.053	1.562	1.053	1.562
3:20	1.053	1.053	1.562	1.053	1.562
3:25	1.002	1.002	1.511	1.002	1.511
3:30	1.254	1.254	1.763	1.254	1.763
3:35	1.009	1.009	1.513	1.009	1.513
3:40	1.002	1.002	1.511	1.002	1.511
3:45	1.009	1.009	1.513	1.009	1.513
3:50	1.002	1.002	1.002	1.002	1.002
3:55	1.353	1.353	1.353	1.353	1.353
4:00	1.009	1.009	1.009	1.009	1.009
4:05	1.053	1.053	1.053	1.053	1.053
4:10	0.902	0.902	0.902	0.902	0.902
4:15	1.101	1.101	1.101	1.101	1.101
4:20	1.009	1.009	1.009	1.009	1.009
4:25	0.911	0.911	0.911	0.911	0.911
4:30	0.902	0.902	0.902	0.902	0.902
4:35	1.152	1.152	1.152	1.152	1.152
4:40	1.101	1.101	1.101	1.101	1.101
4:45	1.152	1.152	1.152	1.152	1.152
4:50	0.902	0.902	0.902	0.902	0.902
4:55	0.902	0.902	0.902	0.902	0.902
5:00	1.101	1.101	1.101	1.101	1.101
5:05	1.002	1.002	1.002	1.002	1.002
5:10	1.108	1.108	1.108	1.108	1.108
5:15	1.513	1.513	1.513	1.513	1.513
5:20	1.305	1.305	1.305	1.305	1.305
5:25	1.601	1.601	1.601	1.601	1.601
5:30	1.754	1.754	1.754	1.754	1.754
5:35	1.312	1.312	1.312	1.312	1.312
5:40	1.053	1.053	1.053	1.053	1.053
5:45	1.009	1.009	1.009	1.009	1.009
5:50	1.101	1.101	1.101	1.101	1.101
5:55	1.101	1.101	1.101	1.101	1.101

6:00	1.009	1.009	1.009	1.009	1.009
6:05	1.101	1.101	1.101	1.101	1.101
6:10	1.254	1.254	1.254	1.254	1.254
6:15	0.851	0.851	0.851	0.851	0.851
6:20	0.902	0.902	0.902	0.902	0.902
6:25	1.002	1.002	1.002	1.002	1.002
6:30	1.254	1.254	1.254	1.254	1.254
6:35	1.254	1.254	1.254	1.254	1.254
6:40	1.312	1.312	1.312	1.312	1.312
6:45	1.312	1.312	1.312	1.312	1.312
6:50	1.152	1.152	1.152	1.152	1.152
6:55	1.002	1.002	1.002	1.002	1.002
7:00	1.152	1.152	1.152	1.152	1.152
7:05	1.652	1.652	1.652	1.652	1.652
7:10	1.972	1.972	1.972	1.972	1.972
7:15	1.904	1.904	1.904	1.904	1.904
7:20	1.972	1.972	1.972	1.972	1.972
7:25	1.913	1.913	1.913	1.913	1.913
7:30	1.805	1.805	1.805	1.805	1.805
7:35	1.652	1.652	1.652	1.652	1.652
7:40	1.601	1.601	1.601	1.601	1.601
7:45	1.513	1.513	1.513	1.513	1.513
7:50	1.254	1.254	1.254	1.254	1.254
7:55	1.108	1.108	1.108	1.108	1.108
8:00	1.053	1.053	1.053	1.053	1.053
8:05	0.902	0.902	0.902	0.902	0.902
8:10	0.851	0.851	0.851	0.851	0.851
8:15	0.851	0.851	0.851	0.851	0.851
8:20	0.851	0.851	0.851	0.851	0.851
8:25	0.86	0.86	0.86	0.86	0.86
8:30	0.851	0.851	0.851	0.851	0.851
8:35	0.812	0.812	0.812	0.812	0.812
8:40	0.803	0.803	0.803	0.803	0.803
8:45	0.812	0.812	0.812	0.812	0.812
8:50	0.803	0.803	0.803	0.803	0.803
8:55	0.812	0.812	0.812	0.812	0.812
9:00	0.803	0.803	0.803	0.803	0.803
9:05	0.812	0.812	0.812	0.812	0.812
9:10	0.851	0.851	0.851	0.851	0.851
9:15	0.911	0.911	0.911	0.911	0.911
9:20	0.851	0.851	0.851	0.851	0.851

