2017

# An Iterative Pricing Control Scheme For Renewable Integration In Residential Applications Using Inherent Thermal Energy Storage

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AN ITERATIVE PRICING CONTROL SCHEME FOR RENEWABLE INTEGRATION IN RESIDENTIAL APPLICATIONS USING INHERENT THERMAL ENERGY STORAGE

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A DISSERTATION

Submitted to the graduate faculty of The University of Alabama at Birmingham,
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

BIRMINGHAM, ALABAMA

2017

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INTERDISCIPLINARY ENGINEERING

ABSTRACT

Renewable energy continues to proliferate throughout the world as costs decrease and the public desire for clean energy rises. These sources are intermittent by nature, providing added complexity to its integration with existing grid infrastructure. This paper proposes an iterative pricing and energy consumption strategy between a utility and home energy management (HEM) system, acting on behalf of homeowners, with the goal of easing this integration while also decreasing homeowner energy costs, increasing utility profit and minimizing utility energy storage requirements.

The strategy begins with a day-ahead energy cost profile developed by the utility using a mix of traditional and renewable resources. The HEM receives this cost profile and develops a schedule for the home based on preprogrammed preferences. The HEM then estimates its energy usage profile and sends it to the utility, who receives one aggregated profile from all participating homes. The utility then calculates an updated pricing scheme to encourage a shift of usage towards times where generation is in excess of demand. This process iterates until the supply and demand of energy are reasonably aligned, annual homeowner energy costs are decreased and utility profit is increased. Finally, a new fifteen-minute ahead price is sent to the HEM throughout the day to address forecasting errors and is associated only with energy storage devices within the home.

The algorithm's effectiveness was simulated with a group of ten homes. Implementation resulted in an increased correlation between usage and renewable generation from 12% to 40%, reduced the annual energy costs to consumers by 4%, increased utility profit by 2% and decreased energy storage requirements by 46%. A second simulation was performed with highly efficient homes, which resulted in an increased correlation coefficient of 43%, decreased energy costs of 5%, an increase in profit by 6% and a decrease in energy storage requirements of 32%.

Keywords: renewable integration, real-time pricing, home energy management, iterative, optimization, thermal energy storage

ACKNOWLEDGMENTS

First, I would like to thank Southern Company, specifically the Research and Development department, for funding my research and allowing me to further my education while working full time. I would also like to thank Pradeep Vitta for the support and schschedule flexibility that was afforded to me, otherwise this experience would have not been possible.

I am grateful for the experience and expertise shared by my committee chair, Hessam Taherian, who not only provided critical technical feedback but also worked hard to ensure I was aware of best practices for the research process and had all opportunities available to be successful.

I would not be where I am today without the motivation, guidance and support from both my parents and sister. I have never met a harder working person than my Dad and am thankful for the sacrifices he and my Mom made to give me the opportunity to attend college. To Leslie, you graduating and becoming successful before me really showed me that it takes hard work and dedication but that it was all worth it. Nevertheless, just so we are clear, I won three to two.

Lastly, I would like to thank my wife, Jessica, for her unwavering support throughout this whole process and sticking with me through all the late nights and listening to all my frustrations along the way. Without your push and support to be the best, I would have given up a long time ago.

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| | |
|---|---|
| AGC | Automatic Generator Control |
| AMI | Advanced Metering Infrastructure |
| BPA | Bonneville Power Administration |
| CAISO | California Independent System Operator |
| DOE | Department of Energy |
| DR | Demand Response |
| EERE | Energy Efficiency and Renewable Energy |
| EPRI | Electric Power Research Institute |
| ERCOT | Electric Reliability Council of Texas |
| EV | Electric Vehicle |
| HEM | Home Energy Management |
| HSPF | Heating Seasonal Performance Factor |
| HVAC | Heating, Ventilation and Air Conditioning |
| IECC | International Energy Conservation Code |
| ISO | Independent System Operator |
| NEEA | Northwest Energy Efficiency Alliance |

| | |
|---|---|
| NREL | National Renewable Energy Lab |
| PPA | Power Purchase Agreement |
| PV | Photovoltaic |
| RBSA | Residential Building Stock Assessment |
| RTO | Regional Transmission Organization |
| RTP | Real-Time Pricing |
| SOC | State of Charge |

# INTRODUCTION

As demand for low cost and clean renewable energy continues to be pushed globally [1], [2], [3], the need for developing strategies to match demand side resources more closely with supply side electricity availability is becoming increasingly important. This is necessary because certain issues are created when utilizing renewable generation, some of which are often overlooked by conservation groups, such as a lack of base load generation resources and the intermittent (constant cycling based on weather patterns) nature of renewables [4]. Matching electricity supply and demand resources allows the electric generating utility to more fully utilize these intermittent renewable generation resources such as wind and solar [5] which allows the utility to decrease the amount of time it must operate expensive and/or inefficient peaking generation assets which are generally only used to meet high electrical demand over short periods of time. An additional benefit to matching these resources is that it also reduces the amount of energy wasted through spinning reserves on the grid - a spinning reserve is an on-line reserve generating capacity that is operating synchronized with the grid system and is ready to meet electrical demand within 10 minutes of dispatch [6]. This capability is afforded because matching the supply and demand creates less uncertainty in the load disparity and can act like a buffer to account for rapid changes in either demand or generation, which would normally be addressed with spinning reserves.

Another major concern that matching these two entities helps alleviate is that current approaches of integration utilize fossil fuel plants out of their initial design condition for ramping up and down to match the supply with demand. This has been shown through an Electric Power Research Institute (EPRI) study to cause premature failure of the system's components, increasing the cost to generate electricity for the utility while increasing the imbalance with the demand side even further [7]. Furthermore, relying on these plants to match the system demands could potentially offset a portion of the environmental savings seen from renewable generation and will increase local emissions at these generation plants as they will operate at lower efficiency levels than under optimal operating conditions [8], [9]. Finally, matching the supply and demand of energy reduces the amount of time each year where free renewable generation is curtailed and wasted even when the resource is available [10]. With no intervention from electric utilities, this mismatch will only continue to increase as more and more intermittent renewable energy is introduced onto the grid.

The most prominent examples of intermittent renewable energy generation sources are wind and solar photovoltaic (PV). Their addition onto the grid is coming at a rapidly increasing pace [11], [12], therefore there is a growing need from the utility to ensure that homeowners do not encounter an interruption in their electrical service as a cloud passes or the wind ceases to blow.

The consequences that result from this variability not only include grid reliability issues but also the generation output variability can cause large fluctuations in energy delivery costs throughout the day depending on the resource availability and the amount of base load generation currently operating on the system. This is already becoming a reality in some cases, particularly in the mid-west, where prices have reached $0/kWh (free) or even negative where the utility pays the consumer to take the energy during the night while wind is abundant and power demand is low [13]. This represents a large incentive to the consumer to receive low cost energy off-peak and give them the potential to lower their energy costs substantially while also benefiting the utility by helping to balance the grid in times of high or low renewable production.

Additionally, increasing the amount of intermittent renewables on the grid greatly increases the complexity of deploying generation assets to meet the current and future demand. Currently the electric grid is controlled and scheduled based on hour-ahead energy demand forecasts which are used to match hourly energy generation projections. This information is used by the utility to determine the best mix for generation resources that can be combined to meet the load requirements based on fuel costs, ramp rate, capacity, maintenance schedules, emission rates, etc. [14]. The system then designates certain generation resources with fast ramping capabilities such as hydro, combustion turbines, etc. to follow the electricity demand and compensate for any errors in the demand side forecasts. However, with the introduction of intermittent renewable energy generation, an extra layer is added to the complexity of this approach by causing the generation side to vary along with the demand side and very likely taking the load following resources outside their generation capabilities.

## Problem Statement

The factors described above have led to the realization that a relatively low-cost and effective method for storing energy when it is abundant and minimizing the energy production requirements when it is not must be developed if the renewable energy generation era is to continue. This project seeks to addresses this mismatch in energy supply and demand and develops a method for integrating intermittent renewable energy into the grid utilizing some form of distribution level energy storage and existing infrastructure on the customer side through demand response. This concept development can be seen graphically in Figure 1 and is seen as the most economically and technologically feasible approach for the near to mid-term future.

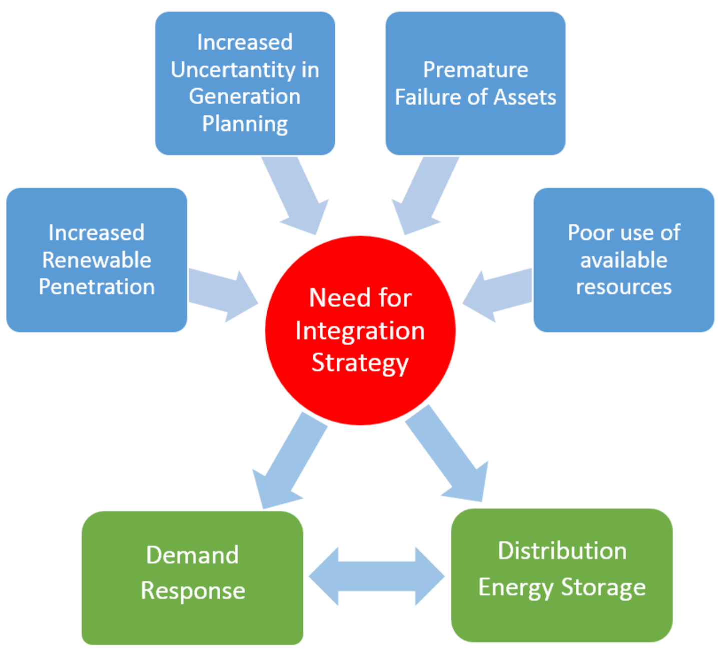


*Figure 1. Overview of Project Concept Development.*

## Project Strategy

It has already been noted that it is very costly and undesirable or sometimes even impossible to manipulate traditional generation levels to match the real-time energy demands of customers when high penetration level of renewable generation resources exists [4]. Therefore, other approaches must be taken to absorb the energy fluctuations caused by the constant increase and decrease of energy output caused by renewable energy generation [15]. Figure 2 describes the way the grid network is setup and can be used to visualize methods available to match the supply with the demand of energy.

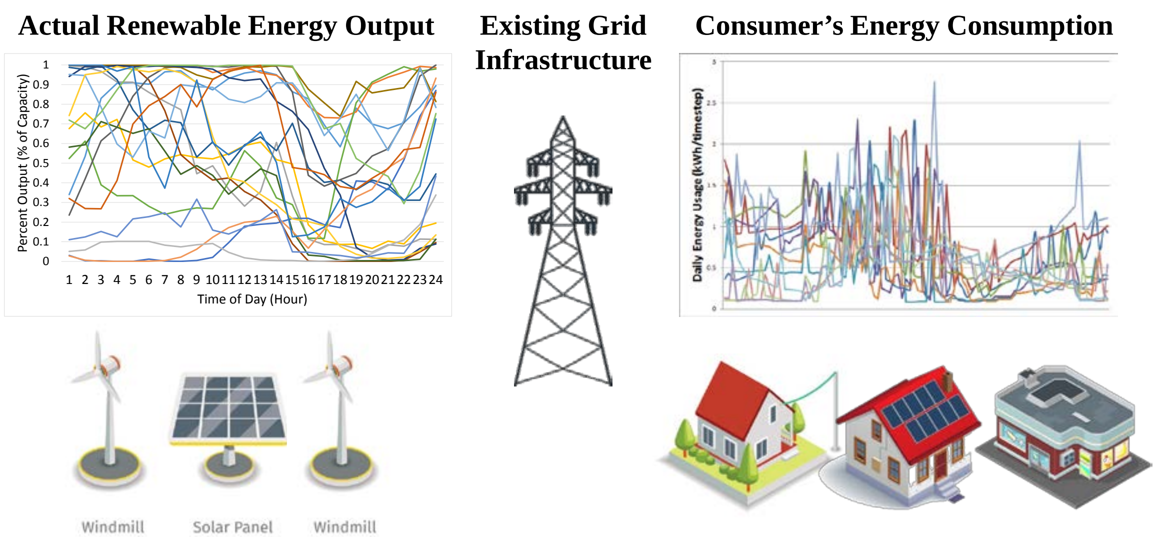


*Figure 2. Grid Interactions with Current Infrastructure.*

The two sides around the transmission and distribution systems in the figure must become more in sync with one another and be able to respond, up or down, depending on what the other is doing. This change must occur at a dynamic pace and can be seen as a balancing act with the existing infrastructure acting as the center of the scale (imagine the Legal Scales of Justice) and the supply and demand for electricity moving up and down to keep the system balanced. Take for example the electricity generation of the wind farm shown in the left chart in Figure 2. The output is steady at 600 MW of output at 7am but the wind suddenly slows from 25 mph to a calmer 10 mph, which decreases the output of the wind farm substantially. To compensate for this reduction in wind energy generation there must either be an increase in some other generation source to match the energy demanded or the energy demanded on the system must be reduced to match the reduction in the wind energy generation. The next portion of the paper seeks to describe the generic proposed approach for compensating for this discrepancy.

*Current Options for Supply and Demand Balancing*

Today there are three major options which can be utilized to help match the supply and demand of energy from situations similar to the example above and prevent issues on the grid which can lead to failures, brown-outs and even black-outs [8]. The strategies are shown below in Figure 3 and are explained in more detail later in this section and in future sections.

1. Vary the output of traditional generation assets (coal, combustion turbines, combined cycle plants, etc.) to follow the difference between the energy demanded from the system and the generation supply, including the variability in renewable generation.
2. Install energy storage into the grid which can absorb energy as renewable energy generation output is high and discharge energy as renewable energy generation decreases.

3. Utilize energy storage existing on the grid such as water heaters, HVAC and plug-in electric vehicles (PEVs) through demand response to absorb or discharge energy as needed.

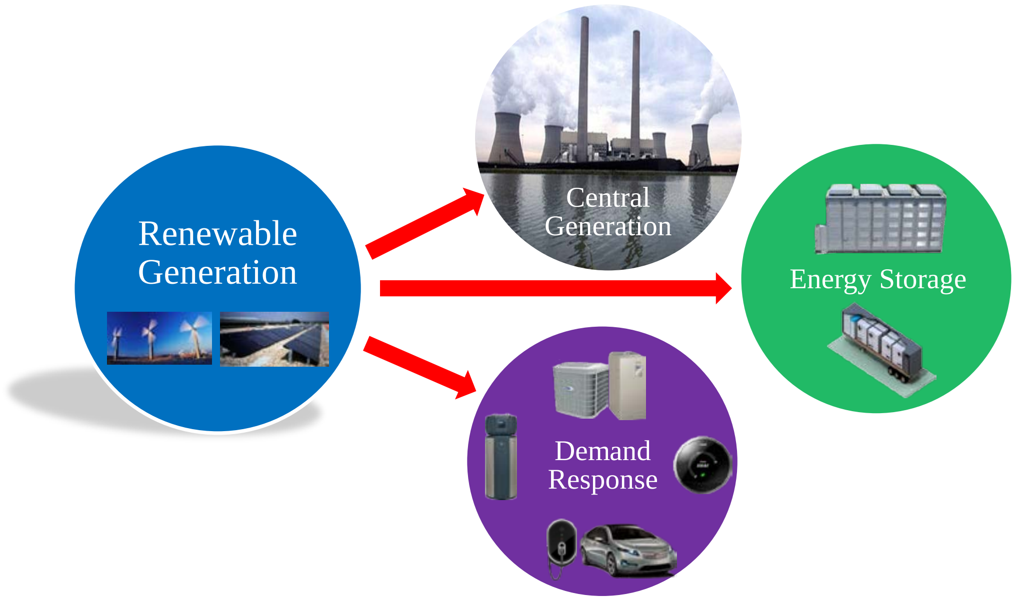


*Figure 3. Current Options for Supply and Demand Balancing.*

*Traditional Generation*. The first strategy available is to vary the output of traditional generation plants (e.g. coal, hydro and natural gas) up and down continuously to match the demand of the system. This section is meant to describe a portion of how the grid is operated today which are seen as relevant to this research topic and is only described at a generic level. This information is intended to be used for background support material for the reader to understand some of the complexities associated with operating an electric grid.

The most important thing to note about the current operation of the electrical grid is that it is continuously operated in real-time since there is little to no way for the utility to store the energy once it is produced. This implies that the energy must only be generated when it is required or demanded from the energy consuming devices on the grid, however there are relatively few parameters at which the grid can be controlled. These include things such as voltage readings, frequency guidelines and import/export energy readings between a utility's physical boundary and another utility's through their interconnection.

To plan for generation resource a utility develops an inventory of their generating units and purchasing options – or demand response options where applicable. The units are put into a "stack" from least costly to operate to the most expensive and are dispatched in the order to meet the system's energy demands. Note that the cost of operation is a very broad term and includes things such as maintenance schedules, fuel costs, environmental costs, heat rate, start up and shut down costs, etc. [14]. This process is generally performed as an hourly day-ahead forecast based on projected hourly energy demand at which point the units are committed to ensure they are online when necessary [16].

This process is then re-optimized on an hourly basis throughout the day with intra-hour discrepancies being accounted for through different reserve options, known as *operating reserves* which are basically capacity that is available and awaiting dispatch beyond what the demand on the system is forecasted to be. The first type of operating reserve is regulating reserves which are setup to follow advanced generator controls (AGC) to account for rapid variations in demand by ramping available, on-line, generating units up and down. The AGC signal is determined based on the grid control parameters mentioned earlier but focus mostly on maintaining the expected import/export of energy at the utility's interconnection. The second type of operating reserve is a contingency reserve which purpose is to be available in the event an operating unit trips and is unable to produce generating capacity suddenly. This type of reserve is often referred to as a spinning reserve since it is required to be available on the system in a very short time period; therefore, it is required to be synchronized with the grid and available for dispatch within ten minutes [6]. Thirdly, electric utilities are beginning to add flexible generation reserves which are intended to respond to additional changes on the grid that are not captured in the other reserve categories and are used to meet ramping needs between dispatch intervals – see the CAISO report on the “Duck Curve” [17].

*Grid Scale Energy Storage.* The second approach for integration is to introduce energy storage onto the system which can be used to store large amounts of energy (and power) while demand is low and renewable energy generation is high and release this energy as demand increases [9]. This option can require very high capital investments from the utility and, for the most part, the technology has not been proven to be a long-term reliable solution e.g. battery storage [18]. However, there are technology options available that can act on a smaller scale, most notably distribution level energy storage, which can have a lesser energy and power capacity but are much more economical and can be used as an enhancement of a secondary option to assist with the integration process. These smaller scale energy storage technologies have been reported to be decreasing in cost at a rapid rate as the technology continues to advance and mature while also not having to deal with the same issues of scalability associated with grid level energy storage [19].

*Energy Storage through Demand Response.* Finally, the third option considered a feasible approach is to utilize energy storage that is already in place on the grid, either consumer or utility owned, to absorb the fluctuations in supply by altering end-device demand. This method utilizes a form of demand response and can signal end devices to either absorb energy or shed energy based on supply availability and can come in the form of an economic incentive to the customer. Demand response (DR) can be defined several ways and can include many different approaches but according to FERC (Federal Energy Regulation Commission) it is "*changes in electric usage by demand side resources from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized*" [20]. This approach of using DR to address this integration problem is already not unheard of and one study suggests that 50% of utilities facing this integration problem will use some type demand response to mitigate complex commodity management brought on by intermittent renewables [15].

## Choosing the Project Strategy

As noted in the previous subsections, the electric utility industry is currently developing strategies of how to integrate renewables into the grid. To date, these approaches have all been unitary solutions and are individualized from one another. This solitary method of integration leads to potentially significant negative impacts caused to the utility as well as their customer. These impacts could include things such as increased costs of implementation and operation, high homeowner comfort or operational impacts, and even brownouts or blackouts. Therefore, the proposed project is to utilize a demand response approach paired with a distribution level energy storage system to integrate intermittent renewable generation into the grid. This is demonstrated in Figure 4.

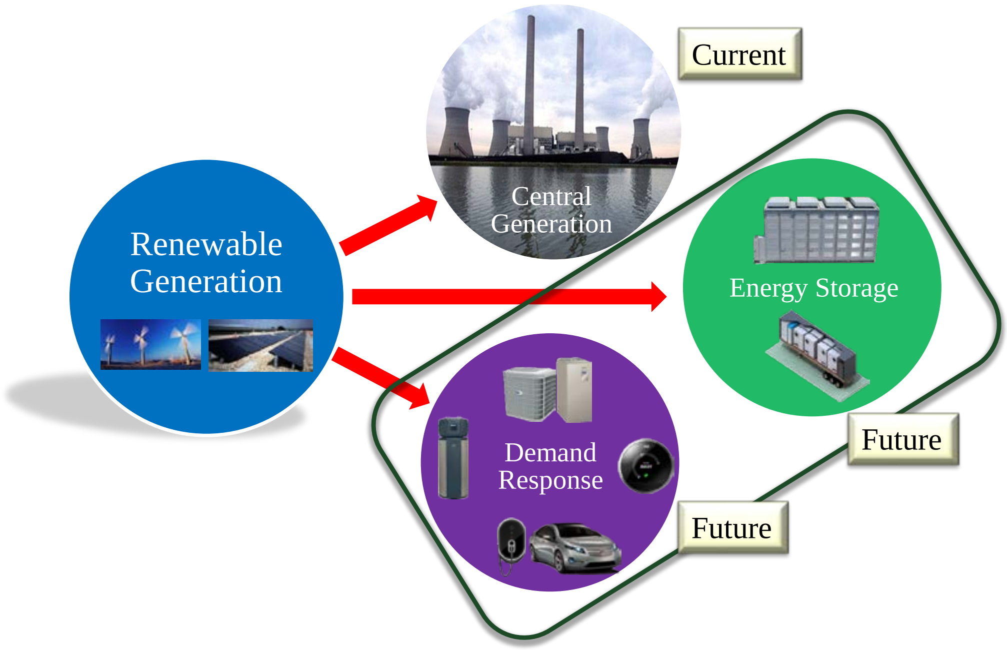


*Figure 4.High-Level Project Research Strategy.*

This project seeks to prove that this strategy is an economically and technologically feasible approach for the short to mid-term to solve the issue for both grid scale and distributed scale renewable energy generation integration. In the long-term future, additional technological advancements in battery and other storage technologies could be used to solve the majority of this issue [21], [22], however the rapid increase in deployment of renewable technologies forces a need for a short to intermediate term solution that can be provided at a lower cost while still being reliable and operationally functional.

*Project Control Strategy Overview*

The following sections describe the research area of the project going forward. The strategy is shown here as an overview and only touches on the major points in the strategy. More details are discussed in subsequent sections that seek to answer relevant research gaps and justify the strategy chosen by providing modeling results.

On the highest level, the overall strategy chosen for research is to utilize energy storage on the grid through demand response through the use of real-time pricing (RTP) rate structures and more sophisticated control algorithms compared to current controls on the grid and distribution level energy storage technologies. For this research, residential homes were chosen exclusively to investigate due to their more simplified and well understood energy usage patterns. However, this strategy is intended to be generic enough to incorporate commercial applications as an extension of the same control algorithms.

The following list focuses on the initial six steps that will be included during the control sequence:

1. The electric utility will develop sub-hourly, day-ahead energy supply projections and convert that into a cost pattern for residential customers. This task will be undertaken similarly to current day-ahead RTP rate structures and will be estimated based on demand projections from historical Advanced Metering Infrastructure (AMI) data, weather patterns, etc. The hourly energy costs developed will take the traditional energy generation source costs and include critical information from projected renewable energy generation output from the utility scale (this step should not consider consumer owned distributed generation output at this point as this will be considered as a negative energy consumption from the home). An example of

this is shown in Figure 5 which is used as an illustration of what a pricing scheme would resemble. This process will output a cost data set that includes fossil fuel generation as well as renewable sources.

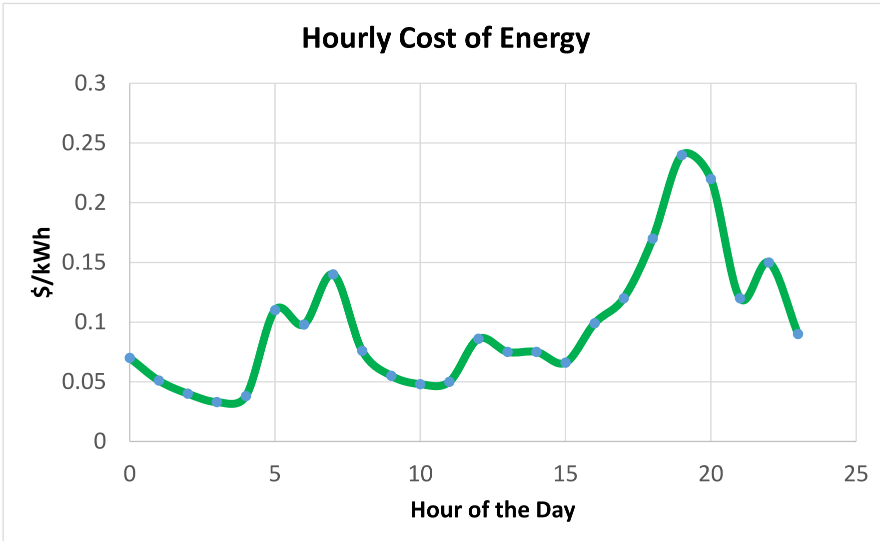


*Figure 5. Example Time-Varying Cost of Energy*

2. This developed hourly energy cost information shown in Figure 5 will be sent from the utility to the residential homeowner, as shown in Figure 7.

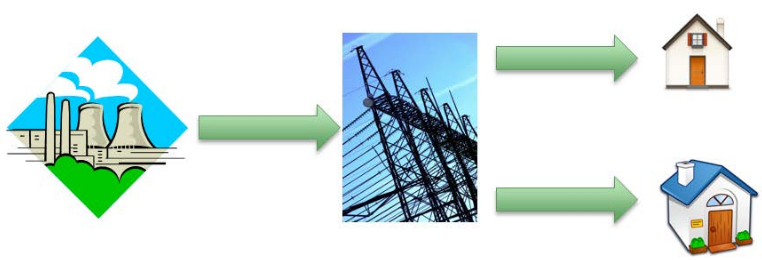

*Figure 6. Flow of Pricing from Utility to Consumers*

The homeowner then inputs the pricing information into an advanced home energy management system and builds granular energy consumption profiles, which are based on pricing and their specific homeowner preferences. Note that this will change from homeowner to homeowner and will ultimately be in the homeowner's complete control to use energy as they wish. This is illustrated in Figure 7 where the control system combines energy costs and homeowner preferences to develop a daily load schedule for appliances.

| Hour | Energy Cost ($/kWh) |
|---|---|
| 0 | 0.07 |
| 1 | 0.051 |
| 2 | 0.04 |
| ... | |
| 20 | 0.22 |
| 21 | 0.12 |
| 22 | 0.15 |
| 23 | 0.09 |

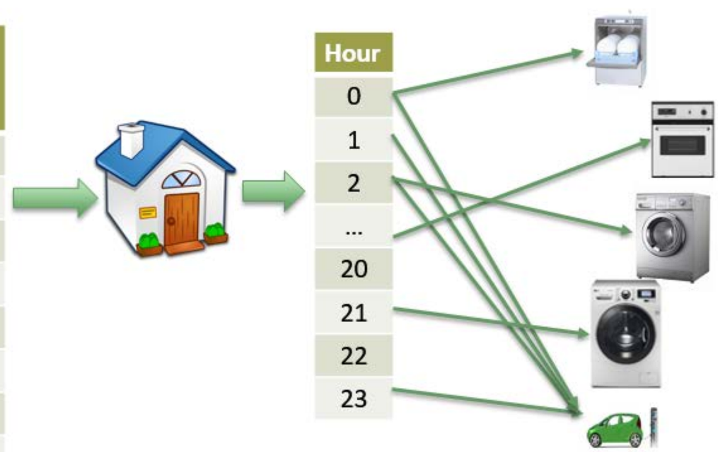


*Figure 7. HEM Optimizing Energy Usage based on Preference and Energy Cost*

3. Once each home within the distribution network has developed their daily schedule for both energy demand and usage, the energy usage profiles are aggregated and sent to the utility as one combined load shape. An example of this is shown in Figure 8.

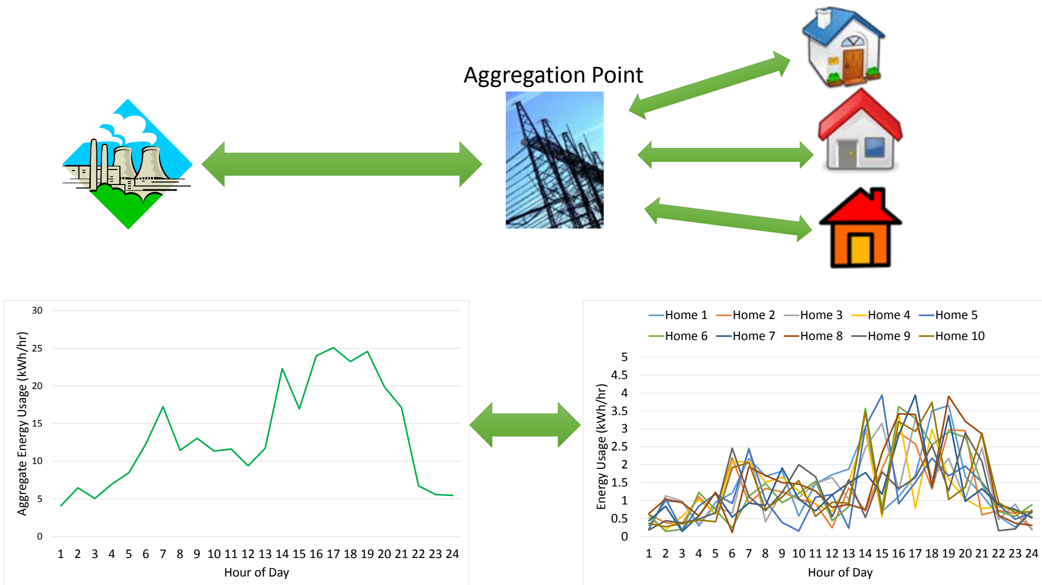


*Figure 8. Energy Usage Information Aggregated and Sent to Utility.*

4. The electric utility then takes this information, combines it with details about the available distribution level energy storage capabilities for the day, and develops an optimized energy storage dispatch strategy to achieve the lowest energy costs for the load shape scenario. Based on this information the utility then republishes the sub-hourly energy costs to the homeowners as it did in Task 1.
5. Each home then individually receives the new sub-hourly energy cost data and reevaluates its daily energy consumption strategy. Once this has been redefined based on the new energy cost, the system's sub-hourly load shape is sent back to the utility.
6. At this point, steps 4 and 5 are iterated until a reasonably accurate alignment of energy supply and demand can be found. Steps 4 through 6 are shown in Figure 9.

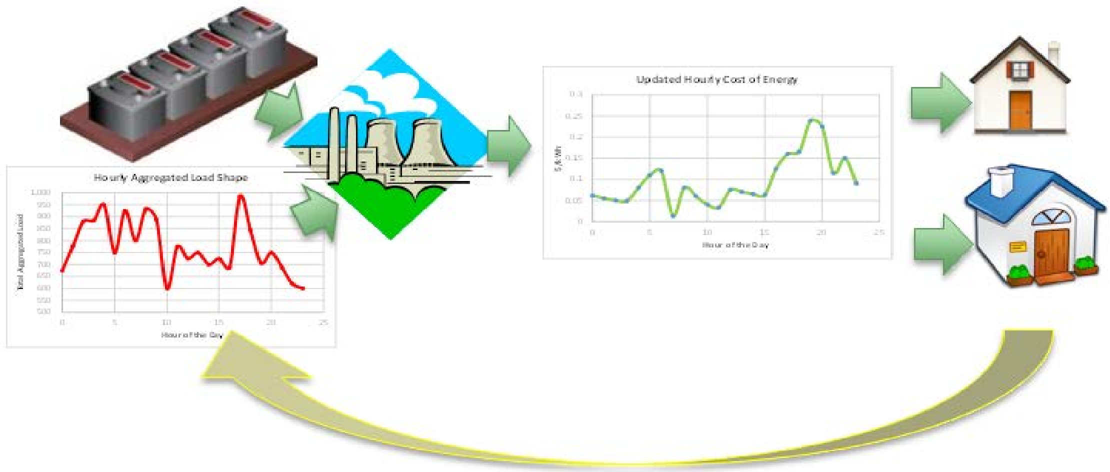


*Figure 9. Iteration of Steps 4 to 6.*

Although this process outlined above will allow the utility to have a reasonably accurate load profile for the upcoming day there will still be two major issues to overcome. The first issue is intra-hour inaccuracies in renewable energy generation output. In addition, there will also be inconsistencies from the energy consumption patterns developed and reported to the utility and their actual sub-hourly (2) and hourly (3) energy consumption.

To help address the issues presented by items one and two, the homeowner's water heating (presumably electric resistance or heat pump) and any on-site energy storage will be implemented on a separate RTP rate which is calculated and redistributed to homeowners on a fifteen-minute basis based on the updated renewable energy generation output and projected energy demand forecasting. This updated RTP rate will only be applicable to energy storage devices within the home and will require additional submetering of loads which for these scenarios makes sense at the circuit breaker level. This can be referred to as step 7 in the control strategy.

The following subsections introduce the topics in slightly more detail and reference the sections of the report where more details can be found into how each step of the control algorithm will be setup and executed.

*Step 1: Utility Hourly Cost Estimation*

The first step in the control strategy requires the utility to develop a fifteen-minute energy cost profile for each day, the day prior. This type of energy cost profile is already done in today's energy markets and are available to customers, [23], [24], although not typically in intervals lower than hourly. These rate structures are also typically only available to large commercial and industrial customers where large energy consumption is present. Even though these rates are typically only available to large customers that have the means available to control their energy usage in a more real time manner through automation, it is not seen as a large hurdle to translate the energy costs on a sub-hourly basis to the residential market. Examples of this type of pricing structure can already be seen in Comed's Hourly Pricing Program [25] which is a program where their customers can pay the PJM market price in either a real-time manner or based on the day ahead PJM hourly wholesale market rate. This rate is a pass through of PJM market prices to customers which does not exist throughout the country but all energy markets would have some type of market cost mechanism to allow for the utility to implement a similar type of rate structure. Additional details on the rates are discussed in the section titled *Rate Structures* on page 26.

*Step 2: End-Device Load Management Selection Process*

The second step in the process begins with transmitting the pricing rates to the homeowner. This can be done today using different automated metering infrastructure (AMI) that is used for billing purposes and is used in current rate structures similar to the ones described in Step 1. Other methods of delivering the rate structure can be implemented and the control strategy is agnostic to the method of delivery. The key is to have the rates available and to be received by the homeowner's home automation system.

Once the pricing schemes are delivered to the homeowners, a home automation system must be in place that is capable of receiving the energy costs as an input and is connected to the necessary appliances with the ability to control their operation and have scheduling capability. The key appliances in this control algorithm are the HVAC through the thermostat, electric water heater, clothes washer and dryer and the oven. These devices are all commercially available as of this writing by multiple large manufacturers.

In the future, this profile will be developed with systems similar to the research performed in [26], [27], [28], [29], [30], [31], [32], [33], [34], [35] and will be tailored to the homeowner's preferences and ultimately be fully controllable by the end user. These systems utilized advanced optimization algorithms and cost minimization techniques which replicating is out of the scope of this project. For the research and model presented, a simplified home automation controller was developed to demonstrate the results which can be improved as more advanced home optimizations are put in place. Additional details can be found in the section titled *Load Management within the Home* on page 30.

*Step 3: Delivering Energy Consumption Profile to Utility*

Individually all the homes in the program will develop their daily load shape based on when their appliances will operate and forecasted HVAC usage. These individual energy profiles will be combined into aggregate load shapes as the information gets closer to the utility. This can be done at a community, substation or down to the neighbor level with the intent being at each layer, less and less data sharing is required. An example of this communication and data architecture is shown in Figure 10.

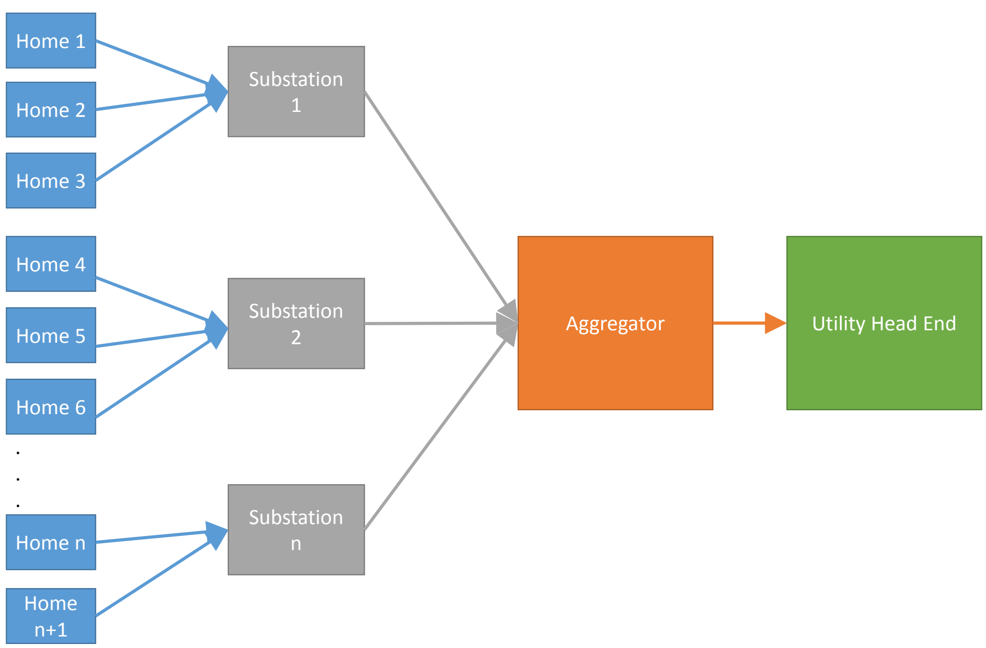


*Figure 10. Tree Communication Setup Example*

*Step 4: Aggregating Energy Usage and Combining with Energy Storage*

Once the utility receives the combined load shape from all of the participating homes, the next step is to include any energy storage the system contains. This will further enhance the ability to shift energy usage from low renewable energy generation times to over-generation times by storing energy within a battery or similar technology. This flexibility added to the system gives the operator and grid-controls many options of how to better optimize the grid but for this study, cost reduction by aligning energy usage with generation is assumed to be the priority. However, this does require some type of control logic to not charge when prices are above a certain threshold and discharge when the energy prices are below a threshold. The control algorithm and sizing method can be seen in the section titled *Scaling Renewable Energy Output* on page 61.

*Step 5: Iterating the Energy Usage Profile Based on New Energy Costs*

Now that the utility has received the energy usage load shapes for all the homes in the program for the upcoming day and combined that with an optimized battery dispatch, the algorithm now recalculates a price of energy for each timestep and sends that information back out to the individual homes. These new energy costs are based on the fifteen-minute difference between the energy usage in that time period and the renewable energy generation for that same period. If the energy usage is greater than the renewable generation, the energy cost will increase to incentivize the homeowners to shift their usage to lower cost time-periods. These lower costs time-periods occur when the renewable energy generation is higher than energy usage, which drives the cost lower with each iteration. Once the homeowner receives the updated price, their home automation system then develops a new fifteen-minute profile for the upcoming day based on the new energy costs and their previously entered preferences. The information is then fed back to the utility as previously described. The method for updating the energy costs to be resupplied to the homeowner is discussed in the section titled *Calculating an Updated Fifteen-minute Energy Cost* on page 87.

*Step 6: Continue the Process until Reasonable Alignment Occurs*

At this point, the components of the control algorithm have been put into place and implemented between the utility and the homeowner. The process is then repeated multiple times until a reasonable alignment of the usage and generation occurs. For the purposes of this model, a set of parameters are established to demonstrate the concept but reduce the computing power required to run the system to that of a desktop PC. These parameters include to reduce the annual energy costs to all of the homeowners, increase the profit by a minimum of 1% while decreasing the energy storage requirements by 15%. This portion of the control algorithm is discussed in the section titled *Modeling the Control Algorithm* on page 98.

*Step 7: Supply energy storage systems an updated RTP rate*

Since the daily schedules are developed for each home on a day ahead basis, there will ultimately be errors in daily forecasting for both renewable energy generation and energy consumption. To help alleviate these forecasting errors, a final step is introduced in the control algorithm. This final step works on a fifteen minute ahead forecast of both energy generation and consumption and sends an updated RTP rate to energy storage specific devices within the homes. This updated cost is meant to encourage energy storage devices within the home – e.g. battery energy storage, electric vehicles, electric water heating – to either consume or shift energy consumption to better align the energy consumption with renewable energy generation. This portion of the control algorithm is explained in more detail in *Adding in Thermal Energy Storage to improve flexibility* on page 91.

## What the Control Strategy is aimed to Solve and What it is not

It is very important to the research project to define what issues the proposed control strategy is meant to solve and what is beyond the scope of this solution. This allows the project to focus on its major research goals without expanding beyond them to solve issues that are better fit for other solutions and technologies.

The core technology involved with this control strategy, homeowner appliances, is a device not owned by the electric utility. This is fundamentally different from virtually all other programs developed today. It can be argued that battery storage is also a core technology but it is seen as a supplemental piece of this strategy and the goal is to minimize its size as much as possible with customer owned assets. This leads to requiring a different set of rules and considerations before focusing solely on the more traditional economic decision making from the utility perspective. These considerations include homeowners comfort impacts and allowing the homeowner to maintain control of their energy usage however they see fit for their lifestyle. This means that for this control strategy, the electric utility can provide a homeowner with a pricing signal meant to incentivize them to shift their energy consumption but ultimately has no control over how much or when the homeowner chooses to use the energy. This is similar to how c homeowner utilize energy today but is in sharp contrast to most demand response programs which typically use direct load control as a means to reduce energy consumption immediately when the utility needs it.

Additionally, since the core technology is owned by the homeowner, a lower limit on a timeframe of events must be made. As was mentioned previously in this report, a major issue utilities face when integrating renewable energy is the second-by-second changes that can be seen on the grid caused by rapid fluctuation in renewable energy generation output. This however is not the focus of the proposed control strategy and is outside the scope of the project. While the energy storage aspect of the strategy may be capable of performing a limited amount of this service, the proposed control strategy is only meant to better align the supply and demand of energy so that the issues related to sub-second or even sub-cycle can be handled with dedicated assets. Therefore, the timeframe chosen for the project is fifteen-minutes, which is seen as adequate for helping aligning supply and demand while also not causing negative impacts to the consumer.

Although PJM operates in timeframes down to five minutes [23] a fifteen-minute timeframe is chosen for multiple reasons, most notably the facts that 1) a residential or commercial customer will only have a limited amount of appliances that can react in a shorter timeframe and 2) to minimize any maintenance issues that could be caused by increased cycling of equipment. The best example for both of these criteria is the home's HVAC system. For the first situation, a home's HVAC system will typically take several minutes of operation to reach a steady-state of operation [36] where the output of the system increases throughout that time while energy consumption stays relatively constant. This means that ideally an HVAC system should operate for longer run times at a smaller kW capacity and without frequent on and off commands. The second reason listed is done to prevent rapid cycling of the HVAC system. While [36] points out that efficiency can be negatively impacted by operating the unit for short timeframes, turning equipment on/off rapidly can cause increased maintenance issues and decreased lifespan of the equipment.

These constraints on the control strategy are not seen as limiting factors which decrease its value, rather the whole strategy is seen as a way to help optimize the way energy is consumed to match renewable generation and not as a "fix-all" solution. This in turn will allow other technologies and ancillary services to perform their tasks more effectively and have their required installed capacity and costs reduced.

# LITERATURE SURVEY AND DIFFERENTIATION METHODS

There have been several studies published which focus on developing the best approach to autonomously integrate homes into a variable pricing rate structure with cost minimization to the customer being the common end goal between them. All the systems require some form of home energy management (HEM) system which communicates to a set of the homeowner's appliances and has the ability to control the state in which the appliance is in, e.g. on or off, it can also have control of temperature setpoints on systems such as Heating, Ventilation and Air Conditioning (HVAC) and water heating. This section seeks to discuss a number of these approaches and how they can be used as a tool to meet the overall goal of this project. This section is broken down into four major subsets, the first focusing on the overall control strategy and how previous research can be leveraged to enable this type of algorithm. The second section discusses what type of utility rate structure is the most effective for flattening the overall demand load shape and how this strategy can be used to avoid load synchronization with real time pricing. The third section focuses on control within the home and what local control strategies exist to convert the interval pricing delivered to the home into a meaningful schedule. Finally, the fourth section focuses on how different appliances are labeled and quantified in the load management system.

*Overall Control Strategy*

Previous work in this field has been performed, most notably the work done by Bakker et al. in [32] and [35] which presents a three step optimization methodology which includes building a daily load shape for the house and can be used to find an optimal solution for different use cases by making operating decision for all appliances in real time using a centralized controller. This approach stops short of utilizing any inherent thermal energy storage in the home and its appliances and also does not provide negotiations between the homeowner and the utility to provide a more optimal solution. This approach also provides the utility the ability to perform real-time control of appliances within the home and also leans more towards traditional load control programs which removes the customer's ultimate control of their systems and can lead to comfort impacts and negative homeowner satisfaction. Another noteworthy project is presented by Li et al. in [26] which presents a method to determine the daily energy usage of a home and optimize its performance based on a learned thermal model of the home from thermostat data.

*Rate Structures*

There has been a large amount of research into what types of varying rate structures can be implemented by utilities to encourage customers to more closely align their energy consumption patterns to the cost-to-serve from utilities. Today, typical rate structures do not vary throughout the day, with research from the Brattle Group stating that only about one percent of the United States population is on a dynamic rate structure [37]. These traditional rates change only based on an inclining or declining block rate structure – an inclining or declining block rate is one in which the cost per energy unit increases or decreases after a certain amount of energy is consumed, respectively. However, a more effective method of matching the demand for energy with the supply is to implement a variable pricing rate structure that changes throughout the day, including real-time pricing, day-ahead pricing, time-of-use pricing and critical-peak pricing [38]. This not only closer matches supply costs to rates paid by customers but it also encourages consumers to shift when they use energy to lower cost periods during the day. While encouraging customers to control their usage and shift to lower cost periods is a major goal of variable pricing rate structures, too much success at large scales of the program during a certain time period can actually cause too drastic of a shift and create a new, artificial peak caused by everyone shifting their usage to the lower cost time – referred to as load synchronization [34], [39].

Multiple approaches have been documented in research on how to avoid this problem, the first can be found in [32] as presented by Bakker et al. This research presents a method of randomly assigning energy costs to different customers throughout the day, within a certain band, to spread out and flatten the load shape as an aggregate. This research makes sense on a theoretical level as it would incentivize customers at a different level to use energy at the optimal time and quantity which meets the goals of a variable pricing program from the utility perspective. However, charging customers within the same neighborhood a different cost for energy throughout the day while the cost-to-serve remains uniform between them makes an approach like this nearly impossible to implement in a highly regulated industry. This would be true even if randomization were setup to equalize the pricing structures over time for each customer. The second resolution is proposed in [38] which implements a simple addition of an inclining block rate on top of the real-time pricing component. This allows the customer to respond to true market signals through real-time pricing rates but also allows the utility to cap the number of kWhs consumed at each pricing tier per customer during a particular time block. This approach incentivizes the customer to flatten their load shape to remain in the low-cost tier of the inclining block rate structure while optimizing their building's energy usage to reduce their utility bills, preventing load synchronization from occurring.

A third approach to avoiding load synchronization is presented in this research. By allowing the homeowners in the program across the territory and the utility to negotiate a day-ahead sub-hourly pricing schedule, a true cost-of-service can be achieved and passed along to the customer. The algorithm developed for this research runs through many iterations and negotiations between the homeowner and the utility (see steps 4-6 in *Project Control Strategy Overview* on page 12). This algorithm sends the same fifteen minute, day-ahead pricing scheme to each participant's home automation system who then calculates the energy usage for each time period throughout the day based on that price. This information is aggregated and sent back to the utility. At this point, the algorithm calculates the difference between the energy generation profile (including renewables) and the energy consumption profile on an aggregate and if adjusts the price accordingly. This means that as the energy consumption is greater than the energy generation profile, the price will increase and if the energy consumption profile is less than the generation profile the energy costs will decrease in that time block. This is iterated until certain parameters are met, changing the price at each iteration for each timestep. This will be shown in the section titled *Annual Energy Costs to Home Owners* on page 114 to actually reduce the annual energy costs to the customer while also increasing the profit a utility can make which is shown in the section titled *Profit earned by the Energy Utility* on page 118.

