KTH Industrial Engineering and Management

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


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| KTH Industrial Engineering and Management | **Master of Science Thesis EGI 2012:xxx**<br><br>**Development of an Energy-Information Feedback System for a Smartphone Application**<br><br>Joseph J. Elliott | |
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# Abstract

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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, including carbon dioxide ($CO_2$), 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 oxides (SOx), mercury, and particulate emissions which have far-reaching environmental impacts (United States Environmental Protection Agency, 2007). Reduction of fossil fuel use through efficiency and conservation will lessen the global environmental impact of energy consumption and reduce greenhouse gas emissions (Pacala, et al., 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 and Co. 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.

Feedback is only one method of implementing energy efficiency and conservation programs, but it is an important component in an overall strategy to reduce consumption, especially in the residential sector. 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, 2011). 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).

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, et al., 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, et al., 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, et al., 2010). Studies examining energy-saving measures report that consumers consistently underestimate the savings that can result from simple efficiency improvements (Attaria, et al., 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, 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, 1977/78), (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, et al., 2010). In addition, feedback programs are showing enormous promise in reducing energy consumption (EPRI, 2009), (Darby, 2006), (Ehrhardt-Martinez, et al., 2010). 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, et al., 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 US. 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, et al., 2010), (LaMarche, et al., 2011b). 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[1], best described as an educational and entertaining game focused on helping players reduce energy waste and save money (Joulebug, 2012). The basic functions of Joulebug can be broken down into three categories: **Badges**, **Leaderboard**, and **Energy Graph**.


**Figure 1.1** Joulebug app screenshots: Badge Ribbon, Leaderboard, and Profile with Energy Graph.

The main purpose of a Joulebug player is to earn badges and compete with their friends. A **badge** is a grouping of similar energy-saving actions. Each energy-saving action is called a **pin**. A player may earn a pin by performing an energy-saving action a certain number of times (termed a "do-it"). Along with a short description of the action being taken, the pin may have information about how to perform the action. Pins also provide a numerical estimate of savings in kWh, dollars, and $CO_2$, called the **pin stat**. Earning one or more of the pins under a badge grouping earns a badge. Badges feature unique artwork and are stored in a **trophy case** which serves as a visual record of the energy saving actions completed. The user also has a chance to share their progress via social media. The figure below shows these steps visually:

[1] As of this writing, Joulebug is available in the U.S. Apple app store. More information is available at www.joulebug.com.

**Figure 1.2** Badge earning process: earn, share, trophy case

For each step in the process, the user also earns points, which illustrate their relative commitment to performing the energy saving actions. The **Leaderboard** (see Figure 1.1) shows a listing of Joulebug users ranked by their point totals or number of badges earned. Through a Facebook connection badge, the Leaderboard has the ability to show a Joulebug user's ranking compared to their Facebook friends, or alternatively, compared to all Joulebug players.

The final component of the Joulebug system is the **Energy Graph** (see Figure 1.1, profile). 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 links with 25 million electric utility accounts and 6.6 million natural gas accounts in the U.S.

The proposed feedback system will directly impact the Energy Graph component of Joulebug. The feedback system will gather information about the user's actions, and will display information on the Energy Graph about how much energy and money a user has saved. This feedback will translate into positive reinforcement for the user and encourage them to continue saving energy through Joulebug.

## 1.3 Objectives

The objective of this thesis proposal is to design a feedback system for the Joulebug mobile application which will estimate a residential consumer's energy savings and display it along with their energy bill via the Joulebug Energy Graph. The feedback system will utilize motivational strategies to encourage users of Joulebug to save more energy. The system should be informative so that consumers begin to understand their energy consumption and gain the ability to make better 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 creates several sub-tasks in two categories: engineering and psychology.