9:25	0.851	0.851	0.851	0.851	0.851
9:30	0.86	0.86	0.86	0.86	0.86
9:35	0.851	0.851	0.851	0.851	0.851
9:40	0.86	0.86	0.86	0.86	0.86
9:45	0.851	0.851	0.851	0.851	0.851
9:50	0.86	0.86	0.86	0.86	0.86
9:55	0.851	0.851	0.851	0.851	0.851
10:00	0.812	0.812	0.812	0.812	0.812
10:05	0.86	0.86	0.86	0.86	0.86
10:10	0.902	0.902	0.902	0.902	0.902
10:15	0.911	0.911	0.911	0.911	0.911
10:20	0.803	0.803	0.803	0.803	0.803
10:25	0.803	0.803	0.803	0.803	0.803
10:30	0.803	0.803	0.803	0.803	1.312
10:35	0.803	0.803	0.803	0.803	1.312
10:40	0.86	0.86	0.86	0.86	1.36
10:45	0.86	0.86	0.86	0.86	1.36
10:50	0.86	0.86	0.86	0.86	1.36
10:55	0.86	0.86	0.86	0.86	1.36
11:00	0.86	1.36	0.86	0.86	1.36
11:05	0.86	1.36	0.86	0.86	1.36
11:10	0.86	1.36	0.86	0.86	1.36
11:15	0.803	1.312	0.803	0.803	1.312
11:20	0.86	1.36	2.832	0.86	1.36
11:25	1.002	1.502	2.974	1.002	1.502
11:30	0.86	1.36	2.832	3.084	3.084
11:35	0.803	1.312	2.775	3.027	3.027
11:40	0.803	1.312	2.775	3.027	3.027
11:45	0.803	1.312	2.775	3.027	3.027
11:50	0.86	1.36	2.832	3.084	3.084
11:55	0.86	1.36	2.832	3.084	3.084
12:00	0.911	0.911	2.883	3.135	3.135
12:05	0.86	0.86	2.832	3.084	3.084
12:10	0.86	0.86	0.86	3.084	3.084
12:15	0.902	0.902	0.902	0.902	2.874
12:20	1.002	1.002	1.002	1.002	2.974
12:25	0.86	0.86	0.86	0.86	2.832
12:30	0.803	0.803	0.803	0.803	2.775
12:35	0.803	0.803	0.803	0.803	2.775
12:40	0.803	0.803	0.803	0.803	2.775
12:45	0.803	0.803	0.803	0.803	2.775

12:50	0.803	0.803	0.803	0.803	2.775
12:55	1.053	1.053	1.053	1.053	3.025
13:00	1.002	1.002	1.002	1.002	2.974
13:05	1.053	1.053	1.053	1.053	1.053
13:10	1.002	1.002	1.002	1.002	1.002
13:15	0.86	0.86	0.86	3.084	3.084
13:20	0.86	0.86	0.86	3.084	3.084
13:25	1.002	1.002	1.002	3.226	3.226
13:30	0.902	0.902	0.902	3.126	3.126
13:35	0.902	0.902	0.902	3.126	3.126
13:40	1.002	1.002	1.002	3.226	3.226
13:45	1.002	1.002	1.002	3.226	3.226
13:50	1.002	1.002	1.002	3.226	3.226
13:55	0.86	0.86	0.86	3.084	3.084
14:00	1.002	1.002	1.002	1.002	1.002
14:05	1.002	1.002	1.002	1.002	1.002
14:10	1.254	1.254	1.254	1.254	1.254
14:15	1.152	1.152	1.152	1.152	1.152
14:20	1.101	1.101	1.101	1.101	1.101
14:25	1.305	1.305	1.305	1.305	1.305
14:30	1.101	1.101	1.101	1.101	1.101
14:35	1.101	1.101	1.101	1.101	1.101
14:40	1.009	1.009	1.009	1.009	1.009
14:45	1.254	1.254	1.254	1.254	1.254
14:50	1.553	1.553	1.553	1.553	1.553
14:55	1.353	1.353	1.353	1.353	1.353
15:00	1.312	1.312	1.312	1.312	1.312
15:05	1.06	1.06	1.06	1.06	1.06
15:10	1.353	1.353	1.353	1.353	1.353
15:15	1.353	1.353	1.353	1.353	1.353
15:20	1.254	1.254	1.254	1.254	1.254
15:25	1.305	1.305	1.305	1.305	1.305
15:30	1.404	1.404	1.404	1.404	1.404
15:35	1.511	1.511	1.511	1.511	1.511
15:40	1.404	1.404	1.404	1.404	1.404
15:45	1.254	1.254	1.254	1.254	1.254
15:50	1.254	1.254	1.254	1.254	1.254
15:55	1.652	1.652	1.652	1.652	1.652
16:00	1.862	1.862	1.862	1.862	1.862
16:05	1.101	1.101	1.101	1.101	1.101
16:10	1.353	1.353	1.353	1.353	1.353