Another issue that must be taken into consideration is the frequency of rate structure changes and how often rate prices are updated. This issue influences three major areas, the first of which is the ability for HEM to optimize the home's energy consumption at the chosen time step. The development of an optimized control strategy requires time and computational power, which could render a previous iteration obsolete if the energy price changes mid-calculation [32]. In addition, secondly, several appliances within a home are damaged with frequent cycling on and off – see an incandescent lightbulb and more importantly the lockout timer on an HVAC system [36]. When the pricing structures are chosen to be too short then the risk of premature failure of the homeowner's equipment becomes important although having a time step too large can minimize the benefits of the variable pricing program. The third majorly impacted area is the communications network that must be implemented to support sending and receiving these pricing signals. Communications networks have come a long way over the past decade there are still many challenges that must be overcome to ensure information can be safely and securely passed between the utility and the customer [40]. Even with these advances, the more bandwidth and throughput of communication signals that are required, the more the upfront and recurring costs for the system will be. Authors in [32] attempted to alleviate the bandwidth issue by developing a control scheme that spreads out the resources and combines them into a tree structure with less and less data being passed at each level, minimizing the communications infrastructure requirements at the utility.

Currently, electric utilities operate down to five minute increments in real-time bidding markets like PJM [23] which calculate locational marginal prices based on grid operating conditions. Other utilities operate their real-time pricing structures based on hourly marginal costs such as Georgia Power's Real Time Pricing – Day Ahead Schedule [24] and PJM's day-ahead energy market [23].

Based on the current industry practices and to accommodate the communications and home owner reliability issues, the modeling in this project focuses on a combined approach. This approach provides day-ahead, fifteen minute pricing to the customer to allow their home energy usage to be optimized but provides cost updates throughout the day based on short-term forecasted renewable energy generation which will be used by the homeowner to control things such as electric water heating (see Interruptible loads in the section titled Categories of Appliances) and any energy storage systems to help compensate for errors in the day-ahead renewable energy generation forecasting.

### *Load Management within the Home*

After the utility provides the customer with interval rates, the customer must then be able to take that information and perform actions based upon it. This is where load optimization platforms come into play and can be used to develop energy consumption strategies to meet the customer's needs while shaping their energy usage around the needs of the utility. Research has been performed in this area and this section summarizes some of the relevant systems found and how they apply to this project. All the systems found have the initial goal of reducing the home owner's energy bill with the secondary benefit of matching their energy consumption with the supply of energy available. The research in this report does not contradict any of those benefits but refocuses the primary objective on matching the home's energy demand with the supply of energy available while also maintaining the home owner's comfort within certain boundaries and lowering their energy bill.

The first set of HEM platforms focus on optimizing a single home's energy use with battery energy storage and time varying pricing. This is the simplest method of optimization which uses a form of energy arbitrage to store as much energy as possible in the batteries when it is at a low cost and then consume the energy from the batteries rather than the grid as prices rise. In [41]**,** a model is built around this concept to develop a Nash equilibrium game theory control method to determine the optimal control method for the batteries in the home. Nash equilibrium is a form of game theory where each player acts separately and selfishly and meets equilibrium when none of the participants can gain by changing their strategy to the game [42]. These control strategies are enacted based on home load shapes, energy supply load shapes which translate into pricing signals from the utility in each time period – generally an hour and generally in a day-ahead market. This means that the utility tries to influence the patterns of the home by utilizing pricing signals but ultimately has no control over any of the customer's loads directly. A similar study was done in [28] which focuses on a stochastic optimization of HEMs when a home has onsite renewable generation and battery energy storage. This study adds in the element of uncertainty in both load demand and generation which is accounted for by their method of estimating the future energy usage impacts from control decisions.

There have been several other research projects found related to this topic and serve as a foundation for this project, however the available research focuses on different objectives. These include factors like solely minimizing the cost to the customer and do not allow the utility to utilize the information to optimize the grid and benefit all consumers served [26], [28], [29], [30], or focus on only one technology in the home [31], or plan to operate in a continuous real-time manner [32], [33], [27], [34] requiring unnecessarily high levels of computing power, communication bandwidth and has a high potential to cause customer inconvenience.

The research of this paper builds upon the separate research performed in the papers discussed in this section but also includes major differences such as a) longer time horizons for scheduling of different appliances, b) overall simulation goals of incorporating renewable generation sources using demand side resources and energy storage to supplement the grid rather than having an additional local fuel based generation source c) optimizing the grid rather than solely minimizing the energy costs to the customer and d) utilizing the same pricing signal to all customers at all times rather than steering customers individually with customized cost signals. These four major differences are seen as gaps in the present research in the area and can be used to improve the work done previously while also making it more relevant to current US energy market.

The first change (a) allows for sub-hourly planning of individual appliances through the use of pricing signals, increasing the granularity of accuracy while also adding rules to the algorithm to prevent the systems from short cycling by implementing a minimum run time. This is done day-ahead. The control strategy also includes a more real-time approach to send a second pricing scheme to energy storage devices which can be used to compensate for errors not seen in day-ahead forecasting. The second change (b) shifts the overall focus of the research from a self-serving algorithm to minimize the cost for one individual to a system which allows the players involved to minimize their energy costs while also working together to optimize the grid and decrease the amount of fossil fuel based generation required to meet their needs. This also allows the utility to ensure they are increasing their profit, providing a business justification. The third change (c) addresses a major flaw with high penetration of real-time pricing rates, load synchronization. This is when virtually all shiftable energy usage moves to the lowest cost period in the day. By including multiple negotiations between the homeowner and utility, this synchronization can be avoided by leveraging the iterations to flatten energy usage out over the true low cost periods. Finally, the fourth change (d) is implemented to maintain fairness to all customers involved. This change increases the complexity of the algorithms required and also increases the number of iterations required but is seen as the only feasible option for field implementation due to the amount of government regulation in the utility industry and maintaining an unbiased control algorithm.

### *Categories of Appliances*

To be able to interact with household appliances in a near real-time manner, the load management system must know which loads can be shifted, started and stopped or ones that are mandatory to operate when the customer requests. Several research reports were found that have investigated this breakdown [34], [28], [43], [44]. The research in [28] utilizes a system that breaks out appliances into two categories; controllable and must-run. The controllable appliances include things like electric stoves, clothes dryers and pool pumps and represent appliances that operate over longer periods of time and the impact to the consumer by interrupting the device is minimal. The must-run appliances are things that could potentially cause the customer a large and immediate impact if their power source were interrupted including a television, a desktop computer and clothes iron. In [43] the authors also include energy storage devices as a final category which can be used to charge or discharge at any time based on market prices, capacity and storage capabilities.

For a more complete categorical breakdown of appliances, more options were needed to ensure that the system can operate with full functionality. In [34], the loads are split into three categories; first are delayed appliances which can be postponed if they are already in the off position but if they are already turned on then they will remain in the on position. An example of this is a washing machine which can generally easily be shifted but cycling the machine mid-cycle could damage the equipment, clothing or just cause unnecessary inconvenience on the customer. The second category are appliances that are interruptible no matter which mode they are currently in – the best example of an interruptible appliance is a water heater since its energy consumption pattern can easily be manipulated due to the thermal energy storage buffer built in with the hot water storage tank. Finally, the third category mentioned are non-interruptible appliances such as a television or a desktop computer. A fourth category is added in [44] which includes appliances that have elastic energy consumption with storage available. The best example of this category of appliances is an electric vehicle (EV) with a varying charge rate. This type of device can have its energy consumption rate manipulated overnight since the only thing the consumer is concerned with is the state of charge in the morning.

# HOUSE ENERGY MODELING

For the research project to be evaluated, a detailed building energy model must be developed which includes all the appliances included in Table 1 along with any others which will be beyond the scope of this project to control. There are several options commercially available which can be utilized for home energy modeling. The first set of software packages are developed and distributed by major HVAC manufacturing companies and provide hourly breakdowns of energy usage for the building and also offer recommended HVAC product sizing based on these models, including Carrier Hourly Analysis Program (HAP) [45] and Trane Trace [46]. These two programs are largely focused on commercial building, are not designed for residential applications, and are therefore not the best option for this project. The second set of energy modeling programs are based off a simulation engine developed by Lawrence Berkeley National Labs for the US Department of Energy called DOE-2 [47], which is able to predict energy usage and costs for all types of buildings – including residential [48]. From this simulation engine, visual based front-ends have been developed including eQuest [49] and VisualDOE [50]. This simulation engine and its associated tools have since been replaced with an updated building energy modeling engine called EnergyPlus which contains additional advanced features such as variable speed heat pumps and thermal energy storage [51]. EnergyPlus is a text based platform, which does not contain a graphical user interface, therefore other software packages have been developed to pass information to the EnergyPlus engine and return the outputs, which can be found at the EnergyPlus website. The most prominent frontend for residential applications is BEopt, which was developed by the National Renewable Energy Lab as part of the US DOE Building America Program to assist engineers in developing minimum energy designs and retrofits for homes across the country [52].

*Building Energy Model and Verification*

For the project a typical home was modeled in BEopt where a reasonably accurate inventory of appliances and their usage schedules were known along with the major structural and architectural features of the home. The home, shown in Figure 11, was chosen because, along with the appliance inventory and architectural data, the author has access to interval meter data and the permission to utilize this information to develop a side-by-side comparison to ensure the accuracy of the thermal characteristics from the BEopt model to the actual performance of the home.

*Figure 11. Model Home for Building Simulation Verification.*

This home is located in a suburb south of Birmingham, AL and is a one story, ranch style home with three bedrooms, two baths and is approximately 1,850 square feet. The physical dimensions of the home were found using satellite imagery software to estimate the various dimensions needed and a thorough walkthrough provided the structural information needed such as windows and types, wall thickness, insulation levels in the attic, etc. This information was entered into the BEopt software package and the layout of the home is shown in Figure 12.

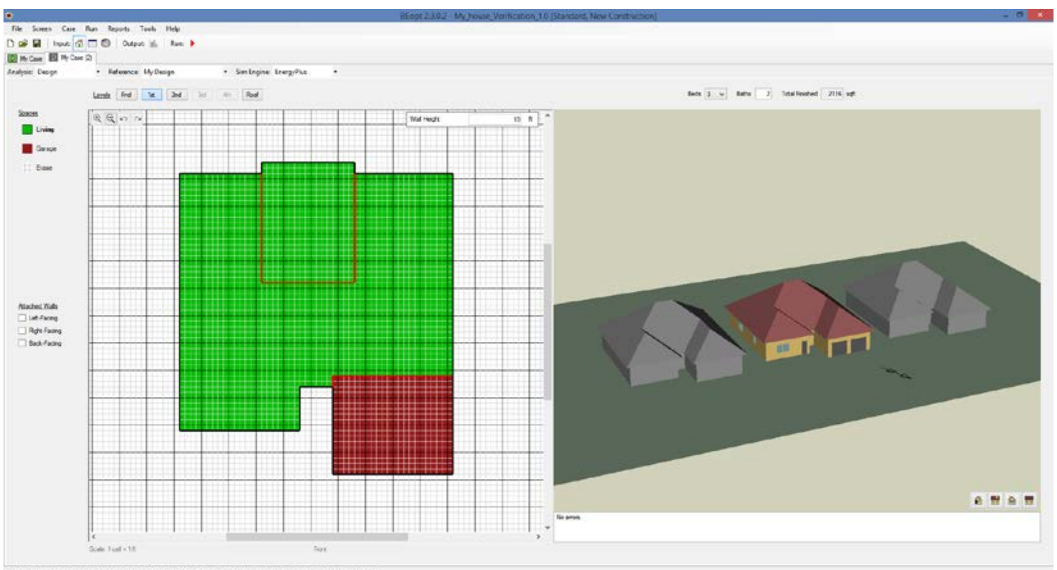

*Figure 12. Modeling Layout and Dimensions of Residential Home.*

The home contains both electric and gas appliances which are all included in the model. The major appliances and their size and efficiency are described in more detail in Table 1 which is utilized as an input to the simulation model while the smaller, remaining energy consuming devices were combined into a miscellaneous category but still entered into the model to account for its energy usage and internal heat gain to the space.

*Table 1. Major Appliance Descriptions*

| Appliance Type | Fuel Type | Size | Efficiency |
|---|---|---|---|
| Central HVAC | Heat Pump with NG Aux Heat | 3.5 tons | 15 SEER/9 HSPF |
| Water Heater | Natural Gas | 50 gal | Approx. 59% |
| Stove/Oven | Electric | 5 kW* | n/a |
| Refrigerator | Electric | 157 W* | Standard |
| Dishwasher | Electric | 1 kW* | Standard |
| Clothes Washer | Electric | 400 W* | Standard |
| Clothes Dryer | Electric | 4.6 kW* | Standard |
| Lighting | Electric | 400 W* | CFL/LED mix |
| Microwave | Electric | 1.1kW | Typical |

* Design wattage but will vary depending on mode of operation

The schedules of these appliances and temperature setpoints are required by the energy model to replicate the internal loads imposed on the space and also to tell the HVAC system what temperature to maintain the space. To do this, several weeks of circuit level sub-metered data and thermostat setpoint data was recorded in one-minute and five-minute intervals, respectively. The first use of this information was to develop detailed schedules for appliances and the thermostat setpoints throughout the day to match the model with the actual energy consumption characteristics of the home. Major appliances were separated and had their own schedules developed to match their energy usage while a miscellaneous category was also created to compensate for the energy usage that was not submetered. This was done by calculating the maximum energy consumption over a fifteen-minute span and then dividing the measured energy consumption at each time-step into that number to create a fractional schedule. The thermostat setpoints were added into the model in fifteen-minute intervals for the entire year corresponding the data gathered from the thermostat. The appliance schedules and thermostat setpoints were input to the EnergyPlus model directly by referencing them in a comma separated variables (.CSV) file which must be done using the tool's built in IDF editor and cannot be done using BEopt.

The final step needed before being able to accurately model the home, a weather file containing actual data for the time period consider must be created rather than relying on a typical meteorological year (TMY) data set. To do this, a software tool developed by Big Ladder Software and the Rocky Mountain Institute entitled Elements [53] was used to combine weather data from multiple sources into the correct format to be modeled in EnergyPlus. The air side of the weather such as temperature, relative humidity and dew point temperature were found using the Iowa Environmental Mesonet [54] website which includes historical weather data for locations across the country. The data was found for the Birmingham, AL airport and includes hourly data for dates specified by the user – for this evaluation August 28, 2014 to August 27, 2015 were used to align with the submetered data on the house. This data was downloaded and imported into a spreadsheet where missing data was replaced with the preceding and/or following weather information and times where multiple readings were taken in a single hour were removed to reduce the data set to 8,760 hours. The second set of weather data needed is the solar radiation data which is not available through [54] but is available from SolarAnywhere [55] and the information was downloaded for the same time scale as the air side weather data. This data was already cleaned before downloading so it was given in an 8,760 format. These two sources of data were then pasted into their corresponding columns in the Elements software and an EnergyPlus weather file was created.

Once the input file (.idf for EnergyPlus) and the weather file (.epw) have been developed, the model is ready to be simulated. Since customized schedules and inputs were made for the input file, this simulation must occur directly in the EnergyPlus launch window shown in Figure 13.

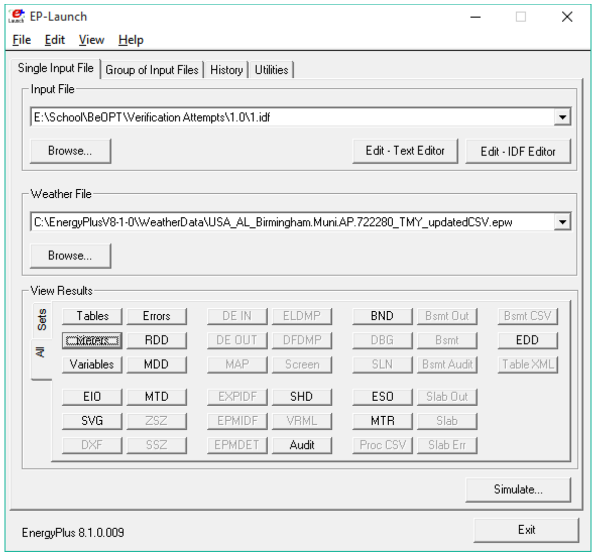


*Figure 13. EnergyPlus Simulation Launcher*

This window only contains two locations to add information which are the paths for the program to find the input file and the weather file. Once these two paths are set, the Simulate icon is pressed and EnergyPlus opens a command line window that shows the simulation status and progress. An example of this is shown in Figure 14.

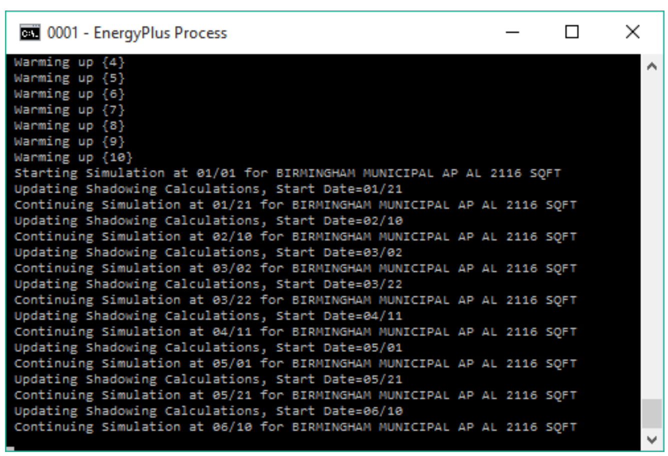


*Figure 14. EnergyPlus Simulation Progress.*

Once the simulation is completed, a list of errors and warnings are shown to notify the user of any missing information, convergence issues during the simulation process or similar issues that occur within the model. However not all issues cause the model to lose any accuracy and may just be caused by extra information in the input file. Finally a list of all the meters entered into the input file will provide an hourly interval energy consumption output for each. The model shows items such as cooling energy, heating energy, HVAC fans, appliances, water heating and a total facility output. This information was utilized to compare the simulation results to the baseline meter data.

Once the model was simulated in 15 minute intervals over the full year, the results from the simulation were compared to the measured baseline for this model. The relevant data from the model that can be compared is from 08/05/2015 through 08/21/2015 which is the timeframe where minute-by-minute sub-metered data is available for the home. The first simulations demonstrated a similar load shape as the metered data, however the magnitude of the peaks were not aligned. The unknowns in the model were tweaked, most notably the air infiltration rate but other items were investigated such as the performance of the HVAC system and the occupancy patterns for people in and out of the conditioned space. The model was simulated several times, making minor adjustments each time to increase the accuracy of the model compared to the baseline data until the model output a very similar total home and HVAC load shape while also matching the energy usage closely. The simulated and measured home and HVAC usage for this time period is shown in Figure 15.

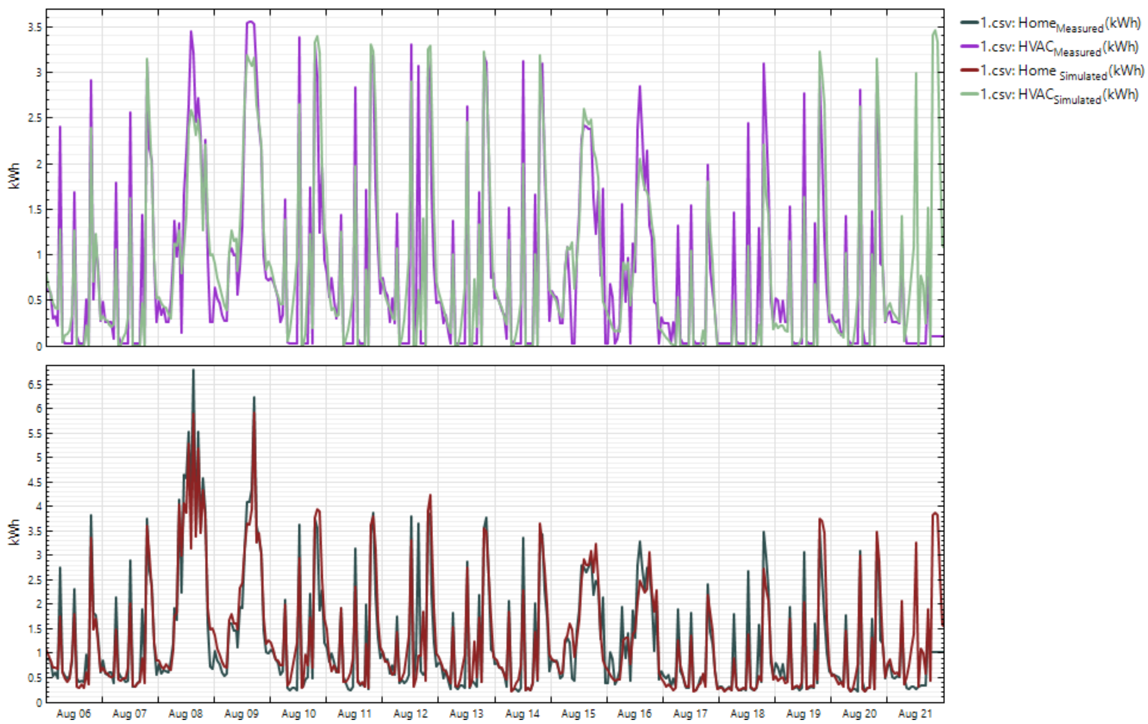


*Figure 15. Hourly Simulation vs. Metered data for Model Home 08/05 – 08/21.*

The data in Figure 15 shows hourly energy usage data for the measured HVAC usage (purple line) and simulated HVAC usage (light green line) at the top and also the whole home hourly usage data in the bottom graph. The bottom chart shows the measured energy usage in dark green and the simulated energy usage in red. As can be seen in Figure 15, the data does not align perfectly for each simulation period but the overall trends are very similar and the energy consumption totals and peaks are nearly identical. This information can be seen in Table 2.

*Table 2. Comparison of Simulated and Metered Energy Usage.*

| | Usage (kWh) | Peak Hourly Demand (kW) | Percent Diff. |
|---|---|---|---|
| Metered HVAC | 306 | 3.55 | 0.5%, 3.4% |
| Simulated HVAC | 304 | 3.44 | |
| Metered Home | 470 | 6.8 | 1.4%, 14.2% |
| Simulated Home | 478 | 5.9 | |

While most parameters in the building model are within a 5% accuracy, the simulated peak hourly kW is slightly above 14% different. This error in the model is related to multiple sources including variations in actual weather conditions from the home site to the measurement source, inaccuracies in sub-meters used for baseline data, missing data from sub-meters. The simulation is still seen as a representative model of the actual home as the load shapes follow each other rather closely in Figure 15 while the overall HVAC energy consumption matched almost identically in Table 2.

Since modeling the control strategy requires a number of houses that can represent a neighborhood or a group of homes that aggregate together and use their combined load shapes to feed into the utilities planning, other building models must be developed that can accurately simulate the effects of changing schedules and temperature setpoints on a home. To do this, the US Department of Energy has released single-family home models in the EnergyPlus (version 5.0) format that meet the requirements in each of the fifty states for energy codes in the years of 2006, 2009 and 2012 [56]. For the purposes of this project, homes in Alabama were chosen which contained heat pumps as their primary form of heating to give the most effective integration into the control strategy. Additionally, the building models have the option of four foundation types; slab, crawlspace, heated basement or unheated basement. This provides a total of twelve building models to choose from, however multiple fatal errors were found when modeling the heated and unheated basement. This was determined to be caused during the transition of versions from 5.0 to the version used in this project, version 8.4. To avoid these errors, the homes chosen for the simulation were limited to the slab and crawlspace foundation types for each code year. Table 3 summarizes the ten homes used in the modeling of this project.

*Table 3. Energy Model Home Types*

| Home Number | Foundation Type | Code Year |
|---|---|---|
| 1 | Slab | 2006 |
| 2 | Slab | 2009 |
| 3* | Slab | n/a |
| 4 | Slab | 2012 |
| 5 | Slab | 2006 |
| 6 | Slab | 2009 |
| 7 | Slab | 2012 |
| 8 | Crawlspace | 2006 |
| 9 | Crawlspace | 2009 |
| 10 | Crawlspace | 2012 |

**not part of DOE models, home model verified as part of this project*

As can be seen in Table 3, the majority of the homes are built on a slab foundation, which follows the general trend of homes being produced today. It is also important to note that Home 3 is the home previously described in this section and is not included in the DOE set of homes.

These homes are used as the basis for the system modeling, however certain changes to each of the homes were made to provide a diversity of loads and occupancies to more accurately simulate a neighborhood or group of homes. Additionally, the home models were initially setup to autosize all water heating and HVAC equipment. This was seen as a way to introduce unnecessary error into the modeling since the HVAC systems would change size based on internal loads during each iteration of modeling which is not realistic to how homes operate today. Therefore, all the autosizing features were overwritten by simulating the homes individually and replacing the autosize commands with the output from the model. Also, occupancy and occupancy patterns were updated and changed to simulate diversity in home and away patterns and to take into account different total number of occupants in the home from a single owner to five total occupants. Lastly the appliance energy usages and miscellaneous schedules were updated to match the styles needed for to model them as a system.

*Developing Fifteen-minute RTP Starting Point data*

To model the system for the project, a basis for the initial set of day-ahead pricing must be developed to describe a day-ahead pricing scheme from the utility. This allows the home's control system to develop realistic schedules based off of this information. To develop this starting point for the pricing scheme, data was pulled from several publicly available sources for both typical costs of supplying energy in today's market and the variability of wind and solar generation sources.

The first set of data needed is a historical annual real-time pricing cost structure. This information can be found through publicly available sources for different energy markets throughout the country. This data provides a baseline proxy to correlate the energy demand on the grid for each hour of the year. This allows the model to begin utilizing realistic historical data to estimate the demand which will be seen during the coming day. This data is available for and can be found where electric markets are operated in either an unregulated market such as Texas or in large geographic areas where the grid is controlled and managed by a separate entity than the one serving the end-consumer such the independent system operator (ISO) and regional transmission organizations (RTO) markets. There are several ISOs and RTO located in the US, however the three major are PJM [23] which is located in the northeast, CAISO [57] which is the California ISO and ERCOT [58] which is the Electric Reliability Council of Texas. Since the project consists of modeling in the southeast US, the northern ERCOT market was chosen due to its most similar longitude and climate. The most recent data set available at the time of the download, 2014, was chosen to most accurately represent energy prices which were provided at a wholesale rate. A sample of this data is shown in Figure 16 which shows the hourly cost data for February through April. Note that overall the cost is consistently under $0.10 per kWh but during early March 2014, the wholesale cost of energy spiked to over $1.30 per kWh for a short period of time.

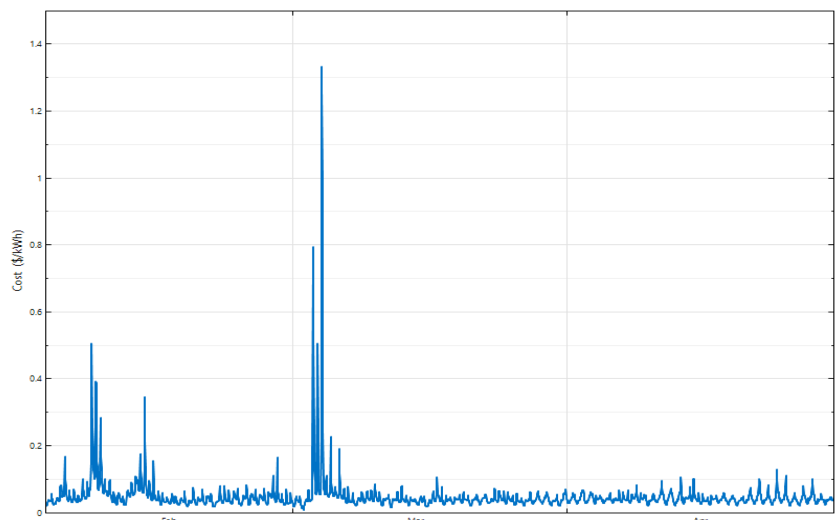


*Figure 16. Sample Real-Time Cost Data from ERCOT February to April 2014 [58].*

The next set of data that is needed for the development of the real-time pricing scheme to be used for modeling is wind and solar generation output over a full year in fifteen-minute intervals. For the wind data, there are two major sources of data which are freely available to the public and both are provided through the National Renewable Energy Lab (NREL). The first set of data comes from a project that focuses on the eastern grid wind integration [59] and contains simulated wind farm output data in ten minute intervals over a three-year period from 2004 to 2006 for 1,326 locations in thirty-four states. However, Alabama was not included in this initial data set so another data set option was investigated. The second set can be found using the NREL Wind Prospector tool [60] which is a graphical map overlay that houses many different types of wind energy data from environmental concerns to wind generation potentials. Within this tool, two sites were found in the Birmingham, AL area (sites 12,747 and 12,865) which are both simulated to be 16 MW generating capacity and provide energy output in five minute intervals.

Finally, the model must have fifteen-minute solar energy output from the same area to simulate a mixture of both major types of renewable energy. This information is also provided by NREL and was used during their transmission renewable generation integration study. This data is simulated at five minute intervals using sub-hour irradiance algorithms and any of their approximately 6,000 sites can be downloaded on a state-by-state basis from their website [61]. The two sites chosen for this project are simulated at 39 MW capacity each and are located in the Birmingham, AL area; one at the airport and the other located southwest of the city along Red Mountain.

The latest year of data available to the public from NREL for wind energy generation was 2012 and the latest available data for solar PV output was 2006. While these dates do not align with each other or the real-time pricing data from the previous section, it was decided to be irrelevant since the modeling is based on typical weather data and is used to prove the concept on a more generic basis which is based on realistic data but not all conditions present during one specific timeframe. All four sites, two wind and two solar, are shown in Figure 17 for a typical daily load pattern averaged over each day in the month of June.

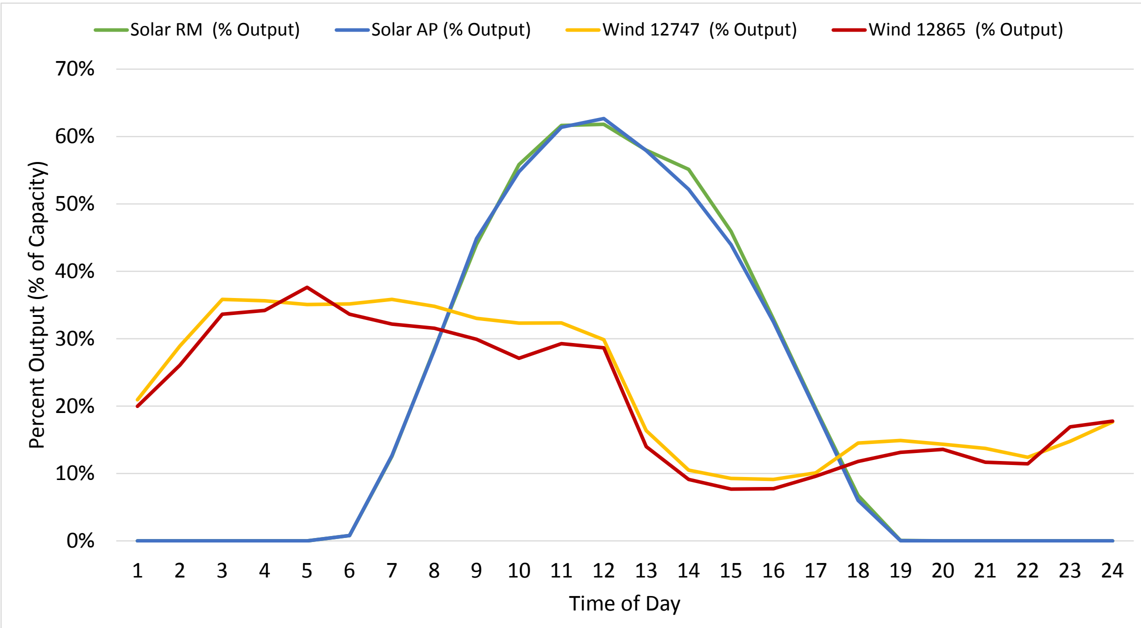


*Figure 17. June Daily Load Profile for Wind and Solar PV Generation [60], [61].*

As can be seen in Figure 17 where the Y-axis corresponds to percent output as a function of total capacity and the X- axis corresponds to the hour of the day, the two wind profiles (red and gold) and the two solar PV profiles (green and blue) follow very similar patterns however they do differ some throughout the month. The other months have a similar profile as June where solar peaks around noon and drops to zero output once the sun sets. Wind has a less defined profile and does not have a set peak and valley since the wind is still active during all hours of the day. Figure 18 shows the same generation output data on an hourly percentage output scale.

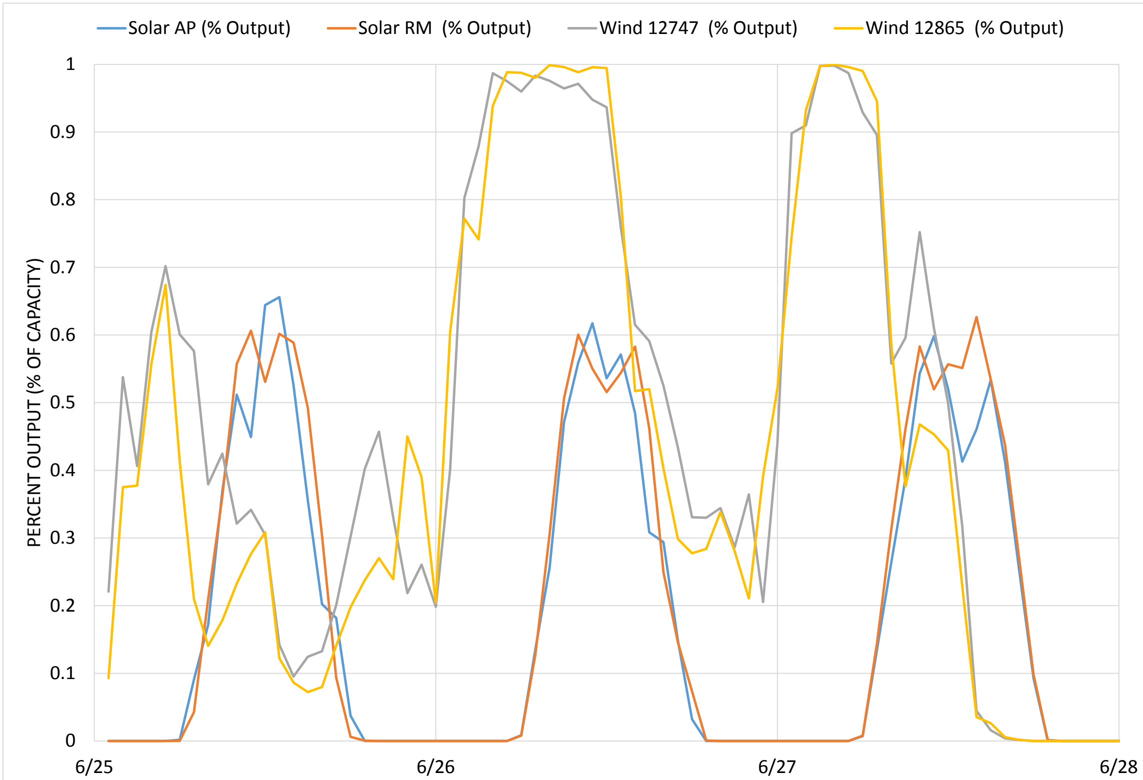


*Figure 18. Hourly Renewable Output Data; June 25 to June 27 [60], [61]*

The data in Figure 18 shows a greater variability throughout the day for each site which becomes an important variable when developing the hourly cost of energy profile and also demonstrates the difficulties in accurately predicting the output of each system throughout the day. The next figure, Figure 19, shows the combined weighted average output from all four sites.

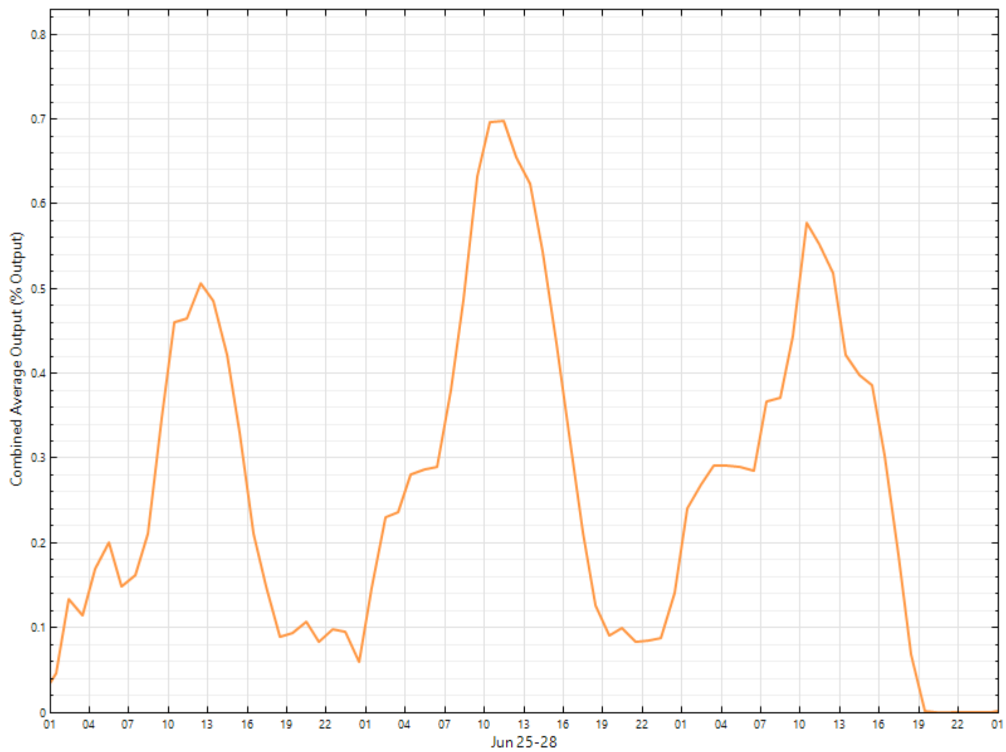


*Figure 19. Combined Weighted Average of all Four Selected Sites [60], [61].*

The data represented in Figure 19 shows three days of hourly generation data weighted for the size of generation capacity of each unit and is what will be used as an input to the price cost model as the electric utility as well as the customer will see only the aggregated output from these sources.

Once a baseline of actual hourly energy costs and renewable generation has been found, the next step is to develop a way to combine these two sets of information and develop a combined, new annual real-time pricing scheme at each fifteen-minute interval. To begin this process, an impact curve was developed to correlate the amount of renewable energy generated in each period to a cost multiplier. For example, if the amount of renewable being generated is very small it will increase the fifteen-minute price of energy whereas if the energy generation is very high it will reduce the energy cost for that period. It was decided that this was not a linear relationship and not a continuous function so the correlation was broken into four separate sections. There is one correlation curve for when energy generation is between 0 and 25% output, a second curve for generation between 25-50%, a third for 50-75% and finally a curve for 75-100%. Note that although each of these intervals use a different cost curve shape, they align at the endpoints as to not affect the results if either equation is used for the transition points. The curve and the associated formulas are shown in Figure 20.

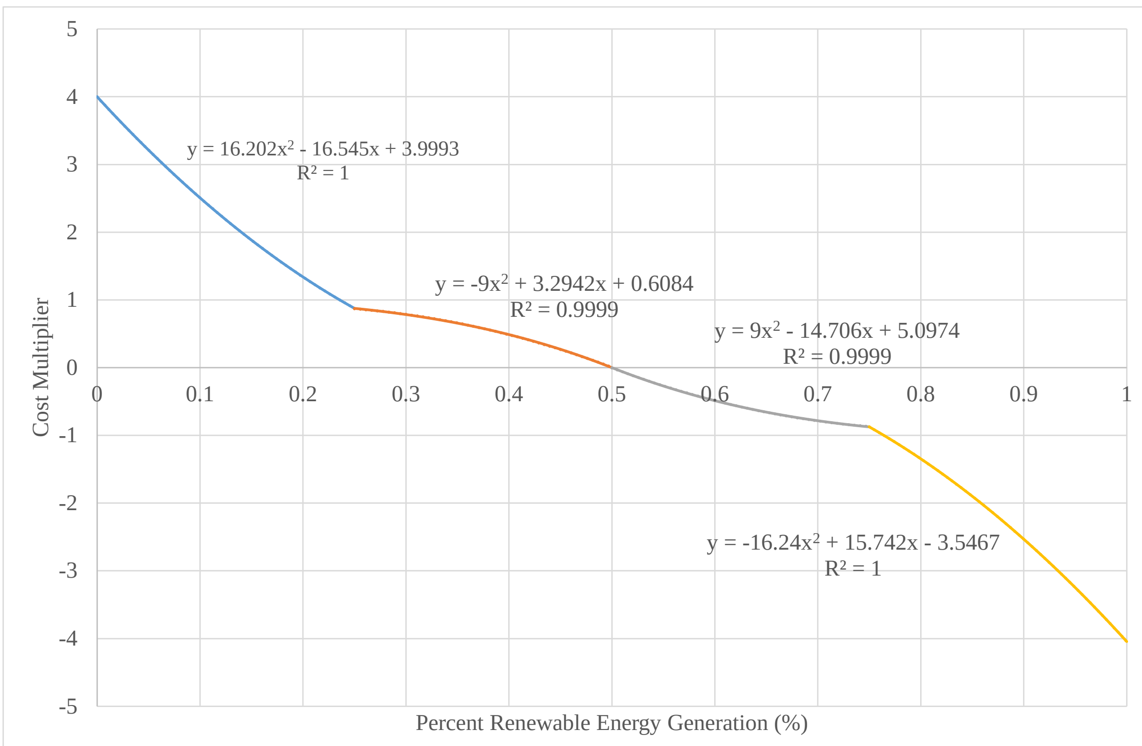


*Figure 20. Renewable Energy Generation and Cost Correlation Curve.*

This curve was developed to account only for the portion of renewable energy in the utility's cost plan, for example if the renewable portfolio standards of California were met at 33% by 2020 [1], this cost curve would be applied to 33% of the total cost of energy to the customer. This assumes that at all times throughout the year, renewable energy makes up 33% of the cost to serve the energy and not necessarily that renewable energy makes up 33% of the generation at any one time. This assumption is a simplification of the actual energy market but detailed analysis on the breakdown of energy supply and costs would require knowledge about the generation stack for the utility, their associated costs and demand on the grid at fifteen-minute intervals which is not publicly available information. Therefore, the assumption must be made that this breakdown is reasonably accurate for the purposes of this project.

A spreadsheet was developed that includes fifteen-minute ERCOT real-time price data (each hourly price is repeated four times to get to fifteen-minute intervals) and renewable energy data from each of the previously described four sites. This tool is then used to calculate the cost multiplier from the renewable energy output at each time step for four different scenarios using the formulas previously described. The first scenario evaluated includes all four renewable sites combined, the second combines the two wind profiles with one solar, the third combines the two wind profiles with the other solar and finally the forth combines one wind with one solar PV system. These scenarios were chosen to investigate the diversity of each combination and look at each for the best fit. Ultimately it was decided to use the combination of all four sources since it would more accurately represent a long term look at renewable generation with larger amounts of diversification of the generation would lead to a slightly smoother load shape.

After the cost multiplier was calculated, the updated cost of energy supply must be calculated. This process includes several variables that are identified in Table 4.

*Table 4. Variables for Rate Setup*

| Variable Type | Amount | |
|---|---|---|
| Renewable Energy Base Cost [62] | $0.025 | /kWh |
| Percentage Renewable Energy Generation [1] | 33 | % |
| Multiplier from wholesale energy costs to delivered cost [58], [63] | 3.15 | |

The information in this table was found from several sources, the first one about the base cost of renewable energy comes from a report released by the US DOE office of Energy Efficiency and Renewable Energy (EERE) about the market of wind technologies [62]. In this report, there is a summary of recent power purchase agreements (PPAs) made with time horizons of the year 2040 where the cost of energy remains relatively constant at less than $25 per MWh ($0.025/kWh). The second variable was chosen to model after the California Public Utilities Commission ruling requiring 33% of energy load come from renewable energy sources [1]. The third variable is a multiplication factor used to convert the wholesale energy costs downloaded from the ERCOT site [58] to the cost of energy delivered to customers.

The spreadsheet is then able to calculate the combined energy cost by first adding the weighted amount of renewable and traditional energy and multiplying it all by the multiplier described above. This process is repeated for each fifteen-minute period in the year and is shown, along with the combined renewable energy generation and the baseline RTP data from the ERCOT market [58] for the same period. This information can be seen in Figure 21.

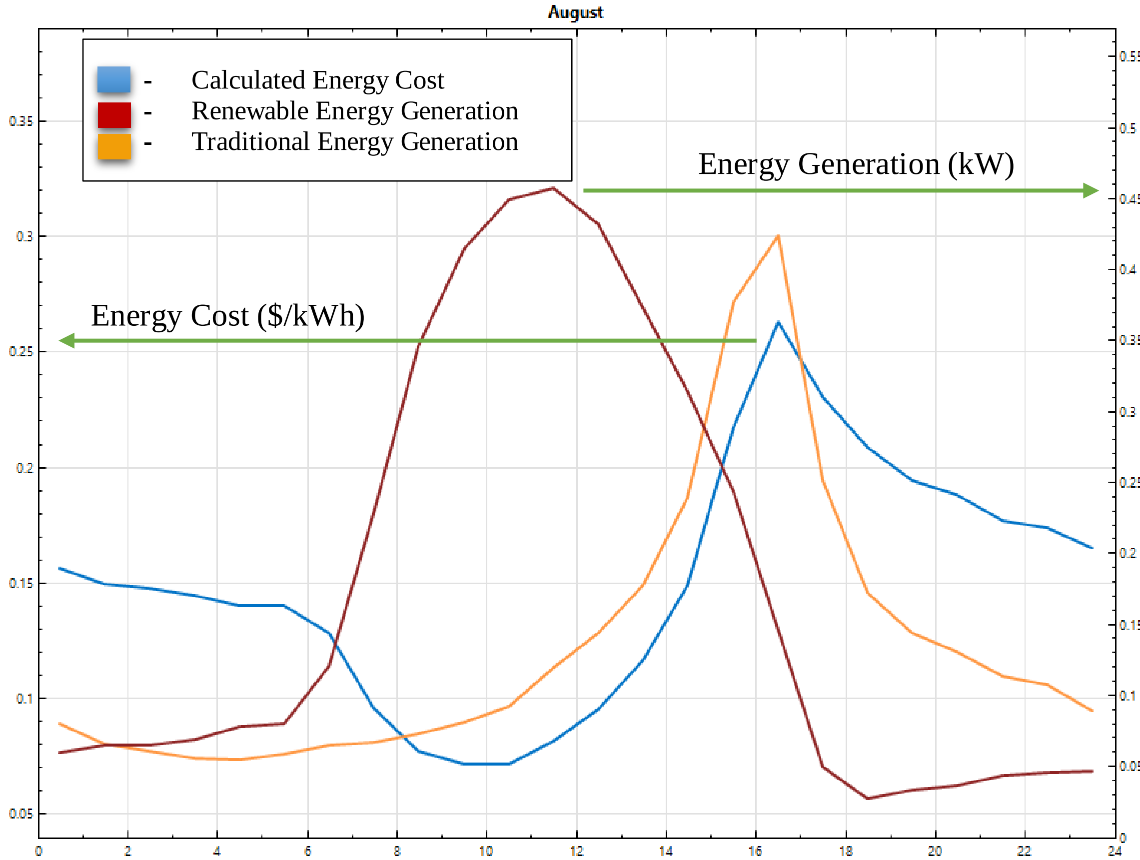


*Figure 21. Monthly Profile of Energy Cost and Renewable Output – August*

In Figure 21 it can be seen that, in general, when the renewable generation (red line) increases, the calculated energy costs (blue line) decreases. This is not always true since the cost is heavily tied to the traditional generation cost as well which can be seen by the orange line in the figure.

*Finding End-Use Load Shapes*

The next type of data needed to build the model is customer energy usage data and their characteristics which is used to come up with a more accurate representation of how human behavior is a factor in energy consumption and to minimize the risk of forcing an appliance to operate in the model when a resident would not want it to. To do this, actual sub-metered data was utilized. This data is made available to the public through a project located in the Pacific Northwest, United States and sponsored by the Northwest Energy Efficiency Alliance (NEEA) and conducted by Ecotope, Inc. in coordination with Bonneville Power Administration (BPA) [64]. The referenced project is called the Residential Building Stock Assessment (RBSA) and contains appliance level sub-metered, fifteen (15) minute energy usage data for 101 homes in the Pacific Northwest starting in April 2013 through July 2014, which can be downloaded from the project's website [65].

While this information is very valuable to the project, the climate region for the data is vastly different from the region of the country being modeled. However, it is reasonable to believe that not all appliance energy consumption and their times of operation vary based on weather, such as a clothes washer and dryer, oven and a dishwasher. For this reason, the project is able to include these non-weather dependent loads as a basis to determine typical load shapes and behavior patterns to expect.

This data was downloaded in a tab-delimited format and imported into a database viewing software to observe. This allows the user to view all the raw data and sort and filter different appliances, components and between participating homes. Since the data set is very large (all combined is approximately 7.5 million rows), randomly selected homes were extracted from the database and put into a spreadsheet. From there, appliance level data was collected and put into a separate spreadsheet that consists of a full year's data for four major non-weather dependent appliances – oven, clothes washer and dryer and dishwasher. Since the initial download, the data has been uploaded to the EPRI Load Shape Library 3.0 [66], which allows users to more easily view and download the RBSA data. This same library is used for additional load shapes and is discussed later in this section.

