Want to Reduce Energy Consumption? Don't Depend on the Consumers!

Haroon Rashid[1], Priyanka Mary Mammen[2], Siddharth Singh[2], Krithi Ramamritham[2], Pushpendra Singh[1], Prashant Shenoy[3]
[1]IIIT Delhi, India; [2]IIT Bombay, India; [3]University of Massachusetts, Amherst, USA
[1]{haroonr, psingh}@iiitd.ac.in, [2]{priyankam, siddharths, krithi}@cse.iitb.ac.in, [3]shenoy@cs.umass.edu

ABSTRACT

Motivating users to save energy is considered to be the holy grail of smart energy management. However, many studies have shown that changing user behavior from an energy standpoint is a very difficult problem. Furthermore, in countries such as the United States, users do not have sufficient monetary incentives to become energy conscious, given the low cost of electricity, and more generally, energy. In this paper, we study this issue in a developing economy and present a user study of 41 apartments in a high-rise apartment complex in India. Through a combination of fine-grain energy meter usage data and detailed user surveys, we find that these users may be no more energy conscious or motivated to adopt energy efficiency measures than their counterparts in Western nations. Our study challenges the belief that energy prices are higher in developing regions and hence, users in developing regions tend to be more energy-aware than those elsewhere. Consequently, and importantly, we argue that utility companies, rather than end-users, should be the vanguard for realizing energy efficiency improvement at consumer premises in order to obtain grid-wide benefits such as peak load reduction or avoiding blackouts. Towards this goal, we argue for a sustained research effort into utility-scale energy analytic approaches, for example, to identify end users who are large consumers along with the underlying causes of their consumption. Utilities can deploy such approaches and then aggressively target these users for energy efficiency improvements.

CCS CONCEPTS

•**General and reference →Empirical studies; Evaluation;** *Surveys and overviews;*

KEYWORDS

User Behavior and Incentives, Buildings energy consumption, Energy awareness programs

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1 THE PROBLEM: LARGE ENERGY CONSUMPTION

Buildings currently comprise nearly 50% of the electricity consumption in many countries [1]. Consequently enhancing the energy efficiency of buildings has been the focus of much research as well as utility-driven energy improvement programs. Since users residing and working in a building primarily drive its energy consumption, involving and motivating users to become energy conscious by adopting energy efficiency and energy conservation measures is an important component of overall building energy efficiency. However behavioral studies have shown that incentivizing and changing human behavior from an energy standpoint remains challenging, especially in Western nations. The reasons for this are many. The price of electricity is low, relative to monthly incomes, for many consumers, this provides little monetary incentive to change one's behavior. Users are often unaware of their energy consumption profiles and how they need to modify their consumption to achieve energy efficiency goals. Changing daily routines and long-established habits is also hard—for example, changing when to do laundry[16] or not using air-conditioning during peak load periods of a heat-wave can be inconvenient or can impact user comfort. Consequently how to achieve aggregate energy efficiency goals (e.g., at utility or city-scale) despite the challenges in changing user behavior remains a key challenge.

In this paper, we present a user study conducted in India, a developing region, with the goal of shedding light on the broader problem. While prior studies have established the challenges of changing user behavior in Western nations, where electricity prices are "cheap", it is believed that users in other parts of the world, especially in developing regions, tend to be more energy conscious. Our user study focuses on 41 apartments in a high-rise apartment complex in India, which represents urban middle-class users. We note at the outset that this sample is not representative of the general population in India, where the median income is much lower; nor is it representative of other developing regions such as Africa. However, it is a good representative of an urban middle class population in many developing regions which is well-educated, tech-savvy and consumes relatively much higher amounts of energy (due to its affordance of appliances such as air conditioners (ACs), water heaters and washing machines) than lower-income groups. Through a combination of fine-grain meter data and user surveys, we found that such users are not very energy conscious, as previously believed. For instance, a significant number (61%) did not know the quantum of their electricity bill and 83% of consumers could not identify their energy usage pattern over the course of a day. Today's existing systems do not communicate energy usage information to the end-user and therefore does not encourage changes in human behavior. Furthermore, the monthly electricity bills for such users