16:15	1.661	1.661	1.661	1.661	1.661
16:20	1.862	1.862	1.862	1.862	1.862
16:25	1.763	1.763	1.763	1.763	1.763
16:30	1.254	1.254	1.254	1.254	1.254
16:35	1.502	1.502	1.502	1.502	1.502
16:40	1.502	1.502	1.502	1.502	1.502
16:45	1.754	1.754	1.754	1.754	1.754
16:50	1.652	1.652	1.652	1.652	1.652
16:55	1.502	1.502	1.502	1.502	1.502
17:00	1.502	1.502	1.502	1.502	1.502
17:05	1.511	1.511	1.511	1.511	1.511
17:10	1.862	1.862	1.862	1.862	1.862
17:15	1.862	1.862	1.862	1.862	1.862
17:20	1.404	1.404	1.404	1.404	1.404
17:25	1.553	1.553	1.553	1.553	1.553
17:30	1.754	1.754	1.754	1.754	1.754
17:35	1.904	1.904	1.904	1.904	1.904
17:40	1.652	1.652	1.652	1.652	1.652
17:45	1.511	1.511	1.511	1.511	1.511
17:50	2.323	2.323	2.323	2.323	1.862
17:55	2.374	2.374	2.374	2.374	1.913
18:00	2.122	2.122	2.122	2.122	1.661
18:05	1.805	1.805	1.805	1.805	1.305
18:10	2.224	2.224	2.224	2.224	1.763
18:15	2.724	2.724	2.724	2.724	2.224
18:20	2.071	2.071	2.071	2.071	1.601
18:25	2.523	2.523	2.023	2.523	0.303
18:30	2.974	2.974	2.481	0.752	0.752
18:35	2.883	2.883	2.374	0.659	0.659
18:40	3.124	3.124	2.622	0.902	0.902
18:45	2.874	2.874	2.374	0.65	0.65
18:50	2.775	2.775	2.275	0.551	0.551
18:55	2.784	2.784	2.275	0.56	0.56
19:00	2.775	2.775	2.275	0.551	0.551
19:05	2.775	2.775	2.275	0.551	0.551
19:10	2.631	2.631	2.122	0.402	2.122
19:15	2.263	2.263	2.263	2.263	1.754
19:20	2.224	2.224	2.224	2.224	1.763
19:25	2.883	2.883	2.883	2.883	2.374
19:30	2.413	1.904	2.413	2.413	1.904
19:35	2.622	2.122	2.622	2.622	0.402