The data sets for each appliance contain some missing data at sporadic intervals, presumably due to communication and hardware issues from the large deployment project and the vast amount of sensors involved. To help alleviate this issue, a formula was added to the spreadsheet to assign each missing data point to a zero value and then two homes were averaged together to account for any gaps. By averaging multiple homes for a single load shape in the model, a potentially larger diversity set of run times to allow a modeled home to operate each appliance within a certain timeframe. This does not affect the energy usage of the home and is only used to determine when appliances should be operated based on actual home data and will be explained in more detail later. This also takes into account the behavior load shapes over multiple years of a single homeowner. This averaging allows the control algorithm to operate more effectively while also still keeping the appliance energy usage within the timeframes the homeowner wants.

Finally, to provide the algorithm with more options to shift energy consumption of the clothes washer and dryer, dishwasher and oven, the EPRI Load Shape Library [66] was used to input average energy usage patterns into the customer's home automation algorithm. The intent of this load shape data is only to provide additional flexibility to the controller and not increase the energy usage of the home or shift the usage of the appliances outside of their preferred operating hours. Therefore, if there is no energy usage of a specific appliance for a day as determined by averaging the RBSA data, the EPRI load shape data was not input into the schedule to maintain no energy usage of that appliance for that specific day.

Load shapes for both lighting and miscellaneous plug loads are needed to build the whole home load shapes but are not manipulated by the control strategy. For lighting schedules two sources of data were used, the EPRI Load Shape Library [66] and a residential lighting hours-of use study performed by NMR Group, Inc. [67]. These reports provided an hourly overview of what percentage of lighting is used during different periods of the year, included summer and winter months. These end-use surveys were then utilized to generate average lighting usage profiles for a home. For miscellaneous plug loads, the default data in BEopt was used which is pulled from a study performed by NREL for the Building America program and sets baseline energy usage in residential applications to assist engineers when comparing energy retrofit options [68]. To create diversity between the national average home and the homes used in the model simulations a randomized multiplier was added to the default data with the overall energy consumption remaining constant. This was seen as the most accurate way to represent both lighting and miscellaneous plug loads in simulation models where physical metered data is difficult to gather and verify.

## Modeling it All Together

The background information described earlier in this section is utilized as input to model the overall control strategy for the project utilizing detailed annual home energy simulations. An initial model was developed for a single home as a means to troubleshoot the modeling approach and ensure its accuracy and model flow. The model was created utilizing a Matlab [69] script that calls an external command to operate an EnergyPlus batch file to simulate the home's energy usage. The Matlab script calculates the inputs to the EnergyPlus model by reading and writing CSV files which can be used by EnergyPlus as schedule inputs. Figure 22 summarizes the flow of the model simulation.

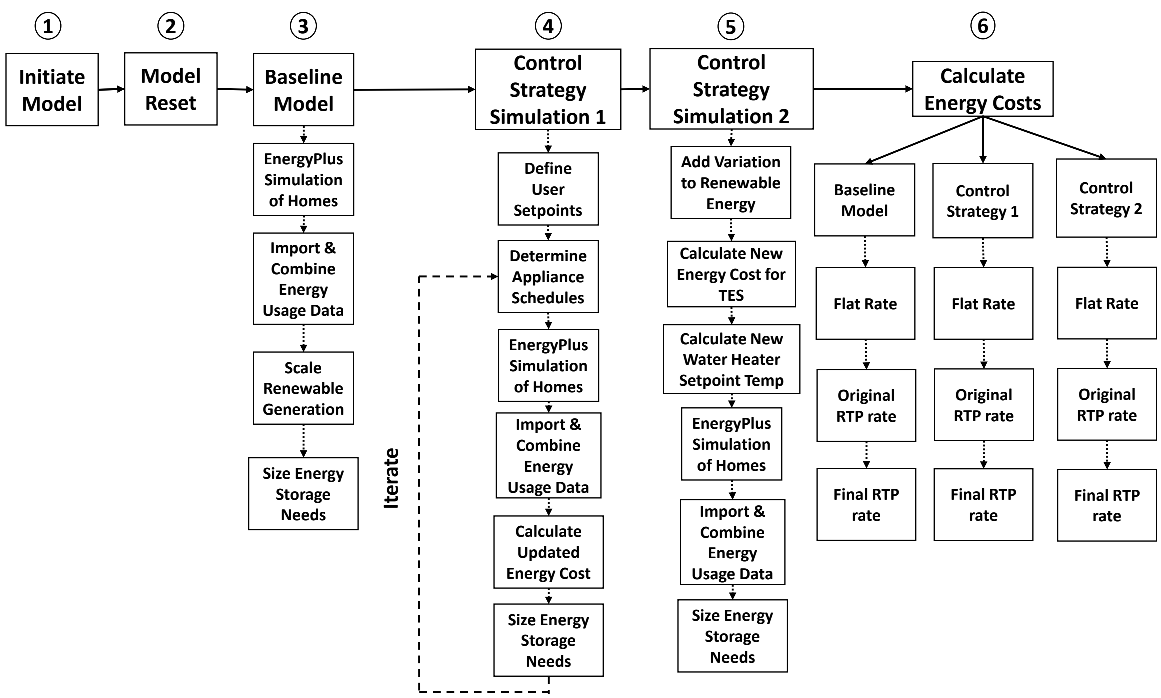


*Figure 22. Simulation Flowchart.*

The following subsections describe the different components shown in Figure 22 and go into detail on how each of the schedules are developed and input into the EnergyPlus model along with how the results from the model are utilized.

*Baseline Energy Model*

To begin the model with an accurate representation of how the homes in the control strategy perform under traditional circumstances with a flat electric rate, compared to the results from the modified control strategy, a baseline model was developed. The model takes the same homes described in Table 3 and uses default schedules available in BEopt for all of the appliances. These schedules were developed by the US Department of Energy under the Building America program and are used as a simulation baseline for comparing energy efficiency retrofits when using building simulation software [68]. All other items remain consistent between the baseline model and all future models except for the four appliance schedules and thermostat setpoints for HVAC and water heating. These changes are discussed in greater detail in future sections of this report starting in

*Implementing the Control Strategy*, Part I on page 67.

For the baseline energy model using one home, for troubleshooting purposes, the first step is to call for an external command using the Matlab function "!" to activate the EnergyPlus simulation to run in the Windows command prompt. For the simulation(s), the built in EnergyPlus batch file titled "RunDirMulti.bat" is used which executes all IDFs –

EnergyPlus input files – in parallel that are located in the same directory using the designated number of processors available. Finally, the Matlab script is paused using the “pause” command. This is done to allow the EnergyPlus files to complete their simulations and output their results before the Matlab script continues as there is no direct feedback from the Windows command module to Matlab indicating when the simulations are complete. The Matlab syntax for this is shown below in Figure 23 and is described further in the section titled *Running EnergyPlus from Matlab* on page 84.

```
%Call Energy Plus to run file
cd('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\EPlusFiles_Mulibatch\BL');
!RunDirMulti_BL.bat
cd('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\MainMatlab');
pause(pause_all);
```

*Figure 23. Use Matlab to Call EnergyPlus Batch File for Baseline Model.*

The baseline energy model then imports the energy usage output files from the EnergyPlus model by utilizing the built-in Import Data Tool for both the facility total and the water heating energy usage. This tool generates a script that imports the fifteen-minute energy consumption data from EnergyPlus’ CSV output files and converts it into a matrix in Matlab. The Matlab syntax for this process is shown below in Figure 24 but a more detailed description of this process is given in the section titled *Importing the EnergyPlus Results into Matlab* on page 86.

```
%% Initialize variables.
i_filename_BL = 'C:\Users\justin\Documents\Dissertation\BCVTBModel_a\EPlusFiles_Mulibatch\BL\i_homeMeter.csv';
i_delimiter_BL = ',';
i_startRow_BL = 2;
% Format string for each line of text:
%   column2: double (%f)
% For more information, see the TEXTSCAN documentation.
i_formatSpec_BL = '%*s%f%*s%*s%*s%*s%*s%[^\n\r]';

% Open the text file.
i_fileID_BL = fopen(i_filename_BL,'r');

% Read columns of data according to format string.
% This call is based on the structure of the file used to generate this
% code. If an error occurs for a different file, try regenerating the code
% from the Import Tool.
i_dataArray_BL = textscan(i_fileID_BL, i_formatSpec_BL, 'Delimiter', i_delimiter_BL, 'EmptyValue' ,NaN,'HeaderLines' ,i_startRow_BL-1, 'ReturnOnError', false);

% Close the text file.
fclose(i_fileID_BL);
% Allocate imported array to column variable names
i_ElectricityFacilityJTimeStep_bl = i_dataArray_BL{:, 1};

% Clear temporary variables
clearvars i_filename_BL i_delimiter_BL i_startRow_BL i_formatSpec_BL i_fileID_BL i_dataArray_BL i_ans_BL;
```

*Figure 24. Import Data from EnergyPlus Output Files into Matlab.*

## *Scaling Renewable Energy Output*

The baseline model is also used to calculate how to scale the renewable energy generation so that results from the overall control strategy can be seen in the results. To do this scaling, it was chosen to simulate the renewable energy generation required to make the system net zero over the course of the year. The Matlab syntax is shown in Figure 25.

```
%% Start my code
csvwrite('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Output_Files\BaselineModel\BLineMeter.csv', EnergyUse_Neighborhood_bl);
xlswrite('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Output_Files\EnergyOutput\Model2\Combined_with_Renewables_mii.xlsx',...
    EnergyUse_Neighborhood_bl,'E2:E35041');
RenOutput_raw = csvread('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\RenewableScale\RenOutput_raw.csv');
%Scale based on total energy usage
% % %Scale renewable energy generation to match the consumption of the home
global RenOutUpdated
global Total_RenGen_Capacity
Total_RenGen_Capacity = 110; %MW/1000 to get to kW
global Renout_max
%Energy based Scale
EPlusUsage_BL = EnergyUse_NHood_BL_sum_bl;
RenOut_generation_bl = RenOutput_raw*(Total_RenGen_Capacity/4);
RenOutsum = sum(RenOut_generation_bl);
ScaleFactor_multip_bl = 1.0;
ScaleFactor_energy_bl = (EPlusUsage_BL/RenOutsum)*ScaleFactor_multip_bl;
RenOutUpdated = RenOut_generation_bl*ScaleFactor_energy_bl;
Renout_max = max(RenOutUpdated);
ECost_BL = csvread('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\EnergyCosts\ZeroEnergyCost.csv');
```

*Figure 25. Renewable Generation Scaling Calculation.*

The script first defines the variable “RenOutput_raw” as the raw data used from the NREL energy generation data [60], [61]. This is done by using the *csvread* function in Matlab which pulls in the available CSV file and converts it into a matrix containing the data from the original file. Next multiple variables are defined as global in Matlab as they will be used later in the control scheme model. The next line redefines the combined energy usage of the neighborhood, for this model it is only one house but will be multiple homes in future models, to be “EPlusUsage_BL”. After that has been completed, Matlab calculates the actual energy generation during each timestep, “RenOut_generation_bl”, by multiplying the “RenOutput_raw” data which is in the form of a percentage by the total renewable energy generation capacity, “Total_RenGen_Capacity”, as defined from the NREL installed capacity data [60], [61]. The generating capacity is divided by four since the energy generation is in fifteen-minute timesteps rather than hourly. The annual energy generation, “RenOutsum” is then calculated by adding the generation in each time period into one total number. The next line, “ScaleFactor_multip_bl” refers to the slight increase in total annual renewable generation that is to compensate for inefficiencies the control algorithm cannot address. Finally, a scale factor is calculated, “ScaleFactor_energy_bl” that moves the renewable energy generation output to the same output, plus the buffer, as the total EnergyPlus energy usage data.

An alternative approach to scaling the renewable energy generation was also investigated however it was determined that using a total energy usage method where the energy generated is equal was more effective. This also aligns the research with projects ongoing in the industry where net-zero neighborhoods are being investigated as a way to cost-effectively install energy storage and renewable generation into the grid, such as a project currently under construction in California [70]. Other details about this can be found in the *Major Challenges Improved from Initial Model Approach* section found on page 164. It should be noted however that the purpose of this research is not to enable net-zero energy communities, rather serves as an appropriate use case but will perform better as more and more homes participate to provide additional load side flexibility.

### *Sizing a Distribution Scale Energy Storage system for the Model*

The baseline model then calculates the size of energy storage that would be required to operate the system of homes without energy from the grid for a defined number of hours within the year. To calculate the storage capacity required, a state-of-charge (SOC) calculation is performed based off the methodology presented in [71] which uses an eight-step process and adds a lower limit on the battery SOC to 30% which is meant to prevent over discharging the battery and causing permanent damage. While the methodology from [71] was used, several steps were not relevant to this application and were therefore skipped. The first portion of the Matlab syntax used to calculate the energy storage capacity needed is shown in Figure 26.

```
%Energy Storage Model
SOC_calc_mBL = zeros(35040,1);
Undermin_charge_mBL = 35041;
Overmax_charge_mBL = 35041;
Battery_multiplier_mBL = 1.5;
BatteryLoadShape_bl = RenOutUpdated - EnergyUse_Neighborhood_bl;
Battery_max_add_fromGrid = max(abs(BatteryLoadShape_bl))*4; %kW;
Battery_add_fromGrid_BL = zeros(35040,1);
Charge_Cost = 0.05;
Discharge_Cost = 0.25;

for row_BLS_BL = 1:35040;
    %increase SOC
    if BatteryLoadShape_bl(row_BLS_BL,1) >= Battery_max_add_fromGrid && BatteryLoadShape_bl(row_BLS_BL,1)...
            >= 0 && ECost_BL(row_BLS_BL,1) < Discharge_Cost
        Battery_add_fromGrid_BL(row_BLS_BL,1) = -Battery_max_add_fromGrid;
    elseif BatteryLoadShape_bl(row_BLS_BL,1) < Battery_max_add_fromGrid && BatteryLoadShape_bl(row_BLS_BL,1)...
            >= 0 && ECost_BL(row_BLS_BL,1) < Discharge_Cost
        Battery_add_fromGrid_BL(row_BLS_BL,1) = - BatteryLoadShape_bl(row_BLS_BL,1);
    end
end

% Decrease SOC
for row_BLS_BL_a = 1:35040;
    if abs(BatteryLoadShape_bl(row_BLS_BL_a,1)) >= Battery_max_add_fromGrid && BatteryLoadShape_bl(row_BLS_BL_a,1)...
            <= 0 && ECost_BL(row_BLS_BL_a,1) > Charge_Cost
        Battery_add_fromGrid_BL(row_BLS_BL_a,1) = Battery_max_add_fromGrid;
    elseif abs(BatteryLoadShape_bl(row_BLS_BL_a,1)) < Battery_max_add_fromGrid && BatteryLoadShape_bl(row_BLS_BL_a,1)...
            <= 0 && ECost_BL(row_BLS_BL_a,1) > Charge_Cost
        Battery_add_fromGrid_BL(row_BLS_BL_a,1) = - BatteryLoadShape_bl(row_BLS_BL_a,1);
    end
end
```

*Figure 26. Energy Storage Sizing Tool Using SOC Calculations – Setup*

The SOC model begins by defining a matrix of all zeros in Matlab the correct size that the final solution will be presented, "SOC_calc_mBL". This is done as a time saving step within Matlab. Next an initial value is setup for both the amount of times the model calculates a value under the minimum state of charge, "Undermin_charge_mBL" and the initial energy storage multiplier, "Battery_multiplier_mBL. These were chosen to ensure the model always ran and converge to a correct solution in a reasonable amount of time. Additionally, the energy storage system load shape, "BatteryLoadShape_bl" is calculated over each timestep in the year by subtracting the energy usage output from the EnergyPlus model(s) from the updated renewable energy generation. The next parameter to be defined is the storage/discharge rate capacity of the system which is set by "Battery_max_add_fromGrid" to be the max energy export or import from the grid to ensure the capacity required is always available. Finally, the energy costs that signal the energy storage system to not receive or discharge energy to the homes are defined. The "Charge_Cost" variable is set at $0.05/kWh to tell the system to never discharge to the grid when the energy costs are below while the "Discharge_Cost" variable is set at $0.25/kWh and does the opposite.

The script then enters a "for" loop and calculates at each timestep the amount of charge or discharge from the energy storage system requested. The fist loop calculates when the energy storage system should receive energy from the grid or renewable energy generation while the second "for" loop calculates when and the amount of energy to be supplied to the homes when not enough renewable energy is present. This information is used as an input to the remainder of the energy storage model, shown in Figure 27.

```
while (Undermin_charge_mBL + Overmax_charge_mBL) >= Outside_chargelimit_max

    Loss_coeff_mBL=0.92;
    BatteryEnergyCapacity_mBL = Battery_multiplier_mBL*1;
    SOC_calc_mBL_a=zeros(35040,1);
    SOC_initial_mBL_a = ones(35040,1)*0.65;
    for row_Bah_mBL_a =1:35040;
        if SOC_initial_mBL_a(row_Bah_mBL_a,1)< 1.0  && SOC_initial_mBL_a(row_Bah_mBL_a,1) >= SOC_min
            SOC_calc_mBL_a(row_Bah_mBL_a,1)= (SOC_initial_mBL_a(row_Bah_mBL_a,1)) + (1/BatteryEnergyCapacity_mBL)...
                *Loss_coeff_mBL*(BatteryLoadShape_bl(row_Bah_mBL_a,1));
        elseif SOC_calc_mBL_a(row_Bah_mBL_a,1)>= 1.0 && Battery_add_fromGrid_BL(row_Bah_mBL_a,1) < 0
            SOC_calc_mBL_a(row_Bah_mBL_a,1)= 1 + (1/BatteryEnergyCapacity_mBL)*Loss_coeff_mBL*(BatteryLoadShape_bl(row_Bah_mBL_a,1));
        elseif SOC_calc_mBL_a(row_Bah_mBL_a,1)>= 1.0 && Battery_add_fromGrid_BL(row_Bah_mBL_a,1) >= 0
            SOC_calc_mBL_a(row_Bah_mBL_a,1)= 1 + (1/BatteryEnergyCapacity_mBL)*Loss_coeff_mBL*(BatteryLoadShape_bl(row_Bah_mBL_a,1));
        elseif SOC_calc_mBL_a(row_Bah_mBL_a,1)< SOC_min && Battery_add_fromGrid_BL(row_Bah_mBL_a,1) > 0
            SOC_calc_mBL_a(row_Bah_mBL_a,1)= (SOC_min) + (1/BatteryEnergyCapacity_mBL)*Loss_coeff_mBL*(BatteryLoadShape_bl(row_Bah_mBL_a,1));
        elseif SOC_calc_mBL_a(row_Bah_mBL_a,1)< SOC_min && Battery_add_fromGrid_BL(row_Bah_mBL_a,1) <= 0
            SOC_calc_mBL_a(row_Bah_mBL_a,1)= (SOC_min) + (1/BatteryEnergyCapacity_mBL)*Loss_coeff_mBL*(BatteryLoadShape_bl(row_Bah_mBL_a,1));
        end
        SOC_initial_mBL_a(row_Bah_mBL_a+1,1) = SOC_calc_mBL_a(row_Bah_mBL_a,1);
    end

    for row_Bah_mBL_ab =1:35040;
        if SOC_calc_mBL_a(row_Bah_mBL_ab,1)>1
            SOC_calc_mBL_a(row_Bah_mBL_ab,1) = 1;
        elseif SOC_calc_mBL_a(row_Bah_mBL_ab,1)< SOC_min
            SOC_calc_mBL_a(row_Bah_mBL_ab,1) = SOC_min;
        end
    end

    Undermin_charge_mBL = sum(SOC_calc_mBL_a <= SOC_min);
    Overmax_charge_mBL = sum(SOC_calc_mBL_a >= 1);
    Battery_multiplier_mBL = Battery_multiplier_mBL+2;
end
```

*Figure 27. Energy Storage Sizing Tool Using SOC Calculations*

The actual energy storage model begins with the “while” loop which runs the model as-long-as the number of instances where the energy storage SOC is outside of the parameters setup on min/max SOC is greater than the maximum set by the user. Within the while loop, variables are defined which are used in the SOC calculation including the initial SOC for the battery at time zero, “SOC_initial_mBL” and the energy storage loss coefficient, “Loss_coeff_mBL” which is a representation for the energy storage system’s round trip efficiency. The battery energy capacity, “BatteryEnergyCapacity_mBL” is used to incrementally increase the energy storage size after each iteration which corresponds to a variable multiplier, “Battery_multiplier_mBL”.

The next portion of the “while” loop calculates the SOC at each time step using the formula provided in [71]. This calculates the SOC at each timestep without considering any practical limits to the technology, namely the maximum and minimum SOC. To create a model where the SOC cannot exceed one or go below the predefined minimum, a second calculation is performed at each time step where an IF statement is included to reference back to the original calculation and if the SOC is less than one but greater than the minimum, the calculation is performed as provided in [71]. However, if the SOC found in the original calculation is greater than one or less than the minimum, the new SOC calculation is reset to where the initial SOC of the energy storage system can be no greater than the maximum or less than the minimum at that timestep. Although this resets the maximum state of charge to initially be the max or min at each timestep, if there is excess renewable energy available, the final calculation can still remain above the physical limitation of the maximum SOC or vice versa for the minimum. To correct this, all values in the new SOC calculation which are greater than 100% are reset to the maximum SOC physically possible.

At this point in the model the number of instances where the calculated SOC is found to be at or below the minimum state of charge as defined by the user is counted. This information is used to determine whether or not to continue looping the calculation. Once this variable has been defined, the minimum SOC physically possible must also be reset to the value defined by the user, similar to before when the maximum value possible was reset.

Finally, the variable "Battery_multiplier_mBL" is incremented up and the loop repeats again until the amount of the timesteps below the battery minimum SOC are less than the total number defined by the user. This information can then be used to compare the effectiveness of the control strategy as it is utilized in all three phases of the modeling process and the variable related to energy storage capacity will decrease as the supply and demand for energy become more aligned throughout the year.

*Implementing the Control Strategy, Part I*

The next portion of the report focuses on the main portion of the control strategy. This includes components from Steps 2 through 6 as described in the section titled *Project Control Strategy Overview* found on page 12. The section discusses how appliance schedules and thermostat settings were developed based on a probability of operation determined using load shape data and on the energy costs provided by the utility during each time step. Next it discusses how an EnergyPlus model for the home is executed with the updated appliance schedules and how the energy usage data is brought back into Matlab to use in future calculations. The updated energy cost data is then calculated for each timestep and sent back to the homeowner. Finally, an energy storage system is simulated to determine the capacity requirements to maintain the system above its minimum state of charge for the desired number of hours in the year before starting the model again using the updated energy cost data.

*Creating Clothes Washer Schedules*

To begin the process of developing the EnergyPlus model inputs, two sources of information which were previously discussed are called into Matlab using the csvread command. The two sources of data are combined line-by-line in a manner to represent the probability of a homeowner operating an appliance divided by the energy costs for that same time period. This input is shown in Figure 28 where ECost is equal to the fifteen-minute energy cost calculated using the method earlier and i_A_CWash represents the base load shape for the clothes washer.

```
%%
% Multiply CWash load shape from RBSA data by the energy cost data line by
%line
i_A_CWash = csvread('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\CSV_Files\Home1\CWash\i_Origin_CWash.csv');
i_C_CWash = i_A_CWash./ECost_mii;
%Find the max probablilty and write in the load factor for each day
i_CWash_PTS_a = i_C_CWash;
[i_CWash_nrows, i_CWash_ncols] = size(i_CWash_PTS_a);
```

*Figure 28. Matlab Syntax to combine Clothes Washer Probability with Energy Costs*

Once the energy cost and load shape probability are combined, the next step of the model is to search for the period during each day where the highest probability of the customer operating the clothes washer but also when the lowest cost to operate is achieved – lowest cost and highest operation likelihood. To do this, the appliance run time and energy usage during each time period must be determined. This information was found using sub-metered data from an actual clothes wash cycle, the energy usage load shape over two cycles is shown in Figure 29. This approach is used for modeling purposes while in reality the customer would be able to choose which time period to operate the appliance based on the provided cost information if desired.

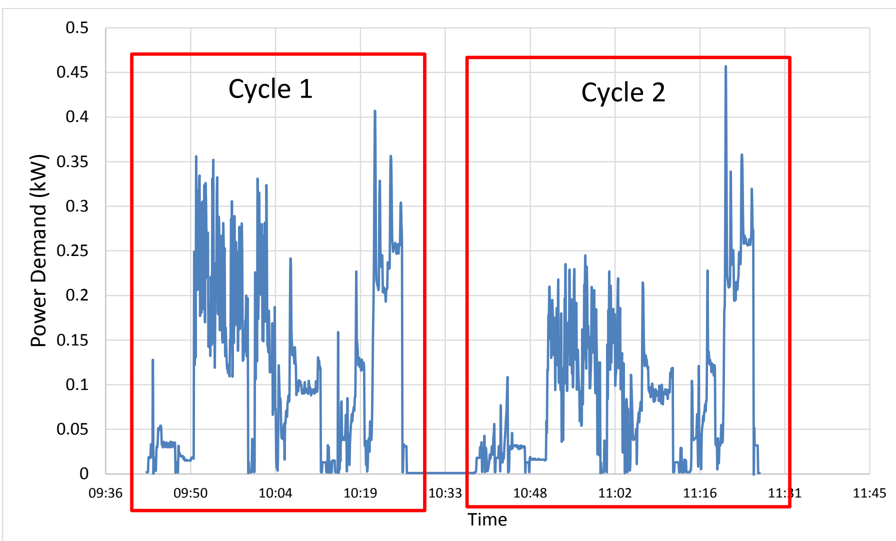


*Figure 29. Clothes Washer Energy Usage Load Shape, as Measured*

Using the information available in Figure 29, the clothes washer's average run time was found to be 45 minutes and the energy usage in each fifteen-minute time step is shown below in Table 5 which was derived from Cycle 1.

*Table 5. Clothes Washer Load Factor*

| | Usage (kWh) | Max Usage Possible (kWh) | Load Factor (%) |
|---|---|---|---|
| Time step 1 | 0.033 | 0.10175 | 32.4 |
| Time step 2 | 0.024 | 0.10175 | 23.6 |
| Time step 3 | 0.027 | 0.10175 | 26.5 |

The Matlab script takes this information and searches for the maximum consecutive forty-five-minute period during each day of the year from the file generated previously by dividing the usage probability by energy cost. When this maximum forty-five-minute period is found, the load factors shown in Table 5 are substituted into their timeslot in a separate CSV file while all other time periods of the day are changed to have a zero for energy usage. This process is repeated for each day of the year and add generates a fifteen-minute schedule for the clothes washer throughout the year (35,040 data points). Although the Matlab script is setup to search for the maximum probability of operation of each day it is known that not all homes will operate all appliances each day of the year. To account for this, the algorithm will fill in all zeros into days where there is a zero probability of usage from the combined data, therefore not running the appliance in the model. The newly generated CSV file is supplied to the EnergyPlus model as the energy usage schedule for a home's clothes washer. The syntax from the Matlab script is shown in Figure 30.

```
i_CWash_Loadfactor_a = 0.324324324;
i_CWash_Loadfactor_b = 0.235872236;
i_CWash_Loadfactor_c = 0.265356265;

i_CWash_DayStartRow = 1;
i_CWash_MaxLocation = 0;
%iterate through the data from the beginning to the end
while i_CWash_DayStartRow < i_CWash_nrows - 95
    i_CWash_k = i_CWash_DayStartRow;
    i_CWash_MaxLoad = 0;
    %find the 45 minute load and its location
    for i_CWash_k = i_CWash_k:i_CWash_k+95
        i_CWash_Load = i_CWash_PTS_a(i_CWash_k,1) + i_CWash_PTS_a(i_CWash_k+1,1) +i_CWash_PTS_a(i_CWash_k+2,1);
        %determine if the load is greater than the previous load - save the value and location if it is
        if i_CWash_Load > i_CWash_MaxLoad
            i_CWash_MaxLocation = i_CWash_k;
            i_CWash_MaxLoad = i_CWash_Load;
        end
        i_CWash_PTS_a(i_CWash_k,1) = 0;
    end
    %change the three maximum values to the specified load factors
    i_CWash_PTS_a(i_CWash_MaxLocation,1) = i_CWash_Loadfactor_a;
    i_CWash_PTS_a(i_CWash_MaxLocation + 1,1) = i_CWash_Loadfactor_b;
    i_CWash_PTS_a(i_CWash_MaxLocation + 2, 1) = i_CWash_Loadfactor_c;
    i_CWash_DayStartRow = i_CWash_DayStartRow + 96;
end
for i_CWash_k = i_CWash_k:i_CWash_k+95
    i_n_CWash = 1:365;
    i_CWash_PTS_a(96*i_n_CWash) =0;
end
 for i_CWash_nrows = 33601:35040
    i_CWash_PTS_a(i_CWash_nrows, 1) = 0;
end
csvwrite('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\CSV_Files\Home1\i_SchCWash.csv',i_CWash_PTS_a);
```

*Figure 30. Matlab Syntax for Clothes Washer Schedule Generation*

*Creating Dryer Schedules*

The same approach was used when determining the dryer schedule as before with the clothes dryer. The RBSA and the EPRI Load Shape Library data was used as a starting point for the initial probability of the appliance operating at any given fifteen-minute period of the year. This data was combined with the fifteen-minute energy costs for the year by dividing the probability of operating by the energy rate. This portion of the model in shown in Figure 31 where i_A_Dryer is defined as the dryer probability matrix and i_C_Dryer is defined as the combined matrix of probability and energy costs.

```
%Dryer - Multiply load shape from RBSA data by the energy cost data line by
%line
i_A_Dryer = csvread('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\CSV_Files\Home1\Dryer\i_Origin_Dryer.csv');
i_C_Dryer = i_A_Dryer./ECost_mii;

%Find the max probablilty and write in the load factor for each day
i_Dryer_PTS_a = i_C_Dryer;
[i_Dryer_nrows, i_Dryer_ncols] = size(i_Dryer_PTS_a);
```

*Figure 31. Matlab Syntax to combine Dryer Probability with Energy Costs*

Again, the next step in the model is to search for the period of each day where there is the highest probability of the dryer operating at the lowest cost. This process takes the most effective run time for energy cost and probability and substitutes the appliance load shape into a CSV file to be used in the EnergyPlus model to simulate its impact on the overall control strategy. For this to occur the fifteen-minute load shape for a typical dryer cycle must be known. A dryer was submetered and energy data was recorded in five second intervals during the span of three complete cycles, all set to automatic mode where the cycle completed once the clothes were sensed to be dry. Each cycle contained different clothing and was meant to get a representation of different cycle lengths and energy usage. This information is shown in Figure 32.

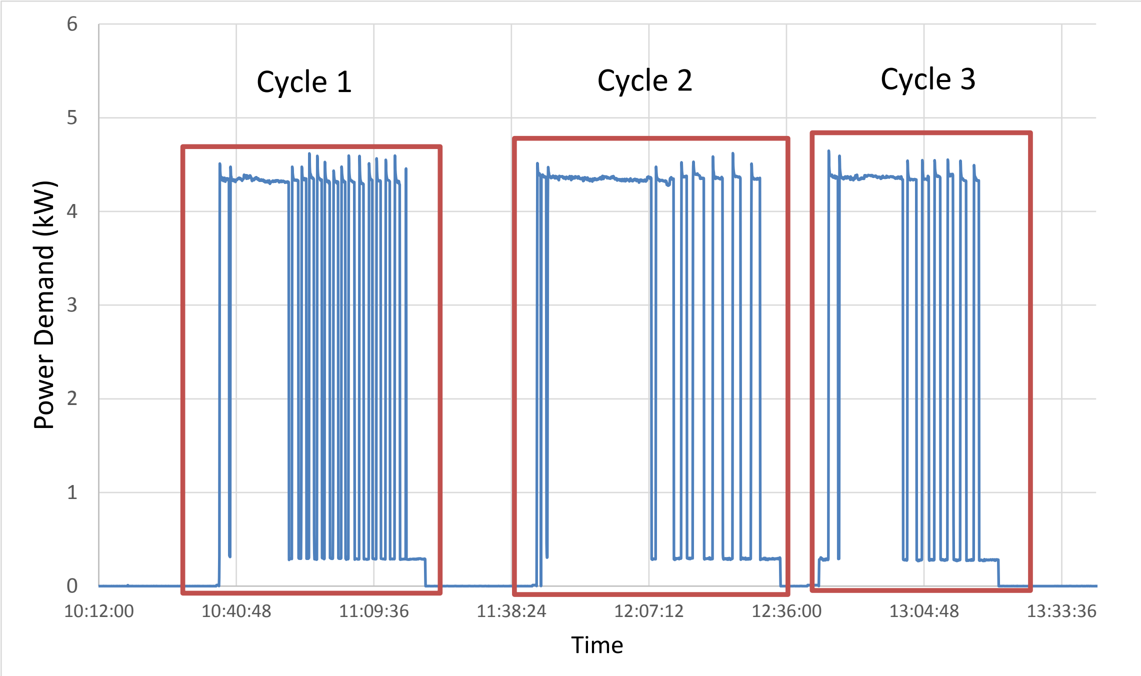


*Figure 32. Dyer Energy Usage Load Shape, as Measured*

This submetered data was then used to calculate a typical load shape for a dryer that can be input into EnergyPlus to simulate the dryer energy usage. To do this the averages were taken and converted into a fifteen-minute load shape over a forty-five-minute time period.

*Table 6. Dryer Load Factor*

| | Usage (kWh) | Max Usage Possible (kWh) | Load Factor (%) |
|---|---|---|---|
| Time step 1 | 0.91 | 0.155 | 78.8 |
| Time step 2 | 0.73 | 0.155 | 63.2 |
| Time step 3 | 0.41 | 0.155 | 35.5 |

The Matlab script then finds the daily location of the maximum forty-five-minute period for the largest probability at the lowest operating cost. The load factors are then input into those time periods while all other schedule values are set to zero, indicating no energy consumption during those times. The script outputs a CSV file which is used by EnergyPlus as the annual, fifteen-minute schedule for the dryer (35,040 data points). The syntax for this operation in Matlab is shown in Figure 33.

```
i_Dryer_Loadfactor_a = 0.7880493613;
i_Dryer_Loadfactor_b = 0.632171466;
i_Dryer_Loadfactor_c = 0.355055207;

i_Dryer_DayStartRow = 1;
i_Dryer_MaxLocation = 0;
%iterate through the data from the beginning to the end
while i_Dryer_DayStartRow < i_Dryer_nrows - 95
    i_Dryer_k = i_Dryer_DayStartRow;
    i_Dryer_MaxLoad = 0;
    %find the 45 minute load and its location
    for i_Dryer_k = i_Dryer_k:i_Dryer_k+95
        i_Dryer_Load = i_Dryer_PTS_a(i_Dryer_k,1) + i_Dryer_PTS_a(i_Dryer_k+1,1) +i_Dryer_PTS_a(i_Dryer_k+2,1);
        %determine if the load is greater than the previous load - save the value and location if it is
        if i_Dryer_Load > i_Dryer_MaxLoad
            i_Dryer_MaxLocation = i_Dryer_k;
            i_Dryer_MaxLoad = i_Dryer_Load;
        end
        i_Dryer_PTS_a(i_Dryer_k,1) = 0;
    end
    %change the three maximum values to the specified load factors
    i_Dryer_PTS_a(i_Dryer_MaxLocation,1) = i_Dryer_Loadfactor_a;
    i_Dryer_PTS_a(i_Dryer_MaxLocation + 1,1) = i_Dryer_Loadfactor_b;
    i_Dryer_PTS_a(i_Dryer_MaxLocation + 2, 1) = i_Dryer_Loadfactor_c;
    i_Dryer_DayStartRow = i_Dryer_DayStartRow + 96;
end
for i_Dryer_k = i_Dryer_k:i_Dryer_k+95
    i_n_Dryer = 1:365;
    i_Dryer_PTS_a(96*i_n_Dryer) =0;
end
for i_Dryer_nrows = 33601:35040
    i_Dryer_PTS_a(i_Dryer_nrows, 1) = 0;
end
csvwrite('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\CSV_Files\Home1\i_SchDryer.csv',i_Dryer_PTS_a);
```

*Figure 33. Matlab Syntax for Dryer Schedule Generation*

*Creating Dishwasher Schedule*

Again, a similar approach was taken to develop the dishwasher schedule as was demonstrated previously in the clothes washer and dryer section. The Matlab script combines the fifteen-minute energy cost and the probability of running and seeks to generate an energy usage schedule to be output and used in the EnergyPlus model to simulate the dishwasher energy usage. This process is shown in Figure 34 where i_A_DWash is defined as the probability of dishwasher operation and i_C_DWash is equal to the combination of the cost and probability.

```
%%
%DWash - Multiply load shape from RBSA data by the energy cost data line by
%line
i_A_DWash = csvread('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\CSV_Files\Home1\DWash\i_Origin_DWash.csv');
i_C_DWash = i_A_DWash./ECost_mii;

%Find the max probablilty and write in the load factor for each day
i_DWash_PTS_a = i_C_DWash;
[i_DWash_nrows, i_DWash_ncols] = size(i_DWash_PTS_a);
```

*Figure 34. Matlab Syntax to combine Dishwasher Probability with Energy Costs*

The next step is to determine the load shape of a dishwasher cycle that can be input into the EnergyPlus model to simulate the dishwasher energy usage. The same submetering setup as before was utilized where a full cycle energy usage pattern was recorded in five second intervals. This load shape is shown in Figure 35.

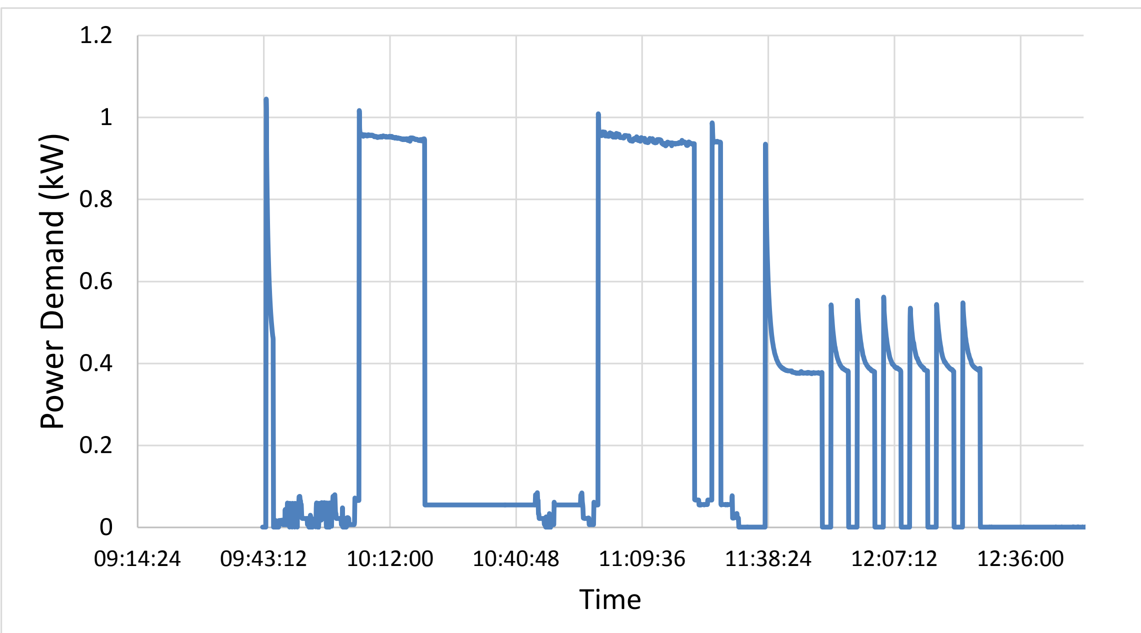


*Figure 35. Dishwasher Energy Usage Load Shape as Measured.*

This load shape is converted from the five-second interval data into fifteen-minute average energy consumption to be used as an input to the EnergyPlus model. The dishwasher load shape is different from other appliances in the model however, since, as can be seen in Figure 35, a full cycle lasts for multiple hours. This leads to the following data shown in Table 7, which totals two hours and forty-five minutes for the full cycle, start to finish.

*Table 7. Dishwasher Load Factor*

| | Usage (kWh) | Max Usage Possible (kWh) | Load Factor (%) |
|---|---|---|---|
| Time step 1 | 0.120 | 0.254 | 4.7 |
| Time step 2 | 0.159 | 0.254 | 62.5 |
| Time step 3 | 0.084 | 0.254 | 33.0 |
| Time step 4 | 0.015 | 0.254 | 5.9 |
| Time step 5 | 0.015 | 0.254 | 5.9 |
| Time step 6 | 0.231 | 0.254 | 90.9 |
| Time step 7 | 0.135 | 0.254 | 53.1 |
| Time step 8 | 0.051 | 0.254 | 20.1 |
| Time step 9 | 0.072 | 0.254 | 28.3 |
| Time step 10 | 0.075 | 0.254 | 29.5 |
| Time step 11 | 0.057 | 0.254 | 22.4 |

The Matlab script then determines the daily location of the maximum two hours and forty-five-minute period for the largest probability at the lowest operating cost. The load factors are then input into those time slots while all other schedule values are set to zero, indicating there will be no energy consumption from the dishwasher during those times. The script then writes a CSV file with these values which is used by EnergyPlus as the annual, fifteen-minute schedule for the dishwasher (35,040 data points). A portion of the syntax for this operation in Matlab is shown in Figure 36. The equation to calculate the sum of the combination of energy cost and the probability for dishwasher cycle, “i_DWash_PTS_a”, is cut off in the figure but continues to complete all eleven timesteps.

```
i_DWash_Loadfactor_a = 0.04719764;
i_DWash_Loadfactor_b = 0.625368732;
i_DWash_Loadfactor_c = 0.330383481;
i_DWash_Loadfactor_d = 0.05899705;
i_DWash_Loadfactor_e = 0.05899705;
i_DWash_Loadfactor_f = 0.908554572;
i_DWash_Loadfactor_g = 0.530973451;
i_DWash_Loadfactor_h = 0.200589971;
i_DWash_Loadfactor_i = 0.283185841;
i_DWash_Loadfactor_j = 0.294985251;
i_DWash_Loadfactor_k = 0.224188791;

i_DWash_DayStartRow = 1;
i_DWash_MaxLocation = 0;
%iterate through the data from the beginning to the end
while i_DWash_DayStartRow < i_DWash_nrows - 95
    i_DWash_k = i_DWash_DayStartRow;
    i_DWash_MaxLoad = 0;
    %find the full cycle load and its location
    for i_DWash_k = i_DWash_k:i_DWash_k+95
        i_DWash_Load = i_DWash_PTS_a(i_DWash_k,1) + i_DWash_PTS_a(i_DWash_k+1,1) + i_DWash_PTS_a(i_DWash_k+2,1) + i_DWash_PTS_a(i_DWas
        %determine if the load is greater than the previous load - save the value and location if it is
        if i_DWash_Load > i_DWash_MaxLoad
            i_DWash_MaxLocation = i_DWash_k;
            i_DWash_MaxLoad = i_DWash_Load;
        end
        i_DWash_PTS_a(i_DWash_k,1) = 0;
    end
    %change the maximum values to the specified load factors
    i_DWash_PTS_a(i_DWash_MaxLocation,1) = i_DWash_Loadfactor_a;
    i_DWash_PTS_a(i_DWash_MaxLocation + 1,1) = i_DWash_Loadfactor_b;
    i_DWash_PTS_a(i_DWash_MaxLocation + 2, 1) = i_DWash_Loadfactor_c;
    i_DWash_PTS_a(i_DWash_MaxLocation + 3,1) = i_DWash_Loadfactor_d;
    i_DWash_PTS_a(i_DWash_MaxLocation + 4,1) = i_DWash_Loadfactor_e;
    i_DWash_PTS_a(i_DWash_MaxLocation + 5, 1) = i_DWash_Loadfactor_f;
    i_DWash_PTS_a(i_DWash_MaxLocation + 6,1) = i_DWash_Loadfactor_g;
    i_DWash_PTS_a(i_DWash_MaxLocation + 7,1) = i_DWash_Loadfactor_h;
    i_DWash_PTS_a(i_DWash_MaxLocation + 8, 1) = i_DWash_Loadfactor_i;
    i_DWash_PTS_a(i_DWash_MaxLocation + 9,1) = i_DWash_Loadfactor_j;
    i_DWash_PTS_a(i_DWash_MaxLocation + 10,1) = i_DWash_Loadfactor_k;
    i_DWash_DayStartRow = i_DWash_DayStartRow + 96;
end
for i_DWash_k = i_DWash_k:i_DWash_k+95
    i_n_DWash = 1:365;
    i_DWash_PTS_a(96*i_n_DWash) =0;
end
for i_DWash_nrows = 33601:35040
    i_DWash_PTS_a(i_DWash_nrows, 1) = 0;
end
csvwrite('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\CSV_Files\Home1\i_SchDWash.csv',i_DWash_PTS_a)
```

*Figure 36. Matlab Syntax for Dishwasher Schedule Generation*

## *Creating Oven Schedule*

The final appliance included in the Matlab script to change the operational schedule based on the energy costs is the oven – see the section titled *Categories of Appliances* on page 32 for a breakdown of why certain appliances were included or excluded. For this portion of the model the same approach was taken as with other appliances where the algorithm seeks to determine a time where a homeowner is most likely to use an oven while also using energy cost data to perform that at the lowest possible operating cost. To find this time energy cost data and oven energy usage load shape data were combined as shown in Figure 37.

```
%%
%Oven - Multiply load shape from RBSA data by the energy cost data line by
%line
i_A_Oven = csvread('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\CSV_Files\Home1\Oven\i_Origin_Oven.csv');
i_C_Oven = i_A_Oven./ECost_mii;
i_Oven_PTS_a = i_C_Oven;
[i_Oven_nrows, i_Oven_ncols] = size(i_Oven_PTS_a);
```

*Figure 37. Matlab Syntax to combine Oven Probability with Energy Costs*

Once this data is combined, the next step in the process is to convert a typical oven cycle energy usage data into a form that can be used by EnergyPlus to simulate the impacts to a home’s energy usage. For this, a submetering system was installed to monitor the energy usage profile of actual oven cycles. Multiple oven times and food preparations were monitored and averaged to develop an average load shape. This data was recorded in one-minute intervals and was not from the same metering system as the previous appliances were and because of this, an example of one of the oven cycles used in the analysis is shown in Figure 38. This cycle takes place for a 350°F baking of a casserole, demonstrating that the oven modulates the heating elements on/off to control the temperature throughout the cycle.

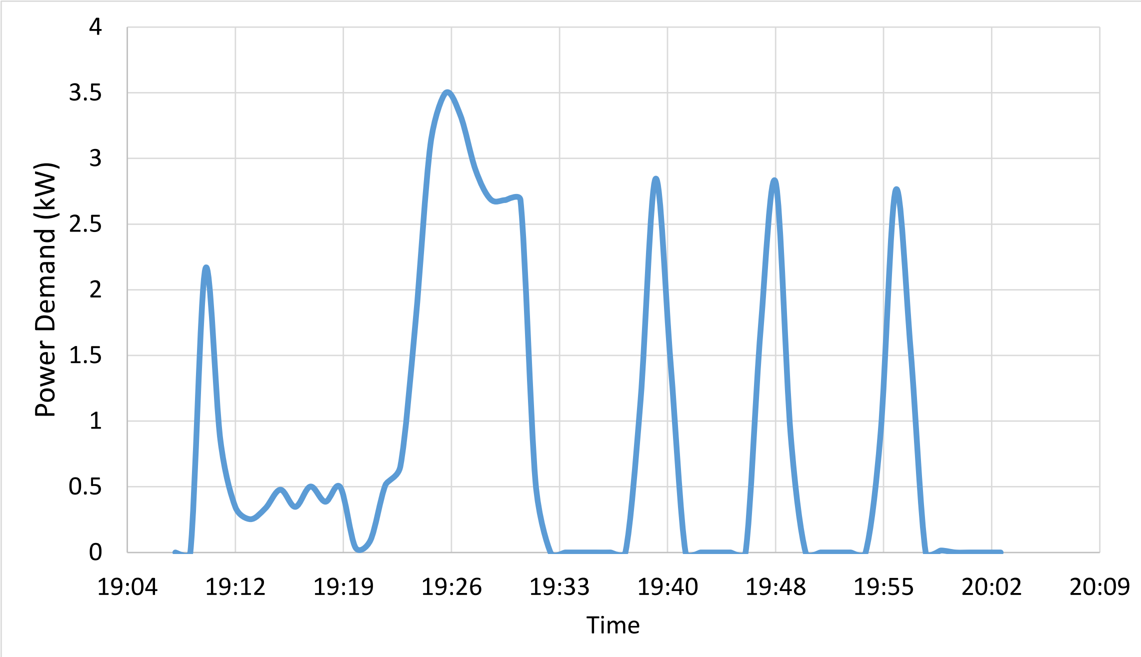


*Figure 38. Oven Energy Usage Load Shape as Measured.*

This information is used to develop the fifteen-minute schedules for the oven in the model for the year. This requires converting the minute-by-minute data into a fifteen-minute average and a total runtime must be chosen. From the data gathered, the average time for the oven to operate is around one hour and thus four fifteen-minute periods were chosen as the typical oven cycle to add into the EnergyPlus model. The oven's load factor information used in EnergyPlus scheduling is shown in Table 8.

