Development of an Energy-Information Feedback System for a Smartphone Application

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November 5th, 2012

Master of Science Thesis
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Energy Technology EGI-2012-035MSC
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Abstract

Energy conservation and efficiency are often widely touted as non-controversial, cost-positive methods of reducing energy consumption and its associated environmental effects. However, past programs to encourage residential energy efficiency and conservation have failed to make an impact. A growing amount of research identifies energy feedback as a method to provide consumers with the information and motivation necessary to make appropriate energy-saving decisions.

JouleBug is a social, playful, mobile smartphone application designed to help users in the U.S. reduce energy consumption and live sustainably through behavioral changes. This project initiated the design of an energy feedback system for JouleBug that provides estimates of a user’s energy savings for completing 38 residential energy saving actions. Mathematical models were developed to estimate JouleBug users’ energy savings for each of the energy saving actions, based on 13 input parameters. A method was developed to aggregate each of the savings actions across various energy end-uses into a summary of the user’s energy savings over a given time period. Additionally, the energy models were utilized to analyze an average user’s potential energy, cost, and greenhouse gas savings over a year.

Research into the design components of effective feedback systems was applied in the context of JouleBug to compliment the engineering work. The components of frequency, measurement unit, data granularity, recommended actions, and comparisons were examined. Design suggestions based on these components that utilized the energy models to provide effective energy feedback to JouleBug’s users were proposed. Finally, this report describes opportunities for future research using simple energy modeling methods to provide effective consumer energy feedback in a mobile smartphone application.
Acknowledgements

This project would not have been possible without the support from many colleagues and loved ones. I am especially grateful to Grant Williard, my advisor and the creator of JouleBug. His vision for JouleBug is truly groundbreaking, and his previous engineering experience was invaluable for the completion of this report.

I also wish to express my gratitude toward my parents, who provided vital support and helpful critiques of this project. I would like to thank my professors and fellow students at KTH, as well as the JouleBug team for their comments, criticisms, and encouragement. Finally, thanks to my girlfriend Hannah for keeping me focused and providing love and support.

This project was made possible by funding from Cleanbit Systems, Inc., the parent company of JouleBug.
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1 Introduction

As global energy consumption continues to rise, energy efficiency and conservation has been championed as a way to reduce consumption and environmental impact. There is significant potential to reduce energy consumption in residential buildings through efficiency improvements, many of which are net-value positive. A major impediment to achieving reduced consumption goals remains a lack of awareness and motivation by consumers. Increasingly, program designers and utilities are turning to informative energy feedback as a way to motivate people to consume less energy. Creating a behavioral change through energy feedback has the potential to reduce energy consumption. However, energy and behavioral scientists are aware of many challenges to creating a feedback method that is easily deployable, cost effective, and able to achieve measurable savings. The purpose of this thesis project is to develop an energy-information feedback system that will calculate and display an estimate of a consumer’s energy savings in a motivational, educational, and engaging way. This feedback system will be part of the development of a mobile smartphone application called JouleBug. Included within this report is technical engineering knowledge required to create the feedback system architecture, as well as a proposed method of implementation - based on behavioral science principles - that will overcome the challenges that have plagued prior feedback programs.

1.1 Rationale

As the world’s energy consumption continues to increase, the environmental impact of the fossil-fueled energy system cannot be ignored. In 2009, the United Nation’s Intergovernmental Panel on Climate Change (IPCC) concluded that fossil fueled energy use is a leading contributor to the production of greenhouse gases (GHGs), including carbon dioxide (CO2), which are “very likely” the cause of global warming (IPCC, 2007). In addition, the combustion of coal, commonly used for electricity production, produces high levels of nitrogen oxides (NOx), sulfur dioxide (SO2), mercury, and particulate emissions which have far-reaching environmental impacts. For example, particulate emissions and SO2 have been found to cause respiratory illnesses and increased risk of asthma. NOx and SO2 are major components of acid rain, while mercury is a toxic chemical that can accumulate in fish, making them unfit for human consumption (U.S. Environmental Protection Agency, 2007; U.S. Environmental Protection Agency, 1997). Reduction of fossil fuel use through efficiency and conservation will lessen the global environmental impact of energy consumption and reduce greenhouse gas emissions (Pacala & Socolow, 2004).

Reducing dependence on fossil fuels will require a composite solution, with energy efficiency and conservation playing a large and vital role, often at a positive economic benefit. The analysis group McKinsey & Company estimated that in the United States, there is potential for net-value positive energy efficiency improvements in the residential sector that could save 3.16 quadrillion BTUs (926 TWh) of primary energy by 2020 (Granade, et al., 2009). This total only includes investment opportunities and does not include conservation approaches or changes in consumer habits, which could substantially increase the potential savings well beyond these measures. The prospective impact of a comprehensive energy efficiency and conservation program is immense.

Energy efficiency and conservation programs, especially in the residential sector, are necessary components of an overall strategy to reduce environmental impact. The residential sector accounts for 23% of the energy consumption in the U.S., equivalent to 22.2 quadrillion BTUs (6506 TWh) of total energy in 2010 (U.S. Energy Information Administration, 2011a). Due to its diverse and fragmented nature, it is difficult to enact energy efficiency reforms in the residential sector. There have been many programs to encourage energy efficiency and conservation in the residential sector, including technological improvements like more efficient appliances, and financial incentives such as tax credits or utility rebates to encourage homeowners to make energy improvements. However, adoption of energy-saving technologies such as insulation, efficient HVAC systems, lighting and appliances have been slowed by a
lack of consumer awareness about the potential energy-savings (Granade, et al., 2009). This lack of consumer awareness about energy is tied to a concept called the “invisibility of energy.”

For those of us in the field of energy engineering, the flows of energy are readily identifiable. However, for the ordinary consumer, energy is invisible as it enters our homes, and we can rarely track where the consumption occurs (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). Furnaces, thermostats, dishwashers and other energy-consuming devices have no gauge or display that shows the consumption directly, so the relative amount of energy being used is unknown to the consumer. Instead, the consumer receives only a single monthly bill, which does not delineate where the energy usage is occurring within the home, as there is no end-use disaggregation. Even tracking total energy consumption is difficult, as fluctuating weather and energy prices obscure other trends in usage (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). Without clear knowledge of their consumption patterns, ordinary people have a very limited ability to make informed energy decisions. The effect of energy invisibility contributes fundamental misunderstandings most consumers have about energy. Stern noted that residential consumers typically suffer from misperceptions of energy use within their homes, overestimating energy uses that are visible such as lights, and underestimating less visible end uses such as water heating (Stern, 1992). Attaria and colleagues conducted a recent study which surveyed 505 participants about their perception of energy consumption and savings. The survey asked participants to estimate energy use for household appliances and energy savings from different energy saving actions (such as using more efficient lighting or line-drying clothes). People surveyed underestimated energy use and savings by a factor of 2.8, with minimal overestimates for low energy-saving measures and underestimates for substantial energy saving measures (Attaria, DeKayb, Davidson, & de Bruin, 2010). Studies examining energy-saving measures report that consumers consistently underestimate the savings that can result from simple efficiency improvements (Attaria, DeKayb, Davidson, & de Bruin, 2010; Granade, et al., 2009).

There is growing need for a new approach which focuses on the consumer’s behavior rather than on technological or economic measures (Froehlich J. , 2009). Stern identifies nonfinancial motives for implementing energy conservation measures, including consumer preference, social/group pressures, and personal values and attitudes. These motives can have a more significant impact than price especially where low-cost energy saving measures are concerned (Stern, 1992). Behavior is often the dominant factor that drives energy consumption within the home, and is very significant even when compared with a consumer’s physical surroundings (home size, climate, heat loss coefficient, etc). Past research has shown that a person’s behavior has a sizeable effect on energy consumption. For similar type houses, occupant behavior is more influential than climatic or construction factors (Sonderegger, 1978; Pettersen, 1994). Altering behavior can be the “key ingredient” in a carbon-neutral future.

So what is the connection with feedback? Feedback has been identified as a way to “provide consumers with the information, motivation, and timely insights that can help them develop new energy consumption behaviors and reduce wasteful energy practices” (Ehrhardt-Martinez, Donnelly, & Laitner, 2010, p. 1). In addition, feedback programs are showing enormous promise in reducing energy consumption. A recent meta-review of feedback practices found that feedback initiatives of all types can reduce electric energy consumption of single households by 4%-12%, with a potential nationwide savings ranging from 0.4% to 6% of total residential electricity consumption. By 2030, the electrical savings of feedback programs could reach 100 TWh annually (Ehrhardt-Martinez, Donnelly, & Laitner, 2010).

However, the savings from feedback programs is dependent both on the effectiveness of the feedback program in influencing individual behavior, and on the wide adoption of feedback technologies across the U.S. Both components are necessary in order to see measureable energy savings on a national scale. This concept is crucial to the development of a feedback system, especially one that will be adopted in a capitalist free market. A feedback system that is extremely effective in focus groups, but not widely desired or accessible by the public will fail to make an impact. Similarly, a wide-spread (utility implemented) feedback program will also fail unless it can create a meaningful behavioral change in the participants. Both factors are largely influenced by the specific design of feedback programs.
Developing a design that is motivational, engaging, educational, and widely implementable is no small task.

Adding to the challenge of feedback system design is the consideration of format in which to deliver the feedback information directly to the consumer. The smartphone, or mobile, format has been noticed as a promising area for feedback systems (Ehrhardt-Martinez, Donnelly, & Laitner, 2010; LaMarche & Sachs, 2011). However, the mobile format comes with unique challenges to the design of a feedback system. Although the adoption of smartphones in the market is now reaching unprecedented levels, the research into the design of energy feedback systems on smartphones has been limited, making this an area that deserves attention in academic research.

1.2 Background on JouleBug

In order to fully understand the scope and constraints of this specific feedback system, a discussion of the background of JouleBug is necessary. JouleBug is an Iphone application, best described as an educational and entertaining game focused on helping players reduce energy waste and save money\(^1\) (Cleanbit Systems, Inc., 2012a)

The main goal of a JouleBug user is to earn Badges, and compete with friends. A Badge is a grouping of similar energy-saving actions. Each unique energy-saving action is called a Pin. Examples of Pins include taking shorter showers, using energy efficient light bulbs, or adjusting the thermostat for energy savings. Each time the user performs the action is termed a “Buzz”. A player earns a Pin by Buzzing (performing the energy-saving action) a required number of times. Along with a short description of the action being taken, each Pin contains information about how to perform the action, in a spot called the Info Ribbon, visible in the left screen of Figure 1.1. The Info Ribbon provides a numerical estimate of average savings for completing the action – called the Pin Stat – in kWh, dollars, and CO\(_2\). In addition, infographics and embedded YouTube videos are available for additional educational content. Earning one or more of the Pins under a Badge grouping earns a Badge. For each step in the process, the user also earns Points, which illustrate their relative commitment to performing the energy saving actions. After earning a Pin or Badge, the user also has a chance to share their progress via social media. Badges feature unique artwork and are stored in a Trophy Case which serves as a visual record of the energy saving actions completed. Figure 1.1 below shows the steps of earning a Pin visually:

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\(^1\) As of this writing, JouleBug v2.0.2 is available in the U.S. Apple App Store. More information is available at http://joulebug.com.
The basic functions of JouleBug can be broken down into three categories: **Badge Ribbon**, **Leaderboard**, and **Energy Graph**. The Badge Ribbon organizes the Badges and is the main interface for the app. The **Leaderboard** (see Figure 1.2, middle screen) shows a listing of JouleBug users ranked by their point totals or number of Badges earned. Through a Facebook and Twitter connection, the Leaderboard has the ability to show a JouleBug user's ranking compared to their Facebook and Twitter friends, or alternatively, compared to all JouleBug players. The final component of the JouleBug system is the **Energy Graph** (see Figure 1.2, right screen). A utility connection Badge allows a player to link his online utility account with JouleBug, allowing the utility bill to be displayed on their mobile device through the application. JouleBug currently has coverage for 25 million electric utility accounts and 6.6 million natural gas accounts in the U.S.

**Figure 1.2** JouleBug app screenshots: Badge Ribbon, Leaderboard, and Profile with Energy Graph. (Cleanbit Systems, Inc., 2012b).

### 1.3 Objectives

The objective of this thesis proposal is to design an energy feedback system for the JouleBug mobile application. This feedback system will use energy modeling to develop estimates of the amount of energy, cost, and environmental impact (GHG) that a user is saving by using JouleBug. The latest energy behavioral research will be utilized to determine the feedback design components that most effectively utilize the energy models developed. The desired design should be highly motivational and should encourage users of JouleBug to save more energy. The feedback system should be informative so that consumers begin to understand their energy utilization habits and gain the ability to make more informed energy decisions. In addition, the system will also need to be readily accessible to a wide segment of the population, intuitive to use, and should be entertaining and engaging so users are encouraged to use it continuously. Developing a feedback system that will display a consumers’ energy savings in a motivational and educational way on a smartphone encompasses sub-tasks in two categories: engineering and psychology. The subtasks involved for this project are visible in Table 1.1.

The two components of engineering and psychology are required to make tradeoffs in order to build the most effective system. A system which is exquisitely accurate and comprehensive from an engineering standpoint may greatly impair the usability and entertainment aspects of the application. On the other hand, a system which is not based on sound engineering may be seen as superficial or “unscientific”, which would decrease consumer acceptance of the feedback. A balanced approach is necessary to design a feedback system which will be interesting and fun to use but also motivational and informative.
### Table 1.1 Subtasks for design of a JouleBug feedback system.

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<th>Psychology</th>
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<td>• Determine what information will be needed from the user to accurately calculate estimated energy savings.</td>
<td>• Investigate the frequency of feedback required.</td>
</tr>
<tr>
<td>• Create mathematical models to calculate an estimate of the energy savings for each Pin depending on the data given by the user.</td>
<td>• Choose an effective measurement unit (cost, energy, or environmental impact) for displaying feedback data.</td>
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<tr>
<td>• Implement a method for converting the energy savings estimates into cost and GHG savings.</td>
<td>• Determine the best way to break down the information, both over time and by end use.</td>
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<td>• Develop a way to aggregate the savings amounts into a comprehensive savings estimate for all Pins earned by a user.</td>
<td>• Integrate user-specific energy saving recommendations into the feedback to serve as ‘triggers’ (cues to perform action).</td>
</tr>
<tr>
<td>• Calculate the energy and cost savings for an average user and compare with reference data.</td>
<td>• Determine what types of energy use comparisons (temporal, normative, social, etc) are best suited to JouleBug.</td>
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<td>• Make an assessment of the effect that each user-provided parameter has on the final result.</td>
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### 1.4 Limitations

Like all projects, this thesis project has some limitations that should be discussed. Due to the inherent limit of time and resources, the boundary of this project is limited to the engineering and psychology challenges outlined in the objectives section. There are limitations on the graphic design of the feedback system, the verification of the final design, and the application of this project to other countries and cultures.

#### 1.4.1 Graphic Design

This thesis project will not attempt to perfect the graphic design or layout of the graphical user interface. It is recognized that graphical and user interface design is a challenge best left to trained artist and graphic design professionals. This project only intends to determine the overall strategies that will utilize a user’s energy consumption and savings data in the way which is most effective at producing behavioral change.

#### 1.4.2 Verifying the Design

As this study is concerned with generating a viable design for the energy-information system, no user surveys or studies about the effectiveness of the design will be completed at the time of publishing. Recognizing that design is an iterative process, future studies may be carried out to confirm the effectiveness of the design and re-evaluate the design if necessary.

#### 1.4.3 International Considerations

This paper focuses on the United States as the “design criteria” for the feedback system, as JouleBug is being developed for the U.S. market first. International research contributions to feedback technology, psychology, and energy engineering will be a vital component of this Master’s thesis project. However, a single-country focus is necessary in order to design the system to be as effective as possible.

According to Fischer, preferences in feedback design vary between countries and cultures. Fischer found that graphical designs that worked well in the U.S. were not well received in Norway. For comparative
feedback, consumers in the United Kingdom and Sweden preferred to be compared with their own previous consumption, while those in Japan were more interested in comparisons with others (Fischer, 2008). Likely, this is caused by differences in psychological norms and values, especially pertaining to energy and the environment. Additionally, the portrayal of climate change in politics varies between countries, and has influenced the effectiveness of feedback (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). These studies indicate that design of a feedback system must be tailored to a regional context.

In addition to the psychological and social concerns, there are differences in energy consumption habits, appliances, energy distribution system, fuels, and building envelope characteristics between different countries. For example, the predominate space heating system in the United States is the natural gas furnace (U.S. Energy Information Administration, 2009), while in Sweden, electric heat pumps and district heating are the most common residential space heating systems (Swedish Energy Agency, 2011). Additionally, there are differences in building codes and standards, which significantly influence energy consumption. These differences make it prohibitive to accurately estimate energy savings across all nations. However, this report can be a useful starting point for researchers in other nations with similar objectives and motivation.

The international focus of this project is evident from the multiple unit systems which are used throughout the report. In the U.S., the U.S Customary System of Units (foot-pound-second) is the system of choice, whereas in the majority of the world, the International System of Units (SI) is used (meter-kilogram-second). When information is extracted from references, the original source's units are preserved where possible, and a conversion into the other unit system is given. A few notable exceptions exist: kWh and kgCO₂eq. The kilowatt-hour (kWh) is a common unit of energy measure, especially for electricity billing, that used in both the U.S. and the rest of the world. The derived unit for carbon dioxide equivalent utilized is kgCO₂eq (kilograms of CO₂ equivalent), which is has widespread usage (along with metric tons of CO₂eq) as a measure of greenhouse gas emissions. The measures of cost used in this report will be given solely in $ (USD), as the different energy prices in other countries would make currency conversions meaningless.

2 Literature Review

Reviewing past experiences is critical when developing a new system. This section contains a review of relevant literature that provides guidance for designing an energy-information feedback system. First, a review of energy/environmental behavior models will also briefly explore the science of behavioral change. The second section will discuss feedback in detail, including a review of types of feedback, the effectiveness of feedback as determined by past studies, and components or considerations for feedback systems. A review of feedback format (mobile, in-home display, web) will also be included. In the third and final section, energy modeling approaches will be explored.

2.1 Energy Behavior

As mentioned earlier, behavior has a crucial and substantial influence on energy use in residential homes. A classic study by Sonderegger evaluated the gas and electric energy consumption of 205 townhouse residents over two years. He divided the study participants into two groups, “movers” who left after the first year of study, and “stayers” who maintained their residence and served as a control group. Sonderegger determined that occupant behavior was responsible for 71% of the variation in consumption between identical houses (Sonderegger, 1978). A modern simulation by Pettersen confirms these findings. In a Monte Carlo simulation, Pettersen determined that 80-85% of the total variation was explained by changes in occupant behavior. This variation of energy usage was much larger than the variation caused by climatic factors (Pettersen, 1994). As the influence of the energy behavior has been shown to be a significant factor in reducing energy consumption, a review of behavioral research as it pertains to energy consumption is necessary. The first section will categorize energy behaviors into distinct groups. The
following section will explain briefly some psychological models that have been applied to energy and environmental behavior. The subsequent sections will discuss behavioral change models and strategies that can be used to affect energy behavior.

2.1.1 Categorizing Energy Behaviors

Many researchers have found it useful to categorize the multitude of energy saving behaviors into a few distinct groups. There have been many attempts to describe the separate types of behavioral actions that occur (Barr, Gilg, & Ford, 2005; EPRI, 2009; Ehrhardt-Martinez, Donnelly, & Laitner, 2010). In general, most authors divide energy behaviors into two or three of the categories described below.

**Habitual behaviors** are actions that follow along with a set pattern or routine, occur frequently, and have a low-cost (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). Habitual behaviors may include shutting off lights, doing full loads of laundry, or taking shorter showers. These actions have also been described as ‘usage behavior’ (van Raaij & Verhallen, 1983) or ‘direct energy using actions’ (Stern, 1992).

**Purchase decisions** are normally one-time or infrequent actions that involve a significant amount of investment and conscious decision-making, such as buying new appliances (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). They have been described variously as ‘purchase behaviors’ (van Raaij & Verhallen, 1983) or ‘technology choices’ (Stern, 1992).

**Energy-Stocktaking Behavior** encompasses behaviors that are low/no cost but are performed infrequently, such as changing to energy-efficient lighting or installing weatherstripping, as well as making lifestyle choices (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). This concept is similar to ‘maintenance behavior’ described by van Raaij and Verhallen which consists of small repairs and improvements to home systems. (van Raaij & Verhallen, 1983).

2.1.2 Psychological Models

Researchers have noted that design of feedback systems is influenced by the type of environmental behavior model that is applied (Froehlich, Findlater, & Landay, 2010). Froehlich and colleagues completed a literature survey from both environmental psychology and Human-Computer Interaction (HCI) disciplines, dividing the environmental behavior models into the following two streams of thought.

**Rational choice models** explain that human behavior is controlled by careful consideration of the usefulness of an action. These types of models generally assume that behavior is driven by self-interest (Froehlich, Findlater, & Landay, 2010).

**Norm-activation models** are used by psychologists who view social motives as more important than self-interest. These models theorize that the most important influence on behavior is personal norms or morals, which may include concern for the society at large (Froehlich, Findlater, & Landay, 2010).

Bamberg and Möser described pro-environmental behavior as a mixture of self-interest and concern for others and the environment. Therefore, a mixture of theoretical frameworks can be a suitable option for consideration when selecting an environmental behavioral model (Bamberg & Möser, 2007).

2.1.2.1 Models of Residential Energy Use

Many authors have applied psychological models to residential energy use and feedback specifically. Van Raaij and Verhallen's model of residential energy behavior identified the following seven factors influencing energy use: energy-related household behavior, energy-related attitudes, home characteristics, sociodemographic and personality variables, energy prices, and feedback information. Feedback information influences various stages of the decision making process. Based on the target influence, they divided feedback into three types: habit formation, learning, and internalization. Through the different types of feedback, behavioral change, increased energy knowledge, and attitudinal changes respectively can be affected (van Raaij & Verhallen, 1983).
A general model by Stern proposes eight variables that affect residential energy consumption. Feedback works in two paths: learning and self-justification. The learning pathway is opened when energy bills or comfort levels influence attitudes and beliefs about energy. Self-justification occurs when energy-saving behaviors influence general attitudes and beliefs (Stern, 1992). Stern and Froehlich both mention that financial incentives may not be effective if consumer knowledge is lacking or consumer attitudes are not favorable. This may invalidate a model of “rational economic choice” (Stern, 1992; Froehlich, Findlater, & Landay, 2010).

Taking a different approach, Fischer cites and translates Matthies’ (2005) model of environmentally relevant behavior, and applies it to energy consumption (Fischer, 2008). This model discusses “environmentally detrimental habits” and “conscious decisions” as two types of energy behavior (Fischer, 2008, p. 81). According to the model, habitual behaviors are undertaken to reduce the amount of time and thought required to do an action. Fischer gives several reasons why a detrimental habit may form, including lack of awareness about environmental issues, changing technology or situations, or misunderstanding of the environmental impact. The environmental behavior model advocates for interrupting environmentally detrimental habits in a three step process. In the first step, called norm activation, the person realizes that there is a problem with the habit. The person must also realize that his or her behavior is influential, and they must be aware that they have the possibility to correct the behavior. The next step is motivation, where a person considers the social and personal norms along with other factors such as cost and time. In the final step, evaluation, a compromise is reached between these different motivators and a decision is reached. Fischer believes that energy feedback will provide the information to feed the model’s various steps (Fischer, 2008).

2.1.3 The Science of Behavioral Change

Understanding how to cause a behavioral change is crucial in order to accomplish the goal of creating feedback that will influence the consumer’s behavior toward less energy consumption. Looking at behavioral change in general, BJ Fogg developed a model for motivating behavioral change (Fogg, 2009). The Fogg Behavioral Model (FBM) describes three necessary elements for behavioral change: ability, motivation, and a trigger. The following figure, used with permission from Fogg’s website, describes the relationship between the three key elements.

![Figure 2.1 The Fogg Behavioral Model (Fogg, 2011).](image-url)

Both ability and motivation must be present to create a behavioral change. In Fogg’s model, the optimum location for behavioral change is at a point of high motivation and high ability, above an “activation
threshold”. A mechanism that seeks to influence a behavioral change must increase ability, increase motivation, or increase both until the Activation Threshold is reached. The last component, the “trigger”, is vital to creating the behavioral change. The trigger prompts an individual to complete an action once the time is right. General thinking about the FBM is important to making feedback an effective behavioral change tool.

2.1.4 Various Energy Behavior Change Strategies

Behavioral science research often classifies behavioral change strategies into basically two groups. Antecedent strategies are those that take place before the action, while consequence strategies take place after an action has been performed. Ehrhardt-Martinez and colleagues cite Geller (1990) as the source of this classification (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). Examples of antecedent strategies are described in detail by Abrahamse and colleagues, including commitment (signing a pledge), goal-setting, information in mass-media campaigns or more personal energy audits and modeling of desired behavior (Abrahamse, Steg, Vlek, & Rothengatter, 2005). Froehlich and colleagues (2010) also mention incentives and disincentives as a type of antecedent behavior (Froehlich, Findlater, & Landay, 2010). Feedback, along with rewards/penalties, is a consequence strategy (Abrahamse, Steg, Vlek, & Rothengatter, 2005; Froehlich, Findlater, & Landay, 2010). Feedback is a strategy that is getting abundant attention recently as technological advances have made more capabilities possible (Ehrhardt-Martinez, Donnelly, & Laitner, 2010; EPRI, 2009; Froehlich J., 2009). In addition, the feedback mechanism makes it possible to introduce antecedent information for habitual actions (in between the previous action and the next one) (EPRI, 2009). In fact, researchers concluded that antecedent strategies are most effective when combined with feedback (Abrahamse, Steg, Vlek, & Rothengatter, 2005; Froehlich, Findlater, & Landay, 2010). This makes feedback a powerful tool from a behavioral change standpoint.

2.2 Feedback

Feedback is the reporting of information on the result of a past action, with the hope of improving the results of future actions. While feedback in general can be applied to many different behavioral change situations, this section will discuss feedback as it specifically applies to residential energy consumption. The first section will categorize feedback methods into a spectrum, while the second section will provide an in-depth examination of the effectiveness of feedback as reported by several well-documented meta-reviews. A section on the design of feedback will outline the important criteria for effective feedback design and provide some commentary on what designs are the most effective. Finally, a section on similar projects will outline two previous attempts at developing a mobile energy feedback application.

2.2.1 The Spectrum of Feedback

As research into feedback has grown, there have been efforts to classify types of feedback based on the frequency it occurs, the time when it occurs, or amount of information provided. Darby first described two categories of feedback – direct and indirect. Direct feedback shows consumption information nearly instantaneously, normally in the form of a display monitor or smart meter. Darby’s version of indirect feedback is information that “has been processed in some way” before reaching the user, one example being enhanced billing (Darby, 2006, p. 3). Building off Darby’s classification scheme, in 2009 the Electrical Power Research Institute (EPRI) developed a spectrum of feedback classifications, depicted in the figure below (EPRI, 2009).
The spectrum utilizes Darby's two categories and expands within each to describe four versions of indirect feedback and two types of direct feedback. For EPRI's classification system, indirect feedback is provided after consumption occurs, while direct feedback occurs in near real-time. The feedback types are organized with respect to their information availability and cost. A detailed description of each of the categories provided by EPRI is provided below (EPRI, 2009).

**Standard Billing** – This simplest and least effective type of feedback consists of the monthly or bi-monthly bills from a utility without additional analysis. Normally only the consumption amount (in kWh for electricity, or CCF or Therms for gas) for the bill period is given along with the total cost for each service over the billing period.

**Enhanced Billing** – The monthly bill statement is analyzed and additional information is presented on the bill to help consumers track their behavior. This is most often comparisons to previous usage periods, or less frequently, to other consumers. Some enhanced bills also try to estimate the end-use consumption of different segments such as space heating, cooling, and lighting by using average usage patterns developed for typical homes.

**Estimated Feedback** – This segment has typically consisted of web-based “energy audits” which take bill information and house characteristics and use statistics from national or utility level energy surveys to analyze the bill. Typically these reports are more detailed than what enhanced billing would provide. Estimated feedback includes breakdowns of energy consumption by end-use and comparisons of consumption with other similar homes. However, the end-use breakdown is not based on the home’s actual consumption pattern but is based on statistical patterns of consumption from similar homes. Estimated feedback is often performed on a one-time basis but can also be provided continually.

**Daily/Weekly Feedback** – With finer resolution than monthly bills, weekly or daily feedback relies on more frequent meter readings (often with the help of the consumer). This type of feedback can help reveal trends that may not have been visible in a monthly bill. Smart meters that read consumption data nearly every 15 minutes are now available and allow the consumer to view consumption data from the previous day.

**Real-Time Feedback** – As direct feedback, this shows electricity consumption information in real-time, most often on an in-home display, a dedicated screen that shows consumption data. This method tends to be more expensive as it requires a dedicated device to constantly measure electricity consumption, such as a smart meter or third-party electricity monitor, as well as a dedicated display. This has been predicted.

**Figure 2.2** The EPRI spectrum of feedback (EPRI, 2009).

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as a way to track changing prices of electricity as real-time pricing becomes more widespread. More about the in-home display will be discussed in the section on “format” below.

**Real-Time Plus** – The most informative and expensive type of feedback, real-time plus combines real-time feedback with information about the end-uses, and so it is able to show what devices are actually consuming electricity in real-time (as opposed to estimating end-use consumption). This is often accomplished through a Home Area Network (HAN) which connects appliances and devices and allows additional control over their operation.

### 2.2.2 Effectiveness of Feedback

Recent meta-reviews of feedback studies have done a good job at combining many past studies on feedback effectiveness. These reviews include the work of Darby (2006), Fischer (2007), EPRI (2009) and Ehrhardt-Martinez and colleagues (2010). Darby’s meta-review determined that indirect feedback achieved energy savings in the range of 0-10%, while direct feedback commonly achieved 5-15% (Darby, 2006).

The most recent and comprehensive publication, Ehrhardt-Martinez and colleagues conducted a review of 57 studies from the past 36 years, in nine countries including the U.S. In general, feedback produced an average energy savings of 4-12% across all years and countries. This review determined that the savings from feedback varied with the type of feedback according to Figure 2.2. Real-time plus feedback had the highest median impact, at 14%, followed by daily/weekly feedback at 11%. Real-time and estimated feedbacks were approximately 7%, while enhanced billing managed 5.5% savings (Ehrhardt-Martinez, Donnelly, & Laitner, 2010).

The results of these studies were classified depending on the time period. Ehrhardt-Martinez and colleagues divided the studies into roughly two periods. The “Energy Crisis Era” is defined from 1974 to 1994, where most of the studies utilized real-time feedback, daily/weekly feedback, and enhanced billing. The “Climate Change Era” from 1995 to 2010, focused more heavily on advanced technologies including in-home displays for real-time feedback, and web-based feedback. The meta-review identified that studies in the Energy Crisis Era achieved a higher savings of 11% compared with 8.2% in the Climate Change Era (Ehrhardt-Martinez, Donnelly, & Laitner, 2010).

The studies were also classified by location. In general, there were only small variations between locations, although it was determined less average energy savings was achieved in the US (8%) compared with 10% in Europe. The disparity became greater when only focusing on the Climate Change Era, and also for studies with greater sample size or longer duration. The regional and era factors likely illustrate the lack of public concern over climate change (Ehrhardt-Martinez, Donnelly, & Laitner, 2010).

The studies were evenly divided between small studies of under 100 people, and larger studies. The meta-review revealed that studies involving small numbers of participants tended to show higher levels of savings than the studies with more participants. Studies involving small numbers of people (under 100) recorded 11.6% average savings, while studies involving large groups (over 100) managed an average savings of 6.6% overall. Finally, the duration of the study had an effect on savings, but only for studies with a small sample size. For small studies of less than 100 people, longer duration (over 6 months) studies tended to have lower savings than short duration studies (7.5% compared to 10.1%). However this trend did not appear in larger sample size groups. Ehrhardt-Martinez and colleagues recommend that future studies of feedback should be carried out with larger sample sizes and for a longer duration (Ehrhardt-Martinez, Donnelly, & Laitner, 2010).
2.2.3 Design Components of Feedback

The EPRI spectrum for feedback is very useful in characterizing along a single axis. However, within each category there are a multitude of possibilities for different design components for feedback methods. The method of transmission of information is critical, as better delivery of messages can reduce energy consumption by 10-20% (Stern, 1992). However, minimal guidance exists on the design of specific features of information feedback systems. A recent meta-review simply stated: “Maximum feedback-related savings will require an approach that combines useful technologies with well-designed programs that successfully inform, engage, empower, and motivate people” (Ehrhardt-Martinez, Donnelly, & Laitner, 2010, p. iv).

Darby first identified factors that influence the effectiveness of feedback, including the social context, scale (how data should be broken down), synergies between feedback and other information, and timing (or frequency) (Darby, 2006). Fischer also investigated these parameters in a review of 26 feedback projects, including frequency and duration, feedback content (energy, cost, environmental impact), breakdown of data, medium/mode of presentation, comparisons, and other instruments (Fischer, 2008). Froehlich presented “ten design dimensions” that can be used to aid feedback designers (Froehlich J., 2009). Selected dimensions relevant to the specific case of JouleBug will be presented and research pertaining to them will be reviewed in this section.

Frequency: How often that feedback is presented is related to the type of feedback from the EPRI spectrum. Direct feedback is presented in real-time, while various types of indirect feedback have a frequency of daily or less. In 1983, van Raaij and Verhallen noted that feedback is more effective when it is delivered in the shortest period and is highly related to a specific activity (van Raaij & Verhallen, 1983). This was supported by Fischer who determined that feedback given at a frequency of daily or more was judged highly effective, while results for weekly or monthly feedback were mixed (Fischer, 2008). However, Darby suggests that indirect feedback shows large end-uses and trends (e.g. space heating usage) the most effectively, while direct feedback works best for small loads that change frequently, such as appliance usage or turning off lights (Darby, 2006).

Measurement Unit: Feedback on energy consumption can be displayed in many different units, including energy (kWh for electricity, CCF or Therms for gas), cost, and environmental impact (carbon load). According to Fischer, the unit will serve to activate different social and personal norms or beliefs and so different units may have a different response. Research has shown that presenting environmental data may be at least as effective as other kinds of information, but the most common emphasis is on energy consumption and cost (Fischer, 2008). Jacucci and colleagues claim that financial feedback alone is not enough to motivate savings in the long term and that “efficiency” or “conservation” are better motivators (Jacucci, et al., 2009). However, Petkov and fellow researchers discovered in a survey of users from a particular mobile application that the unit of preference depended on the motivation of the user, those who wanted to save money preferred dollars, while, those with more environmental motives chose kWh or CO₂. For comparisons, kWh was preferred as CO₂ and cost can vary by utility (Petkov, Köbler, Foth, & Kramar, 2011). Another study from Fitzpatrick and colleagues involving four types of energy feedback devices in the UK found that participants preferred cost to energy consumption, with CO₂ not being at all preferred. However, the study found that some users thought that the measure of £/yr was meaningless, while other users dismissed a measure of pence per hour as too small to be motivating (Fitzpatrick & Smith, 2009). The variety of responses in the literature indicates that more research about measurement units is needed.

Data Granularity: According to Froehlich, data granularity refers to the breakdown of data that is presented, which can be broken down by time (per day, per month, etc), space (specific rooms), source (refrigerator, washing machine), or source category (lighting, appliances, etc) (Froehlich J., 2009). Breaking down feedback as specifically as possible to end-use and time period helps users to identify and address their usage in a targeted way (Fischer, 2008).
**Presentation Medium:** The significance of presentation medium is of the utmost concern for a mobile feedback system, which must rely on a mobile device’s portability to overcome lack of screen space and computing power. Two broad types of presentation medium are paper and electronic technology (Fischer, 2008). Electronic technology can be found in many forms, including in-home displays, web dashboard/portals, smartphone applications, other devices (televions), and ambient displays (for example, colored lights that signal consumption levels) (LaMarche, Cheney, Christian, & Roth, 2011; Ehrhardt-Martinez, Donnelly, & Laitner, 2010). Interactive web pages, personal computers, or television displays have been found to be highly effective in trial studies (Fischer, 2008; Darby, 2006).

Mobile technology looks especially promising as adoption rates for this technology are reaching high levels (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). In a recent study by LaMarche an online survey of 50 individuals was carried out requesting that they rate twelve different Home Energy Management (HEM) systems in three different mediums, including online, mobile, and on-wall devices. Users preferred a diversity of multimedia choices, but mobile applications were highly desired and preferred over web dashboards and in-home displays (LaMarche, 2011; LaMarche, Cheney, Christian, & Roth, 2011). Most users surveyed estimated they would spend 1-5 minutes per day using energy management technology (LaMarche, 2011), compared with traditional billing right now that achieves interaction rates of 9 minutes per year (Accenture, 2012).

**Visual Design:** According to LaMarche, visual design elements contribute to a consumer’s experience with home energy technology and thus can affect their energy behavior (LaMarche, 2011). The exact combination of aesthetic, ease of understanding, choice of measurement units and graphical display, and wording all affect a visualization’s effectiveness (Froehlich J., 2009). According to Pierce and colleagues 2008, visualizations can be either pragmatic, concentrating on presenting the information directly, or aesthetic, by using artistic metaphors (Pierce, Odom, & Blevis, 2008). Pragmatic visualizations provide quantitative information, but may have a learning curve, while artistic visualizations may not be explicit (Froehlich J., 2009). Fischer gives guidance on visual design, espousing that households prefer “easy to understand” information, which includes aspects including using an actual consumption period for feedback presentation, clear labeling of technical terms, clearly showing components of energy price, and clearly labeled graphics. Households prefer pie charts for breakdowns, while vertical bar charts are desired for consumption with previous periods and horizontal bar charts for comparisons with others (Fischer, 2008). Fischer also notes that design preference may vary between cultures, making it more difficult to determine what will be effective (Fischer, 2008).

