Understanding Home Energy Saving Recommendations

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Abstract. Energy recommender systems attempt to help users attain energy saving goals at home, however previous systems fall short of tailoring these recommendations to users' devices and behaviors. In this paper we explore the foundations of a user-centered home energy recommendation system. We first conduct a study on a set of recommendations published by utility companies and government agencies to determine the types of recommendations may be popular among typical users. We then design micro-models to estimate energy savings for popular recommendations and conduct a followup study to see if users are likely to carry out these recommendations to achieve estimated savings. We found that users prefer low-cost but potentially tedious recommendations to those that are expensive, however users are unwilling to adopt recommendations that will require long-term lifestyle changes. We also determine that a subset of popular recommendations can lead to substantial energy savings.

1 Introduction

Recommendation-based approaches for saving energy in the home have historically been, and continue to be, widely used. Though automated solutions, for example the Nest thermostat, are becoming more common, utility companies and governmental agencies such as the U.S. Department of Energy still aggressively encourage individual energy saving through a wide variety of behavioral recommendations. Additionally, the research community has advocated technology-enhanced systems to persuade users to adopt energy-saving recommendations, for example by making it easy to set goals, providing timely nudges, or offering feedback on progress. Some popular recommendations, for example `Consider installing a solar water heater` are expensive home upgrades while others, such as `Clean the lint screen in the dryer after every load` are small behavioral changes that may or may not be adopted by users.

For energy-saving recommendations and recommendation-based systems to effectively influence user behavior it is necessary to understand which recommendations users prefer and are likely to adopt; how best to communicate recommendations and feedback to the user; and whether the recommendations a user is willing to implement are likely to have an impact on energy usage. Unfortunately, these areas are not well understood. Utility companies offer banks of static recommendations, some of which may be generally unpopular and some of which may only apply to some users, for instance home owners rather than renters. Moreover, some recommendations may be popular, but have little potential for energy savings in all or some homes.

In this work, we conduct a three-pronged study that (1) identifies user perceptions and barriers to adoption of common energy-saving recommendations; (2) proposes personalized models to quantify savings of popular recommendations; and (3) applies the models to understand potential energy savings in typical homes. Our initial study, a survey completed by approximately 650 participants on Amazon Mechanical Turk, asked users to provide feedback about 181 common energy-saving recommendations. The survey found that users prefer low-cost but potentially tedious recommendations to those that are more expensive, however users are unwilling to adopt recommendations that will require long-term lifestyle changes. From the study, we identified 13 of the most popular recommendations pertaining to the refrigerator, computer, lighting, and heating and cooling, and designed a set of micro-models that accept user-specific input and calculate personalized potential savings of each recommendation. Finally, we conducted a follow-up survey that used our models to determine potential savings for each participant. The study asked participants to provide energy usage profile and rate his/her willingness to adopt popular recommendations. We found that a small subset of popular recommendations can lead to substantial energy savings.

2 Understanding User Preference for Energy-Saving Recommendations

Energy-saving recommendations, for example those offered by utilities companies, span a wide spectrum. Expensive recommendations, such as `replace windows`, may have a significant potential for savings but are relevant only to home owners and not renters. Similarly, minor behavioral changes such as `wash full loads of clothes when possible`, may be broadly applicable but unpopular or unlikely to be adopted.

The goal of our initial study is twofold. First, we explore the kinds of recommendations users prefer and would be likely to adopt. Second, we explore how users would prefer to receive recommendations and feedback in order to encourage energy savings. This section describes the setup and results of a survey completed by 650 Amazon Mechanical Turk (AMT) participants.

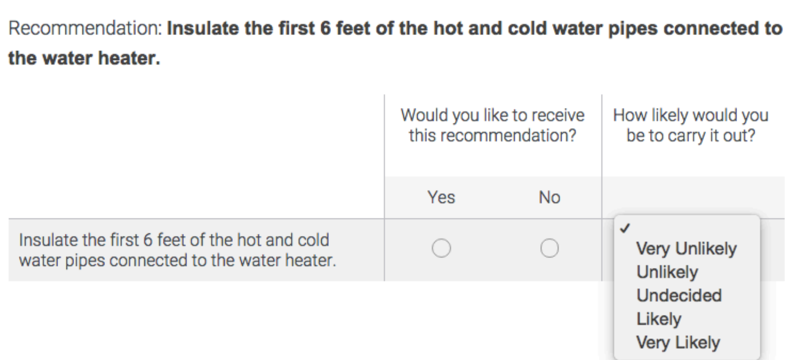

Fig. 1. Participants were asked whether they would like to receive a particular recommendation as well as how likely they would be to carry out the recommendation.