*Table 8. Oven Load Factors*

| | Usage (kWh) | Max Usage Possible (kWh) | Load Factor (%) |
|---|---|---|---|
| Time step 1 | 0.45 | 3.5 | 12.96 |
| Time step 2 | 1.56 | 3.5 | 45.44 |
| Time step 3 | 0.725 | 3.5 | 20.71 |
| Time step 4 | 0.475 | 3.5 | 13.58 |

The Matlab script then takes the previous information and searches for the most cost effective time to operate the oven, taking into account when the homeowner would want to operate it based on the RBSA and EPRI Load Shape data. The load factors shown in Table 8 are input into the schedule while all other time periods are filled with zeros to indicate the oven is not operating during these times. The Matlab script then writes the data to a CSV file which is used by EnergyPlus as the fifteen-minute schedule. The syntax for the script is shown in Figure 39.

```
%%
%Oven - Multiply load shape from RBSA data by the energy cost data line by
%line
i_A_Oven = csvread('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\CSV_Files\Home1\Oven\i_Origin_Oven.csv');
i_C_Oven = i_A_Oven./ECost_mii;
i_Oven_PTS_a = i_C_Oven;
[i_Oven_nrows, i_Oven_ncols] = size(i_Oven_PTS_a);

i_Oven_Loadfactor_a = 0.129674;
i_Oven_Loadfactor_b = 0.454431;
i_Oven_Loadfactor_c = 0.207128;
i_Oven_Loadfactor_d = 0.135766;

i_Oven_DayStartRow = 1;
i_Oven_MaxLocation = 0;
%iterate through the data from the beginning to the end
while i_Oven_DayStartRow < i_Oven_nrows - 95
    i_Oven_k = i_Oven_DayStartRow;
    i_Oven_MaxLoad = 0;
    %find the 45 minute load and its location
    for i_Oven_k = i_Oven_k:i_Oven_k+95
        i_Oven_Load = i_Oven_PTS_a(i_Oven_k,1) + i_Oven_PTS_a(i_Oven_k+1,1) +i_Oven_PTS_a(i_Oven_k+2,1) + i_Oven_PTS_a(i_Oven_k+3,1);
        %determine if the load is greater than the previous load - save the value and location if it is
        if i_Oven_Load > i_Oven_MaxLoad
            i_Oven_MaxLocation = i_Oven_k;
            i_Oven_MaxLoad = i_Oven_Load;
        end
        i_Oven_PTS_a(i_Oven_k,1) = 0;
    end
    %change the three maximum values to the specified load factors
    i_Oven_PTS_a(i_Oven_MaxLocation,1) = i_Oven_Loadfactor_a;
    i_Oven_PTS_a(i_Oven_MaxLocation + 1,1) = i_Oven_Loadfactor_b;
    i_Oven_PTS_a(i_Oven_MaxLocation + 2, 1) = i_Oven_Loadfactor_c;
    i_Oven_PTS_a(i_Oven_MaxLocation + 3, 1) = i_Oven_Loadfactor_d;
    i_Oven_DayStartRow = i_Oven_DayStartRow + 96;
end
for i_Oven_k = i_Oven_k:i_Oven_k+95
    i_n_Oven = 1:365;
    i_Oven_PTS_a(96*i_n_Oven) =0;
end

for i_Oven_nrows = 33601:35040
    i_Oven_PTS_a(i_Oven_nrows, 1) = 0;
end
csvwrite('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\CSV_Files\Home1\i_SchOven.csv',i_Oven_PTS_a)
```

*Figure 39. Matlab Syntax for Oven Schedule Generation.*

*Creating Thermostat Setpoint Schedule*

To define what the thermostat settings should be for the home a simple process is used where the homeowner would define their comfort settings based on the time of day and the cost of energy. This process is replicated to develop setpoints for the heating season too, based on the time of year – for the purposes of this model the cooling season is from May to October and the heating season makes up the remainder of the year. The comfort settings for the first home is shown in Table 9.

*Table 9. Home i Thermostat Comfort Settings (°C)*

| | Lowest Cost | Low Cost | Normal Price | High Price | Highest Price |
|---|---|---|---|---|---|
| Cooling Setpoint – Pk hours | 20 | 22.2 | 23.3 | 25 | 27.7 |
| Cooling Setpoint – Offpk hours | 21.5 | 23.7 | 24.8 | 26.5 | 29.2 |
| Heating Setpoint – Pk hours | 23.9 | 22.8 | 21.1 | 19.4 | 17.8 |
| Heating Setpoint – Offpk hours | 22.4 | 21.3 | 19.6 | 17.9 | 16.3 |

These temperature settings correspond to changing energy costs which are shown in Table 10. For example, when the cost of energy is \$0.025/kWh the peak time cooling setpoint would be 20°C but as the energy cost changes to \$0.05/kWh, the cooling setpoint is increased to 22.2°C. This table can be read from left to right where the energy cost listed is the maximum cost per kWh where the temperature setting is used, therefore any price greater than \$0.45/kWh signals the temperature setting to be the far-right column in Table 9.

*Table 10. Home i Energy Cost Breakpoints ($/kWh)*

| | Lowest Cost | Low Cost | Normal Price | High Price |
|---|---|---|---|---|
| Energy Cost Breakpoint | 0.035 | 0.085 | 0.165 | 0.45 |

A simple Matlab script with IF statements was then created to read the home's cooling comfort setting preferences and the fifteen-minute energy costs and generate a temperature setpoint for each period of the year. This script goes through each hour of the day and, based on which hour is defined as peak and off peak, will write the temperature based solely on the energy cost during that time period. Once that temperature setting has been determined the script moves onto the next timestep and repeats the process until 35,040 settings are generated, or an annual profile in fifteen-minute increments. This information is then written to a CSV file and used by EnergyPlus as the thermostat settings for the energy simulation. This process is then repeated for the heating setpoints and follows the same process, only now it writes the temperature settings for the months of January 1 through April 30$^{th}$ and November 1 to December 31$^{st}$. It should be noted that for each respective script, the opposing months, May to October for the heating setpoints, must be written to include a temperature that does not conflict with the cooling schedule. Otherwise, the EnergyPlus model will fail on an error message where the thermostat does not understand what to set the temperature to within the home. A sample of the Matlab script is shown in Figure 40 where each time step is evaluated to determine which hour of the day it falls into and the energy cost during that fifteen-minute window and determines the thermostat setting based on the homeowner's preprogrammed preferences.

```matlab
for i_r_Tcoo =11521:29184
    for i_c_Tcoo = 1:ncols_Tcoo
%On peak
%hour 1
        if i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 1 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceRL
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_RealLow_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 1 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceLow && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceRL
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_Low_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 1 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceNorm && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceLow
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_Norm_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 1 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceHigh && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceNorm
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_High_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 1 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceHigh
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_RealHigh_offpk;
%hour 2
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 2 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceRL
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_RealLow_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 2 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceLow && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceRL
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_Low_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 2 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceNorm && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceLow
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_Norm_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 2 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceHigh && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceNorm
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_High_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 2 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceHigh
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_RealHigh_offpk;
%hour 3
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 3 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceRL
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_RealLow_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 3 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceLow && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceRL
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_Low_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 3 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceNorm && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceLow
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_Norm_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 3 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceHigh && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceNorm
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_High_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 3 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceHigh
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_RealHigh_offpk;
%hour 4
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 4 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceRL
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_RealLow_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 4 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceLow && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceRL
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_Low_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 4 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceNorm && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceLow
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_Norm_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 4 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) < i_PriceHigh && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceNorm
            i_C_Tcoo(i_r_Tcoo,i_c_Tcoo) = i_Tcoo_High_offpk;
        elseif i_A_Tcoo(i_r_Tcoo,i_c_Tcoo) == 4 && i_B_Tcoo(i_r_Tcoo,i_c_Tcoo) >= i_PriceHigh
```

*Figure 40. Example Portion of Matlab Script to Calculate Temperature Settings.*

*Creating Other Appliance Schedules*

Other Appliances exist within the home that are not included in the Matlab script to generate and vary depending on the energy costs. These other appliances are seen as either non-interruptible or in Category 3 as described on page 32. The most notable of these appliances are lighting and miscellaneous plug loads. For lighting schedules two sources of data were used, the EPRI Load Shape Library [66] and a residential lighting hours-of use study performed by NMR Group, Inc. [67]. These reports provided an hourly overview of what percentage of lighting is used during different periods of the year, included summer and winter months. These end-use surveys were then utilized to generate average lighting usage profiles for a home. For miscellaneous plug loads, the default data in BEopt was used which is pulled from a study performed by NREL for the Building America program and sets baseline energy usage in residential applications to assist engineers when comparing energy retrofit options [68]. To create diversity between the national average home and the homes used in the model simulations a randomized multiplier was added to the default data with the overall energy consumption remaining constant. This was seen as the most accurate way to represent both lighting and miscellaneous plug loads in simulation models where physical metered data is difficult to gather and verify.

Lastly, a major energy consuming device is missing from this section and for now is set to the default temperature and let to run as needed. This is the water heating equipment and is not included in this portion of the simulation because it is utilized exclusively in a different portion where its thermal energy storage characteristics can be utilized to maximize the benefits to both the homeowner and the electric utility. More on how this is utilized is explained in *Adding in Thermal Energy Storage to improve flexibility* on page 91.

### *Running EnergyPlus from Matlab*

The previous subsections discuss how appliance schedules are generated and the logic that goes behind their creation. Once they have been generated and output into a

CSV file, the next step in the modeling process is to simulate the home using EnergyPlus with the updated appliance schedules for a typical weather year in the Birmingham, AL area. To do this a simple command is used in Matlab to call an external command, in this case an EnergyPlus batch file that calls the simulation files and executes them. The Matlab syntax for this is shown in Figure 41. The "cd" command is used to change the Matlab directory to the location where the EnergyPlus simulation file is housed and the "!" command is used to signal an external command, the EnergyPlus batch file, to execute in the operating system command window. Once this command is executed, the "cd" command is utilized again to change the Matlab directory back to its original state.

```
%%
%Call Energy Plus to run file
cd('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\EPlusFiles_Mulibatch');
!RunDirMulti.bat
cd('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\MainMatlab');
pause(pause_all);
```

*Figure 41. Matlab Syntax to Call an External Command*

The "RunDirMulti.bat" is a batch file that comes with the standard EnergyPlus download and is used to execute all the EnergyPlus IDF files in the directory where it is located [72]. This means that all the IDF files that are maintained in the directory shown in Figure 41 are executed in parallel once the command is called – IDF files are the text files that contain all the details for an energy simulation and is what is read by the EnergyPlus simulation engine as the input file. Finally, the "pause" function is used to pause the Matlab script from continuing to execute as there is no feedback from the Windows command windows to indicate when the simulation files are complete. This is an important step to ensure that the remainder of the Matlab script can execute properly and use the correct output files from the EnergyPlus simulation.

### *Importing the EnergyPlus Results into Matlab*

At this point in the model appliance schedules have been generated and EnergyPlus has utilized these schedules to simulate the energy usage profile for the home in fifteen-minute increments over a full year. These profiles are output from the EnergyPlus model as CSV files and are housed external to Matlab. To allow Matlab to use this information for future calculations, it must be imported as a matrix. To do this the built-in Import Data Tool in Matlab was utilized which allows the user to select a set or subset of data from a spreadsheet (or CSV) file and import it directly into the Matlab directory as a matrix variable. This tool also gives the user the option to auto generate a script to perform this task multiple times. The output of this auto-generated script was slightly modified for the specific application and is shown in Figure 42.

```
%% Import data from text file.
% Initialize variables.
i_filename = 'C:\Users\justin\Documents\Dissertation\BCVTBModel_a\EPlusFiles_Mulibatch\i_homeMeter.csv';
i_delimiter = ',';
i_startRow = 2;
% Format string for each line of text:
%   column2: double (%f)
% For more information, see the TEXTSCAN documentation.
i_formatSpec = '%*s%f%*s%*s%*s%*s%*s%[^\n\r]';
% Open the text file.
i_fileID = fopen(i_filename,'r');
% Read columns of data according to format string.
% This call is based on the structure of the file used to generate this
% code. If an error occurs for a different file, try regenerating the code
% from the Import Tool.
i_dataArray = textscan(i_fileID, i_formatSpec, 'Delimiter', i_delimiter, 'EmptyValue' ,NaN,'HeaderLines' ,i_startRow-1, 'ReturnOnError', false);
% Close the text file.
fclose(i_fileID);
% Allocate imported array to column variable names
i_ElectricityFacilityJTimeStep = i_dataArray{:, 1};
% Clear temporary variables
clearvars i_filename i_delimiter i_startRow i_formatSpec i_fileID i_dataArray i_ans;
```

*Figure 42. Script to Import EnergyPlus Output Data into Matlab.*

This same step is repeated to import the water heater energy consumption as well for the home energy model. This information, "i_ElectricityFacilityJTimeStep", can then be used in the model as any other matrix. For future models, it can be added together with other home's energy usage to allow the utility to only see the energy usage as one aggregate and develop its updated pricing based on that one number. It is important to note that the EnergyPlus output files are in Joules rather than kWh so they must be converted before calculations are performed.

*Calculating an Updated Fifteen-minute Energy Cost*

Now that the energy usage profile for the home has been simulated and imported into Matlab (simulating that the utility has now received the energy usage data back from all participating homes) and the renewable energy generation is known, the utility now must calculate updated fifteen-minute energy costs. To do this, the combined energy usage of the homes must be subtracted from the renewable energy generation that is projected. This difference is used to determine how much the updated energy cost needs to be scaled during each fifteen-minute time difference. This relationship is setup to encourage energy usage to match the renewable energy generation at each time step where the larger the gap in usage, the higher the change in cost. Figure 43 shows the relationship.

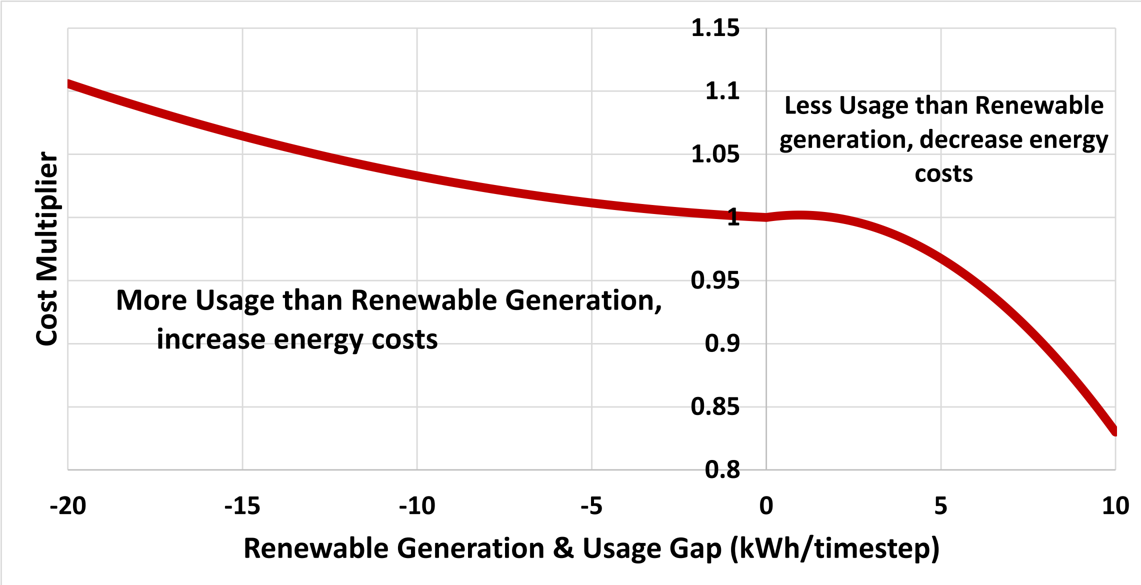


*Figure 43. Cost Multiplier equations to equalize renewable generation & usage*

This information is based on the scaled renewable output and the combined energy usage of the homes participating in the program. As the gap between the two components gets larger, the cost multiplier is increased (further away from one) while as the gap shrinks, the cost multiplier gets closer to unity. To keep the cost contained to reasonable numbers, for instances where the gap is greater than ten or negative twenty, the multiplier is capped at 0.7 and 1.125 respectively. The cost multiplier calculated using the equations in Figure 43 are performed at each timestep and multiplied by the original energy cost supplied from the previous iteration of the model. A sample of this method is in Table 11.

*Table 11. Sample of Updated Energy Costs Methodology*

| Date | Time | Renewable Generation (kWh) | Energy Usage (kWh) | Difference(kWh) | Multiplier | Original Cost ($/kWh) | Updated Cost ($/kWh) |
|---|---|---|---|---|---|---|---|
| 1/1 | 0:00 | 1.816 | 2.708 | -0.893 | 1.026 | 0.139 | 0.143 |
| 1/1 | 0:15 | 2.081 | 3.569 | -1.488 | 1.026 | 0.134 | 0.138 |
| 1/1 | 0:30 | 2.441 | 2.821 | -0.380 | 1.025 | 0.128 | 0.131 |
| 1/1 | 0:45 | 2.890 | 2.941 | -0.051 | 1.024 | 0.120 | 0.123 |
| 1/1 | 1:00 | 3.182 | 3.141 | 0.041 | 0.928 | 0.109 | 0.101 |

Once this process has been completed for each timestep in the year, the data is written to the original energy cost CSV file and overwrites the original data. This information is used later as the base energy cost for the next iteration of the model.

*Calculating the Size of Energy Storage Required for Current Configuration*

The next step of the model is to calculate the amount of energy storage that must be present in the system to compensate for the differences between renewable energy generation and the energy usage. A state-of-charge (SOC) analysis using the method presented by Kalkhambkar, Kumar and Bhakar in [71] was performed to find the required energy storage capacity. This storage capacity was set to limit the number of times the SOC goes above or below a minimum and maximum threshold, 30% minimum and 100% maximum. The limits were set at a total of 10,512 timesteps as the maximum amount of times the SOC can be outside of either threshold, which equates to 2,628 hours a year outside of the limits, or 30% of the year. Since the system is connected to the grid, the energy storage system, mixed with the renewable energy generation is not required to supply the full energy requirements to the group of participating homes, greatly reducing the size of the energy storage. The Matlab script is shown in Figure 44.

```
for row_BLS_miii = 1:35040;
    %increase SOC
    if BatteryLoadShape_miii(row_BLS_miii,1) >= Battery_max_add_fromGrid_miii && BatteryLoadShape_miii(row_BLS_miii,1) >= 0 && ECost_BL(row_BLS_miii,1) < Discharge_Cost
        Battery_add_fromGrid_miii(row_BLS_miii,1) = -Battery_max_add_fromGrid_miii;
    elseif BatteryLoadShape_miii(row_BLS_miii,1) < Battery_max_add_fromGrid_miii && BatteryLoadShape_miii(row_BLS_miii,1) >= 0 && ECost_BL(row_BLS_miii,1) < Discharge_Cost
        Battery_add_fromGrid_miii(row_BLS_miii,1) = - BatteryLoadShape_miii(row_BLS_miii,1);
    end
end

% Decrease SOC
for row_BLS_miii_a = 1:35040;
    if abs(BatteryLoadShape_miii(row_BLS_miii_a,1)) >= Battery_max_add_fromGrid_miii && BatteryLoadShape_miii(row_BLS_miii_a,1) <= 0 && ECost_BL(row_BLS_miii_a,1) > Charge_Cost
        Battery_add_fromGrid_miii(row_BLS_miii_a,1) = Battery_max_add_fromGrid_miii;
    elseif abs(BatteryLoadShape_miii(row_BLS_miii_a,1)) < Battery_max_add_fromGrid_miii && BatteryLoadShape_miii(row_BLS_miii_a,1) <= 0 && ECost_BL(row_BLS_miii_a,1) > Charge_Cost
        Battery_add_fromGrid_miii(row_BLS_miii_a,1) = - BatteryLoadShape_miii(row_BLS_miii_a,1);
    end
end

while (Undermin_charge_miii + Overmax_charge_miii) >= Outside_chargelimit_max
    Loss_coeff_miii=0.92;
    BatteryEnergyCapacity_miii = Battery_multiplier_miii*1;
    SOC_calc_miii_a=zeros(35040,1);
    SOC_initial_miii_a = ones(35040,1)*0.65;
    for row_Bah_miii_a =1:35040;
        if SOC_initial_miii_a(row_Bah_miii_a,1)< 1.0  && SOC_initial_miii_a(row_Bah_miii_a,1) >= SOC_min
            SOC_calc_miii_a(row_Bah_miii_a,1)= (SOC_initial_miii_a(row_Bah_miii_a,1)) + (1/BatteryEnergyCapacity_miii)*Loss_coeff_miii*(BatteryLoadShape_miii(row_Bah_miii_a,1));
        elseif SOC_calc_miii_a(row_Bah_miii_a,1)>= 1.0 && Battery_add_fromGrid_miii(row_Bah_miii_a,1) < 0
            SOC_calc_miii_a(row_Bah_miii_a,1)= 1 + (1/BatteryEnergyCapacity_miii)*Loss_coeff_miii*(BatteryLoadShape_miii(row_Bah_miii_a,1));
        elseif SOC_calc_miii_a(row_Bah_miii_a,1)>= 1.0 && Battery_add_fromGrid_miii(row_Bah_miii_a,1) >= 0
            SOC_calc_miii_a(row_Bah_miii_a,1)= 1 + (1/BatteryEnergyCapacity_miii)*Loss_coeff_miii*(BatteryLoadShape_miii(row_Bah_miii_a,1));
        elseif SOC_calc_miii_a(row_Bah_miii_a,1)< SOC_min && Battery_add_fromGrid_miii(row_Bah_miii_a,1) > 0
            SOC_calc_miii_a(row_Bah_miii_a,1)= (SOC_min) + (1/BatteryEnergyCapacity_miii)*Loss_coeff_miii*(BatteryLoadShape_miii(row_Bah_miii_a,1));
        elseif SOC_calc_miii_a(row_Bah_miii_a,1)< SOC_min && Battery_add_fromGrid_miii(row_Bah_miii_a,1) <= 0
            SOC_calc_miii_a(row_Bah_miii_a,1)= (SOC_min) + (1/BatteryEnergyCapacity_miii)*Loss_coeff_miii*(BatteryLoadShape_miii(row_Bah_miii_a,1));
        end
        SOC_initial_miii_a(row_Bah_miii_a+1,1) = SOC_calc_miii_a(row_Bah_miii_a,1);
    end

    for row_Bah_miii_ab =1:35040;
        if SOC_calc_miii_a(row_Bah_miii_ab,1)>1
            SOC_calc_miii_a(row_Bah_miii_ab,1) = 1;
        elseif SOC_calc_miii_a(row_Bah_miii_ab,1)< SOC_min
            SOC_calc_miii_a(row_Bah_miii_ab,1) = SOC_min;
        end
    end
    Undermin_charge_miii = sum(SOC_calc_miii_a <= SOC_min);
    Overmax_charge_miii = sum(SOC_calc_miii_a >= 1);
    Battery_multiplier_miii = Battery_multiplier_miii+2;
end
```

*Figure 44. Battery SOC Calculation Script*

This script begins by defining the desired energy storage input/output to compensate for the remaining mismatch of energy usage and renewable generation. This is shown in the first two “for” loops at the beginning of Figure 44. Next the local variables used to calculate the SOC of the energy storage are defined. The script uses a While loop to continue adding to the energy storage capacity until the conditions are met to where the amount of time outside of the minimum and maximum thresholds are under the defined amount – 10,512 timesteps for this model. The initial SOC is set to 65% and a round trip efficiency of 92% is assumed. The first “For” loop is used to calculate the SOC, assuming that the capacity of the system can range infinitely. However, this is not realistic so the second For loop ensures that once the energy storage goes outside of the bounds of the system, energy is neither consumed nor added. After the SOC calculations are completed, the number of times the system is outside of the thresholds are counted. If the threshold requirements are not met, the storage multiplier is increased to increase the energy storage capacity. This process is repeated until the thresholds are met, at which point the calculations from all the previous sections are written to CSV files for later use and evaluation. This process is the same as discussed beginning on page 63.

*Adding in Thermal Energy Storage to improve flexibility*

To provide additional flexibility to the model and to account for errors in renewable energy generation forecasting, a new model is created to calculate an updated energy cost for each fifteen-minute interval of the year. This new energy cost is passed to the homes and is only applied to the water heater energy usage but in return directs the temperature setpoints. This portion of the model is intended to be a more real-time control strategy when implemented in the field as the impact to changing the water heater setpoints are minimal to the customer while having the potential to store large amounts of energy when desired.

This model begins by importing the renewable energy generation at each fifteen-minute interval as well as the combined energy usage of all participating homes at each interval outputted from the previous model. This information is used to determine a new difference between the energy usage and the renewable energy generation for each fifteen-minute interval which will in turn help determine the updated cost of energy.

A personalized cost curve is necessary for this model to be effective. To begin the development process, the ERCOT for each interval must be known to represent the utility's cost to serve in each time interval. A profit margin is then set to ensure energy sales are profitable when having real-time influence over the thermal energy storage within a water heater. This cost of service and profit number is then used as the minimum cost for perfect alignment of energy usage and renewable energy generation and times when renewable energy is generated in excess of demand. For times when the energy demand is greater than renewable energy generation, the energy cost grows using a second order polynomial up to the maximum cost of $2/kWh. The correlation between energy costs and the energy usage and generation gap is shown in Figure 45.

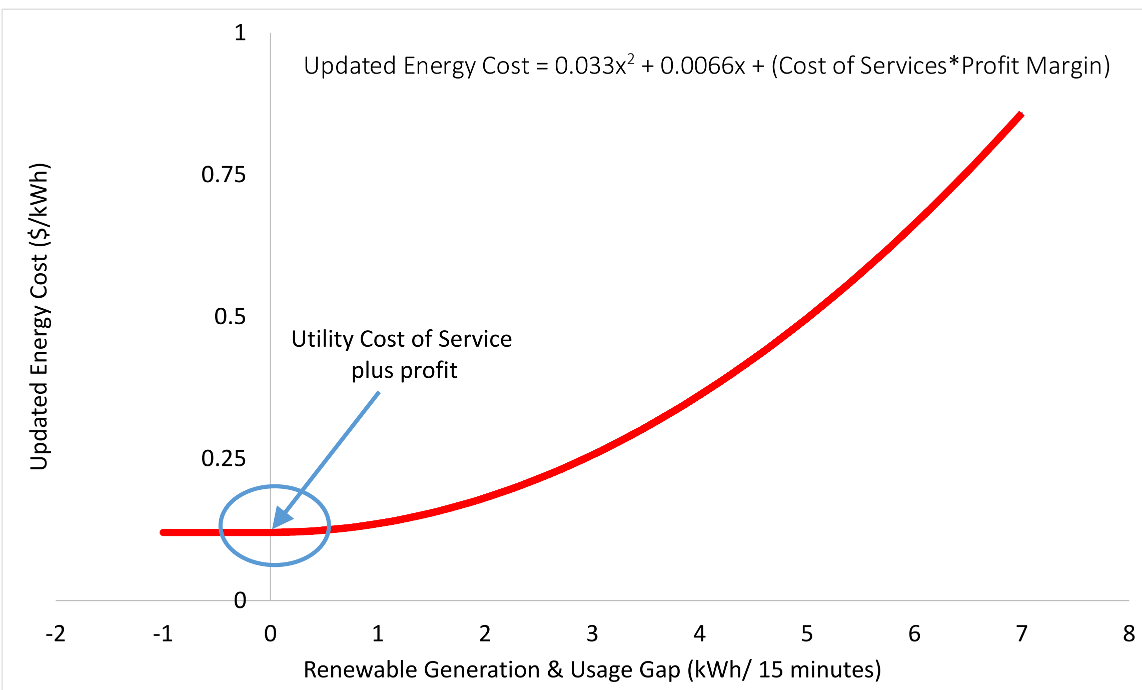


*Figure 45. Model iii Energy Cost and Renewable Generation & Usage*

This process calculates a new energy cost for all timesteps in the model and assigns the appropriate energy costs using the method shown in Figure 45. This information is sent to the homeowner's energy management system where the cost signals are passed along to the water heater. Customer preferences dictate the individual response to the signal but each home maintains a maximum safe water temperature of 90°C (194°F) as defined in [73]. An example of the response of a home to the energy cost signal is shown in Figure 46.

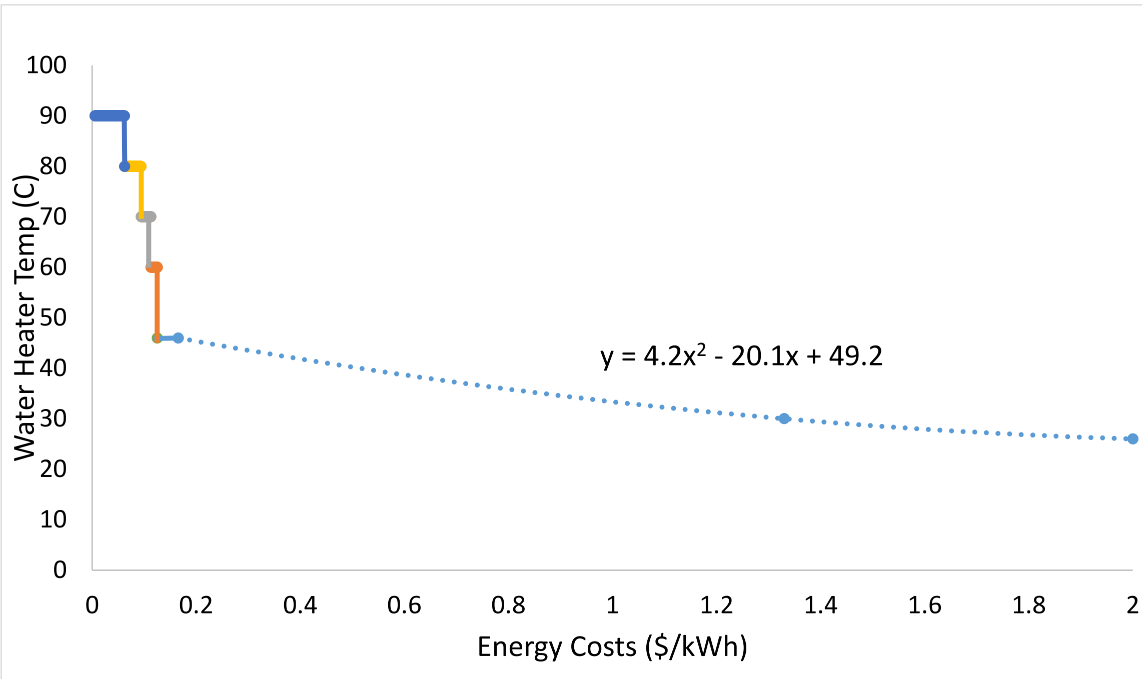


*Figure 46. Home Water Heater Setpoint Response to Energy Costs*

As can be seen by the small blue line in Figure 46, there is a dead-band where the temperature stays the same over a small level of cost change. This was found necessary in each home as the energy usage impact of water heaters when the difference between renewable generation and energy usage is small can cause the relationship to reverse and overshoot the goal of the program. The program calculates an updated water heater temperature for each timestep and then writes the values to a CSV file, used in a new EnergyPlus simulation.

The EnergyPlus simulation is called in the same method as presented on page 84 and the energy usage and water heater temperatures are imported into Matlab using the Import Data tool. Finally, a battery-sizing model is performed to compare with the baseline and initial model. This process is the same as presented beginning on page 63 and on page 89.

*Annual Energy Cost & Utility Profit Calculations*

To complete the model and to enable comparisons of the effectiveness for each model scenario, the annual energy costs to the customer are calculated for each scenario as well as the revenue comparison of each model run to the energy utility.

Calculating the annual energy costs to the customer requires importing the energy costs from the utility in each scenario and for each iteration of the model run. For each run, there are three types of energy cost calculations that must be performed. This includes using the base energy cost ($0.1252/kWh) as the flat rate year round. This energy cost represents the average energy costs for residential energy costs in the US for 2014 [63]. The second type uses the RTP developed for each iteration in the second model and finally using the RTP from the second model for all the energy consumption except the water heating and assigning that energy cost to the RTP developed in model iii. The equations used for these calculations with the baseline energy costs are shown in Figure 47. Similar calculations are used for the remaining annual energy costs.

```
%% Baseline Calculations
i_yearly_ECost_BL_flatrate =  sum((i_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);
ii_yearly_ECost_BL_flatrate =  sum((ii_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);
iii_yearly_ECost_BL_flatrate =  sum((iii_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);
iv_yearly_ECost_BL_flatrate =  sum((iv_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);
v_yearly_ECost_BL_flatrate =  sum((v_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);
vi_yearly_ECost_BL_flatrate =  sum((vi_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);
vii_yearly_ECost_BL_flatrate =  sum((vii_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);
viii_yearly_ECost_BL_flatrate =  sum((viii_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);
ix_yearly_ECost_BL_flatrate =  sum((ix_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);
x_yearly_ECost_BL_flatrate =  sum((x_ElectricityFacilityJTimeStep_bl./3600000).*Avg_BasekWhRate);

i_yearly_ECost_BL_RTP = sum((i_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);
ii_yearly_ECost_BL_RTP = sum((ii_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);
iii_yearly_ECost_BL_RTP = sum((iii_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);
iv_yearly_ECost_BL_RTP = sum((iv_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);
v_yearly_ECost_BL_RTP = sum((v_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);
vi_yearly_ECost_BL_RTP = sum((vi_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);
vii_yearly_ECost_BL_RTP = sum((vii_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);
viii_yearly_ECost_BL_RTP = sum((viii_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);
ix_yearly_ECost_BL_RTP = sum((ix_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);
x_yearly_ECost_BL_RTP = sum((x_ElectricityFacilityJTimeStep_bl./3600000).*ECost_original_noChange);

i_yearly_ECost_BL_RTP_update = sum(((i_ElectricityFacilityJTimeStep_bl./3600000)- i_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange)+sum((i_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
ii_yearly_ECost_BL_RTP_update = sum(((ii_ElectricityFacilityJTimeStep_bl./3600000)- ii_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange )+sum((ii_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
iii_yearly_ECost_BL_RTP_update = sum(((iii_ElectricityFacilityJTimeStep_bl./3600000)- iii_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange )+sum((iii_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
iv_yearly_ECost_BL_RTP_update = sum(((iv_ElectricityFacilityJTimeStep_bl./3600000)- iv_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange )+sum((iv_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
v_yearly_ECost_BL_RTP_update = sum(((v_ElectricityFacilityJTimeStep_bl./3600000)- v_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange )+sum((v_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
vi_yearly_ECost_BL_RTP_update = sum(((vi_ElectricityFacilityJTimeStep_bl./3600000)- vi_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange )+sum((vi_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
vii_yearly_ECost_BL_RTP_update = sum(((vii_ElectricityFacilityJTimeStep_bl./3600000)- vii_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange )+sum((vii_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
viii_yearly_ECost_BL_RTP_update = sum(((viii_ElectricityFacilityJTimeStep_bl./3600000)- viii_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange )+sum((viii_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
ix_yearly_ECost_BL_RTP_update = sum(((ix_ElectricityFacilityJTimeStep_bl./3600000)- ix_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange )+sum((ix_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
x_yearly_ECost_BL_RTP_update= sum(((x_ElectricityFacilityJTimeStep_bl./3600000)- x_wh_BL_WaterHeatUsage_kWh).* ...
    ECost_original_noChange )+sum((x_wh_BL_WaterHeatUsage_kWh.*ECost_new_miii));
```

*Figure 47. Annual Energy Costs to Consumers in Modeled Scenarios*

Finally, the profit generated by the utility in each of the scenarios are calculated and written to an Excel file for later comparison. To do this, the initial RTP rate is used as the true cost to the utility to generate and supply the energy to the end customer. Therefore, it is assumed that this is the true cost to them. For calculating the profit for the baseline model described in the report, the profit to the utility is found first by summing the total amount of energy used by the participating customers over the course of the year at each timestep. Next, the program subtracts the initial RTP rate at each timestep from the base energy rate ($0.1252/kWh). This number can be either positive or negative and describes whether the utility is profiting or losing money from each kWh sold in that particular timestep.

To calculate the profit to the utility for the second model, the same basic structure is used where the only difference is that the cost to the customer now changes at each timestep too. The calculation can still output a positive or negative number and describes if the utility is making or losing money at each particular timestep. This process is repeated for each iteration and the equations used in the program are shown in Figure 48.

```
COS_BL = (Avg_BasekWhRate_matrix - Cost_of_Service);
Profit_BL = sum(EnergyUse_Neighborhood_bl.*COS_BL);
Profit_mii_run1 = sum(EUsage_run1.*(ECost_run1 - Cost_of_Service));
Profit_mii_run2 = sum(EUsage_run2.*(ECost_run2 - Cost_of_Service));
Profit_mii_run3 = sum(EUsage_run3.*(ECost_run3 - Cost_of_Service));
Profit_mii_run4 = sum(EUsage_run4.*(ECost_run4 - Cost_of_Service));
Profit_mii_run5 = sum(EUsage_run5.*(ECost_run5 - Cost_of_Service));
Profit_mii_run6 = sum(EUsage_run6.*(ECost_run6 - Cost_of_Service));
Profit_mii_run7 = sum(EUsage_run7.*(ECost_run7 - Cost_of_Service));
Profit_mii_run8 = sum(EUsage_run8.*(ECost_run8 - Cost_of_Service));
Profit_mii_run9 = sum(EUsage_run9.*(ECost_run9 - Cost_of_Service));
Profit_mii_run10 = sum(EUsage_run10.*(ECost_run10 - Cost_of_Service));
```

*Figure 48. Profit Calculations for Model ii Simulations*

The calculations for model iii are similar to the results in Figure 48. However, for this calculation, the water heating energy usage must be separated as the customer is presented with a new price for energy specifically for it. This calculation can be seen in Figure 49 where the first equation calculates the profit from the water heater usage and the third equation calculates the profit from the remaining energy consumption. Finally, the final equation in Figure 49 combines the two profit streams to calculate the true profit of model iii.

```
Profit_miii_TES = sum(EUse_Nhood_waterheat_miii.*(ECost_new_miii - Cost_of_Service));
Rev_miii_TES = sum(EUse_Nhood_waterheat_miii.*(ECost_new_miii));
Profit_miii_other = sum((EUsage_miii - EUse_Nhood_waterheat_miii).*(ECost_last_run - Cost_of_Service));
Profit_miii_total = Profit_miii_TES + Profit_miii_other;
```

*Figure 49. Model iii Profit Calculation*

# MODELING THE CONTROL ALGORITHM

The previous section discussed the process and flow of the model for one home. However, this control scheme works best with large number of homes where the effects from diversity of loads and the impact of aggregating multiple users to absorb or dissipate energy usage while reducing the negative drawbacks from manipulating temperature setpoints. Therefore, for this model, ten homes were included at once. These homes are described in Table 3 on page 44.

The program follows the same structure, shown in Figure 22 on page 58, as the single home model. The difference being that development of schedules must be performed over the population of homes individually and input into separate EnergyPlus models. This information must also be imported separately into Matlab for evaluation. This information is summed into one aggregated data set, since to the energy provider the system does not differentiate between homes and only seeks to supply the appropriate energy requirements for all homes at once. Each of the calculations are based on a timestep (or fifteen-minute) analysis and provides the same granularity as before.

The combined model is run from the initial Matlab script screen which calls several additional Matlab scripts to complete the simulation. This screen is shown in Figure 50 and includes variables that are used throughout the simulation. The “pause_all” parameter is described in the *Baseline Energy Model* section on page 59 but is used to pause the Matlab model to allow the EnergyPlus home simulations to complete since there is no direct way to receive feedback between the two programs. The "Outside_charge_Limit_max" variable defines the number of timesteps the energy storage calculations can be outside of the set state-of-charge. The 10,512 timesteps corresponds to 30% of the year, meaning that the energy storage system remains within its operating parameters for the other 70% of the time. The "Avg_BasekWhrate" variable defines the average energy costs used for baseline energy cost calculations and corresponds to the average energy costs in 2014 [63]. Finally, 'SOC_min" defines the minimum state of charge the energy storage system will allow.

```
%run each Script in order from here
pause_all = 300; %265sec for laptop, 275 for desktop
Outside_charge_Limit_max = 10512; %30% of the year
Avg_BasekWhRate = 0.1252;  %2014 average $/kWh 0.1252
SOC_min = 0.30; % minimum state of charge that the battery will accept
run('b_Read_WritetoCorrectfolder')
run('c_Run_One_forbaseline_2')
run('d_Define_variables')
run('e_Combined_multiplehomes2')
run('o_Random_renewable_wDiff_2_1')
run('p_AnnualECostCalc')
run('r_plots')
```

*Figure 50. Start Screen for Combined Control Algorithm Model*

The "run" functions are then used to execute other Matlab scripts within the same directory. The first run function calls for a reset in all the parameters and reads a core set of CSV or Excel files and overwrites any changes made in a previous run of the program. This ensures that all data in the model is current and is not the result of a previous simulation with different parameters included. The next script simulates the baseline energy usage of the ten homes. Thirdly, variables such as thermostat setpoints and price sensitivities are defined for each home. The “e_Combined_multiplehomes2” script runs several subscripts to complete the majority of the model while “o_Random_renewable_wDiff_2_1” initiates the thermal energy storage portion of the model and calculates water heating temperature setpoints for each home. The final two scripts calculate the annual energy costs, profit to the utility and produce graphs showing the results. The following paragraphs go into more detail into these steps of the model.

During the baseline energy calculation, the EnergyPlus batch file initiates once called by Matlab, and begins each of the ten homes to start their simulations. The “pause_all” function is setup to pause the Matlab simulation to wait for all ten EnergyPlus simulations to complete. Once the EnergyPlus simulations are completed and the “pause_all” function releases the Matlab script, the whole home and water heating energy usage from each of the homes is imported and summed together to get the neighborhood’s combined energy load shape throughout the year. The same process as with the single home simulation is used to calculate the scaled renewable energy generation magnitude and then to calculate the baseline energy storage capacity.

The combined model then calculates the load-shapes and homeowner setpoints for each of the ten homes. This information is set to demonstrate the variation in customer preferences for space temperature and water heater setpoints. This information was found by performing an informal survey of peers. This information is passed along to the combined homes iteration model which is demonstrated by column 4 in Figure 22 on page 58. This model establishes a While loop to perform iterations of negotiations between the utility and each homeowner until three parameters are met. These three parameters are used as the basis for analyzing the effectiveness of the algorithm and include the annual energy cost to the customer, annual profit to the utility and the energy storage capacity required for the set of homes. These parameters are discussed more in the results section starting on page 114. For each iteration, the Matlab script shown in Figure 51, calls a program to generate each of the ten home's schedules for clothes washer, dish washer, clothes dryer, oven and thermostat setpoints.

```
%% set initial directory for Matlab
EPlus_run = 1; %Set to 1
RenOutput_raw_mii = csvread('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\RenewableScale\RenOutput_raw.csv');
Annual_Costs_difference = 0;
Profit_utility_mii = -1000;
Batt_Cap_mii = -100;

while (Annual_Costs_difference < 10 || Profit_utility_mii < 0 || Batt_Cap_mii < 0) && EPlus_run < 31   %set to one more than desired iterations
% Read updated Energy cost file
ECost_mii = csvread('C:\Users\justin\Documents\Dissertation\BCVTBModel_a\Homes\EnergyCosts\ZeroEnergyCost.csv');
run('f_CWash')
run('g_DWash')
run('h_Dryer')
run('i_oven')
run('j_Tstat_cool')
run('k_Tstat_heat')
run('l_importandupdate')
run('m_battery_model')
run('n_write_files')

Desired_profit_increase_mii =0.005;
Desired_batt_decrease_mii = 0.15;

Annual_Costs_difference = (((i_Annual_cost_diff)/(abs(i_Annual_cost_diff))) + ((ii_Annual_cost_diff)/(abs(ii_Annual_cost_diff)))...
    + ((iii_Annual_cost_diff)/(abs(iii_Annual_cost_diff))) + ((iv_Annual_cost_diff)/(abs(iv_Annual_cost_diff))) ...
    + (v_Annual_cost_diff/(abs(v_Annual_cost_diff))) + ((vi_Annual_cost_diff)/(abs(vi_Annual_cost_diff)))...
    + ((vii_Annual_cost_diff)/(abs(vii_Annual_cost_diff))) + ((viii_Annual_cost_diff)/(abs(viii_Annual_cost_diff)))...
    + ((ix_Annual_cost_diff)/(abs(ix_Annual_cost_diff))) + ((x_Annual_cost_diff)/(abs(x_Annual_cost_diff)))) %want this to be positive 10
Profit_utility_mii = Profit_mii - (Profit_BL*(1+Desired_profit_increase_mii)) % want this to be positive +
Batt_Cap_mii = (1-Desired_batt_decrease_mii)*BatteryEnergyCapacity_mBL - BatteryEnergyCapacity_mii % want to be +
EPlus_run = EPlus_run + 1
end
```

*Figure 51. Combined Homes Iteration Model Matlab Script*

During the "l_importandupdate" script, EnergyPlus is called to perform an energy simulation on each of the ten homes and then import the results from the simulations into Matlab for evaluation. The combined energy usage load-shape for the iteration is used to calculate a required energy storage capacity to meet the defined requirements. The relevant information is written to files for comparison and then the model returns to the beginning and cycles through each step of the analysis again, further optimizing the outcomes.

The next step in the model, column 5 in Figure 22, adds in a new cost structure used for local energy storage systems, in this model an electric resistance water heater. The energy cost structure is created based on the remaining differences between renewable energy generation and energy usage of the ten homes. This cost is passed on to each home, which is able to respond accordingly for either consuming or shedding energy usage. Once the new temperature setpoint schedules are created, EnergyPlus simulations for each of the ten homes must be completed once again. The updated energy usage load-shape is imported into Matlab and used to calculate a new required energy storage capacity with the same stipulations as the baseline and iterative model.

To complete the Matlab model, the energy costs and utility profit models are completed. Once again, this is performed in a similar method as described in *Annual Energy Cost & Utility Profit Calculations* on page 94. All the information is stored and is used to evaluate the effectiveness of the control algorithm, which is discussed in the following section.

# RESULTS OF CONTROL ALGORITHMS

The results of the control algorithm are discussed in this section. To understand how well the control algorithm performed, the objective of the system must be known. This can be summarized to two major points, which often become the same, but may occur at different times depending on the scenario. The first objective (1) is to align energy consumption with the lowest cost of energy generation. Secondly, (2), the goal of the algorithm is to align energy consumption with the load shapes presented by renewable energy generation.

For this model, the three parameters that determine the number of iterations performed between the homeowner and the utility are met after nine iterations. This means that during the negotiations, the annual energy costs for each customer are reduced compared to their baseline energy costs. This also means that the energy storage requirement is at least 15% lower than during the baseline scenario and the annual profit to the utility is positive and increased by at least 0.5% over the baseline (see Figure 51 on page 101).

## *Alignment of Energy Usage and Renewable Energy Generation*

The data in Figure 52 shows the scaled renewable energy generation for the simulations. The renewable energy generation capacity has a maximum generating output of about 90kW throughout the year, with a maximum energy generation of about 23 kWh in one fifteen-minute timestep. This shows the variations from minute-to-minute and demonstrates the target for energy consumption to align. For this comparison, a random time slot is used for all the graphical comparisons – this translates to January 22nd to January 30th as the dates.

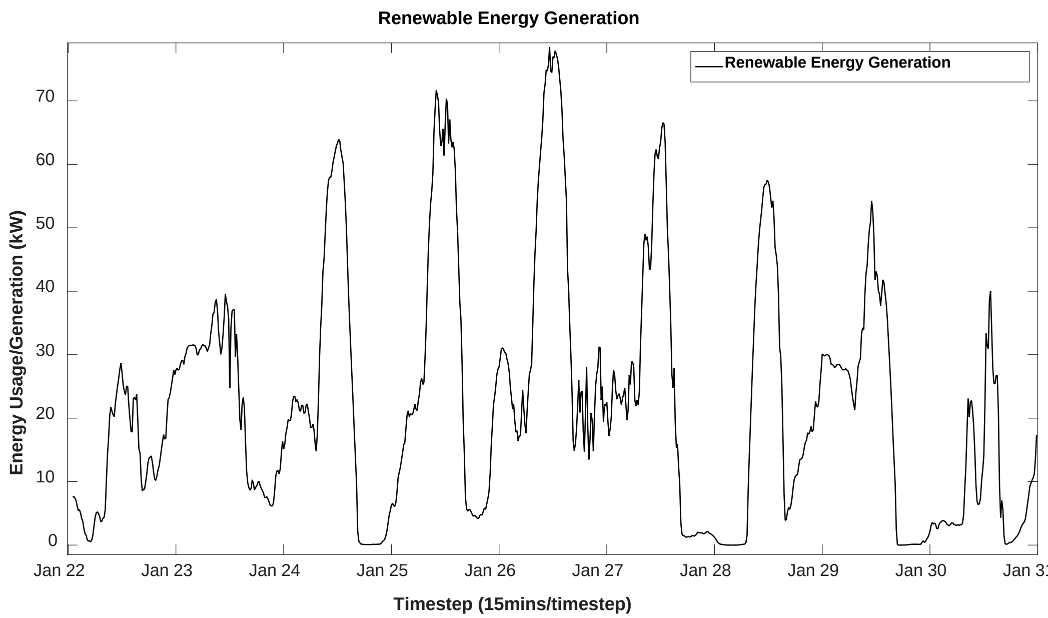


*Figure 52. Renewable Energy Generation Load Shape*

The renewable energy generation load shape can then be compared to the combined energy usage of the simulated homes for each model. This information shows, at a high level, whether or not the control algorithms help align the generation with the energy usage. To start, Figure 53 shows the data from the baseline energy model scenario and tracks renewable energy generation in the black line and the baseline energy consumption in purple.