**Recommending Action:** Suggesting specific energy conservation or energy efficiency measures can be an important aspect of feedback design. These suggestions can serve as trigger mechanisms in the Fogg Behavioral Model (Fogg, 2009). Froehlich theorizes that computer systems can make it possible to tailor information and recommendations to the consumer’s household based on information about the home’s energy usage (Froehlich J., 2009). The idea of tailoring information has been tied to the idea of goal setting by Abrahamse (2007). In a study of 189 Dutch households, the researchers presented to the participants tailored information regarding savings actions, combined with a 5% goal and tailored feedback. The tailored information showed how much the specific savings action was contributing to an overall savings goal. This resulted in a savings of 5.1% compared with a control group who increased consumption 0.7% (Abrahamse, Steg, Vlek, & Rothengatter, 2007). Ehrhardt-Martinez and colleagues mention OPower as an example of a company using recommendations for action. Working through a utility, OPower issues monthly energy reports that include personalized energy-saving tips, or “Action Steps”, along with current and historical consumption information and comparisons to similar houses. In a large sample size of 85,000 households, OPower’s monthly energy reports resulted in a statistically significant energy savings of 1.1-2.5% (Ehrhardt-Martinez, Donnelly, & Laitner, 2010).

**Comparisons:** A popular design component, comparisons may be created in a multitude of different ways, which have can have different behavioral influences on the feedback users. Many researchers identify two types of comparisons:
Temporal or historical comparison is a comparison to past performance (Petkov, Köbler, Foth, & Kramar, 2011; Ehrhardt-Martinez, Donnelly, & Laitner, 2010; Darby, 2006; Froehlich, Findlater, & Landay, 2010). Providing historical comparisons has been identified as a desirable method of feedback (Petkov, Köbler, Foth, & Kramar, 2011; Darby, 2006), especially when normalized with weather (Froehlich J., 2009). However, there are some shortcomings of historical comparison. It may not reveal abnormally high consumption patterns as it does not compare between groups (Petkov, Köbler, Foth, & Kramar, 2011). In addition, when a certain threshold of energy savings is reached, it may be difficult to show further improvement (Froehlich J., 2009; Froehlich, Findlater, & Landay, 2010).

Social comparison is a comparison with another household or individual, within a group, or to a norm (Petkov, Köbler, Foth, & Kramar, 2011). The opinion on these types of comparisons is mixed. Studies reviewed by Darby have cited that households may not necessarily be motivated by comparisons; especially if they feel that they are already taking many appropriate steps to save. Other studies mentioned that users often felt that comparison groups were not valid, and so they were unwilling to take action based on comparative feedback (Darby, 2006). Literature suggests that the effectiveness of the comparison is strongly dependant whether the group assignment is perceived as appropriate by the people in the group (Ehrhardt-Martinez, Donnelly, & Laitner, 2010).

Social norming serves to influence behavior also through direct normative comparison or through normative messaging. Fischer identifies that normative feedback does not seem to be effective, as the studies that used it showed no difference between the control group and the group receiving the feedback. Likely, the low-consumption groups unconsciously raise their consumption to conform to the norm, canceling out the effect of the conservation by high-consumption groups, the “boomerang effect” (Fischer, 2008).

However, recent research delving deeper into social norming has developed new theories. Ehrhardt-Martinez and colleagues explain that there are two types of social norms, descriptive norms which are related to actual behavior, and injunctive norms which are an illustration of what people believe is the “right thing to do” (Ehrhardt-Martinez, Donnelly, & Laitner, 2010, p. 51). In a review of several studies, Ehrhardt-Martinez and fellow researchers found that social norming through both descriptive and injunctive methods shows potential to be a useful tool for reducing energy consumption. In a study of 290 households, Schultz and colleagues placed door hangers on homes displaying the home’s consumption along with consumption levels for the neighbors (descriptive norm). In addition, a positive emoticon (😊) was added if the home’s energy consumption was below the average, while a negative emoticon (☹) was added for homes above the average. This emoticon served as an injunctive norm by indicating to the homeowner whether or not their energy performance was approved of. The researchers found that the descriptive norms can lead to boomerang effect in consumers who already are at low levels, but injunctive norms can result in the elimination of this effect (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). Ehrhardt-Martinez and colleagues also extensively describe the work of OPower in using social normative messaging to reduce energy consumption. OPower’s monthly energy reports include comparisons to “energy-efficient neighbors” as an injunctive norm, and have shown a savings of 1.1-2.5% in a large sample size. However, due to the combination of methods used in the reports, the amount of savings that can be attributed to normative comparison is unclear (Ehrhardt-Martinez, Donnelly, & Laitner, 2010).

**Social Sharing:** New social media applications such as Facebook and Twitter have made it possible for an individual to publicize personal energy savings quickly and on a large scale. Although little research has been performed at the time of this writing, there is the possibility that social sharing may pressure consumers into becoming more energy efficient (Froehlich J., 2009).
2.2.4 Previous Similar Projects

Because the field of mobile applications for energy feedback is just now emerging, few previous studies have been performed on the design of mobile feedback applications. This section will briefly review two previous studies on mobile feedback applications.

2.2.4.1 EnergyLife

In 2009, Jacucci and colleagues submitted a paper on the development of the EnergyLife mobile phone application as part of a European Union project called BeAware (Jacucci, et al., 2009). The objective of EnergyLife was to incorporate psychological and social aspects into a mobile application aimed at improving energy consumption by using feedback. EnergyLife was developed for a touch-enabled smartphone and is a part of a whole-house system of feedback. In addition to the mobile application, the house lights provided additional feedback by dimming if a consumption goal was not met. The system consisted of “two pillars”, energy awareness tips and feedback on consumption.

As background research, Jacucci and fellow researchers extensively reviewed the literature on energy feedback and the design of feedback tools. They concluded that “historical, sensitive and aesthetically attractive feedback is more likely to be effective” (Jacucci, et al., 2009, p. 269). The team placed a high emphasis on tailoring the feedback to the user by correcting feedback for weather and region, and providing specific tips based on the user’s consumption profile. Interestingly, they chose not to use financial indicators of feedback, but instead used “efficiency or conservation” ideas as a measure of the user’s performance.

With regards to user interface, the team determined that information displayed should be simple and self-explanatory, to avoid “information overload”. Many levels of detail were available to the user, rather than viewing all the data at once. The application was also designed to work within a person’s daily habits and to provide the feedback to where it was always actionable, through a mobile device. It was designed with a game-like framework, providing goals and sub-goals, and then testing the user’s knowledge of energy periodically with quizzes. The EnergyLife user interface was designed as a “carousel” of cards, which each represented a different appliance or electrical device. Each card provided information about current electricity consumption of the device on the front, and historical analysis, quizzes, and tips on the back (Jacucci, et al., 2009).

At the time of the writing, the application was still under development, and not all of the goals of the EnergyLife system were accomplished. The future versions of the game proposed adding levels of rising complexity for goals and adding the opportunity to earn points that would act as a positive feedback mechanism. (Jacucci, et al., 2009)

Making the feedback context-dependent, historical, and tailored were still in the “planned” stages at publishing time. However, a group of 20 users evaluated the EnergyLife application in a questionnaire using a Likert scale with 1=”totally disagree” and 6=”totally agree”. Overall, the users responded positively in the questionnaire (Jacucci, et al., 2009). The EnergyLife system presents an interesting example of mobile applications being used for feedback. However, the tailored information provided by the system requires a fully instrumented house including sensors for consumption at the device level and would be impractical for widespread quick adoption.

2.2.4.2 EnergyWiz

The team of Petkov and colleagues also created a mobile energy feedback application called EnergyWiz. According to the researchers, the development of EnergyWiz was intended to provide design guidelines for the different feedback types as they related to different user’s motivation levels. The study objectives also included determining the effectiveness of using social media (Facebook) to motivate users to conserve energy. In contrast to EnergyLife, the main focus for EnergyWiz was both social and historical comparison.
The EnergyWiz application contained five main features which correlated with different types of comparative feedback. These main features included 1) Live Data, 2) History, 3) Neighbors, 4) Challenge, and 5) Ranking. The application relied on direct, real-time consumption data from the household, and the game was designed so users could switch between different units (kWh, cost, and CO₂). The material impact was illustrated using a comparison of “number of trees” equivalent to the amount of CO₂ produced by the player, also given in real time. The “History” function was provided as a temporal comparison, while social and normative comparison between two groups of neighbors (efficient and inefficient) was used, and injunctive messaging was included in the form of text and smiley faces for those who were low users of energy. The EnergyWiz also used a ranking tool to rate similar players based on energy consumption, attempting to keep the ranking as relevant as possible. Finally, sharing via Facebook was encouraged within the game. Users could share their current energy consumption on Facebook, as well as challenge their friends to an energy saving competition (Petkov, Köbler, Foth, & Kramar, 2011).

To confirm their design, the EnergyWiz development team surveyed 17 participants, primarily young males, about their energy behavior and motivation to conserve energy. The study participants then reviewed each feedback type and gave suggestions on how to improve it. The participants expressed various concerns about the comparisons. Some users questioned how similar their neighbors were to them in consumption. The majority of testers preferred using their friends during competitive aspects of the game, but preferred similar people (known or unknown) for comparison and benchmarking of energy consumption. The participants enjoyed the graphics showing consumption related to a visual tally (explanatory comparison) including illustrations of environmental impact as a number of trees, or energy consumption depicted as a number of laptops. The motivations of the user had an impact on the units desired; players interested primarily in saving money preferred cost, and users with stronger environmental tendencies chose kWh or CO₂. However, kWh was preferred as a unit of comparison between players because cost and environmental impact (CO₂) are utility specific. The research team also determined that the application lacked tips on how to save energy and did not provide enough support for increasing energy knowledge. The Facebook integration with the application may have been undesirable to some users who were unwilling or unable (through lack of a Facebook account) to participate in social sharing. Finally, researchers speculated that people may become unmotivated to play the game after they reach a certain level of savings. An additional rewarding incentive was proposed to encourage sustained use of the application (Petkov, Köbler, Foth, & Kramar, 2011).

### 2.3 Energy Analysis and Modeling

In order for feedback to be most effective, it is necessary to have a system to analyze (and predict) energy consumption and savings. **Residential energy analysis** may be used for various purposes, including building design, creation of policy, testing of technologies, and rating or labeling buildings (Polly, Kruis, & Roberts, 2011). However, as this project is concerned with saving energy, the focus will be on using energy analysis for predicting energy and cost savings from energy efficiency and conservation measures.

Nowadays, nearly all energy analyses are carried out using a computer program or software package. Typical methods used for whole-building residential energy analysis include annual energy simulation, statistical analysis based on measured data, and spreadsheet calculations (Polly, Kruis, & Roberts, 2011). This section will first review the theoretical basics of energy modeling and provide several relevant examples of energy analysis tools that could be used to predict energy and cost savings. Following that, literature reviewing residential analysis tools in general will be summarized.

#### 2.3.1 Energy Modeling

**Energy modeling** is the creation of a mathematical way of relating energy use with physical parameters. Models consist of three components: input, system structure and parameters, and output. Energy modeling is designed to determine one of the three components when the other two are known (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009).
ASHRAE cites Rabl (1988) as classifying the two methods of energy modeling depending on the desired result (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009). In the forward modeling approach, the objective is to predict the output (energy use) when given the input and system structure. These models require knowledge of the specific energy parameters of the system including the climate, thermal properties, etc. This method is most often used to predict energy consumption in buildings prior to construction for purposes of design. Most often forward modeling systems are built on simulation engines, including powerful systems such as BESTEST, BLAST, DOE-2 and EnergyPlus (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009).

The data-driven or inverse approach to modeling is intended to determine the system’s mathematical parameters when the input and output are known. This is often used when the system has been built and energy use data is available. Data-driven modeling is often simpler to develop and provides an accurate prediction of system performance, but depends on the availability of usable end-use data (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009).

### 2.3.2 Energy Analysis Tools

Since the early 1990s, increasing access to powerful computer software and the Internet has created a multitude of energy analysis tools. These tools have a varied range of uses, from advanced software for building designers to consumer education. Building energy analysis tools are intended to evaluate energy use and savings opportunities in a cost-effective way, and may also evaluate non-energy issues such as cost, environment, comfort, safety, or aesthetics (Mills, 2004). Energy analysis tools utilize energy simulation engines or algorithms that are supported with data from the user as well as weather and property data (Mills, 2004). These tools can utilize either forward or data-driven modeling procedures, depending on the purpose. Tools for prediction of energy savings take advantage of the forward method, while tools for verifying energy saving measures after the fact use the data-driven approach. Comparison of the prediction against the actual measured values can lead to refinement and improvement of the tools (Polly, Kruis, & Roberts, 2011).

The first Internet-based tool for evaluating whole-building energy consumption was LBNL’s Home Energy Saver (HES), developed in the mid 1990s. The HES calculates the home’s energy consumption as well as the savings for major energy saving measures, with three tiers of input required. The most basic level only requires a location, while the intermediate level asks a few basic questions about the home’s structure, HVAC, and appliances. The advanced level offers a chance to make detailed inputs about all home characteristics including locations of lighting, window orientation, and specific electronic devices. The HES utilizes the DOE-2 annual energy simulation engine to calculate the HVAC consumption from the building. LBNL has developed algorithms, often based on empirical data, for calculating the other end uses including water heating, lighting, appliances, and other loads (Lawrence Berkeley National Laboratory, 2012a).

One example of the inverse modeling approach is a steady-state model that can be used to normalize building energy consumption based on climate data. This is often known as the ‘energy signature’ or regression method. The procedure for developing this model is to plot the monthly energy consumption against the degree-days for the monthly period, and identify the balance-point (change point) temperature of the building. Fels developed the Princeton Scorekeeping Method (PRISM) for residential buildings, originally as a three-parameter (single change point) model for either heating-only or cooling-only cases (Fels M., 1986). Later, in 2003, a five-parameter heating-and-cooling model was developed for cases where a single fuel (electricity) might be used (Fels, Kissock, & Marean, 1994).

The PRISM method used degree-days as the correlating weather factor; however, the outdoor temperature might be used as well, as in the Inverse Modeling Toolkit (IMT) developed by Kissock and colleagues (Kissock, Haberl, & Claridge, 2003). Because steady-state data-driven models are able to eliminate the effect of varying weather, they can be used to determine the effectiveness of energy conservation measures. Fels used a parameter called Normalized Annual Consumption (NAC) as a measure of energy
savings. The NAC is determined by applying the regression lines from the pre- and post-retrofit cases to a normal (average) year's weather data (Fels M., 1986). This ‘energy signature’ model is useful, although cannot be considered a whole-building tool as it does not separate end uses any further than space heating, cooling, and baseload consumption.

### 2.3.3 Reviews of Home Energy Audit Tools

In one of the few energy reviews targeted at tools for end-users, Mills performed an evaluation of 50 web-based and 15 disk-based residential energy analysis tools. In his research, Mills was interested in the tool's output, amount of input required, accuracy, and other characteristics. He found that the current set of tools had various shortcomings in measuring home energy performance, and that the lack of standardization among tools made it difficult to make measurements of accuracy (Mills, 2004).

While categorizing the tools, Mills noted that there was a large variation in the tools available. Less than half of the web-based tools normalized the energy results to actual costs. Most tools provided baseline bill estimates, but only a minority had recommendations or estimates of energy savings, and only a few included cost-effectiveness or environmental emissions as outputs. This means that decision-making help for consumers is limited (Mills, 2004).

The tool's input methods also received criticism. Poorly designed user input questions contributed to inaccuracy of the tools. Questions were often phrased in confusing ways or required information that few residential users would be able to provide, such as specific running hours of the heating system or appliances. In addition, the large amount of time required to input the data has been a contributing factor to the low adoption rates of energy analysis tools among consumer, often needlessly (Mills, 2004). As Mills put it, “More detail (questions asked) does not, however, automatically translate into a “better”, more thorough, or more accurate tool” (Mills, 2004, p. 870).

An attempt was made to compare the estimates made by the tools with two test houses in California and Ohio as an approximate measure of accuracy. However, Mills found that evaluating “accuracy” of energy tools was fraught with problems, as the unique nature of each tool required multiple approaches. The “accuracy” may have different definitions depending on the particular characteristics of the tool. In general, problems of accuracy fall into several groups. A tool’s engineering calculations or simulation technique may be inaccurate. The savings calculations may be inaccurate even if baseline calculations are correct (however, finding data to verify savings calculations is quite difficult). Changes in input may not correlate correctly with calculated energy use, or user input options may not be available, or the calculations may not represent the whole building. Poor interface and confusing questions may result in inaccurate or undesired results. Finally, not all tools can be used in every location due to shortcomings with climate data. In the limited accuracy analysis of 12 web-based tools, the predicted energy bill varied by a factor of three between tools, a range of $1179 USD per year. All tools over-estimated the total energy use compared with the test houses, with higher variability at end-uses. Energy savings estimates varied from $46 per year (5% of baseline) to $625 (50% of baseline). However each tool provided different recommendations so this is not a real measure of ‘accuracy’ (Mills, 2004).

To conclude, Mills provides general recommendation for design of web-based energy analysis tools. He recommends providing the user guidance on energy decisions, and focusing on usability and convenience. Other recommendations about tool design include providing estimates of potential savings and cost-effectiveness as well as the uncertainty of the estimates. For technical design, Mills recommended keeping data current, using actual billing data to normalize results, allowing for a maximum range of climates, and modeling of complex interactions within the system (Mills, 2004).
3 Methodology

The methods used to develop an energy feedback system for JouleBug are founded in principles of engineering and psychology as discussed in Section 1.3. These two disciplines have a give-and-take relationship, so an iterative design process is necessary to optimize the benefit while maintaining a manageable workload.

3.1 Energy Savings Models

As mentioned in Section 1.3, the main engineering objective of the project is to calculate the energy savings of the user. This section of the manuscript will discuss the steps taken to develop the models used to estimate a user’s energy savings.

3.1.1 List of Energy Saving Actions

The U.S. Department of Energy lists over 200 energy-saving tips (U.S. Department of Energy, 2012). In order to avoid “sticker shock” at the investments required, JouleBug presents energy-saving actions that are low-cost and easy to accomplish first, in order to gradually lead a person toward an energy-conscious attitude. At the time of the writing, there were 38 home energy saving actions (Pins) that are included in JouleBug. Table 3.1 contains the list of these JouleBug Pin names along with a description of the energy-saving action required to earn the Pin. These actions are grouped into the following end-uses: space heating, cooling, water heating, appliances, electronics, and lighting.

The end-use category is important for the aggregation of the user’s overall energy savings. Pins must be aggregated within the end-use categories before they can be summed. One reason for this is that heating end-uses may use different fuel sources (such as natural gas, fuel oil, propane) which have different costs and environmental impacts. Second, the end-use categories are important in calculating the diminishing returns. The methodology and results from these calculations can be viewed in Section 4.1.3.

In some cases, a Pin may save energy in multiple end-use categories. To simplify these cases, the end-use that contributes the smaller savings (for a single Pin) is neglected if the average consumer would see less than $12 per year in cost savings on their energy bill. Figure 3.1 shows the process for determining which end-uses are included.

For example, a dishwasher requires both the energy to run the dishwasher’s motor (appliance energy) and heat the water (water heating energy). During a dishwasher cycle, 80% of the energy required goes to heating the water (California Energy Commission, 2012b). Running full loads (compared to partial loads) in the dishwasher saves both water heating energy and appliance energy, but the amount of savings from water heating energy is much greater. In this case, the appliance energy savings is less than $12/yr, so it is neglected.

Figure 3.1 Flow chart for Pins with multiple end-uses.
<table>
<thead>
<tr>
<th>Pin Name</th>
<th>End-Use</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dress the Part</td>
<td>Space Heating</td>
<td>Wear warm clothing and keep the thermostat 2°F lower when you are home.</td>
</tr>
<tr>
<td>Dress for Success</td>
<td>Space Heating</td>
<td>Dress warmly and use blankets, and turn the thermostat down 2°F when you are home.</td>
</tr>
<tr>
<td>Babysit Winter Thermostat</td>
<td>Space Heating</td>
<td>Turn down your thermostat by 8°F during the day when you are not home.</td>
</tr>
<tr>
<td>Winter Nighttime Thermostat</td>
<td>Space Heating</td>
<td>Turn down the thermostat by 8°F during the night when you are in bed.</td>
</tr>
<tr>
<td>Get with the Program</td>
<td>Space Heating/Cooling</td>
<td>Program your thermostat to the Energy Star recommended temperatures.</td>
</tr>
<tr>
<td>Seal the Deal</td>
<td>Space Heating</td>
<td>Seal around leaky doors and windows.</td>
</tr>
<tr>
<td>Bubble Wrap</td>
<td>Space Heating</td>
<td>Shut the curtains or blinds at night to retain heat.</td>
</tr>
<tr>
<td>Catch Some Rays</td>
<td>Space Heating</td>
<td>Open the south-facing blinds during the day to gain solar heat.</td>
</tr>
<tr>
<td>Clearly Warmer</td>
<td>Space Heating</td>
<td>Add plastic window covers during the winter to reduce heat loss.</td>
</tr>
<tr>
<td>Fan Club</td>
<td>Cooling</td>
<td>Use a fan and raise the thermostat temperature by 4°F.</td>
</tr>
<tr>
<td>Dress for Less</td>
<td>Cooling</td>
<td>Wear light clothing and keep the thermostat 2°F higher when you are home.</td>
</tr>
<tr>
<td>Babysit Summer Thermostat</td>
<td>Cooling</td>
<td>Turn up your thermostat by 7°F during the day when you are not home.</td>
</tr>
<tr>
<td>Summer Nighttime Thermostat</td>
<td>Cooling</td>
<td>Turn up the thermostat by 4°F during the night when you are in bed.</td>
</tr>
<tr>
<td>Sun Block</td>
<td>Cooling</td>
<td>Use blinds or curtains to reflect the sunlight during the day.</td>
</tr>
<tr>
<td>Fill er Up</td>
<td>Water Heating</td>
<td>Run a full load in the dishwasher instead of a partial load.</td>
</tr>
<tr>
<td>Washing Cold</td>
<td>Water Heating</td>
<td>Wash your clothes in cold water.</td>
</tr>
<tr>
<td>Super Soaker</td>
<td>Water Heating</td>
<td>Replace your showerhead with an energy-efficient low-flow model.</td>
</tr>
<tr>
<td>Shower Sprinter</td>
<td>Water Heating</td>
<td>Take a shower that is 1 minute less than normal, and aim for a 5 minute shower.</td>
</tr>
<tr>
<td>Star Status Dishwasher</td>
<td>Water Heating</td>
<td>Buy an Energy Star qualified dishwasher.</td>
</tr>
<tr>
<td>Star Status Clothes Washer</td>
<td>Water Heating</td>
<td>Recycle your old washing machine.</td>
</tr>
<tr>
<td>Faucet Fixer</td>
<td>Water Heating</td>
<td>Fix a leaky faucet to save hot water.</td>
</tr>
<tr>
<td>Pressure Investor</td>
<td>Water Heating</td>
<td>Fix a leaky showerhead to save hot water.</td>
</tr>
<tr>
<td>Dry Naturally</td>
<td>Appliances</td>
<td>Avoid using the &quot;heat dry&quot; function on the dishwasher.</td>
</tr>
<tr>
<td>Washing Smart</td>
<td>Appliances</td>
<td>Wash only full loads of clothes.</td>
</tr>
<tr>
<td>Smart Drying</td>
<td>Appliances</td>
<td>Clean the lint trap of your clothes dryer.</td>
</tr>
<tr>
<td><strong>Pin Name</strong></td>
<td><strong>End-Use</strong></td>
<td><strong>Action</strong></td>
</tr>
<tr>
<td>-------------------</td>
<td>--------------</td>
<td>---------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Star Status Fridge</td>
<td>Appliances</td>
<td>Buy an Energy Star qualified refrigerator or freezer.</td>
</tr>
<tr>
<td>CFLs</td>
<td>Lighting</td>
<td>Replace 4 incandescent lights with CFLs.</td>
</tr>
<tr>
<td>LEDs</td>
<td>Lighting</td>
<td>Replace 4 incandescent lights with LEDs.</td>
</tr>
<tr>
<td>Afraid of the Dark</td>
<td>Lighting</td>
<td>Install a motion sensor exterior light instead of using a porch light all night.</td>
</tr>
<tr>
<td>CFLs Outside</td>
<td>Lighting</td>
<td>Use a CFL in your exterior light.</td>
</tr>
<tr>
<td>Sunny Nights</td>
<td>Lighting</td>
<td>Install solar-powered walkway lighting instead of using a floodlight.</td>
</tr>
<tr>
<td>Home Computer</td>
<td>Electronics</td>
<td>Set the power settings on your computer so it shuts down or hibernates when you aren't using it.</td>
</tr>
<tr>
<td>Turn off Monitor</td>
<td>Electronics</td>
<td>Shut off your monitor when you are done working on your computer.</td>
</tr>
<tr>
<td>DeVampirizeR</td>
<td>Electronics</td>
<td>Use a timer or power strip to prevent your DVR or set-top box from consuming energy when it's not in use.</td>
</tr>
<tr>
<td>Home Entertainment Center</td>
<td>Electronics</td>
<td>Use a timer or power strip at your home entertainment center to stop your TV, Blu-Ray player, subwoofer and other electronics from consuming energy when not in use.</td>
</tr>
<tr>
<td>Office Slayer</td>
<td>Electronics</td>
<td>Use a timer or power strip in your office to stop your printer and computer from consuming energy when not in use.</td>
</tr>
<tr>
<td>Star Status Electronic</td>
<td>Electronics</td>
<td>Buy an Energy Star qualified small electronic device (audio/video system).</td>
</tr>
<tr>
<td>Star Status TV</td>
<td>Electronics</td>
<td>Buy an Energy Star qualified TV.</td>
</tr>
</tbody>
</table>
3.1.2 Data Flow

The figure below is a flow chart of how the data will flow from the user (and other data sources) to the energy models. As mentioned in the Objectives, a model will be developed for each pin listed in the Table 3.1.

![Data Flow Chart](image)

The data flows begin from the mobile device, where a user’s information is input in the form of energy parameters. The mobile device also provides the location of the user, which is used to determine the local climate and GHG (CO₂) factors. The energy costs are determined from the utility bill, which is also displayed on the phone in the form of the graph from Figure 1.2. These energy parameters are the inputs to the energy models. The assumptions in the energy models are developed from 3rd-party empirical data sources, including Energy Star, ASHRAE, Lawrence Berkeley National Laboratory, and more. Once the calculation is complete, the calculated energy, cost, and GHG savings are output and can be used to feedback into the mobile device. Each of the following blocks will be discussed in detail below.

3.1.3 Energy Parameters

As Mills noted, the adoption of energy-saving tools has been slowed by the time required to input information, analyze the often-extensive outputs, and evaluate potential energy saving opportunities (Mills, 2004). Thus, the amount of data that can be obtained about each user must be limited to what is absolutely necessary. These pieces of information can are referred to as the energy parameters which are utilized in the model being developed. To reduce the amount of inputs required by a user, only the factors that have the most significant effect on energy consumption, cost, and environmental impact should be considered. The parameters were selected based on theoretical engineering knowledge of energy utilization combined with experimental results. An examination of the variability each parameter contributes to the overall energy model can be seen in Section 4.1.4.3. The final list of selected energy parameters are depicted in the following table.
Table 3.2 Energy parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Form of Information</th>
<th>Default</th>
<th>Variable Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>A/C Type</td>
<td>Central/Room/None</td>
<td>Central</td>
<td>AC sys type</td>
</tr>
<tr>
<td>Electricity Price</td>
<td>Number ($/kWh)</td>
<td>0.1150 $/kWh</td>
<td>Elec price</td>
</tr>
<tr>
<td>Space Heating Fuel</td>
<td>Gas/Electricity/Fuel Oil/LPG</td>
<td>Average</td>
<td>Heat fuel</td>
</tr>
<tr>
<td>Space Heating System Type</td>
<td>Furnace/Boiler/Baseboard/Heat Pump</td>
<td>Furnace</td>
<td>Heat sys type</td>
</tr>
<tr>
<td>Home Size (conditioned)</td>
<td>Number 500-5000 (sqft)</td>
<td>1769 sqft</td>
<td>Home size</td>
</tr>
<tr>
<td>Laundry in Home</td>
<td>Yes/No</td>
<td>Laundry in Home</td>
<td>Laundry on/off</td>
</tr>
<tr>
<td>Location (Climate)</td>
<td>TMY3 Weather dataset</td>
<td>Rolla, MO</td>
<td></td>
</tr>
<tr>
<td>Location (Electric Carbon Factor)</td>
<td>Number (kg-CO₂e/kWh)</td>
<td>0.709 kg-CO₂e/kWh</td>
<td>Elec Carbon Factor</td>
</tr>
<tr>
<td>Natural Gas Price</td>
<td>Number ($/Therm, $/CCF)</td>
<td>0.0378 $/kWh</td>
<td>Gas price</td>
</tr>
<tr>
<td>Number of Occupants</td>
<td>Number 1-10</td>
<td><strong>2.6</strong></td>
<td>Num occupants</td>
</tr>
<tr>
<td>Water Heating Fuel</td>
<td>Gas/Electricity</td>
<td>Average</td>
<td>WH fuel</td>
</tr>
<tr>
<td>Window Type</td>
<td>Single/Double/Better</td>
<td>Double</td>
<td>Window type</td>
</tr>
<tr>
<td>Year of Construction</td>
<td>Number 1700-present</td>
<td>1973</td>
<td>Year built</td>
</tr>
</tbody>
</table>

† Table 5A. Residential Average Monthly Bill by Census Division, and State 2010, (U.S. Energy Information Administration, 2011b)
‡ This information was obtained for the existing U.S. home stock through the American Housing Survey (U.S. Census Bureau, 2008)
* Natural Gas annual residential price, 2010 (U.S. Energy Information Administration, 2012c),
** The number of occupants was determined from 2010 U.S. Census data (U.S. Census Bureau, 2012)
All other data was gathered from the 2005 Residential Energy Consumption Survey (U.S. Energy Information Administration, 2009).

Default values were assigned to each parameter based on the U.S. national average. Weighted averages were used when assuming a single value would give large changes in the energy consumption results (for example, fuel type). More about weighted averages of fuel types can be seen in Section 4.1.4.1. For parameters where a single characteristic could be found in a large majority of homes, the majority characteristic is considered the default (for example, around 80% of homes have in-home laundry machines, so this is considered the default case (U.S. Energy Information Administration, 2009)).

In total, 13 energy parameters are required for the JouleBug energy, cost, and GHG savings calculations. In addition, many of these parameters can be obtained without asking a question of the user, through use of the smartphone’s geolocation services to obtain location (providing Climate and Electric Carbon Factor) and connection with the user’s utility to obtain electricity and gas prices, requiring a maximum of nine inputs from the user. This can be compared with the web-based energy analysis tools analyzed by Mills, where the vast majority of tools had over 20 inputs (Mills, 2004).

3.1.4 Engineering Calculations and Data Sources

Developing mathematical models of energy savings for each Pin will be accomplished using a simplified version of the forward-modeling method. Due to the time and cost required, full energy simulation via an energy modeling software is not possible, nor is it necessary. The additional cost of using a simulation tool is not justified, as the energy saving calculations are only intended to be an estimate for the
consumers. The use of data-driven modeling techniques such as the ‘energy signature’ was also rejected, as only space heating and cooling-related energy saving actions could be evaluated using it, and the significant time lag due to data collection (e.g. a few months of bills are required after the energy-saving action) makes it an unlikely candidate for effective feedback. Instead, mathematical models for each energy-saving action will be developed from empirical data. The models will use the energy parameters found in Table 3.2 as inputs to a mathematical function, which will output energy savings (a forward modeling approach). Each energy-saving action is treated as a unique case, and so the mathematical model for each Pin will be unique. Data from reputable sources including engineering handbooks, utilities, industry trade groups, national research laboratories, and the government will be utilized to calculate the energy and cost savings. However, as many actions rely on interpreting the user’s behavior, they are difficult to calculate exactly. Engineering estimation will be used where necessary. The primary data sources used to develop the energy models are explained below.

### 3.1.4.1 Weather Data

The weather data set utilized for the calculations is the TMY3, provided by the National Renewable Energy Laboratory. Typical Meteorological Year (TMY) data provides annual weather data of the most likely conditions at a location over an extended period of time, often 30 years. The TMY data is commonly used by building simulation programs and renewable energy system designers. Among the parameters in the TMY3 data set are the characteristics of solar radiation, dry-bulb temperature, dew-point temperature, wind speed, and precipitation. The data is provided hourly for each of the 8760 hours of the year, making it easy to break down the data to the hourly level. The TMY3 data was selected for this project over other similar weather data sets because of the hourly granularity, the large number of stations covered (1020 stations in the U.S.), and the inclusion of the solar radiation data. In addition, the TMY3 data set is fully completed through interpolation, so no gaps exist in the data (Wilcox & Marion, 2008).

Fields lacking from the TMY3 dataset are Heating Degree Days (HDD) and Cooling Degree Days (CDD). Degree-days are used to estimate how much space heating or cooling is required by a building. Calculating degree days starts with a balance temperature, the outdoor temperature at which the heat losses from the building (from transmission, infiltration, etc) are equal to the gains of the building (due to solar radiation, lighting, equipment, and occupants) (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009). In the simplest model, at outdoor temperatures ($t_o$) below the balance point ($t_{bal}$), heating is required, and above the balance point, cooling is required. Annual heating degree-days (DD_h) are the time integral of the temperature falling below the balance point over a year. Equation 3.1 from the ASHRAE Handbook can be utilized to calculate the heating degree days (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009).

$$HDD(t_{bal}) = (1 \text{ day}) \sum_{days} (t_{bal} - t_o)^+$$  \hspace{1cm} \text{Equation 3.1}

Similarly, Equation 3.2 can be used for cooling degree days (DD_c):

$$CDD(t_{bal}) = (1 \text{ day}) \sum_{days} (t_o - t_{bal})^+$$  \hspace{1cm} \text{Equation 3.2}

The TMY3 data set is an hourly data set, so in this case, it is possible to adapt the previous equations to compute degree-hours in the same manner for Heating Degree Hours (HDH) for each of the 8760 hours of the year. The degree hours are a more accurate measure of the temperature variation over the day and can easily be converted into degree days by dividing by degree-hours by 24.

$$HDH(t_{bal}) = \sum_{i=1}^{8760} (t_{bal} - t_o)^+$$  \hspace{1cm} \text{Equation 3.3}
As well for Cooling Degree Hours (CDH):

\[
CDH(t_{bal}) = \sum_{t=1}^{8760} (t_d - t_{bal})^+
\]

Equation 3.4

The “traditional” balance point temperature which degree days are calculated for in the U.S. is 65°F (18.3°C), which has been commonly accepted as the balance point for residential buildings in the past (McQuinston, Parker, & Spitler, 2004). Although there is criticism of the use of the 65°F balance temperature, many sources still tabulate degree-days based on this temperature, including the widely used Residential Energy Consumption Survey (RECS), which is the basis for many of the empirical regressions for space heating and cooling energy consumption created for this project (Eto, 1988; McQuinston, Parker, & Spitler, 2004; U.S. Energy Information Administration, 2009). Some of the savings calculations for heating and cooling in this project are being derived from these survey results rather than being calculated using the heat losses from the building. To properly utilize the survey data, it is most appropriate to use the 65°F balance temperature. More about the calculation procedures is included in the Appendix – Energy Calculations.

3.1.4.2 Energy Star

The Energy Star program, founded in 1992, is a joint initiative between the U.S. Environmental Protection Agency and the U.S. Department of Energy. The mission of Energy Star is to “protect the environment through energy efficient products and practices” (Energy Star, 2011c). This program promotes voluntary standards and labeling of over 60 energy-consuming products including home appliances, consumer electronics, HVAC equipment, and office equipment. In addition, Energy Star provides information about building shell improvements, home air sealing and insulation, and commercial/industrial energy utilization. Recently, Energy Star started an energy assessment program for both commercial and residential buildings. As of 2010, the Energy Star program has contributed avoided emissions of 2980 MMTCO₂e (million metric tons of CO₂-equivalent) over its history (Energy Star, 2011a). Since the Energy Star program has proven to be a successful endeavor and has gained widespread acceptance, much of the information for energy savings calculations will be based on information gathered from Energy Star’s reports, websites, and spreadsheet calculators.

3.1.4.3 Residential Energy Consumption Survey

The Residential Energy Consumption Survey (RECS) is completed every four years by the U.S. Energy Information Administration, from 1978 to 2009. However, the full results from 2009 were not available at the time of this report writing, so results from 2005 RECS are utilized instead. The RECS is intended to measure the energy usage characteristics and consumption levels across a representative sample of the U.S. population. Trained interviewers conduct interviews of residents about their housing unit, usage patterns, and demographics. Energy suppliers provide information about consumption levels and this data is combined to estimate the energy consumption and expenditure for end-uses such as space heating, cooling, lighting, etc (U.S. Energy Information Administration, n.d.). The results of the survey are then assigned a weighting factor that indicates how representative the survey point is of the entire U.S. population.

The RECS data used in this report is publicly available microdata files that contain the original survey data along with the weighting factor. The summary statistics from RECS were also utilized to draw conclusions about energy characteristics of U.S. homes (such as type of space heating fuel, water heater type, etc.)

3.1.4.4 ASHRAE Handbook of Fundamentals

The ASHRAE Handbook of Fundamentals is produced by “the world’s foremost technical society in the fields of heating, ventilation, air conditioning, and refrigeration” (American Society of Heating,
Refrigerating and Air-Conditioning Engineers, Inc., 2009, p. x). The ASHRAE Handbook explains the basics of building energy usage and provides the equations and tables that make it possible to estimate energy consumption in various situations. The principles and data in the 2009 ASHRAE Handbook of Fundamentals (SI edition) are utilized to develop some of the equations in this report, most of which are focused on heat transfer.