19:40	2.784	2.275	0.812	0.56	0.56
19:45	2.622	2.122	0.65	0.402	0.402
19:50	2.832	2.323	0.86	0.608	0.608
19:55	3.124	2.631	1.152	0.902	0.902
20:00	2.974	2.472	1.002	0.752	0.752
20:05	2.874	2.374	0.902	0.65	0.65
20:10	2.974	2.481	1.002	0.752	0.752
20:15	3.124	2.622	1.152	0.902	0.902
20:20	2.883	2.374	0.911	0.659	2.374
20:25	2.472	1.972	0.5	2.472	1.972
20:30	2.374	2.374	2.374	2.374	1.913
20:35	2.472	2.472	2.472	2.472	1.972
20:40	2.883	2.883	2.883	2.883	2.374
20:45	2.374	2.374	2.374	2.374	1.913
20:50	2.161	2.161	2.161	2.161	1.661
20:55	2.275	2.275	2.275	2.275	1.814
21:00	2.323	2.323	2.323	2.323	1.862
21:05	2.724	2.724	2.724	2.724	2.224
21:10	2.631	2.631	2.631	2.631	0.659
21:15	2.374	2.374	2.374	2.374	0.402
21:20	2.314	2.314	2.314	2.314	0.303
21:25	2.532	2.532	2.532	2.532	0.56
21:30	2.523	2.523	2.523	2.523	0.551
21:35	2.622	2.622	2.622	2.622	0.65
21:40	2.374	2.374	2.374	2.374	0.402
21:45	2.374	2.374	2.374	2.374	0.402
21:50	2.481	2.481	2.481	2.481	0.509
21:55	2.481	2.481	2.481	2.481	0.509
22:00	2.011	2.011	2.011	2.011	2.011
22:05	1.904	1.904	1.904	1.904	1.904
22:10	2.224	2.224	2.224	2.224	2.224
22:15	2.122	2.122	2.122	2.122	2.122
22:20	1.853	1.853	1.853	1.853	1.853
22:25	1.661	1.661	1.661	1.661	1.661
22:30	1.754	1.754	1.754	1.754	1.754
22:35	2.122	2.122	2.122	2.122	2.122
22:40	1.904	1.904	1.904	1.904	1.904
22:45	1.661	1.661	1.661	1.661	1.661
22:50	1.502	1.502	1.502	1.502	1.502
22:55	1.763	1.763	1.763	1.763	1.763
23:00	1.763	1.763	1.763	1.763	1.763

23:05	1.502	1.502	1.502	1.502	1.502
23:10	1.511	1.511	1.511	1.511	1.511
23:15	1.652	1.652	1.652	1.652	1.652
23:20	1.502	1.502	1.502	1.502	1.502
23:25	1.108	1.108	1.108	1.108	1.108
23:30	1.511	1.511	1.511	1.511	1.511
23:35	1.904	1.904	1.904	1.904	1.904
23:40	1.652	1.652	1.652	1.652	1.652
23:45	1.101	1.101	1.101	1.101	1.101
23:50	1.101	1.101	1.101	1.101	1.101
23:55	1.502	1.502	1.502	1.502	1.502