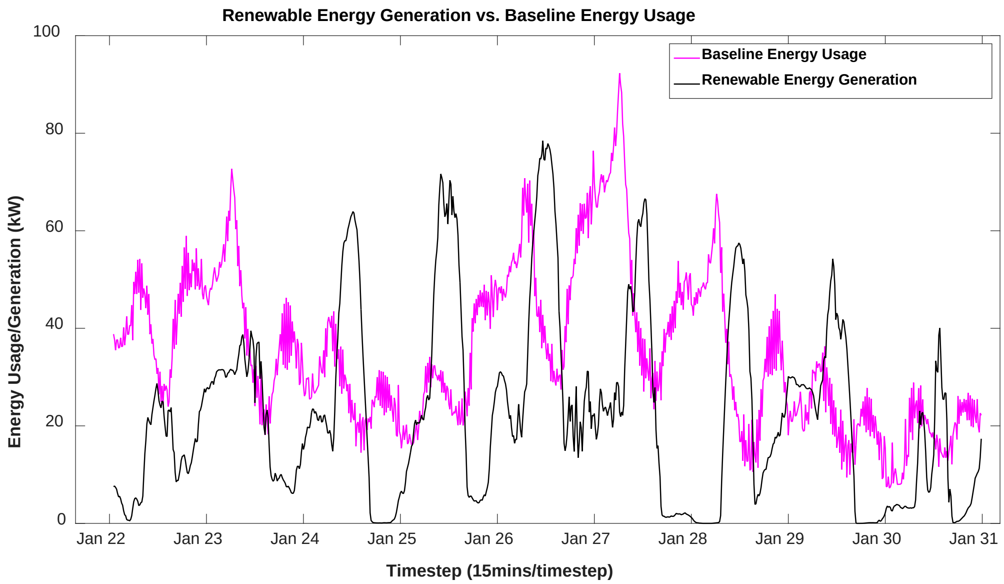


*Figure 53. Baseline Energy Load Shape Compared to Renewable Generation*

In Figure 53 it can be seen that there is not a direct correlation between energy usage and renewable energy generation and the two variables operate almost completely independent of one another in this model. This can be seen by calculating the correlation coefficient over the year between the renewable energy output and the baseline energy consumption, which yields an 11.5% linear correlation. The peaks in both usage and generation occur in the day when the sun is both generating solar energy and increasing the solar heat gain on the homes. However, note that when using the local time for both energy generation and usage, the energy usage tends to peak later in the day than the renewable energy generation (PV specifically) since, for a large portion of the year, the time when families arrive home is after the time of day when the largest PV generation occurs. This relationship can be seen in Figure 54 where the energy usage and renewable energy generation for July 13th are shown. Note that the energy usage continues to remain high after the renewable energy generation drops to almost nothing.

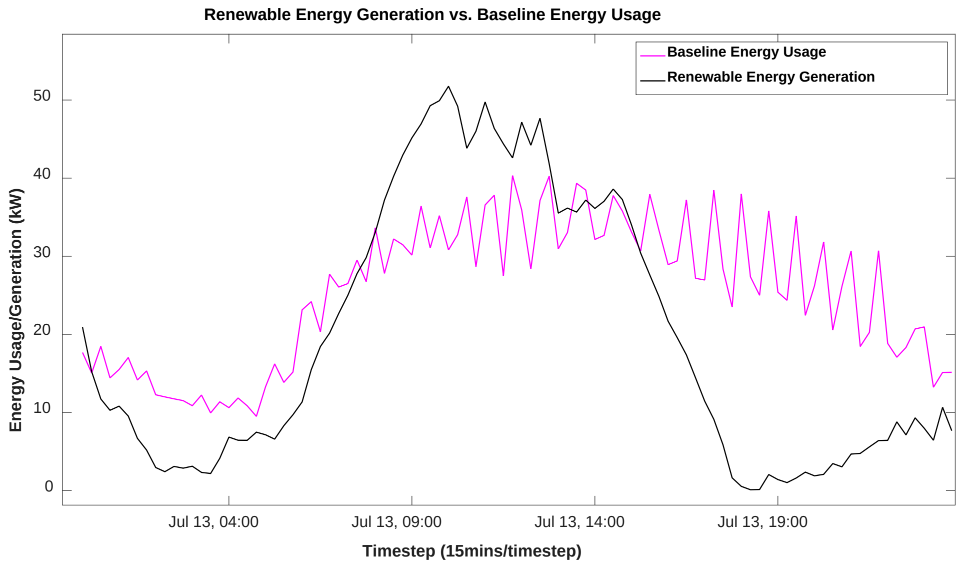


*Figure 54. Shift of Energy Usage from PV generation*

The next step in the model is to negotiate a price and energy usage load shape between the utility and the homeowner's energy management system. This provides the first level of optimization within the control algorithm and should begin moving the energy usage load shape towards the renewable energy generation load shape for each timestep in the year. This will never be a perfect alignment since the homeowner maintains their free will to use energy whenever they prefer. This process iterates for ten times before moving on to the next model, with each pass adjusting the schedule of appliance to better align the usage to generation. Figure 55 shows the difference in the renewable energy generation and the combined energy usage for each model iteration on January 23rd. Each line represents and follows an hour for each of the iterations as the strategy attempts to move each line to the zero on the Y-axis by iteration ten.

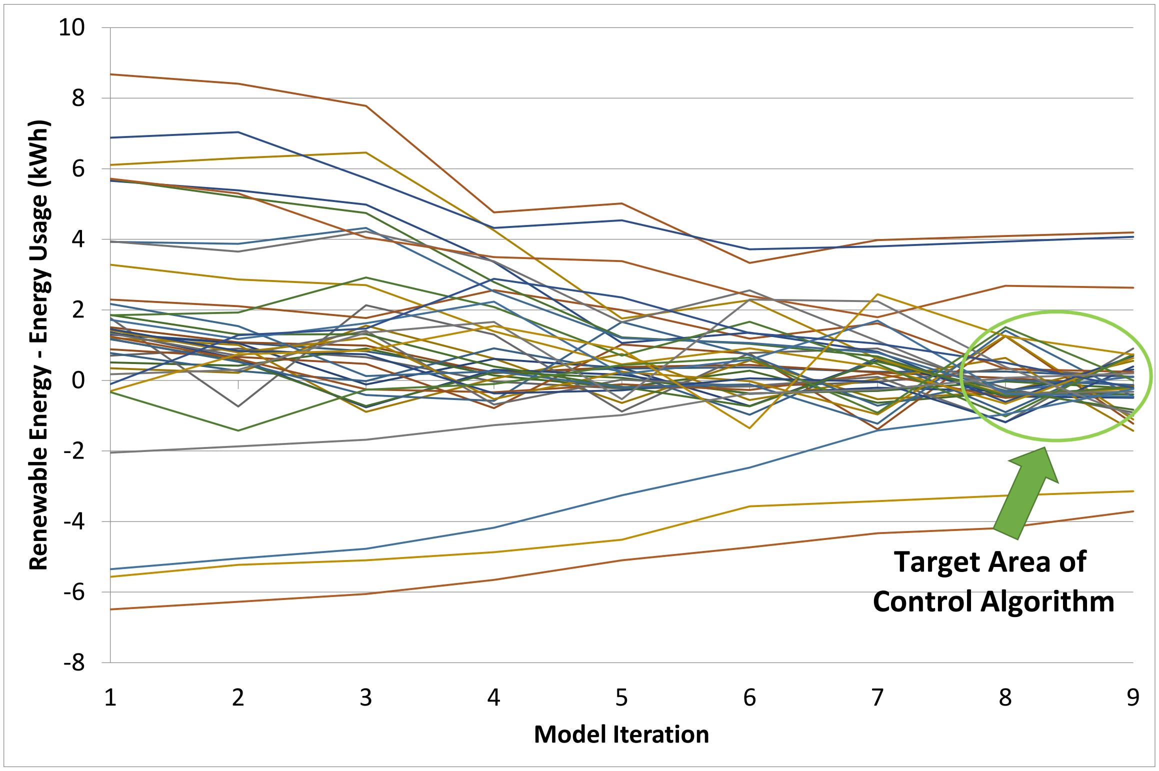


*Figure 55. Renewable Gen. minus Usage at Model Iterations per Timestep.*

The data shows that the general trend after each iteration is to move the energy consumption to the target area for the control algorithm but with some exceptions. This shows that the algorithm proposed is working as expected but does show that homeowner energy consumption is not infinitely flexible and will never allow for a perfect match. Hour five (top orange line) in Figure 55 shows that the algorithm will not always align the energy usage and renewable generation and that the relationship between hour-to-hour energy usage can affect how well other hours align, since energy usage remains relatively constant and usage is merely shifted. In this case, the variance occurs at 6am on a winter morning when morning activity is at its peak and thermostat schedules begin to switch from their nighttime setback, thus showing that energy usage is not completely flexible as long as homeowners have ultimate control of their energy usage.

The combined energy usage at the completion of model ii is plotted and compared to the renewable energy generation in Figure 56.

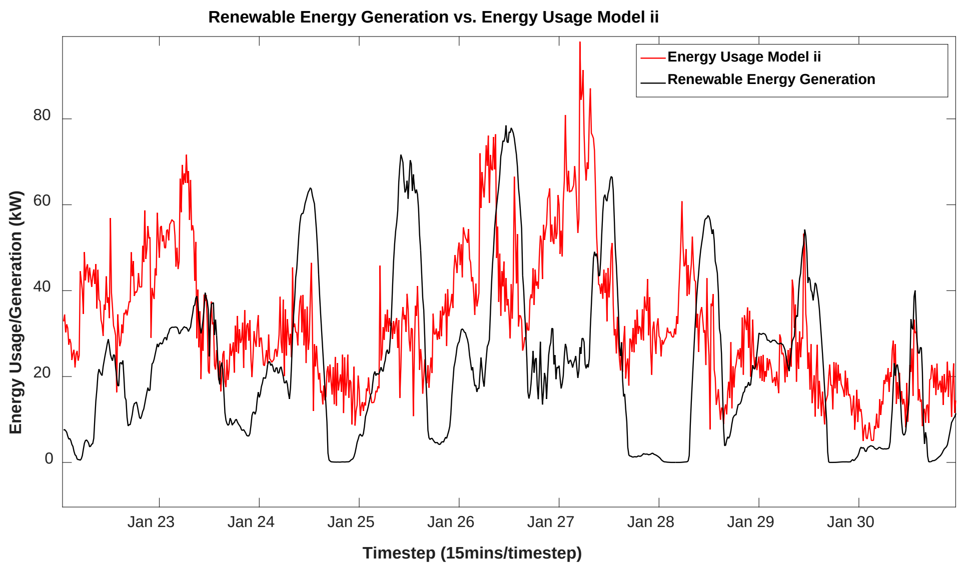


*Figure 56. Model ii Energy Load shape Compared to Renewable Generation*

The information in Figure 56 shows a better correlation between energy usage and renewable energy generation. Although it is not easy to tell from this graph, the annual correlation coefficient is increased to 33.2%. Figure 57 shows the energy usage load shape for the baseline energy model (purple) and the results from model ii (red), both compared to the renewable energy generation (black).

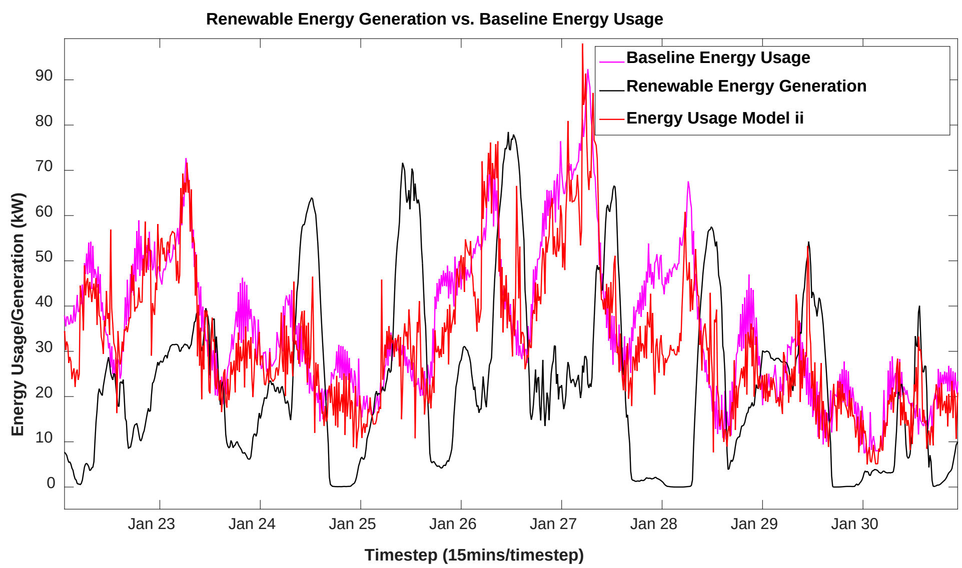


*Figure 57. Baseline & Model ii Usage Load shape vs. Renewable Generation*

Figure 57 demonstrates that there is some optimization in the load shapes, especially when there is lower energy generation. The control algorithm, while not perfect, does attempt to shift the energy usage, red line, toward the renewable energy generation in black. This remains a non-perfect method as residential energy usage is typically peaky – meaning there are a limited number of appliances that make up a large portion of the energy demand which are generally have an on/off control strategy. This implies that when one of those appliances come on, the energy usage for that time period increases substantially. Additionally, for safety and comfort reasons, certain loads cannot be shifted outside of low renewable energy generation periods – for the January time frame an example would be the space heating overnight when temperatures are below freezing outside and no PV is generating. There are certain comfort and safety impacts that come with not operating the heating system, therefore those take precedence over the control algorithm goals.

The third portion of the control algorithm is to implement an additional control strategy affecting the energy storage systems available at the homeowner's site. In the model presented, this specifically refers to electric water heaters, but could apply to any designated thermal energy storage systems for HVAC or even battery energy storage when available. The goal of this portion of the control algorithm is to additionally shift, in a more real-time manner, the energy usage in a home to match the renewable generation by sending an updated pricing signal to the water heater and manipulate the water heater temperature while not impacting customer comfort. Figure 58 shows the combined energy usage load shape, in blue, plotted against the renewable energy generation in black.

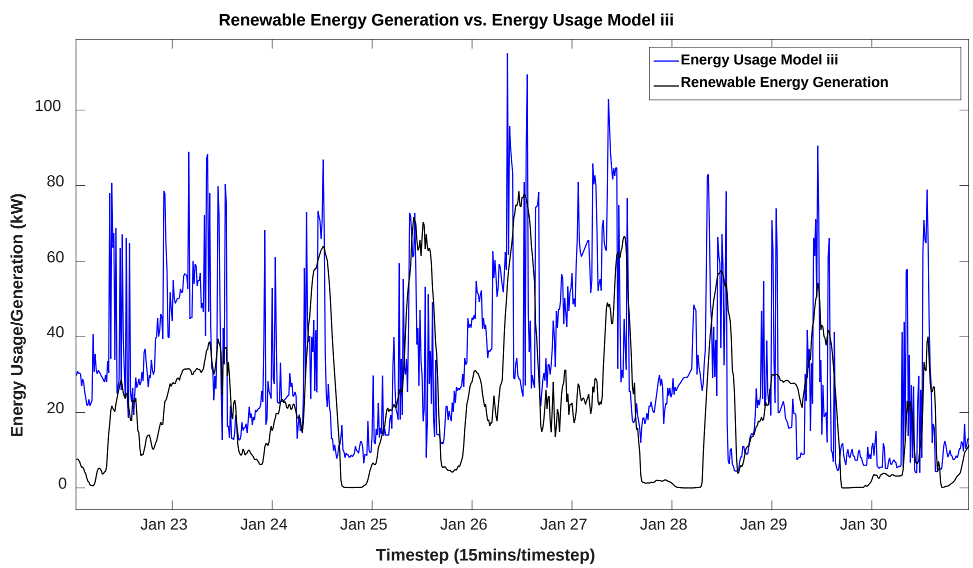


*Figure 58. Model iii Energy Load shape Compared to Renewable Generation*

The data presented in Figure 58 shows overlap in the combined energy usage of the homes and the renewable energy generation but still does not provide exact alignment between the two. Again, this is due to comfort and safety concerns along with the limitations of having a fixed wattage under control. The water heaters are controlled under a minimum and maximum temperature band and must maintain a temperature between them and average out to approximately the midpoint to ensure comfort. This also ensures a safe operation of the system by limiting the maximum and minimum temperatures to remain within an acceptable water temperature range, e.g. not boiling. This setup does require a mixing valve to be installed to ensure scalding does not occur at higher temperatures. One auxiliary benefit of increasing the temperature is an improvement in the safety of water by killing any bacteria associated with Legionnaires' disease. According to OSHA [74], 100% of the bacteria are rapidly killed at temperatures above 160°F and therefore storing energy in hot water above that temperature effectively eliminates the risks associated with Legionnaires' disease from domestic hot water.

The results from Model iii include a correlation coefficient of 40.2%, which continues to improve from the previous model iterations. To demonstrate how the results from Model iii continue to align the energy usage with renewable energy generation over the baseline models and even Model ii, a chart was developed presenting all three model results compared to the renewable energy output. This information is shown in Figure 59.

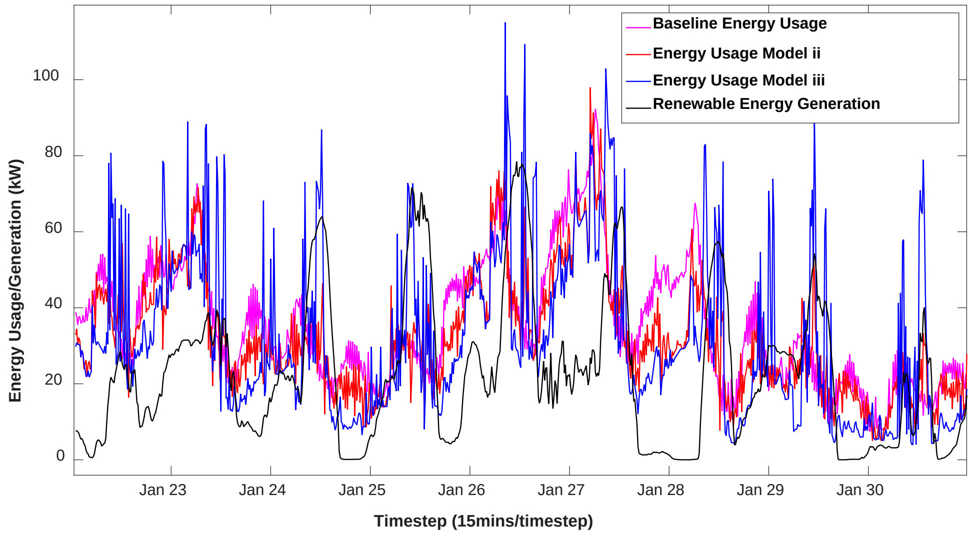


*Figure 59. Renewable Generation Comparison to Energy Usage Models*

The data shows a general trend of the energy usage in Model iii to align better than the other two models to the renewable energy generation. There are instances where the energy usage attempts to align with the renewable energy but overshoots the target, see Figure 60.

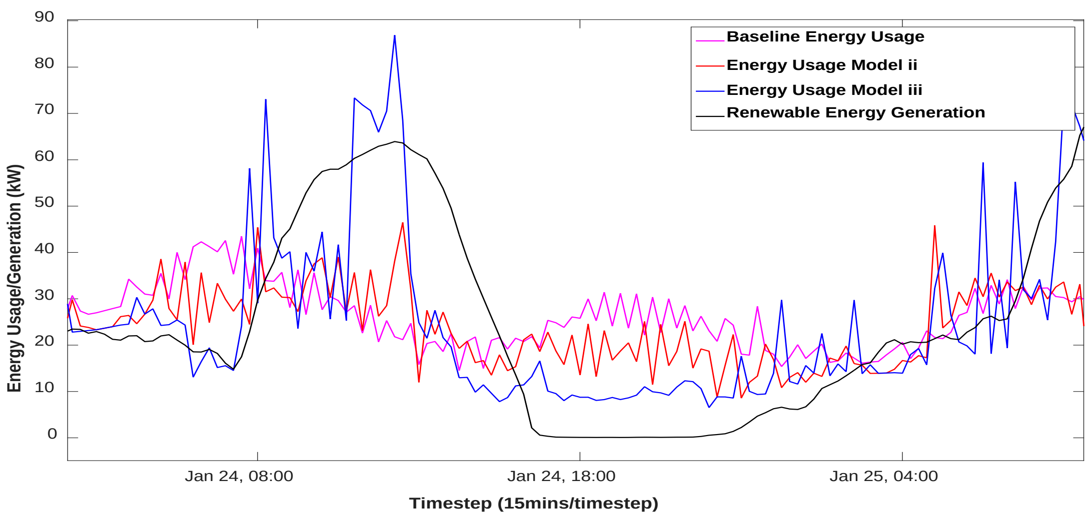


*Figure 60. Energy Usage Overshooting Renewable Generation*

This over compensation is exaggerated in this model with the low number of homes (ten) as each home contributes a large percentage of the flexibility and can be spread out more evenly between participants when a large penetration can be seen, thus minimizing this over usage. Figure 59 and Figure 60 show that, on average, the alignment of energy usage and renewable energy generation improve after each model iteration. This is summarized for each model simulation in Table 12.

*Table 12. Model Iteration Correlation Coefficient*

| Model Iteration | Correlation Coefficient |
|---|---|
| Baseline | 11.5% |
| Model ii | 33.2% |
| Model iii | 40.2% |

The data shows for the baseline energy usage is almost completely independent of the generation, resulting in patterns that respond independently and are only loosely coupled by solar radiation impacts on PV generation and heating and cooling loads within the home. However, in Model ii, adding a proxy for the energy generation in the form of pricing signals helps encourage the homeowner to shift their usage from low generation periods to higher generation periods, within certain limits. This is further improved in Model iii where water heating can be used as thermal energy storage and responds to an updated energy cost to further encourage the homeowner to shift their usage to a mutually beneficial time.

*Comparison of Three Major Model Outputs to Verify Modeling Approach*

Beyond demonstrating that the algorithm helps align energy usage with costs and/or renewable energy generation, three major outputs from the model are used to determine the effectiveness of the control algorithm. The first parameter is the annual energy cost to the customer for each home and to make sure the algorithm reduces the energy costs from the baseline energy model to the final output of model iii. The second parameter is the size of energy storage calculations for each model and to ensure the required capacity decreases after each model iteration. Finally, the third parameter is to compare the profit to the utility and confirm the profit remains constant or increases from the baseline model to the output of model ii. With all three of these parameters being met, the algorithm can show that by aligning energy usage with renewable energy generation in an iterative manner, it can reduce the annual energy costs to the customer while also increasing profits to the utility and reducing the amount of energy storage required to optimize the system.

*Annual Energy Costs to Home Owners*

The first consideration is the annual energy costs to the customer. The results from the model are shown in Table 13. This baseline energy costs information is calculated at a flat rate of $0.1252/kWh [63] and is multiplied by the annual energy consumption. There are no other taxes or fees considered for this comparison. In the completed algorithm energy costs, the annual energy cost is calculated using the results from model ii to calculate the energy costs for all non-energy storage devices. The water heating energy costs are then calculated using the results from model iii cost data and multiplying the usage by the cost at each time-step.

*Table 13. Annual Cost Reductions with Algorithm*

| House | Baseline Energy Costs ($/yr) | Completed Algorithm Energy Costs ($/yr) | Percent Reduction in Energy Costs (%) |
|---|---|---|---|
| 1 | $2,372 | $2,319 | 2.3% |
| 2 | $2,561 | $2,463 | 3.8% |
| 3 | $2,386 | $2,297 | 3.8% |
| 4 | $2,360 | $2,234 | 5.4% |
| 5 | $2,664 | $2,591 | 2.8% |
| 6 | $2,419 | $2,334 | 3.5% |
| 7 | $1,952 | $1,835 | 6.0% |
| 8 | $2,550 | $2,483 | 2.6% |
| 9 | $2,268 | $2,164 | 4.6% |
| 10 | $2,465 | $2,380 | 3.5% |
| **Total** | **$23,998** | **$23,100** | **3.8%** |

The data in Table 13 shows that it is possible to reduce the energy costs of to the customer with this algorithm. This data does not represent a large reduction in energy costs but is only a portion of the advantage of the control algorithm. The information in Figure 61 and Figure 62, on pages 117 and 119 respectively, show that the algorithm can greatly reduce the energy storage requirements and increase profit to the utility. The prioritization of these parameters can be debated in future implementations but for now, demonstrates that all three benefits are possible with this algorithm.

*Energy Storage System Requirements*

The second major consideration is the energy storage capacity required to ensure the state-of-charge calculation remains above the lower threshold (30% SOC) and below the maximum threshold for a combined maximum of 10,512 timesteps (2,628 hours). It was assumed for these calculations that the energy storage has a minimum state-of-charge of 30% of its maximum capacity and the maximum storage capacity is 100%. The significance of this calculation is to show how much closer, in terms of time, the renewable energy generation and energy usage are. It is also assumed that the energy storage has the charge/discharge capacity to meet the cycling needs for the entire year – which for these ten homes was always found to be less than 120kW. This is set to the maximum difference in energy generation and supply and is shown as the blue line in Figure 61 . The required energy storage capacity to meet the previously listed requirements during the three major system models is shown in Figure 61 with the baseline capacity the green column, the results from model ii as the gray column and finally the yellow column representing the results from model iii.

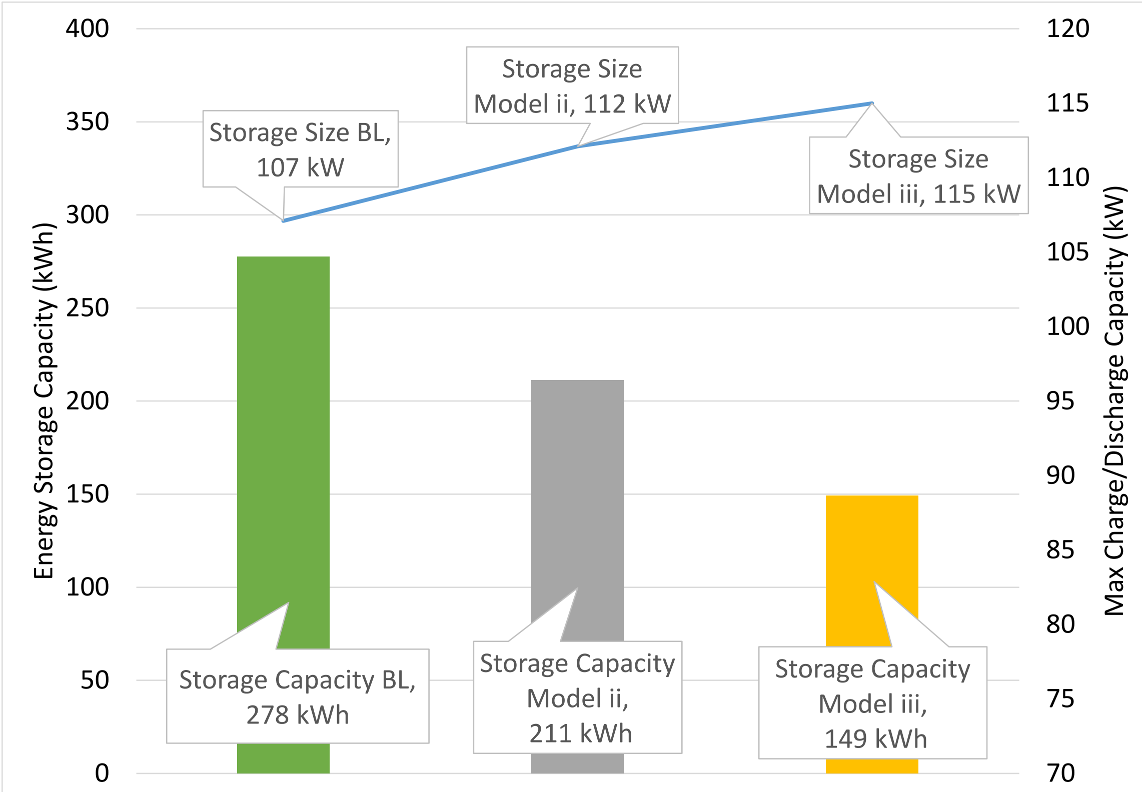


*Figure 61. Energy Capacity Requirements per Model Run*

The data in Figure 61 shows that about half of the optimization occurs during the day-ahead negotiations between the home automation system and the utility, decreasing the energy storage requirements by 24%. Further optimization in the system is seen when adding in the element of thermal energy storage as additional energy storage is introduced into the system. This leads to a reduction of an additional 29% in energy storage requirements, or 46% reduction from the baseline model. The maximum charge/discharge rate is fairly constant throughout but does increase by 4.7% from the baseline to the results from Model ii and then increases by 2.7% during Model iii. This increase in maximum charge/discharge rate from Model ii to Model iii is due to the overcompensation of water heater energy usage as discussed previously in Figure 60 and also includes energy usage as a result of encouraging it during low cost periods.

It is interesting to note that under the parameters listed for the energy storage system calculations, the model's sizing is driven by the minimum state-of-charge condition. This means that the storage capacity is increased because it is not capable of supplying energy to the homes and must pull additional energy from the grid. Model iii shows a much better alignment between the two parameters than either of the previous models. This demonstrates that the water heaters are able to absorb energy in the form of hot water when excess renewable energy generation is present and store that energy so it is not required to run as often when low renewable energy generation is present.

*Profit earned by the Energy Utility*

The final major parameter analyzed for the control algorithm is the profit to the utility. The idea is that, even with less energy sales to customers, having more energy sold at times when it is more profitable and less energy sales when the utility loses money can lead to increased profits. For the control algorithm to be effective, the balance between the annual energy cost to the customer and the utility must be aligned so that more profitable energy sales are increased while also decreasing the total cost to the customer. The calculation methodology for this is discussed in *Annual Energy Cost & Utility Profit Calculations* on page 94 and the results are shown in Figure 62.

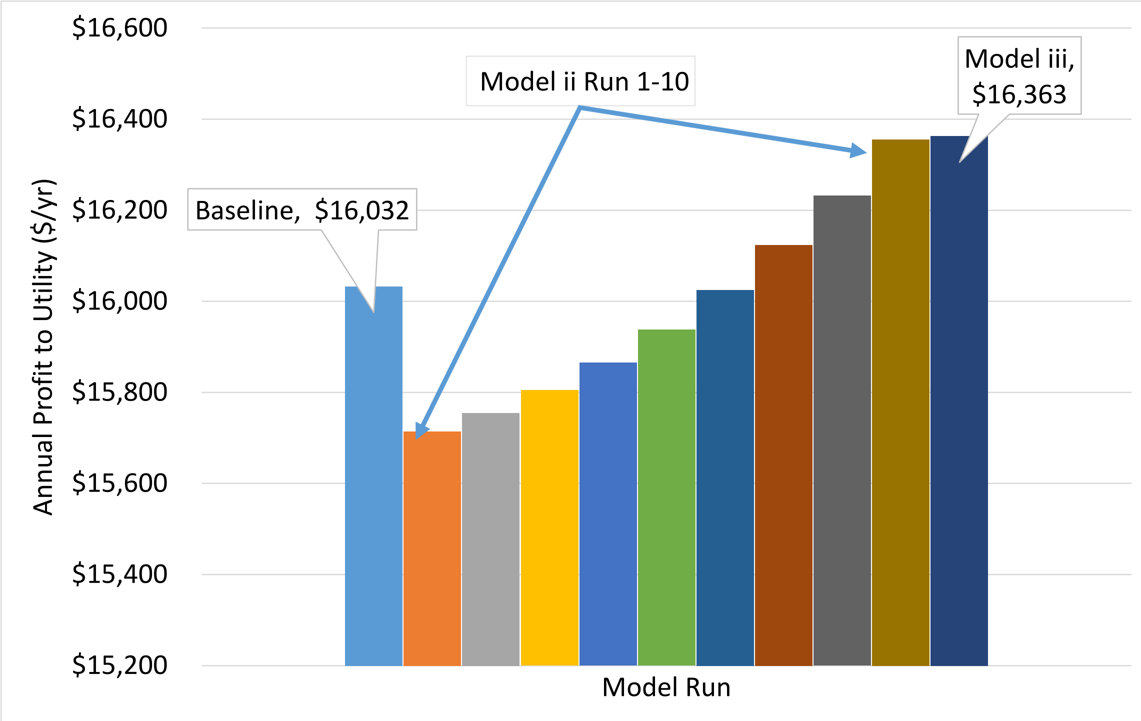


*Figure 62. Utility Profit for each Model Run*

The data shows that the baseline model provides a profit of $16,032 per year for the ten homes in the model. This is operating at a flat rate to the customer and ranges anywhere from losing money for each kWh sold to greatly overcharging the customer to use energy during super off-peak hours. This rate only attempts to average that cost over the course of the year and does not account for variations in true generating costs nor does it align the true costs to the consumers causing it. When beginning optimization in the model, the homeowner's system set to develop their energy usage model based on their preferences, which do not typically align with the lowest cost to produce energy. As the negotiations continue between the utility and the home automation system, it can be seen by the upwards trend that energy usage is incentivized to adjust to the more profitable hours and profits are increased while energy cost to customers remain below the baseline.

Finally, in Model iii, the water heater energy usage is aligned directly with the cost of energy and allows for further reduction in annual energy costs to customers by shifting usage to lower cost and increasing the profit to the utility over the baseline case. This results in a new profit of $16,363 in the year for those ten homes or an increase of 2.1%

## Advanced Home Equipment to Improve Performance of Control Algorithm

To improve the control strategy and understand how the control algorithm will react in the future when variable speed HVAC systems, rooftop PV generation, and large thermal energy storage capacity water heaters are prevalent. For this simulation, the same ten homes are used from before but each is equipped with high efficiency, variable capacity HVAC and an 80-gallon resistive water heater to maximize energy storage capacity. Additionally, a 4.5kW PV system was added to a subset of the homes which provide energy for the home and back to the grid when available. The breakdown of new features is shown in Table 14.

*Table 14. Advanced Home Equipment Features*

| Home | Variable Capacity HVAC | 80-gallon Water Heater | Rooftop Solar PV |
|---|---|---|---|
| 1 | Y | Y | 4.5 kW |
| 2 | Y | Y | 0 kW |
| 3 | Y | Y | 4.5 kW |
| 4 | Y | Y | 0 kW |
| 5 | Y | Y | 4.5 kW |
| 6 | Y | Y | 4.5 kW |
| 7 | Y | Y | 0 kW |
| 8 | Y | Y | 0 kW |
| 9 | Y | Y | 4.5 kW |
| 10 | Y | Y | 0 kW |

The same control strategy and user parameters are used for the advanced home model, with the exception of two changes. This was to maintain consistency between models but negative comfort impacts will be reduced with the advanced equipment since there is greater control and flexibility with the newer equipment.

The first change for the advanced home model is to how the water heater temperature setpoint is calculated in the third portion of the model. While in the base case home model, the water heater temperature increased as cost decreased in steps, the advanced home is continuous. Due to the increased thermal storage capacity and added flexibility offered, this continuously variable temperature setpoint was found to greatly enhance the effectiveness of its storage capability and decreased the homeowner's energy costs while improving the ability to reduce energy storage needs. An example of the updated response can be seen in Figure 63. It can be seen that the dead band is still included to maintain the base temperature setting for small energy cost changes.

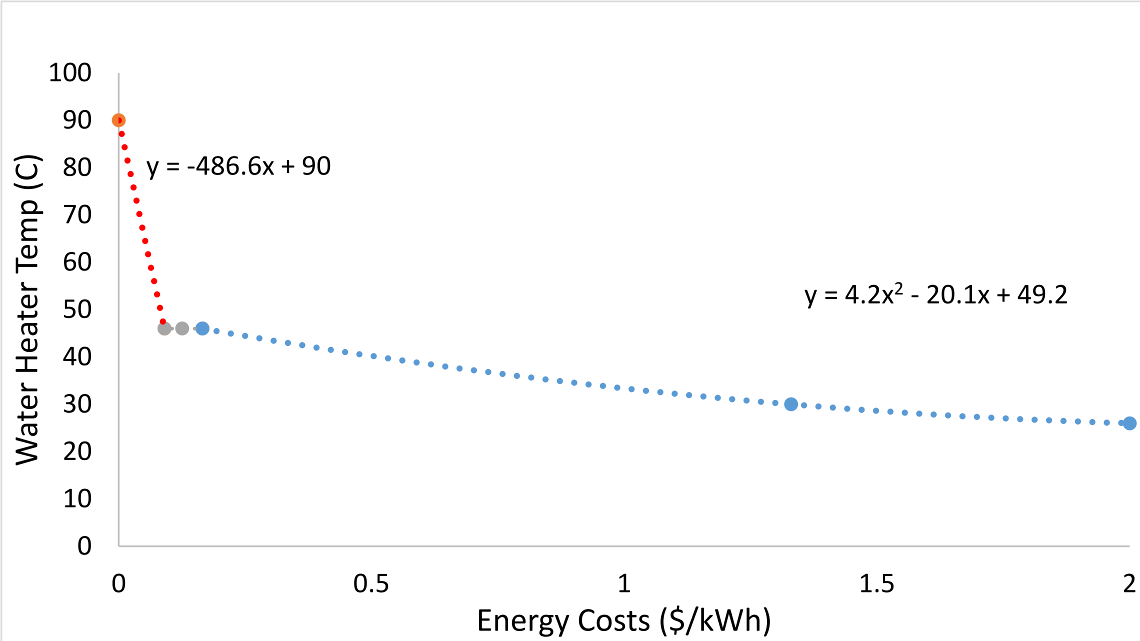


*Figure 63. Example Updated Model iii Water Heater Response*

The second change also relates to the water heater response in Model iii but now includes an increase in the profit margin implemented by the utility. This allows the utility to compensate for the additional thermal energy storage and flexibility with the larger storage tanks while maintaining a positive profit in the overall control strategy and still reducing the overall energy costs to the homeowner. The results to the Advanced model are discussed in the following section.

*Advanced Home Model Results*

The results from this model follow the same general trends as the previous models where the annual energy cost to the customer and the energy storage requirements are reduced while the profit to the utility is increased. In this section, the same results as in

*Results of Control* Algorithms on page 103 are discussed and while the general trends are the same, some interesting differences are also noted and discussed later in the section titled Advanced Home Model Differences on page 133. The three parameters that continue the negotiations between the homeowner and the utility – annual energy costs, energy storage capacity reduction by 15% and an increase in profit by 1.5% – were satisfied after thirteen iterations.

For the advanced home model, the same method for calculating the scaled renewable energy is used which pulls data from the same energy generation load shape. This results in the same energy generation shape but a different magnitude since the homes now consume less energy than before. The same time frame for energy generation as in Figure 52 is shown here in which corresponds to January 22nd to January 30th as the dates.

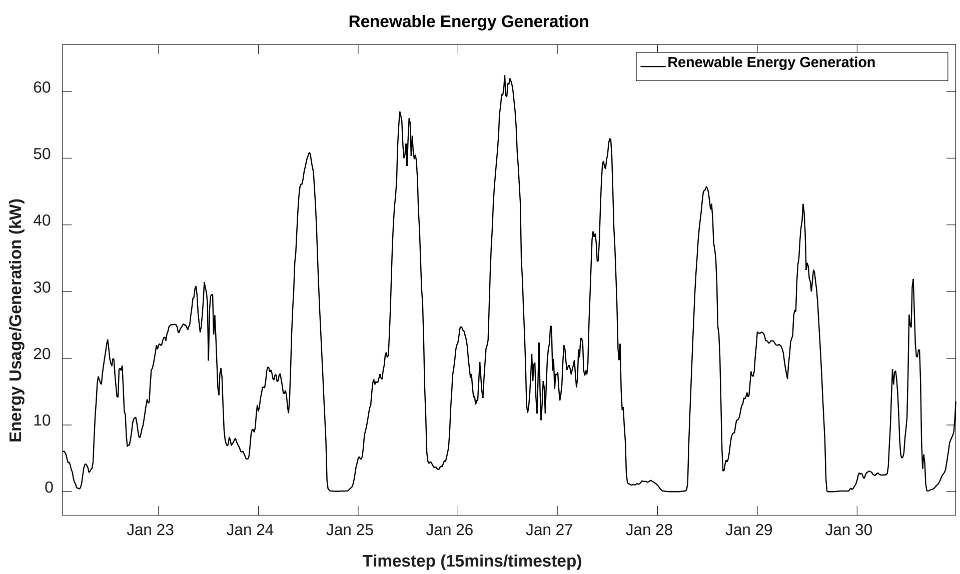


*Figure 64. Renewable Energy Generation Load Shape – Advanced Homes*

When comparing the results from Figure 64 to those of Figure 52, the load shape is exactly the same. However, the magnitude is reduced from a peak generation previously of around 80 kW to a current peak of just over 60 kW in Figure 64. The renewable energy generation is then used to compare the energy consumption load shape for each model iteration to visually compare how well the generation and energy consumption align.

As with the typical home model from before, the baseline energy consumption of the advanced homes does not show a direct correlation between energy usage and renewable energy generation as these two things are still only loosely coupled by thermal heat gain. This actually proves to have less of an impact when homes are built tighter and with better insulation as the impacts are reduced and/or delayed, causing an even smaller correlation. For the results in the advanced home baseline model, the linear correlation between energy usage and renewable generation for the entire year is -0.139 (-13.9%) which means there is a negative correlation between the two. This implies that at a given timestep, as the energy generation increases over the year, the energy consumption tends to decrease and vice versa. This is the opposite of the desired behavior as the goal is to align the energy consumption to the renewable energy generation as closely as possible.

The second portion of the model uses the iterative process to help align the energy consumption to the generation. The same process of alignment was used as in the initial home model and the same temperature setpoints and appliance usage requirements were carried over. The results after the ten iterations for this model lead to a linear correlation of 0.092 (9.2%) between the renewable generation and the energy consumption. This is an improvement from the negative correlation in the baseline model but still only shows a very small correlation between usage and generation. The combined energy usage of the ten homes is plotted for both the baseline and for Model ii case and compared against the scaled renewable energy generation in Figure 65.

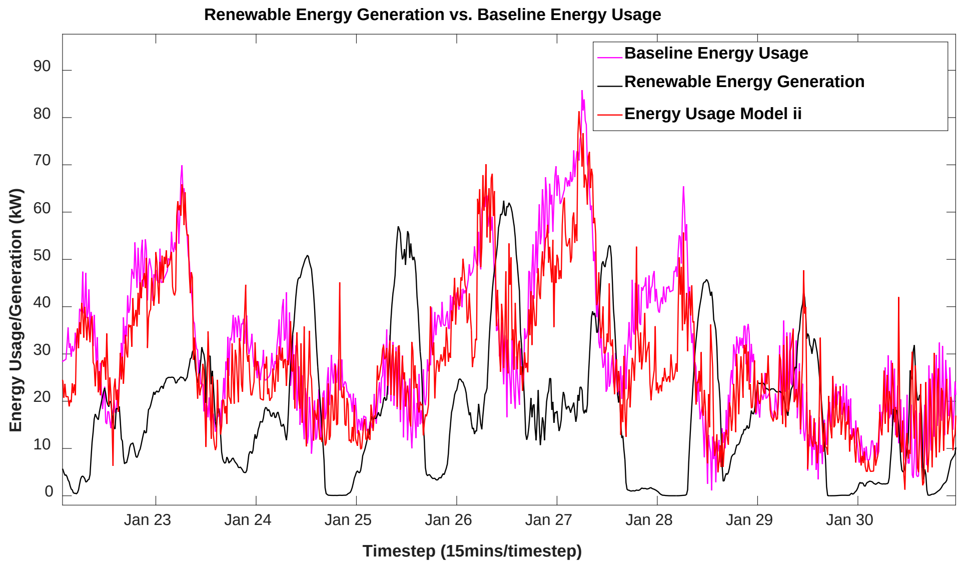


*Figure 65. Baseline & Model ii Load shape vs. Ren. Generation – Adv. Homes*

This information shows that the iterations of this model help bring the energy usage towards the renewable generation – the red line attempts to either increase or decrease in several locations to match the black line.

The third portion of the model (Model iii) is used to supplement the results from Model ii to help match the energy usage to the renewable energy generation by storing thermal energy in water heaters. This concept can be applied to any device that can store energy, electrical, chemical or thermal, however for this model only the water heater is used to minimize cost and comfort impacts to the homeowner. This portion of the model is also improved over the initial homes model as the tank size is increased from 50 gallons to 80 gallons. Additionally, the same temperature setpoints are used which range from 20-90°C (68 – 194°F). The results of Model iii are plotted with the results of Model ii and the baseline energy usage profile against the energy generation in Figure 66 to show the improvement as the model progresses.

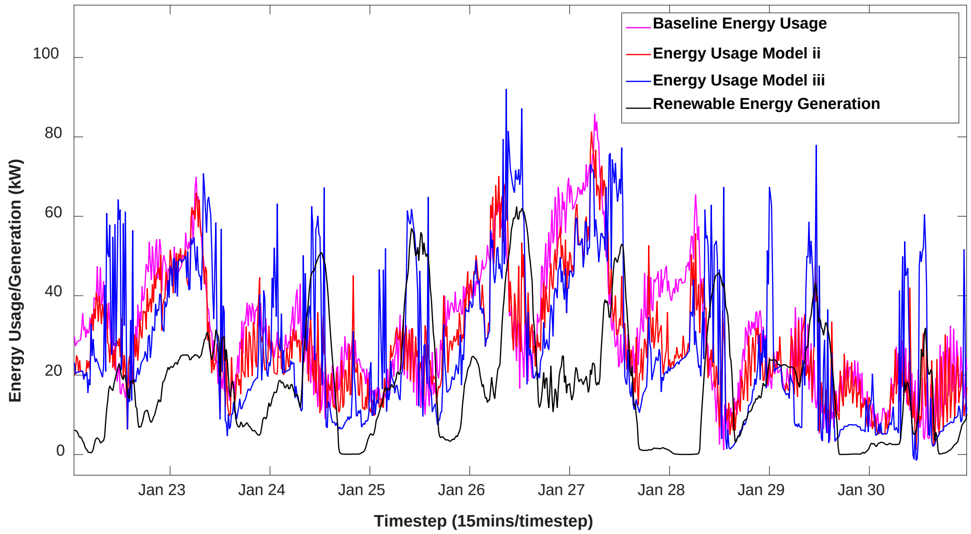


*Figure 66. Renewable Generation vs. Energy Usage Models – Adv. Homes*

The data again shows a general trend to move the energy usage towards the energy generation (blue line towards the black line). This is better demonstrated with the linear correlation coefficient which for this model is 0.295 (29.5%) which is an increase from 9.2% at the end of Model ii. This information is summarized in Table 15.

*Table 15. Model Iteration Correlation Coefficients – Advanced Homes*

| Model Iteration | Correlation Coefficient |
|---|---|
| Baseline | -13.9 % |
| Model ii | 9.2 % |
| Model iii | 29.5 % |

The data in Table 15 shows the same basic trend throughout the advanced home model process as with the traditional homes model where it starts with a low correlation in the baseline model, is improved after Model ii and is further improved after Model iii. The results in the advanced home model are consistently less correlated to the renewable generation than it was previously in the traditional home model. This is due to the addition of rooftop PV into half of the advanced homes and is discussed in more detail in *Advanced Home Model Differences* on page 133.

*Comparison of Three Major Model Outputs to Verify Approach – Adv. Homes*

To demonstrate that the algorithm not only helps align the energy usage with the renewable energy generation output, but also helps reduce the energy costs to customers while also increasing the profit to the utility, three parameters were analyzed. The first is the annual energy cost to the homeowner that shows shifting energy usage to lower cost times will lower their annual energy bills. The second is the sizing of energy storage requirements to ensure capacity is decreased after each model is completed. Thirdly, the profit to the utility is compared for all models to ensure both parties benefit from the control algorithm. With all three of these parameters being met, the algorithm can show that by aligning energy usage with renewable energy generation in an iterative manner, it can reduce the annual energy costs to the customer while also increasing profits to the utility and reducing the amount of energy storage required to optimize the system. It is important to note that this is the same set of parameters evaluated in the tradition home model and all the same setup parameters are used.

*Annual Energy Costs to Home Owners*

The first consideration for the model is to ensure the annual energy cost to the homeowner is reduced, providing the incentive to participate in this type of program. The comparison of costs is shown in Table 16. The energy costs are calculated using the same method described in *Annual Energy Costs to Home Owners* on page 114 but in summary calculates the baseline energy cost as the annual energy usage multiplied by the average energy rate. The completed algorithm energy cost is calculated at each fifteen minute timestep by multiplying the energy consumed in that timestep by the final energy cost for that same time period. This energy cost is also separated with the water heater charged on a different rate (see page 114) and its energy costs are calculated separately. Finally, the total energy cost in each timestep are summed over the course of the year and presented in Table 16.