3.1.5 Cost

Once models have been developed to calculate energy savings for each of the Pins in Table 3.1, it should be possible to convert energy savings into a measure of cost or environmental impact. These units are better understood by consumers and can be an important design consideration. Conversion from energy to cost requires the price (in kWh/$) paid for energy, unit cost of energy for the user. However, different utilities have different rate structures, including the following:

- **Flat rate** - A single price is paid regardless of usage.
- **Seasonal flat rates** – A flat rate that may change seasonally. Typically electricity prices are higher in the summer, and natural gas rates are higher in the winter.
- **Tiered rate** – The price varies depending on total energy used in the billing period. Typically, customers are allotted a ‘baseline’ amount of energy, and for each unit of energy consumption over the baseline, the price per unit (on that portion) increases. Utilities may have two to five (or more) tiers, with higher consumption resulting in a higher unit price (Pacific Gas and Electric Company, 2012).
- **Time-of-use rate** – For electricity consumption, the price of energy varies depending on the time of day, with peak usage times being billed at higher rates.

Other less-common rate structures exist, and the specifics of the rate structure are normally not included in the customer’s bill. Because of these complicated rate structures, creating a cost model for each utility’s specific case would be a laborious task. In addition to rate structures, the utility company will often bill the customer for fees, taxes, regulatory charges, or other items in addition to the energy consumption. These charges may be fixed each month, or may vary proportionally with the energy usage, depending on the utility.

The complicated nature of utility billing makes it difficult to predict exactly what the cost savings will be. The easiest way to estimate the cost savings for a particular billing period is to calculate an “effective unit price” for the previous year’s equivalent billing period. For example, to predict the energy savings for a May-June 2012 billing period, the rates from May-June 2011 billing period will be used. Utilizing the equivalent billing period (which often have similar starting and ending dates) eliminates the seasonal rate changes. The effective unit price is the bill (including all taxes, fees, and charges) divided by the energy consumption for the billing period.

\[
\text{Effective Unit Price} = \frac{\text{Bill Amount (\$)}}{\text{Energy Used (kWh or Thers)}}
\]

**Equation 3.5**

Appropriate unit conversions will be used to convert natural gas into the unit it is being metered by the utility. If a unit of volume is being metered, such as hundred of cubic feet (CCF), the following energy conversion will be used, based on the heat content of natural gas delivered in 2010 (U.S. Energy Information Administration, 2012b):

\[
1 \text{ CCF} = 102500 \text{ BTU} = 30.039 \text{ kWh}
\]

**Equation 3.6**

The effective unit price for the energy will then be utilized to predict the cost savings from the various energy conservation measures listed in Table 3.1.

There are two main drawbacks to the approach outlined above. The first is that predictions for customers with tiered or time-of-use rates depend heavily on their usage from the previous year, and the weather is a
major factor in energy usage. If a previous year’s billing period was unusually hot (or cold), a customer would be likely to exceed their baseline rate and be subjected to higher cost tiers. This would result in a very high predicted cost reduction for the following year. However, since year-over-year weather data is not yet incorporated into the application, there is no way to correct for this effect. Future versions may tackle this issue. The second shortcoming of using past billing data is that the effect of rate increases (or decreases) will not be seen in the cost savings prediction. In the future, a way of comparing the current season rates to the previous season may be utilized to add this capability; however that is outside the scope of this master’s thesis.

For users that do not have an available utility connection, or utilize non-metered fuels such as fuel oil or Liquefied Petroleum Gas (LPG, or propane), U.S. national average prices per unit as of 2010 are used.

Table 3.3 U.S. average residential fuel costs, 2010.

<table>
<thead>
<tr>
<th>Fuel</th>
<th>Cost ($/kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity†</td>
<td>$0.1150</td>
</tr>
<tr>
<td>Natural Gas‡</td>
<td>$0.0378</td>
</tr>
<tr>
<td>Fuel Oil*</td>
<td>$0.0724</td>
</tr>
<tr>
<td>LPG*</td>
<td>$0.0922</td>
</tr>
</tbody>
</table>

† Table 5A. Residential Average Monthly Bill by Census Division, and State 2010, (U.S. Energy Information Administration, 2011b)
‡Natural Gas annual residential price, 2010 (U.S. Energy Information Administration, 2012c),

### 3.1.6 Greenhouse Gas Factors

In addition to cost, it is useful to measure energy savings in terms of environmental impact. The environmental impact from energy conservation measures is determined from the amount of greenhouse gas emissions (GHGs) avoided due to the action. GHGs are most easily measured in kilograms of CO₂-equivalent (kg-CO₂e), which accounts for all types of GHGs that are commonly produced.

A standard GHG emission factor is utilized for combusting fuels such as natural gas, fuel oil, and LPG. These factors were obtained from the U.S. Environmental Protection Agency (EPA) in units of kilograms of carbon per million BTU (kg C/1e6 BTU) (U.S. Environmental Protection Agency, 2008). The following conversion factor was used to convert the results into kgCO₂/kWh, and the results are show in Table 3.4.

\[
Emissions \left( \frac{kg \ CO_2}{kWh} \right) = Fuel \ Combusted \ (BTU) \times \left( \frac{1 \ kWh}{3412 \ BTU} \right) \times \left( \frac{44 \ CO_2}{12 \ C} \right)
\]

Table 3.4 GHG factors for residential fuels (U.S. Environmental Protection Agency, 2008).

<table>
<thead>
<tr>
<th>Fuel</th>
<th>kg C/1e6 BTU</th>
<th>kg CO₂/kWh</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Gas</td>
<td>14.47</td>
<td>0.181</td>
</tr>
<tr>
<td>Distillate Fuel Oil</td>
<td>19.95</td>
<td>0.250</td>
</tr>
<tr>
<td>LPG</td>
<td>17.19</td>
<td>0.215</td>
</tr>
</tbody>
</table>

Electricity differs from combustion fuels in that the amount of GHGs produced varies depending on the region of the country where the electricity generation is taking place. The nature of the grid-connected utility system makes it very difficult to tell exactly where the electricity supplying a particular city (or home) is coming from, as utilities buy and sell power throughout the day to cover demand. The U.S.
Environmental Protection Agency’s eGrid program has divided the country into 26 eGrid subregions, which are designated as regions that import or export a minimum amount of electrical power. These region’s boundaries are purely representational and are not exact geographic boundaries. The U.S. EPA provides data on the GHG emissions in kg-CO$_2$e per MWh of electricity generated (GHG$_{\text{generated}}$) for each of the 26 eGrid subregions. eGrid’s publications recommend the use of “non-baseload emissions factors” when estimating emissions benefit of energy conservation measures. The non-baseload emissions are calculated for power plants with a capacity factor less than 0.8. The generation from these plants is most likely to be displaced by energy conservation measures (E.H. Pechan & Associates, Inc., 2012).

![eGrid subregions map](image)

This is a representational map; many of the boundaries shown on this map are approximate because they are based on companies, not on strictly geographical boundaries.

USEPA eGRID2010 Version 1.0  
December 2010

**Figure 3.3** eGrid subregions map (U.S. Environmental Protection Agency, 2012).

The eGrid subregions and their emission levels are linked to U.S. postal zip codes through the Power Profiler tool (U.S. Environmental Protection Agency, 2011), which can be correlated with geographical location. Thus, it is possible to relate the geographical location of the user to their corresponding electric GHG generation factor.

The North America Electric Reliability Corporation (NERC) divides the U.S. into major electric grid regions as specified in Figure 3.4.

There are five major grids in the U.S., which are largely operated independently: (1) Eastern (which encompasses the subregions of MRO, SPP, SERC, RFT, NPCC, and FRCC), (2) Western, (3) Texas, (4) Alaska and (5) Hawaii. The eGrid data provides only the GHG emission factor for generation and does not account for grid losses, which can be up to 10% in some cases. A grid loss factor for each of the 5 major U.S. grids is required to account for grid losses.
The grid loss factors for the five major grids, as of 2009, are depicted in the table below.

**Table 3.5 Grid Loss Coefficients (U.S. Environmental Protection Agency, 2012).**

<table>
<thead>
<tr>
<th>Grid Region</th>
<th>NERC abbrv.</th>
<th>Grid Loss Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>East</td>
<td>MRO, SPP, RFC, NPCC, FRCC, SERC</td>
<td>5.82%</td>
</tr>
<tr>
<td>West</td>
<td>WECC</td>
<td>8.21%</td>
</tr>
<tr>
<td>Texas</td>
<td>ERCT</td>
<td>7.99%</td>
</tr>
<tr>
<td>Alaska</td>
<td>ASCC</td>
<td>5.84%</td>
</tr>
<tr>
<td>Hawaii</td>
<td>HICC</td>
<td>7.81%</td>
</tr>
<tr>
<td>US Total</td>
<td></td>
<td>6.50%</td>
</tr>
</tbody>
</table>

The equation below is used to determine the GHG consumption factor (GHG$_{consumed}$) utilizing the GHG generation factor and the grid loss coefficient.

$$\text{GHG}_{consumed} = \text{GHG}_{generated} \times (1 + \text{GridLossCoeff}) \quad \text{Equation 3.8}$$

This factor is stored for all 26 eGrid subregions, and is to be used when a measure of environmental benefit is required.

If data on the location is not available, the U.S. national average carbon emission factor for 2009, for non-baseload emissions, will be utilized (U.S. Environmental Protection Agency, 2012).

$$U.S. \text{ national electric GHG factor} = 1562 \frac{lb\text{CO}_2\text{eq}}{MWh} = 0.709 \frac{kg\text{CO}_2\text{eq}}{kWh} \quad \text{Equation 3.9}$$

This is a representational map; many of the boundaries shown on this map are approximate because they are based on companies, not on strictly geographical boundaries.
3.2 Psychology

To accomplish the psychologically-focused objectives outlined in Section 1.3, an extensive review of the literature must be carried out. The psychological design aspects of the feedback system will be designed with the literature in mind. Section 2.2.3 provides an excellent summary of feedback design components necessary for an effective system. The use of particular design components for JouleBug will be based on the following criteria:

- The potential effectiveness of the design to reduce energy consumption, based on an evaluation of previous studies. Feedback designs that have been shown to be effective on a large scale, over extended periods of time, and in many separate studies are the preferred methods.
- The assumptions and functionality of the energy models developed. A feedback system must generate reasonably accurate results, so the energy models must be utilized in a way that preserves the model's integrity. Designs that are in sync with the underlying assumptions and methodology used in the energy models are necessary.
- The applicability to JouleBug’s particular case, past designs, and mission. A design that retains the current structure and serves to make JouleBug more engaging and useful to users is desired.
- The ability of the design to facilitate behavioral change by increasing motivation and education, and providing “triggers” as described in Section 2.1.3.

3.3 Computing and Development

The energy models will be developed utilizing Microsoft Excel. Excel is capable of handling large amounts of data (including weather data and RECS data) which will be used to create the model. The Excel tool will accomplish linear regression, calculation of statistical measures, and general numerical operations. Excel will be utilized for the development of the energy models to make it easy to visualize the results through graphical output.

After the equations have been created using Excel, the models will be converted into the programming language Python, which will be used to perform the calculations within the JouleBug Iphone application. A non-relational database called MongoDB will be used to organize energy-related data for each user, including calculated savings, energy bill information, user achievement data, and gathered energy parameters. However, the scope of this project is simply to create the models, and not to implement them into the application.
4 Results

4.1 Energy Calculations

As mentioned in Table 1.1, one of the main objectives for this thesis project was to develop mathematical models which could be used to calculate the energy, cost, and GHG savings for a JouleBug user, given the input parameters outlined in Table 3.2. The following sections begin with a discussion of how the time period and user’s achievement affect the calculations and display of the results. After that, the mathematical models used to determine the user’s energy savings for each JouleBug Pin are summarized and classified by end-use (space heating, cooling, water heating, etc.). The method of summing the various Pins to determine the overall user’s energy, cost and GHG savings will be discussed. Finally, the resulting total energy, cost, and GHG savings for the test case of an “average user” will be determined using the models, and an analysis of the variation caused by each of the input parameters will take place.

4.1.1 Time Period

For display of the energy (or cost, or GHG) savings on a graph, the time periods of the graph are very important. Logically, it makes sense to plot the savings calculations in conjunction with each utility bill that is received by the user (monthly for most utilities). In the future, as smart grid technology becomes more widespread, it may be possible to plot points with smaller time intervals.

It is rather straightforward to determine the calculated savings for any period of time as long as the starting date and time, \( t_1 \), and ending date and time \( t_2 \) of the desired time period are known. The length of the time period of interest (for example, a billing cycle) is referred to as \( \Delta t \), which is given in some unit of granularity (for example, hours or days).

\[
\Delta t = t_1 - t_2 \tag{Equation 4.1}
\]

As explained in Section 4.1.3, the energy savings mathematical models were developed to give a result in kWh-saved/yr for baseload end-uses (those not affected by climate) like water heating, appliances, electronics, or lighting. A granularity for \( \Delta t \) of hours was selected for this project, mainly for the reason that the TMY3 weather data provides this level of granularity. In addition, smart metering data in the future could provide energy in hourly (or less) increments. For graphing savings over a billing cycle, where the time period is given by a number of days, it is necessary to convert the starting and ending dates into their respective hour of the year to determine the \( \Delta t \) in hours.

The annual savings values for a user determined through the equations in Section 4.1.3 are divided by 8760 hours in the year, and then multiplied by the time period of interest, \( \Delta t \), in hours. This determines the energy saved over the time period of interest.

\[
E_{\text{saved,} \Delta t} = \frac{E_{\text{saved, annual}}}{8760} \times \Delta t \tag{Equation 4.2}
\]

For space heating and cooling Pins, the savings are calculated on an hourly basis using the TMY3 weather data. To determine the amount of savings for the given time period, the equivalent time period is isolated from the TMY3 weather data file based on the hour of the year (out of 8760). The first hour of the given time period is \( t_1 \), and the final day of the given period is \( t_2 \). Then the resulting energy savings for that time period can be summed to determine the energy savings.

\[
E_{\text{saved,} \Delta t} = \sum_{i=t_1}^{t_2} \Delta E_i \tag{Equation 4.3}
\]
4.1.2 Achievement

As mentioned in the Objectives, a goal of this project was to calculate an estimate of a JouleBug user's savings, depending on input parameters. However, the savings of the user is also dependent on which particular Pins have been earned, and the time at which they were earned. It is assumed that if a user has earned a Pin, they are completing the energy saving action, and are awarded the full value of the savings (from the time of earning to the current time). These two additional variables are necessary for calculating the savings for a Pin over the time period given.

- Pin_Earned = Binary (1 or 0)
- Pin_Earned_Time = Date and Time

The savings are calculated from the time the Pin is earned. In the previous section, a time period of interest, \( \Delta t \), was discussed. To incorporate the idea of Pin earning dependent on time, the concept of each Pin having a time period of \( \Delta t_{\text{pin}} \) is introduced. If a Pin was earned prior to starting time \( t_1 \), then the full value of savings for the time period is calculated. If a Pin was earned between \( t_1 \) and \( t_2 \), within the time period of interest, then the time period for that Pin is adjusted so that \( \Delta t_{\text{pin}} \) runs from the Pin earned time to \( t_2 \). If the Pin is not earned before \( t_2 \), then \( \Delta t_{\text{pin}} = 0 \). These concepts are illustrated in Equation 4.4.

\[
\Delta t_{\text{pin}} = \begin{cases} 
  t_1 - t_2, & \text{if } Pin_{\text{earn\_time}} < t_1 \\
  Pin_{\text{earn\_time}} - t_2, & \text{if } t_1 < Pin_{\text{earn\_time}} < t_2 \\
  0, & \text{if } Pin_{\text{earn\_time}} > t_2 
\end{cases}
\]

Equation 4.4

4.1.3 Mathematical Models for Energy Savings

This section provides a summary of the resulting energy saving equations developed for each JouleBug Pin listed in Table 3.1. This section will first outline the basic common traits for all of the mathematical equations developed, and will provide a short discussion on how the savings for each use will be aggregated. Following that, subsections for each energy end-use will provide the actual equations for each Pin along with calculations necessary to aggregate the Pins within the end-use.

A corresponding mathematical model to determine the energy savings was developed for each of the energy saving actions listed in Table 3.1. These models were developed to be reliant on the parameters listed in Table 3.2, without any supplemental energy information from the user. Many of the models are simple equations requiring a single variable. In some cases where the parameters in Table 3.2 had no bearing on a Pin’s energy savings, a single number was calculated to represent the savings for all users. In more complicated cases, sets of equations dependent on logical statements were utilized. Regardless of the model’s form, the savings amounts calculated from the model are given in kWh of energy per year (kWh-saved/yr), for all fuel types. This provides a consistent unit for comparison across all models, including those which may encompass multiple fuel types.

Many assumptions about the user’s baseline behavior, improved behavior, and home energy characteristics were necessary to develop mathematical models for the energy saving actions found in Table 3.1. These models were developed using sources listed in Section 3.1.4 along with other relevant and well-researched data. The full derivation of each of these equations along with important assumptions, data tables, and supporting information can be viewed in the Appendix – Energy Calculations.

The cost and GHG savings for any Pin can be determined from the energy savings calculated from the model, using the methodology outlined in Sections 3.1.5 and 3.1.6. In most cases, this is accomplished by simply multiplying the energy savings for a Pin by the corresponding cost or GHG factor. In cases of multiple fuels, it is necessary to devise logical statements based on the parameters in Table 3.2 to ensure that the correct cost and GHG factors are used. Once the Pin savings are in terms of cost and GHG, the procedure below can be followed for aggregating the savings.
After the energy savings for any particular period of time have been determined, each end-use category is summed to determine the total amount of savings for the user. However, the potential for interaction between energy saving actions creates problems for summing of Pin savings. Essentially, Pins can interact in three ways:

- **Non-Interacting** – Two or more Pins that have actions that do not affect each other. An example of non-interacting Pins is “Wash Cold” and “Shower Sprinter”. Washing clothes in cold water does not affect the consumption of hot water in the shower. The total savings amounts for both actions can be achieved within the same household. Different end-uses can also be considered to be non-interacting. Non-interacting savings amounts can be summed directly:

\[
\Delta E_{\text{total}} = \Delta E_1 + \Delta E_2 + \cdots + \Delta E_n
\]

- **Duplicate** – The same savings result occurs as a result of two distinct Pins in two separate Badges. The organization scheme of the Badge and Pins is designed to be intuitive to the user, so similar actions are grouped together. One example of two Pins with the same action is “Dress for Success” and “Dress the Part” Pins. In both Pins, the action is to decrease indoor occupied temperature by 2°F. In cases where the same action is being performed, either Pin may contribute to the total savings, but not both.

\[
\Delta E_{\text{total}} = \Delta E_1 \quad \text{OR} \quad \Delta E_{\text{total}} = \Delta E_1
\]

- **Interacting (diminishing returns)** – Calculating the savings of each Pin separately rather than using a comprehensive simulation tool results in overlap between the energy conservation measures. For example, consider a consumer in a known baseline situation that is given two options, where turning down the thermostat “Smarty Pants” is estimated to save $50, or sealing leaks “Seal the Deal” is also estimated to save $50. The consumer cannot expect to save $100 from their baseline case by performing both actions, as these two actions overlap in that both actions reduce the heat transfer out of the house. The consumer would see savings between $50 and $100 by doing both actions.

In order to solve the problem of diminishing returns, a system was devised to convert each saving measure into a percentage of the baseline consumption (for a particular end-use). Each percentage was then multiplied by the percentages of other overlapping actions, to get a total percentage reduction from baseline. This can be seen in the equation below, where \( \Delta E_i \) are savings from individual Pins, \( E_{\text{consumed}} \) is the baseline consumption for the end use, and \( \Delta E_{\text{total}} \) is the diminished total savings of all the actions.

\[
\frac{E_{\text{consumed}} - \Delta E_{\text{total}}}{E_{\text{consumed}}} = \left( \frac{E_{\text{consumed}} - \Delta E_1}{E_{\text{consumed}}} \right) \times \cdots \times \left( \frac{E_{\text{consumed}} - \Delta E_n}{E_{\text{consumed}}} \right)
\]

Although this method of calculating savings is not as accurate as a simulation program, it is an attempt to account for some measure of the diminishing returns expected.

The following sections outline the energy models for each of the following end-uses: Space Heating, Cooling, Water Heating, Appliances, Lighting, and Electronics. The energy models developed for each Pin are summarized in their appropriate end-uses. Following the summary of the energy models, pseudocode (logical statements) is utilized to illustrate how each end-use is aggregated.

### 4.1.3.1 Space Heating

The space heating end-use was one of the most complicated to model, as there are many factors affecting space heating energy consumption, including multiple fuel types such as natural gas, electricity, fuel oil, and LPG (propane). However, for all fuels, savings for thermostat setback Pins was estimated as a percentage from the total space heating fuel consumption, \( E_{\text{heat,fuel consumed}} \) from Section 8.1.3.4 in the
Appendix. The remaining space heating Pins involved heat transfer calculations and TMY3 weather data, which are resulted in complicated equations, often involving extensive logical statements. For this reason, they cannot be easily displayed in this table. The full derivation as well as the final results for these Pins can be viewed in the Appendix – Energy Calculations. The following table shows the resulting model for energy savings from each space heating Pin.

### Table 4.1 Equations for space heating energy savings.

<table>
<thead>
<tr>
<th>Pin Name</th>
<th>Notation</th>
<th>Energy Savings, ΔE (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dress the Part</td>
<td>( \Delta E_{\text{Dress the part}} )</td>
<td>( E_{\text{heat, fuel consumed}} \times 0.016 )</td>
</tr>
<tr>
<td>Dress for Success</td>
<td>( \Delta E_{\text{Dress for success}} )</td>
<td>( E_{\text{heat, fuel consumed}} \times 0.016 )</td>
</tr>
<tr>
<td>Babysit Winter Thermostat</td>
<td>( \Delta E_{\text{Babysit winter thermostat}} )</td>
<td>( E_{\text{heat, fuel consumed}} \times 0.064 )</td>
</tr>
<tr>
<td>Winter Nighttime Thermostat</td>
<td>( \Delta E_{\text{Winter nighttime thermostat}} )</td>
<td>( E_{\text{heat, fuel consumed}} \times 0.064 )</td>
</tr>
<tr>
<td>Get with the Program</td>
<td>( \Delta E_{\text{Get with the program}} )</td>
<td>See Appendix 8.1.7.3</td>
</tr>
<tr>
<td>Seal the Deal</td>
<td>( \Delta E_{\text{Seal the deal}} )</td>
<td>See Appendix 8.1.7.3</td>
</tr>
<tr>
<td>Bubble Wrap</td>
<td>( \Delta E_{\text{Bubble wrap}} )</td>
<td>See Appendix 8.3.7.2</td>
</tr>
<tr>
<td>Catch Some Rays</td>
<td>( \Delta E_{\text{Catch some rays}} )</td>
<td>See Appendix 8.3.7.3</td>
</tr>
<tr>
<td>Clearly Warmer</td>
<td>( \Delta E_{\text{Clearly warmer}} )</td>
<td>See Appendix 8.3.7.4</td>
</tr>
</tbody>
</table>

To aggregate the space heating end-use, Pins were grouped into sub-categories of use depending on how they relate to each other with respect to duplications and diminishing returns. For space heating, the subcategories are as follows:

### Table 4.2 Space heating sub-categories.

<table>
<thead>
<tr>
<th>Actions included in sub-category</th>
<th>Sub-category variable name</th>
<th>Sub-category notation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermostat adjustments during occupied hours</td>
<td>Thermostat\textunderscore occupied\textunderscore heat</td>
<td>( \Delta E_{\text{THERMOSTAT occupied,heat}} )</td>
</tr>
<tr>
<td>Thermostat adjustments during unoccupied hours</td>
<td>Thermostat\textunderscore unoccupied\textunderscore heat</td>
<td>( \Delta E_{\text{THERMOSTAT unoccupied,heat}} )</td>
</tr>
<tr>
<td>All thermostat adjustments</td>
<td>Thermostat\textunderscore Total\textunderscore heat</td>
<td>( \Delta E_{\text{THERMOSTAT Total,heat}} )</td>
</tr>
<tr>
<td>Changes to window blinds</td>
<td>Window\textunderscore Blinds</td>
<td>( \Delta E_{\text{Window Blinds}} )</td>
</tr>
</tbody>
</table>

The pseudocode below illustrates through logical statements how the Pins were combined into sub-categories. The Pin names in this pseudocode represent the amount of savings the Pin in a given time period \( \Delta t \).

```plaintext
#BEGIN PSEUDOCODE

"""Dress the Part" and "Dress for Success" has duplication of action.

IF Dress_the_Part>Dress_for_Success:
    Thermostat\textunderscore occupied\textunderscore heat=Dress_the_Part
ELSE
    Thermostat\textunderscore occupied =Dress_for_Success
```

-40-
“Get with the Program” is targeted at programmable thermostat setback. It is possible to setback a manual thermostat as well. The manual thermostat actions are broken into daytime setback “Babysit Winter Thermostat” and nighttime setback “Winter Nighttime Thermostat”. The savings do not depend on the method of setback, so this is also duplication of energy savings.

IF
Get_with_the_Program_heating>(Babysit_Winter_Thermostat+Winter_Nighttime_Thermostat):

Thermostat_unoccupied_heat=Get_with_the_Program_heating
ELSE

Thermostat_unoccupied_heat=Babysit_Winter_Thermostat+Winter_Nighttime_Thermostat
#the thermostat setback during the unoccupied period and occupied periods are non-interacting, so they can be summed directly.
Thermostat_Total_heat=Thermostat_occupied_heat+Thermostat_unoccupied_heat
#the actions dealing with window blinds, opening them during the daytime “Catch Some Rays” and shutting them at night “Bubble Wrap” are non-interacting and can be summed.
Window_Blinds=Catch_Some_Rays+Bubble Wrap

After the sub-categories were created, it was possible to aggregate them. However, the thermostat setting, the solar heat gain, the transmission “Clearly Warmer,” and the infiltration “Seal the Deal” from the building all affect the total amount of space heating savings. They can be seen as interacting and so Equation 4.7 was utilized to account for diminishing returns, where $E_{\text{consumed}}=E_{\text{heat,fuel consumed}}$ from Section 8.1.3.4. The total energy savings for the space heating end-use, $\Delta E_{\text{total,heat}}$ can be viewed below.

$$\frac{E_{\text{heat,fuel consumed}} - \Delta E_{\text{total,heat}}}{E_{\text{heat,fuel consumed}}} = \left( \frac{E_{\text{heat,fuel consumed}} - \Delta E_{\text{Seal the deal}}}{E_{\text{heat,fuel consumed}}} \right) \times \left( \frac{E_{\text{heat,fuel consumed}} - \Delta E_{\text{Clearly Warmer}}}{E_{\text{heat,fuel consumed}}} \right) \times \left( \frac{E_{\text{heat,fuel consumed}} - \Delta E_{\text{Thermostat total,heat}}}{E_{\text{heat,fuel consumed}}} \right) \times \left( \frac{E_{\text{heat,fuel consumed}} - \Delta E_{\text{Window blinds}}}{E_{\text{heat,fuel consumed}}} \right)$$  

Equation 4.8

4.1.3.2 Cooling

The table below shows the energy savings over a year for cooling Pins. Similar to space heating, cooling energy savings were also quite complicated to determine due to the use of TMY3 weather data and the logical statements that were involved. The results for these Pins can be viewed in Appendix – Energy Calculations. Savings for thermostat setback Pins are given as a percentage of the total cooling energy consumption, where $E_{\text{cool,el consumed}}$ is determined in Section 8.2.3.4 in the Appendix.
Table 4.3 Equations for cooling energy savings.

<table>
<thead>
<tr>
<th>Pin Name</th>
<th>Notation</th>
<th>Energy Savings, ΔE (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fan Club</td>
<td>ΔE_{Fan club}</td>
<td>See Appendix 8.2.7.1</td>
</tr>
<tr>
<td>Dress for Less</td>
<td>ΔE_{Dress for less}</td>
<td>E_{cool,el consumed} * 0.04</td>
</tr>
<tr>
<td>Babysit Summer Thermostat</td>
<td>ΔE_{Babysit summer thermostat}</td>
<td>E_{cool,el consumed} * 0.14</td>
</tr>
<tr>
<td>Summer Nighttime Thermostat</td>
<td>ΔE_{Summer nighttime thermostat}</td>
<td>E_{cool,el consumed} * 0.08</td>
</tr>
<tr>
<td>Get with the Program</td>
<td>ΔE_{Get with the program,cool}</td>
<td>E_{cool,el consumed} * 0.22</td>
</tr>
<tr>
<td>Sun Block</td>
<td>ΔE_{sun block}</td>
<td>See Appendix 8.3.7.1</td>
</tr>
</tbody>
</table>

Aggregating the cooling energy savings involved some of the same sub-categories used for space heating. These sub-categories can be seen in the table below.

Table 4.4 Cooling sub-categories.

<table>
<thead>
<tr>
<th>Actions included in sub-category</th>
<th>Sub-category Pseudocode variable name</th>
<th>Sub-category notation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermostat adjustments during occupied hours</td>
<td>Thermostat_occupied_cool</td>
<td>ΔE_{Thermostat_occupied, cool}</td>
</tr>
<tr>
<td>Thermostat adjustments during unoccupied hours</td>
<td>Thermostat_unoccupied_cool</td>
<td>ΔE_{Thermostat_unoccupied, cool}</td>
</tr>
<tr>
<td>All thermostat adjustments</td>
<td>Thermostat_Total_cool</td>
<td>ΔE_{Thermostat_total,cool}</td>
</tr>
</tbody>
</table>

The pseudocode below outlines how the Pins were arranged into sub-categories in preparation for aggregation.

```plaintext
#BEGIN PSEUODOCODE

# “Get with the Program” for cooling duplicates the actions of “Summer Nighttime Thermostat” and “Babysit Summer Thermostat”.

IF Get_with_the_Program_cooling>(Babysit_Summer_Thermostat+Summer_Nighttime_Thermostat):
    Thermostat_unoccupied_cool=Get_with_the_Program_cooling
ELSE
    Thermostat_unoccupied_cool=Babysit_Summer_Thermostat+Summer_Nighttime_Thermostat
#the thermostat setback during the occupied period is a single Pin for cooling, “Dress for Less”. This does not interact with the thermostat setting during unoccupied period, and can be summed.
    Thermostat_Total_cool=Thermostat_unoccupied_cool+Dress_for_Less

#END PSEUODOCODE
```

The remaining actions for cooling all have the possibility to interact, so the total with diminishing returns can be calculated using Equation 4.7. For cooling, \( E_{\text{consumed}} = E_{\text{cool,el consumed}} \) as determined in Section 8.2.3.4. The final equation for cooling energy savings, \( \Delta E_{\text{total,cool}} \) can be seen below.
Water heating savings equations are given in terms of Number of Occupants, from Table 3.2, and the Energy Factor of the water heater, EF_{WH}, which can be determined by the fuel type. Water heaters are predominantly fueled by natural gas or electricity. The EF_{WH} can be determined for the fuel type by using Table 8.31 in the Appendix – Energy Calculations.

\[
\frac{E_{cool,el \text{ consumed}} - \Delta E_{total,cool}}{E_{cool,el \text{ consumed}}} = \left( \frac{E_{cool,el \text{ consumed}} - \Delta E_{Fan \text{ Club}}}{E_{cool,el \text{ consumed}}} \right) \times \left( \frac{E_{cool,el \text{ consumed}} - \Delta E_{Sun \text{ block}}}{E_{cool,el \text{ consumed}}} \right) \times \left( \frac{E_{heat, fuel \text{ consumed}} - \Delta E_{Thermostat \text{ total,cool}}}{E_{cool,el \text{ consumed}}} \right)
\]

\textbf{Equation 4.9}

\section*{4.1.3.3 Water Heating}

Water heating savings equations are given in terms of Number of Occupants, from Table 3.2, and the Energy Factor of the water heater, EF_{WH}, which can be determined by the fuel type. Water heaters are predominantly fueled by natural gas or electricity. The EF_{WH} can be determined for the fuel type by using Table 8.31 in the Appendix – Energy Calculations.

\begin{table}[h]
\centering
\begin{tabular}{|l|l|l|}
\hline
\textbf{Pin Name} & \textbf{Notation} & \textbf{Energy Savings, \( \Delta E \) (kWh)} \\
\hline
Fill er Up & \( \Delta E_{\text{Fill er up}} \) & \((11.88\times\text{Num\_occupants})/EF_{WH}\) \\
Washing Cold & \( \Delta E_{\text{Washing cold}} \) & \((81.32\times\text{Num\_occupants})/EF_{WH}\) \\
Super Soaker & \( \Delta E_{\text{Super Soaker}} \) & \((144.87\times\text{Num\_occupants})/EF_{WH}\) \\
Shower Sprinter & \( \Delta E_{\text{Shower sprinter}} \) & 79.54/EF_{WH} \\
Star Status Dishwasher & \( \Delta E_{\text{Star status dishwasher}} \) & \((65.63\times\text{Num\_occupants})/EF_{WH}\) \\
Star Status Clothes Washer & \( \Delta E_{\text{Star status clothes washer}} \) & \((58.80\times\text{Num\_occupants})/EF_{WH}\) \\
Faucet Fixer & \( \Delta E_{\text{Faucet Fixer}} \) & \((15.20\times\text{Num\_occupants})/EF_{WH}\) \\
Pressure Investor & \( \Delta E_{\text{Pressure investor}} \) & \((15.20\times\text{Num\_occupants})/EF_{WH}\) \\
\hline
\end{tabular}
\caption{Equations for water heating energy savings.}
\end{table}

Water heating sub-categories are based on appliances, specifically the washing machine and the dishwasher. The table below shows the sub-categories selected.

\begin{table}[h]
\centering
\begin{tabular}{|l|l|l|}
\hline
\textbf{Actions included in sub-category} & \textbf{Pseudocode variable name} & \textbf{Sub-category notation} \\
\hline
Clothes washer energy actions & CW\_Savings\_Total & \( \Delta E_{CW,\text{total}} \) \\
Dishwasher actions & DW\_Savings\_Total & \( \Delta E_{DW,\text{total}} \) \\
\hline
\end{tabular}
\caption{Water heating sub-categories.}
\end{table}

Savings for washing machine pins “\textbf{Wash Cold}” and “\textbf{Star Status Washer}” are interacting. Equation 4.7 is applied for the washing machine, where \( E_{\text{consumed}} = E_{\text{CW,WH, consumed}} \) (depending on the fuel type selected) as determined in Section 8.4.6.2.3.
\[
\frac{E_{CW,WH\text{ consumed}} - \Delta E_{CW,\text{ total}}}{E_{CW,WH\text{ consumed}}} = \left( \frac{E_{CW,\text{ consumed}} - \Delta E_{\text{Wash Cold}}}{E_{CW,WH\text{ consumed}}} \right) \times \left( \frac{E_{CW,\text{ consumed}} - \Delta E_{\text{Star Status Dishwasher}}}{E_{CW,WH\text{ consumed}}} \right)
\]

Equation 4.10

The dishwasher savings equation was created in a similar manner, with “Fill er Up” and “Star Status Dishwasher” contributing to the diminishing returns. 

\[
\frac{E_{DW,WH\text{ consumed}} - \Delta E_{DW,\text{ total}}}{E_{DW,WH\text{ consumed}}} = \left( \frac{E_{DW,\text{ consumed}} - \Delta E_{\text{Fill er up}}}{E_{DW,WH\text{ consumed}}} \right) \times \left( \frac{E_{DW,\text{ consumed}} - \Delta E_{\text{Star Status Dishwasher}}}{E_{DW,WH\text{ consumed}}} \right)
\]

Equation 4.11

The remaining Pins are focused around fixing leaks and showering. The Pins involving showering do not need to be adjusted for diminishing returns, as the baseline for the shorter shower case assumes that the showerhead is low-flow already (additional assumptions can be viewed in Section 8.4.6.3). Therefore, these Pins are non-interacting and can be summed by using Equation 4.5.

\[
\Delta E_{\text{total,WH}} = \Delta E_{1_{CW,\text{ total}}} + \Delta E_{2_{DW,\text{ total}}} + \Delta E_{3_{\text{Super soaker}}} + \Delta E_{4_{\text{Shower sprinter}}} + \Delta E_{5_{\text{Pressure inventor}}} + \Delta E_{6_{\text{Faucet fixer}}}
\]

Equation 4.12

### 4.1.3.4 Appliances

The appliance end use includes electrical energy consumed by the major appliances in the home including the dishwasher, clothes washer, clothes dryer, refrigerator, and stovetop. It does not include the energy required to heat water. A table containing the energy saving equations developed for appliance Pins can be seen in Table 4.7. Note that the Pin Star Status Fridge does not depend on any variables.

<table>
<thead>
<tr>
<th>Pin Name</th>
<th>Notation</th>
<th>Energy Savings, ΔE (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry Naturally</td>
<td>ΔE\text{Dry naturally}</td>
<td>9.17*\text{Num_occupants}</td>
</tr>
<tr>
<td>Washing Smart</td>
<td>ΔE\text{washing smart}</td>
<td>31.10*\text{Num_occupants}</td>
</tr>
<tr>
<td>Smart Drying</td>
<td>ΔE\text{smart drying}</td>
<td>18.66*\text{Num_occupants}</td>
</tr>
<tr>
<td>Star Status Fridge</td>
<td>ΔE\text{star status fridge}</td>
<td>123.26</td>
</tr>
</tbody>
</table>

Table 4.7 Equations for appliance energy savings.