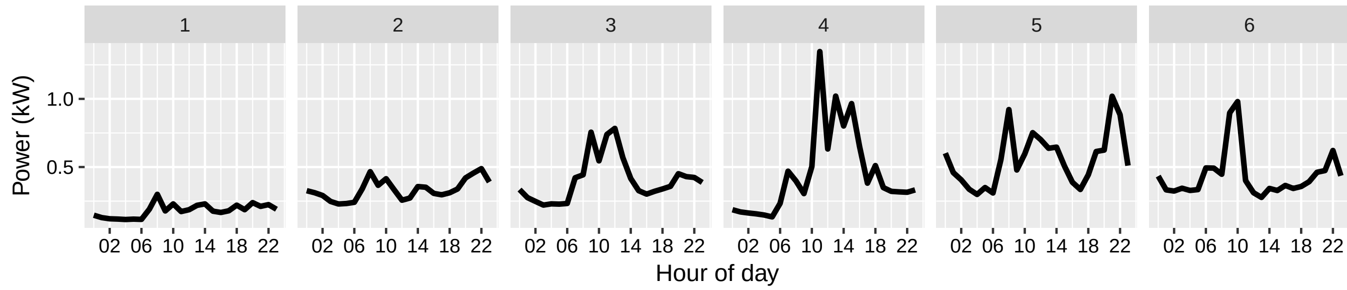

Figure 1: Energy consumption profiles of consumers on weekdays

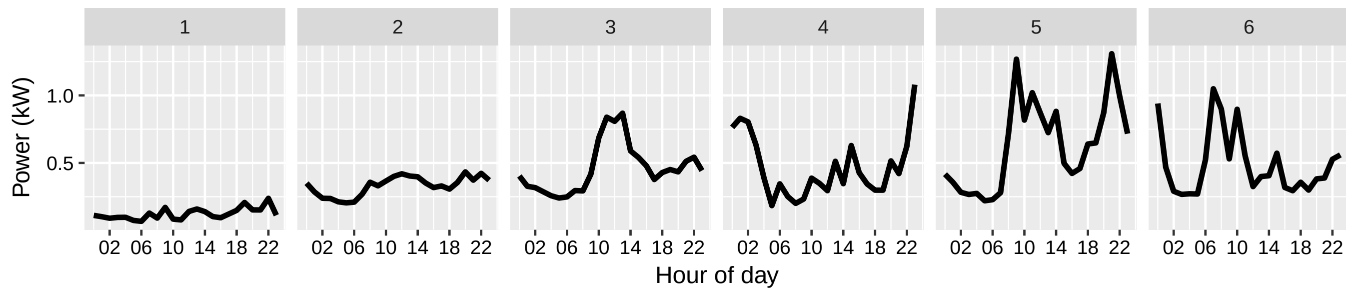

Figure 2: Energy consumption profiles of consumers on weekend

as a proportion of the monthly income is still relatively low. The low-awareness of energy usage as well as low costs point to the overall difficulty in getting users to adopt energy efficiency measures. In this sense, this group of urban middle-class users is no different from their counterparts in the Western world.

We then argue that in areas where electricity prices are low relative to user incomes, it may not be feasible to expect users to lead the way in meeting long-term energy efficiency goals. Instead it may be better for utility companies to take responsibility for these efforts by identifying their least efficient users and aggressively targeting them for energy improvements, possibly using energy subsidies [5]. While many such programs already exist, there are some important missing pieces; (i) the development of new automated tools that can be deployed by utilities (e.g., consumer demand response) and (ii) the design of new analytic techniques that mine usage data to identify causes of inefficiencies. The latter will enable careful matching of users to the required intervention. These topics offer a rich set of challenges for the Buildsys research community.

2 THE CAUSE: POOR USER BEHAVIOR AND LACK OF ENERGY AWARENESS

Several user studies have focused on user behavior from an energy standpoint [4, 6, 7, 9, 14, 15]. These studies have highlighted user literacy in energy consumption [14], user understanding of factors that impact electricity bill [7], awareness of energy use in shared households [6], and impact of user feedback [15]. Most of these efforts have focused on users in Western nations and the results broadly show that changing user behavior from an energy standpoint is a non-trivial issue. At the same time, conventional wisdom has held that users in developing nations may be "different" in terms of being more energy conscious, partly since lower incomes make electricity costs relatively higher in such regions.

Our study focuses on India, a developing economy which has a large and growing middle class population (about 75 million people based on consumption levels). Importantly due to rising incomes, the middle class population is growing rapidly and has grown by over 43% since the year 2000. We specifically focus on a high-rise apartment complex in India that comprises over 60 apartments in 15 floors. Each apartment consists of 3 bedrooms, hall and a kitchen. The residents of this apartment complex represent urban middle class users. They are well educated with graduate or post-graduate degrees and are able to afford "typical" middle-class appliances.