*Table 16. Annual Energy Costs with Algorithm – Adv. Homes*

| House | Baseline Energy Costs ($/yr) | Completed Algorithm Energy Costs ($/yr) | Percent Reduction in Energy Costs (%) |
|---|---|---|---|
| 1 | $2,163 | $2,127 | 1.7% |
| 2 | $2,313 | $2,234 | 3.4% |
| 3 | $2,265 | $2,170 | 4.2% |
| 4 | $2,034 | $1,979 | 2.7% |
| 5 | $2,458 | $2,349 | 4.4% |
| 6 | $2,197 | $2,093 | 4.7% |
| 7 | $1,743 | $1,522 | 12.7% |
| 8 | $2,341 | $2,114 | 9.7% |
| 9 | $2,020 | $1,971 | 2.4% |
| 10 | $2,581 | $2,486 | 3.7% |
| **Total** | **$22,116** | **$21,045** | **4.8%** |

The energy costs are reduced on average by just under 5% with a maximum annual reduction of 12.7% and a minimum reduction of 1.7%. The total energy cost reduction for the ten homes was $1,071. This cost reduction is higher than the average savings of about 3.8% in the traditional home model. The two major contributors of this much larger energy savings is the variable capacity heat pumps capability to operate in part-load conditions when energy is expensive. Additionally, the larger capacity water heater allows for most of the water heating to be accomplished at the lowest cost possible and stored while the energy costs are high, thus minimizing the energy costs associated with hot water.

*Energy Storage System Requirements – Advanced Homes*

The second parameter that is evaluated is the energy storage capacity required to ensure that the system of ten homes can maintain within the state-of-charge limits for a minimum of 10,512 timesteps over the year. The maximum state-of-charge is set to 100% with the minimum state-of-charge set at 30%. This calculation helps in understanding how well the energy usage lines up with the energy generation where the excess generation is stored and provided back to the set of homes when under-generation occurs. The results of the energy storage capacity are shown in Figure 67.

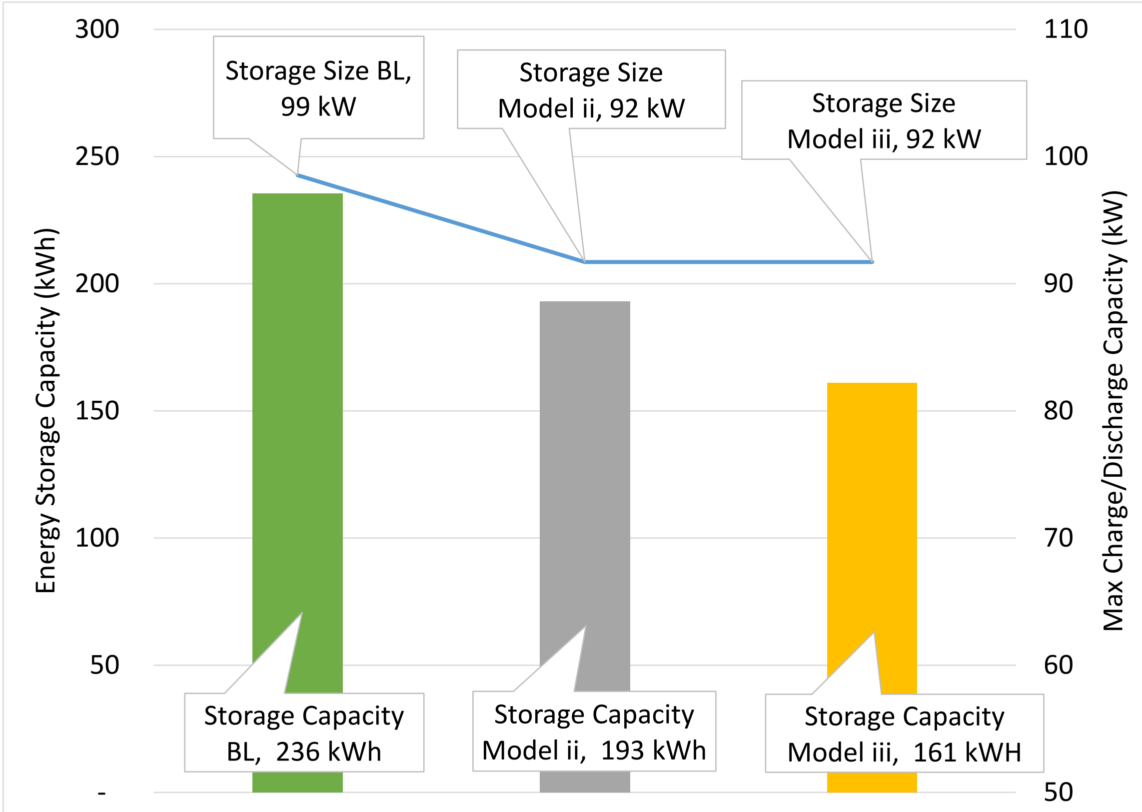


*Figure 67. Energy Capacity Requirements per Model Run – Adv. Homes*

The information presented in Figure 67 represents the energy storage requirements to ensure that a system's state-of-charge (SOC) does not go outside of its boundaries (30%-100%) over 30% of the year. This timeframe was chosen to decrease the energy storage capacity and since the system is grid-connected, there is no need for the storage to be capable of supplying the entire energy the ten homes need. The method of calculation was discussed in *Calculating the Size of* Energy Storage Required for Current Configuration on page 89 and uses the maximum difference of energy generation and usage as the charge/discharge capacity for the system to ensure all hours of the year can be served from the energy storage system. This information can be seen in Figure 67 with the blue line. The storage size remains relatively constant through all three of the models, with only a slight reduction from 99 kW to 92 kW for both Model ii and Model iii, this is a reduction of 7%. When looking into the storage energy capacity, the baseline requirement is a capacity of 236 kWhs. After implementing the initial negotiation between the home automation and the utility, the energy capacity is reduced by 18% to 193 kWhs. After the thermal energy storage algorithms are introduced in the system, the energy capacity is further reduced by an additional 17% to 161 kWhs. This is a total reduction from the baseline model to the results from Model iii of 32%. This shows the control algorithm, when fully implemented, can greatly reduce the size of energy storage needed to meet the needs of the ten homes. This translates into reduced upfront costs due to, in this scenario, only requiring about sixty percent of the energy to be stored in the battery at one time.

*Profit earned by the Energy Utility – Advanced Homes*

The third parameter analyzed, as with the traditional home model, is the profit to the utility. The calculation methodology for how this profit was determined is discussed in *Annual Energy Cost & Utility Profit Calculations* on page 94 but in short the energy consumed in each time-step is compared to the real-time costs calculated from the hub prices in the ERCOT market. This is feasible even with reduction in annual energy costs – decreased revenue to the utility – because times when real-time costs are above the rate charged to the customer will be reduced and more profitable energy sales outweigh the loss in revenue. Therefore, the goal of the algorithm is to reduce energy costs to consumers while increasing the profit of the utility which can be seen in Figure 68.

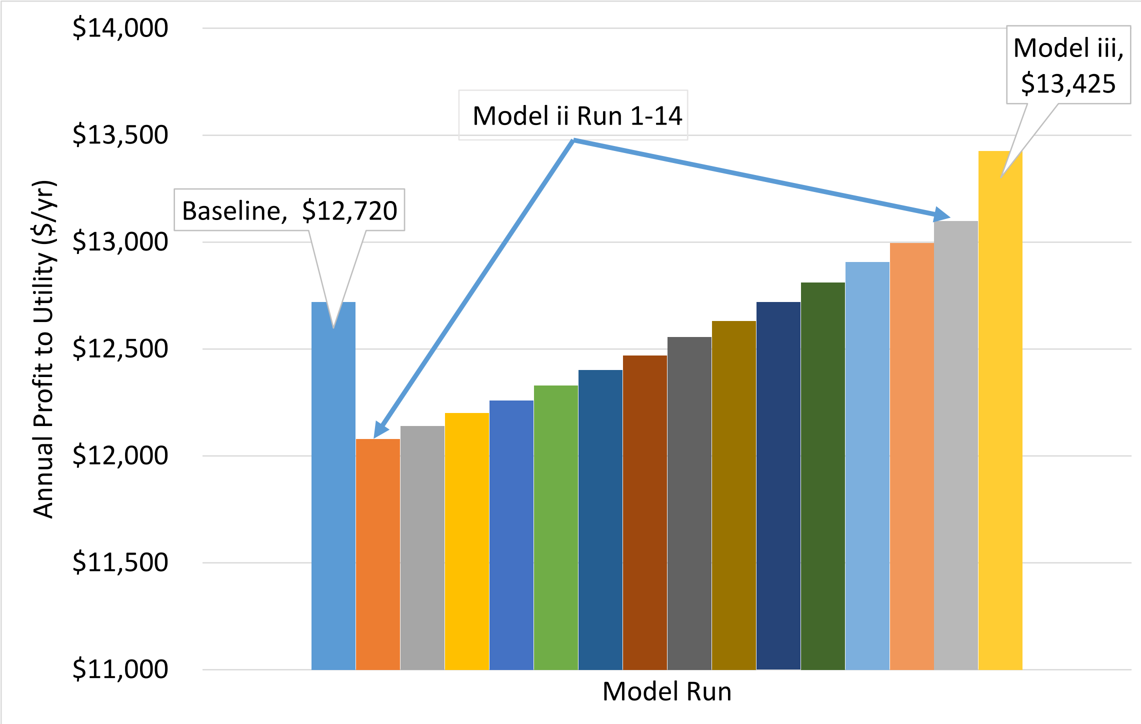


*Figure 68. Annual Utility Profit for each Model Run – Adv. Homes*

The simulation results in an annual profit for all ten homes of $12,720 for the baseline model and a profit for the same ten homes of $13,425 after the completion of the control algorithm in Model iii. This demonstrates an increase in profit from the baseline run to the results in Model iii of 5.5%. It is important to note that this increase in profit occurs while decreasing the annual energy cost by an average of 4.8%, which is shown in more detail in Table 16. As mentioned previously, it was the intent of this simulation to show the feasibility of increasing profit to utilities while reducing costs to the customer with minimal impact on their comfort and the priorities can be adjusted later to bring the profit and energy cost savings better in line.

*Advanced Home Model Differences*

The first major difference in the model is the necessary profit parameter changes from the base model. This can be seen in Model ii by changing the iteration While loop requirements from a 0.5% to a 1.5% increase in profit. Additionally, this can be seen during Model iii when the profit margin applied to the more real-time pricing scheme is increased to 33% from the 10% applied in the base model. These changes are due to the increased flexibility with end uses – variable speed HVAC and increased hot water storage. This added flexibility allows the homeowner to meet their comfort needs while shifting more energy from high cost times to a much lower cost period. Therefore, the model must be adapted to the changes seen with highly flexible homes to compensate for their ability to use energy in different time frames with little-to-no impact on comfort.

The second difference seen is an increased energy storage capacity required for all three model iterations; the baseline, model ii and model iii. This is attributed to the homes with additional rooftop PV installed since this further increases the local energy mismatch to the grid scale renewable generation. For example, rooftop PV generation will more-or-less align with the utility PV. This causes an increased mismatch in the home energy usage since the utility is encouraging additional usage during that period, however the rooftop PV is locally reducing or eliminating the energy consumed by that home. This is also apparent when investigating the linear correlation between the energy consumption and the renewable energy generation. The results of both models are shown in Table 17.

*Table 17. Summary of Correlation Coefficients for both Models*

| Model Iteration | Correlation Coefficient Typical Homes | Correlation Coefficient Advanced Homes |
|---|---|---|
| Baseline | 11.5% | -13.9 % |
| Model ii | 33.2% | 9.2 % |
| Model iii | 40.2% | 29.5 % |

Both models show the same trend of starting with a small correlation and improving over the course of the model. However, the results are consistently lower in the advanced home model when compared to the typical home. This is due to the addition of rooftop solar PV in a subset of the advanced homes. The model is built to optimize for the forecasted renewable energy generation of the system in a wide area, say the entire state. The model also relies on a limited number of homes and therefore a limited number of appliances available to shift to times of need. This can be partially improved by adding in additional homes without rooftop PV but for this model, the outcome is the increased battery storage as described earlier in this section. Other options that can improve the performance is to have the home automation platform capitalize on this and optimize the home with the inclusion of the local generation and use energy arbitrage to sell energy back to the grid when the costs are high and use energy at its lowest cost. Another is to include local energy generation forecasting at each PV generation site and input that information to the day-ahead energy usage profile as a negative usage when over generation occurs. This option allows the energy provider to optimize their system based on all the available data rather than being blind to local PV generation on the system. It also allows the utility and homeowners to negotiate a more appropriate price for each timestep as they are more representative of the true costs and allow energy consumption to align more directly with the totalized renewable energy generation.

The advanced model shows improvement through all three model components, however it was noticed that the larger water heater capacity limited the amount of additional load shed possible within the homes but improved the capability to add load to the system. This is due to the larger water volume storage capacity holding more thermal energy and in times when water usage is normal, the system is able to maintain the setpoint without using additional energy, therefore is typically not available (turned on) during these times when load is needed to be reduced.

A final difference noted between the traditional home model and the advanced home model is the trend in utility profit. In the traditional home model the profit is high in the baseline case, drops substantially in the model ii results but increases from iteration one to iteration seventeen. The profit then jumps to levels right at the baseline in Model iii. This can all be seen in Figure 62 on page 119. This differs from the results in the advanced home model – see Figure 68 on page 132. The results in the advanced home model show a lower profit in the baseline run with increasing profits through Model ii iterations, then for Model iii, the profit increases to a level higher than the baseline. This can be explained by the advanced home's ability to quickly adjust its usage from high price periods to low price periods which, at each iteration becomes times of higher margins.

## Model Run with Updated ERCOT Prices

Since beginning the development of the model, an updated cost profile has been released by ERCOT. To verify that the algorithms work independently from the specific cost profile, the updated costs were fed into the existing model to analyze the differences.

The initial data set was for 2014 and described earlier in *Developing Fifteen-minute RTP Starting Point data* on page 45. The updated data set of data comes from the 2015 historical real-time market Load Zone and Hub Prices downloaded directly from the ERCOT website [58]. From the data, the market prices for Houston were selected and are given in each fifteen-minute increment for the year. The starting price to the consumer was calculated the same was as before, described in the section titled *Developing Fifteen-minute RTP Starting Point data* on page 45 where the average rate throughout the year is set to a cost below the average energy cost of the year. This was done to allow the average energy cost to be driven higher by the algorithm without automatically starting at a point above the annual baseline energy costs. This updated cost information was input into the model by updating the CSV file titled "StartingPt_EnergyCosts_allcombined.CSV" which is used to reset the model to the original costs as the model initiates. The model was then completed as before. The comparison of both the traditional model and the advanced model are shown below.

*Traditional Home Model – Updated ERCOT Costs*

To measure the success of the algorithm, the same measures were compared for the model with updated starting costs. The first parameter compared is the correlation coefficients for each model run to ensure they are increasing as the algorithm progresses. The second is the annual energy costs of the homeowner during the baseline model, after model ii and finally after model iii. Thirdly, the energy storage system requirements are compared after all three segments. Finally, the profit to the utility is compared to ensure both the homeowner and the electric utility is benefiting from this algorithm.

The updated costs in the new model do not impact the baseline energy usage or baseline energy costs as they are not coupled to any variable pricing scheme and operate under the assumption that energy costs are constant throughout the year. Because of this, the following section will focus on the results after the baseline model has been developed. It is useful to remember that the correlation coefficient in the baseline model is 11.5% between energy usage and renewable energy generation.

The model's iterative process operates the same way as before and continues looping between negotiations (up to 30 times due to limited computing power – 30 since the iterations are n-1) until each homeowner's annual energy cost to the consumers is lower than their baseline energy cost, the profit to the utility is increased by at least 0.5% over the baseline case and the energy storage capacity is lowered by at least 15%. For this model, this negotiation takes place eleven times. The graphical results of Model ii are shown in Figure 69.

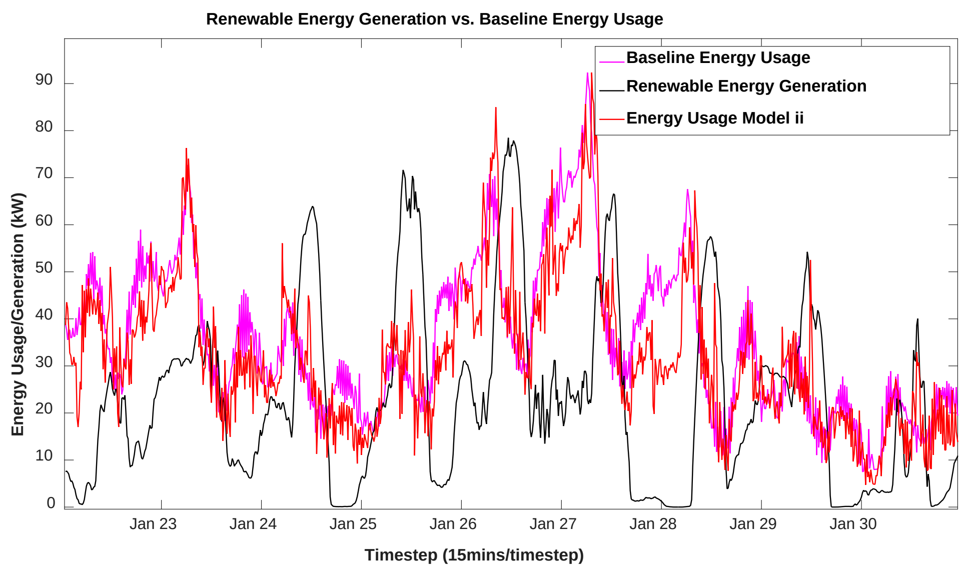


*Figure 69. Baseline & Model ii Load shape vs. Ren. Generation – Updated Costs*

Figure 69 can be compared to the results in Figure 57 on page 109 for the original energy cost breakdown and corresponds to a new correlation coefficient of 35.9% compared to the original of 33.2%. At this point, the simulation then moves on to Model iii where the thermal energy storage is included and continues to improve the correlation between energy usage and renewable energy generation. For this model, the profit margin was increased to 27.5% from 22.5% in the previous cost structure. This is to ensure all three parameters are effectively met for the simulation. The results are graphically shown in Figure 70.

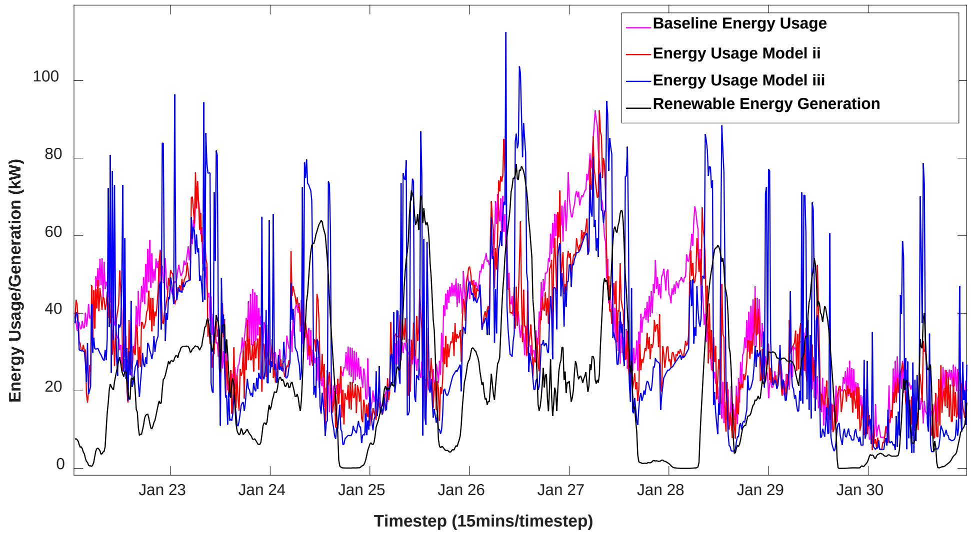


*Figure 70. Renewable Generation vs. Energy Usage Models – Updated Cost*

As with the previous model, the correlation continues to improve after the thermal energy storage is introduced into the control algorithm. For this model, the updated correlation is 43.1% between the energy usage and the renewable energy generation. This shows an increase of 7.2% with the addition of thermal energy storage in this model and is in line with the results from the original ERCOT pricing scheme. The comparison for correlation coefficients between the original and the updated cost profile are shown in Table 18.

*Table 18. Correlation Coefficient Comparison for Updated Cost Profile.*

| Model Iteration | Correlation Coefficient Original Cost Profile | Correlation Coefficient Updated Cost Profile |
|---|---|---|
| Baseline | 11.5% | 11.5% |
| Model ii | 33.2% | 35.9% |
| Model iii | 40.2% | 43.1% |

Since the control algorithm was able to improve the correlation between energy consumption and renewable energy generation, the next step to ensure the algorithm is independent of the original cost profile is to compare the three major components of the updated cost model. These three parameters are the annual energy cost to the homeowner, the energy storage capacity requirements and the annual profit to the utility. These parameters are all calculated using the exact method presented in the original cost profile case.

The annual cost to the homeowner is calculated using an average energy cost of \$0.1252/kWh with no additional fees included. This energy cost is simply multiplied by the energy consumption for each home. The energy costs at the end of the control algorithm use the energy costs from the final iteration of Model ii as the energy charge for all devices in the home that are not considered energy storage devices while the remaining usage is charged at the rate developed in Model iii. The results for the updated cost model are shown in Table 19.

*Table 19. Annual Cost Reductions with Algorithm – Updated Cost*

| House | Baseline Energy Costs ($/yr) | Completed Algorithm Energy Costs ($/yr) | Percent Reduction in Energy Costs (%) |
|---|---|---|---|
| 1 | $2,377 | $2,339 | 1.6% |
| 2 | $2,567 | $2,506 | 2.4% |
| 3 | $2,388 | $2,321 | 2.8% |
| 4 | $2,363 | $2,300 | 2.7% |
| 5 | $2,670 | $2,598 | 2.7% |
| 6 | $2,424 | $2,337 | 3.6% |
| 7 | $1,956 | $1,823 | 6.8% |
| 8 | $2,555 | $2,479 | 3.0% |
| 9 | $2,270 | $2,163 | 4.7% |
| 10 | $2,470 | $2,358 | 4.5% |
| **Total** | **$23,998** | **$23,223** | **3.2%** |

The data shows that the baseline energy consumption remains constant to the original cost model, as expected. The updated cost algorithm costs are increased slightly when compared to the information before but, as will be seen later, the profit follows this relationship inversely. However, it should be noted that the energy cost to the homeowner remains at levels below that of the baseline energy model. These are rather modest savings (average of $78 per homeowner over the course of the year) but do signify that energy cost savings can be seen under this control algorithm.

The second parameter to be evaluated in the updated cost model is the energy storage capacity after each model iteration. Again, note that the change in cost profile does not impact the results from the baseline model and the storage capacity remains constant at 278 kWhs and a maximum output of 107 kW required. This information and the results from the other model iterations are shown in Figure 71.

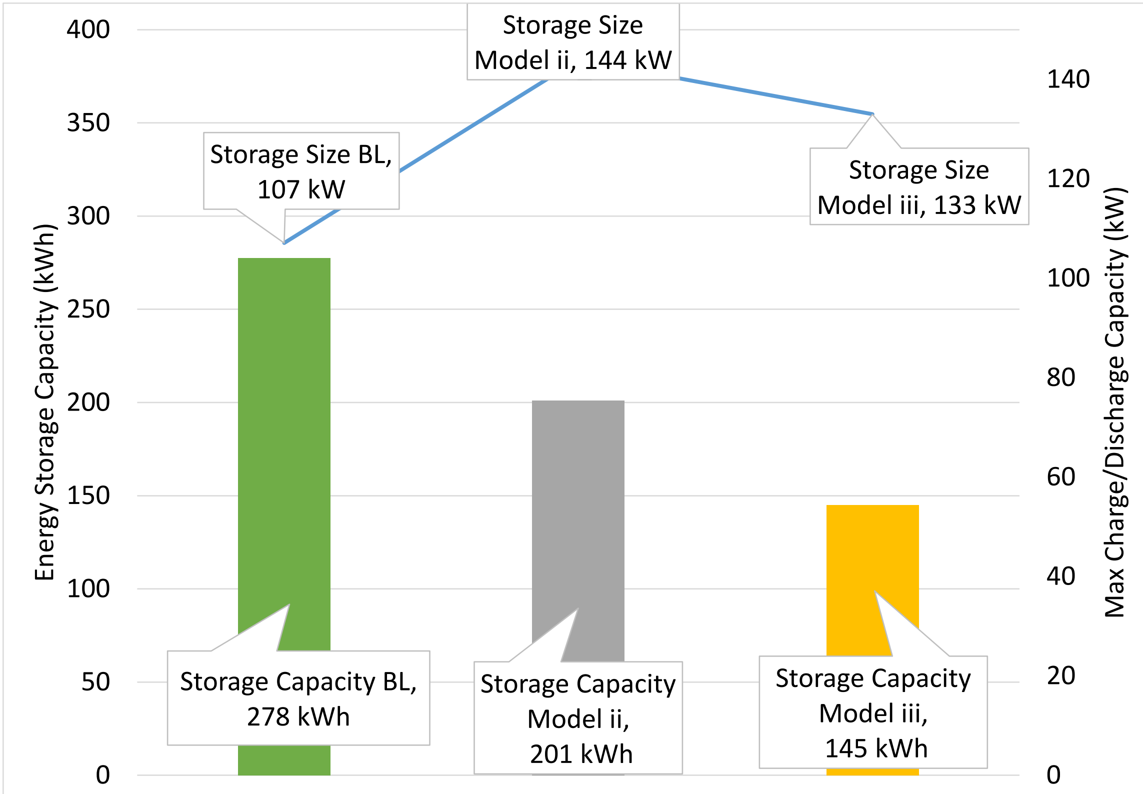


*Figure 71. Energy Capacity Requirements per Model Run – Updated Cost*

The results show a similar trend as the original model. The storage size increases from 115kW max to a new maximum of 144kW however after the algorithm is completed is reduced down to 133kW. This is caused by an increased maximum energy usage during a single fifteen minute timestep and can be correlated to a low-cost period where a shift in energy usage is encouraged and achieved. The storage capacity also follows a similar trend which is summarized in Table 20.

*Table 20. Energy Storage Capacity Requirement Comparison*

| Model Iteration | Original Cost Profile (kWh) | Updated Cost Profile (kWh) |
|---|---|---|
| Baseline | 278 | 278 |
| Model ii | 211 | 201 |
| Model iii | 149 | 145 |

As can be seen in Table 20, the baseline energy storage requirements are the same while the results after Model ii are within ten kWhs of each other. Finally, the energy storage capacity at the completion of the control algorithm is within four kWhs of the original cost model. This demonstrates that the energy storage calculations are independent of the cost profile and the control algorithm is able to adjust the load shape of homes regardless of the starting cost profile.

The final parameter that must be validated is the annual profit to the utility. This information is calculated using the method described in *Annual Energy Cost & Utility Profit Calculations* on page 94. Unlike the other parameters, the baseline model profit is not the same as in the original cost profile since the cost-to-serve data has changed with the updated ERCOT data. The annual profit for the utility was calculated for each model iteration – baseline, Model ii and Model iii. This information is shown in Figure 72 and starts on the left with the baseline model profit then shifts to each of the iterations of Model ii until the results from Model iii are shown on the far-right hand side.

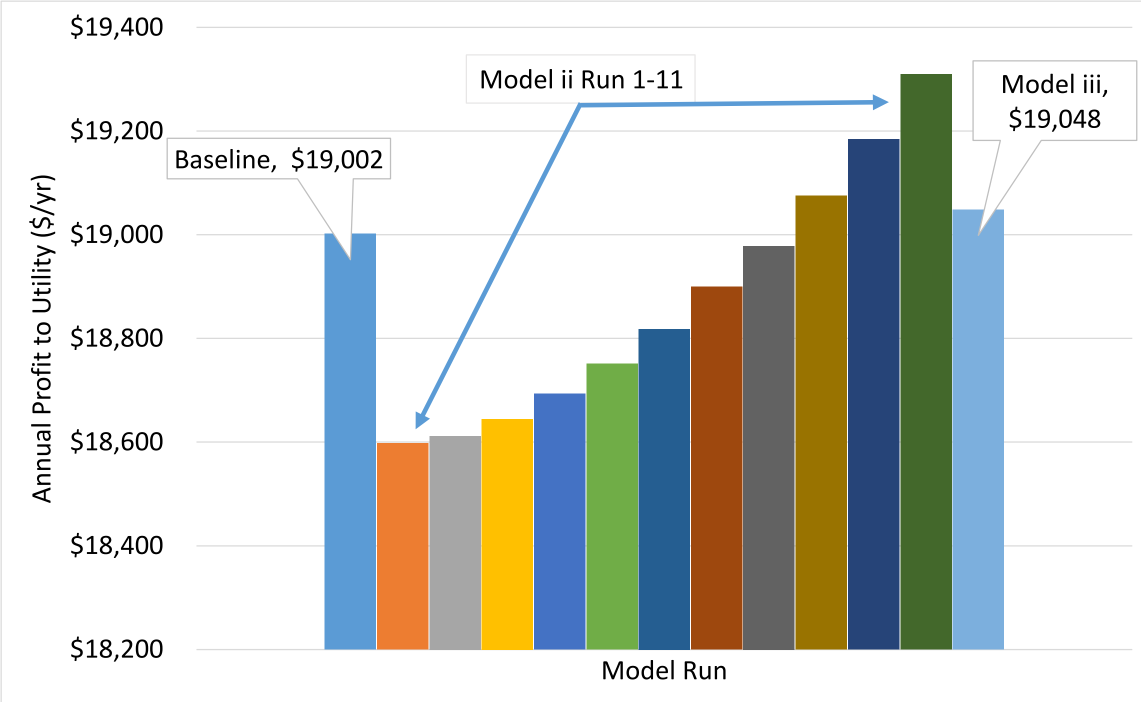


*Figure 72. Utility Profit at each Model Run – Updated Cost*

The profit for the baseline model increases to $19,002 for the ten homes due to a drop in cost-of-service in year 2015. The profit immediately drops when starting the negotiations between the utility and the homeowner. This profit then gradually increases over the course of the eleven iterations as energy usage is encouraged to lower cost time periods. The results from Model iii then decreases the profit to a level slightly higher than the baseline energy usage model. This increase is only 0.2% but again represents the potential to increase the profit to the utility while reducing the energy costs to homeowners. This profit is also supplemented in the control algorithm by the reduced capital cost requirements with the reduced energy storage requirements. This too shows that the control algorithm works in multiple cost profile setups and meets all the defined success criteria under both the original energy cost profile and the updated ERCOT cost data.

*Advanced Home Model – Updated ERCOT Costs*

Identically to the traditional home model, the same parameters are compared and presented within this section to demonstrate that the algorithm is able to improve the alignment of energy usage and renewable energy generation using the advanced homes. This is also meant to prove that the algorithm is agnostic to the starting point energy cost and improves the alignment of usage and generation independently while also providing value to consumers and the utility. The same results as shown in *Traditional Home Model – Updated ERCOT Costs* on page 136 are presented in this section for the advanced home model. Also, note that the results from changing the real-time pricing structure does not change any output from the baseline energy models, therefore they will not be discussed in this section.

The graphical results showing the energy consumption at each timestep for the renewable energy generation, baseline energy usage and the results after Model ii is seen in Figure 73. This represents a snapshot of the annual energy usage and demonstrates how the control algorithm attempts to shift energy usage towards the renewable energy generation when possible. This is limited by the number of adjustable loads within a home as well as the number of homes in the simulation which limits the diversity of usage.

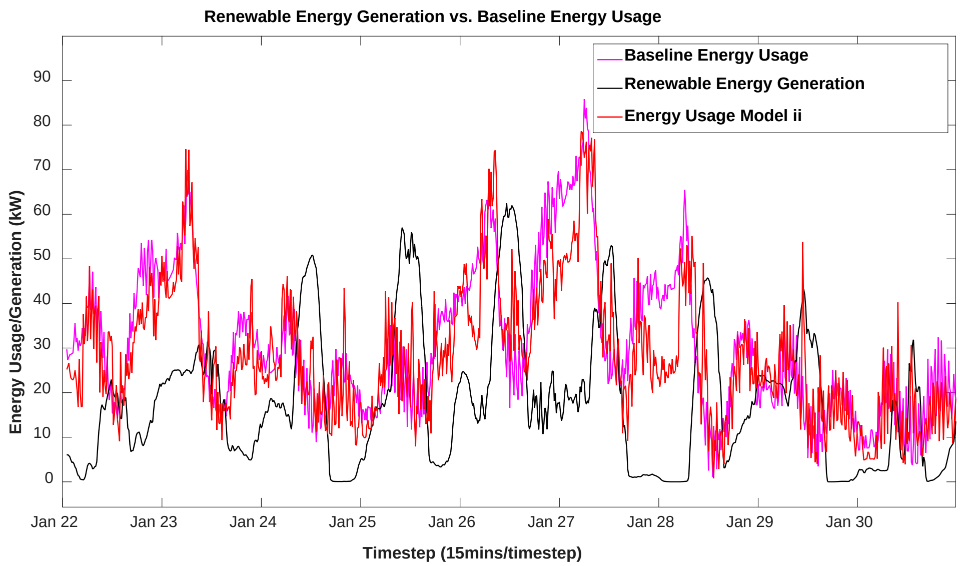


*Figure 73. BL & Model ii Load vs. Renewable Gen. – Updated Costs, Adv. Homes*

In Figure 73, the relationship between the energy usage is difficult to determine so a correlation coefficient was calculated for the baseline energy profile and the Model ii profile. The baseline coefficient remains steady at -13.9%, the same as in the original cost model, while the coefficient on the results of Model ii is at 11.7%. This is in comparison to 9.2% in the original cost model.

The model then adds in the additional thermal energy storage in the form of electric resistance water heaters. The energy usage in all three portions of the model, as well as the renewable energy generation are shown in Figure 74. This data shows that the blue line (results from Model iii) trends closer to the renewable energy generation throughout the time-period. This is not uniformly true as some portions are overshot by over incentivizing homeowners to shift their usage to certain periods of the day. This is caused by the lack of granularity and diversity in loads within these ten homes. This would be levelized when greater adoption is implemented as each home's impact to the load shape becomes less.

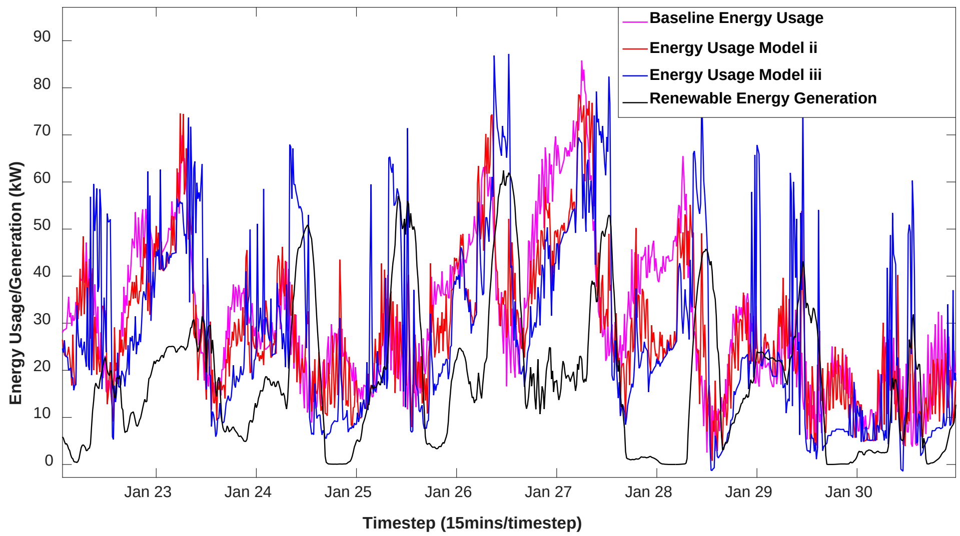


*Figure 74. Renewable Gen. vs. Energy Usage Models – Updated Cost, Adv. Homes*

The correlation coefficient of Model iii is 34% for this model, which is in line with the coefficient of 29.5% under the original cost profile. Table 21 compares the correlation coefficients for each portion of the model from the original cost model and the updated cost model.

*Table 21. Correlation Coeff. Comparison for Updated Cost Profile – Adv. Homes*

| Model Iteration | Correlation Coefficient Original Cost Profile | Correlation Coefficient Updated Cost Profile |
|---|---|---|
| Baseline | -13.9 % | -13.9% |
| Model ii | 9.2 % | 11.7% |
| Model iii | 29.5 % | 34.1% |

This information shows that the new cost profile does not negatively influence the results of the control algorithm and actually improves the outcome. Both models start with a negative correlation between usage and generation in the baseline scenario that improves to a correlation slightly above zero after Model ii. In both cases, the correlation is improved greatly with the addition of thermal energy storage to around one-third.

Although the correlation between energy usage and renewable energy generation is consistent with the results from the original cost model, the other three parameters must also be verified to demonstrate that changing the cost profile does not ruin the control algorithm's effectiveness. The first parameter is the annual energy costs to the homeowner, the second is the energy storage capacity requirements and the final parameter is the profit to the utility. These parameters are all calculated using the same methods as before in the original cost profile case.

The annual cost to the homeowners utilize a flat energy rate of \$0.1252/kWh and the costs are simply multiplied by the energy usage to calculate the energy costs for the year. The energy cost calculations after the control algorithm are more complicated and include charging the homeowner based on the final energy rate as calculated in Model ii for all appliances in the home with the exception of energy storage systems. Those systems are then charged a separate rate calculated during Model iii – for this model the electric water heater is the thermal energy storage system and is the only appliance charged on this rate. The summary of annual energy costs is shown in Table 22.

*Table 22. Annual Cost Reductions with Algorithm – Updated Cost, Adv. Homes*

| House | Baseline Energy Costs ($/yr) | Completed Algorithm Energy Costs ($/yr) | Percent Reduction in Energy Costs (%) |
|---|---|---|---|
| 1 | $2,163 | $2,086 | 3.6% |
| 2 | $2,313 | $2,225 | 3.8% |
| 3 | $2,265 | $2,143 | 5.4% |
| 4 | $2,034 | $1,993 | 2.0% |
| 5 | $2,458 | $2,313 | 5.9% |
| 6 | $2,197 | $2,062 | 6.1% |
| 7 | $1,743 | $1,483 | 14.9% |
| 8 | $2,341 | $2,101 | 10.3% |
| 9 | $2,020 | $1,955 | 3.2% |
| 10 | $2,581 | $2,478 | 4.0% |
| **Total** | **$22,116** | **$20,840** | **5.8%** |

The annual energy costs to the homeowners are reduced by an average of 5.8% with a maximum decrease of just under 15% and a minimum cost reduction of 2%. This variance is correlated to the amount of flexibility in the homeowner's load shape, if there is greater flexibility then there is the potential for much larger energy savings. This savings amount is in line with the energy savings in the original cost profile, which was 4.8%. This implies that the updated cost profile does not negatively affect the results of the control algorithm as is relates to the annual energy costs to the homeowner.

The next parameter to be evaluated is the energy storage capacity required to maintain the system within the operating parameters for at least 70% of the year (6,132 hours of the year). This parameter evaluation helps describe how well the energy usage is aligned with the renewable energy generation throughout the course of the year and includes storing excess generation and providing energy back to the homes when renewable generation is not able to meet the demand. The results for each model iteration for both storage size (kW) and energy storage capacity (kWh) are shown in Figure 75.

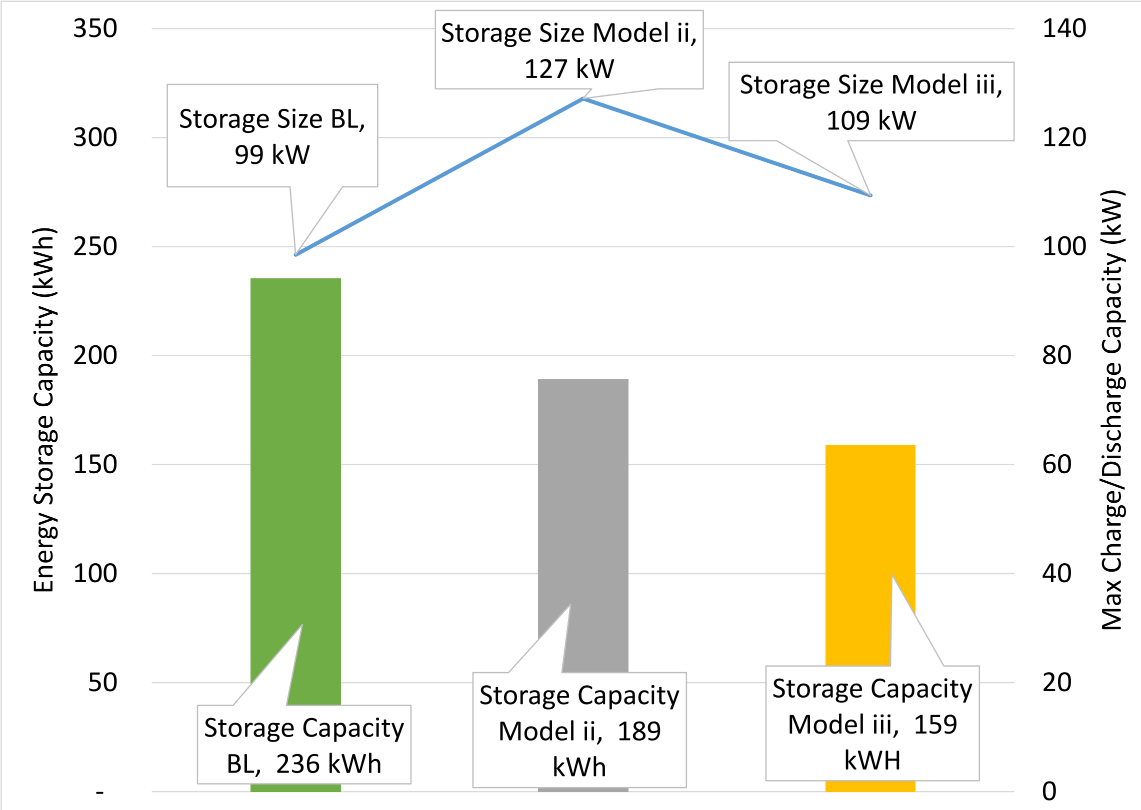


*Figure 75. Energy Storage Capacity per Model Run – Updated Cost, Adv. Homes*

The energy storage size in the new model increases compared to the original cost analysis by increasing after both Model ii and Model iii. The storage size goes from 99 kW in the baseline model to 127 kW after Model ii and back down to 109 kW after Model iii. While the energy storage requirements are increased, the energy storage capacity during all three models is similar to the base pricing model. This shows that overall energy consumption during a singular timestep in the year is increased by 10% for Model iii in this pricing scenario, however the energy storage capacity decreases to 159 kWhs which allows the system to remain inside the parameters for the year. The comparison of energy storage capacity for the original cost profile and updated cost profile are shown in Table 23.

*Table 23. Energy Storage Capacity Comparison – Adv. Homes*

| Model Iteration | Energy Storage Capacity (kWh) Original Cost Profile | Energy Storage Capacity (kWh) Updated Cost Profile |
|---|---|---|
| Baseline | 236 | 236 |
| Model ii | 193 | 189 |
| Model iii | 161 | 159 |

The data in Table 23 shows that the baseline energy storage capacity remains consistent with the energy storage capacity after Model ii being reduced to around 190 kWh for both cost profiles. The results for Model iii output are also consistent between cost profile models with the original cost profile resulting in 161 kWhs and the updated profile output being 159 kWhs. These results show that the change in cost profile does not negatively impact the results of energy storage capacity.

The final parameter to be analyzed is the annual profit to the utility. This is calculated using the raw ERCOT data as the cost of service from the utility at each timestep and using that information to determine how much profit is received from each kWh sold during that timestep. During this calculation, the baseline data changes from cost profile to cost profile as the cost of service to the utility changes based on the ERCOT data profile even when the rate charged to the customer remains constant. The annual utility profit is summarized in Figure 76 and shows a trend similar to the traditional homes model using the original cost profile.

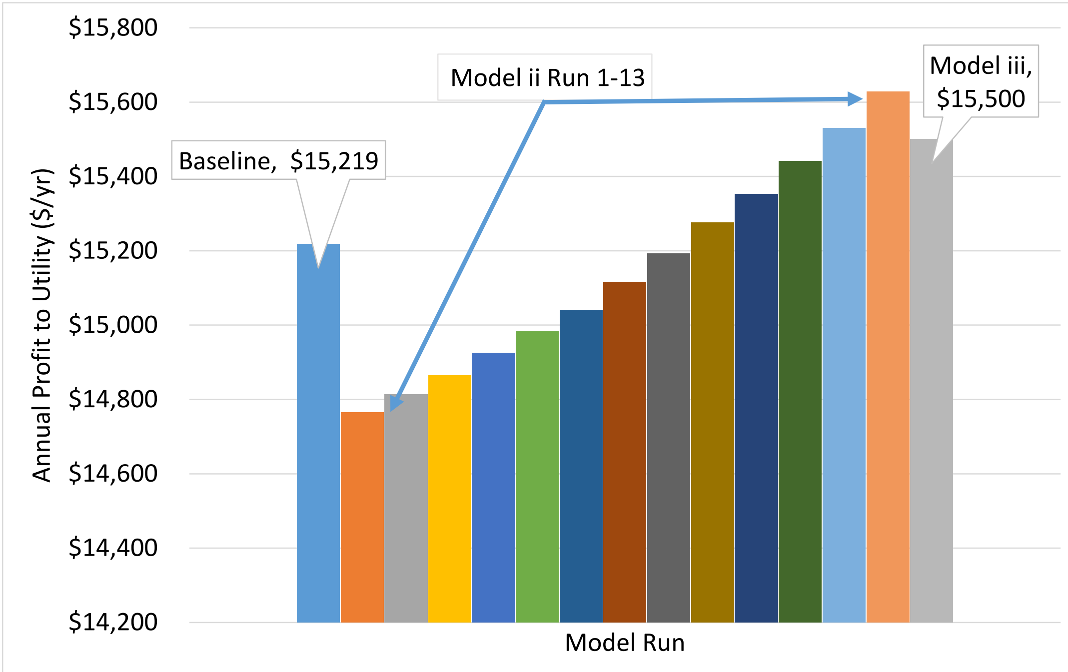


*Figure 76. Annual Utility Profit for each Model Run – Updated Cost, Adv. Homes*

For this model, the baseline model yields a profit of $15,219 for the ten homes over the year. The utility profit drastically drops once negotiations begin but slowly increases over each iteration. After the model runs its thirteen iterations, the profit is already increased above the baseline profit. After Model iii is completed, the annual profit for the ten homes is $15,500. This represents a small increase of 1.8% in profit. This is a decline from the original model which resulted in a profit increase of 5.5%. However, the gain shows that the updated cost profile does not prevent the functionality of the control algorithm.

*Suboptimal Solutions in Updated ERCOT Costs*

The control algorithms, as run for differing cost basis years, show that the grid and the homes work together and are able to find a solution to increasing profits and decreasing costs. The solution is not always optimal, meaning the results are swayed to benefit the consumer or the utility but not finding a balance between the two and can show limited incentive for the homeowner or the utility to participate. Additional test runs of the model showed that by altering the method in which Model iii pricing is calculated, changing the coefficients to the pricing change polynomial, and/or changing the method of recalculating pricing between iterations in Model ii, the results can be improved for each specific test case. These test runs were not optimized for both solutions but demonstrate that the control algorithm may require adjustment, within an acceptable band, throughout the year to provide the best results while maintaining the ability to increase profits and reduce energy costs to the customers.

## Daily Control Strategy Implementations

The final simulation performed for the control strategy was on a daily optimization of the homes with the grid. This was performed to demonstrate that allowing adjustments of the model on a day-by-day basis to account for variations in weather and demand can improve the results. This change allows the model to optimize for only the upcoming day and not over the entire year, allowing for a more optimal solution rather than a yearly optimal solution. For the simulations, three days were randomly selected to represent different seasons along with the winter and summer design days for Birmingham that were also included. The first day is January 21st to represent winter (heating design day), the second is April 12th to represent spring, next is July 21st as the cooling design day, August 14th to represent summer and finally October 25th to represent fall.

*Results of Daily Implementation*

The first day simulated was January 21st and is the design day for Birmingham, AL in the EnergyPlus model. This date was chosen as a representation of winter and, since it is the chosen design day, can be assumed to be the worst-case scenario for the control strategy for those months. The model utilized the same structure as the full year model, but was developed to only import data for the day of interest and EnergyPlus was modified to only simulate the one day. The only difference for the daily model was the criteria needed to move from Model ii to Model iii. These requirements were relaxed to accommodate the fact that not all three parameters will "win" each day in the year but will over the course of the year. The new requirements were that eight of the ten homes must have lowered energy costs and the profit margin required was reduced.