APPENDIX C: EXPERIMENTAL CONDITION DEVIATIONS

Load Profile	Date	Sun Hrs	PV Only SC %	PV Only Deviation	PV+Batt SC %	PV+Batt Deviation	Generation SC %	Generation Deviation	PV Only Bin Avg	PV+Batt Bin Avg	Generation Bin Avg
Baseline	21-Jan-17	0.9	7.8%	-0.1%	0.7%	-0.1%	83.0%	-6.0%	7.9%	0.8%	89.0%
Baseline	23-Jan-17	0.9	8.0%	0.1%	1.0%	0.1%	95.0%	6.0%			
Baseline	29-Jan-17	1.0	8.5%	-2.4%	2.1%	-2.4%	88.6%	14.0%	10.9%	4.5%	74.6%
Baseline	3-Feb-17	1.4	14.4%	3.5%	7.8%	3.3%	80.9%	6.2%			
Baseline	22-Jan-17	1.6	9.8%	-1.1%	3.6%	-0.9%	54.4%	-20.2%			
Baseline	1-Feb-17	2.1	18.2%	-3.7%	11.6%	-2.1%	78.5%	14.7%	21.9%	13.6%	63.7%
Baseline	24-Jan-17	2.3	29.3%	7.4%	12.0%	-1.6%	67.3%	3.5%			
Baseline	5-Feb-17	2.4	23.1%	1.3%	19.1%	5.4%	54.4%	-9.3%			
Baseline	20-Jan-17	2.4	16.8%	-5.0%	11.9%	-1.7%	54.7%	-9.0%			
Baseline	31-Jan-17	3.7	22.9%	-16.7%	18.8%	0.3%	56.2%	1.7%	39.6%	18.5%	54.6%
Baseline	25-Jan-17	3.8	56.3%	16.7%	18.3%	-0.3%	52.9%	-1.7%			
Baseline	4-Feb-17	4.5	24.3%		20.1%		51.9%				
Water Heater	4-Dec	0.3	3.2%	0.1%	-2.9%	-0.4%	100.0%	5.0%	3.1%	-2.5%	95.0%
Water Heater	30-Nov	0.5	2.1%	-1.1%	-2.8%	-0.3%	100.0%	5.0%			
Water Heater	6-Dec	0.6	4.1%	1.0%	-1.9%	0.6%	84.9%	-10.1%			
Water Heater	7-Mar	1.2	10.4%	-4.5%	2.6%	-5.7%	79.0%	-3.9%	14.9%	8.2%	82.8%
Water Heater	6-Mar	1.4	14.7%	-0.2%	6.8%	-1.4%	90.4%	7.6%			
Water Heater	3-Dec	1.5	14.5%	-0.3%	8.2%	-0.1%	88.1%	5.3%			
Water Heater	5-Dec	1.9	19.9%	5.0%	15.4%	7.1%	73.8%	-9.0%			
Water Heater	28-Feb	2.4	18.5%	1.5%	11.6%	-0.1%	71.8%	-14.0%	17.0%	11.7%	85.8%
Water Heater	1-Mar	2.5	15.5%	-1.5%	11.9%	0.1%	99.9%	14.0%			
Water Heater	7-Dec	3.3	31.3%	12.9%	26.8%	-0.2%	68.0%	0.4%	18.3%	26.9%	67.6%
Water Heater	1-Dec	3.5	5.4%	-12.9%	27.1%	0.2%	67.2%	-0.4%			
Water Heater	3-Mar	5.4	34.6%	-0.9%	29.7%	-0.8%	64.4%	-0.7%	35.5%	30.5%	65.2%
Water Heater	5-Mar	5.5	35.6%	0.1%	30.3%	-0.2%	65.5%	0.3%			
Water Heater	4-Mar	5.5	35.8%	0.3%	30.4%	-0.1%	66.2%	1.0%			
Water Heater	2-Mar	5.8	36.1%	0.5%	31.5%	1.0%	64.6%	-0.6%			
Dishwasher	8-Feb	1.5	13.1%		4.2%		94.4%				
Dishwasher	15-Feb	2.4	21.2%	-0.1%	17.0%	1.0%	67.0%	0.8%	21.3%	16.0%	66.2%
Dishwasher	7-Feb	2.6	21.4%	0.1%	15.0%	-1.0%	65.4%	-0.8%			
Dishwasher	16-Feb	4.8	25.9%		21.5%		52.2%				
Washer/Dryer	22-Feb	0.7	7.4%		1.0%		90.7%				
Washer/Dryer	19-Feb	1.8	19.1%		14.1%		70.1%				
Washer/Dryer	18-Feb	2.3	17.2%	-0.8%	11.4%	-0.7%	75.7%	2.1%	18.1%	12.2%	73.6%
Washer/Dryer	21-Feb	2.8	18.9%	0.8%	12.9%	0.7%	71.5%	-2.1%			
Washer/Dryer	23-Feb	3.1	16.7%	-2.9%	10.0%	-3.1%	67.1%	3.8%	19.6%	13.0%	63.3%
Washer/Dryer	13-Mar	3.6	22.4%	2.9%	16.1%	3.1%	59.6%	-3.8%			
Washer/Dryer	10-Mar	4.1	25.9%	-1.9%	19.6%	-2.9%	59.7%	-1.8%	27.7%	22.5%	61.5%
Washer/Dryer	25-Feb	4.1	26.5%	-1.2%	22.6%	0.0%	64.9%	3.4%			
Washer/Dryer	20-Feb	4.3	28.3%	0.5%	23.4%	0.8%	62.8%	1.3%			
Washer/Dryer	24-Feb	4.9	30.2%	2.5%	24.6%	2.0%	58.6%	-2.9%			
Washer/Dryer	11-Mar	5.2	27.7%	-2.0%	22.1%	-2.2%	60.3%	0.8%	29.7%	24.3%	59.5%
Washer/Dryer	26-Feb	5.5	31.1%	1.3%	26.4%	2.1%	58.4%	-1.1%			
Washer/Dryer	9-Mar	5.9	30.3%	0.6%	24.4%	0.2%	59.8%	0.3%			
Washer/Dryer	12-Mar	6.2	30.2%		24.6%		55.9%				
All Loads Shift	18-Dec	0.2	0.2%	-3.9%	-2.8%	-2.1%	100.0%	0.3%	4.2%	-0.8%	99.7%
All Loads Shift	16-Dec	0.9	8.1%	3.9%	1.3%	2.1%	99.3%	-0.3%			
All Loads Shift	14-Dec	1.0	16.7%	-0.9%	9.7%	-1.2%	91.9%	5.5%	17.7%	10.9%	86.4%
All Loads Shift	17-Dec	1.1	18.6%	0.9%	12.1%	1.2%	80.9%	-5.5%			
All Loads Shift	17-Mar	2.6	24.3%	-4.2%	16.8%	-5.5%	83.1%	2.6%	28.6%	22.4%	80.5%
All Loads Shift	19-Dec	2.6	32.8%	4.2%	27.9%	5.5%	77.9%	-2.6%			
All Loads Shift	15-Dec	3.1	36.4%	3.2%	32.2%	4.9%	77.1%	3.9%	33.2%	27.3%	73.2%
All Loads Shift	18-Mar	3.9	30.0%	-3.2%	22.4%	-4.9%	69.4%	-3.9%			
All Loads Shift	20-Mar	5.0	36.6%	-0.9%	30.3%	-1.1%	71.4%	-1.5%	37.5%	31.4%	72.9%
All Loads Shift	19-Mar	5.5	38.4%	0.9%	32.5%	1.1%	74.3%	1.5%			
All Loads Shift	15-Mar	6.3	38.0%	-2.9%	31.7%	-3.5%	78.1%	4.9%	40.8%	35.2%	73.2%
All Loads Shift	16-Mar	6.6	43.7%	2.9%	38.8%	3.5%	68.3%	-4.9%			