Setup: The recommendation survey consists of four components. The **background and goals** portion of the survey asks users general questions about their awareness of energy usage in their homes; their goals for saving energy; and how they would prefer to receive recommendations and feedback regarding their goals. Next, we ask users to choose which **general category of recommendation** would be most useful from the options *Specific Appliances*, *Activities*, *Rooms in the Home*, and *Seasons*. Based on the category selected, we then present the user with a set of five **specific recommendations** taken from existing sources including the U.S Department of Energy website and several utility company sites. Our bank of recommendations, which is an aggregate of all of the resources we were able to identify, includes a total of 181 recommendations. As shown in Figure 1, for each recommendation, we ask the user (1) whether he/she would like to receive such a recommendation and (2) to rate the likelihood of carrying out the recommendation on a scale of 1 (Very Unlikely) to 5 (Very Likely). Finally, we collect **demographics** including age, education, and household income.

The survey was available on AMT from August 3 through September 6, 2015. Though a total of 748 people started the study, some questions were not answered by all participants—a total of 650 participants completed the survey. Most general questions received between 700 and 705 responses, and since each user only saw five of 181 recommendations, each specific recommendation received an average of 18.5 responses.

To better understand the general types of recommendation that were popular or unpopular, we manually tagged each of the 181 recommendations in three categories. Category 1 identified recommendations as behavioral, infrastructural, or both; Category 2 identified easy, medium, or hard recommendations; and Category 3 identified low, medium, high, or no cost recommendations.

2.1 Findings

The results of our survey provide insight into the types of recommendations participants find most useful as well as how they would prefer to set goals and receive feedback. Users were optimistic about goal-setting with the majority preferring a goal of reducing energy usage by 20% or more. We hypothesized that frequent feedback via smart phone application would be popular, however our results indicated otherwise. When asked how often they would like feedback on their progress, most users preferred monthly or weekly feedback. When asked about the medium for feedback, users strongly preferred email or a website. Only 12% of participants preferred daily feedback and less than 25% preferred feedback via a phone app. Finally, the most popular recommendations pertained to lighting, heating, computer usage, and kitchen appliances.

Insight 1: Users prefer low-cost to low-effort recommendations

Financial cost, not surprisingly, was reported as the main motivation for reducing energy use. We asked users to select one or more of the following in response to the *I would like to reduce*: financial cost, environmental impact, energy usage relative to neighbors, or other cost. A large majority, 83.86% of users, reported that they were interested in reducing the financial cost of their home's energy usage with 47.57% caring about environmental impact. Moreover, with $p < 0.001$, users are more aware of how much money they spend on energy bills each month than either how much energy their home uses each month or the environmental impact of their home's energy usage.

When asked whether they would like to receive specific recommendations, users preferred inexpensive or free recommendations over expensive recommendations even though many low-cost recommendations require significant effort. Many highly rated recommendations included tedious tasks, such as weatherstripping or caulking gaps around doors. Similarly, recommendations such as `install ENERGY STAR-rated routers and modems`, which are cheap investments, were more popular than more expensive upgrades, such as replacing windows.

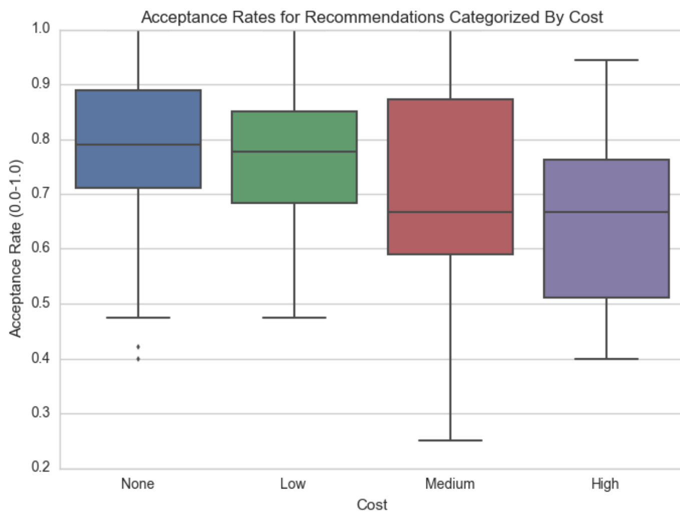

Fig. 2. Percentage of *Yes* responses in reply to the question *Would you like to receive this recommendation?* broken down by cost category.