**Table 1.1 –** Subtasks for design of a Joulebug feedback system.

| Engineering | Psychology |
|---|---|
| • Determine the data that will be needed from the user to calculate estimated energy savings.<br>• Develop an unobtrusive method for obtaining the necessary data from the user or from literature references.<br>• Create mathematical models to calculate the energy savings depending on the data given.<br>• Make an assessment of the accuracy and precision is required in order for the feedback system to be effective. | • Investigate the frequency of feedback required.<br>• Choose an effective measurement unit (cost, energy, or environmental impact) for displaying feedback data.<br>• Determine how to break down the information, both over time and by end use.<br>• Evaluate the effect of presentation medium (mobile device).<br>• Explore visual designs to determine the best way to display the feedback.<br>• Integrate user-specific energy saving recommendations into the feedback to serve as 'triggers'.<br>• Determine what comparisons (if any) are best suited to Joulebug. |

The two components of engineering and psychology are required to make tradeoffs in order to build the most effective system. A system which is excruciatingly 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.

## 1.4 Limitations

### 1.4.1 Graphic Design

This thesis project will not attempt to perfect the graphic design or layout of the graphical user interface. Recognizing that graphical and user interface design is a challenge best left to trained artist and graphic design professionals, this project only intends to determine what overall strategies for display of the user's energy consumption and savings data will be the most effective in producing behavioral change, and facilitate the production of that data through energy analysis.

### 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. 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, et al., 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 heating system in the United States is the natural gas furnace (U.S. Energy Information Administration, 2008), while in Sweden, electric heat pumps and district heating are the most common residential 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.

# 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, 1977/78). 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.

### 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, et al., 2005), (EPRI, 2009), (Ehrhardt-Martinez, et al., 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, et al., 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, et al., 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, et al., 2010). They have been described variously as 'purchase behaviors' (van Raaij, et al., 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, et al., 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, et al., 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, et al., 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, et al., 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, et al., 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, et al., 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, et al., 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, et al., 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. 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 components for behavioral change: ability, motivation, and a trigger. The following figure describes the relationship between the three key elements.

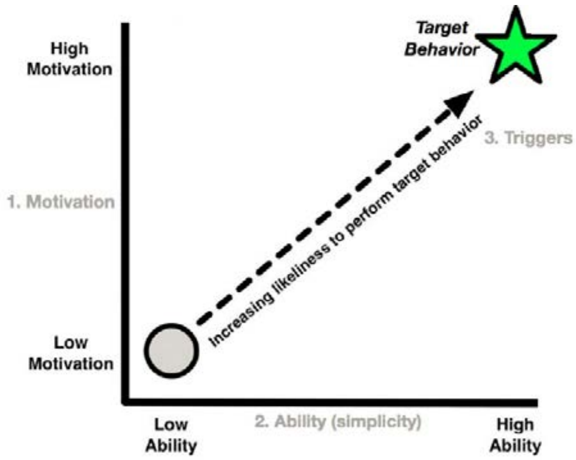


**Figure 2.1** The Fogg Behavioral Model (Fogg, 2009).

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. A mechanism that seeks to influence a behavioral change must increase ability, increase motivation, or increase both until the appropriate level 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, et al., 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, et al., 2005). Froehlich and colleagues (2010) also mention incentives and disincentives as a type of antecedent behavior (Froehlich, et al., 2010) Feedback, along with rewards/penalties, are consequence strategies (Abrahamse, et al., 2005), (Froehlich, et al., 2010). Feedback is a strategy that is getting abundant attention recently as technological advances have made more capabilities possible (Froehlich, et al., 2010), (Ehrhardt-Martinez, et al., 2010), (EPRI, 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, et al., 2005), (Froehlich, et al., 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).

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).