Similar to water heating, the end-use area of appliances is segmented by the type of appliance. This end-use includes the energy that appliances consume directly (not including the hot water). The clothes dryer in the home is the subject of the Pins “Smart Drying” and “Washing Smart”. The calculation of diminishing returns that takes place is similar to the calculation for the clothes washer above. $E_{\text{consumed}} = E_{\text{dryer,consumed}}$, as in Section 8.5.1.2.2.
The savings actions for appliances can then be considered non-interacting and are able to be summed directly.

\[
\Delta E_{total, \text{appliances}} = \Delta E_{\text{dryer}} + \Delta E_{\text{Galactic fridge}} + \Delta E_{\text{Air dry}}
\]

Equation 4.14

### 4.1.3.5 Lighting

The table below shows the energy saving results for the lighting Pins. Rather than requiring the user to input information about the lighting characteristics of their home (such as time lights are on, number of light bulbs, and specific Wattages), national averages were used to develop the energy savings models. Using national averages eliminated the need for the user to tediously input additional information which would be of questionable accuracy. The resulting energy savings models are single values calculated based on national averages rather than expressions in terms of the energy parameters.

**Table 4.8 Equations for lighting energy savings.**

<table>
<thead>
<tr>
<th>Pin Name</th>
<th>Notation</th>
<th>Energy Savings, ΔE (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFLs</td>
<td>ΔE\text{CFLs}</td>
<td>127.60</td>
</tr>
<tr>
<td>LEDs</td>
<td>ΔE\text{LEDs}</td>
<td>131.77</td>
</tr>
<tr>
<td>Afraid of the Dark</td>
<td>ΔE\text{Afraid of the dark}</td>
<td>191.63</td>
</tr>
<tr>
<td>CFLs Outside</td>
<td>ΔE\text{CFLs outside}</td>
<td>156.22</td>
</tr>
<tr>
<td>Sunny Nights</td>
<td>ΔE\text{Sunny nights}</td>
<td>219.00</td>
</tr>
</tbody>
</table>

Pins for lighting may be divided into two sub-categories: indoor lighting and outdoor lighting. These categories can be seen below.

**Table 4.9 Lighting sub-categories.**

<table>
<thead>
<tr>
<th>Actions included in sub-category</th>
<th>Sub-category</th>
<th>Sub-category notation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indoor lighting</td>
<td>Indoor_Light_Total</td>
<td>ΔE\text{Indoor light total}</td>
</tr>
<tr>
<td>Outdoor lighting</td>
<td>Outdoor_Light_Total</td>
<td>ΔE\text{Outdoor light total}</td>
</tr>
</tbody>
</table>

The indoor lighting Pins are considered non-interacting. It is assumed that if a user replaces a light bulb, they are always replacing an incandescent.

Outdoor lighting Pins do have interacting actions. Installing a motion sensor “Afraid of the Dark” affects the time the bulb is on, while replacing outdoor lights with CFLs “CFLs Outside” affects the power consumption. Both affect the energy consumption of the outdoor light, so diminishing returns must be accounted for. The diminishing returns for these two Pins can be calculated in Equation 4.15.
The baseline consumption for outdoor lighting is \( E_{\text{outdoor light consumed}} = E_{\text{outdoor light consumed}} \), as calculated in Section 8.6.2.

\[
\frac{E_{\text{outdoor light consumed}} - \Delta E_{\text{outdoor light total}}}{E_{\text{outdoor light consumed}}}
= \left( \frac{E_{\text{outdoor light consumed}} - \Delta E_{\text{Afraid of the dark}}}{E_{\text{outdoor light consumed}}} \right) \times \left( \frac{E_{\text{outdoor light consumed}} - \Delta E_{\text{CFLs outside}}}{E_{\text{outdoor light consumed}}} \right)
\] \hspace{1cm} \text{Equation 4.15}

Using a solar-powered outdoor light “Sunny Nights” is maximum savings that could occur, as zero grid-tied electricity would be used. This can duplicate the savings from \( \Delta E_{\text{Outdoor lighting total}} \). Therefore, some logical statements must be used to determine what the overall savings value is. The pseudocode below shows how the logic works for this case.

\#BEGIN PSEUDOCODE
   IF Sunny_Nights > Outdoor_Light_Total
      Outdoor_Light_Total = Sunny_Nights
   ELSE
      Pass
   #if ‘Sunny Nights’ is not greater than the Outdoor lighting total from ‘CFLs Outside’ and ‘Afraid of the Dark’, #then the Outdoor lighting total remains the same.
   #END PSEUDOCODE

The final total for the lighting end-use, both indoor and outdoor, can then be summed using Equation 4.5. The lighting categories of indoor and outdoor are assumed to be non-interacting.

\[
\Delta E_{\text{total light}} = \Delta E_{\text{CFLs}} + \Delta E_{\text{LEDs}} + \Delta E_{\text{outdoor light}}
\] \hspace{1cm} \text{Equation 4.16}

### 4.1.3.6 Electronics

The electronics end-use includes all of the smaller devices throughout the home including the TV, computer, entertainment equipment, and various smaller plug loads. Similarly to the lighting end-use, Pins for electronics do not require information from the user. The annual energy savings for each of the electronics Pins can be seen in Table 4.10.

<table>
<thead>
<tr>
<th>Pin Name</th>
<th>Notation</th>
<th>Energy Savings, ( \Delta E ) (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home Computer</td>
<td>( \Delta E_{\text{Home computer}} )</td>
<td>53.55</td>
</tr>
<tr>
<td>Turn off Monitor</td>
<td>( \Delta E_{\text{Turn off monitor}} )</td>
<td>37.57</td>
</tr>
<tr>
<td>DeVampirizeR</td>
<td>( \Delta E_{\text{DeVampirizeR}} )</td>
<td>121.05</td>
</tr>
<tr>
<td>Home Entertainment Center</td>
<td>( \Delta E_{\text{Home entertainment center}} )</td>
<td>146.10</td>
</tr>
<tr>
<td>Office Slayer</td>
<td>( \Delta E_{\text{Office slayer}} )</td>
<td>67.68</td>
</tr>
<tr>
<td>Star Status Electronic</td>
<td>( \Delta E_{\text{Star status electronic}} )</td>
<td>15.83</td>
</tr>
<tr>
<td>Star Status TV</td>
<td>( \Delta E_{\text{Star status TV}} )</td>
<td>99.81</td>
</tr>
</tbody>
</table>
All of the Pins regarding electronics are non-interacting, so they can be summed without regard for diminishing returns using Equation 4.5.

\[
\Delta E_{\text{total-electronic}} = \Delta E_{\text{home computer}} + \Delta E_{\text{Turn off monitor}} \\
+ \Delta E_{\text{Home entertainment center}} + \Delta E_{\text{Devampirizer}} \\
+ \Delta E_{\text{Office Slayer}} + \Delta E_{\text{Star status TV}} + \Delta E_{\text{Star status electronic}}
\]

4.1.3.7 Summing All End-Uses

The end-uses of space heating, cooling, water heating, appliances, lighting, and electronics are non-interacting, and can be summed using Equation 4.5.

\[
\Delta E_{\text{total}} = \Delta E_{\text{total-heat}} + \Delta E_{\text{total-cool}} + \Delta E_{\text{total-WH}} \\
+ \Delta E_{\text{total-appliances}} + \Delta E_{\text{total-lighting}} \\
+ \Delta E_{\text{total-electronic}}
\]

Equation 4.18

Special care must be given to summing end-uses that have different fuel types. However, when a common unit system is applied, this is still possible. For determining cost and GHG savings, the cost and GHG factors must be applied at the level of each Pin, and then aggregated for each end-use using the procedure outlined above for energy savings.

4.1.4 Results for the Average User

This section will explore the case of the “default user”, who is expected to have the input energy parameters of the U.S. average household. The expected savings from the average U.S. household provides an important metric for comparison with other energy audit programs. In addition, the average user case allows for a fair assessment of the variability possible with each input parameter (a sensitivity analysis). The default inputs from Table 3.2 were input into the equations developed in the Appendix – Energy Calculations to determine the annual energy, cost, and greenhouse gas savings that can be expected for an average user.

4.1.4.1 Averaging Fuels

The calculation of energy, cost, and greenhouse gas savings varies greatly depending on the fuel type or system type for the end-uses of space heating and water heating. For example, homes with efficient electric heat pumps use much less energy than similar homes with electric furnaces, therefore the amount of savings they can achieve through reduced space heating consumption is much less. Developing an average value for all fuels is important in cases where information about the user’s fuel type or space heating system type may be incomplete. It also provides a baseline savings amount for the average JouleBug user for comparison purposes.

The method of averaging each of the quantities being measured (energy, cost, and greenhouse gases) is simply the weighted average of each type of fuel or system. The energy, cost, and greenhouse gas savings (in full) for each system type is calculated. The distribution fraction, \( d \), represents the percentage of households throughout the U.S. that utilize a particular fuel or system type. The distribution of fuel and system types was determined from RECS 2005. In order to simplify user input, only the most popular fuel and system types are considered as part of the distribution fraction, eliminating highly uncommon systems. The resulting distribution of space heating systems is found in Figure 8.1 and the distribution of water heating fuels is located in Figure 8.8.
\[ \Delta E_{\text{fuel,avg}} = \frac{\Delta E_{\text{fuel,i}} d_i}{\sum d_i} \]  

Equation 4.19

The weighted average results for cost and greenhouse gases are determined in the same way. For cases where no information is known about the fuel cost, national average fuel costs found in Table 3.3 are utilized. Similarly, if no information about electricity greenhouse gas coefficients exists, the U.S. average from Table 3.5 can be utilized. For the case of the average user, these averages were utilized in Equation 4.20 and Equation 4.21.

\[ \Delta \text{Cost}_{\text{fuel,avg}} = \frac{\sum \Delta \text{Cost}_{\text{fuel,i}} d_i}{\sum d_i} \]  

Equation 4.20

\[ \Delta \text{GHG}_{\text{fuel,avg}} = \frac{\Delta \text{GHG}_{\text{fuel,i}} d_i}{\sum d_i} \]  

Equation 4.21

This weighted average savings is determined for each Pin that involves space heating or water heating end uses. As mentioned above, this method of weighting fuels is necessary when no information is known about a user’s heating or water heating system, and in the case of the average user.

### 4.1.4.2 Breakdown Savings by End Use

This section will give the results for an average user’s energy, cost, and greenhouse gas savings annually. To calculate the total savings for an average user, the energy, cost, and greenhouse gas savings for each Pin was computed using the default assumptions provided in Table 3.2. The time period given is the typical 8760 hour year, with the user having earned every Pin before the time period began (the full savings value for each Pin is awarded). Pins with multiple fuels types such as space heating and water heating were averaged using the procedure outlined in the previous section, utilizing the national average cost and greenhouse gas factors for each fuel. The total savings for each end use was then calculated using the diminishing returns formulas in Section 4.1.3. Finally, the end use savings was summed to give the resulting savings for the entire home. The calculated energy, cost, and GHG savings for an average user can be seen in Table 4.11.

<table>
<thead>
<tr>
<th>End Use</th>
<th>Energy Savings (kWh)</th>
<th>Cost Savings (USD)</th>
<th>GHG Savings (kg CO₂-eq)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space Heating</td>
<td>4493</td>
<td>$ 263.32</td>
<td>1288</td>
</tr>
<tr>
<td>Cooling</td>
<td>1203</td>
<td>$ 138.78</td>
<td>852</td>
</tr>
<tr>
<td>Water Heating</td>
<td>1608</td>
<td>$ 102.18</td>
<td>572</td>
</tr>
<tr>
<td>Lighting</td>
<td>471</td>
<td>$ 55.20</td>
<td>339</td>
</tr>
<tr>
<td>Electronics</td>
<td>540</td>
<td>$ 62.33</td>
<td>383</td>
</tr>
<tr>
<td>Appliances</td>
<td>273</td>
<td>$ 31.55</td>
<td>194</td>
</tr>
<tr>
<td>Total</td>
<td>8588</td>
<td>$ 653.37</td>
<td>3627</td>
</tr>
</tbody>
</table>

The amount of energy savings for an average user completing every action in JouleBug to the fullest extent is around $650. Lawrence Berkeley National Laboratory (LBNL) estimates that the average household spends around $2,100 per year on energy (Lawrence Berkeley National Laboratory, 2012b). This results in a savings of 31% overall on energy costs by accomplishing all of the tasks outlined in Table 3.1. While this estimate is certainly very high, it is not unreasonable, as LBNL also estimates that efficient homes can save well over 50% of the cost of energy compared to typical homes (Lawrence Berkeley National Laboratory, 2012b). However, LBNL’s estimate would likely include capital-intensive projects to improve the building shell and HVAC systems, which were not addressed in JouleBug’s behavioral-focused energy saving actions.
The following figures illustrate the results from Table 4.11 by showing the percentage of energy, cost, and GHG savings that can be attributed to each end-use.

![Energy usage by end use](image)

**Figure 4.1** Energy usage by end use.

![Cost by end use](image)

**Figure 4.2** Cost by end use.

![Greenhouse gases by end use](image)

**Figure 4.3** Greenhouse gases by end use.

As the figures show, the shares of water heating and space heating end uses dominate the total energy end use, however, make up smaller (although considerable) shares of the cost and greenhouse gas breakdown. Water heating and space heating include the weighted average of all fuels, including combustion fossil fuels which utilize considerably more end-use energy than electricity. For the typical residential consumer, electricity is much more expensive per unit energy (kWh), and creates more greenhouse gases per kWh than fuels such as natural gas. This is due to the high percentage of coal-fired electricity generation, and the considerable losses from the generation and distribution of electricity. An examination of the unit cost of energy and greenhouse gas coefficients from Sections 3.1.5 and 3.1.6 reinforces this fact. This results in the fraction of space heating and water heating being smaller for cost and GHG savings compared to energy savings.
4.1.4.3 Variability Analysis

This section will determine which parameters from Table 3.2 can cause the most significant changes in the final result. This helps provide a “tolerance” to the result in the case that one of the parameters is unknown or is inaccurately entered by a user. A sensitivity analysis also helps to determine which parameters are most important in achieving an accurate result, which can affect the layout and design of the user input areas. Completing important parameters should be strongly encouraged by the user interface and design of the application, while encouragement to fill in inputs to less significant parameters can be more subtle.

This analysis was completed by entering reasonable “maximum” or “minimum” values into the energy calculation model that was developed. The inputs to the model can be seen in tables in Appendix – Parameter Variability Analysis. These inputs are considered reasonable bounds to each of the parameters and represent what annual savings the vast majority of the users will experience (assuming they have fully completed all energy saving actions suggested). One parameter at a time was changed in this analysis. No attempt to evaluate the cumulative effect of multiple parameters was made. This analysis is not intended to illustrate the most extreme cases or put any sort of maximum or minimum range on the energy savings that can be achieved. The cumulative effect of parameters and the interaction between parameters makes it impossible to determine this from changing a single variable. For this reason, this analysis is intended to explore a range of likely possible variations only for reasons of user interface design. Determining the absolute maximum or minimum energy savings that could be reasonably achieved using this energy calculation model is work for a future study.

The figures below show the range of variability for energy, cost, and GHG savings. The parameters are ranked left to right in order of amount of total variability.

![Figure 4.4 Variability of energy savings with input parameters.](image-url)
Judging from Figure 4.4 through Figure 4.6, the most important parameters are Home Size, Climate, Electricity Price, Electric Carbon Factor, Space Heating System Type, Number of People, and Window Type. The resulting total variability for each of the parameters can be seen in the Appendix – Parameter Variability Analysis.
4.2 Proposed Design Components

This section will propose some guidelines for utilizing the energy models from Section 4.1 within a mobile application such as JouleBug. The design components of a feedback system as outlined in Section 2.2.3 will be examined in the context of JouleBug and the derived energy models in particular. Suggestions of how the energy models may be used in the context of these design components will be provided, relating to the specific case of JouleBug. A comprehensive design of the feedback system will not be attempted in this project but may be a topic for future study.

4.2.1 Frequency

How often feedback is presented, or frequency, is an important factor to determine when designing an effective feedback system. Studies (Fischer, 2008; van Raaij & Verhallen, 1983) suggest that providing feedback that is at a frequency of daily or more is highly effective. JouleBug is designed for the user to interact with it several times per day, whenever an energy-saving action is possible. However, the frequency that is possible to provide is related to the amount of data that is gathered, and nearly all utilities provide energy bills only on a monthly basis. Thus, the energy modeling calculations can be most effectively utilized at two frequency levels: through custom Pin Stats, and through the Energy Graph.

When a user completes an energy-saving action (Buzzes a Pin), the energy model can provide an estimate of the annual energy savings for completing the action through a customized Pin Stat. This measure of savings will be generated utilizing the user's energy parameters, and is immediately visible after the user completes the action. This granular, real-time feedback should be highly effective in providing encouragement for the user to continue to play and save energy.

Additionally, the energy modeling calculations can be utilized in conjunction with the energy graph, as a form of “estimated feedback” or “enhanced billing”. Providing a summary of the savings achieved during the past month's billing cycle will allow the user to track larger trends in space heating and cooling energy usage, as suggested by Darby (Darby, 2006).

4.2.2 Data Granularity

The granularity of the feedback provided is most dependent on what data is provided. Traditional utility bills and even enhanced billing techniques provide no granularity: they rely on an aggregate bill over a month time span. However, the nature of the energy models derived for this project allow the savings estimates to be broken down spatially (by end-use, or even by Pin) or temporally (days, hours, minutes, etc).

Spatial granularity of energy savings is a real possibility for JouleBug with the energy models provided. Each energy-saving action is represented by a unique Pin, which allows information granularity not possible in most whole-building simulation tools. Additionally, the model provides a breakdown of end-uses including space heating, cooling, water heating, appliance, lighting, and electronics. Although the actual energy usage (from the bill) is not possible to disaggregate in this manner, the estimated savings calculations could be used to provide spatial granularity down to end-uses or Pins.

Temporal granularity past the monthly level is not recommended for Joulebug, due to the nature of the estimates being used. Many of the assumptions used in the energy modeling calculations are long-term averages, which cannot be utilized in small time increments. In time increments smaller than a billing cycle, weather patterns play a significant role, as does user behavior patterns. The difference week-to-week or day-to-day in weather and user behavior can result in very significant differences in energy consumption (and savings) levels. Consider if the energy models were used to predict savings day-to-day. One potential scenario is that a user takes a sick day from work and stayed home. The thermostat setting, lighting consumption, and hot water consumption would all be at greater levels during that day. The savings would be expected to drop; however, the energy model has no way to adjust for this deviation from the average case. The savings estimate would remain the same throughout the week and would not
reflect the actual situation, confusing the user who is expecting an accurate daily measure of his energy savings. However, when examining an entire month, the single day of increased consumption becomes insignificant, and the relative accuracy of the model’s estimate increases. Small time increments are not possible because the energy models are only estimations and do not rely on real-time granular data.

4.2.3 Measurement Unit

Many measurement units are possible for display of feedback information, including energy, cost, and GHG emissions. The energy modeling system created in this project allows for the following units to be calculated: kWh for energy, $ (USD) for cost, or kgCO₂eq for GHG. Existing research shows that the motivation of the user can be very important when choosing a measurement unit (Petkov, Köbler, Foth, & Kramar, 2011; Fischer, 2008). The ability to switch between various units will appeal to the largest amount of potential users. As cost has been shown to be preferred in many cases, it should be the default measurement unit, with a built-in option to toggle between the three measurement types. Designing for multiple units is the best solution until more research can be conducted on this topic.

4.2.4 Recommending Actions

Recommending actions to the user can be a compliment to feedback and encourages goal-setting. The energy model that has been developed makes it possible to recommend actions to the user based on the impact of those actions, so that the actions can be taken at the appropriate time. Because the energy savings calculations are estimates of savings that do not require past data, the savings are the same for predicting past savings amounts or future ones. Utilizing the TMY3 data set, which stands for a Typical Meteorological Year, it is possible to estimate the average savings over any time period regardless of whether it is in the past or the future. This is a powerful advantage of the method of energy modeling utilized in this project.

Using the TMY3 weather data and the average length of time (Δt) of past billing cycles, it would be possible to calculate the estimated savings for each Pin during any month’s billing cycle. When each utility bill is issued, the user would receive a “shopping list” of recommended actions for the next month. The Pins that will save the most cost, energy and GHG for the next month would be ranked and suggested to the user. In winter months, Pins involving space heating consumption will dominate the list, and in summer, cooling Pins will dominate, with Pins for base load end-uses becoming predominate during spring and fall. A recommended action can “trigger” a behavior and encourage behavioral change better than simple feedback alone.

4.2.5 Comparisons

Comparisons can be an extremely influential component of a feedback design. As mentioned in Section 2.2.3, comparisons may be either temporal or social. Temporal comparison – comparing a user to his or her past performance – appears to be very influential and widely accepted by many cultures. As JouleBug already incorporates the feature of the Energy Graph, it can be easy to integrate temporal comparisons on this graph by displaying the estimated energy savings a user is achieving (as calculated by the energy models). As the user earns Pins and Badges, the amount of savings will continually increase until all Pins are achieved. One noted drawback of this system is that once a certain threshold of savings is reached (all Pins and Badges earned), it will not be possible to show further improvement through temporal feedback.

Social comparison has received mixed reaction in the literature. Research has found that the effectiveness of social comparison is strongly linked to the validity (or perception of validity) of the comparison group. Consumers who perceived the comparison group as not representative of their own situation tended to have a negative reaction to social comparison. Additionally, normative comparison seems to elicit a “rebound effect” which can cause a low energy consumer to increase consumption to become closer to the average. However, other applications (notably OPower) have had success in comparing utility bills between groups of users using injunctive social norms.

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The energy modeling system designed for JouleBug only estimates the potential savings of the user, and does not analyze their utility bill. However, comparison of savings (based on Pins earned, calculated by the energy models) could take place within groups of users. The energy parameter information gathered from Table 3.2, including home size, fuel type, and location can be used to accurately group users for effective social comparisons within a local group. Injunctive norms, which would refer to the top tier of JouleBug users as the desired behavior, will be the most effective in motivating users. The comparison information can be distributed with the recommended action along with the monthly utility bill, stating how much money, energy, and GHG was saved by the “top JouleBug users like you”. Care must be taken to ensure that users understand that the savings is an estimate only. The addition of these injunctive normative comparisons based on energy, cost, or GHG savings could have a strong motivational impact on the JouleBug user base, and would complement the current competitive aspects of the app.

5 Discussion

5.1 Summary and Implications of Work Completed

JouleBug is a playful, social smartphone application that encourages users to complete 38 energy saving actions (found in Table 3.1). These actions – called Pins in the context of the app – include simple behavioral changes ranging from habitual behaviors to larger purchase decisions. Research shows that energy feedback systems can be used to create behavioral change with regards to energy usage, especially in a residential setting. However, the design of a feedback system is critical to its effectiveness, so this thesis project was carried out to develop both the engineering calculations and possible applications of an energy feedback system specific to the JouleBug mobile application.

The methodology behind this feedback system is founded on energy modeling principles. Typical energy modeling systems require extensive amounts of input information, but in this case, only 13 input parameters were utilized. The inputs selected (visible in Table 3.2) are easily obtainable from a typical residential energy consumer. Requiring few inputs increases the likelihood that a user will supply the information and eliminates the need for long surveys that could be annoying or cumbersome in the context of a playful mobile app. Keeping in mind these 13 inputs, mathematical energy models were developed for each of the 38 energy saving actions in the application. Empirical data from reputable sources including Energy Star, the RECS survey, TMY3 weather data, and ASHRAE was used to develop forward-approach energy models. The resulting models utilize the user’s 13 energy parameters to calculate the energy savings for each of the 38 actions in kWh/yr.

Each of the Pin models for energy savings was then grouped into an end-use category: space heating, cooling, water heating, appliances, lighting, and electronics. As the Pin models were developed in terms of annual energy savings (kWh/yr), a procedure was developed to break this energy savings down over a relevant time period, Δt. Many applications of energy feedback rely on a billing cycle (typically one month). Energy consumption for baseload end-uses (water heating, appliances, lighting, and electronics) does not vary significantly between months and can be divided and extrapolated as necessary to fit a billing cycle. Space heating and cooling Pins utilize TMY3 weather data, which can be summed according to start and end dates of the billing cycle. The date of a user’s completion of the Pin is also factored into the calculation of the energy savings.

Once the energy savings for the time period Δt is determined for each Pin, a procedure, outlined in Section 4.1.3 was utilized to aggregate the Pins within their end-uses. Sub-categories within each end-use were created to isolate interacting Pins and ensure that the total savings amount accounts for diminishing returns and overlapping actions. Factors for cost savings in U.S. dollars and GHG savings in kg-CO$_2$eq were utilized to convert the energy savings from kWh into units that could be more meaningful to consumers.
After the energy models for each Pin and the aggregation procedures were created, values for an average user were input into the models to determine energy, cost, and GHG savings. The results determined that an average JouleBug user who completed every action required could achieve a savings of $660 (or 31% cost savings) and 3625 kgCO$_2$eq per year. The majority of the savings was found in the space heating and cooling end uses. To further extend knowledge of the energy models, reasonable maximum and minimum values for each of the 13 input energy parameters were tested to determine the variability of the final result. It was determined that the parameters of climate, home size, electricity price, electric carbon factor, space heating system type, number of occupants, and window type had the largest effects on the final amount of energy, cost, and GHG savings.

After development of the energy models, the feedback design components of frequency, measurement unit, data granularity, recommending action, and comparison were examined. Guidelines for using the energy models to fulfill each of these design components were developed in Section 4.2. Suggestions of possible uses for the models within the guidelines were also provided. The models could provide customized predictions of energy savings before actions take place, to help individuals set goals and prioritize. Graphical feedback could be provided through a user’s energy bill, comparing the total predicted savings with the actual expenditures. The energy savings calculations could be used to recommend actions at appropriate times (cooling in summer, heating in winter), serving as a “trigger” for behavioral change with each new bill received. Finally, the energy savings calculation could be used with injunctive normative comparison techniques to motivate users.

5.2 Limitations and Future Work

The energy models developed in this report are intended to be used for energy-information feedback to residential energy consumers. Although the energy models developed in this report are tied specifically to the energy saving actions outlined in Table 3.1, the methodology used to develop these models can be utilized in similar projects that may require estimates of customized energy savings for individual actions, based on limited user input. An important limitation to note is that the mathematical energy models for each savings measure are estimates only, based on a limited amount of input data. These models are not intended to replace energy simulation programs for purposes of design or verification of energy saving measures. The models are intended to provide savings estimates of individual energy conservation measures when actual end-use consumption data is not available (as is the case for most residential cases).

A potential area of future research is to apply actual end-use residential energy consumption data (gathered from smart meters, or granularly within the home) to develop a measure of accuracy for the predictive models developed in this report. Additionally, such data can be utilized to provide continuous improvements to the predictive savings models, as outlined in (Polly, Kruis, & Roberts, 2011).

As discussed in Section 1.4, there are inherent limitations of this work due to its focused nature. One of the most notable limitations is the focus of this research solely on energy consumers in the U.S. The direct results of this work cannot be translated to other countries, as the differences in consumer behaviors, energy parameters, climate, prices, etc. make each country a unique case when considering residential energy usage. Future research may use the basic procedures and methodology outlined in the report to translate the results to other cultural and geographical contexts.

Additionally, the energy models developed rely on very specific assumptions regarding the energy saving action being undertaken. Therefore, it is not possible to alter the energy saving action and expect the models to still be applicable. Future work may add additional energy saving actions to the models developed or broaden the scope of the existing energy saving actions.

This project applied the feedback design components, including frequency, data granularity, recommended actions, and comparisons (as described in Section 2.2.3) to the design of the JouleBug mobile smartphone application. The specific designs selected for this project are unique to JouleBug and were developed
based on the app’s existing structure and desired user experience. More research on how to effectively use the feedback design components for mobile applications is needed.

Future work necessary with respect to JouleBug includes the graphical design and implementation of the selected feedback components into the mobile application. The mere selection of feedback components is only a small step toward a fully designed system, and many technical and graphical details must be considered before the application is fully functional. Once the development is finished, user surveys, expert design reviews, and repeated testing are necessary to verify that the design is indeed effective.

6 Conclusion

To combat rising energy consumption, a novel and effective strategy is needed to motivate consumers to reduce energy consumption. JouleBug is a mobile smartphone application that aims to create behavioral change by making energy conservation and efficiency engaging. One of the key components of JouleBug is an energy feedback system which relies on mathematical energy models created in this report to provide the information and motivation required to trigger energy saving behaviors. The mathematical energy models require only minimal information from the user and utilize fundamental engineering methods to estimate energy savings for 38 energy saving actions. In conjunction with a user's actions, the models can be utilized to provide graphical energy feedback on a monthly utility bill that tracks a user's progress over time and can be compared with other similar users. The mathematical calculation models can also generate a list of customized energy saving actions to serve as “triggers” for users. Although significant development is still required to implement the energy feedback system into JouleBug, the foundations of an effective design have been developed. The potential for reducing environmental impact through feedback of energy information is enormous, and this project represents a small step on the road to an environmentally sustainable future.
7 Bibliography


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8 Appendix – Energy Calculations

This appendix contains the detailed assumptions, references and calculation procedure to determine the energy savings for each of the Pins (actions) outlined in Table 3.1. These calculations will outline the general procedure utilized to arrive at the result. The calculations will be in terms of the parameters given in Table 3.2. For actions involving heating and cooling, the TMY3 weather data will be utilized, often in conjunction with the calculation of degree-days as outlined in Section 3.1.4.1.

All savings calculations are calculated for a year (annual savings), in units of kWh. The ‘energy savings’ calculated is the savings the home dweller would expect to see on their utility bill over the course of a year (the meterable energy savings). This is not a calculation of primary energy.

The appendix is organized by each of the major end-uses, including space heating, cooling, water heating, lighting, electronics, and appliances. The section of “windows” is also included following space heating and cooling, as there are many additional assumptions that are involved with calculation of window-related energy actions that can affect both space heating and cooling end-uses. Each end-use section will begin by outlining the general assumptions made for all actions. Then each Pin (action) will be outlined underneath the most appropriate end-use (with both space heating and cooling actions involving windows under the “windows” section). Each Pin will have its own unique additional assumptions, followed by the calculation procedure and the final resulting equations.

8.1 Space Heating

Space heating is a major (often the largest) energy end-use in the home. The diversity of fuels and system types used for heating homes makes it a difficult end-use to analyze, but the enormous savings potential makes it an ideal target for energy conservation measures. The energy savings for space heating measures are often expressed as a percentage of space heating energy consumption, so it is important to know the baseline consumption of the user’s home. Space heating energy consumption is dependent on the following factors:

- Home size
- Type of space heating equipment/distribution system (furnace, boiler, electric radiators, etc)
- Space heating fuel
- Efficiency of space heating system
- Climate
- Indoor temperature setpoint
- Home’s heat loss coefficient (U-value)
- Leakiness of the home or amount of air infiltration, often related to home age

The factors of home size, climate, space heating fuel, type of space heating equipment, and home age are easily obtainable from the user. The home’s insulation, leakiness, and efficiency of the space heating system must be inferred from this data, as most homeowners (or renters) will be unlikely to provide accurate estimates of these values.

8.1.1 Space Heating System

The specifics of the space heating system strongly affect how much savings the user will experience. The space heating energy and cost depends on two components: the space heating fuel and the space heating equipment type. These two components make up the space heating system.

The space heating fuel refers to the input to the space heating system. There are four principle types of space heating fuel used in the U.S.: electricity, natural gas, fuel oil, and Liquefied Petroleum Gas (LPG, or propane). The space heating fuel used affects not only the price that a user pays for energy and the environmental impact of space heating, but also the efficiency of the system. The space heating
equipment refers to the configuration of the space heating unit itself, encompassing the type of
distribution medium and the operation of the system. The most common type of space heating
equipment is the warm-air furnace, which can be fueled by any of the fuels above. This centralized space
heating system distributes warm air throughout the house through ducts. Another common type of space
heating equipment is the hot-water boiler, which is primarily fueled by natural gas, fuel oil, or LPG. The
boiler heats the water through combustion of the fuel and distributes the hot water or steam throughout
the home in pipes which feed radiators. This system is most common in colder climates where the
outdoor air temperatures drop below freezing for extended days during winter. Several types of space
heating systems are solely fueled by electricity. Electric heat pumps (most commonly air-to air) are used in
warmer climates and operate much more efficiently than electric warm-air furnaces. However, they often
have a backup heating unit, normally an electric coil similar to an electric furnace. Electrical resistance
units built into the walls – commonly referred to as “baseboard heating” – are another type of space
heating system that is common in older homes. The table below outlines the various combinations of
space heating systems.

Table 8.1 Space heating system types and distribution percentages (U.S. Energy Information
Administration, 2009).

<table>
<thead>
<tr>
<th>Fuel</th>
<th>Equipment Type</th>
<th>Number of Households (millions)</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Gas</td>
<td>Central Furnace</td>
<td>44.7</td>
<td>41%</td>
</tr>
<tr>
<td></td>
<td>Steam or Hot Water (boiler)</td>
<td>8.2</td>
<td>7%</td>
</tr>
<tr>
<td>Electricity</td>
<td>Central Furnace</td>
<td>16.0</td>
<td>15%</td>
</tr>
<tr>
<td></td>
<td>Heat Pump</td>
<td>9.2</td>
<td>8%</td>
</tr>
<tr>
<td></td>
<td>Built-in Electric Units (baseboard)</td>
<td>5.0</td>
<td>5%</td>
</tr>
<tr>
<td>Fuel Oil</td>
<td>Steam or Hot Water (boiler)</td>
<td>4.7</td>
<td>4%</td>
</tr>
<tr>
<td></td>
<td>Central Furnace</td>
<td>2.8</td>
<td>3%</td>
</tr>
<tr>
<td>Propane (LPG)</td>
<td>Central Furnace</td>
<td>4.1</td>
<td>4%</td>
</tr>
<tr>
<td>Other Heating Systems (various)</td>
<td>15.2</td>
<td>14%</td>
<td></td>
</tr>
<tr>
<td>No Heating System</td>
<td></td>
<td>1.2</td>
<td>1%</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>111.1</td>
<td>100%</td>
</tr>
</tbody>
</table>

The category “other heating systems” includes a diversity of less common fuel types including: wood,
kerosene, solar, coal, and district steam. It also includes other types of equipment of any fuel type
including portable space heaters, fireplaces, heating stoves, and geothermal heat pumps. As the operation
of these systems is very diverse and the amount of people who have these systems is small, they will be
omitted from this analysis. The following figure shows the percentage of households that have the most
common types of systems, which will be selectable choices for JouleBug and are fully analyzed below.
8.1.2 Heating Degree Days

Heating degree days (based on 65 °F) as calculated in Section 3.1.4.1 are used to estimate the relationship between space heating consumption and climate. The space heating energy consumption is assumed to scale linearly with heating degree days, which is a good assumption for warm-air furnace systems (Fels M., 1986). Electric heat pumps have a more complex relationship with outdoor temperature, as the efficiency of the heat pump drops as outdoor temperature decreases, and a backup system is used for a certain percentage of the year. Therefore, the results for electric heat pump systems are expected to be rather inaccurate especially when used in short time periods, and in locations with extreme weather.

8.1.3 Correlating Space Heating and Home Size

The space heating energy consumption is affected by the home size. As the size of a home increases, the surface area that experiences heat transfer (walls, windows, roof, etc) also increases, causing the home to require more space heating energy to maintain a comfortable indoor temperature. An analysis of the trends produced by the relationship between heated square footage and the energy consumed per degree day fit a logarithmic pattern, where ln(HomeSize) can be used to predict the space heating energy required over a year.

8.1.3.1 Methodology

The RECS 2005 survey data was utilized to predict the amount of space heating energy that is being used in the home (U.S. Energy Information Administration, 2009). As the RECS survey data is weighted (NWEIGHT) by the number of homes that are expected to fall close to the particular survey point, the method that is most appropriate for drawing a correlation is Weighted Least Squares (WLS) analysis. The RECS variables that are to be used in the correlation with space heating energy consumption are heated home area (TOTHSQFT), climate (HDD65), and type of space heating fuel (FUELHEAT) and space heating equipment type (EQUIPM) (U.S. Energy Information Administration, 2009).

To evaluate the survey data, the entire dataset was separated by space heating system type (from Figure 8.1). There were several records where space heating consumption was non-zero, yet the heating degree days or heated square footage was zero. These data points were considered as survey errors or outliers so records with zero heating degree days or zero heated square footage were discarded.

The data had to go through some minimal amount of pre-processing. The data technique known as “data binning” was utilized to reduce noise in the data, as well as to simplify the entry of user data. Data binning is a discretization technique that can be used to reduce noise in a dataset as well as to prepare it for processing (Nisbet, Elder, & Miner, 2009). As there are a multitude of factors that influence the space...
heating energy consumption, binning the data isolates the square footage and eliminates the effect of the other variables which are not relevant to this project. The bins were based on the amount of heated square footage of the home, in steps of 500 sqft up to 4000 sqft, which are the bins utilized by the RECS summary data (U.S. Energy Information Administration, 2009).

Bin sizes: \{(0-500),[500-1000),[1000-1500),[1500-2000),[2000-2500),[2500-3000),[3000-4000),[4000<]\}

Next, a weighted least squares analysis will be performed to develop linear trendlines relating space heating energy usage per degree day (kWh/HDD65) with ln(HomeSize). In general, the form of the linear equation is (Holman, 2001):

\[
y = ax + b
\]

Equation 8.1

A distinct equation will be developed for each type of space heating system (as this is a non-numeric parameter). The variable ln(HomeSize) will be used as a predictive variable \(x\) in the weighted linear regression analysis to predict the amount of energy that is used for space heating in the home per degree day \(y\). The equation (for each type of heating unit) will take the form of:

\[
\frac{E_{\text{heat,fuel consumed}}}{HDD65} = a \cdot \ln (\text{HomeSize}) + b
\]

Equation 8.2

Where \(a\) and \(b\) are coefficients determined from the regression analysis.