2.1 User Study Design

In addition to collecting fine-grain meter data, we conducted a user survey for all apartments using a questionnaire. The availability of meter data allows us to compare the survey results with actual consumption behavior. Such meter data has already been used in various works to segment consumers into various groups [8, 11]. Out of the 60 apartments, 41 participated in the survey, and the remaining 19 were not available. Table 1 shows the distribution of family size in the surveyed apartments. The designed questionnaire[1] has six questions, but here we discuss only three major questions, which are: (**1**) What is your average monthly electricity bill (in national currency)? The five responses provided in terms of ranges were: below 500, $501-1000, 1001-1500, 1501-2000$, and above 2000. (**2**) At what time of the day do you think you consume energy highest? The five options provided in the form of range hours were: $0600-0900, 0900-1200, 1200-1800, 1800-2000$, and $2000-0600$. (**3**) Which profile do you think your usage lies on a typical weekday of September 2016? Figure 1 shows the six profiles for a weekday. Usually, a weekday usage differs from the weekend usage. Accordingly, six profiles as shown in Figure 2 were presented for weekend usage. The user survey was based on the following methodology:

Family Size	Apartments (#)
1	02
2	03
3	18
4	10
5	07
6	01

Table 1: Consumer distribution in apartments.

[1] https://goo.gl/2uJMpp

(1) **Profile Generation**: First, we selected weekdays (five consecutive days) and weekend (two consecutive days) data of the 4th week of September 2016 for all the apartments of the building. We chose this week because most of the data pertaining to this week was available and there were no holidays that week. The data used for profile generation is down sampled at hourly average granularity. Next, we computed average consumption of weekdays and weekend data separately for each apartment by taking hour-wise average across selected days. With this step, we obtained 24 readings corresponding to a weekday and 24 readings corresponding to a weekend for each apartment. Note that all operations were done separately for weekdays and weekend data. We then used K-means clustering to categorize apartments into six ($k = 6$) clusters based on their similarity in usage pattern [13]. We chose $k = 6$ empirically, as at this value, we found that all clusters differ significantly. Finally, we computed representative profiles for each cluster by taking mean of apartments within each cluster separately. Representative profiles of each cluster show the average consumption pattern for the apartments within that cluster.
(2) **Survey Notification**: An email was sent to all residents on Monday (7 Nov. 2016) residing in the apartment complex, mentioning that we planned to conduct a survey on the coming Saturday.
(3) **Survey Execution**: On survey day, a team of 3 students visited door to door and filled the questionnaire. We presented the questionnaire on a paper as it was easier to explain profiles on paper.
(4) **Survey storage and Analysis**: We fed paper-based information in a database so that it will remain available for further study. Finally, we compared consumer responses with the actual data.

2.2 Results and Key Findings

Bill Awareness Check: This question focuses on whether residents of an apartment know the amount of their electricity bills. Surprisingly, five consumers responded that they "didn't know" the monthly electricity cost, although they were ready to answer this question after checking their e-bills. To compare the accuracy of the consumer responses with the actual bill, we obtained bills for four consecutive months for each consumer and computed the average bill. Next, we compared the actual monthly bill amount to the survey answers provided by the users. We found that 16 out of 41 users could accurately identify their mean monthly bill range, 20 out of 41 users identified an incorrect range for their monthly electricity usage and 5 users answered that they did not know. This implies that 61% of consumers within this group did not have an awareness of their monthly electricity bill. A violin plot on bill awareness question in Figure 3 shows the distribution of consumers who answered wrongly. It shows by how many ranges consumers were away from the actual bill range. In India, bill is calculated only on the number of energy units consumed.

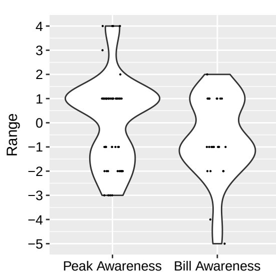

Figure 3: Violin plots: Range difference between actual and provided answer.

Peak Awareness Check: Next we asked users if they could identify the hours of the day when they consume the maximum electricity. To simplify the question, we asked users for peak consumption time-ranges, instead of asking for exact peak consumption hour. Our intuition here was that if users had a general awareness of when they run large loads (e.g., water heaters), they may be able to identify their peak consumption periods.

To evaluate the accuracy of reported responses, we determined the actual peak usage periods for each apartment from the meter data. To do so, we computed the average hourly mean usage over a three month period (July to September). We then determined the hour of the day with the maximum usage and mapped it to the time periods given in the questionnaire. Our results showed that 9 out of 41 consumers were able to identify their peak usage period over the course of a day, while 32 out of 41 provided incorrect answers. Thus over 75% of users were unable to translate their daily activity patterns into when they might be consuming the maximum electricity. A violin plot in Figure 3 on peak awareness shows by how many ranges such users were away from the actual peak range.
Profile Awareness Check: This question differs from the previous question since it includes consumption pattern for the entire day. Figure 1 shows six different energy profiles for a weekday. Each profile shows the magnitude and pattern of energy consumption for a day. For example, in Figure 1, profiles 4 and 6 have peak at 1000 hours but whole day patterns differ significantly.