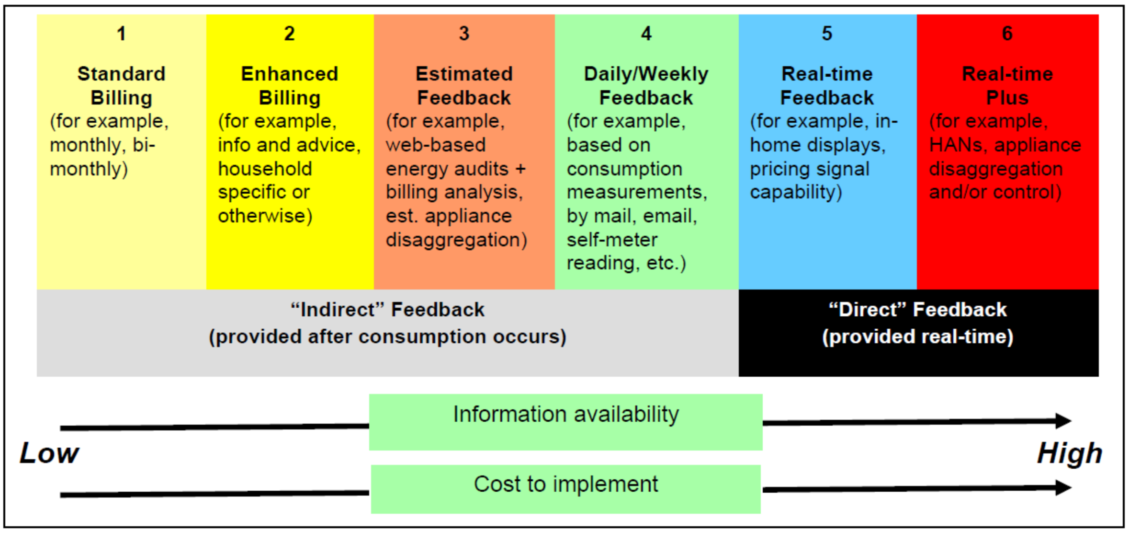


**Figure 2.2** The EPRI spectrum of feedback (EPRI, 2009).

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 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 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, et al., 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, et al., 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, et al., 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, et al., 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 savings result from combining useful technology with well-designed programs that successfully inform, engage, empower, and motivate people" (Ehrhardt-Martinez, et al., 2010).

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, 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, et al., 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. 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 (Fischer, 2008). Jacucci and colleagues claims 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 $CO_2$. For comparisons, kWh was preferred as $CO_2$ and cost can vary by utility (Petkov, et al., 2011).

**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, 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 (televisions), and ambient displays (for example, colored lights that signal consumption levels) (Granade, et al., 2009), (LaMarche, et al., 2011a). 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, et al., 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, et al., 2011a). Most users surveyed estimated they would spend 1-5 minutes per day using energy management technology (LaMarche, 2011).

**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, 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, et al., 2008). Pragmatic visualizations provide quantitative information, but may have a learning curve, while artistic visualizations may not be explicit (Froehlich, 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, 2009). The idea of tailoring information has been tied to the idea of goal setting by Abrahamse and colleagues (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, et al., 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, et al., 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, et al., 2011), (Ehrhardt-Martinez, et al., 2010), (Froehlich, et al., 2010), (Darby, 2006). Providing historical comparisons has been identified as a desirable method of feedback (Petkov, et al., 2011), (Darby, 2006), especially when normalized with weather (Froehlich, 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, et al., 2011). In addition, when a certain threshold of energy savings is reached, it may be difficult to show further improvement (Froehlich, 2009), (Froehlich, et al., 2010).

Social comparison is a comparison with another household or individual, within a group, or to a norm (Petkov, et al., 2011). The opinion on these types of comparisons is mixed. Studies reviewed by Darby have citied 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, et al., 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, et al., 2010). 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, et al., 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, et al., 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, 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, Jancucci 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). 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 Italian 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 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 $CO_2$). The material impact was illustrated using a comparison of "number of trees" equivalent to the amount of $CO_2$ 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, et al., 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 $CO_2$. However, kWh was preferred as a unit of comparison between players because cost and environmental impact ($CO_2$) 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, et al., 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, et al., 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, et al., 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, et al., 2011).

The first Internet-based tool for evaluating whole-building energy consumption was Lawrence Berkeley National Laboratory's (LBNL) 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, 2012).

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, 1986). Later, in 2003, a five-parameter heating-and-cooling model was developed for cases where a single fuel (electricity) might be used (Fels, et al., 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, et al., 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, 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 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 through, or more accurate tool" (Mills, 2004).