The weighting process controls the error so that the smallest error is present for the highest weighted data points. This ensures that the majority of homes have the smallest error possible. To perform the least squares analysis, the following equations are utilized, adapted from Holman to include a weighted term (Holman, 2001).

\[
a = \frac{\sum w_i(\sum w_i x_i y_i) - (\sum w_i x_i)(\sum w_i y_i)}{(\sum w_i)(\sum w_i x_i^2) - (\sum w_i x_i)^2}
\]

Equation 8.3

\[
b = \frac{\sum w_i x_i y_i)(\sum w_i x_i^2) - (\sum w_i x_i)(\sum w_i y_i)}{(\sum w_i)(\sum w_i x_i^2) - (\sum w_i x_i)^2}
\]

Equation 8.4

Where \(y_i\) refers to binned values of space heating energy per degree day (kWh/HDD65), \(x_i\) refers to binned values of ln(HomeSize), and \(w_i\) is the binned weighting of the observed values.

**8.1.3.2 Correlations Developed**

The following figures show these derived relationships between space heating energy consumption and floor area for the major fuel types based on RECS 2005 data (U.S. Energy Information Administration, 2009). The size of the bubble indicates the number of homes (the weighting) that fall into the applicable bin.
Figure 8.2 Space heating consumption trendlines, natural gas.

Figure 8.3 Space heating consumption trendlines, electricity.
To measure how well the trendline fits the data, the correlation coefficient $r$ is calculated. A correlation coefficient of $r=1.0$ indicates a good fit of the data, while $r=0$ indicates a poor fit with a significant amount of scatter. The correlation coefficient also may be calculated as a coefficient of determination, or $r^2$ value (Holman, 2001). The coefficient of determination is based on the weighted mean $y_m$ which is computed as follows:

$$y_m = \frac{\sum w_i y_i}{\sum w_i} \quad \text{Equation 8.5}$$

The $r^2$ value is dependent on the following equations derived from Holman, but adjusted for the weighted case (Holman, 2001).

$$\sigma_y^2 = \frac{\sum (y_i - y_m)^2}{\sum w_i} \quad \text{Equation 8.6}$$

$$\sigma_{yx}^2 = \frac{\sum (y_i - y_{ic})^2}{\sum w_i} \quad \text{Equation 8.7}$$

Where $y_i$ is the actual surveyed values of space heating energy/degree day, $y_{ic}$ are the values computed from the correlation, and $w_i$ is the weighting. The $r^2$ value is determined from the quantities obtained from the above equations.

$$r^2_{\text{weighted}} = \frac{\sigma_y^2 - \sigma_{yx}^2}{\sigma_y^2} \quad \text{Equation 8.8}$$

The summary of the regression coefficients ($a$ and $b$) as well as the weight-adjusted $r^2$ value for space heating can be seen below in Table 8.2.
Table 8.2 Space heating correlation coefficients and weighted $r^2$ value.

<table>
<thead>
<tr>
<th>Fuel</th>
<th>Equipment</th>
<th>a</th>
<th>b</th>
<th>Weighted-$r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Gas</td>
<td>Central Furnace</td>
<td>0.575</td>
<td>-1.070</td>
<td>0.879</td>
</tr>
<tr>
<td></td>
<td>Steam or Hot Water</td>
<td>1.343</td>
<td>-5.206</td>
<td>0.935</td>
</tr>
<tr>
<td>Electricity</td>
<td>Central Furnace</td>
<td>0.295</td>
<td>-1.025</td>
<td>0.904</td>
</tr>
<tr>
<td></td>
<td>Heat Pump</td>
<td>0.223</td>
<td>-0.857</td>
<td>0.978</td>
</tr>
<tr>
<td></td>
<td>Built-in Electric Units</td>
<td>0.140</td>
<td>-0.268</td>
<td>0.830</td>
</tr>
<tr>
<td>Fuel Oil</td>
<td>Steam or Hot Water</td>
<td>0.415</td>
<td>1.827</td>
<td>0.289</td>
</tr>
<tr>
<td></td>
<td>Furnace</td>
<td>0.049</td>
<td>4.138</td>
<td>0.004</td>
</tr>
<tr>
<td>Propane (LPG)</td>
<td>Furnace</td>
<td>-0.092</td>
<td>4.035</td>
<td>0.018</td>
</tr>
</tbody>
</table>

The high value for the coefficient of determination (weighted-$r^2 > 0.8$) for natural gas and electrically fueled space heating systems indicates that there is a high correlation between space heating energy consumption and $\ln(\text{HomeSize})$. However, it should be noted that this analysis ignores all other factors (including user behavior), as there can be extreme variation of the energy consumption within each bin. As mentioned in Section 2.1, user behavior can be an extremely significant factor in determining energy consumption. However, the value of space heating energy consumed for an average U.S. resident can be approximated through this method. The user’s behavior while using JouleBug (what Pins they earn and when) influences the final savings calculations over time.

The correlations are extremely poor to non-existent for fuel oil and LPG. These fuels are not only less common, but they suffer from a unique problem in that they are non-meterable fuels. Fuel oil and LPG (propane) are delivered only periodically, making it very difficult to determine what the consumption level is for any set period of time (such as a month, or even a year). Additionally, fuel oil and LPG are delivered by a multitude of smaller, locally-owned providers rather than larger utilities as is the case for natural gas and electricity. The RECS energy consumption levels are determined by a modeling methodology utilizing data from the homeowner and also their energy supplier. It is quite likely that the energy consumption data provided for homes utilizing fuel oil and LPG is substantially less accurate than natural gas and electricity. In addition, the smaller number of homes using these fuels amplifies the effect of inaccurate data. More about the RECS methodology can be viewed at their website (U.S. Energy Information Administration, 2011c).

### 8.1.3.3 Data Summary

The following tables summarize the average bin values for the pertinent variables as well as the weighting and sample counts. A calculation of percent difference between the binned survey data and the regression model is also included, which measures how well the correlation fits with the binned dataset. The equation for percent difference can be seen below.

$$\%\text{diff} = \frac{|y_t - f_t|}{0.5 \cdot (y_t + f_t)} \quad \text{Equation 8.9}$$
Table 8.3 Data summary for natural gas furnaces.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Heating Energy (kWh)</th>
<th>HDD65</th>
<th>kWh per HDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>367</td>
<td>10488</td>
<td>4131</td>
<td>2.486</td>
<td>55</td>
<td>1.4</td>
<td>6.7%</td>
</tr>
<tr>
<td>500 to 999</td>
<td>788</td>
<td>11564</td>
<td>4413</td>
<td>2.676</td>
<td>345</td>
<td>8.9</td>
<td>3.3%</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1233</td>
<td>12745</td>
<td>4221</td>
<td>3.069</td>
<td>417</td>
<td>10.7</td>
<td>1.5%</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1749</td>
<td>13724</td>
<td>4295</td>
<td>3.301</td>
<td>306</td>
<td>8.1</td>
<td>2.4%</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2232</td>
<td>15119</td>
<td>4809</td>
<td>3.265</td>
<td>207</td>
<td>5.3</td>
<td>3.0%</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2720</td>
<td>14961</td>
<td>4551</td>
<td>3.299</td>
<td>147</td>
<td>4.1</td>
<td>5.3%</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>3233</td>
<td>18816</td>
<td>5017</td>
<td>3.993</td>
<td>74</td>
<td>2.0</td>
<td>11.0%</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3749</td>
<td>20305</td>
<td>5694</td>
<td>3.683</td>
<td>44</td>
<td>1.1</td>
<td>0.6%</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>5295</td>
<td>18766</td>
<td>5087</td>
<td>3.802</td>
<td>100</td>
<td>2.7</td>
<td>1.5%</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>1872</td>
<td>13940</td>
<td>4497</td>
<td>3.162</td>
<td>1695</td>
<td>44.3</td>
<td>3.1%</td>
</tr>
</tbody>
</table>

Table 8.4 Data summary for natural gas boilers.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Heating Energy (kWh)</th>
<th>HDD65</th>
<th>kWh per HDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>345</td>
<td>15663</td>
<td>5152</td>
<td>3.152</td>
<td>27</td>
<td>0.7</td>
<td>17.5%</td>
</tr>
<tr>
<td>500 to 999</td>
<td>716</td>
<td>17934</td>
<td>5413</td>
<td>3.446</td>
<td>104</td>
<td>2.5</td>
<td>5.1%</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1234</td>
<td>23051</td>
<td>5332</td>
<td>4.329</td>
<td>83</td>
<td>1.9</td>
<td>0.6%</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1703</td>
<td>26360</td>
<td>5559</td>
<td>4.763</td>
<td>50</td>
<td>1.0</td>
<td>0.5%</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2242</td>
<td>28920</td>
<td>5893</td>
<td>4.909</td>
<td>28</td>
<td>0.6</td>
<td>4.9%</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2705</td>
<td>29395</td>
<td>5284</td>
<td>5.836</td>
<td>19</td>
<td>0.5</td>
<td>7.6%</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>3274</td>
<td>31335</td>
<td>5585</td>
<td>5.685</td>
<td>12</td>
<td>0.3</td>
<td>0.3%</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3747</td>
<td>36620</td>
<td>5810</td>
<td>6.317</td>
<td>13</td>
<td>0.3</td>
<td>7.7%</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>4621</td>
<td>36440</td>
<td>6046</td>
<td>6.039</td>
<td>14</td>
<td>0.3</td>
<td>1.5%</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>1510</td>
<td>23352</td>
<td>5461</td>
<td>4.329</td>
<td>350</td>
<td>8.0</td>
<td>4.4%</td>
</tr>
</tbody>
</table>
### Table 8.5 Data summary for electric furnaces.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Heating Energy (kWh)</th>
<th>HDD65 kWh per HDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>399</td>
<td>1595</td>
<td>2652</td>
<td>0.724</td>
<td>10</td>
<td>0.8</td>
</tr>
<tr>
<td>500 to 999</td>
<td>767</td>
<td>1939</td>
<td>2755</td>
<td>0.903</td>
<td>75</td>
<td>5.0</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1221</td>
<td>1986</td>
<td>2416</td>
<td>1.109</td>
<td>63</td>
<td>4.9</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1737</td>
<td>2130</td>
<td>2424</td>
<td>1.245</td>
<td>30</td>
<td>2.1</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2206</td>
<td>2073</td>
<td>2227</td>
<td>1.234</td>
<td>17</td>
<td>1.2</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2704</td>
<td>2848</td>
<td>2633</td>
<td>1.219</td>
<td>10</td>
<td>0.6</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>3188</td>
<td>4273</td>
<td>3718</td>
<td>1.176</td>
<td>5</td>
<td>0.3</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3755</td>
<td>3014</td>
<td>2855</td>
<td>1.297</td>
<td>4</td>
<td>0.3</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>5196</td>
<td>4170</td>
<td>3445</td>
<td>1.498</td>
<td>4</td>
<td>0.3</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>1395</td>
<td>2117</td>
<td>2587</td>
<td>1.067</td>
<td>218</td>
<td>15.6</td>
</tr>
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</table>

### Table 8.6 Data summary for electric heat pumps.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Heating Energy (kWh)</th>
<th>HDD65 kWh per HDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>456</td>
<td>851</td>
<td>1670</td>
<td>0.492</td>
<td>5</td>
<td>0.2</td>
</tr>
<tr>
<td>500 to 999</td>
<td>813</td>
<td>1609</td>
<td>2832</td>
<td>0.623</td>
<td>32</td>
<td>1.3</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1256</td>
<td>1719</td>
<td>2528</td>
<td>0.752</td>
<td>47</td>
<td>2.2</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1734</td>
<td>1659</td>
<td>2248</td>
<td>0.793</td>
<td>50</td>
<td>2.1</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2199</td>
<td>2195</td>
<td>2886</td>
<td>0.889</td>
<td>26</td>
<td>1.1</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2726</td>
<td>2875</td>
<td>3139</td>
<td>0.919</td>
<td>25</td>
<td>0.8</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>3276</td>
<td>2773</td>
<td>3128</td>
<td>0.933</td>
<td>9</td>
<td>0.4</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3755</td>
<td>3167</td>
<td>3207</td>
<td>1.004</td>
<td>4</td>
<td>0.2</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>5100</td>
<td>3762</td>
<td>3912</td>
<td>1.028</td>
<td>20</td>
<td>0.8</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>1989</td>
<td>2080</td>
<td>2747</td>
<td>0.805</td>
<td>218</td>
<td>9.0</td>
</tr>
</tbody>
</table>
### Table 8.7 Data summary for electric baseboard.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Heating Energy (kWh)</th>
<th>HDD65 kWh per HDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>361</td>
<td>1872</td>
<td>3727</td>
<td>0.584</td>
<td>40</td>
<td>0.9</td>
</tr>
<tr>
<td>500 to 999</td>
<td>729</td>
<td>2509</td>
<td>4482</td>
<td>0.635</td>
<td>100</td>
<td>2.1</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1166</td>
<td>3205</td>
<td>4690</td>
<td>0.755</td>
<td>36</td>
<td>0.9</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1667</td>
<td>3576</td>
<td>5057</td>
<td>0.737</td>
<td>21</td>
<td>0.6</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2221</td>
<td>4678</td>
<td>6134</td>
<td>0.795</td>
<td>6</td>
<td>0.1</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2682</td>
<td>4695</td>
<td>4892</td>
<td>0.965</td>
<td>8</td>
<td>0.2</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>***</td>
<td>***</td>
<td>***</td>
<td>***</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3731</td>
<td>4124</td>
<td>4979</td>
<td>1</td>
<td>1</td>
<td>0.0</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>4661</td>
<td>5030</td>
<td>6114</td>
<td>1</td>
<td>2</td>
<td>0.1</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>1036</td>
<td>2819</td>
<td>4504</td>
<td>0.677</td>
<td>214</td>
<td>4.9</td>
</tr>
</tbody>
</table>

*** No home samples exist for this bin

### Table 8.8 Data summary for fuel oil furnace.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Heating Energy (kWh)</th>
<th>HDD65 kWh per HDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>***</td>
<td>***</td>
<td>***</td>
<td>***</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>500 to 999</td>
<td>768</td>
<td>25866</td>
<td>6196</td>
<td>4.437</td>
<td>26</td>
<td>0.5</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1261</td>
<td>27089</td>
<td>5773</td>
<td>4.957</td>
<td>37</td>
<td>0.6</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1726</td>
<td>23626</td>
<td>6022</td>
<td>3.976</td>
<td>30</td>
<td>0.7</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2236</td>
<td>25597</td>
<td>6405</td>
<td>4.144</td>
<td>23</td>
<td>0.4</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2737</td>
<td>29868</td>
<td>5914</td>
<td>5.200</td>
<td>13</td>
<td>0.2</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>3237</td>
<td>30996</td>
<td>6581</td>
<td>4.780</td>
<td>5</td>
<td>0.1</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3667</td>
<td>29158</td>
<td>6019</td>
<td>4.924</td>
<td>8</td>
<td>0.1</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>5689</td>
<td>29552</td>
<td>6384</td>
<td>4.580</td>
<td>6</td>
<td>0.1</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>1952</td>
<td>26419</td>
<td>6086</td>
<td>4.501</td>
<td>148</td>
<td>2.8</td>
</tr>
</tbody>
</table>

*** No home samples exist for this bin
Table 8.9 Data summary for fuel oil boiler.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Heating Energy (kWh)</th>
<th>HDD65</th>
<th>kWh per HDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>329</td>
<td>24692</td>
<td>5783</td>
<td>4.303</td>
<td>7</td>
<td>0.2</td>
<td>1.7%</td>
</tr>
<tr>
<td>500 to 999</td>
<td>753</td>
<td>23231</td>
<td>5511</td>
<td>4.612</td>
<td>36</td>
<td>1.2</td>
<td>0.8%</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1236</td>
<td>27876</td>
<td>5753</td>
<td>4.996</td>
<td>21</td>
<td>0.8</td>
<td>4.4%</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1753</td>
<td>26499</td>
<td>5787</td>
<td>4.686</td>
<td>15</td>
<td>0.5</td>
<td>5.0%</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2185</td>
<td>28601</td>
<td>6031</td>
<td>4.795</td>
<td>29</td>
<td>0.7</td>
<td>4.6%</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2760</td>
<td>29240</td>
<td>6051</td>
<td>4.960</td>
<td>19</td>
<td>0.5</td>
<td>3.1%</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>3241</td>
<td>22475</td>
<td>5729</td>
<td>3.958</td>
<td>7</td>
<td>0.2</td>
<td>26.8%</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3746</td>
<td>41497</td>
<td>6360</td>
<td>6.411</td>
<td>6</td>
<td>0.2</td>
<td>20.1%</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>5261</td>
<td>37926</td>
<td>6338</td>
<td>6.078</td>
<td>8</td>
<td>0.2</td>
<td>12.1%</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>1844</td>
<td>27480</td>
<td>5825</td>
<td>4.863</td>
<td>148</td>
<td>4.6</td>
<td>5.4%</td>
</tr>
</tbody>
</table>

Table 8.10 Data summary for LPG furnace.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Heating Energy (kWh)</th>
<th>HDD65</th>
<th>kWh per HDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>406</td>
<td>12061</td>
<td>3471</td>
<td>3.716</td>
<td>2</td>
<td>0.0</td>
<td>6.5%</td>
</tr>
<tr>
<td>500 to 999</td>
<td>809</td>
<td>14243</td>
<td>4647</td>
<td>3.628</td>
<td>27</td>
<td>0.6</td>
<td>6.0%</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1259</td>
<td>14514</td>
<td>4608</td>
<td>3.498</td>
<td>35</td>
<td>0.9</td>
<td>3.5%</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1752</td>
<td>13533</td>
<td>5282</td>
<td>2.678</td>
<td>36</td>
<td>0.9</td>
<td>22.2%</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2231</td>
<td>12862</td>
<td>4391</td>
<td>3.704</td>
<td>17</td>
<td>0.5</td>
<td>10.8%</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2780</td>
<td>17123</td>
<td>5292</td>
<td>3.801</td>
<td>4</td>
<td>0.1</td>
<td>14.0%</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>3119</td>
<td>22657</td>
<td>6193</td>
<td>3.733</td>
<td>5</td>
<td>0.2</td>
<td>12.5%</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3725</td>
<td>19927</td>
<td>5930</td>
<td>3.220</td>
<td>9</td>
<td>0.3</td>
<td>1.8%</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>5076</td>
<td>18244</td>
<td>5282</td>
<td>3.326</td>
<td>13</td>
<td>0.4</td>
<td>2.4%</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>2108</td>
<td>15294</td>
<td>4998</td>
<td>3.344</td>
<td>148</td>
<td>4.0</td>
<td>9.7%</td>
</tr>
</tbody>
</table>

8.1.3.4 Baseline Space Heating Energy Consumption

The energy consumption of any particular space heating system over the entire year can be determined by summing the heating degree days over the year and multiplying this by the correlation developed in Equation 8.2 and Table 8.2.

\[
E_{heat, fuel \, consumed} = \sum_{i=1}^{365} HDD65 \cdot a \cdot [\ln (HomeSize) + b]
\]

Equation 8.10
8.1.4 Efficiency of Space Heating Systems

The efficiency of fossil-fueled space heating systems such as furnaces and boilers is measured by the Annual Fuel Utilization Efficiency (AFUE), given in a percentage. This value corresponds to the seasonal efficiency of the device, as the actual efficiency changes depending on the running state.

For air-source heat pumps, the measure of efficiency is the Heating Seasonal Performance Factor (HSPF). This value is the total space heating provided divided by the total electric consumption over the heating season, in BTU/watt-hr (Air Conditioning, Heating and Refrigeration Institute, 2012). This measure is designed to take into account the heat pump’s variable efficiency and use of a backup system.

Energy Star provides values on both qualified and non-qualified space heating systems including natural gas furnaces and boilers, fuel oil furnaces and boilers, and heat pumps. LPG furnaces are assumed to have the same AFUE as natural gas devices. The values for electric baseboard and electric furnace calculations are taken from LBNL’s home energy saver (Lawrence Berkeley National Laboratory, 2012a). The average of the conventional and Energy Star units is utilized as the overall average efficiency for all homes. Few recent studies have been completed on the national average efficiency of existing space heating units. A more accurate method would take into account the year the space heating system was installed, similar to LBNL’s Home Energy Saver methodology. However, the additional degree of accuracy is probably not required for this estimation, and determining the year of installation requires an additional user input which can be subject to inaccuracy as well.

This efficiency does not affect the calculated space heating consumption (which is determined by the correlation in the previous section). It is necessary for some energy saving actions which are calculated in a “bottom-up” approach where the heat loss is determined through engineering equations, and efficiency is required to calculate the total space heating fuel demand.

Table 8.11 Space heating system efficiencies.

<table>
<thead>
<tr>
<th></th>
<th>Gas Furnace AFUE*</th>
<th>LPG Furnace AFUE</th>
<th>Gas Boiler AFUE**</th>
<th>Oil Boiler AFUE**</th>
<th>Oil Furnace AFUE*</th>
<th>Electric Baseboard†</th>
<th>Electric Furnace†</th>
<th>Heat Pump HSPF‡</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy Star</td>
<td>90%</td>
<td>90%</td>
<td>85%</td>
<td>85%</td>
<td>85%</td>
<td>N/A</td>
<td>N/A</td>
<td>8.2</td>
</tr>
<tr>
<td>Non Qualified</td>
<td>75%</td>
<td>75%</td>
<td>80%</td>
<td>80%</td>
<td>80%</td>
<td>98%</td>
<td>98%</td>
<td>7.7</td>
</tr>
<tr>
<td>Average</td>
<td>83%</td>
<td>83%</td>
<td>83%</td>
<td>83%</td>
<td>83%</td>
<td>98%</td>
<td>98%</td>
<td>7.95</td>
</tr>
</tbody>
</table>


Converting the measure of HSPF to a seasonally averaged “efficiency” for the heat pump is accomplished through a simple unit conversion.

\[
\eta_{seasonal} = \frac{HSPF}{3.412 \text{ Wh}/\text{BTU}}
\]

Equation 8.11

In most engineering texts, COP is utilized instead of efficiency for \(\eta>1\). The term efficiency is used here for consistency with other types of space heating systems.
8.1.5 Space Heating System Summary

The table below is a summary of the important characteristics of each heating system.

<table>
<thead>
<tr>
<th>Fuel</th>
<th>a</th>
<th>b</th>
<th>Efficiency</th>
<th>Distribution</th>
<th>Average Fuel Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Gas Furnace</td>
<td>0.575</td>
<td>-1.070</td>
<td>83%</td>
<td>47%</td>
<td>$ 0.0379</td>
</tr>
<tr>
<td>Natural Gas Boiler</td>
<td>1.343</td>
<td>-5.206</td>
<td>83%</td>
<td>9%</td>
<td>$ 0.0379</td>
</tr>
<tr>
<td>Electric Baseboard</td>
<td>0.140</td>
<td>-0.268</td>
<td>100%</td>
<td>5%</td>
<td>$ 0.1154</td>
</tr>
<tr>
<td>Electric Furnace</td>
<td>0.295</td>
<td>-1.025</td>
<td>98%</td>
<td>17%</td>
<td>$ 0.1154</td>
</tr>
<tr>
<td>Electric Heat Pump</td>
<td>0.223</td>
<td>-0.857</td>
<td>233%</td>
<td>10%</td>
<td>$ 0.1154</td>
</tr>
<tr>
<td>Fuel Oil Furnace</td>
<td>0.049</td>
<td>4.138</td>
<td>83%</td>
<td>3%</td>
<td>$ 0.0724</td>
</tr>
<tr>
<td>Fuel Oil Boiler</td>
<td>0.415</td>
<td>1.827</td>
<td>83%</td>
<td>5%</td>
<td>$ 0.0724</td>
</tr>
<tr>
<td>LPG Furnace</td>
<td>-0.092</td>
<td>4.035</td>
<td>83%</td>
<td>4%</td>
<td>$ 0.0922</td>
</tr>
</tbody>
</table>

The fuel costs can also be seen in Table 3.3.

8.1.6 Indoor Temperatures for the Heating Season

The Energy Star program recommends the following setpoints for thermostats in the winter to achieve energy savings. As a baseline, when the outdoor temperature is below the recommended occupied temperature (70 °F), the user is assumed to be constantly holding the temperature at the recommended occupied temperature (70 °F), unless the energy saving action specifically mentions thermostat setback.

<table>
<thead>
<tr>
<th>Recommended Temperature</th>
<th>Setup (ΔT)</th>
<th>Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>During occupied hours</td>
<td>70 °F (21.1 °C)</td>
<td>0°F</td>
</tr>
<tr>
<td>Unoccupied Daytime</td>
<td>62 °F (16.6 °C)</td>
<td>-8°F (-13.3 °C)</td>
</tr>
<tr>
<td>Unoccupied Nighttime</td>
<td>62 °F (16.6 °C)</td>
<td>-8°F (-13.3 °C)</td>
</tr>
</tbody>
</table>

The length of each time period in Table 8.13 is assumed to be 8 hours long. Energy Star suggests a 10 hour unoccupied daytime period, however this does not consider occupant behavior and comfort. There is a lag between the thermostat setpoint and the actual indoor temperature of the house, as A/C requires time to transfer the heat out of the house. Most occupants will set the thermostat to switch to the desired temperature a few hours before they arrive home, so that the home will be cool upon arrival. Although there are “smart” thermostats that have sensing technology, these are certainly in a very small minority of homes.

8.1.7 Space Heating Pins

8.1.7.1 Dress for Success/Dress the Part

Description: Wear warm clothing and keep the thermostat 2°F lower when you are home.

8.1.7.1.1 Additional Assumptions

The Pins “Dress for Success” and “Dress the Part” are the same energy saving action. Temperature setup – By dressing in warm clothing, it is possible to set back the thermostat -2 °F (-1.1°C) in the winter, assumed to occur during occupied hours (8 hrs per day).
Thermostat setup savings percentage – The is a rule of thumb for space heating energy setback (suggested by Energy Star) is a savings of 3% per °F of setup held for 24 hrs (or 1% savings per °F for each 8 hr setup period) (Energy Star, 2010b). An experiment conducted by the National Research Council of Canada examined heating season setback at two identically-constructed houses and found a savings of 10% for the heating season for a 7.2°F (4°C) setback over 7 hours (Manning, Swinton, Szadkowski, Gusdorf, & Ruest, 2007). This is roughly equal to 0.8% per °F for each 8 hr period, or 2.4% over 24hrs. The savings percentage used is this more conservative value.

Thermostat setup savings percentage = 2.4% per °F for 24 hrs

8.1.7.1.2 Calculation Procedure

The energy savings of this action is dependent on the baseline energy consumption of the home as determined in Equation 8.10. Utilizing this equation and the savings percentage, it is possible to determine the energy savings for any particular fuel type given the constants in Table 8.12.

\[ \Delta E_{fuel} = E_{heat,fuel}\text{consumed} \cdot 2.4\% \cdot \left(\frac{8}{24} \text{ hrs}\right) \cdot 2 \, ^\circ F \]  
Equation 8.12

8.1.7.1.3 Final Equation

<table>
<thead>
<tr>
<th>Space Heating Fuel (kWh)</th>
<th>( \Delta E_{dress \text{ for success}} = \Delta E_{dress \text{ the part}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( = E_{heat,fuel}\text{consumed} \cdot 0.016 )</td>
</tr>
</tbody>
</table>

Equation 8.13

8.1.7.2 Babysit Winter Thermostat/Winter Nighttime Setup/Get with the Program

Description:
Get with the Program: Program your thermostat to the Energy Star recommended temperatures.
Babysit Winter Thermostat: Turn down your thermostat by 8°F during the day when you are not home.
Winter Nighttime Thermostat: Turn down the thermostat by 8°F during the night when you are in bed.

8.1.7.2.1 Calculation Procedure

There is some overlap between these three Pins. “Get with the Program” assumes that the manual setup and setback outlined in Table 8.13 is accomplished by a programmable thermostat. The other two Pins simply split the actions into daytime and nighttime setbacks for manual thermostats. The sum of the savings from “Babysit Winter Thermostat” and “Winter Nighttime Thermostat” is the savings from “Get with the Program” (space heating only). Table 8.13 will be used as a guide for the winter thermostat setback. The savings from daytime and nighttime will be the same, as the setback for is recommended at 8 °F, and the time periods are both 8 hours long.

The thermostat saving percentage from Section 8.1.7.1 will be used for these Pins as well.

“Babysit Winter Thermostat”/“Winter Nighttime Thermostat”:

\[ \Delta E_{fuel} = E_{heat,fuel}\text{consumed} \cdot 2.4\% \cdot \left(\frac{8}{24} \text{ hrs}\right) \cdot 8 \, ^\circ F \]  
Equation 8.14

“Get with the Program” (space heating):

\[ \Delta E_{fuel} = \left[E_{heat,fuel}\text{consumed} \cdot 2.4\% \cdot \left(\frac{16}{24}\right) \right] 8 \, ^\circ F \]  
Equation 8.15
8.1.7.2.2 Final Equations

“Babysit Winter Thermostat”/ “Winter Nighttime Thermostat”:

\[
\Delta E_{\text{Babysit Winter Thermostat}} = \Delta E_{\text{Winter Nighttime Thermostat}} = E_{\text{heat, fuel consumed}} \cdot 0.064
\]  

Equation 8.16

“Get with the Program” (space heating):

\[
\Delta E_{\text{Get with the Program, heat}} = E_{\text{heat, fuel consumed}} \cdot 0.128
\]  

Equation 8.17

8.1.7.3 Seal the Deal

Description: Seal around leaky doors and windows.

8.1.7.3.1 Prediction of Air Leakage

This Pin’s (“Seal the Deal”) energy savings is the result of a reduced amount of infiltration in the home. Infiltration, or air leakage, contributes to heat loss in winter and heat gain in summer through air exchange. There are many metrics of air leakage, including Normalized Leakage (NL), Effective Leakage Area (ELA), and Air Change per Hour (ACH) at various pressures. The most common way to determine the air leakage of a house is through a blower door test. During this procedure, the house is pressurized (normally to 50 Pa) and a measurement of the air flow rate required to achieve the specified pressure is taken. For many years, leakage data has been compiled into a national database in an attempt to correlate the air leakage of homes with certain house characteristics. The work of Chan and colleagues analyzed this database of over 70,000 air leakage measurements to create a regression equation that predicts the amount of leakage in a home based on a few variables (Chan, Price, Sohn, & Gadgil, 2003). The correlation, given in Equation 8.18 and Table 8.14, for conventional homes will be used to predict the normalized leakage given the home size and year of construction.

\[
NL = \exp[\beta_0 + \beta_1 \cdot \text{YearBuilt} + \beta_2 \cdot \text{Area}]
\]  

Equation 8.18

Table 8.14 Coefficients for leakage correlation (Chan, Price, Sohn, & Gadgil, 2003).

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$</td>
<td>Interception</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>Year Built</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>House Area</td>
</tr>
</tbody>
</table>

McWilliams and Jung also developed a regression using a more current leakage dataset from 2006, utilizing several additional parameters including climate, building height and house characteristics. Upon comparison, McWilliams and Jung found that Chan’s model described the data equally well as their new model. Therefore, the simpler Chan model will be utilized in this paper to reduce complexity (McWilliams & Jung, 2006).

Infiltration Flow Rate – According to the ASHRAE Handbook, the infiltration flow rate is related to the effective leakage area (ELA, or $A_L$) and the driving pressure caused by stack effects and wind (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009). Using a relation from Chan and colleagues, the normalized leakage (NL) can be related to the ELA at the reference pressure of 4 Pa by the buildings height (H), and floor area (A). The equation is based on a building height of 2.5 m. The resulting ELA is in cm² (Chan, Price, Sohn, & Gadgil, 2003).
Building Height – The height of a one-story building is assumed to be 9.8 ft (3 m), with 8.2 ft (2.5 m) for the floor and 1.6 ft (0.5 m) for the roof height. Although larger buildings are likely to be multiple stories, the error is small as the NL is affected by $H^{0.3}$.

### 8.1.7.3.2 Reduced air leakage

Sealing of leaky windows and doors is the result of reduced air leakage, so the new amount of air leakage after sealing is important. It is unlikely that a homeowner will be able to totally reduce the air leakage, and in extremely leaky homes it may not be possible to reduce the leakage even to the level of today’s current buildings. There are three cases to consider. First, the case of an extremely leaky home, that is sealed to the best of the homeowner’s abilities but does not reach the threshold of a “minimum amount of leakage”. The second is a home that is leaky, but can be sealed to the threshold leakage value. Finally, the case could be that the home is already at or below the minimum leakage and no additional sealing is possible. Determining a minimum leakage threshold that is achievable by the homeowner is not an easy task. An estimate of the reduction that is possible comes from the study by McWilliams and Jung, who determined that energy-efficient houses are on average 40% tighter than regular houses (McWilliams & Jung, 2006). In reality, a homeowner will not be able to reach the level of an air-sealing professional builder, so it is estimated that a homeowner could achieve a 30% reduction in air leakage.

Leakage reduction percentage=30% reduction in current leakage

The same study also found that the median normalized leakage for energy-efficient houses is NL=0.25 (McWilliams & Jung, 2006). This can be considered a reasonable minimum leakage that can be achieved by a homeowner doing air-sealing projects.

Minimum new leakage= 0.25 NL.

Thus, when evaluating the leakage savings of the home, leakage is either 30% less, or it is reduced to a minimum of 0.25 NL. Homes with <0.25 NL are considered already tight and no further savings can be achieved.

$$NL_{\text{reduced}} = \begin{cases} NL_{\text{baseline}} \cdot 0.30, & \text{if } NL_{\text{baseline}} \cdot 0.30 > 0.25 \\ 0.25, & \text{if } NL_{\text{baseline}} \cdot 0.30 < 0.25 \\ NL_{\text{baseline}}, & \text{if } NL_{\text{baseline}} < 0.25 \end{cases}$$  \quad \text{Equation 8.20}

After the reduced Normalized Leakages has been determined, the reduced ELA can be determined from Equation 8.13. Subtracting the reduced ELA from the baseline ELA determines the change in leakage that occurred by sealing the home.

### 8.1.7.3.3 Determining Infiltration Heat Loss

Once the ELA has been determined, Equation 8.21 from the ASHRAE Handbook can be used to determine the infiltration flow rate, $\dot{V}_I$ in m$^3$/s, based on the Infiltration Driving Force (IDF).

$$\dot{V}_I = ELA \cdot IDF$$ \quad \text{Equation 8.21}

In the ASHRAE Handbook, the IDF is calculated by the following equation (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009):

$$IDF = \frac{I_0 + H|\Delta t|[I_1 + I_2 \cdot (A_{L,\text{flue}}/A_L)]}{1000}$$ \quad \text{Equation 8.22}

Where:

<table>
<thead>
<tr>
<th></th>
<th>Cooling, 3.4 m/s</th>
<th>Heating 6.7 m/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>I₀</td>
<td>25</td>
<td>51</td>
</tr>
<tr>
<td>I₁</td>
<td>0.38</td>
<td>0.35</td>
</tr>
<tr>
<td>I₂</td>
<td>0.12</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Where \( H \) is the building height in meters, \( \Delta t \) is the heat loss in K, and \( \Lambda_{L,\text{flue}} \) is the flue leakage area. For the purposes of this report, \( \Lambda_{L,\text{flue}}=0 \), \( H=3 \text{m} \), and \( \Delta t \) is determined from the weather data and the indoor temperatures.

Hours with outdoor temperatures below 70°F (21.1°C) will have an indoor setpoint of 70°F to determine the heat loss. The sensible heat gain through infiltration (during the cooling season) was found to have negligible effect on the energy consumption, even for the hottest climates, so it is neglected. This method only accounts for the sensible loads of the building and neglects the latent loads. Although the latent loads are considered to be important in determining the overall heat gains and losses, without knowing more about the house's cooling system and the latent gains of the space, it is difficult to account for this. Additionally, the latent cooling required due to infiltration will be minor in all but the most extreme hot/humid climates.

Once the infiltration flow rate has been determined from Equation 8.21, the sensible heat loss (or gain) from the infiltration can be estimated by using the following equation from Jonsson and Bohdanowicz (Jonsson & Bohdanowicz, 2010)

\[
Q_{\text{heat loss}} = \dot{V}_i \cdot \rho \cdot C_p \cdot (t_i - t_o)
\]  

Equation 8.23

By itself, this equation simply gives the heat loss (or gain) at any point in time. As the TMY3 weather data we have is given in an hourly format for each of the 8760 hours of the year, the total heat loss over the year is the sum of each hour's loss.

\[
Q_{\text{heat loss}} = \sum_{t=1}^{8760} \dot{V}_i \cdot \rho \cdot C_p \cdot (t_i - t_o)
\]  

Equation 8.24

To determine the amount of energy that is actually consumed, the heat loss efficiency of the space heating (or cooling) system, \( \eta \), must be accounted for. The average efficiency over the year from Table 8.11 will be utilized.

Space Heating Fuel
(kWh):

\[
E_{\text{loss}} = \frac{Q_{\text{heat loss}}}{\eta_{\text{heat}}}
\]  

Equation 8.25

Attributing air leakage to windows and doors – The total amount of air leakage in the home comes in at a variety of spots, as shown in Figure 8.5.
“Seal the Deal” specifically instructs the user about reducing leakage through windows and doors, a total of 21% of the leakage. Other Pins in the future will account for the sealing of other areas in the home.

Affected Leakage Percentage = 21% of total leakage

8.1.7.3.4 Final Equations

Combining the steps from above, the final space heating fuel savings for this Pin, in kWh, can be determined by the following equation.

\[
\Delta E_{\text{Seal the Deal}} = \frac{\sum_{i=1}^{9760} (ELA_{baseline} - ELA_{reduced}) \cdot IDF_{\text{heat}} \cdot \rho \cdot C_p \cdot (t_i - t_0)}{\eta_{\text{heat}}} \cdot 0.21
\]

8.2 Cooling

Cooling energy consumption shares many of the same characteristics with heating energy consumption. The cooling energy consumption of a home depends on many factors, including but not limited to:

- Home size
- Type of cooling system
- Efficiency of cooling system
- Climate
- Internal loads
- Solar gain
- Indoor temperature setpoint

Of these different factors, home size, climate, and type of cooling system are the variables that are easily obtainable from the user without asking many complicated questions. In addition, these variables are correlated with cooling energy consumption in RECS data and so are easily analyzed.