Vita

Zachary Wyckoff Sprau was born in Greenville, North Carolina to Dan and Kathy Sprau. He graduated from South Central High School in 2006, and Appalachian State University in 2011 with a Bachelor of Music degree in Double Bass Performance, and a Bachelor of Science degree in Psychology with a Human Services concentration.

Upon graduation from undergrad he accepted a position at Samaritan's Purse International Relief Headquarters in August 2011, and worked in various roles until May of 2013. He and his wife Annie moved to Haiti in May of 2013 where Mr. Sprau worked as the base manager for Samaritan's Purse's ongoing relief and development efforts after the 2010 earthquake. Mr. Sprau has also been a part of the Disaster Assistance Response Team for Samaritan's Purse since April of 2015. Other relief and development experience includes responding to the 2015 earthquake in Nepal as a distributions coordinator and field-base operations manager, and in 2016 as distributions coordinator for relief efforts in Northern Iraq for refugees fleeing from Mosul.

In August of 2015, Mr. Sprau entered graduate school at Appalachian State University to pursue a Master's of Science in Appropriate Technology. While in school, he worked as a graduate research assistant at the Appalachian State University Solar Lab.

Mr. Sprau has also worked in the construction and renewable sectors doing electrical work for Capehart and Washburn Electric, and SunVolt Electric & Renewable Energy. He currently works for SunVolt in Boone, North Carolina and is working towards getting more technical experience in the PV, residential, and commercial electrical fields. Within two years of graduation, he and his Annie wife plan to return to the field in the international relief and development sector where Mr. Sprau hopes to utilize renewable energy and appropriate technologies to address energy poverty in underserved nations.