On presenting this question to consumers, we explained the difference between different profiles like, "*Profile 1 shows that usage remains constant throughout the day, but around 1000 hours, the consumer uses some high energy consuming appliance* ". To ensure that consumers could correlate their appliances usage with one of the provided profiles, we mentioned that appliances like water heater, air conditioner, hair dryer are high energy consuming as compared to refrigerator, fans etc. Although we observed that participants found this question difficult, they were able to answer the question after a little explanation. Similar responses were collected for weekend consumption profiles. On comparing the recorded responses with the actual profiles, we found that only 16% of consumers were able to identify their usage pattern on a weekday and 18% could identity their usage profile for a weekend.

Question	Awareness (%)
Avg. monthly bill	39
Peak usage time	22
Weekday profile	16
Weekend profile	18

Table 2: Awareness percentage response to questions.

Table 2 summarizes the results for the questions. Overall, we infer that a large fraction of users are not even aware of their monthly bills and a still larger number is unaware of when or how they consume electricity. We note that this group of consumers is well-educated and tech-savvy, and yet has low awareness of their energy use. We believe there are three key reasons for this low awareness. First, many users use automated payment for their monthly electricity bills (e.g., through direct paycheck deduction), which means all do not see the bills on a monthly basis. Second, consumers only see their monthly usage and are not able to extrapolate their daily usage patterns due to the lack of exposed data. Third, and perhaps most important, we find that the monthly electricity bill is a small fraction of their monthly income (around 1.5% or lower). This is similar to the fractions reported in Western nations, implying that there are few monetary incentives for a consumer to care about one's usage.

Overall, our findings challenge the belief that users in developing regions tend to be more conscious about their energy usage. For the urban middle class population that is sufficiently affluent to afford middle-class comforts, our survey finds that the low energy awareness is similar to consumers in Westerns nations. We note that our findings may not translate to low-income groups or to other developing regions, but it does point to similarities within educated and affluent middle-class groups across geographies.

3 THE NEED: UTILITY-DRIVEN APPROACHES EXPLOITING CONSUMER DATA

Our user study points to the broad difficulty in making users energy conscious and incentivizing them to change their behavior to become more energy efficient. Consequently, depending on consumers to lead the way for meeting a society's broader energy goals may not be a successful strategy. Instead, we argue that utility companies should take responsibility for making their consumers energy-efficient through various approaches.

First, a utility company can deploy automated approaches for energy management on behalf of their consumers. Such approaches can perform "smart" scheduling of large loads across residential consumers to reduce aggregate peaks. For instance, the ability to schedule duty cycles of air-conditioners across apartments (e.g., similar to approaches such as [2, 10]) or electric water heaters can yield substantial benefits while being completely transparent to end-users and requiring no change in behavior. A slightly more intrusive method is to deploy automated consumer demand-response (DR), where the consumer agrees to let the utility defer the use of a large load such as an AC for a small time period (e.g., an hour) during peak hours. The NEST thermostat offers such a program (called Rush Hour Rewards) to its users in the United States, where the users get discounts on their bill (e.g., $25 per year) for the ability to change the set-point temperature 6-10 times per year, especially during very hot or very cold days. The design of smart scheduling techniques or automated DR methods require additional research and offers a rich set of challenges for the BuildSys community.

Second, utility companies can take energy-reducing measures to their consumer premises and homes [3]. This may include replacing very old and inefficient HVAC equipment with energy-efficient versions or adding better insulation to walls and roofs of buildings to enhance its thermal characteristics. Utilities aim to reduce the aggregate energy along with the peak consumption because India is an energy deficit nation. Many utility companies already have programs in place that offer energy rebates or subsidies to users making such energy improvements. These have their origins in the energy crisis era of the 80s. The main challenge is that such programs are not well targeted to consumers and depend on users taking advantage of the offered programs. Given the low awareness of energy issues by consumers as shown by many studies, including our own, it is not clear that the consumers who have the greatest need for such energy improvements will be aware of it and will take proactive steps to address the problems. A better approach is for utility companies to employ energy analytics algorithms on their consumer usage data to identify the least efficient consumers [12]. Similar to network anomaly detection algorithms, advanced analytics algorithms can be developed to identify the possible root causes for the inefficient use, which can point to specific interventions or remedies. The design of such analytics algorithms is yet another research challenge for our research community. Once the inefficient consumers as well as possible causes of the inefficiency have been identified, the utility company can pro-actively target these specific consumers to make energy improvements and take advantage of subsidy programs for such improvements. In many cases, utility companies can even offer to make such improvements at no cost to consumers since it yields benefits such as peak load reduction for the grid, which reduces their operational costs.

4 CONCLUDING REMARKS

This paper highlighted the broad challenges in making users energy aware and incentivizing them to adopt energy efficiency measures. We argued that it might be prudent for utilities to take responsibilities for making consumers more energy efficient through a mix of home automation and energy analytics [12]. We highlighted several research challenges in meeting this goal, which offers new avenues for future research.

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