8.2.1 Cooling System

Residential cooling systems in the U.S. are nearly always electrically powered air conditioning (A/C) units. These can be divided into two main system configurations: central A/C, and room A/C. Homes that utilize central A/C have a system of ductwork to circulate cooled air throughout the house from a single
large A/C unit usually located outside. Room A/C units are small cooling systems that are mounted in the windows or openings in the walls of a home and directly blow cooled outdoor air into the room, without ductwork. They are often used in older dwellings that were designed without central A/C, and a large home may have several room units. There are also homes without A/C units, mostly located in cooler climates, but there are also low income families in warmer climates that lack A/C as well. The number of homes that have each type of cooling system can be determined from RECS 2005 data (U.S. Energy Information Administration, 2009). The breakdown of A/C systems between all homes can be seen in Figure 8.6.

8.2.2 Cooling Degree Days

The amount of typical cooling degree days (base 65 °F), as calculated in Section 3.1.4.1, will be used as a parameter to estimate the cooling energy consumption of a particular location. It is assumed that cooling energy consumption scales linearly with cooling degree days, so energy usage per degree day (kWh/CDD65) can be determined through statistical correlations. In reality, the declining efficiency of the A/C unit with increasing temperature creates a more complex relationship between cooling energy and degree-days. In addition the latent heat associated with removal of water vapor in humid climates can have a substantial effect on the cooling energy consumption (Jonsson & Bohdanowicz, 2010). However, the linear approximation is fairly close for our purposes of estimation. The results are expected to be rather inaccurate if used over short time periods, and in cases of extreme weather.

8.2.3 Correlating Cooling Energy and Home Size

In general, there is a relationship between home size and cooling energy consumption. As the home grows larger, it takes more energy to keep it cool due to additional heat transfer into the envelope, but also due to the increased solar gain (assuming the windows grow in proportion to the home’s floor area) and increased internal loads such as lighting. Similar to space heating, plotting the house size vs. cooling energy consumption per degree day the best fit is a logarithmic relationship, ln(HomeSize).

8.2.3.1 Methodology

The amount of cooling energy used in the home can be used to estimate the amount of savings that a home could see by undertaking certain conservation measures, such as thermostat setback. A path analysis by Yun and Steemers found that climate and number of air-conditioned rooms had a strong effect on cooling energy consumption, as well as behavioral patterns regarding how the resident used the A/C (Yun & Steemers, 2011). The type of cooling system, economic status of the residents, and home size were also found to be contributors. The variables from Table 3.2 that appear to have the strongest effect on cooling energy consumption are the climate, home size, and type of air conditioning unit. Number of rooms cooled is related to square footage of the home, and the economic and behavioral variables were omitted because they would be problematic to gather from users in a mobile application.

The method of analyzing cooling energy consumption will be identical to the method utilized in Section 8.1.3.1. An equation relating ln(HomeSize) with cooling energy consumption will be developed for each type of cooling unit. The equation will take the form of:
\[
\frac{E_{\text{cool, consumed}}}{\text{CDD65}} = a \cdot \ln (\text{HomeSize}) + b
\]

Equation 8.27

Where \(a\) and \(b\) are coefficients determined from the regression analysis.

The RECS survey data was utilized to develop the correlations about cooling energy consumption. The variables that are easiest to obtain and correlate well with cooling energy consumption are cooled home area (TOTCSQFT variable in RECS), climate (CDD65), and type of A/C unit (COOLTYPE). The data was separated into homes based on the type of cooling unit, with central A/C units (houses with both central and room A/C were included in this group), and those with room A/C. The data was then binned in the same manner as in Section 8.1.3.1. The number of homes (NWEIGHT) in each bin was utilized as the weighting function for the Weighted Least Squares analysis.

### 8.2.3.2 Correlations Developed

The following bubble chart shows the trendlines that were developed, with the number of homes in each data bin represented by the area of the bubble.

![Figure 8.7 Cooling consumption trendlines.](image)

The table below displays the coefficients and weight-adjusted \(r^2\) value associated with each of the correlations.

<table>
<thead>
<tr>
<th>Type of Cooling System</th>
<th>(a)</th>
<th>(b)</th>
<th>Weighted-(r^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central</td>
<td>0.677</td>
<td>-3.220</td>
<td>0.971</td>
</tr>
<tr>
<td>Window/Wall</td>
<td>0.327</td>
<td>-1.161</td>
<td>0.980</td>
</tr>
</tbody>
</table>

As can be judged from the weighted-\(r^2\), the weighted trendlines using \(\ln(\text{HomeSize})\) can predict the cooling energy consumption within a bin quite well. As with space heating, there can be variation of the energy consumption within each bin, and user behavior can be an extremely significant factor in
determining energy consumption. It is expected that these results will work well for average cases, but perform rather poorly in extreme cases.

### 8.2.3.3 Data Summary

The binned data that was gathered from RECS 2005, along with a calculation of the percent difference for each bin (based on the regression equations developed) can be seen in following tables. See Equation 8.9 for the calculation of percent difference.

**Table 8.17** Data summary for window/wall cooling units.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Cooling Energy (kWh)</th>
<th>CDD65 kWh per CDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>291</td>
<td>998</td>
<td>1363</td>
<td>0.689</td>
<td>658</td>
<td>15.2</td>
</tr>
<tr>
<td>500 to 999</td>
<td>703</td>
<td>1479</td>
<td>1443</td>
<td>0.986</td>
<td>329</td>
<td>7.5</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1206</td>
<td>1669</td>
<td>1309</td>
<td>1.139</td>
<td>104</td>
<td>2.4</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1705</td>
<td>2202</td>
<td>1543</td>
<td>1.358</td>
<td>45</td>
<td>1.0</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2263</td>
<td>1811</td>
<td>1381</td>
<td>1.343</td>
<td>16</td>
<td>0.4</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2681</td>
<td>1838</td>
<td>1303</td>
<td>1.264</td>
<td>12</td>
<td>0.3</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>3132</td>
<td>2767</td>
<td>1635</td>
<td>1.572</td>
<td>4</td>
<td>0.1</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3755</td>
<td>1431</td>
<td>1305</td>
<td>1.097</td>
<td>1</td>
<td>0.0</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>4685</td>
<td>1380</td>
<td>1113</td>
<td>1.240</td>
<td>1</td>
<td>0.0</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>597</td>
<td>1259</td>
<td>1385</td>
<td>0.853</td>
<td>1170</td>
<td>26.9</td>
</tr>
</tbody>
</table>

**Table 8.18** Data summary for central cooling units.

<table>
<thead>
<tr>
<th>Home Size Bin (sqft)</th>
<th>Home Size (sqft)</th>
<th>Cooling Energy (kWh)</th>
<th>CDD65 kWh per CDD65</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer than 500</td>
<td>395</td>
<td>2174</td>
<td>2116</td>
<td>1.022</td>
<td>100</td>
<td>2.7</td>
</tr>
<tr>
<td>500 to 999</td>
<td>763</td>
<td>2651</td>
<td>2004</td>
<td>1.268</td>
<td>452</td>
<td>12.4</td>
</tr>
<tr>
<td>1,000 to 1,499</td>
<td>1238</td>
<td>3139</td>
<td>1951</td>
<td>1.589</td>
<td>428</td>
<td>11.9</td>
</tr>
<tr>
<td>1,500 to 1,999</td>
<td>1754</td>
<td>3767</td>
<td>1998</td>
<td>1.818</td>
<td>321</td>
<td>8.9</td>
</tr>
<tr>
<td>2,000 to 2,499</td>
<td>2224</td>
<td>3673</td>
<td>1771</td>
<td>1.975</td>
<td>256</td>
<td>7.1</td>
</tr>
<tr>
<td>2,500 to 2,999</td>
<td>2729</td>
<td>3611</td>
<td>1689</td>
<td>2.070</td>
<td>208</td>
<td>5.9</td>
</tr>
<tr>
<td>3,000 or 3,499</td>
<td>3236</td>
<td>3497</td>
<td>1645</td>
<td>2.085</td>
<td>149</td>
<td>4.2</td>
</tr>
<tr>
<td>3,500 to 3,999</td>
<td>3746</td>
<td>4175</td>
<td>1680</td>
<td>2.301</td>
<td>102</td>
<td>2.8</td>
</tr>
<tr>
<td>4,000 or More</td>
<td>5415</td>
<td>4710</td>
<td>1701</td>
<td>2.745</td>
<td>306</td>
<td>8.7</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>2228</td>
<td>3473</td>
<td>1865</td>
<td>1.840</td>
<td>2322</td>
<td>64.5</td>
</tr>
</tbody>
</table>

### 8.2.3.4 Baseline Cooling Energy Consumption

The total annual energy consumption of the cooling system over a year is determined by multiplying the result of Equation 8.27 and Table 8.16 with the number of cooling degree days for the year.
Electricity (kWh) \[ E_{\text{cool,el consumed}} = \sum_{i=1}^{365} CDD65 \cdot a \cdot [\ln (\text{HomeSize}) + b] \] \[ \text{Equation 8.28} \]

### 8.2.4 Efficiency of Cooling System

The efficiency of A/C systems in the U.S. is measured by Seasonal Energy Efficiency Ratio (SEER) rating. The SEER is a measure of the total heat removed from a conditioned space (in BTUs) divided by the total electrical energy consumed (in Wh), over a cooling season (Air Conditioning, Heating and Refrigeration Institute, 2012). The SEER rating can be related to the Energy Efficiency Ratio (EER) through Equation 8.29 (Hendron & Engebreh, 2010).

\[ \text{EER} = -0.02 \cdot \text{SEER}^2 + 1.12 \cdot \text{SEER} \] \[ \text{Equation 8.29} \]

The EER is a measure of the efficiency of the A/C unit, measured in BTU/h of heat removed divided by the electrical consumption in Watts. The EER can be related to the COP by Equation 8.30 (a unit conversion).

\[ \text{EER} = \text{COP} \cdot 3.412 \] \[ \text{Equation 8.30} \]

Although the EER (and COP) vary depending on the running conditions of the cooling unit, this is a rough measure of the “average” COP over the cooling season.

The efficiency of an A/C unit in general depends on the age of the installation, as well as the type of A/C unit. To reduce the number of inputs required, a single average efficiency will be used rather requiring the year of installation. To determine the average SEER of a residential A/C unit, some data is required. Energy Star provides a calculator for both conventional and room units that includes data about the efficiency ratings of conventional and Energy Star units. It is assumed that the average A/C unit has an efficiency that is the average between the Energy Star and conventional units.

#### Table 8.19 A/C Unit Efficiencies (Energy Star, 2009d; Energy Star, 2009f).

<table>
<thead>
<tr>
<th></th>
<th>SEER</th>
<th>COP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Central A/C Units</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy Star</td>
<td>14.5</td>
<td>3.5</td>
</tr>
<tr>
<td>Conventional</td>
<td>13</td>
<td>3.3</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>13.75</td>
<td>3.4</td>
</tr>
<tr>
<td><strong>Room A/C Units</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy Star</td>
<td>10.8</td>
<td>3.2</td>
</tr>
<tr>
<td>Conventional</td>
<td>9.8</td>
<td>2.9</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>10.3</td>
<td>3.0</td>
</tr>
</tbody>
</table>

The COP of the A/C system is not an input to the calculation of cooling energy consumption which is determined by the correlation above, but it is required for calculations that are focused on savings from preventing heat gain in the home (bottom-up calculations).

### 8.2.5 Cooling System Summary

A final summary of the cooling system characteristics including coefficients and COP can be seen in the table below. The distribution column refers to the distribution within the population of homes with A/C systems.
Table 8.20 Cooling systems summary.

<table>
<thead>
<tr>
<th>Type of Cooling System</th>
<th>a</th>
<th>b</th>
<th>COP</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central AC</td>
<td>0.677</td>
<td>-3.220</td>
<td>3.4</td>
<td>70%</td>
</tr>
<tr>
<td>Window/Wall Units</td>
<td>0.327</td>
<td>-1.161</td>
<td>3.0</td>
<td>30%</td>
</tr>
</tbody>
</table>

8.2.6 Indoor Temperatures for the Cooling Season

The Energy Star program recommends setpoints for thermostats in the summer. Like space heating, for times where the outdoor temperature is above the recommended occupied temperature of 78 °F, the setpoint will be assumed to be a constant 78 °F. This will be the setpoint for calculating all energy-saving actions. Only actions that specifically involve thermostat setup will have different setpoints.

Table 8.21 Energy Star recommended cooling setpoints (Energy Star, 2009e).

<table>
<thead>
<tr>
<th></th>
<th>Recommended Temperature</th>
<th>Setup</th>
<th>Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>During occupied hours</td>
<td>78 °F (25.5 °C)</td>
<td>0°F</td>
<td>8 hrs</td>
</tr>
<tr>
<td>Unoccupied Daytime</td>
<td>85 °F (29.4 °C)</td>
<td>+7°F (+3.8 °C)</td>
<td>8 hrs</td>
</tr>
<tr>
<td>Unoccupied Nighttime</td>
<td>82 °F (27.7 °C)</td>
<td>+4°F (+2.2°C)</td>
<td>8 hrs</td>
</tr>
</tbody>
</table>

8.2.7 Cooling Pins

8.2.7.1 Fan Club

Description: Use a fan and raise the thermostat temperature by 4°F.

8.2.7.1.1 Additional Assumptions

According to the U.S. Department of Energy, utilizing a ceiling fan creates a “wind chill” effect allowing an occupant to raise the temperature of the room by 4°F (2.2°C) without a reduction in comfort (U.S. Department of Energy, 2011a). The cooling energy savings for this Pin occurs from this temperature setup, as a higher indoor temperature will allow the A/C unit to work more efficiently and use less energy.

Setup temperature = 4°F (2.2°C)

Thermostat setup hours - For this savings measure, it is assumed that the occupants are utilizing the fan on average 8hrs per day when the air conditioning would be on. This is assumed to be any time the temperature rises above 78 °F (the recommended occupied temperature).

Thermostat setup savings percentage – The savings from setting up the thermostat has been generalized as a percentage “rule of thumb” for many years. Energy Star suggests a cooling energy savings of 6% per °F of setup in the cooling season held for 24 hrs (or 2% savings per °F for each 8 hr setup period) (Energy Star, 2010b). Alternatively, an experiment by the National Research Council of Canada examined cooling set-up at a two identically-constructed houses (Manning, Swinton, Szadkowski, Gusdorf, & Ruest, 2007). This experiment found that cooling setup was dependent on solar gain and climate. During the experiment held in Ottawa, Canada, a daytime setup of 5°F for 7 hours yielded a cooling season savings of 11% (or 2.5% per °F over 8 hrs). However, Manning and colleagues caution that there can be long recovery times associated with A/C setup, and that additional humidity may cause occupant discomfort. The more conservative estimate from Energy Star will be used.

Thermostat setup savings percentage = 6% per °F for 24 hrs
Ceiling fan power – The power consumed by a typical ceiling fan can be determined from a sampling of fans from typical retailers.

\[ \text{Ceiling fan power} = 60 \text{ W} \]

### 8.2.7.1.2 Calculation Procedure

The first step is to determine the amount of cooling energy saved. This is done by multiplying the savings percentage by the total cooling energy consumption from Equation 8.28.

\[ \Delta E_{cool} = E_{cool, consumed} \cdot 6\% \cdot \left( \frac{8}{24} \text{ hrs} \right) \cdot 4 \text{ °F} \quad \text{Equation 8.31} \]

Next, determine the amount of running time for the fan by using the TMY3 data. This will be the total of all hours when the temperature is above 78 °F. The energy of the fan in kWh is the total hours of fan running time, multiplied by the power of the fan (60W), divided by 1000.

\[ E_{fan} = \frac{60 \text{ W}}{1000 \text{ W/kW}} \sum_{i=1}^{8760} \text{hrs, if } (t_o > t_i) \quad \text{Equation 8.32} \]

### 8.2.7.1.3 Final Equation

The net energy savings is the cooling savings, minus the energy required to operate the fan.

Electricity (kWh):

\[ \Delta E_{elec} = \Delta E_{cool} - E_{fan} \quad \text{Equation 8.33} \]

Combining the equations into a single equation gives the following:

\[ \Delta E_{fan, club} = E_{cool, consumed} \cdot 0.08 \]

Electricity (kWh):

\[ - \left[ 0.06 \sum_{i=1}^{8760} \text{hrs, if } (t_o > t_i) \right] \quad \text{Equation 8.34} \]

### 8.2.7.2 Dress for Less/Babysit Summer Thermostat/Summer Nighttime Setup/Get with the Program

**Description:**

Dress for Less: Wear light clothing and keep the thermostat 2°F higher when you are home.

Get with the Program: Program your thermostat to the Energy Star recommended temperatures.

Babysit Summer Thermostat: Turn up your thermostat by 7°F during the day when you are not home.

Summer Nighttime Thermostat: Turn up the thermostat by 4°F during the night when you are in bed.

### 8.2.7.2.1 Additional Assumptions

There is an overlap between the energy-saving actions of these Pins, depending on the type of thermostat the user has in their home. The Pins “Babysit Summer Thermostat” and “Summer Nighttime Thermostat” are targeted at users who like using a manual thermostat, but still would like to save energy. The two Pins calculate savings for thermostat setup during the day and at night as two separate actions. “Get with the Program” encourages proper use of a programmable thermostat. As programming the thermostat is a single action, the setup for day and night are achieved in a single step, so the resulting
cooling savings for “Get with the Program” is the sum of “Babysit Summer Thermostat” and “Summer Nighttime Thermostat”.

“Dress for Less” temperature setup – It is assumed that by dressing in light clothing, it is possible to set the thermostat +2 °F (+1.1°C) in the summer. This setup occurs during occupied hours (8 hrs per day) and is considered a pure behavioral change resulting from a reduction in desired comfort.

“Babysit Summer Thermostat” and “Summer Nighttime Thermostat” temperature setup – The Energy Star recommended setups for unoccupied daytime and nighttime can be found in Table 8.21. For these Pins, it is assumed that the user follows these recommendations. This results in a 7°F setup for “Babysit Summer Thermostat” and a 4°F setup for “Summer Nighttime Thermostat”.

The thermostat savings percentage utilized for these calculations is the same as that used in Section 8.2.7.1 Fan Club.

8.2.7.2.2 Calculation Procedure

The energy savings of this action is dependent on the baseline energy consumption of the home as determined in Equation 8.28, multiplied by the savings percentage, number of hours, and setup.

“Dress for Less”:
\[ \Delta E_{elec} = E_{cool,el\ consumed} \cdot 6\% \cdot \left( \frac{8}{24} \text{ hrs} \right) \cdot 2 \degree \text{ F} \quad \text{Equation 8.35} \]

“Babysit Summer Thermostat”:
\[ \Delta E_{elec} = E_{cool,el\ consumed} \cdot 6\% \cdot \left( \frac{8}{24} \text{ hrs} \right) \cdot 7 \degree \text{ F} \quad \text{Equation 8.36} \]

“Summer Nighttime Thermostat”:
\[ \Delta E_{elec} = E_{cool,el\ consumed} \cdot 6\% \cdot \left( \frac{8}{24} \text{ hrs} \right) \cdot 4 \degree \text{ F} \quad \text{Equation 8.37} \]

“Get with the Program” (cooling):
\[ \Delta E_{elec} = E_{cool,el\ consumed} \cdot 6\% \cdot \left( \frac{8}{24} \text{ hrs} \right) \cdot \left( 7 \degree \text{ F} + 4 \degree \text{ F} \right) \quad \text{Equation 8.38} \]

8.2.7.2.3 Final Equation

“Dress for Less”:
Electricity (kWh) \[ \Delta E_{\text{Dress for Less}} = E_{cool,el\ consumed} \cdot 0.04 \quad \text{Equation 8.39} \]

“Babysit Summer Thermostat”:
Electricity (kWh) \[ \Delta E_{\text{Babysit Summer Thermostat}} = E_{cool,el\ consumed} \cdot 0.14 \quad \text{Equation 8.40} \]

“Summer Nighttime Thermostat”:
Electricity (kWh) \[ \Delta E_{\text{Summer Nighttime Thermostat}} = E_{cool,el\ consumed} \cdot 0.08 \quad \text{Equation 8.41} \]

“Get with the Program” (cooling):
Electricity (kWh) \[ \Delta E_{\text{Get with the Program,cool}} = E_{cool,el\ consumed} \cdot 0.22 \quad \text{Equation 8.42} \]
8.3 Windows

Windows are often a major contributor to the space heating and cooling loads of the home. Windows are points of high heat loss in the winter, and are the major source of solar gain in the summer. Improving the performance of windows through user actions can be an important way to reduce energy consumption. There are many additional assumptions to be made regarding windows, so space heating and cooling pins that are directly involved with windows are grouped into this section.

8.3.1 Distribution of Windows

The average home is assumed to have window area equally distributed in the four cardinal directions: North, South, East and West. This is an extreme oversimplification but can be considered a good average over the population. The windows are assumed to be vertical (no skylights).

Window Tilt Angle, $\beta = 90^\circ$

The window area is approximated at 15% of floor area for a typical home. The window area $A_w$ includes the area of the frame $A_f$ and the glazing $A_g$.

$$A_w = A_f + A_g = 0.15 \times \text{HomeSize} \quad \text{Equation 8.43}$$

8.3.2 Solar Radiation

The solar radiation the home experiences determines how much heat enters the home through the windows. The TMY3 weather data provides important measures of solar radiation, including:

- GHI - Global Horizontal Irradiance (Wh/m$^2$)
- DNI – Direct Normal Irradiance (Wh/m$^2$)
- DHI – Diffuse Horizontal Irradiance (Wh/m$^2$)

Some steps must be taken to convert these values into the amount of solar radiation that falls on the windows in each of the four directions. This is accomplished through the calculation of several solar angles for each hour timestep from the 8760 hours of TMY3 data. The calculation of the incidence angle $\theta$ for each cardinal direction was determined from the book Solar Energy Engineering by Kalogirou (Kalogirou, 2009). The midpoint of each TMY3 hour timestep was used to calculate the angles for that hour. Daylight savings time was neglected as the TMY3 data points are for Local Standard Time (LST) only (Wilcox & Marion, 2008).

The total solar radiation that falls on a tilted surface $G_t$ can be determined from the sum of the beam radiation $G_{Bn}$ (called “direct radiation” by TMY3), diffuse radiation $G_{dn}$, and ground reflected radiation $G_G$.

$$G_t = G_{Bn} + G_{dn} + G_G \quad \text{Equation 8.44}$$

These three terms can be determined by utilizing the solar angle through the following equation derived from Kalogirou.

$$G_t = G_{Bn} \cos(\theta) + G_d \left[ \frac{1 + \cos(\beta)}{2} \right] + (G_B + G_d) \rho_g \left[ \frac{1 + \cos(\beta)}{2} \right] \quad \text{Equation 8.45}$$

Where $G_{Bn}$ is the beam radiation on a normal surface, $\beta$ is the tilt angle, $\theta$ is the incidence angle, and $\rho_g$ is the ground albedo. In the following equation, TMY3 data names have been used instead of the notation provided by Kalogirou.

$$G_t = DNI \cdot \cos(\theta) + DHI \cdot \left[ \frac{1 + \cos(\beta)}{2} \right] + GHI \cdot \rho_g \cdot \left[ \frac{1 + \cos(\beta)}{2} \right] \quad \text{Equation 8.46}$$
The ground albedo can be assumed to be for ordinary ground, $\rho_g = 0.2$. Although this equation is for radiation (measured in Watts) and the TMY3 data is irradiance (the sum of radiation over the hour timestep, in Wh), as the timestep is small we can assume that each timestep has uniform radiation.

In calculating the heat gain through a fenestration, the ground reflected radiation is added to the diffuse radiation term. Breaking the solar radiation down into only beam and diffuse radiation:

$$G_B = DNI \cdot \cos(\theta) \quad \text{Equation 8.47}$$

$$G_d = DHI \cdot \left[1 \frac{1 + \cos(\beta)}{2}\right] + GHI \cdot \rho_g \cdot \left[1 \frac{1 + \cos(\beta)}{2}\right] \quad \text{Equation 8.48}$$

### 8.3.3 Heat Gain through Fenestration

In general, the heat gain through a fenestration due to solar radiation is described by the ASHRAE Handbook as follows:

$$\dot{q}_{solar} = SHGC \cdot A_{pf} \cdot G_t \quad \text{Equation 8.49}$$

Where SHGC is the Solar Heat Gain Coefficient, $A_{pf}$ is the area of the window opening, and $G_t$ is the total solar radiation that falls on the window (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009). The SHGC is a dimensionless parameter that characterizes the fraction of solar radiation that is transmitted, plus the inward-flowing fraction of the radiation absorbed by the fenestration. Essentially it is the percentage of solar heat flowing into the home from the total radiation. The calculation of SHGC is quite complicated and depends on the incidence angle and glazing properties. As an annual estimation of solar heat gain is being calculated, the incidence angle $\theta$ is changing the value of SHGC for each hour.

The total solar heat gain of the window can be determined for each hour determined by breaking the SHGC down into component parts for the window frame (SHGC$_f$) and glazing, for both diffuse (SHGC$_{gd}$) and beam (SHGC$_{gb}$) radiation. The following equation calculates the solar heat gain ($\dot{q}_{SHG}$) through a fenestration without internal shading (McQuinston, Parker, & Spitler, 2004). The notation is adjusted to be consistent with the terms used in Kalogirou.

$$\dot{q}_{SHG} = [SHGC_{gb}A_{slgb} + SHGC_{fb}A_{slf}G_{bb}] + [SHGC_{gd}A_g + SHGC_{fd}A_f]G_d \quad \text{Equation 8.50}$$

### 8.3.4 Glazing Properties

The type of window glazing is limited to three choices in Table 3.2 Energy parameters: Single pane, Double pane, or Triple pane. All windows are assumed to have clear, 3mm thick glazing. The representative windows’ important glazing properties are determined from the ASHRAE Handbook, including the incidence-angular dependent center-of-glazing SHGC values. These values will not be reproduced here.

**Table 8.22 Window Glazing Types (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009).**

<table>
<thead>
<tr>
<th>ASHRAE ID</th>
<th>Glazing Type</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>1a</td>
<td>Uncoated Single Glazing, Clear</td>
<td>glass 3mm</td>
</tr>
<tr>
<td>5a</td>
<td>Uncoated Double Glazing, Clear</td>
<td>glass 3mm, 12mm airspace</td>
</tr>
<tr>
<td>29a</td>
<td>Triple Glazing, Clear</td>
<td>glass 3mm, 12mm airspace</td>
</tr>
</tbody>
</table>
Frame type – The windows are assumed to have non-aluminum frames (wood or vinyl), and the windows are assumed to be operable. The ASHRAE Handbook uses some rules of thumb for the properties of operable, non-aluminum framed windows.

\[
\text{Frame Area} = 20\% \text{ of window area} \\
\text{Frame SHGC} = 0.04
\]

8.3.5 Shading

Adding internal shading reflects solar radiation and reduces the amount of solar gain that enters the house. The effect of shading is characterized by the Interior Attenuation Coefficient (IAC). The incidence angle dependency of the IAC is neglected for simplification.

8.3.5.1 Interior Shading

There are various types of shading that a home could have, including Venetian blinds, vertical blinds, curtains, roller blinds, honeycomb shades, etc. The variation between these different types of shading devices is fairly small, and due to the lack of information it is easiest to assume a single type of interior shading. Therefore, the shading device used in this analysis is white opaque roller blinds.

The calculation of solar heat gain through a window with interior shading devices can be determined from Equation 8.51 (McQuinston, Parker, & Spitler, 2004).

\[
q_{SHG,\text{shaded}} = \left[ SHGC_f A_{sl} G_B + SHGC_f A_f G_d \right] + \left[ SHGC_{gB} A_{sl,g} G_B + SHGC_{gd} A_{gd} G_d \right] IAC \\
\text{Equation 8.51}
\]

<table>
<thead>
<tr>
<th>ASHRAE ID</th>
<th>Glazing Type</th>
<th>Specifications</th>
<th>IAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1a</td>
<td>Uncoated Single Glazing, Clear</td>
<td>glass 3mm</td>
<td>0.34</td>
</tr>
<tr>
<td>5a</td>
<td>Uncoated Double Glazing, Clear</td>
<td>glass 3mm, 12mm airspace</td>
<td>0.48</td>
</tr>
<tr>
<td>29a</td>
<td>Triple Glazing, Clear</td>
<td>glass 3mm, 12mm airspace</td>
<td>0.58</td>
</tr>
</tbody>
</table>

8.3.5.2 External Shading Factors

Most residential houses do not have all of the glazing exposed; often there is shading from trees, nearby buildings, window overhangs, bug screens, or various other shading devices. These external shading factors decrease the amount of solar gain that is received by the home. As there is no way to know what sort of external shading may be in place, a Seasonal SHGC multiplier will be used to account for these effects. The factor is 0.8 in the summer (when broadleaf trees are likely to block significant radiation) and 0.9 in the winter. The effect of external shading is neglected for this calculation.

\[
SHGC_{\text{seasonal,summer}} = 0.8 \\
SHGC_{\text{seasonal,winter}} = 0.9
\]

8.3.5.3 Baseline Blind Usage Percentage

A crucial assumption to make when calculating the amount of savings that occur from using the window blinds properly is the baseline amount of time the blinds are closed. This is the average percentage of time the windows are covered before the savings action occurs. No surveys or studies could be found
that had this data, so an engineering estimate is used. It is assumed blinds are used more often at night (for safety reasons).

Baseline blind usage, daytime = 50%
Baseline blind usage, nighttime = 75%

8.3.6 Conduction Heat Loss Calculations

The first type of heat transfer, conduction through the window pane can be quite significant in winter. The equation of conductive heat transfer through a building component such as a window can be seen in the following equation, (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009):

\[
d_{\text{cond}} = UA(t_i - t_o)
\]

Where \( U \) is the overall heat transfer coefficient, \( A \) is the area, \( t_i \) is the indoor temperature during the occupied time, from Table 8.13, and \( t_o \) is the outdoor temperature, as determined by the TMY3 weather data. The overall heat transfer coefficient is used to describe the overall conductance of the window unit including indoor and outdoor convection coefficients. The R-value, or resistance, is simply the inverse of the U-factor:

\[
U = \frac{1}{R}
\]

The U-factor can be determined from tables available from ASHRAE.

<table>
<thead>
<tr>
<th>ASHRAE ID</th>
<th>Wood/Vinyl Frames, operable window</th>
<th>Specifications</th>
<th>U-factor (W/m²-k)</th>
<th>R-value (m²-k/W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1a</td>
<td>Uncoated Single Glazing, Clear</td>
<td>glass 3mm</td>
<td>5.20</td>
<td>0.192</td>
</tr>
<tr>
<td>5a</td>
<td>Uncoated Double Glazing, Clear</td>
<td>glass 3mm, 12mm airspace</td>
<td>2.86</td>
<td>0.350</td>
</tr>
<tr>
<td>29a</td>
<td>Triple Glazing, Clear</td>
<td>glass 3mm, 12mm airspace</td>
<td>2.14</td>
<td>0.467</td>
</tr>
</tbody>
</table>

8.3.7 Window Pins

8.3.7.1 Sun Block

**Description:** Use blinds or curtains to reflect the sunlight during the day.

Using internal blinds to block or reflect solar gain during the day can be an effective method of reducing a home’s cooling load when performed diligently. However, calculating the amount of cooling energy saved by performing this action can be quite difficult without knowing important characteristics such as the orientation of the home, amount of windows, available shading, and other factors. For these reasons, the calculation of the savings for this action is considered only a rough approximation.

8.3.7.1.1 Additional Assumptions

Times when heat gain is unwanted – Preventing heat gain is only desired in the summer months, when the air conditioning would be running. Therefore, the unwanted heat gain is only summed for hours when the outdoor temperature is above the desired indoor temperature for summer, according to Table 8.21. The home is assumed to be set constantly at the “occupied” temperature, which is the baseline behavior.
8.3.7.1.2 Calculating Total Heat Gain Savings

The total heat gain during the summer is determined by summing the solar heat gain times the SHGC Seasonal multiplier for the four cardinal directions (North, South, East, and West). This is the same for the case with and without the blinds. The calculation of solar heat gain in unshaded and shaded cases can be found in Equation 8.50 and Equation 8.51 respectively. The baseline solar heat gain for this Pin is determined by using the baseline blind usage percentage from Section 8.3 for the daytime. The solar heat gain reduction is the baseline solar heat gain minus the heat gain that would occur during a 100% shaded condition.

\[
\dot{q}_{SHG,\text{baseline}} = \sum_{N,S,E,W} 0.8 \cdot \left[ q_{SHG} \cdot (1 - 0.5) + q_{SHG,\text{shaded}} \cdot (0.5) \right] \quad \text{Equation 8.54}
\]

\[
\Delta q_{SHG,\text{saved}} = \dot{q}_{SHG,\text{baseline}} - \sum_{N,S,E,W} 0.8 \cdot \dot{q}_{SHG,\text{shaded}} \quad \text{Equation 8.55}
\]

The total annual solar heat gain savings is the sum of savings for all the hours when the outdoor temperature is above the desired indoor temperature.

\[
\Delta Q_{SHG,\text{saved}} = \sum_{t=1}^{8760} \begin{cases} \Delta q_{SHG,\text{saved}}, & \text{if } t_o > t_i \\ 0, & \text{if } t_o \leq t_i \end{cases} \quad \text{Equation 8.56}
\]

8.3.7.1.3 Final Equations

Finally, the solar heat gain savings is divided by the COP of the selected A/C unit from Table 8.19, to determine the energy savings that is avoided by using the blinds in the summer. The result is also converted into kWh.

Electric (kWh):

\[
\Delta E_{\text{Sun Block}} = \frac{\Delta Q_{SHG,\text{saved}}}{\text{COP} \times 1000 \; \text{Wh/kWh}} \quad \text{Equation 8.57}
\]

8.3.7.2 Bubble Wrap

Description: Shut the curtains or blinds at night to retain heat.

Shutting the curtains or blinds at night can help to trap a layer of still air between the window pane and the interior of the home, adding additional insulating value to the window. The amount of savings is determined by using the heat loss calculation procedure from Section 8.3, assuming opaque roller blinds are used at night to add additional heat transfer resistance (R-value) to the fenestration.

8.3.7.2.1 Additional Assumptions

R-value added by the roller blind – The R-value added by the roller blind is difficult to determine. It cannot be generalized as a “still air space” as there is no sealing between the window and the blind, and thus air is continuously circulating behind the blind. However, there are manufacturer measurements on the additional insulation value provided by window shades such as roller blinds. Table 8.25 gives a product provided by a window shade manufacturer that claims to increase the R-value of a window by approximately 0.18 K/W.
Table 8.25 R-values of window products (Hunter Douglas Inc., 2008).

<table>
<thead>
<tr>
<th>Fenestration</th>
<th>R-value (ft-F-h/BTU)</th>
<th>R-value (K/W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Designer Roller Shades (with double glazed window)</td>
<td>4.52</td>
<td>0.80</td>
</tr>
<tr>
<td>Double glazed window (alone)</td>
<td>3.5</td>
<td>0.62</td>
</tr>
<tr>
<td>Designer Roller Shades (alone)</td>
<td>1.02</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Determining the total R-value for the user’s selected window type with this added shade can be accomplished by summing the resistances.

\[ R_{\text{window+shade}} = R_{\text{shade}} + R_{\text{window}} \]  \hspace{1cm} \text{Equation 8.58}

The heat loss due to conduction can then be calculated by Equation 8.52 and Equation 8.53.

\[ \dot{q}_{\text{cond,window+shade}} = U_{\text{window+shade}} A(t_i - t_o) \]  \hspace{1cm} \text{Equation 8.59}

The baseline case of heat transfer out of the window depends on the usage of the window blinds. In Section 8.3, it was assumed that at night, the blinds are closed 75% of the time as the baseline case. The amount of heat loss prevented by closing the blinds 100% of the time can then be calculated by subtracting the from the baseline case.

\[ \dot{q}_{\text{cond, baseline}} = \sum_{N,S,E,W} \left[ \dot{q}_{\text{cond, window}} \cdot (1 - 0.75) + \dot{q}_{\text{cond, window+shade}} \cdot (0.75) \right] \]  \hspace{1cm} \text{Equation 8.60}

\[ \Delta q_{\text{cond, saved}} = \dot{q}_{\text{cond, baseline}} - \sum_{N,S,E,W} \dot{q}_{\text{cond, window+shade}} \]  \hspace{1cm} \text{Equation 8.61}

Hours when the blinds are shut – The blinds are assumed to be shut only at night (some of them will be open for solar gain during the day) to prevent heat loss. It is assumed that the home’s resident closes the blinds once he or she returns home from work, and opens them in the morning when they wake up and prepare for the day. The hours the blinds should operate are:

- Blinds closed=18:00
- Blinds return to baseline behavior=7:00

Hours when the heat loss is not desired – Trying to prevent heat loss at night is only effective in the winter months, when the outdoor temperature is less than the indoor temperature, according to Table 8.21. The home is assumed to be set constantly at the “occupied” temperature.