Figure 2 shows the distribution of acceptance rate for recommendations in each of the categories: no cost, low cost, medium cost, and high cost. The acceptance rate is defined as the percentage of responses indicating *Yes* in reply to the question *Would you like to receive this recommendation?*. The median acceptance rate for recommendations in the no-cost category was nearly 80%, in contrast to a median acceptance rate of 67% for recommendations in the high-cost category. Only 6.1% and 2.7% of recommendations classified as no and low cost, respectively, had low acceptance rates at or below 50%, while a more significant 26.7% of those recommendations classified as high cost were rejected by participants.

Insight 2: Users are unwilling to make lifestyle changes to save energy

Table 1 shows the most popular recommendations of the survey. Many popular recommendations were in the infrastructural category and have little or no impact on a user's lifestyle. In contrast, unpopular recommendations, for example, `Go to sleep earlier to require less lighting at night`, often require users to change the

Appli-ance	Popular Recommendations	Expected Savings kWh	Expected Savings $
Light-ing	Use natural light during the day	40.14	4.81
	Decrease the light to a desired level by installing and using dimmer switches	93.98	11.28
Com-puter	Use the power management features of your operating system to put your computer to sleep.	1.08	0.13
	Turn off the computer/laptop/monitor when idle.	0.52	0.06
	Turn off your screen saver.	0.10	0.01
	Close applications not in use while using your computer.	1.24	0.15
Refrig-erator	Increase the temperature of your fridge to 40 °.	9.27	1.11
	Cover your food before putting it in the fridge.	0.12	0.01
	Reduce the number of times you open the door.	3.61	0.43
	Reduce the length of time you prop your door open.	0.07	0.01
HVAC	Adjust the thermostat down in the winter and up in the summer when you go to sleep.	9.42	1.13
	Caulk or weatherstrip gaps and seams around windows, doors, vents, etc. to reduce air leakage.	166.01	19.92
	Turn off your fans when you physically leave the room.	37.68	4.52

Table 1. Popular recommendations and mean expected savings for the follow-up study participants.

way they schedule or perform daily activities. As another example, covering drafty windows with plastic was popular, while repainting house walls to better reflect light was not; the latter affects the user's daily life much more than the former. We found that many of the least popular recommendations were those that had an impact on entertainment activities. `Use a Wii instead of XBox One or PS4`; `Use a smaller TV`; and `Watch less TV` all had an acceptance rate of of lower than 50%. The least popular recommendation was `Consider spending more time with family and friends in the same room when planning activities.`

Discussion: This initial study demonstrates that while many common energy-saving recommendations are popular, other recommendations commonly provided by utility companies and other energy-focused websites are unlikely to be adopted. Some popular recommendations have a large potential for energy savings, though the potential savings for several other popular recommendations, for example `Cover liquids and foods you put in the fridge` is less clear. In the next sections, we design a set of models and carry out a follow-up user study to quantify the likely energy savings of a user who applies the popular recommendations identified in Table 1.

3 Modeling Consumption

Based on the responses to the initial study, popular recommendations most frequently pertained to refrigerators, home lighting, computer usage, and heating and cooling. To understand the impact of these recommendations on typical users' energy consumption, we built micro-models of energy consumption for each of these appliances using a combination of prior work and experimentation. Each micro-model was dependent on a set of appliance-level and behavioral parameters. Appliance-level parameters were used to characterize the device while behavioral parameters described its usage. These parameters were used in combination to estimate the current consumption of the device as well as the potential savings achievable using each of the popular recommendations. To make the models more applicable to typical users, parameters were chosen in such a way that ordinary homeowners would be able to estimate them with minimal effort.

Refrigerator: The device parameters for the refrigerator model included refrigerator age, size, and configuration, which were used as inputs to an Energy-Star model to estimate an average baseline energy consumption. Further, experimentation was done on a single refrigerator to determine a linear relationship between temperature settings and energy consumption, a curve which was shifted based on the output from the Energy-Star model. Based on recommendations regarding internal temperature, door-opening, and covering liquids and foods, the behavioral parameters included temperature setting; door opening frequency and the duration of door-propping; and whether the user tended to cover food before storing it. Potential savings were calculated by determining the baseline consumption and then subtracting the estimated consumption using the recommendations.