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 development of Joulebug's energy feedback system to be entertaining, educational, easily accessible, social, and effective at reducing energy consumption relies on the main tenants of engineering and psychology as discussed in the introduction. These two components have a give-and-take relationship, so an iterative design process is necessary to optimize the benefit while maintaining a manageable workload.

## 3.1 Data and Calculations

The main engineering objective of the project is to calculate the energy savings of the user, and provide beneficial suggestions for future energy saving actions as accurately as possible while sustaining the core concepts behind Joulebug discussed above. 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. The first step is to determine what pieces of information are necessary to calculate the user's energy savings to a reasonable accuracy. These can be considered **energy parameters** for determining energy usage and savings. Examples of energy parameters include home size, location/climate and fuel type.

After the required information has been gathered, the energy savings for each possible user action can be calculated using engineering methods. 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 heating and cooling-related energy saving actions could be evaluated using it, and the significant time lag due 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 mathematical models will use the energy parameters as inputs to a function, which will output energy savings. Each energy-saving action is treated as a unique case, and so each mathematical model will be different and customized. 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 are difficult to characterize exactly, engineering estimation will be used where necessary.

The savings must be convertible to cost and environmental impact as well, as these units are better understood by consumers. To determine the unit cost, the billing data provided by the utility will be used. The most recent year of billing data will be used to determine an average unit price (\$/kWh) for electricity or natural gas. Because utilities have many different and often complicated rate structures, programming each one separately would be a laborious task. Instead, each month the "effective rate" will be determined by dividing the cost by the energy usage. The environmental impact is determined by using U.S. national statistics for greenhouse gas output in carbon dioxide equivalent ($kgCO_2$–eq).

The temporal breakdown required for the energy saving actions is important. Many actions are considered "baseload", occurring constantly throughout the year. These include appliance usage, water heating, and lighting. Actions considered "baseload" will be calculated on a yearly basis, and then divided to fit the time period required for display. With this assumption, it is possible to show the savings on a daily basis with reasonable certainty (neglecting the effect of weekends and holidays). For heating and cooling savings actions, the savings follows the pattern of consumption, which is correlated strongly to the outdoor temperature and degree-days. In some cases it will be necessary to use degree-days to determine the energy savings that can be achieved in each day (or even each hour) out of the year. A more extensive explanation of these cases can be found in the Appendix.

When summing the savings from all completed actions (completed badges/pins), a problem of diminishing returns arises. Calculating each action 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 is estimated to save $50, or sealing leaks 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 some 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 $S_n$ are saving measures, and B is the baseline consumption.

$$\frac{B-S_{total}}{B} = \left(\frac{B-S_1}{B}\right) * \left(\frac{B-S_2}{B}\right) * \ldots .* \left(\frac{B-S_n}{B}\right) \qquad \textbf{Equation 3.1}$$

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.

To suggest energy saving actions (pins/badges), each potential action will be included in an ordered list. The badges are removed from the queue temporarily depending on the season (time of year), or permanently when they have been completed or the user indicates that they are not interested. The rank of the energy saving actions within the list will be partially based on the energy savings obtainable for the particular billing month. For example, heating badges will be predominate in the winter, cooling badges in the summer, and other non-seasonal (baseload) badges in spring and fall.

## 3.2 Psychology

The psychological design aspects of the feedback system will be designed with the literature in mind in a collaborative environment. From an extensive review of the literature, the design aspects required for a feedback system are clear. The use of particular design elements for Joulebug will be based on an evaluation of the potential effectiveness (from previous studies), the implementation cost and time required, and the applicability to Joulebug's particular case and mission. As there are already many functions of the application that are already designed, it is necessary to take those into consideration when making the energy feedback portion. A collaborative design approach taken with other members of the Joulebug development team will help ensure that the final design is a successful one.

## 3.3 Computing and Development

The programming language Python will be used to do the mathematics and logic that is required to put the energy calculations into the 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, gameplay data, and gathered energy parameters.

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