8.3.7.2.2 Calculation Procedure

The total heat loss for the year is determined by summing the savings during the nighttime hours where the outdoor temperature is below the indoor temperature.

\[ \Delta Q_{\text{cond, saved}} = \sum_{i=1}^{8760} \begin{cases} \Delta q_{\text{cond, saved}}, & \text{if } h < 7:00 \text{ AND } t_i > t_o \\ 0, & \text{if } 7:00 \leq h \leq 18:00 \text{ or } t_i \leq t_o \\ \Delta q_{\text{cond, saved}}, & \text{if } h > 18:00 \text{ AND } t_i > t_o \end{cases} \]  \hspace{1cm} \text{Equation 8.62}

8.3.7.2.3 Final Equations

To determine the delivered energy saved, it is necessary to divide the heat loss savings by the efficiency of the space heating system from Table 8.11. The result is also converted into kWh.
Space Heating Fuel (kWh): \[
\Delta E_{\text{Bubble Wrap}} = \frac{\Delta Q_{\text{heatloss.saved}}}{\eta_{\text{heat}} \cdot 1000 \text{ Wh/kWh}}
\]  
Equation 8.63

### 8.3.7.3 Catch Some Rays

**Description:** Open the south-facing blinds during the day to gain solar heat.

During the winter, it is advantageous to open the blinds on the south side of the house to gain solar heat and reduce the amount of external space heating energy required. Opening the east and west blinds is often helpful, but the north side is rarely beneficial in terms of providing solar gain. This is because opening the blinds also increases the heat transfer due to conduction through the window pane (and closing them can reduce the heat loss, see Section 8.3.7.2). The south blind receives the most solar radiation, so it is nearly always a good idea to open those windows except in the coldest climates on overcast days.

#### 8.3.7.3.1 Solar Gain

The solar heat gain is calculated for each hour in a method similar to Section 8.3.7, however the south window is the only one taken into consideration. The assumptions for SHGC seasonal multiplier (for winter, 0.9) is and usage percentage (in daytime, 50%) from Section 8.3 are utilized here also.

\[
\dot{q}_{\text{SHG, baseline},S} = 0.9 \cdot \left[ \dot{q}_{\text{SHG},S} \cdot (1 - 0.5) + \dot{q}_{\text{SHG,shaded},S} \cdot (0.5) \right]
\]  
Equation 8.64

\[
\dot{q}_{\text{SHG, saved},S} = \dot{q}_{\text{SHG, baseline},S} - \dot{q}_{\text{SHG,shaded},S}
\]  
Equation 8.65

#### 8.3.7.3.2 Heat Loss

Opening the south blinds 100% of the time will cause additional heat loss (as outlined in Section 8.3.7.2, using the blinds can help reduce heat transfer) over the baseline case, where the blinds are closed 50% of the time. To calculate the net energy saved by allowing additional solar gain, the additional heat loss that takes place must be subtracted from the total solar gain. The additional heat loss can be calculated by the methods outlined in Section 8.3.7.2 using the same assumptions for U-value. The same assumption for daytime blind usage percentage applies as for solar heat gain.

\[
\dot{q}_{\text{cond, baseline},S} = \dot{q}_{\text{cond, window},S} \cdot (1 - 0.5) + \dot{q}_{\text{cond, window+shade},S} \cdot (0.5)
\]  
Equation 8.66

\[
\dot{q}_{\text{cond, loss},S} = \dot{q}_{\text{cond, window},S} - \dot{q}_{\text{cond, baseline},S}
\]  
Equation 8.67

#### 8.3.7.3.3 Final Equations

The solar gain is desired for any time the outdoor temperature is below the occupied indoor temperature for winter as given in Table 8.13. The home dweller is assumed to open the south blind when the sun rises, so hours that receive solar gain (\(\dot{q}_{\text{SHG, south}} > 0\)) are assumed to also experience increased heat loss.

The total annual solar heat gain savings is the sum of savings for all the hours when the outdoor temperature is above the desired indoor temperature, and the sun is up (or solar heat gain is positive).

\[
\Delta Q_{\text{saved},S} = \sum_{i=1}^{365} \left\{ \begin{array}{ll}
\Delta q_{\text{SHG, saved},S} & \text{if } t_o > t_i \text{ AND } \dot{q}_{\text{SHG, saved},S} > 0 \\
0 & \text{if } t_o \leq t_i \text{ OR } \dot{q}_{\text{SHG, saved},S} \leq 0
\end{array} \right\}
\]  
Equation 8.68
Finally, the net savings is divided by the efficiency of the space heating unit ($\eta_{heat}$), from Table 8.11 to determine the energy savings that occurs by opening the south blinds during the winter. The final result is converted into kWh.

$$\Delta E_{catch some rays} = \frac{\Delta Q_{SHG, saved}}{\eta_{heat} \cdot 1000 \text{Wh/kWh}}$$

Equation 8.69

### 8.3.7.4 Clearly Warmer

**Description:** Add plastic window covers during the winter to reduce heat loss.

As those who live in the coldest areas of the country know, sealing a tight layer of plastic over the windows can prevent heat loss. The plastic manages this in two ways. First, the additional layer of air over the window increases the insulating value of the window (R-value) and reduces heat loss. Secondly, the plastic can serve as a barrier to infiltration, preventing loss of heat through cracks around the window frame.

For calculating the savings for adding a plastic window film over all the houses’ windows, some assumptions about the housing structure and its windows must be made. Assumptions about the window area and the types of windows previously made can be seen in Section 8.3.7.

#### 8.3.7.4.1 Additional Assumptions

Heat transfer across an air gap occurs by two methods: convection and radiation (McQuinston, Parker, & Spitler, 2004). Determining the reduction in heat transfer due to adding the plastic film is possible using ASHRAE tables once several characteristics of the space are known.

First, the effective emittance of the space, $E$, must be determined. For this problem, one surface of the space is glass, and the other is a transparent plastic. The effective emittance for both surfaces being glass from the ASHRAE tables is used.

Effective emittance, $E_b = 0.72$

As the heat transfer is horizontally across the space (normal to the window pane), the thickness of the air space is important. Based on normal window frame depths, a thickness $L$ of the air gap is assumed:

$L = 0.04 \text{ m}$

The mean temperature across the air space $t_m$ and temperature difference $\Delta t$ are also assumed. One side of the air space will be at room temperature (around 21 °C in winter), while the other side (the inner pane of the window) will be somewhere between the room temperature and the outdoor temperature, depending on the structure of the window. Single-pane windows will have higher temperature differences than more highly-insulated window types. The R-value of the airspace was determined by using ASHRAE tables, interpolating between values of $E_b$ where needed.

**Table 8.26** Air space R-values (American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2009).

<table>
<thead>
<tr>
<th>ASHRAE ID</th>
<th>at $E_b=0.72$, $L=0.04$ m</th>
<th>$t_m$ °C</th>
<th>$\Delta t$ °C</th>
<th>R-value $(\text{C-m}^2)/\text{W}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1a</td>
<td>Uncoated Single Glazing, Clear</td>
<td>10.0</td>
<td>16.7</td>
<td>0.179</td>
</tr>
<tr>
<td>5a</td>
<td>Uncoated Double Glazing, Clear</td>
<td>10.0</td>
<td>5.6</td>
<td>0.205</td>
</tr>
<tr>
<td>29a</td>
<td>Triple Glazing, Clear</td>
<td>10.0</td>
<td>5.6</td>
<td>0.205</td>
</tr>
</tbody>
</table>

The total R-value for the window including the additional air gap is determined by summing the resistances. The resistance of the plastic itself is neglected.
\[ R_{\text{window+film}} = R_{\text{airgap}} + R_{\text{window}} \quad \text{Equation 8.70} \]

The reduced heat transfer through the window can then be determined from Equation 8.52 and Equation 8.53. The heat transfer savings for each hour can be determined by subtracting the reduced heat transfer from the heat transfer in the baseline case.

\[ \Delta q_{\text{savings}} = A(t_i - t_o) \cdot (U_{\text{window,only}} - U_{\text{window+film}}) \quad \text{Equation 8.71} \]

Time period when window film is in place – the window film is intended to be installed during the first days of winter, and remains in place until the spring. Different areas of the country have differing climates and differing times when it is optimum to put up and take down the window film. However, determining the perfect day to install and take down the window film is beyond the scope of this project. Instead, an average time period will be used that is typical of when most window films will be installed and taken down.

Window film installation – October 15th (6888th day of the year)
Window film takedown – March 15th (1752nd hour of the year)

During times when the window film is not in place, the savings from this Pin is zero.

8.3.7.4.2 Final Equations

The total annual savings from this Pin can be determined by summing the energy savings for each of the 8760 hours of the year.

\[ \Delta Q_{\text{heatloss,saved}} = \sum_{i=1}^{8760} \begin{cases} \Delta q_{\text{savings}}, & \text{if } i < 1752 \\ 0, & \text{if } 1752 \leq i \leq 6888 \\ \Delta q_{\text{savings}}, & \text{if } i > 6888 \end{cases} \quad \text{Equation 8.72} \]

To determine the delivered energy saved, it is necessary to divide the heat loss savings by the efficiency of the space heating system from Table 8.11.

Space Heating Fuel (kWh): \[ \Delta E_{\text{Clearly Warmer}} = \frac{\Delta Q_{\text{heatloss,saved}}}{\eta_{\text{heat}}} \quad \text{Equation 8.73} \]
8.4 Water Heating

After space heating and cooling, water heating is the largest end-use of energy in a home. Hot water is used primarily for cleaning in the home, including in clothes washers, dishwashers, hand washing, showering, and bathing.

8.4.1 Water Heating Systems

In the United States, there are two major fuels used to heat water: natural gas and electricity. Other fuels, such as fuel oil and propane (LPG) are used as well, but to a much smaller extent, just over 8% of households have a water heater that is not fueled by natural gas or electricity. Additionally, natural gas and electricity are easily metered and can be tied into JouleBug’s energy graph, whereas other fuels such as heating oil or propane are periodic deliveries and cannot be easily graphed. Therefore, for simplification purposes, it is possible to neglect these fuels. The breakdown of water heating fuels can be seen in Table 8.27. Figure 8.8 shows the breakdown of the two major fuels, eliminating the others from consideration.

Table 8.27 Distribution of water heating fuels (U.S. Energy Information Administration, 2009).

<table>
<thead>
<tr>
<th>Fuel</th>
<th>Number of Households (millions)</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Gas</td>
<td>58.7</td>
<td>53%</td>
</tr>
<tr>
<td>Electricity</td>
<td>43.1</td>
<td>39%</td>
</tr>
<tr>
<td>Fuel Oil</td>
<td>4.0</td>
<td>4%</td>
</tr>
<tr>
<td>Propane (LPG)</td>
<td>4.0</td>
<td>4%</td>
</tr>
<tr>
<td>Other fuels</td>
<td>0.2</td>
<td>0%</td>
</tr>
<tr>
<td>Do not use hot water</td>
<td>1.1</td>
<td>1%</td>
</tr>
<tr>
<td>Total</td>
<td>111.1</td>
<td>100%</td>
</tr>
</tbody>
</table>

Figure 8.8 Major residential water heating fuels.

8.4.2 Correlating Water Heating and Number of Occupants

The major factor that drives the consumption of hot water is the number of occupants in the home. Homes with more occupants require more showers, more laundry, and more dishwashing than homes with fewer occupants. Based on this logic, a correlation will be developed to estimate the amount of water heating energy required by a home based on the number of full-time occupants. Examining the trendlines, it appears that the correlation is strongest for logarithmic patterns. Therefore, correlations will be developed to determine the annual water heating energy consumption based on ln(NumOccupants).

8.4.2.1 Methodology

Correlations for water heating energy consumption will be developed in a method similar Section 8.1.3.1. An equation relating the ln(NumOccupants) with the water heating energy consumption will take the form of:

\[ E_{WH,fuel\,consumed} = a \cdot \ln(\text{NumOccupants}) + b \quad \text{Equation 8.74} \]

Where \( a \) and \( b \) are coefficients determined from the regression analysis.

The important RECS survey variable that will be used is number of occupants (NHSLDMEM). The data was separated based on the water heating fuel type (natural gas or electricity). The number of homes (NWEIGHT) in each bin was utilized as the weighting function for the Weighted Least Squares analysis.
The data was then binned according to number of occupants, from one to six or more, using the same bins that are utilized in RECS summary data (U.S. Energy Information Administration, 2009).

Bin sizes: \{[1],[2],[3],[4],[5],[6<}\}

### 8.4.2.2 Correlations Developed

The following figure shows the trendlines that were developed, with the number of homes in each data bin represented by the area of the bubble.

![Water heating consumption trendlines](image)

A table summarizing the correlation coefficients and the weighted R² values can be seen below. The procedure for calculating the weight-adjusted r² values is the same as for heating and cooling, using Equation 8.8.

**Table 8.28** Water heating correlation coefficients and weighted r² values.

<table>
<thead>
<tr>
<th>Water Heating Fuel</th>
<th>a</th>
<th>b</th>
<th>Weighted-r²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gas</td>
<td>3343</td>
<td>4153</td>
<td>0.952</td>
</tr>
<tr>
<td>Electric</td>
<td>1644</td>
<td>1604</td>
<td>0.992</td>
</tr>
</tbody>
</table>

According to the weighted-r² values, the correlations developed are quite well suited to the binned data. This shows that the relationship between number of occupants and the water heating energy used in the home is very strong. As with space heating and cooling, there can be quite a bit of variation in each bin, due to occupant behavior. However, this correlation will provide a good estimation of water heating energy usage for the two most popular fuel types relying on a single, easily obtained variable.

### 8.4.2.3 Data Summary

The tables below summarize the binned data that was used to develop the correlations. The percent difference between the correlation and the bin average is calculated according to Equation 8.9.
Table 8.29 Gas water heating summary.

<table>
<thead>
<tr>
<th>Number of Occupants</th>
<th>Average Number of Occupants</th>
<th>Water Heating Energy (kWh)</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.0</td>
<td>4584</td>
<td>506</td>
<td>15.2</td>
<td>3.0%</td>
</tr>
<tr>
<td>2</td>
<td>2.0</td>
<td>6941</td>
<td>711</td>
<td>17.6</td>
<td>3.6%</td>
</tr>
<tr>
<td>3</td>
<td>3.0</td>
<td>7871</td>
<td>403</td>
<td>9.6</td>
<td>0.2%</td>
</tr>
<tr>
<td>4</td>
<td>4.0</td>
<td>8373</td>
<td>369</td>
<td>8.9</td>
<td>3.5%</td>
</tr>
<tr>
<td>5</td>
<td>5.0</td>
<td>9385</td>
<td>187</td>
<td>4.5</td>
<td>0.8%</td>
</tr>
<tr>
<td>6 or more</td>
<td>6.8</td>
<td>10822</td>
<td>116</td>
<td>2.6</td>
<td>6.1%</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>2.5</td>
<td>7063</td>
<td>2292</td>
<td>58.4</td>
<td>2.9%</td>
</tr>
</tbody>
</table>

Table 8.30 Electric water heating summary.

<table>
<thead>
<tr>
<th>Number of Occupants</th>
<th>Average Number of Occupants</th>
<th>Water Heating Energy (kWh)</th>
<th>Sample Count</th>
<th>Homes Represented (millions)</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.0</td>
<td>1610</td>
<td>428</td>
<td>12.8</td>
<td>0.4%</td>
</tr>
<tr>
<td>2</td>
<td>2.0</td>
<td>2748</td>
<td>565</td>
<td>13.8</td>
<td>0.2%</td>
</tr>
<tr>
<td>3</td>
<td>3.0</td>
<td>3412</td>
<td>293</td>
<td>7.3</td>
<td>0.1%</td>
</tr>
<tr>
<td>4</td>
<td>4.0</td>
<td>3850</td>
<td>223</td>
<td>5.6</td>
<td>0.9%</td>
</tr>
<tr>
<td>5</td>
<td>5.0</td>
<td>4079</td>
<td>109</td>
<td>2.7</td>
<td>4.1%</td>
</tr>
<tr>
<td>6 or more</td>
<td>6.7</td>
<td>5145</td>
<td>55</td>
<td>1.2</td>
<td>8.3%</td>
</tr>
<tr>
<td>Weighted Average (totals)</td>
<td>2.5</td>
<td>2814</td>
<td>1673</td>
<td>43.3</td>
<td>0.8%</td>
</tr>
</tbody>
</table>

8.4.2.4 Baseline Water Heating Energy Consumption

The energy consumption of any particular water heating system over the entire year can be determined by using the correlations coefficients developed in Table 8.28 and Equation 8.74.

Water Heating Fuel (kWh): \[ Q_{WH,fuel\,consumed} = a \cdot \ln(Num\,Occupants) + b \] Equation 8.75

8.4.3 Water Temperature and Density

Density of water – The density change of water with temperature is neglected.

\( \rho = 1 \text{ kg/liter} \)

Specific heat of water – The amount of heat required to raise the temperature of one gram of water by one degree Celsius (Cengel & Boles, 2008).

\( C_p = 4.18 \text{ kJ/kg-K} \)

Hot tap water temperature – The set temperature of the water heater. This varies depending on the setting, but assuming that JouleBug players are energy-conscious, the lowest typical setting is used (U.S. Department of Energy, 2011c).

\( T_h = 120 \degree \text{ F (48.8} \degree \text{ C)}\)

Cold tap water temperature – The incoming water to the water heater. This is approximated by using the average groundwater temperature for the U.S. (Eno Scientific, 2010).
\[ T_c = 58 \, ^\circ F \ (14.4 \, ^\circ C) \]

### 8.4.4 Water Heater Energy Factor

The Energy Factor (EF\textsubscript{WH}) is the ratio of useful energy output from the water heater to the total amount of energy delivered to the water heater (Energy Star, n.d.). The energy factor varies depending on the fuel of the water heater. It is assumed that all players have a traditional gas storage water heater, or an electric resistance storage water heater. The storage water heater utilizes a 20-80 gallon tank which is constantly being heated. Storage hot water heaters experience standby losses, mostly from conduction through the tank walls. Gas water heaters experience flue losses as well, as the heated products of combustion must be vented outside the house for safety purposes (U.S. Department of Energy, 2011b). This causes gas water heaters to have lower energy factors than electric water heaters. As of 2009, less than 3% of households have a tankless water heater (U.S. Energy Information Administration, 2012a).

The Energy Factor of the water heater is an estimate based on available data about past water heater regulations. U.S. regulations that went into effect in 2004 set the initial efficiency limits on water heaters, (0.57 for gas storage and 0.9 for electric storage for a 55 gallon tank). However, it is likely that many older and less efficient water heaters still exist in homes, given an expected lifetime of 13 years (U.S. Department of Energy, 2010). Therefore, the EF was reduced to account for this.

**Table 8.31 Water heater energy factor.**

<table>
<thead>
<tr>
<th>Fuel</th>
<th>Energy Factor (EF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Gas</td>
<td>0.50</td>
</tr>
<tr>
<td>Electricity</td>
<td>0.88</td>
</tr>
</tbody>
</table>

### 8.4.5 Energy Required to Heat Water

The equation for determining the energy required to heat a certain volume of water is given by Cengel and Boles (Cengel & Boles, 2008).

\[ E_w = \rho V C_p (T_h - T_c) \quad \text{Equation 8.76} \]

Where \( \rho \) is the density of water, \( V \) is the volume of water, \( C_p \) is the specific heat, and \( (T_h - T_c) \) is the temperature rise required.

### 8.4.6 Water Heating Pins

#### 8.4.6.1 Fill 'er Up

**Description:** Run a full load in the dishwasher instead of a partial load.

**8.4.6.1.1 Additional Assumptions**

**Dishwasher cycles per year** – The number of dishwasher cycles run by the average household. This number is used to estimate the annual energy usage of the appliance. (Energy Star, 2012b)

\[ \text{Cycles per household annually} = 215 \text{ cycles/year} \]

Number of cycles is assumed to scale linearly with household size. As mentioned in Table 3.2, the average household size is 2.6 persons. Therefore, the number of cycles per person per year can be determined.

\[ \text{Cycles per household member} = 82.69 \text{ cycles/year} \]

**Average dishwasher water usage** – The water usage by a dishwasher can be used to evaluate its water heating energy consumption, as all the water used by a dishwasher is hot water. A report by LBNL gives the water consumption of a post-1993 dishwasher (Koomey, Dunham, & Lutz, 1994). From this report the water usage per cycle is determined. Note that the LBNL study gives a different number for cycles per year than Energy Star.

\[ \text{Dishwasher Water Usage} = 5.96 \text{ gallons/day} \ (22.56 \text{ liters/day}) \]
Dishwasher Cycles = 229 cycles/yr
Dishwasher Water Usage = 9.5 gallons/cycle (35.96 liters/day)

Savings by running full loads – This is the approximate percent savings that can be achieved by running full loads rather than partial loads in the dishwasher. No studies on this concept were found, so an estimation based on the expected behavioral change was used.

Savings Percentage = 10% of total energy

8.4.6.1.2 Calculation procedure:

1. Determine the per cycle energy consumption from water heating from Equation 8.76.
   \[ E_w = 1.436 \text{ kWh/cycle} \]
2. Extrapolate over one year by multiplying by number of cycles per person.
   \[ E_w = 118.77 \text{ kWh/person-yr} \]
3. Divide by the Energy Factor from Table 8.31 for the different fuels.
4. Multiply by the savings percentage.

8.4.6.1.3 Final Result

Baseline dishwasher energy consumption:

| Fuel (kWh): Water Heating | \[ \Delta E_{DW,WH \, consumed} = \frac{118.77 \cdot \text{Num. occupants}}{EF_{WH}} \] |

Energy savings “Fill er Up”:

| Fuel (kWh): Water Heating | \[ \Delta E_{\text{Fill er up}} = \frac{11.88 \cdot \text{Num. occupants}}{EF_{WH}} \] |

8.4.6.2 Washing Cold

Description: Wash your clothes in cold water.

8.4.6.2.1 Additional Assumptions

Clothes Washer cycles per year – The number of clothes washer cycles run per year by the average household. This number was developed to test energy consumption of clothes washers (U.S. Department of Energy, 1997).

Clothes Washer Cycles = 392 cycles/year

Number of cycles is assumed to scale linearly with household size. As mentioned in Table 3.2 Energy parameters, the average household size is 2.6 persons. Therefore, the number of cycles per person per year can be determined.

Cycles per household member = 150.8 cycles/year


Washer Size = 3.21 ft³ (0.09 m³)

Water Factor – A maximum on the total amount of water (hot and cold) used per cycle is set by the U.S. federal regulations (Energy Star, 2011b). While it is possible a significant amount of washing machines exceed the federal requirement, the regulation is quite recent, so there are likely a number of machines still...
in homes that do not meet the regulation. Therefore, using the regulation value as an “average” is acceptable. The water factor depends on the capacity of the washing machine.

\[ WF = \frac{W}{C} \]  

Equation 8.79

\[ WF = 9.5 \text{ gallons/ft}^3 (1260.4 \text{ liters/m}^3) \]

Thereby, the total water usage of the average washer can be calculated using Equation 8.79.

Washer Water consumption = 30.5 gallons/cycle (115.5 liters/cycle)

Baseline hot water usage – The amount of hot water currently used by typical consumers, from a survey by LBNL (Koomey, Dunham, & Lutz, 1994). Note that the cycle count in the survey was slightly different from the federal test specification. This represents the hot water consumption of an “average cycle”.

Baseline hot water usage = 7.29 gallons/day

Cycles per year = 380 cycles/year

Baseline hot water consumption = 7.00 gallons/cycle (26.5 liters/cycle)

Reduced hot water usage percentages – Assuming that this Badge will encourage consumers to change their behavior, an assumption on the amount of hot water that will be consumed in the behavioral change case is necessary. A total reduction in hot water is unrealistic. A washing machine has two cycles, wash and rinse, and nearly always the washing machine utilizes cold water to rinse. Hot water is assumed to come from the water heater. A “hot water wash” is assumed to use hot water to wash (hot water=50% of total water consumption). A “warm water load” is assumed to use a 50/50 mix of hot/cold to wash (hot water=25% of total consumption) and cold water to rinse. For “Reduced hot water consumption”, an estimation of 15% of loads using hot water wash, and 15% of loads in warm water wash, with 70% in cold water wash will be used. The resulting average hot water consumption can be calculated below.

Reduced hot water consumption = 3.43 gallons/cycle (13.0 liters/cycle)

8.4.6.2.2 Calculation Procedure

1. Determine the baseline and reduced per cycle energy consumption from water heating from Equation 8.76.
2. For both the baseline and reduced energies, extrapolate over one year by multiplying by number of cycles per person.
3. For both baseline and reduced energy consumption, divide by the Energy Factor from Table 8.31 for the different fuels.
4. For both fuels, subtract the reduced consumption from baseline consumption to calculate the energy savings.

8.4.6.2.3 Final Result

Baseline washer energy consumption:

\[ E_{CW,WH \text{ elec consumed}} = \frac{159.44 \cdot \text{Num Occupants}}{EF_{WH}} \]  

Equation 8.80

Energy savings "Washing Cold":

\[ \Delta E_{\text{wash cold}} = \frac{81.32 \cdot \text{Num Occupants}}{EF_{WH}} \]  

Equation 8.81
8.4.6.3 Super Soaker

Description: Replace your showerhead with an energy-efficient low-flow model.

8.4.6.3.1 Additional Assumptions

Age of Showerhead – A regulation on showerhead flow rate went into effect in 1993 that limited the flow rate to a maximum of 2.5 gallons/min (U.S. Department of Energy, 2011d). It is assumed for this Pin that the showerhead replacement that takes place replaces a pre-1993 showerhead with a current regulated model.

Hot water usage of showerheads – The amount of hot water used for showering in households was measured by the LBNL study specifically for this regulation change (Koomey, Dunham, & Lutz, 1994). Note that the number of household members from this older study is slightly different than the current value.

Baseline household hot water consumption = 26 gal/day (98.4 liters/day)
Reduced household hot water consumption = 19 gal/day (71.9 liters/day)
Number of household members = 2.67 people
Baseline individual hot water consumption = 9.74 gal/person-day (36.9 liters/person-day)
Reduced individual hot water consumption = 7.12 gal/person-day (27 liters/person-day)

Multiple showerheads in a home – This calculation does not account for multiple showerheads within a home. The savings will automatically scale with the number of home occupants. Future measures may be taken to rectify this situation.

8.4.6.3.2 Calculation Procedure

1. Determine the baseline and reduced per person per day energy consumption from Equation 8.76.
2. For both the baseline and reduced cases, extrapolate over one year to get the annual energy required for water heating.
3. To account for the inefficiencies in the water heater, divide by the Energy Factor from Table 8.31 to get equations for the different fuels, for both baseline and reduced energy consumption.
4. For both fuels, subtract the reduced consumption from baseline consumption to calculate the energy savings.

8.4.6.3.3 Final Equations

\[ \Delta E_{\text{Super Soaker}} = \frac{144.87 \cdot \text{Num}_{\text{occupants}}}{EF_{\text{WH}}} \quad \text{Equation} \ 8.82 \]

8.4.6.4 Shower Sprinter

Description: Take a shower that is 1 minute less than normal, and aim for a 5 minute shower.

8.4.6.4.1 Additional Assumptions

Individual savings vs. household – Shower time is considered to be an “individually controlled” behavior. It is unlikely that a household member who is not a JouleBug user would be affected, so the savings for this action are calculated for a single individual (not a per-household basis). This is different than actions like upgrading the showerhead to a lower flow rate, an action which could be performed by a single individual (the JouleBug user) but would affect all the members in the household who use that shower.
Showerhead flow rate – This Pin assumes that the user has a showerhead that meets the U.S. minimum standard put into effect in 1993. It is very unlikely that many homes still have high flow rate showerheads at the time of this writing.

Showerhead flow rate = 2.5 gal/min (9.46 liters/min)

Percentage of hot water – This is the percentage of a typical shower that is hot water. The showerhead flow rate measures total water flow, which is a mixture of hot and cold water, only the hot water utilizes energy within the home. Therefore, it is important to know what fraction of the total water is “hot” (coming directly from the water heater). The LBNL study measures the hot water usage in a household for showering per day as 19 gallons, while the total water usage was measured as 33 gallons. Using these figures, the fraction of hot water can be determined.

\[ \text{Fraction of hot water} = \frac{19 \text{ gallons}}{33 \text{ gallons}} = 58\% \]

Shower time reduction – The Pin assumes a shower time reduction of one (1) minute. It is also assumed that people take one (1) shower per day.

8.4.6.4.2 Calculation Procedure

1. Determine the amount of hot water saved per shower using the flow rate, hot water fraction, and time reduction.
   \[ V_{\text{savings}} = 1.44 \text{ gal/shower (5.5 liters/shower)} \]
2. Determine the energy savings per person per day from Equation 8.76.
3. Extrapolate over one year to get the annual energy required for water heating.
4. To account for the inefficiencies in the water heater, divide by the Energy Factor from Table 8.31 to get the annual savings for the different fuels.

8.4.6.4.3 Final Equations

Water Heating
Fuel (kWh):
\[ \Delta E_{\text{shower sprinter}} = \frac{79.54}{EF_{\text{WH}}} \quad \text{Equation 8.83} \]

8.4.6.5 Star Status Dishwasher

Description: Buy an Energy Star qualified dishwasher.

8.4.6.5.1 Additional Assumptions

This Pin involves replacing a standard dishwasher with an Energy Star model. The assumptions about the dishwasher energy usage from Section 8.4.6.1 “Fill ‘er Up” also apply to this section, and can be considered to be figures for a standard, baseline model dishwasher.

Energy Star energy consumption – The Energy Star criteria for a full-size dishwasher is that it uses less than 295 kWh/yr of energy for both water heating and the electric motor. Another requirement is that it uses less than 4.5 gallons/cycle of water (Energy Star, 2012b). The water usage can be used to determine the energy used by water heating, for a dishwasher, 100% of the water used is hot water.

\[ \text{Energy Star water usage} = 4.25 \text{ gallons/cycle (16.01 liters/cycle)} \]

The machine energy difference between the standard and Energy Star cases is neglected by following the procedure in Section 3.1.1.

8.4.6.5.2 Calculation Procedure

1. Determine the Energy Star per cycle end-use energy consumption from water heating from Equation 8.76.
\[ E_w = 0.64 \text{ kWh/cycle} \]

2. Subtract the Energy Star energy consumption from the standard dishwasher per cycle energy consumption from Section 8.4.6.1 “Fill ‘er Up”.
3. Extrapolate over one year by multiplying by number of cycles per person.
4. Divide by the Energy Factor from Table 8.31 for the different fuels to determine the amount of delivered energy that was consumed (taking into account water heater inefficiency).

### 8.4.6.5.3 Final Equations

Water Heating

\[ \Delta E_{\text{Star Status Dishwasher}} = \frac{65.63 \cdot \text{Num\_occupants}}{EF_{WH}} \]  

Equation 8.84

### 8.4.6.6 Star Status Clothes Washer

**Description:** Buy an Energy Star qualified washing machine.

#### 8.4.6.6.1 Additional Assumptions

In this Pin, a user must replace a standard clothes washer with an Energy Star model. The assumptions about the dishwasher energy usage from Section 8.4.6.2 “Washing Cold” also apply to this section, and can be considered to be figures for a standard washing machine.

Energy Star water consumption – The Energy Star criteria for a clothes washer is a requirement on the Modified Energy Factor (MEF) and Water Factor (WF). The Water Factor can help determine the amount of energy that is used to heat water in the clothes washer.

Energy Star WF \( \leq 6 \text{ gallons/ft}^3 \) (802 liters/m\(^3\))

Using the washer size of 3.21 ft\(^3\) (0.09 m\(^3\)), it is possible to calculate the water usage per cycle using Equation 8.79.

\[ \text{Energy Star washer water consumption} = 19.26 \text{ gallons/cycle} \ (72.91 \text{ liters/cycle}) \]

Hot water consumption percentage – The percentage of the total washer’s water that is hot for an average load is based on the information in Section 8.4.6.2 “Washing Cold”. The hot water usage is dependent on user behavior and so an average using typical consumption data is best suited to estimate this. Dividing the amount of hot water used in a standard washer by the total water use can derive the hot water use percentage. It is assumed that Energy Star washers and standard washers use the same percentage of hot water (hot water use is proportional to the total water use).

Hot water use percentage = 22.96%

The machine energy savings is neglected, as it is below $10/yr.

#### 8.4.6.6.2 Calculation Procedure

1. Determine the amount of hot water used per cycle by multiplying the per cycle water consumption by the hot water use percentage.

   \[ \text{Hot water use} = 4.42 \text{ gallons/cycle} \ (16.73 \text{ liters/cycle}) \]

2. Use the amount of hot water with Equation 8.76 to determine the Energy Star per cycle end-use energy consumption from water heating.

3. Subtract the Energy Star energy consumption from the standard clothes washer per cycle energy consumption from Section 8.4.6.2 “Washing Cold”.

4. Extrapolate over one year by multiplying by number of cycles per person from Section 8.4.6.2.

5. Divide by the Energy Factor from Table 8.31 for the different fuels to determine the amount of delivered energy that was consumed (taking into account water heater inefficiency).
8.4.6.6.3 Final Equations

Water Heating Fuel (kWh):
\[
\Delta E_{\text{Star Status Clothes Washer}} = \frac{58.80 \cdot \text{Num occupants}}{EF_{\text{WH}}}
\]

Equation 8.85

8.4.6.7 Faucet Fixer/Pressure Investor

Description: Fix a leaky faucet or showerhead to save hot water.

8.4.6.7.1 Additional Assumptions

Although two separate Pins, these two actions have similar potential savings, in that they both are fixtures that use both hot and cold water, and have a limited potential for leakage. Leakage is a very difficult issue to determine without an inspection, as there is no widely-published statistics on leakage at different end-use points. In addition, leakage varies widely across the population, with a small minority of households contributing most of the leakage. Therefore, many assumptions are required to calculate a measure of savings for these Pins. However, the relative impact of this action is small, so the effect on a user’s aggregated savings will be minimal.

Leakage reduction – According to the book Residential End Uses of Water by the Water Research Foundation (Water Research Foundation, 1999), cited at the website of the American Water Works Association, homes in the US contribute 9.5 gallons per capita per day (gpcd) of leakage (36.0 liters per capita per day). The website mentions that by “…regularly checking for leaks…” it would be possible to reduce leakage to 4.0 gpcd (15.1 liters per capita per day). The AWWA cites the Handbook of Water Use and Conservation by Amy Vickers as the source of this information (American Water Works Association, 2012).

Total leakage reduction = 5.5 gpcd (20.82 liters per capita per day)

The reduction in leakage is assumed to be attributed to the sink, showerhead, and toilet. According to a publication by Aqua Managers, a wholesaler of water equipment, between 80-90% of water leaks are attributed to the toilet (Aqua Managers Inc., 2008). This statistic is directly referring to the number of leaks (number of service calls), not the actual volume of water leakage. However, leaks that are significant enough to warrant a service call are likely contributing the highest volume of water leakage. A safe estimate is that 80% of the leakage is coming from the toilet, and splitting the other leakage points so that 10% is attributed to the showerhead and 10% to the sink.

Sink/Showerhead leakage percentage = 10%

Hot water percentage – Water faucets can use both cold and hot water, but only the hot water is directly contributing to the energy consumption of the user’s home. It is assumed that leaks from sinks and showerhead are composed of equal parts hot and cold water.

Hot water percentage = 50%

The amount of people within the home is also significant. It is assumed that like most water heating-focused actions, the amount of savings depends on the amount of occupants. For a case like water leakage, this assumption is somewhat flawed, because there could easily be cases of large leaks in a home with a single occupant, and homes with many occupants could have few leaks. However, the amount of fixtures in the home should roughly correlate with the number of occupants. In addition, water usage statistics are given in terms of volume per person per day, which implies that water usage (including leaks) could be dependent on the number of occupants. Regardless, the impact of this action is small enough that even a relatively high uncertainty in calculating the savings can be tolerated.
8.4.6.7.2 Calculation Procedure

1. Determine the amount of hot water conserved by fixing leaks in either the showerhead or sink by multiplying the total leakage reduction by the hot water percentage and the percentage attributed to the sink or showerhead.

   Hot water savings from sink/showerhead = 0.275 gpcd (1 liter per person per day)

2. Use the amount of hot water with Equation 8.76 to determine the energy savings at the end-use.
3. Extrapolate over one year by multiplying by 365 days.
4. Divide by the Energy Factor from Table 8.31 for the different fuels to determine the amount of delivered energy that was consumed (taking into account water heater inefficiency).

8.4.6.7.3 Final Equations

Water Heating
Fuel (kWh):

\[
\Delta E_{Raucet Fixer} = \Delta E_{Pressure Invoer} = \frac{15.20 \times \text{Num occupants}}{EF_{WH}}
\]

Equation 8.86

8.5 Appliances

8.5.1 Appliance Pins

8.5.1.1 Dry Naturally

Description: Avoid using the "heat dry" function on the dishwasher.

8.5.1.1.1 Additional Assumptions

Previous assumptions about dishwashers can be seen in Section 8.4.6.1 “Fill ‘er Up”.

Federal Standard Energy Factor (EF) –Before 2009, Energy Factor was used to rate the performance of dishwashers. According to Energy Star, “EF is expressed in cycles per kWh; so the greater the EF, the more efficient the dishwasher is. EF is the reciprocal of the sum of the machine electrical energy per cycle, M, plus the water heating energy consumption per cycle, W” (Energy Star, 2012b).

\[
EF = \frac{1}{M + W}
\]

Equation 8.87

The U.S. federal standard maximum annual energy usage for dishwashers starting in 1991 was to have an Energy Factor of 0.46. This is outlined in test specification 10 CFR 430 developed by the U.S. Department of Energy (U.S. Department of Energy, 1997). All dishwashers sold must meet this minimum standard. As dishwashers have an average lifetime of 10 years (Energy Star, 2010a), all dishwashers currently in homes are expected to meet this standard. This value was used rather than the current standard to be more representative of models currently in use.

Dishwasher EF <= 0.46

Energy consumption of heat dry – This is the approximate energy consumption of the heated dry function that will be avoided (equivalent to the energy saved). The California Energy Commission estimates this as 15%-50% of the dishwasher’s electrical energy consumption (machine energy) (California Energy Commission, 2012b).

Savings Percentage = 15% of machine electrical energy
8.5.1.1.2 Calculation procedure

1. Use the water heating energy from Section 8.4.6.1.2 with Equation 8.87 to determine the machine energy consumed over one year, substituting $E_w$ for $W$.
2. Extrapolate over one year by multiplying by number of cycles per person from Section 8.4.6.1.1.
3. Multiply the machine energy by the savings percentage.