Home Lighting: Assuming it would be difficult to recall the number and wattages of every light bulb in a user's house, the lighting model takes as device parameters the number of rooms that are typically lit and an average size for each room. It then uses a well-known rule of thumb to calculate the `lux` level that would typically be used to light that amount of space in a residential setting by multiplying the number of square feet by 1.5 [1]. Savings are calculated for two recommendations, one regarding natural light, and one involving dimmer switches. The natural light savings are calculated by simply restricting the baseline calculation to the number of rooms that are both occupied during the day and receive natural light. The dimmer savings are calculated by determining the number of `Watts` necessary to light the occupied square footage to several different light levels recommended for different tasks.

Computer Usage: To calculate the usage of a computer we parameterize the model using the following inputs: (1) whether the system was used as a desktop or a laptop; (2) whether the computer was an Energy-Star system; (3) whether the monitor used is LCD or not; (4) whether the user uses multiple applications simultaneously; and (5) whether the computer is kept in sleep mode when not used. Based on these inputs, a baseline power consumption of the computer (200 W for a desktop and 40 W for a laptop) is multiplied by a preset factor. These factors are based on measurements performed on a computer as part of prior work [2]. For example, if a computer is Energy-Star the power consumption is assumed to be 50% of the baseline [3].

Heating and Cooling: We have developed simple models to calculate the energy savings for recommendations involving the heating and cooling system. For instance, to quantify the energy savings when adjusting the indoor home temperature at night, we first calculate a coarse estimate of the external wall area of the house by dividing the total square footage by the number of floors and taking the square root. Our model then calculates the ideal temperature differentials for the winter and summer using indoor, outdoor, and the minimum and maximum temperature in a user's comfort zone. We then use the model described in [4] to calculate the difference in heat loss rate in BTU/hr between boundary and current temperature. Consequently, we multiply the heat loss rate by the number of hours the user is asleep in a month and convert that value to Kilo-Watt-Hours. In our model, we perform the calculations for summer and winter seasons and provide an average of the two.

For the second recommendation (sealing air leakages) the energy savings are calculated using the following equation: $\texttt{Savings} = \Delta_T \cdot \texttt{ACHact} \cdot \texttt{Volume} \cdot 0.018$ where `ACHact` is air changes per hour and is dominated by `ACHnat`, the natural air changes per hour, when `ACH50`, a measurement of air changes induced during a standard blower test at 50 Pascals, is greater than 1 [5,6]. Further, `ACHnat` can be calculated using a conversion factor, `lblfactor`, as $\frac{ACH50}{lblfactor}$, so savings can be described by: $\Delta_T \cdot \frac{ACH50}{lblfactor} \cdot Volume \cdot 0.018$ where 0.018 is the heat capacity of air at sea level on average and Δ_T is the temperature differential between indoors and outdoors. We estimate the volume of the house, and `ACH50` for leaky, moderate and tight houses using the estimates provided in [7] and a combination of the age and the amount of effort the user has put into sealing leaks in the house. As a rule of thumb, we use 20 for `lblfactor`. For the third recommendation (Turning of fans when not in the room) the savings are calculated as `numfans` · `numhours_fans_run_unattended` · `fan_powerusage` · `dayspermonth` where `fan_powerusage` is set to 75 W [8].

4 Quantifying Potential Savings

We conducted a follow-up study that uses our models to quantify the potential savings of the popular recommendations identified by our initial study.
Setup: The follow-up study focused on four areas: **refrigerator**, **lighting**, **computer usage**, and **HVAC**. For each appliance, the study asked users to provide a usage profile then to rate how likely they would be to modify their usage according to the recommendations. In the case of the refrigerator, for instance, we asked the participants several questions about their fridge itself (e.g., its age), then several questions about its use (e.g., how cold is it?). We then applied our micro-model to generate and display potential energy savings per recommendation. Finally, we asked users to indicate if they would be willing to apply any of the recommendations that would lead to savings and to provide an explanation if not.

The survey was available on AMT from March 19, 2016 to March 24, 2016. We collected a total of 110 complete responses. Some users started the survey but did not complete it and their results were not included in our analysis.

4.1 Findings

Insight 1: Applying a few popular recommendations can lead to substantial energy savings.