*Day 1 – January 21st*

The first model, for January 21st, iterated eight times before moving on to the thermal energy storage portion of the simulation. The average energy savings for the ten homes was 2.7% for the day (seven saving and three losing) and the profit to the utility was found to be decreased by $0.04 (0.1%) compared to the baseline model. The load shapes for the baseline and the final results energy consumption is plotted in Figure 77 along with the cost of service profile for that day.

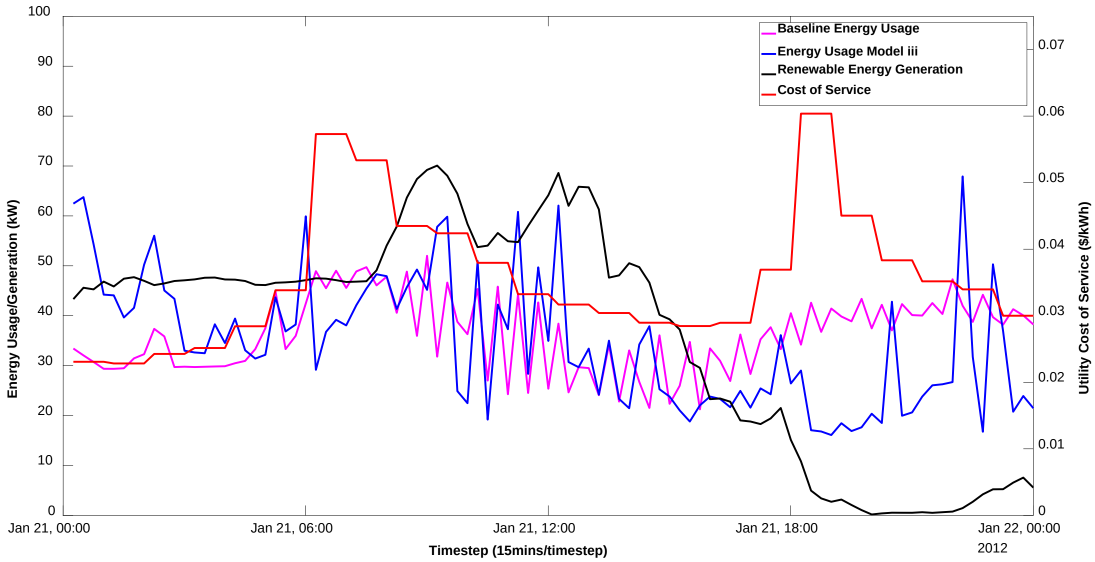


*Figure 77. Daily Control Strategy Alignment – Jan. 21*

The figure shows the energy usage results after the baseline model (magenta line) for January 21st, before any of the control strategy is implemented. As can be seen, the line does not correlate well with the renewable energy generation or cost of service. The results after the implementation of the control strategy are shown by the blue line and show the group of home's energy usage response to both the renewable energy generation and the cost of service. The results attempt to align with the renewable energy generation through the proxy of energy costs. These costs are driven by the utility cost of service (red line) which is influenced by the amount of renewable energy generation at each time step.

*Day 2 – April 12th*

The same analysis was performed for the representative spring day, April 12th. The strategy iterated fifteen times before moving to the thermal energy storage model. The average energy cost savings were 1.7% with seven homes saving money compared to the baseline and three losing money for the day. It is important to note that while three homes are losing money on both January 21st and April 12th, these three homes are not the same for both days – this implies that the daily strategy can lose money while annually the home can still benefit. The profit to the utility was increased by $0.39 (0.7%) compared to the baseline energy model. The load shapes for the energy usage for the baseline model and after the completed algorithm are presented in Figure 78. This figure also contains the renewable energy generation and the utility cost of service for comparison.

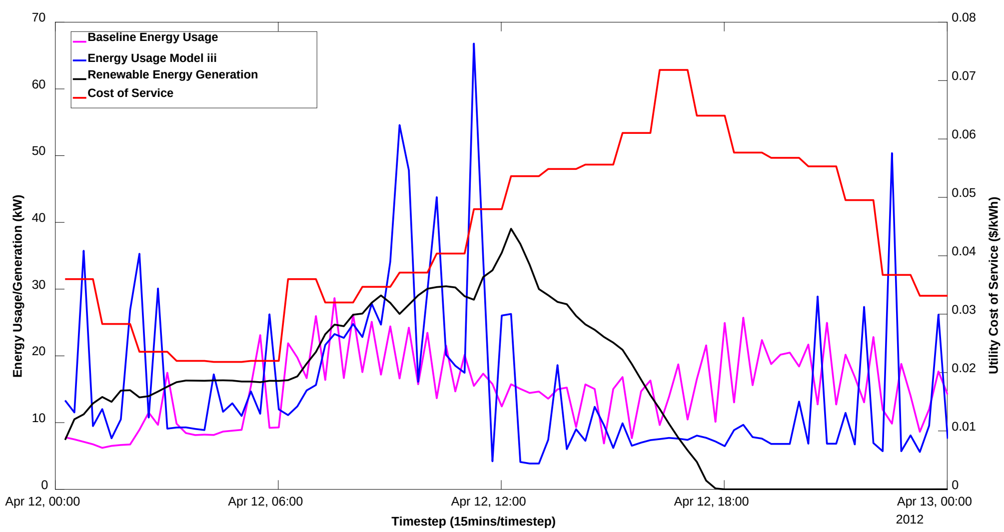


*Figure 78. Daily Control Strategy Alignment – April 12th*

The data in Figure 78 shows the completed algorithm (blue line) attempts to track the renewable energy generation (black line) and the inverse of the cost of service (red line). This is in contrast to the baseline energy usage which maintains the same load shape independently of the renewable generation or the utility's cost of service.

*Day 3 – July 21*

Again, the analysis was repeated for the summer design day – July 21st. The strategy iterated nine times before moving to the thermal energy storage model. The average energy cost savings were 3.9% with eight homes saving money compared to the baseline and two losing money for the day – it should be noted that one of these two homes saw an increase in energy cost of $0.013 during day or 0.17% increase. The profit to the utility was increased by $0.70 (0.3%) compared to the baseline energy model. The load shapes for the energy usage for the baseline model and after the completed algorithm are presented in Figure 79. This figure also contains the renewable energy generation and the utility cost of service for comparison.

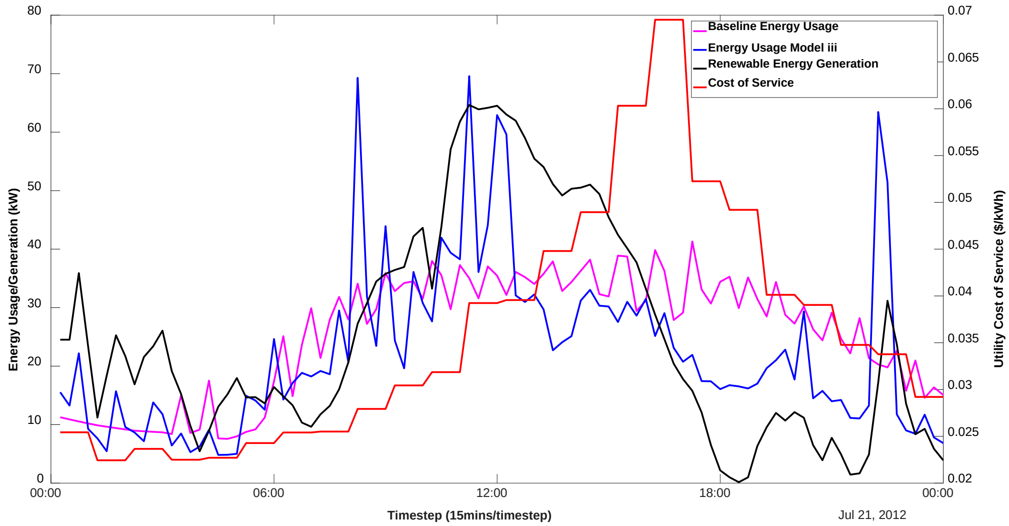


*Figure 79. Daily Control Strategy Alignment – July 21st*

*Day 4 – August 14th*

The fourth day simulated was meant to be representative of the summer period – August 14th. The strategy iterated fourteen times before moving to the thermal energy storage model. The average energy cost savings were 0.98% with eight of the homes saving money compared to the baseline and the other two losing money for the day. The profit to the utility was decreased by $1.50 (4%) compared to the baseline energy model. The load shapes for the energy usage for the baseline model and after the completed algorithm are presented in Figure 80. This figure also contains the renewable energy generation and the utility cost of service for comparison.

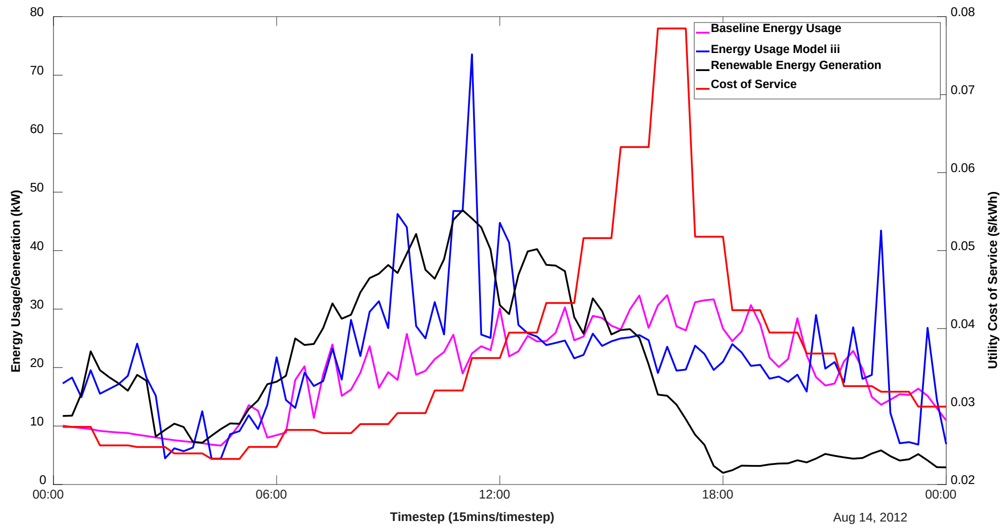


*Figure 80. Daily Control Strategy Alignment – August 14th*

*Day 5 – October 15th*

The final day simulated was meant to be representative of the autumn period – October 15th. The strategy iterated eleven times before moving to the thermal energy storage model. The average energy cost savings were 1.2% with six of the homes saving money compared to the baseline and the other four losing money for the day – one of these homes has an increase in energy costs of $0.012 for the day. The profit to the utility was increased by $1.14 (3.5%) compared to the baseline energy model. The load shapes for the energy usage for the baseline model and after the completed algorithm are presented in Figure 81. This figure also contains the renewable energy generation and the utility cost of service for comparison.

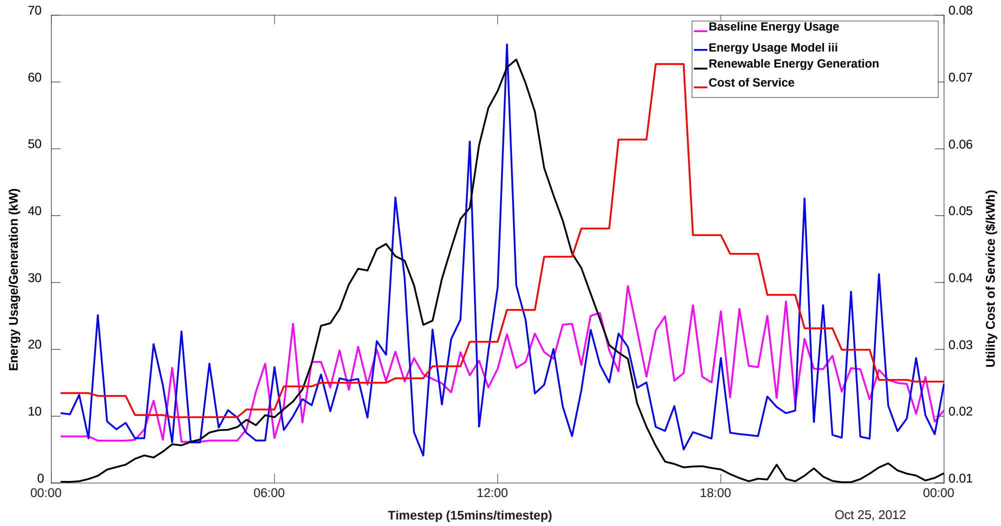


*Figure 81. Daily Control Strategy Alignment – October 15th*

## *Overall Daily Results*

When the control algorithm was implemented as-is on a daily basis, the results show that the system is optimized around the annual simulation method. This allows for higher losses and gains for each day, averaging out to improve the profit and the energy savings over the annual timeframe. When implementing on a daily basis, the algorithm narrows the energy cost savings but also increases the profit over the same days. This can be seen in Figure 82 and Figure 83.

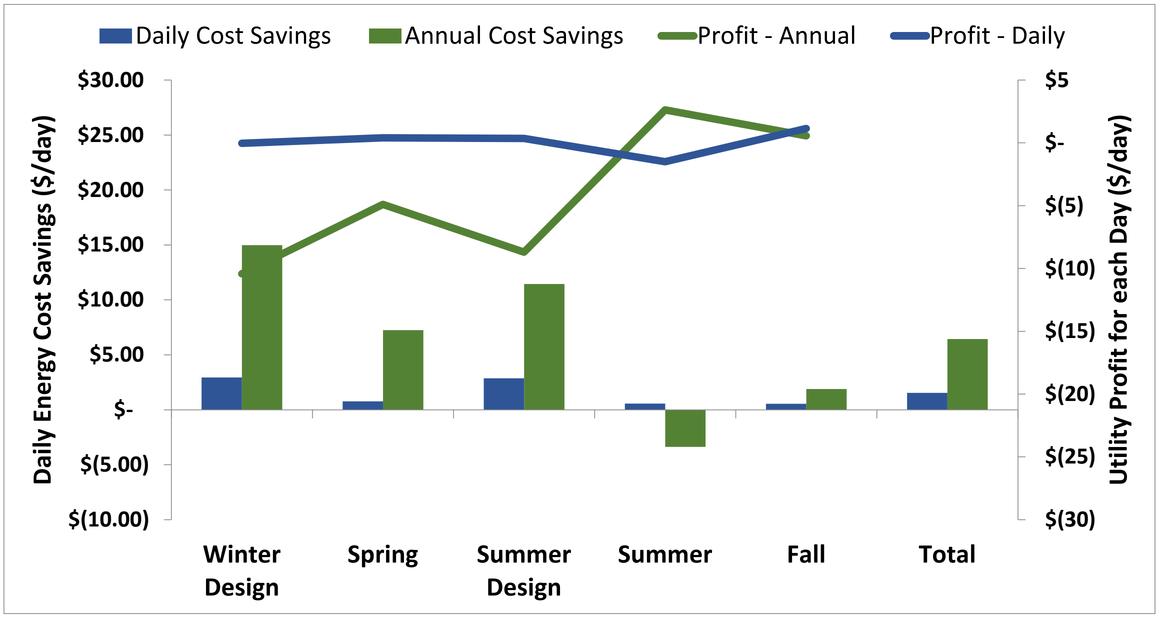


*Figure 82. Daily vs. Annual Control Strategy Implementation*

The algorithm results on homeowner energy savings are shown in more detail in Table 24 for the daily models. The sum of all the homes' energy costs is reduced for each day. However, some homes save energy costs while others lose money compared to the baseline. The results for the daily optimization shows a decrease in energy cost savings by homeowners but does show an increase in utility profit for the days considered – this increase is shown in Figure 83.

*Table 24. Energy Cost Savings Compared to Baseline*

| House | Jan 21 | April 12 | July 21 | August 14 | October 25 |
|---|---|---|---|---|---|
| 1 | $0.31 | $0.52 | $0.68 | $0.10 | $0.69 |
| 2 | $0.35 | $0.15 | -$0.49 | -$0.12 | -$0.46 |
| 3 | $0.51 | -$0.26 | $0.50 | $0.02 | $0.29 |
| 4 | -$0.66 | $0.09 | -$0.01 | $0.01 | $0.11 |
| 5 | $0.29 | $0.33 | $0.49 | $0.67 | $0.15 |
| 6 | $0.89 | $0.20 | $0.38 | $0.06 | $0.03 |
| 7 | $0.24 | $0.24 | $0.61 | -$0.46 | $0.31 |
| 8 | $1.33 | $0.15 | $0.28 | $0.16 | -$0.27 |
| 9 | -$0.24 | -$0.34 | $0.15 | $0.05 | -$0.01 |
| 10 | -$0.10 | -$0.31 | $0.27 | $0.07 | -$0.28 |
| **Total** | **$2.93** | **$0.76** | **$2.87** | **$0.56** | **$0.55** |

The data in Figure 83 shows the change in utility profit for each day ran in the simulation when compared to its respective baseline. As can be seen, the total profit to the utility is increased substantially over the annual model to a slightly positive number from a loss of over $20. This increased profit reallocates the reduction in energy cost savings to the homeowner for the daily models.

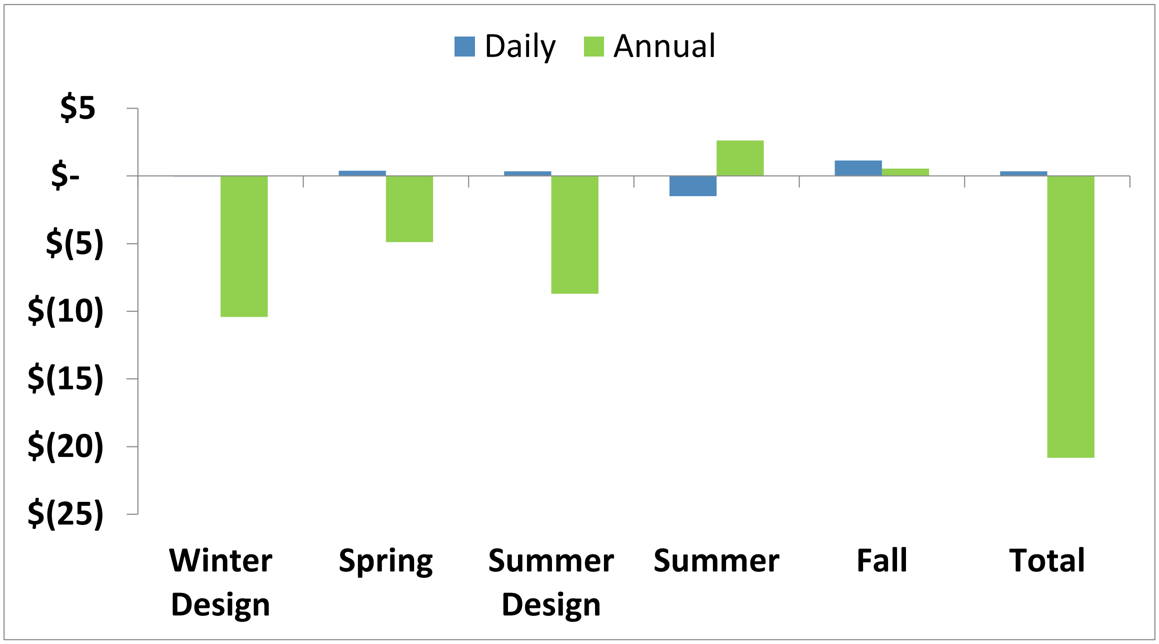


*Figure 83. Profit differences in Daily and Annual Models*

While the daily simulations show the daily profit to the utility is greatly increased, it also shows a reduction in energy cost savings to the customer. This balance has been noted in this report several times and the ultimate determination of priorities will vary depending on many factors and can vary state-to-state or even locality to locality. The goal of this research was not to develop if the utility or the homeowner gained the largest financial incentive, rather it is meant to demonstrate that both parties can benefit from the presented control strategy.

## Major Challenges Improved from Initial Model Approach

While creating the model, there were several lessons learned when running the simulations that led to improvements in different model versions. These also shed light onto some of the unforeseen interactions between different components of the model when everything was tied together. This section of the report focuses on these improvements and how the model evolved because of them.

### *Scaling Renewable Energy to match Energy Consumption Magnitude*

It was known going into the model that selecting a magnitude of several MWs of renewable energy generation would overwhelm and overshadow any of the energy consumption variations of ten homes – which typically would have a maximum peak demand of about 100 kW if each home peaked at the same time. To account for this mismatch in magnitude, a scaling factor was needed. To calculate this scaling factor there were two options seen as viable solutions which were both based off baseline energy consumption for the combined ten homes in the study. The first option was to sum the energy consumption over the full year and match the total renewable energy generation to that of which was consumed, e.g. match total kWhs generated by renewable energy sources with kWhs consumed by the homes combined. This does not imply that all energy is provided from the renewable sources and would require times of over-generation and pushing energy back to the grid to compensate for times when the renewable energy cannot supply 100% of the energy demand. This option emulates a definition of a net-zero energy community whereas the energy generated by the community is equal to the energy consumed by the homes over the course of a year. This is not the same as the definition according to the US Department of Energy which requires the amount of energy generation to match the source energy input over a year – this include inefficiencies in electricity generation and transportation [75]. Since net-zero energy communities was not the goal of the model, this extra renewable energy generation was ignored. The second option was to determine the maximum hourly demand caused to the electric grid from the ten homes and size the renewable energy generation to match that peak kW impact, e.g. match peak kW of the renewable energy generation with the peak kW seen throughout the year of the combined homes.

Both methods were tested in the model and it was determined that since the group of ten homes was never intended to be fully served by the renewable energy generation in an off-grid scenario, the approach to scale the renewable energy generation to match the annual energy consumption was chosen. This implies that renewable energy was not always available to supply the energy needs of the group of homes and therefore required the energy storage and/or grid as a backup. This option also provided a better opportunity to demonstrate influencing energy consumption in both the up and down direction since there was no dictated limit to the capacity of renewable energy generation. Finally, although not the goal of the study, this was also seen as the preferred design solution in the future as the country moves towards net-zero energy homes at a much faster pace than moving to off-grid homes and/or neighborhoods. The final sizing methodology for the renewable energy generation is shown in *Scaling* Renewable Energy Output on page 61.

*Energy Cost Calculations for Water Heating in Model iii*

The original model was developed to have the energy costs for Model iii be determined based on the interval energy costs that were output from Model ii – the energy cost in Model iii would include the output of Model ii multiplied by a certain percent multiplier. This was seen as a way to incentivize homeowners to shift their water heating energy consumption while still maintaining consistency with the day-ahead cost timeframe developed in Model ii. However, as the model was run it was noted that basing the "real-time" pricing signals on the day-ahead pricing signal caused undesirable results and actually decreased the value of the model. This was because the intention of Model iii is to use the thermal energy storage capability of the water heater to more closely align the renewable generation with the energy consumption on the grid. However, the water heater setpoints were setup to change based on an absolute price rather than a relative price which was how the signals in the original model were being sent – the homeowner sets the water heater setpoints based on a certain energy cost, not based on a percent change in energy cost.

Another issue that the relative pricing model did not compensate for is times when the output of Model ii had overshot the desired energy usage. This relative pricing signal then exacerbated the problem by encouraging the water heater to continue in the same direction of energy usage that caused the initial issue. By keeping the two energy costs independent, the price signals are able to meet the grid needs as they occur in real-time. This means that no matter the outcome of Model ii, the energy storage in Model iii can be properly incentivized to consume or shift energy usage to meet the disparity between energy generation and consumption. Therefore, in the finalized version of the model, the energy costs charged to the homeowner are independent of the costs in Model ii and have led to the results presented. The method for calculating the energy costs in Model iii are shown in *Adding in Thermal Energy Storage to improve flexibility* on page 91.

*Calculating the Water Heating Response to Pricing Signals*

Although the energy costs in Model iii are able to be operated independently of the energy costs in Model ii, the response of the water heater at the different prices was found to impact how well the algorithm performed. Several approaches were tried before settling on the approach discussed in *Calculating an Updated Fifteen-minute Energy Cost* on page 87. For reference, see Figure 46 on page 93. This figure shows a linear response to energy costs between the maximum water heater temperature down to the typical water heater setpoint, a dead-band where a small cost change will not move the temperature setpoint and finally a linear reduction of the temperature setpoint in the tank as the cost increases. Other previous variations included an exponential growth or decay from the typical temperature setpoint and a second and third order polynomial relationship. These relationships did not cause the algorithm to function improperly, however they were not found to be an optimal solution. Finally, the relationship was setup with no dead-band at the typical setpoint. This caused the thermal storage to over compensate for slight changes in price, leading to a worsening control algorithm. However, a small dead-band vastly improves this response and decreased the amount of overshoot caused by water heating in the strategy.

Another issued that caused the algorithm to perform sub-optimally was the upper limit on the water heater. This limited the amount of energy that can be stored in the water heater at a given time and was initially set at 160°F but did not provide the amount of flexibility when only ten homes were included in the model. Therefore, the upper bound of temperature was increased to 90°C (194°F) which was found in the literature survey to be the maximum temperature allowable [73]. Several companies exist today that perform energy storage in water heaters such as Carina [76] and Steffus [77] that do not increase the temperature to levels that high but are able to achieve some success in utilizing water heaters as thermal storage mediums. Therefore, it is reasonable to believe that once a large number of homes participate in the program, each home's contribution to thermal energy storage can be decreased and therefore will decrease the maximum temperature setting on the water heater.

## MODEL VERIFICATION

The individual models for each of the ten homes were independently verified under normal operating conditions. Nine of the homes by the US Department of Energy [56], the tenth (home iii) can be seen in *Building Energy Model and Verification* on page 36. However, to further validate the energy consumption and cost savings from the control algorithm, the model outputs for temperature setpoints and appliance schedules were duplicated in an existing home – home iii, see Figure 11 on page 36. This verification is meant to demonstrate the cost savings potential available using the control algorithm and to verify the ability to shift energy consumption while not negatively impacting comfort and convenience.

*Data gathering*

To assist in verification, circuit level energy monitoring was installed and data was collected for individual circuits for approximately one year at home iii. This information is summarized and shown in Figure 84 and represents the average daily load shape for the home.

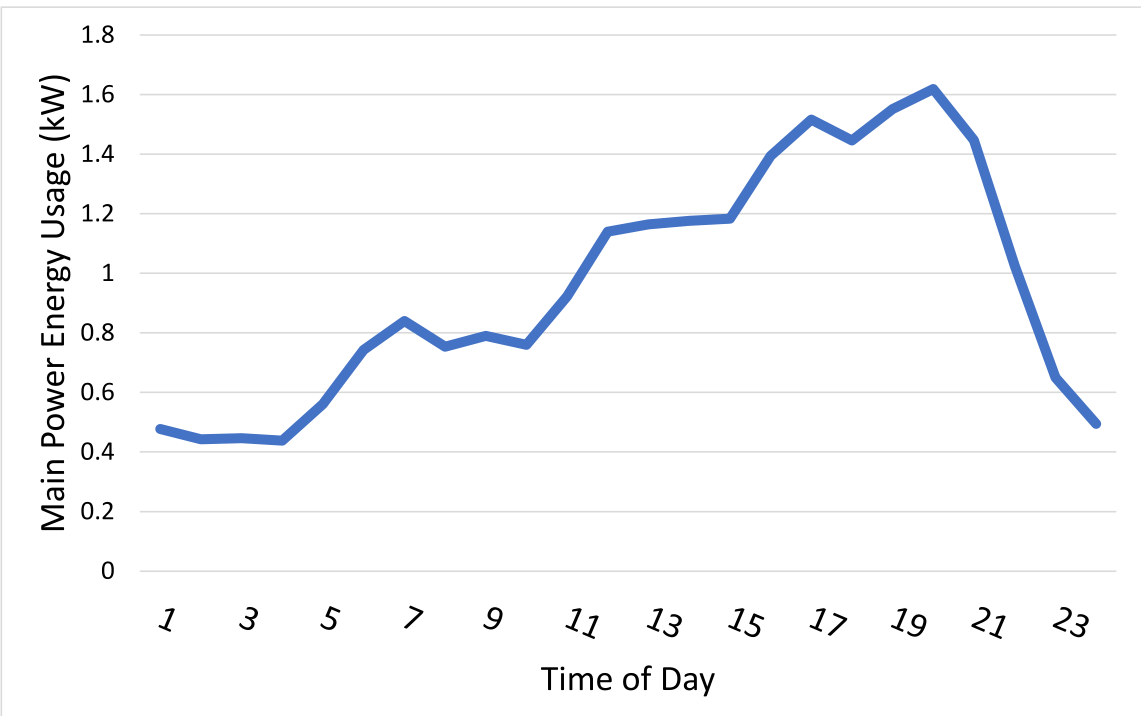


*Figure 84. Average Daily Load Shape for Home iii.*

The raw data for the month of June can also be seen in Figure 85. This data shows the whole home energy consumption in minute intervals and is the aggregate of all appliances within the home. It should be noted that this data does not include water heating, as the setup includes a natural gas system.

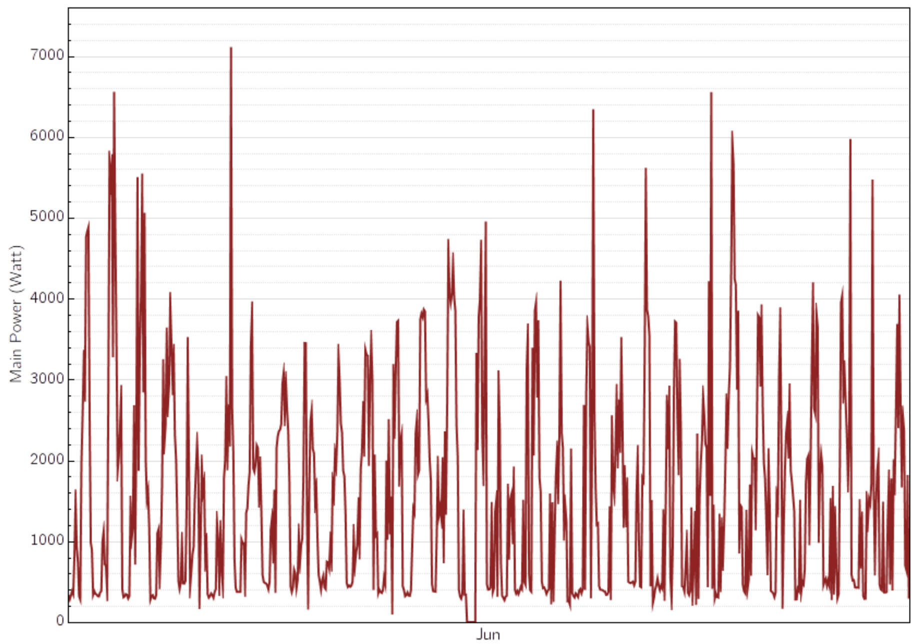


*Figure 85. Hourly Data for June – Home iii*

This data, when coupled with outdoor temperature data and heating/cooling degree days, can be considered as the operation of the home under a normal pricing scenario and used as the baseline energy consumption to compare the control algorithm.

*Weather Forecasting*

To better predict the response of the home to the control algorithm in the model, a weather forecast must be used and input into the home energy model's weather file. This allows the model to realistically predict the thermal infiltration and heat or cooling loads on the home. To do this, two major items are needed. The first is the day-ahead, hourly weather forecast and the second is a tool to convert this information into the EnergyPlus weather file.

The tool used to convert the weather forecast into a usable format also ensures that the appropriate information is input from the forecast. This tool is Elements which was developed by Big Ladder Software in collaboration with the Rocky Mountain Institute [53]. The data required to complete the updated weather file is shown in Table 25 and these are used to calculate additional necessary parameters.

*Table 25. Weather Forecast Parameters*

| **Parameter** | **Units** |
|---|---|
| Dry Bulb Temperature | °C |
| Relative Humidity | % |
| Atmospheric Pressure | kPa |
| Direct Normal Irradiance | W/m$^2$ |
| Diffuse Horizontal Irradiance | W/m$^2$ |
| Wind Speed | m/s |

The data shown in Table 25 is the ideal weather information needed for creating an energy simulation weather file to be input into EnergyPlus, however not all of this information is readily available to the public as a typical forecast. The global solar irradiance information can be estimated using the cloud cover forecast as described in [78]. This gives an output of global solar irradiance but does not break the information into direct normal or diffuse horizontal irradiance. Since this information cannot be calculated using the limited information available in weather forecasts, a sensitivity analysis was performed. This analysis was performed on the EnergyPlus model for home iii to determine the impacts of only having the global solar irradiance rather than having it split into diffuse and direct. The results are summarized in Table 26. The first model uses the complete TMY3 weather data which contains all three types of solar irradiation data; global, direct and diffuse. The second model includes removing all the solar irradiance data from the weather file and reinserting the global solar data back into the software. The Elements software program then calculates the normal solar radiation based on the global solar input while leaving the diffuse solar irradiance at zero. The final model removes all solar irradiance from the model and therefore removes the solar heat gain impacts from the thermal model and only includes weather data and internal heat gains.

*Table 26. Sensitivity Analysis for Solar Irradiance Data, home iii*

| **Weather Data Version** | **Premise Usage (kWh/yr)** | **% Diff.** | **Heating Usage (kWh/yr)** | **% Diff.** | **Cooling Usage (kWh/yr)** | **% Diff.** |
|---|---|---|---|---|---|---|
| Complete TMY | 15,457 | n/a | 2,096 | n/a | 2,377 | n/a |
| Global Irradiance Input | 15,179 | -1.8% | 2,004 | -4.5% | 2,254 | -5.3% |
| No Solar Irradiance | 14,745 | - 4.7% | 3,440 | 48.5% | 694 | -109.6% |

The results from the analysis shown in Table 26 demonstrate that the impact from only having the global solar irradiance data is minimal with less than a 2% decrease in overall energy consumption of the home over the year and a decrease of about 5% in both heating a cooling energy usage throughout the year. Therefore, for the model verification, the cloud cover data is deemed sufficient to approximate the forecasted solar irradiance.

The remaining information is available through Weather Underground [79] using their ten-day weather forecast. Information can be found hourly for temperature, relative humidity, atmospheric pressure, wind speed and direction along with cloud cover. This data for the simulated day, combined with the solar irradiance data is input into the Elements software package to create an EnergyPlus weather file used in the simulation.

*Day-Ahead Pricing Outlook*

Since the model focuses on a local energy model for the home but a macroscale energy cost estimate, the day-ahead pricing outlook is assumed to be the same for the initial model and the actual weather model. This is because the diversity of generation sources and the location of renewable energy generation is not directly linked to the localized weather of an individual home.

*Modeling the Control Strategy with Forecasted Data*

The initial model results were based on TMY data, or a typical meteorological year. This data is an average of how a typical year of weather performs in the specific area. This information is used to represent a response to typical weather data rather than a year of actual weather data. To compare the response of the algorithm and compare it to a real-world example, the weather forecast data was input into the overall weather file used for all ten home models simulated in EnergyPlus. The control strategy was then simulated as normal and operated until the parameters described earlier are met – reduced annual energy costs, increased profit to the utility and reduction of energy storage requirements.

The results from this simulation are then implemented into the actual home with schedules either manually or automatically implemented to match the home energy model. However, the home currently has natural gas water heating so to properly simulate this portion of the model, a lab setup to mimic the water consumption and water heating temperature setpoints was created. This analysis is deemed acceptable since the thermal envelope of the building and the thermal heating and cooling loads are minimally impacted by the water heating system.

*Automating Response within Home*

The home being modeled is partially automated and contains a home automation system and Wi-Fi connected thermostat. The other devices included in this simulation are not automated and will be manually turned on and off based on schedules developed by the control algorithm. Additionally, other energy consuming devices that are not included in the control strategy (all except dishwasher, clothes washer and dryer and oven) will be operated as normal and not differentiated from a typical day. A test setup system will be used to automate the water heater and the water consumption to mimic the usage pattern of the home and the tank temperature setpoints.

To automate the thermostat setpoint, the home automation system platform, Samsung Smartthings, was linked to the Ecobee 3 Wi-Fi enabled thermostat. This link must be established rather than using the thermostat directly as the minimum increments for temperature settings are thirty minutes. The first step in doing this automation after the two systems are linked together is to setup an automation, or routine, to set a thermostat setpoint. This portion of the process is shown in Figure 86.

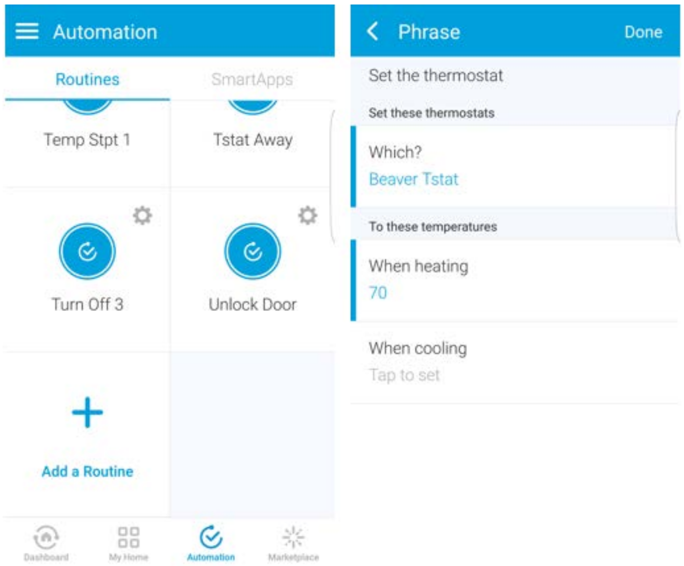


*Figure 86. Temperature Automation – Step 1 & 2*

This temperature setting can be automated and performed at a certain time of the day in any increment desired. For this demonstration, fifteen minute increments are desired and are setup using the process shown in Figure 87.

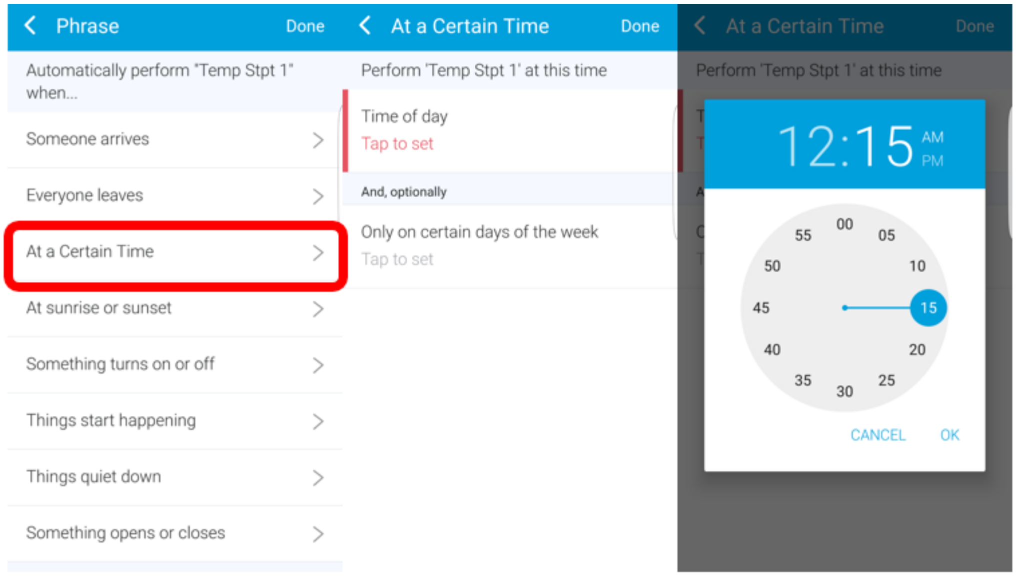


*Figure 87. Automating Thermostat Setpoint Changes at Specified Times*

This process is then repeated for a total of 96 temperature setpoints throughout the day as defined by the control algorithm – four settings per hour times twenty-four hours. Also, the temperature does not change at each time increment, therefore reducing the number of setpoint programs to a number around twenty per day. This reduced number of setpoints still seems extensive and would likely never be done manually to optimize the energy consumption of a home, however a home automation system with an optimization engine could easily manipulate this number of settings for a day. This further demonstrates the need for an optimization platform to improve the control algorithm.

To simulate the water heater energy usage and profile for the home, a test setup was developed to change the water heater setpoint temperature according to the simulation output as well as manipulating the hot water flow throughout the day. The test setup includes a Wi-Fi communicating hybrid heat pump water heater that allows remote control of temperature settings. The heat pump mode is turned off for the testing to match the energy usage of a typical electric resistance water heater. The water heater, along with the data monitoring and recording setup can be seen in Figure 88.

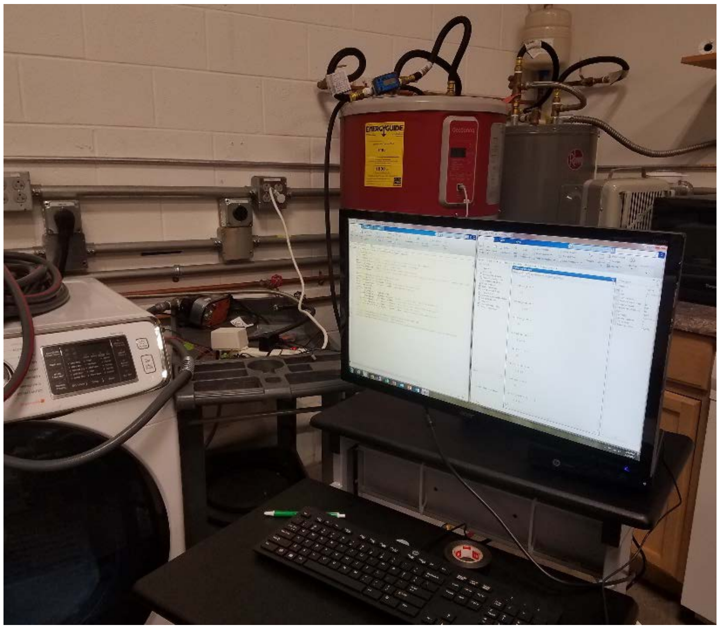

*Figure 88. Lab Test Setup for Water Heating Simulation*

To enable the automation of temperature settings throughout the day, IFTTT [80] was connected to the water heater and rules were developed to push temperature setpoints as needed. IFTTT is a simple rules engine application which stands for IF This, Then That. This program allows linking two unrelated products and when an event occurs, a command is sent to the second program to perform an action – these are called Applets. For the water heater testing, Applets were created that connect the Date & Time application to the GE Geospring Heat Pump Water Heater application. At each timestep, a trigger is sent to the water heater to adjust the temperature to the setting output by the control algorithm. The exception to this is when the temperature is called to be over 140°F by the control algorithm. This temperature is the maximum rated temperature available on the water heater as set by the manufacturer. For the day tested, this scenario occurred during several timesteps and each of the settings were set to the maximum allowable temperature of 140°F. A sample of the Applets can be seen in Figure 89.

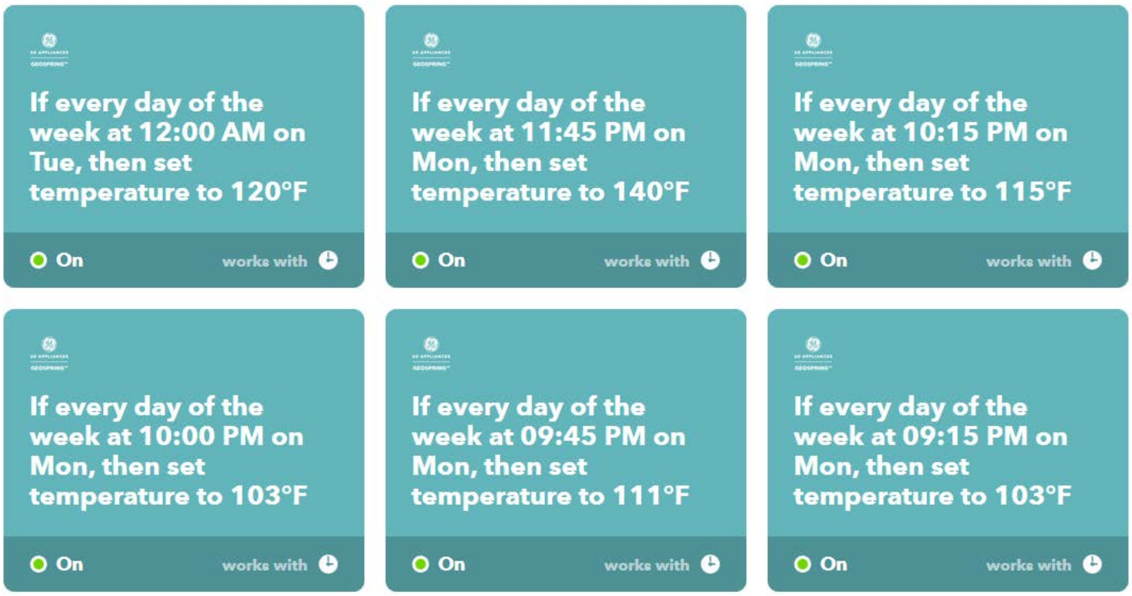


*Figure 89. IFTTT Applets to Automate Water Heater Temperature Settings*

To simulate the hot water flow rate throughout the day, a system was developed using a motorized control valve and an Arduino UNO. The motorized control valve used was a Belimo Characterized Control Valve [81], which was setup to respond to a 2-10V DC control signal. The Arduino utilized is capable of outputting a voltage of 0-5 Volts DC through a pulse width modulation port that can be programmed and used as the control voltage for the valve. To align the voltage requirements of the driving signal and the valve's input, the circuit in Figure 90 below was developed using the resource found in the Arduino help forum [82].

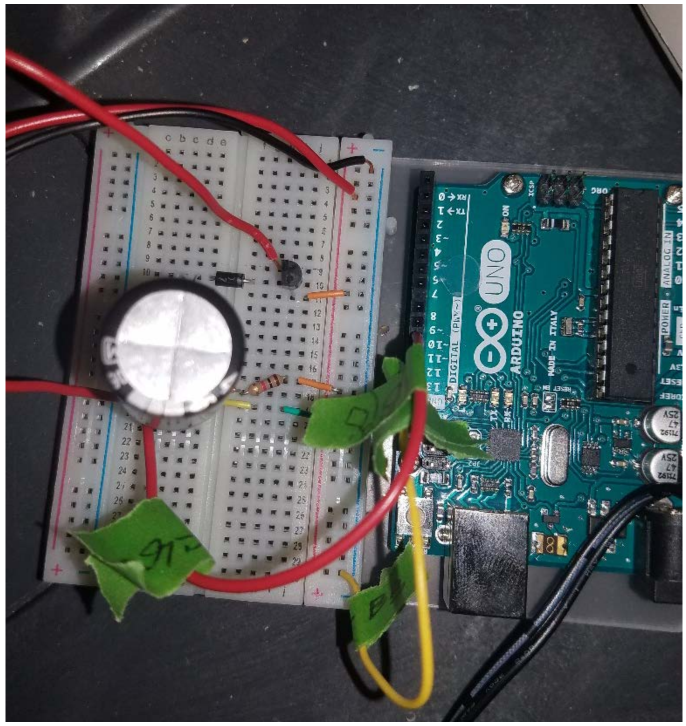

*Figure 90. Breadboard Setup to Manipulate Control Voltage.*

Once the valve was able to receive the correct range of control voltages, the Arduino was linked to Matlab and a schedule was developed to match the hot water usage to the EnergyPlus model. The script in Figure 91 is used to connect Matlab to the Arduino through the computer's COM port 4 and defines the Arduino pin to be used for control. The script also defines parameters around the test setup, specifically the length of the total test and the interval that the water flow rate changes – for this test it is fifteen minutes to match the EnergyPlus models. Finally, the Arduino output voltage (0-5V DC) from an Excel file was imported into Matlab and used as the supply control voltage at each timestep.

```
%% Items to update
clearvars a
a = arduino('COM4','Uno'); % update to match correct COM port for Arduino
pin = 'D10'; %update this to the correct pin number if changed
Number_of_hours = 48; %duration of total test
Interval_each_step = 15; % each schedule interval in minutes
sched_a = xlsread('C:\Users\Irondale\Documents\Arduino_valve\schedule_a.xlsx','B2:B194');

Total_seconds = (60*60)*Number_of_hours; % seconds in total test
Interval_time = Interval_each_step*60; %seconds in 15 mins
Time_step_no = 0;
current_row = 1;
while Time_step_no < Total_seconds;
    sched_update = sched_a(current_row) %update to the correct row from schedule
    writePWMVoltage(a,pin,sched_update); % this should be 0-100%
    pause(Interval_time); %pause and keep the valve at the correct PWM percentage
    current_row = current_row+1    %move schedule to the next row
    Time_step_no = Time_step_no + Interval_time;  %move timer to the next interval
end
```

*Figure 91. Matlab Script for Arduino Schedule*

The script then begins a “While” loop which pulls the control voltage from the Excel spreadsheet and writes that data to the Arduino. The loop then pauses for the time interval selected, fifteen minutes for this project. Once the interval time has completed, the script moves down one row and grabs the updated control signal and writes this to the Arduino, causing the control valve to open or close to the correct position. This process repeats until the total duration of the test is completed.

The valve and Arduino setup was then tested to determine the flow rates at different voltage inputs. The test was done on the same water heater and visually documented flow rates in gallons per minute from an inline flow meter attached to the cold-water inlet of the water heater. The testing shows that the valve’s water flow rate follows a third order polynomial as shown in Figure 92.