8.5.1.1.3 Final Result

Electric (kWh) $\Delta E_{Dry\ naturally} = 9.17 \times Num\_occupants$ Equation 8.88

8.5.1.2 Washing Smart

Description: Wash only full loads of clothes.

8.5.1.2.1 Additional Assumptions

The energy use from doing laundry can be divided into three categories: the water heating energy, the machine energy needed to run the washer’s motor, and the energy needed to dry the clothes. In nearly all cases, the energy required to run the motor is insignificant compared to the water heating and dryer energy. It is also assumed that the user will correctly set the water setting on the washing machine, so there is no effect on the water heating energy. Therefore, the primary savings from doing a full load of laundry occurs in the clothes dryer. Typical clothes dryers utilize a timer to dry the load. Because dryers are designed to dry the maximum load size, smaller loads are prone to over-drying.

Fuel type for clothes dryer – According to RECS 2009, around 15% of U.S. households have natural gas clothes dryers at home (U.S. Energy Information Administration, 2012a). The overwhelming majority of households that have a clothes dryer use an electric dryer. Rather than require this information from the user, only electric dryers will be considered.

Load fullness – It is assumed that 25% of all laundry loads are “not full”. No research was found on laundry habits, although the federal washer test specification uses a “fill factor” that assumes 28% of the washer’s loads are the “minimum size”, and 72% are the “maximum size” (U.S. Department of Energy, 1997).

Load Fullness = 25%

Savings Percentage – It is assumed that converting a partial load to a full load will save 25% of the dryer’s total energy for that cycle.

Savings Percentage = 25%

Dryer energy consumption – The amount of electric energy per one 45-minute cycle of drying (Multi-Housing Laundry Association, 2006).

Dryer Energy Consumption = 3.3 kWh/cycle

8.5.1.2.2 Calculation Procedure

1. Determine the total dryer energy consumption per person per year using the information on number of cycles from Section 8.4.6.2.1

$$E_{dryer\_consumption} = 497.54 \times Num\_occupants$$ Equation 8.89

2. Multiply by the Load Fullness and Savings percentages to get the energy saved.
8.5.1.2.3 Final Result

\[ \Delta E_{\text{Washing Smart}} = 31.10 \times \text{Num\_occupants} \]  \hspace{1cm} \text{Equation 8.90}

8.5.1.3 Drying Smart

**Description:** Clean the lint trap of your clothes dryer.

8.5.1.3.1 Additional Assumptions

This Pin’s savings are based on the fact that a filled lint trap may impede the flow of air through the dryer and cause it to take longer to dry the clothes, as well as it will make the fan work harder to blow air through the dryer because of the increased pressure drop.

Behavioral affected percentage – The user currently cleans the lint trap with a less-than-perfect frequency. The times that the user does not clean the lint trap can be affected by JouleBug-induced behavioral changes. No studies were readily available on this subject, so it is assumed that the user cleans the lint trap 75% of the time and that the remaining 25% can be considered “savings”.

\[
\text{Affected Load Percentage} = 25\% \text{ of the cycles}
\]

Savings Percentage – The amount of savings that can be expected from cleaning the lint trap. The California Energy Commission estimates that cleaning the lint trap can save *up to* 30% of the dryer’s energy consumption (California Energy Commission, 2012a). A more conservative estimate is used for JouleBug.

\[
\text{Savings percentage} = 15\%
\]

8.5.1.3.2 Calculation Procedure

1. Use the total dryer energy consumption from Section 8.5.1.2.2, and multiply it by the Affected Load Percentage and the Savings Percentage to get the dryer energy saved.

8.5.1.3.3 Final Result

\[ \Delta E_{\text{Drying Smart}} = 18.66 \times \text{Num\_occupants} \]  \hspace{1cm} \text{Equation 8.91}

8.5.1.4 Star Status Fridge

**Description:** Buy an Energy Star qualified refrigerator or freezer.

8.5.1.4.1 Additional Assumptions

This Pin will assume that a refrigerator/freezer combo unit is purchased. The Energy Star specification for refrigerators as of April 28, 2008, notes that qualified models must be 20% more efficient than the current federal standard. The current standard was set by National Appliance Energy Conservation Act (NAECA) in 2001, and varies depending on the specific configuration of the refrigerator, the size, and whether or not it has through-the-door ice service (Energy Star, 2008b).

Refrigerator size – The size of the refrigerator/freezer unit that determines energy consumption is the Adjusted Volume (AV). This is based on the equation below, which gives AV in ft$^3$.

\[ AV = \text{Fresh Volume} + 1.63 \times \text{Freezer Volume} \]  \hspace{1cm} \text{Equation 8.92}

The typical size of a modern American refrigerator is 15 ft$^3$ (0.42 m$^3$) of fresh volume and 10 ft$^3$ (0.28 m$^3$) of freezer volume, which determines the Adjusted Volume.

\[ AV = 31.3 \text{ ft}^3 \ (0.89 \text{ m}^3) \]
The formulas to calculate the energy consumption of the standard and Energy Star refrigerators can be seen in Table 8.32.

### Table 8.32 Refrigerator energy consumption (Energy Star, 2008a).

<table>
<thead>
<tr>
<th>Product Category</th>
<th>NAECAs of July 1, 2001 Maximum Energy Usage in kWh/year</th>
<th>Current ENERGY STAR level Maximum Energy Usage in kWh/year (as of April 28, 2008)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Refrigerators and Refrigerator-freezers with manual defrost</td>
<td>8.82*AV+248.4</td>
<td>7.056*AV+198.72</td>
</tr>
<tr>
<td>Refrigerator-Freezer--partial automatic defrost</td>
<td>8.82*AV+248.4</td>
<td>7.056*AV+198.72</td>
</tr>
<tr>
<td>Refrigerator-Freezers--automatic defrost with top-mounted freezer without through-the-door ice service and all-refrigerators--automatic defrost</td>
<td>9.80*AV+276</td>
<td>7.84*AV+220.8</td>
</tr>
<tr>
<td>Refrigerator-Freezers--automatic defrost with side-mounted freezer without through-the-door ice service</td>
<td>4.91*AV+507.5</td>
<td>3.928*AV+406</td>
</tr>
<tr>
<td>Refrigerator-Freezers--automatic defrost with bottom-mounted freezer without through-the-door ice service</td>
<td>4.60*AV+459</td>
<td>3.68*AV+367.2</td>
</tr>
<tr>
<td>Refrigerator-Freezers--automatic defrost with top-mounted freezer with through-the-door ice service</td>
<td>10.20*AV+356</td>
<td>8.16*AV+284.8</td>
</tr>
<tr>
<td>Refrigerator-Freezers--automatic defrost with side-mounted freezer with through-the-door ice service</td>
<td>10.10*AV+406</td>
<td>8.08*AV+324.8</td>
</tr>
</tbody>
</table>

#### 8.5.1.4.2 Calculation Procedure

1. Determine both the standard and Energy Star annual energy consumption of each of the types of refrigerator/freezer combo units in Table 8.32.
2. Average the energy consumption of all the refrigerator/freezer types for both standard NAECAs and Energy Star cases.
3. Subtract the average Energy Star energy consumption from the NAECAs standard case to determine the annual energy savings from purchasing an Energy Star refrigerator.

#### 8.5.1.4.3 Final Result

Electric (kWh) \[ \Delta E_{\text{Star Status Fridge}} = 123.26 \] Equation 8.93

### 8.6 Lighting

This section can be divided into two main types of lighting: indoor and outdoor lighting.

#### 8.6.1 Indoor Lighting

Incandescent light power - It is assumed that the light replaced is a typical incandescent light bulb, which can be assumed to be 60 W. According to a 2001 survey, the average incandescent light wattage in the U.S. is 67 W (Navigant Consulting Inc., 2002). The commercially available bulb closest to this figure is the 60 W.

Incandescent light bulb power = 60 W

Baseline time on - The time that an average light bulb is used per day varies greatly depending on the location. It can be assumed that any bulb that is replaced is an “average” bulb, although the more frequently used bulbs will see more savings while less frequently used bulbs will achieve less savings. The
average hours of bulb usage was determined from an Energy Star survey of CFL lighting (U.S. Department of Energy, 2009a).

Average light bulb usage = 1.9 hrs/day

Number of bulbs - The number of bulbs required for this Pin is four (4), which is assumed to be the minimum amount of bulbs that would exist in a household (a small studio apartment would likely have this number). Houses that have more than 4 bulbs are able to earn the Pin many times. Each time four bulbs are replaced, it can be assumed that the savings is achieved.

Number of bulbs = 4 bulbs

8.6.2 Outdoor Lighting

Incandescent light power – It is assumed that the light replaced is a higher wattage bulb like a porch light, which can be assumed to be 75 W.

Incandescent outdoor light bulb power = 75 W

Baseline time on – The energy savings for this Pin occurs from the reduction of the usage time for the incandescent outdoor light. It is assumed that the user achieving this Pin already leaves at least one outdoor light on the entire night. This occurs in 23% of US households (U.S. Energy Information Administration, 2009).

Baseline Hours On = 8 hrs

Number of bulbs – It’s assumed that the motion sensor light replaces the use of a single outdoor light. In reality, most large houses have several outdoor lights, which may or may not be on at night.

The baseline amount of energy consumed by the outdoor light over a year is calculated as follows:

$$E_{\text{light, consumed}} = n \cdot P \cdot t \cdot \frac{365 \text{ days}}{1000 \text{ W/kW}}$$  \hspace{1cm} \text{Equation 8.94}

Where \(n\) is the number of bulbs, \(P\) is the power of the bulb in Watts, and \(t\) is the hours per day the bulb is on. For a single outdoor light with at \(P=75\) W and \(t=8\) hr, the total energy consumed over a year is as follows:

$$E_{\text{outdoor light, consumed}}=219 \text{ kWh/yr}$$

8.6.3 Lighting Pins

8.6.3.1 CFLs

Description: Replace 4 incandescent lights with CFLs.

8.6.3.1.1 Additional Assumptions

CFL light power – Compact Fluorescent Lamps (CLFs) are rated for wattage equivalencies with incandescent bulbs based on the amount of light they output (lumens). The comparable CFL wattage is determined by an Energy Star publication (Energy Star, 2006).

Equivalent CFL power = 14 W

8.6.3.1.2 Calculation Procedure

1. For both the incandescent and the CFL case, use Equation 8.94 to calculate the lighting energy consumed.
2. Subtract the CFL energy consumption from the incandescent energy consumption to get the energy savings per day.
3. Multiply over one year to get the annual energy savings.

### 8.6.3.1.3 Final Equations

Electric (kWh) \[ \Delta E_{\text{CFLs}} = 127.60 \]  

### 8.6.3.2 LEDs

**Description:** Replace 4 incandescent lights with LEDs.

#### 8.6.3.2.1 Additional Assumptions

Similar assumptions to the section on CFLs can be used for this Pin.

**LED light power** - Light Emitting Diodes (LEDs) are rated for wattage equivalencies with incandescent bulbs based on the amount of light they output (lumens). As LEDs are relatively new, there are few that are exact replacements for incandescent bulbs. One example of a 60 W equivalent LED replacement is a bulb produced by Phillips, the first to earn Energy Star certification (Casanova, 2011).

\[ 60 \text{ W equivalent LED power} = 12.5 \text{ W} \]

#### 8.6.3.2.2 Calculation Procedure

1. For both the incandescent and the LED case, multiply the power consumption by the number of bulbs, and the hours per day to obtain the energy consumed. Use the information from Section 8.6.3.1.2 for incandescent bulbs.
2. Subtract the LED energy consumption from the incandescent energy consumption to get the energy savings per day.
3. Multiply over one year to get the annual energy savings.

#### 8.6.3.2.3 Final Equations

Electric (kWh) \[ \Delta E_{\text{LEDs}} = 131.77 \]  

### 8.6.3.3 Afraid of the Dark

**Description:** Install a motion sensor exterior light instead of using a porch light all night.

#### 8.6.3.3.1 Additional Assumptions

**Reduced time on** – It is assumed that with a motion sensor, the time the light is on is greatly reduced, only coming on during motion events (such as the arrival of a car, or animal activity). Sensor lights typically have a timer that shuts them off after 15-30 minutes.

\[ \text{Reduced Hours On} = 1 \text{ hr} \]

#### 8.6.3.3.2 Calculation Procedure

1. Multiply the power consumption by the hours per day in both the baseline case and reduced case to get the energy consumed.
2. Subtract the reduced case from the baseline case to get the energy savings per day.
3. Multiply over one year to get the annual energy savings.

#### 8.6.3.3.3 Final Equations

Electric (kWh) \[ \Delta E_{\text{Afraid of the Dark}} = 191.63 \]  

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8.6.3.4   **CFLs Outside**

**Description:** Use a CFL in your exterior light.

8.6.3.4.1   **Additional Assumptions**

This Pin replaces an exterior light with an equivalent wattage CFL bulb. Because of the similarity of the situation, this Pin can share the same assumptions about the incandescent wattage, baseline time on, and number of bulbs as in Section 8.6.3.3 Afraid of the Dark.

CFL light power – The comparable CFL wattage is determined by an Energy Star publication (Energy Star, 2006).

Equivalent CFL power = 21.5 W

8.6.3.4.2   **Calculation Procedure**

1. Multiply the power consumption by the usage hours per day in both the incandescent case and CFL case to get the energy consumed.
2. Subtract the CFL case from the incandescent case to get the energy savings per day.
3. Multiply over one year to get the annual energy savings.

8.6.3.4.3   **Final Equations**

Electric (kWh) \[
\Delta E_{\text{CFLs outside}} = 156.22 \quad \text{Equation 8.98}
\]

8.6.3.5   **Sunny Nights**

**Description:** Install solar-powered walkway lighting instead of using a floodlight.

8.6.3.5.1   **Additional Assumptions**

This Pin assumes that an incandescent exterior light is replaced with solar-powered exterior lighting. These systems typically consist of a small photovoltaic panel which charges a battery during the day. At night, the battery is used to power a low-power LED light. The same assumptions about the incandescent wattage, baseline time on, and number of bulbs are identical to Section 8.6.3.3. It is assumed that the solar powered lights are entirely self-contained, have no meterable electrical load, and so the baseline power of the light will be entirely conserved.

8.6.3.5.2   **Calculation Procedure**

1. Multiply the power consumption by the usage hours per day for the incandescent bulb to get the energy consumed. This is equal to the energy savings, because the solar light uses no metered energy.
2. Multiply over one year to get the annual energy savings.

8.6.3.5.3   **Final Equations**

Electric (kWh) \[
\Delta E_{\text{Sunny Nights}} = 219.00 \quad \text{Equation 8.99}
\]
8.7 Electronics

8.7.1 Electronics Pins

8.7.1.1 Home Computer

Description: Set the power settings on your computer so it shuts down or hibernates when you aren’t using it.

8.7.1.1.1 Additional Assumptions

Essentially, the baseline behavior is very important in calculating the savings for this action. Users who are vigilant about turning the computer off will achieve a smaller savings, while users who leave the PC on 24/7 will see more savings. The latest RECS survey shows that only 4.1% of computer owners have no power management configured, with 58.5% turning the computer off and the remaining 37.4% using sleep/standby mode (U.S. Energy Information Administration, 2012a). However, this contradicts the findings by other surveys, including 1E who found that only 63% of Americans “power down” (eg. use power management) computers in their home (1E, 2009).

Reduction in computer usage – The computer running time eliminated by the implementation of power management. This is an estimate of the average reduction in computer running time. In this case, the average is likely skewed, as those who are leaving the computer on 24/7 will see more reduction in computer running time than those who already shut the computer down frequently.

Baseline computer usage = 6 hours/day

Reduced computer usage = 3 hours/day

Computer power and usage percentages – Computers use varying amounts of power depending on their setup and specific running conditions. However, in general, laptops and desktops can be grouped separately as having very different power consumption levels. The following table shows the average power consumption in both “on” (idle) and “off” modes for laptops and desktops as tested by LBNL (Lawrence Berkeley National Laboratory, 2011). Many computers still draw some power, called ‘standby power’ although they are off. The usage percentages are derived from RECS 2009 for the most used computer in residential households (U.S. Energy Information Administration, 2012a).

<table>
<thead>
<tr>
<th>Type of Computer</th>
<th>&quot;On&quot; Power (W)</th>
<th>Off Power (W)</th>
<th>Usage Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laptop</td>
<td>29.48</td>
<td>8.9</td>
<td>44%</td>
</tr>
<tr>
<td>Desktop</td>
<td>73.97</td>
<td>2.84</td>
<td>56%</td>
</tr>
</tbody>
</table>

8.7.1.1.2 Calculation Procedure

1. Use Equation 8.100 to determine the total power used for each type of computer in the baseline (6hr) case.

\[ E = P_{on} \cdot t_{on} + P_{off} \cdot t_{off} \]  

Equation 8.100

2. Use Equation 8.100 to determine the total power for each type of computer used in the reduced usage (3hr) case.

3. Use the Usage Percentage to create a weighted average of energy savings for the two computer types, for both reduced and baseline cases, using Equation 8.101.
\[ \bar{E} = \frac{U_1E_1 + U_2E_2 + \cdots + U_nE_n}{U_1 + U_2 + \cdots + U_n} \]  

Equation 8.101

4. Subtract the power consumption of the average reduced case from the average baseline case to determine the average savings.

**Final Result**

Electric (kWh) \[ \Delta E_{\text{Home Computer}} = 53.55 \]  

Equation 8.102

**8.7.1.2 Turn off your Monitor**

**Description:** Shut off your monitor when you are done working on your computer.

**8.7.1.2.1 Additional Assumptions**

Turning off the computer monitor is a simple task but one that is often forgotten. Similar assumptions to Section 8.7.1.1.1 about the usage of computers can be made for desktop computer displays (monitors). They will be in operation at the same hours as the computers.

Monitor power and usage percentages – Computer monitors use either Liquid Crystal Display (LCD) or Cathode-Ray Tube (CRT) technology. LCD is newer and more energy efficient technology, but many homes still use CRTs. The following table shows the average power consumption for both “on” (idle) and “off” modes for monitors tested by LBNL (Lawrence Berkeley National Laboratory, 2011). The usage percent is the percentage of desktop-using households who own each type of monitor (U.S. Energy Information Administration, 2012a).

<table>
<thead>
<tr>
<th>Type of Monitor</th>
<th>&quot;On&quot; Power (W)</th>
<th>Off Power (W)</th>
<th>Usage Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRT Monitor</td>
<td>65.10</td>
<td>0.80</td>
<td>21%</td>
</tr>
<tr>
<td>LCD Monitor</td>
<td>27.61</td>
<td>1.13</td>
<td>79%</td>
</tr>
</tbody>
</table>

**8.7.1.2.2 Calculation Procedure**

1. Use Equation 8.100 to determine the total power used the baseline (6hr) case.
2. Use Equation 8.100 to determine the total power used the reduced usage (3hr) case.
3. Use Equation 8.101 to determine the weighted average energy consumption for both the baseline and reduced cases.
4. Subtract the power consumption of the average reduced case from the average baseline case to determine the savings.

**8.7.1.2.3 Final Result**

Electric (kWh) \[ \Delta E_{\text{Turn off Monitor}} = 37.57 \]  

Equation 8.103

**8.7.1.3 DeVampirizer**

**Description:** Use a timer or power strip to prevent your DVR or set-top box from consuming energy when it's not in use.
8.7.1.3.1 Additional Assumptions

Electronic devices such as cable/satellite TV boxes and DVRs (together referred to as set-top boxes, or STB) are nearly always in standby mode, consuming power. Standby power, sometimes called “vampire power”, is power consumed by devices “while they are switched off or not performing their primary function” (Lawrence Berkeley National Laboratory, n.d.). This Pin assumes that the JouleBug user installs a timer or power strip to completely cut power (<1W) to the set-top box.

Standby power consumption of the STB – This is the power consumed by the device when it is not in use. This power consumption was surveyed by LBNL for devices including cable boxes, satellite boxes, DVRs, and combinations of these. However, the most commonly used device in the U.S. is the cable box, at 36% of households having one (U.S. Energy Information Administration, 2012a). The following figure is for the average cable box turned off by remote (Lawrence Berkeley National Laboratory, 2011).

Cable box standby power consumption=17.83 W

Usage time – During the day, the STB can be assumed to be either in “usage mode” or “standby mode”. Usage mode for the set-top box occurs when it is actively in use, namely when the user is watching TV. The rest of the day, the STB can be considered to be in standby. The reduction in energy usage only occurs during the time when the STB is in standby mode (or the TV is not on). If the usage time is known, then the standby time can also be determined. From examining data on TV usage patterns for the U.S., the average time that the TV (and STB) is in use can be determined (U.S. Energy Information Administration, 2009).

Usage time = 5.4 hours/day
Standby time = 18.6 hours/day

Multiple devices – The calculation is for a single STB only. The concept of households having multiple devices can be tackled if the JouleBug user earns this Pin more than once. The amount of savings on the subsequent STBs may be larger than the first due to their lower usage time, but this is not easily quantifiable.

8.7.1.3.2 Calculation Procedure

1. Multiply the standby time per day by the standby power consumption of the device.
2. Extrapolate over a year to determine the total standby power savings.

8.7.1.3.3 Final Result

\[ \Delta E_{DeVampirizer} = 121.05 \]  

Equation 8.104

8.7.1.4 Home Entertainment Center

Description: Use a timer or power strip at your home entertainment center to stop your TV, Blu-Ray player, subwoofer and other electronics from consuming energy when not in use.

8.7.1.4.1 Additional Assumptions

Selection of devices – The selection of devices is based on what a typical home entertainment center may contain. The standby power consumption of these devices was measured by LBNL and can be seen in the table below (Lawrence Berkeley National Laboratory, 2011).
Table 8.35 Home entertainment center standby power consumption.

<table>
<thead>
<tr>
<th>Device</th>
<th>Standby Power (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Television Rear Projection</td>
<td>6.97</td>
</tr>
<tr>
<td>Stereo System</td>
<td>8.32</td>
</tr>
<tr>
<td>DVD Player</td>
<td>1.55</td>
</tr>
<tr>
<td>VCR</td>
<td>4.68</td>
</tr>
</tbody>
</table>

Usage time – The home entertainment center is predicted to be in use around the same times as when the TV is in use. As these devices are likely to be on the same power strip or timer, and the TV is likely the most used device in the home entertainment center, the user will control the standby power of all devices based on the TV’s usage time.

8.7.1.4.2 Calculation Procedure

1. Multiply the standby time per day by the standby power consumption for each device.
2. Extrapolate over a year to determine the total standby power savings.
3. Sum the resulting savings for all devices to get the total savings for the home entertainment center.

8.7.1.4.3 Final Result

Electric (kWh) $\Delta E_{\text{Home Entertainment Center}} = 146.10$  

Equation 8.105

8.7.1.5 Office Slayer

Description: Use a timer or power strip in your office to stop your printer and computer from consuming energy when not in use.

8.7.1.5.1 Additional Assumptions

Selection of devices – The selection of devices is based on a typical home office. The standby power consumption of these devices was measured by LBNL and can be seen in the following table (Lawrence Berkeley National Laboratory, 2011).

Table 8.36 Office standby power consumption.

<table>
<thead>
<tr>
<th>Device</th>
<th>Standby Power (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desktop</td>
<td>2.84</td>
</tr>
<tr>
<td>Multifunction Printer, Inkjet</td>
<td>5.26</td>
</tr>
<tr>
<td>Computer Display, LCD, off</td>
<td>1.13</td>
</tr>
</tbody>
</table>

Usage time – The computer is the controlling device in the office, and the peripherals can be assumed to be shut down when the computer is off. These devices are likely to be on the same power strip or timer. The average usage time for the home computer is determined by an analysis of computer usage (U.S. Energy Information Administration, 2012a).

Computer usage time = 3.91 hrs/day

Computer standby time = 20.09 hrs/day
8.7.1.5.2 Calculation Procedure

1. Multiply the computer standby time per day by the standby power consumption for each device.
2. Extrapolate over a year to determine the total standby power savings.
3. Sum the resulting savings for all devices to get the total savings for the home entertainment center.

8.7.1.5.3 Final Result

Electric (kWh) \[ \Delta E_{\text{office standby}} = 67.68 \]  

Equation 8.106

8.7.1.6 Star Status Electronic

Description: Buy an Energy Star qualified small electronic device (audio/video system).

8.7.1.6.1 Additional Assumptions

The Energy Star program for Audio/Video systems covers a wide range of devices, including home theater systems, audio amplifiers, AV receivers, shelf systems, DVD players, Blu-Ray players, and docking stations for audio amplification or optical drive function (Energy Star, 2012a).

Type of Device – The wide range of devices is very diverse and no aggregated information is available about the power consumption of these devices to compare with the Energy Star program. Therefore, a commonly purchased device, the Blu-Ray player, will be selected for the calculation.

Baseline Device power consumption – No aggregated data was available about the non-Energy-star qualified device’s power consumption. However, a popular tech website, CNET, did provide some data on Blu-ray player power consumption (Moskovciak, 2010). Using the data from that site provides the power consumption of the device while playing and while in standby, as well as the test specification for playback time, 10 hrs per week. The average of the devices reviewed by CNET is given. The power consumption while the device is off is neglected, as in most cases it is less than one Watt. The quick-start mode is assumed to be turned off.

Baseline power while playing = 25.44 W

Baseline power in standby = 22.50 W

Hours of playback per week = 10 hrs

Hours of standby – The standard Blu-Ray player, lacking an automatic shutdown feature, is assumed to be in standby 10 hours per week.

Baseline standby hours per week = 10 hrs.

Energy Star power consumption – The Energy Star Audio/Video specification 2.0 Tier 2 for high-definition optical disc players (Blu-Ray players) is the source for the Energy Star power consumption data (Energy Star, 2012b). The Energy Star standard also has a requirement on auto-shutoff. The list of qualified products was consulted to determine the typical auto-shutoff times for Blu-Ray players, as well as typical standby power consumption, as this is not outlined in the standard (Energy Star, 2012a). Most players shut off after 30 minutes of standby. A typical playback period of two hours, over the course of a week, is equivalent to five Blu-Ray discs played.

Energy Star power while playing = 15 W

Energy Star power in standby = 10 W

Energy Star hours of standby per week = 2.5 hrs.
8.7.1.6.2 Calculation Procedure

1. Use Equation 8.100 to calculate the energy consumption in the baseline and Energy Star cases, replacing $P_{off}$ and $T_{off}$ with the standby power consumption and standby time, respectively.
2. Subtract the Energy Star result from the baseline case to determine the savings per day.
3. Extrapolate over a year to get the annual savings.

8.7.1.6.3 Final Result

Electric (kWh) $\Delta E_{\text{Star Status Electronic}} = 15.83$  

Equation 8.107

8.7.1.7 Star Status TV

Description: Buy an Energy Star qualified TV.

8.7.1.7.1 Additional Assumptions

TV Size – The size (screen area) of the television directly affects the power consumption. A new flat-screen (LCD or plasma) TV can range in size from under 20 in (51 cm) to over 52 in (132 cm). Picking a rough midpoint for this range, the size of the TV is assumed to be 32 in (81 cm) measured diagonally, with a total screen area of 438 in$^2$ (2826 cm$^2$).

Baseline TV power – The power consumption of many different TVs currently on the market was measured by the tech website CNET (CNET, 2012). The average default power consumption for 32 in TVs is a good measure for calculations.

Baseline TV power = 105.4 W

Energy Star TV power – The power consumption of an Energy Star qualified product is outlined in Energy Star specification for TVs Version 5.3 (Energy Star, 2011d). Equation 8.108 calculates the maximum power of TV ($P_{\text{max}}$) in Watts, depending on the screen area ($A$) in inches.

$$ P_{\text{max}} = 0.084 \times A + 18 \quad \text{Equation 8.108} $$

Using this equation, the Energy Star TV’s maximum power can be determined.

Energy Star TV power = 54.75 W

The standby power consumption of the TV is neglected.

Hours of usage – The TV is assumed to be in use 5.4 hours per day. See Section 8.7.1.3 DeVampirizer for more information.

Usage hours per day = 5.4 hrs

8.7.1.7.2 Calculation Procedure

1. Multiply the power by the hours of usage to get the daily consumption for the baseline and Energy Star cases.
2. Subtract the Energy Star result from the baseline case to determine the savings per day.
3. Extrapolate over a year to get the annual savings.

8.7.1.7.3 Final Result

Electric (kWh) $\Delta E_{\text{Star Status Watcher}} = 99.81$  

Equation 8.109
# 9 Appendix – Parameter Variability Analysis

Table 9.1 Energy parameter variability analysis inputs and results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Energy Savings</th>
<th>Change from Average</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Home Size (sqft)</strong>†</td>
<td>Minimum</td>
<td>500</td>
<td>5769</td>
<td>-2819</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>1769</td>
<td>8588</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>4000</td>
<td>11935</td>
<td>3347</td>
</tr>
<tr>
<td><strong>Heating System</strong></td>
<td>Minimum</td>
<td>Electric Heat Pump</td>
<td>5641</td>
<td>-2947</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>Average</td>
<td>8588</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>Fuel Oil Boiler</td>
<td>10446</td>
<td>1859</td>
</tr>
<tr>
<td><strong>Climate</strong></td>
<td>Minimum</td>
<td>San Francisco, CA (mild)</td>
<td>6161</td>
<td>-2427</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>Salina, KS (average)</td>
<td>8588</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Maximum 1</td>
<td>Miami, FL (hot)</td>
<td>5817</td>
<td>-2770</td>
</tr>
<tr>
<td></td>
<td>Maximum 2</td>
<td>Duluth, MN (cold)</td>
<td>10989</td>
<td>2401</td>
</tr>
<tr>
<td><strong>Number of People</strong></td>
<td>Minimum</td>
<td>1</td>
<td>7584</td>
<td>-1004</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>2.6</td>
<td>8588</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>6</td>
<td>10720</td>
<td>2132</td>
</tr>
<tr>
<td><strong>Window Type</strong></td>
<td>Minimum</td>
<td>Triple-Pane</td>
<td>7782</td>
<td>-806</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>Double-Pane</td>
<td>8588</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>Single-Pane</td>
<td>11000</td>
<td>2412</td>
</tr>
<tr>
<td><strong>Cooling System Type</strong></td>
<td>Minimum</td>
<td>No AC System</td>
<td>7385</td>
<td>1203</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>Central A/C</td>
<td>8588</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Water Heating Fuel</strong></td>
<td>Minimum</td>
<td>Electricity</td>
<td>8123</td>
<td>-464</td>
</tr>
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<td></td>
<td>Average</td>
<td>Average</td>
<td>8588</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>Natural Gas</td>
<td>8992</td>
<td>404</td>
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<tr>
<td><strong>Year of Construction‡</strong></td>
<td>Minimum</td>
<td>2011</td>
<td>8448</td>
<td>-140</td>
</tr>
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<td></td>
<td>Average</td>
<td>1973</td>
<td>8588</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>1919</td>
<td>8775</td>
<td>187</td>
</tr>
<tr>
<td><strong>Laundry in Home?</strong></td>
<td>Minimum</td>
<td>No</td>
<td>8004</td>
<td>584</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>Yes</td>
<td>8588</td>
<td>N/A</td>
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</table>


‡ 2007 American Housing Survey (U.S. Census Bureau, 2008).  Bin sizes from summary data.
Table 9.2 Cost parameter variability analysis inputs and results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Cost Savings</th>
<th>Change from Average</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Home Size (sqft)</strong>†</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>500</td>
<td>$450</td>
<td>$204</td>
<td>-31%</td>
</tr>
<tr>
<td>Average</td>
<td>1769</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum</td>
<td>4000</td>
<td>$884</td>
<td>$231</td>
<td>35%</td>
</tr>
<tr>
<td><strong>Heating System</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>Electric Heat Pump</td>
<td>$568</td>
<td>-$85</td>
<td>-13%</td>
</tr>
<tr>
<td>Average</td>
<td>Average</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum</td>
<td>LPG Furnace</td>
<td>$867</td>
<td>$214</td>
<td>33%</td>
</tr>
<tr>
<td><strong>Climate</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>San Francisco, CA (mild)</td>
<td>$450</td>
<td>-$203</td>
<td>-31%</td>
</tr>
<tr>
<td>Average</td>
<td>Salina, KS (average)</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum 1</td>
<td>Miami, FL (hot)</td>
<td>$568</td>
<td>-$85</td>
<td>-13%</td>
</tr>
<tr>
<td>Maximum 2</td>
<td>Duluth, MN (cold)</td>
<td>$733</td>
<td>$80</td>
<td>12%</td>
</tr>
<tr>
<td><strong>Number of People</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>1</td>
<td>$585</td>
<td>-$69</td>
<td>-10%</td>
</tr>
<tr>
<td>Average</td>
<td>2.6</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum</td>
<td>6</td>
<td>$799</td>
<td>$146</td>
<td>22%</td>
</tr>
<tr>
<td><strong>Window Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>Triple-Pane</td>
<td>$601</td>
<td>-$52</td>
<td>-8%</td>
</tr>
<tr>
<td>Average</td>
<td>Double-Pane</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum</td>
<td>Single-Pane</td>
<td>$805</td>
<td>$152</td>
<td>23%</td>
</tr>
<tr>
<td><strong>Cooling System Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>No AC System</td>
<td>$515</td>
<td>$139</td>
<td>21%</td>
</tr>
<tr>
<td>Average</td>
<td>Central A/C</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Water Heating Fuel</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>Natural Gas</td>
<td>$627</td>
<td>-$26</td>
<td>-4%</td>
</tr>
<tr>
<td>Average</td>
<td>Average</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum</td>
<td>Electricity</td>
<td>$683</td>
<td>$30</td>
<td>5%</td>
</tr>
<tr>
<td><strong>Year of Construction‡</strong></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>Minimum</td>
<td>2011</td>
<td>$645</td>
<td>-$8</td>
<td>-1%</td>
</tr>
<tr>
<td>Average</td>
<td>1973</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum</td>
<td>1919</td>
<td>$665</td>
<td>$11</td>
<td>2%</td>
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<tr>
<td><strong>Laundry in Home?</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>No</td>
<td>$639</td>
<td>$15</td>
<td>2%</td>
</tr>
<tr>
<td>Average</td>
<td>Yes</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Electricity Price ($/kWh)</strong>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>$0.0799 (Idaho)</td>
<td>$517</td>
<td>-$137</td>
<td>-21%</td>
</tr>
<tr>
<td>Average</td>
<td>$0.1154 (U.S. avg)</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum</td>
<td>$0.1925 (Connecticut)</td>
<td>$950</td>
<td>$296</td>
<td>45%</td>
</tr>
<tr>
<td><strong>Natural Gas Price ($/kWh)</strong>**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>$0.0269 (North Dakota)</td>
<td>$609</td>
<td>-$44</td>
<td>-7%</td>
</tr>
<tr>
<td>Average</td>
<td>$0.0379 (U.S. avg)</td>
<td>$653</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum</td>
<td>$0.0596 (Florida)</td>
<td>$741</td>
<td>$87</td>
<td>13%</td>
</tr>
</tbody>
</table>

‡ 2007 American Housing Survey (U.S. Census Bureau, 2008). Bin sizes from summary data.
** Natural Gas annual residential price, 2010 (U.S. Energy Information Administration, 2012c). Maximum and minimum prices for states in the Continental U.S.
Table 9.3 GHG parameter variability analysis inputs and results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>GHG Savings (kgCO₂)</th>
<th>Change from Average</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Home Size (sqft)†</strong></td>
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</tr>
<tr>
<td>Minimum</td>
<td>500</td>
<td>2515</td>
<td>-1112</td>
<td>-31%</td>
</tr>
<tr>
<td>Average</td>
<td>1769</td>
<td>3627</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum</td>
<td>4000</td>
<td>4859</td>
<td>1232</td>
<td>34%</td>
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<td><strong>Heating System</strong></td>
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<tr>
<td>Minimum</td>
<td>Natural Gas Furnace</td>
<td>3260</td>
<td>-367</td>
<td>-10%</td>
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<td>Average</td>
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<td>N/A</td>
<td>N/A</td>
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<td>Maximum</td>
<td>Electric Furnace</td>
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<td>850</td>
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<td></td>
<td></td>
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<tr>
<td>Minimum</td>
<td>San Francisco, CA (mild)</td>
<td>2477</td>
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<td>-32%</td>
</tr>
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<td>Average</td>
<td>Salina, KS (average)</td>
<td>3627</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum 1</td>
<td>Miami, FL (hot)</td>
<td>3407</td>
<td>-220</td>
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<td>Maximum 2</td>
<td>Duluth, MN (cold)</td>
<td>3861</td>
<td>234</td>
<td>6%</td>
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<tr>
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<td>Maximum</td>
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<td>Minimum</td>
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<td>Average</td>
<td>Central A/C</td>
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<td>N/A</td>
</tr>
<tr>
<td><strong>Water Heating Fuel</strong></td>
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<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>Natural Gas</td>
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<td>N/A</td>
<td>N/A</td>
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<td>Maximum</td>
<td>Electricity</td>
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<td>7%</td>
</tr>
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<td><strong>Year of Construction‡</strong></td>
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</tr>
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<td>Minimum</td>
<td>2011</td>
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<td>-1%</td>
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<td>1973</td>
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<td>N/A</td>
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<td>Average</td>
<td>Yes</td>
<td>3627</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>*<em>Electric Carbon factor (kgCO₂/kWh)</em></td>
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<td></td>
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<tr>
<td>Minimum</td>
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<td>N/A</td>
<td>N/A</td>
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<tr>
<td>Maximum</td>
<td>1.075 (SERC Midwest)</td>
<td>5034</td>
<td>1407</td>
<td>39%</td>
</tr>
</tbody>
</table>


‡ 2007 American Housing Survey (U.S. Census Bureau, 2008). Bin sizes from summary data.