Our results indicate that an average user could expect to save up to 27.9% on a monthly bill, based on the 2014 US average monthly energy cost of $114.09 [9]. Since some of the recommendations for each appliance could lead to overlapping savings, this

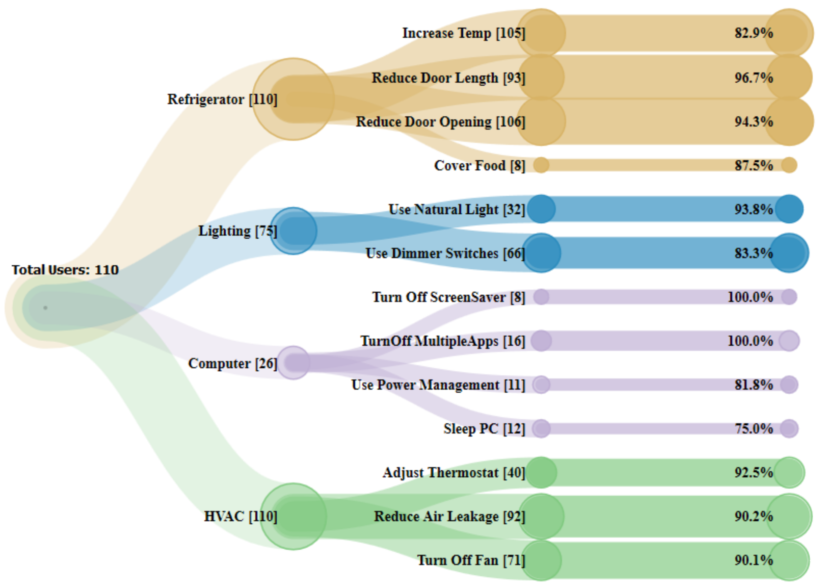

Fig. 3. This figure illustrates how many users saw each recommendation for each appliance and the percentage of users willing to adopt the recommendation.

is a conservative estimate that first averages the savings for each recommendation, then takes the maximum average for each appliance group, and sums the four results.

Figure 3 shows, from left to right, the total number of users, the number of users who saw at least one recommendation in each appliance category, the number of users who saw each specific recommendation, and percentage of users who indicated they were willing to adopt the recommendation. For instance, 110 users received at least one recommendation related to the refrigerator, however only eight saw the recommendation to cover food and, of those eight, 87.5% said they would be willing to adopt this recommendation.

The acceptance rate of all recommendations was very high, with most users indicating they would adopt a recommendation if they were given that recommendation. The recommendation to put a computer to sleep when not in use had the lowest acceptance rate—one user indicated he runs a twitterbot on his computer and therefore cannot put it into a sleep state. Note that users were only asked to evaluate a recommendation if it offered potential savings based on their profile. Several recommendations were seen by a small number of users because the users already performed the recommended behavior. For example, 102 users indicated that they already cover their food before putting it in the refrigerator, 74 users said they already use natural light during the day, and 58 users said they already adjust their thermostat when they go to sleep. Less than 25% of users' profiles offered potential savings through at least one of the computer-related recommendations.

As illustrated in Table 1, the expected savings calculated by our models falls into four clusters. Expected savings per user were calculated as the mean savings across all 110 users for each recommendation, including those users who rejected the recommendation or whose profiles offered no potential savings. Infrastructural changes including sealing air leaks and using dimmer switches yield the greatest savings of more than **90 kWh**. Using natural lighting and turning off fans fall into the next cluster at savings in the **high-30 kWh** range. Increasing the refrigerator temperature and adjusting thermostats had a low, **9–10 kWh** average savings, and savings of **less than 4 kWh** was estimated for keeping the fridge door closed, covering food, turning of screensavers, minimizing applications running on a computer, and using computer power management and sleep features.

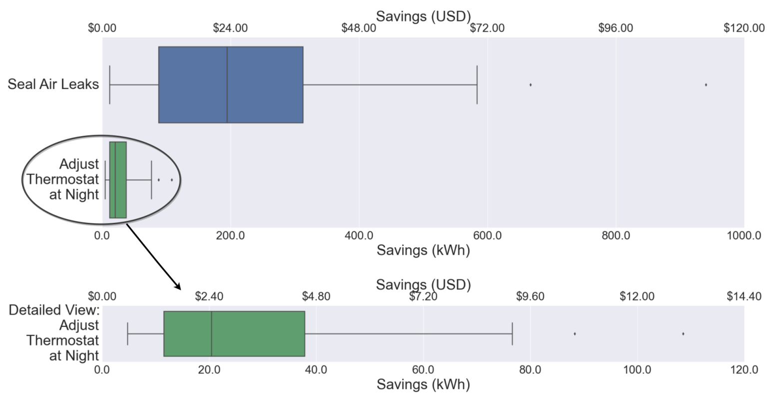

Fig. 4. For users who accepted the recommendation, the figure shows the distribution of potential savings for the recommendations seal air leaks and adjust thermostat at night.