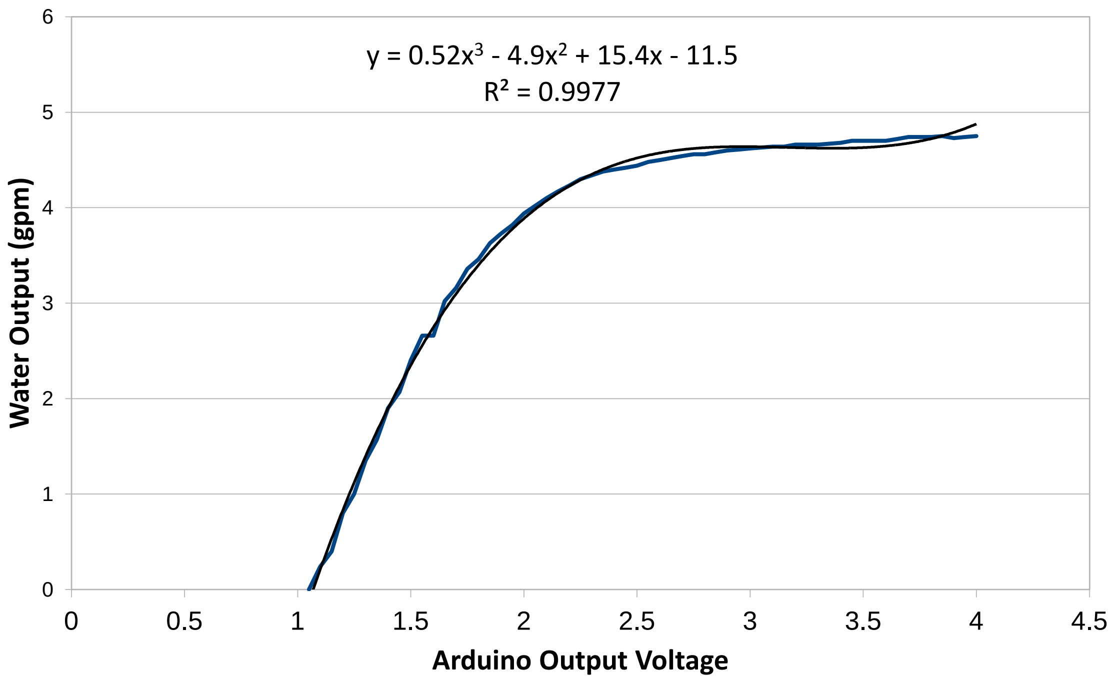


*Figure 92. Water Flow Rate through Valve at Different Output Voltages*

A program was written using Excel VBA to use the Goalseek function during each timestep to convert the desired flow rates from the EnergyPlus model into an output voltage. This voltage then is passed to the Arduino setup using the Matlab script shown in Figure 91 on page 180. The test data and results are discussed in the following section.

*Results of Verification – Day 1*

The first day of implementation within a real home was done on December 10, 2016. The model was used to develop thermostat setpoints for both the water heater and the HVAC system. Additionally, the model output the times when the oven, clothes washer and dryer and dishwasher should be operated. This information was automated to the extent possible as described in *Automating Response within Home* and setup to replicate the information output by the control algorithm.

As the information was being gathered by circuit level energy monitors and an internet connected thermostat, a similar day was investigated that would serve as a baseline for comparison. For this comparison, historical weather data was investigated and parameters such as min/max temperature, heating degree days, precipitation and wind speed were compared. This investigation led to January 24, 2016 as the most similar day to December 10, 2016 where the same level of home data was available. The information was found using [79] and presented in Table 27.

*Table 27. Weather Data Comparison for Baseline*

| Weather Parameter | 01/24/2016 | 12/10/2016 |
|---|---|---|
| Mean Temperature (°F) | 37 | 38 |
| Max Temperature (°F) | 51 | 52 |
| Min Temperature (°F) | 23 | 24 |
| Heating Degree Days | 28 | 27 |
| Precipitation (inches) | 0.00 | 0.00 |
| Wind Speed (mph) | 2 | 2 |

The average and min/max temperatures along with total heating degree days for these two days are very similar, with only one degree Fahrenheit difference in each. Additionally, five-minute outdoor temperature data for both days was downloaded using the internet connected Ecobee 3 thermostat installed in the home. This information is assembled and shown in Figure 93 for each day. As can be seen, the local temperature maintains the same trend throughout the day and maintains a similar temperature at each timestep during the day.

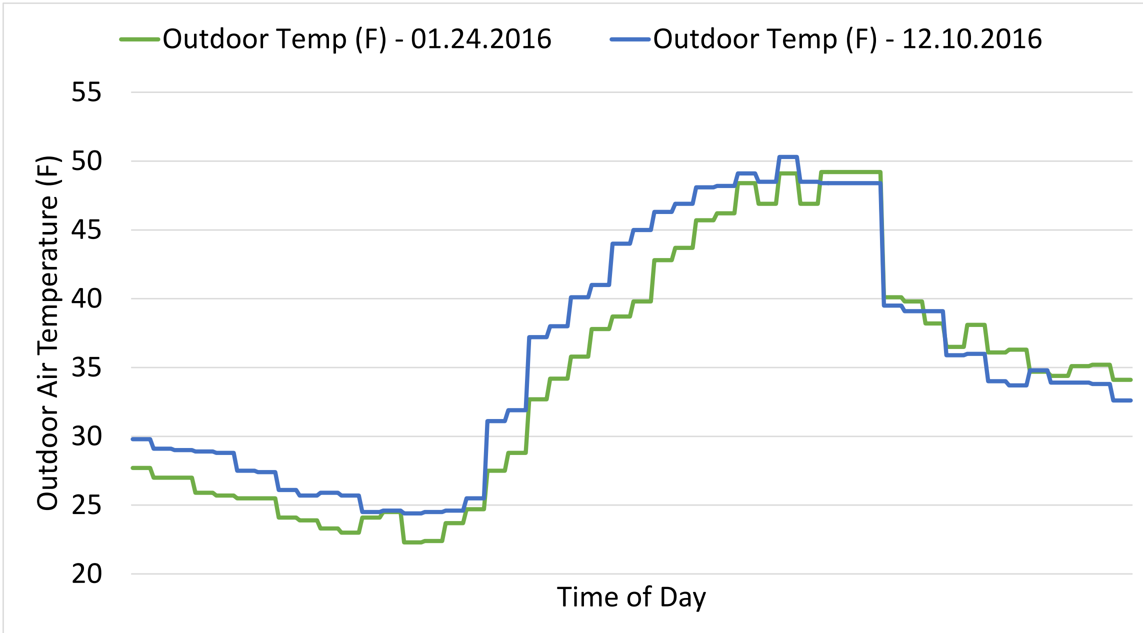


*Figure 93. Temperature Profile Comparison for Baseline Day.*

The internal temperature setpoints can also be tracked and shown in Figure 94. This shows that on January 24th, the temperature settings were consistently lower than on December 10th with only a couple exceptions. The temperature settings on January 24th remain at a base of 68°F and adjust down to either 63°F or 64°F during night and away hours. A similar setback at night and away is present during December 10th, however the temperature setting is adjusted to a maximum of 78°F to take advantage of lower energy costs during those periods and shift more expensive energy usage to those times.

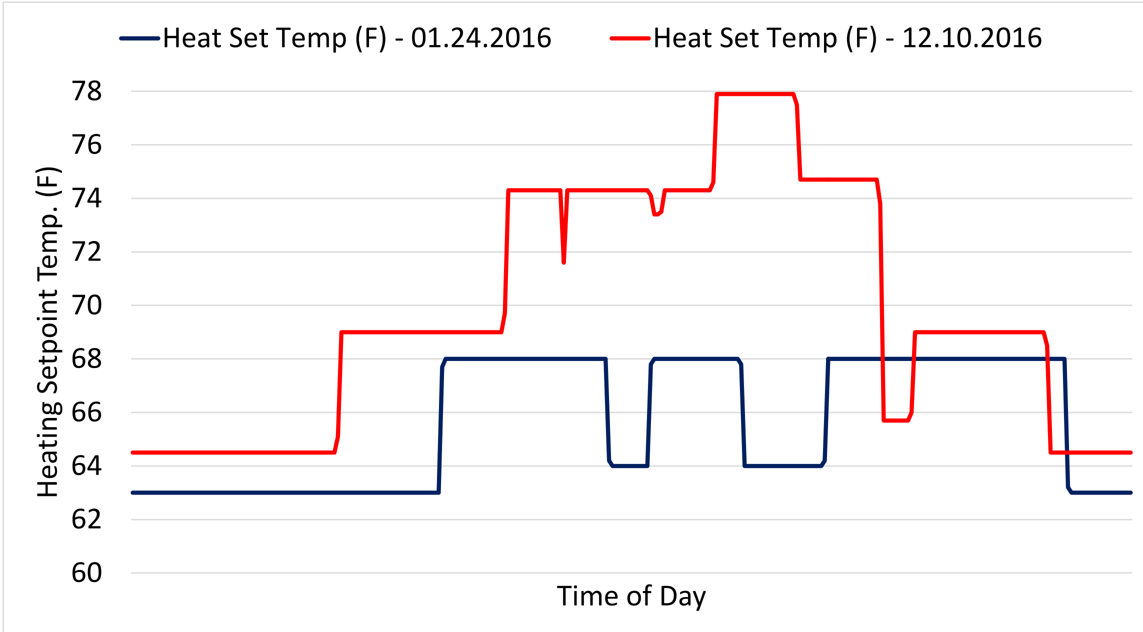


*Figure 94. Heating Temperature Setpoints for Baseline Comparison.*

Once the day was chosen for the baseline, the comparison of energy usage and cost was then performed to help demonstrate the energy costs reduction by aligning the energy usage to the renewable energy generation. For this analysis, water heating is not included and will be compared later. This is due to the home's configuration and presence of natural gas water heating. The impacts of water heating will be discussed later on page 187.

The whole home energy consumption is compared for both days and is shown in Figure 95. The dark grey line is the energy consumption when optimized around the pricing in the control strategy and the green line represents the energy consumption for the baseline day of January $24^{th}$.

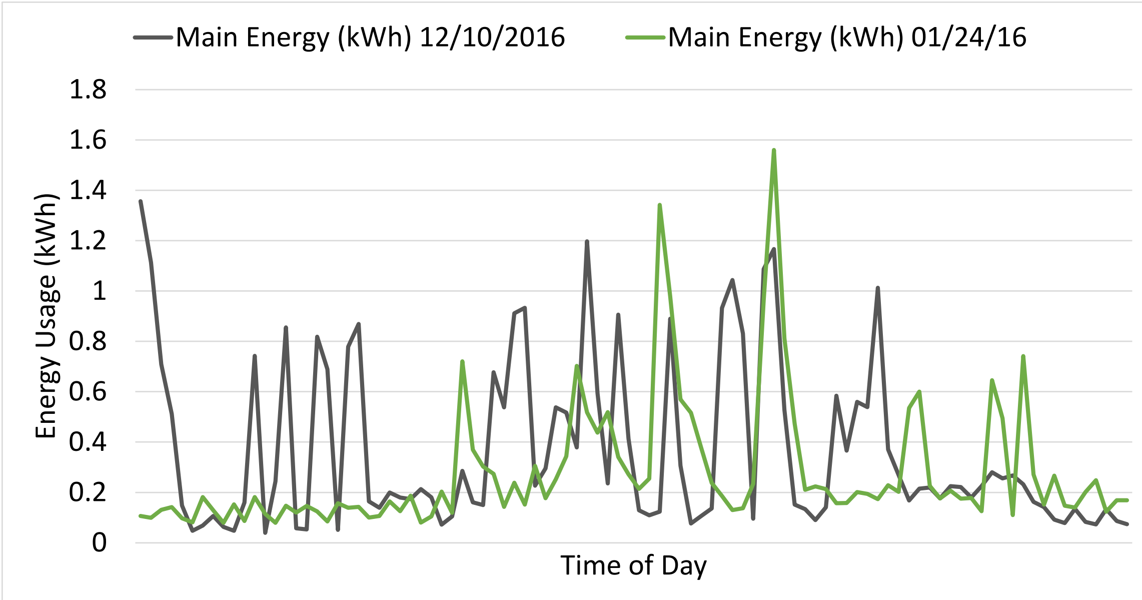


*Figure 95. Comparison Energy Consumption Data for Baseline.*

This information shows the load shapes for each day but it is difficult, if not impossible to understand the details form this data. Table 28 summarizes the total energy consumption on both days and shows the breakdown of energy usage between appliances included in the control strategy.

*Table 28. Energy Consumption Breakdown between Days*

| **Metering Information** | **Energy Usage (kWh/day) 01/24/2016** | **Energy Usage (kWh/day) 12/10/2016** |
|---|---|---|
| Whole Home | 27 | 35 |
| HVAC | 4.2 | 17.3 |
| Oven | 0.7 | 1.1 |
| Clothes Dryer | 5.6 | 3.3 |
| Dishwasher | 1.5 | 1.5 |

Based on the data shown in Table 28, the increase in energy consumption between January 24$^{th}$ and December 10$^{th}$ can be attributed to the increase in HVAC energy consumption. There are two reasons to explain this difference, the first being natural gas backup heat usage during the January 24$^{th}$ day which would decrease the energy usage metered by electricity monitors. The thermostat setting to enable backup heating was changed and an electric heat pump was used more often to meet the heating demands on December 10$^{th}$ – 165 minutes vs. 225 minutes on January 24$^{th}$. It should be noted that the use of natural gas backup heating typically occurs during the coldest hours of the day when the cost of electricity is usually highest, thus forcing December 10$^{th}$ to bare more of the cost during heating in this demonstration. The second parameter that led to the increase in energy consumption is the thermostat settings which are shown in Figure 94 on page 184.

Although the energy consumption is different between the two days, the goal of the control algorithm is to minimize the cost to the homeowner. To show that this is possible, the daily fifteen-minute cost profile is used to calculate the daily energy costs for December 10, 2016. This information is then compared to the total energy consumption from January 24$^{th}$ charged at the flat rate of \$0.1252/kWh. This information is summarized in Table 29.

*Table 29. Summary of Daily Energy Costs – no water heating*

| **Information Date** | **Daily Energy Usage (kWh/day)** | **Daily Energy Costs (\$/day)** |
|---|---|---|
| January 24, 2016 | 27 | 3.38 |
| December 10, 2016 | 35 | 2.53 |

The information contained in Table 29 demonstrates that the control strategy performs as desired. Although the energy consumption on December 10$^{th}$ is increased by 30%, the energy costs for the day are decreased by 25% when compared to January 24$^{th}$.

The water heater analysis utilized a lab setup to mimic the flow rate of hot water throughout the day and recorded the energy consumption. The flow rate of hot water and the water heater setpoint temperature for the first day of testing is shown in Figure 96. The first morning peak around 6:15 am is for two morning showers, the mid-day peak is the dishwasher and clothes washer and the afternoon peaks are handwashing and other minor uses of hot water.

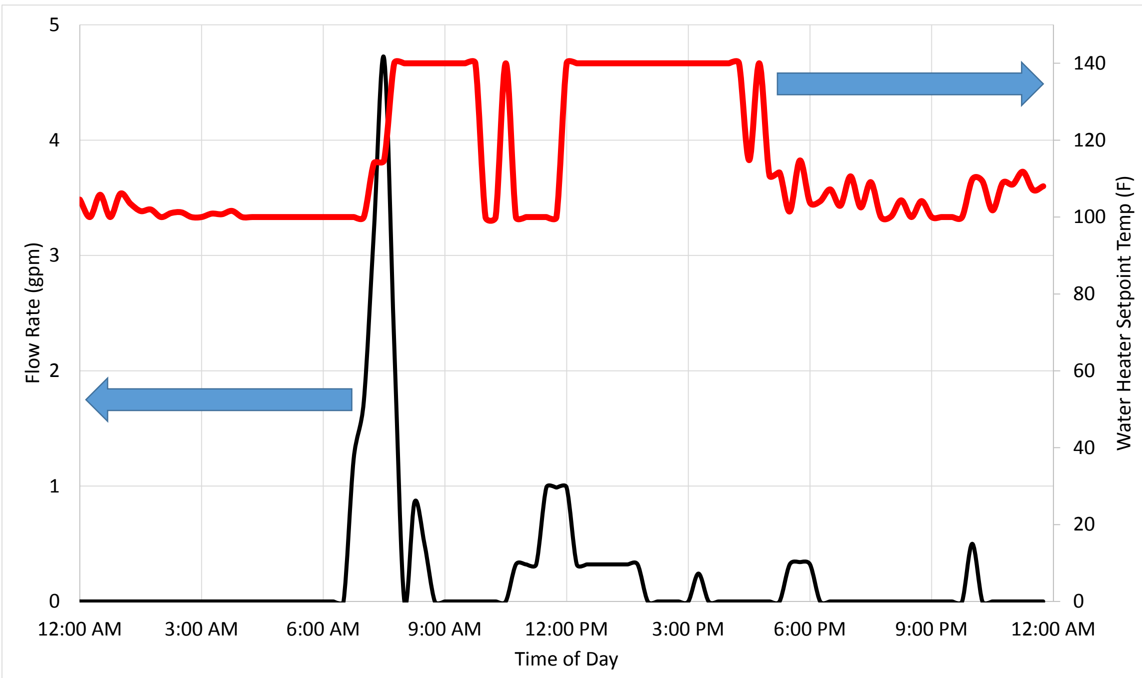


*Figure 96. Day 1 Hot Water Flow Rate & Temperature Settings*

This flow data was converted to a voltage and input into the Arduino and valve setup and the temperature settings were delivered using the IFTTT setup described earlier on page 178. The first day of testing utilized the flow rate and temperature profile shown in Figure 96 and was compared to a baseline day with the same flow rate but with the water heater temperature setting at a constant 125°F.

The updated model attempts to align the energy consumption with the renewable energy generation by associating a pricing signal at each timestep to encourage different setpoints. The change in energy usage based on cost (a proxy to renewable energy generation) can be seen in Figure 97. The black line represents the energy cost to energy storage systems in the home while the blue line is the updated energy usage based on this price. The usage attempts to shift usage to low cost periods while minimizing the amount of energy consumption during high-cost periods – compared to the magenta line for baseline energy usage.

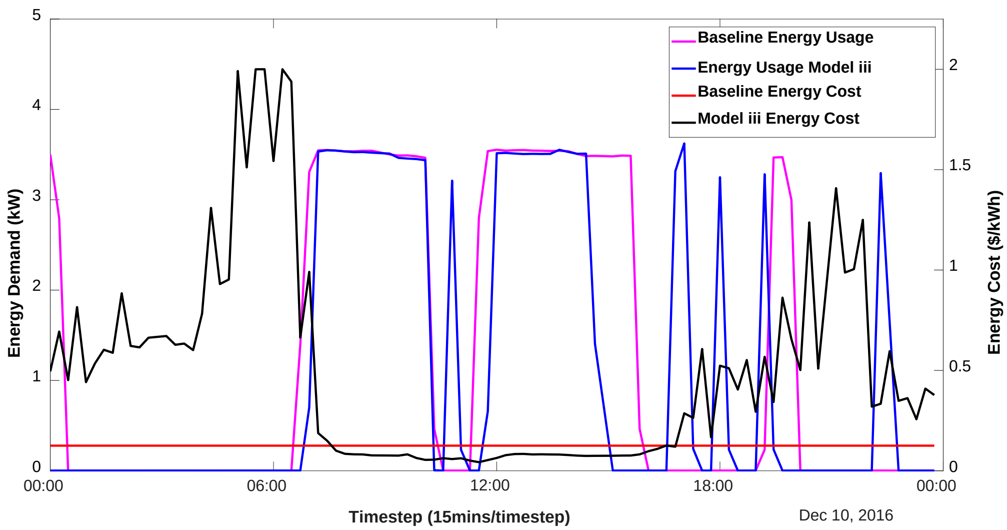


*Figure 97. Day 1 Shift in Water Heater Energy Usage.*

The updated energy cost for the water heater energy consumption is comparable to the baseline energy usage day despite having an average energy cost increase of almost 300% directed to the energy storage systems. This shows that the energy costs can be decreased or remain constant during a high cost day by shifting energy usage from high cost to low cost periods. This also implies that the results can be improved during days where the average energy cost is decreased or when more opportunities are provided to charge the water heater during off-peak times. The energy consumption decreased in the new pricing scenario over the baseline operation, a reduction of 13%. This information is summarized in Table 30.

*Table 30. Day 1 Summary of Results*

| Information Date | Daily Energy Usage (kWh/day) | Daily Energy Costs ($/day) | Average Energy Rate ($/kWh) |
|---|---|---|---|
| Baseline Day | 31 | 3.87 | $0.1252 |
| December 10, 2016 | 27 | 3.86 | $0.4968 |

For the final comparison of Day 1, the water heating energy usage and costs are combined with the remainder of the home. The results are shown in Table 31 and include the total energy consumption and the total energy cost for the baseline day (January 24, 2016 plus the baseline lab test day) and the test day of December 10, 2016.

*Table 31. Complete Energy Cost Comparison – Day 1*

| Information Date | Daily Energy Usage (kWh/day) | Daily Energy Costs ($/day) |
|---|---|---|
| Baseline | 58 | $7.25 |
| December 10, 2016 | 62 | $6.39 |

The data shows a slight increase in energy usage of 4 kWhs or 7% for the control strategy testing day over the baseline. The total energy costs are reversed and the baseline day is $0.86 more expensive than when the control strategy is implemented. This represents a decrease of 12% in energy costs. This shows that the control strategy performed as expected and helps demonstrate that the timing of energy usage is more important than the total amount consumed.

*Results of Verification – Day 2*

The control algorithm was implemented for a second day on December 11, 2016 to continue to understand the benefits of the strategy. The same setup process was performed as was done in day one with the additional weather data added the previous weather file to update the forecasted temperatures, wind and solar radiation. The control algorithm was run to gather the HVAC and water heating setpoints along with the appliance schedules. The schedules and setpoints were then implemented into the home through the internet connected thermostat and by manually turning appliances on and off at the appropriate time.

To determine what day in the past contains similar enough weather and schedules to be considered a baseline to compare the effectiveness of the control algorithm. The same website [79] was used to find an appropriate day where weather was similar and then historical energy usage data was used to ensure that day was occupied and had a similar usage pattern. The date chosen for comparison was December 20, 2015 and the weather comparison is shown in Table 32.

*Table 32. Weather Data Comparison for Baseline – Day 2*

| **Weather Parameter** | **12/20/2015** | **12/11/2016** |
|---|---|---|
| Mean Temperature (°F) | 44 | 45 |
| Max Temperature (°F) | 57 | 62 |
| Min Temperature (°F) | 31 | 28 |
| Heating Degree Days | 21 | 20 |
| Precipitation (inches) | 0.00 | 0.00 |
| Wind Speed (mph) | 3 | 4 |

The baseline day does not reach the same extremes in high and low temperatures but does come within one degree Fahrenheit of the mean temperature and within one heating degree day. This day was also chosen because they are both Sundays and therefore had a similar usage pattern. The five-minute outdoor temperature data from the Ecobee 3 thermostat on both days is presented in Figure 98. The data shows that the temperature in the morning hours remains virtually the same on both days but in the afternoon, the outdoor temperature continues rising on December 11, 2016 to 62°F while the temperature fades sooner on December 20, 2015.

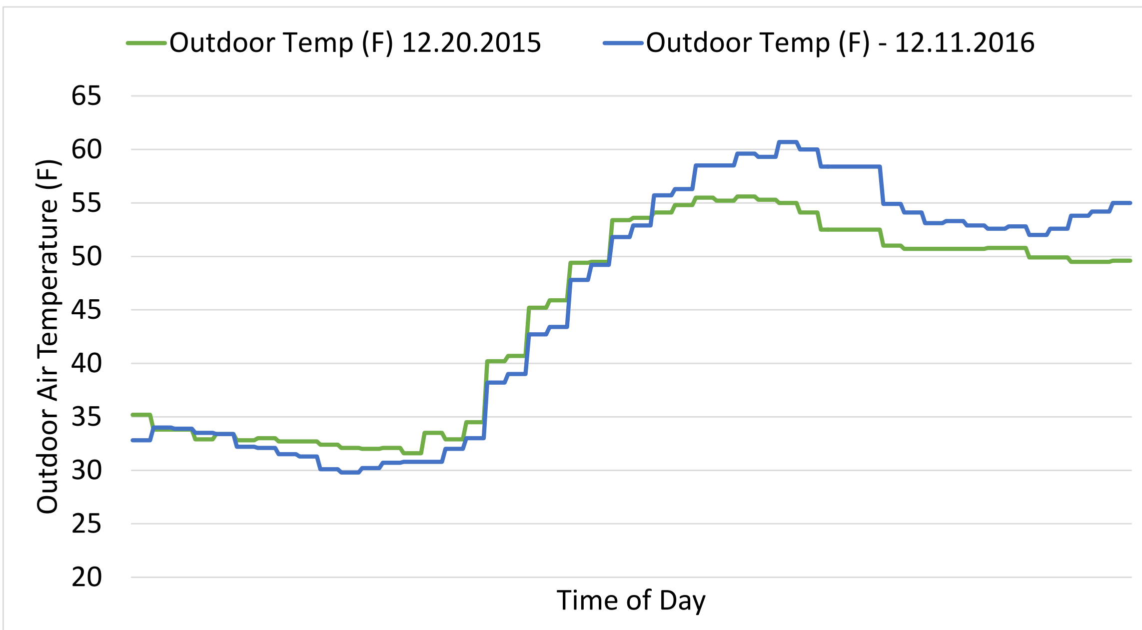


*Figure 98. Temperature Profile Comparison for Baseline Day – Day 2*

The thermostat data can also track the internal temperature setpoints and is shown in Figure 99. This data shows that the temperature settings remain between 65°F – 72°F during the baseline day and in the test day range from 61°F and 74°F.

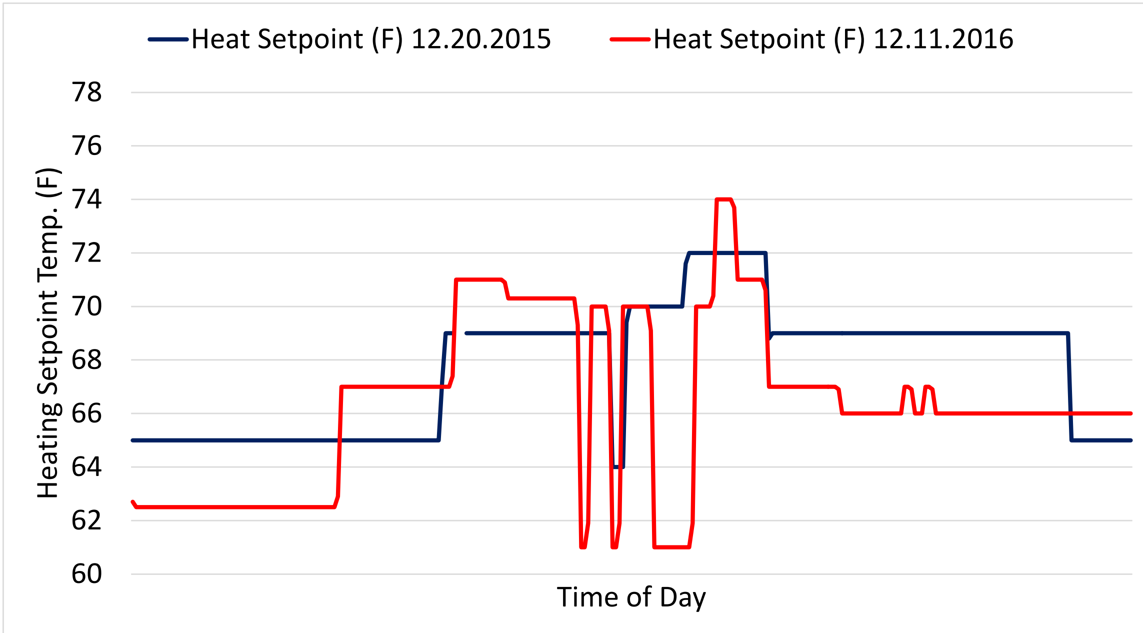


*Figure 99. Heating Temperature Setpoints for Baseline Comparison – Day 2*

Similar to the first day in the test, the energy consumption and costs are compared between the test day and the baseline – excluding water heating energy consumption which will be evaluated separately. This separate analysis begins on page 196.

The whole home energy consumption load shape for both days is plotted and shown in Figure 100. The green line represents the baseline (12/20/2015) energy usage profile while the dark grey line shows the test day load shape (12/11/2016). The total energy consumption is greater in the test day but the peaks in energy usage are located in different times of the day. The absence of the morning peak in the baseline day can be attributed to the use of natural gas backup heating rather than electrical heating using a heat pump.

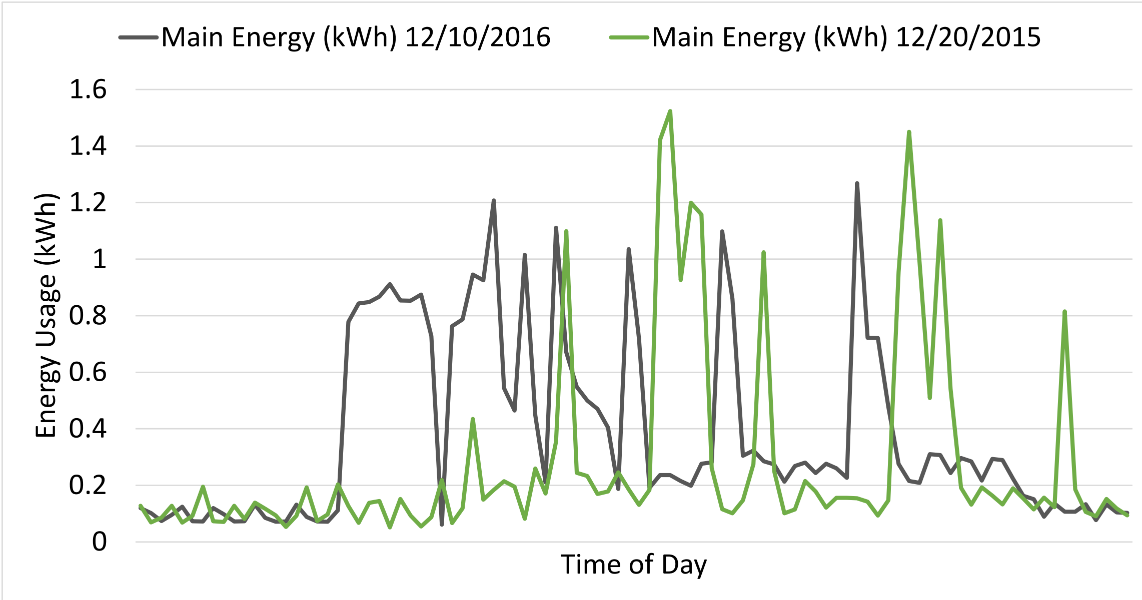


*Figure 100. Comparison Energy Consumption Data for Baseline – Day 2.*

Figure 100 shows the profile of energy consumption throughout both days but does not show the breakdown of appliances or total energy consumption well. This information is summarized in Table 33. The energy consumption in the baseline day is 31% less than during the test day with a reduction of 74% in HVAC energy usage.

*Table 33. Energy Consumption Breakdown between Days – Day 2*

| **Metering Information** | **Energy Usage (kWh/day) 12/20/2015** | **Energy Usage (kWh/day) 12/11/2016** |
|---|---|---|
| Whole Home | 27 | 37 |
| HVAC | 7.7 | 16.8 |
| Oven | 0 | 2.5 |
| Clothes Dryer | 6.8 | 0 |
| Dishwasher | 0 | 1.5 |

The reduction in HVAC usage can be attributed to the reduction in heat pump run hours and an increase in natural gas heating. The natural gas heating ran for approximately

145 minutes in the baseline case and did not operate during the test day. Table 34 shows an estimated electrical energy consumption for the natural gas heating by assuming the heat pump is operating those 145 minutes. The circuit level energy metering shows the average power draw of the heat pump is approximately 3 kW when operating.

*Table 34. Updated Energy Usage with Estimated Heat Pump Usage Included*

| **Metering Information** | **Energy Usage (kWh/day) 12/20/2015** | **Energy Usage (kWh/day) 12/11/2016** |
|---|---|---|
| Whole Home | 34* | 37 |
| HVAC | 7.7 | 16.8 |
| Oven | 0 | 2.5 |
| Clothes Dryer | 6.8 | 0 |
| Dishwasher | 0 | 1.5 |
| Estimated Heat Pump | 7.5* | n/a |

Even with the accounting for natural gas heating during the baseline day, the energy consumption during the test day was 8% more. However, the goal of the control algorithm is not necessarily to reduce energy consumption but rather to reduce the usage of high cost, peaking energy and to consume renewable energy generation as it is available. Therefore, the energy costs of each day must be analyzed. This data is shown in Table 35 where the first set of information for the baseline day excludes the estimated natural gas heating but is included in the second row denoted by the * at the end of the date. The daily cost for the baseline energy consumption is calculated by multiplying the daily energy consumption by the flat energy rate ($0.1252/kWh) while the test day energy costs are calculated by summing the energy costs at each time interval based on the calculated fifteen-minute energy cost from the control algorithm.

*Table 35. Summary of Daily Energy Costs – Day 2*

| Information Date | Daily Energy Usage (kWh/day) | Daily Energy Costs ($/day) |
|---|---|---|
| December 20, 2015 | 27 | 3.36 |
| December 20, 2015* | 34 | 4.30 |
| December 11, 2016 | 37 | 3.95 |

The calculations show that in the true metered comparison, an increase in energy usage of 37% also resulted in an increase in energy costs of 18%. However once a better representation of the HVAC energy consumption was included, the energy consumption was increased by 9% but resulted in a decrease in daily costs of 8.1%. This shows that with the implementation of interval pricing and flexible loads within the home, an increase in energy consumption can still translate into a lower energy bill.

The water heater analysis was performed in the same manner as Day 1 and utilized a lab setup to mimic the hot water flow rate of a typical day in a home and recorded its energy consumption in minute-by-minute increments. The flow rate and temperature settings used for the second day are shown in Figure 101. The early morning peak represents two showers around 6:15am, the mid-morning spike represents the dishwasher and the remaining usage is from hand washing and other miscellaneous uses. This temperature profile was compared to a constant setting of 125°F with the same flow rates.

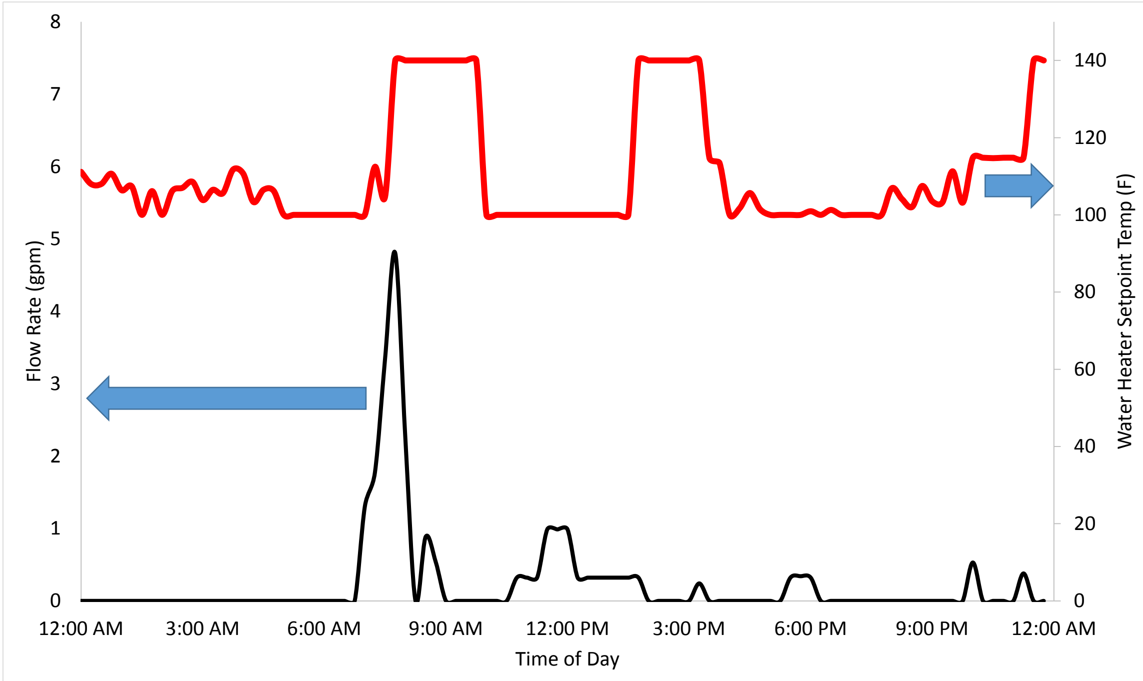


*Figure 101. Day 2 Hot Water Flow Rate & Temperature Settings*

The flow data and temperature setpoints are shown in Figure 101 and are used in the test setup. The first day of testing utilizes both the temperature and the flow rates that were programmed into the water heater and automated control valve respectively. The second test day utilized the same flow rate as described and programmed into the automated control valve but the water temperature setpoint maintained a constant temperature of 125°F.

The results for the second day follow a similar pattern as day 1 where the algorithm shifts energy usage, as best it can within the parameters setup by the homeowner, to lower cost times of the day when renewable energy is abundant. This pattern can be seen in Figure 102 where the blue line is the updated energy usage compared to the baseline represented by the magenta line. The black line represents the updated energy storage rate and it can be seen that the completed algorithm energy usage avoids the high cost periods by shifting the energy usage.

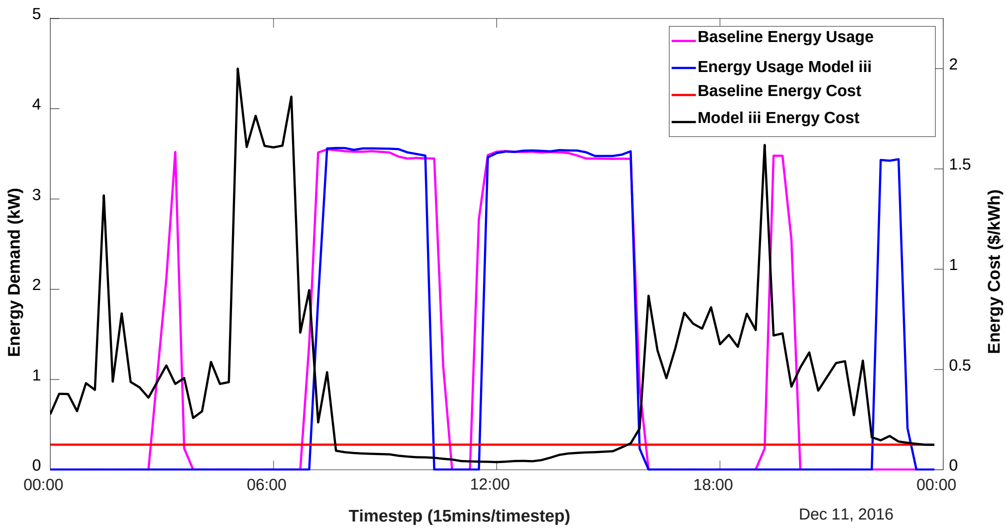


*Figure 102. Day 2 Shift in Water Heater Energy Usage*

The updated energy cost for the second day of the water heater test show a decrease in energy consumption by 2.7 kWhs, or 12%, for the updated energy cost profile when compared to the baseline. The energy costs for the day are reduced by 32% during the variable price structure after Model iii when compared to the same profile during the baseline model. When the baseline energy usage was decreased to match the usage during the control algorithm day, the cost remains 28% higher than the results after Model iii. This occurs with the average energy rate charged to the energy storage increasing during Model iii from $0.1252/kWh to $0.4467/kWh. This implies that the flexibility in the water heater can enable the energy costs to be reduced when the average rate is increased. This information is summarized in Table 36.

*Table 36. Day 2 Summary of Results*

| Information Date | Daily Energy Usage (kWh/day) | Daily Energy Costs ($/day) | Average Energy Rate ($/kWh) |
|---|---|---|---|
| Baseline Day | 31 | 3.86 | $0.1252 |
| December 10, 2016 | 27 | 2.64 | $0.4467 |

The information was then combined with the remainder of the home's energy consumption and costs and are shown in Table 37. This data is for the baseline day, December 20, 2015 and the baseline water heater day, compared to the testing day of December 11, 2016.

*Table 37. Complete Energy Cost Comparison – Day 2*

| Information Date | Daily Energy Usage (kWh/day) | Daily Energy Costs ($/day) |
|---|---|---|
| Baseline | 65 | $8.16 |
| December 11, 2016 | 64 | $6.59 |

From the testing, a slight decrease in energy usage is seen after implementing the control algorithm of 1.5%. In addition to the energy savings, the energy cost savings result in a reduction of $1.57 for the day or almost 20%. This, combined with the test results from Day 1 demonstrate that the control algorithm can be effective at manipulating energy usage within a home to minimize cost while maintaining homeowner comfort.

# FUTURE RESEARCH

The Matlab and EnergyPlus modeling presented in previous sections coupled with the lab and field testing demonstrate the algorithm can be effective at aligning energy consumption in a group of homes with renewable energy generation over a wide area. The project focused on the higher-level optimization scheme at the utility end by adjusting rates for their customer to encourage energy consumption to shift to low cost periods from higher cost, lower renewable energy generation times. This optimization scheme is dependent on the homeowner's response to pricing signals and their flexibility to change usage patterns. As more and more homes participate in the scheme, the response will become more uniform and predictable as daily changes in one home are averaged out. Additionally, the amount of response desired by differing utilities will be different as differing renewable penetrations drive different use cases. Therefore, it is foreseen that the equations shown in both Figure 20 on page 51 and Figure 43 on page 88 will need to be slightly modified and updated to meet the needs of each utility. Even with these modifications, the core algorithm remains the same and allows it to meet additional utility industry needs.

Another key portion of this control algorithm is the home automation and optimization scheme. For this research, a simplified system was implemented using historical appliance usage data combined with updated energy pricing to find the lowest cost combined with the highest historical probability of usage. It was understood throughout the research that this approach is an over simplification of residential energy usage and control but was seen as a realistic method of including diverse load shapes within the ten homes, based on actual usage data, that can allow the focus of the research to be implemented. In the future, home automation and optimization systems will become more advanced and sophisticated and will be able to implement model predictive controls that can incorporate different forecasting models to improve the optimization of the home's energy usage. These systems will also implement more advanced solving algorithms to greatly reduce the computing time and resources required, similar to the one presented in [83]. These advancements are only seen as a way to further improve the value of this project and should be a focus area for future research to advance the level of renewable energy penetration on the grid.

# CONCLUSION

Although the energy generation landscape is changing with new government regulations and consumer preferences that create new challenges to the electric utility industry, strategies are being developed to address these changes and ensure the grid is supplied with clean, safe and affordable energy for decades to come. The control strategy presented herein allows the electric utility and a group of homeowners to negotiate schedules for their day through an automated home automation system to provide the lowest cost to both parties as well as having a fifteen minute ahead pricing structure just for energy storage systems to absorb or generate quickly to align energy usage to renewable generation. This strategy can benefit all parties involved by shifting energy usage during high cost generation times to lower costs and passing that savings onto the homeowner. The three major goals in this research was to reduce the annual energy costs to the homeowner while increasing the profit to the utility and reducing the overall energy storage requirements for a group of homes in this program. To demonstrate the effectiveness of the strategy several models were developed and a home and lab test site were developed.

The first set of simulations included ten residential homes, one which was verified to be thermally accurate for this project in *Building Energy Model and Verification* on page 36 and nine other homes developed by the US Department of Energy for different code years [56] – these home types are summarized in Table 3 on page 44. These homes were modeled in EnergyPlus using typical schedules found from the US Department of Energy's Building America program [68] and used as a baseline to compare the energy usage output of the control algorithm. A set of Matlab scripts were created to develop the schedules used as inputs to the home simulation models as well as calculating the updated utility pricing signals. This process is summarized in Figure 22 on page 58 and demonstrates the link between the Matlab scripts and the external command to initiate EnergyPlus models of each home. The model was setup to iterate the process until three parameters were met; a reduction in each of the ten home's annual energy costs, a reduction in energy storage requirements by at least 15% and an increase in utility profit of at least 0.5%. The algorithm was able to meet these requirements after nine negotiation iterations and resulted in an average energy cost savings of 3.8%, a 46% reduction in energy storage requirements and increase the utility profit by 2%. Lastly the linear correlation between energy usage and renewable energy generation was analyzed and the correlation increased from 11.5% in the baseline model to 40.2% after the control strategy was implemented.

To address future improvements in residential end device flexibility through the adoption of variable capacity HVAC systems and larger capacity water heaters for improved thermal energy storage along with the increasing proliferation of rooftop PV, a second model was developed for the same homes with these new features. To provide differentiation, as not all homes will be right for solar PV due to shading and orientation, a summary of which homes contained rooftop PV is shown in Table 14 on page 121. The same control algorithm and model were run with identical parameters to simulate how effectively the concept aligns energy usage with generation when the new technologies are introduced. The results from the updated run show an improvement over traditional technologies, despite the addition of rooftop PV which counteracts the effectiveness by adding additional generation when generation costs are typically low. This counteraction is outweighed by the flexibility enabled by the variable speed HVAC system and increased thermal energy storage capacity in larger hot water tanks.

For this second model, the algorithm is able to converge and meet the requirements after thirteen iterations and shows an average decrease in annual energy costs of just under 5%. The energy storage requirements are initially increased in the baseline scenario compared to the first model with the addition of rooftop PV but after the control algorithm is implemented, the storage requirements are reduced by 32% to a level similar to the one found in the first model. The third parameter, utility profit, is increased by 5.5%. Finally, the linear correlation between renewable energy generation and the energy consumption in each timestep is improved from -13.9% (an opposite of desired correlation) to 29.5%. This final correlation is lower than during the typical home model but shows a greater improvement of over 40% in correlation between the two variables. This shows that all three parameters can be effectively improved by implementing a negotiation strategy between the utility and the homeowner while also implementing a more real-time pricing strategy to shift the usage of water heating energy consumption. This analysis also shows that as flexible HVAC and larger thermal energy storage systems increase in adoption, the control algorithm's value becomes even greater as it enables better alignment and flexibility with end loads.

Two additional models were simulated for the control algorithm with identical setups as before with the only exception being an updated utility cost profile – 2014 historical ERCOT data updated to 2015 historical ERCOT data for Houston, Texas. This was done to verify the control algorithm could perform effectively independent from the starting energy cost profile. For the traditional home model, the results from the updated model show a decrease in annual energy costs by an average of 3.2%, a 48% decrease in energy storage requirements and an increase in profit of 0.2%. This model converged after eleven iterations with a new linear correlation of 43.1%. The results from this updated cost model were found to be in line with the original ERCOT cost profile. The advanced home model was able to converge after thirteen iterations with a new linear correlation coefficient of 34%. The annual energy costs to homeowners was reduced by an average of 5.8%, the energy storage requirements were reduced by 33% and the utility profit increased by 1.8%. This too is found to be similar to the results from the original cost profile. These results, seen in each of the new models, show that the control algorithm is able to work effectively with different starting energy cost profiles and will be able to adapt to changing energy generating cost profiles.

The last models simulated for the control strategy was on a daily basis rather than annually as previously discussed. This allows the algorithm to optimize the energy consumption and costs for each day individually and vary the number of iterations of negotiations between the homeowner and the utility. Five days were chosen to represent each of the four seasons plus one additional summer day. For the days chosen, the results showed a shift in the beneficiary of the control algorithm from the homeowner to the utility by reducing the amount of cost savings to but increasing the profit. While this occurred in each of the days involved, it showed a leveling out of the results to meet both needs by creating less extremes from day-to-day. Therefore, it was determined that the daily control strategy would maintain the same results, or better, for all parties if implemented in 365 individual models.

Finally, a lab and field test was performed to further validate the control algorithm performance in a real-world environment. The thermal envelope of home iii was used in the field evaluation and a GE Geospring heat pump water heater in electric resistance heating mode only was using in a lab with automated controls to model the water heating energy usage. The control model was run using forecasted weather data and the historical energy costs to develop the appliance and thermostat schedules for two days, December 10 and December 11, 2016. The energy costs for the day were compared to a similar weather day which occurred in the previous year in the same home with similar schedules. The results from the first day show an increase by 25% in energy usage, with the breakdown summarized in Table 28 on page 185. Even with tis energy usage increase, the total energy cost for the day was reduced by 28.6 %. Similar results were seen in the second day of the analysis where the adjusted energy usage is 8.5% lower, however the energy costs for the day are reduced by 8.5%.

The water heating testing demonstrated the impact on energy costs by shifting energy usage from high to low cost times. The first day of water heater lab testing was simulated with a prescribed flow rate and at a constant temperature setting of 125°F while the second day was simulated using the same flow pattern but varying the temperature setting based on energy rates in each time increment. The first simulation resulted in a similar energy cost compared to a baseline but with an average energy cost of almost 300% greater than the flat rate of $0.1252/kWh. The second test period, representing December 11, 2016, resulted in a reduction in energy costs of 32% even with an increase in average energy costs of 257%. This information, when combined with the remainder of the home's energy usage for the two test days, represent a decrease in energy costs by implementing the control strategy.

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