Figure 4 illustrates the distribution of savings for a recommendation with the highest overall savings (seal air leaks) and one in the third tier of savings (adjust thermostat). The figure *excludes* the zero-savings cases where a user did not accept the recommendation or did not see the recommendation based on profile responses. This figure illustrates the wide variance of savings, with many users seeing savings significantly higher than the average. Even in cases where average savings is small, some users may see significant benefit. Other appliances showed similar distributions.

Insight 2: Reasons for rejecting recommendations were consistent with the initial study findings and insufficient savings discouraged some recommendation acceptance.

Users who rejected recommendations were asked to explain their reasoning and most comments were consistent with the findings identified in our initial study. Several users demurred from installing dimmer switches or sealing air leaks in their homes for the sake of cost, supporting our finding that users prefer low-cost to low-effort recommendations. Some users also expressed concern about effort required, for example *I have no idea how to install that in my house and I don't have the time or upfront money*. Investment was also, understandably, a concern for users in rental properties—67% of users who rejected the recommendation to seal air leaks cited the fact that they are renters or do not own the house that they live in. Many comments also reinforced the finding that users are unwilling to make lifestyle changes to save energy. Multiple users rejected the idea of installing dimmer switches because they liked brightly lit rooms. Similarly, when declining a recommendation to reduce fridge door openings one user wrote, *That will be a hard habit to break and I often need to open in quite often*.

In some cases, users found the predicted savings to be too low to justify the cost or effort involved in carrying them out. One user worried that increasing refrigerator temperature would cause food spoilage losses that would not offset the savings. Similarly, a user who had very low savings for reducing the amount the refrigerator is propped open responded, *a penny a month is not enough for me to change*. Another user made a similar comment about the fridge door recommendation, *Because we open it when we want something. It's hardly worth 55 cents a month to try to coordinate family members' thirst or hunger*. Overall, the implication in these cases was that higher savings would have made the recommendation more appealing.

Discussion: Our findings demonstrate that there is ample opportunity to design persuasive systems to encourage users to apply effective energy-saving recommendations. Users are, unsurprinsingly, interested in saving money, and our findings suggest they are willing to put in effort to do so. Though our study identified many recommendations that are unlikely to be adopted, many of the the most popular recommendations, for example dimming lights and turning off fans when leaving a room, require behavioral change. We acknowledge that this work does not consider whether users follow through on the recommendations they report to be appealing, but suggest that our results offer insight into the design of systems to encourage user adoption.

5 Related Work

In this section, we compare our work with the most relevant literature in home energy recommendation systems and modeling energy consumption of home appliances.

Home Energy Recommendation Systems: Several papers study what recommendation attributes are effective for long term adoption. For instance, in [10], the authors study several types of interventions: goal-setting, information tailoring, modeling, and feedback. In [11], the authors study personalized recommendations based on historical usage patterns and demographics. In [12] the authors prototype a context-based recommendation system on a smartphone while [13] and [14] discuss the effectiveness of nudging and social cognition and persuasion in increasing the effectiveness of recommendation systems. Our work takes a more fundamental look at which recommendations users are likely to follow and how much savings they may yield.

Modeling Appliance Energy Consumption: These are several tools available for predicting appliance energy consumption and usage [15,**?**,**?**,**?**,**?**,**?**,**?**,**?**]. These tools take usage patterns as input and estimate the energy consumption of the appliance. In this work we utilize these tools to estimate the energy savings of popular recommendations.

6 Conclusion

In this paper, we perform a three step study to understand the feasibility of home energy saving recommendations. First, we use survey results from approximately 650 AMT users to determine the most popular recommendations from a set of 181 popular recommendations published by utility companies and government agencies. Secondly, we design micro-models to estimate the energy savings of these recommendations. Finally, we perform a followup study to determine the actual energy savings for these popular recommendations based on typical usage patterns. We show through our study that a few of the popular recommendations can lead to significant energy savings. Our insights into which recommendations are popular and useful in terms of energy savings can form the basis of home energy recommendation systems.

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