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Data Analytic Policy Design Applied to Energy Conservation in College Dormitories

Lei Zhan, Dah Ming Chiu
Department of Information Engineering
The Chinese University of Hong Kong
zl011, dmchiu@ie.cuhk.edu.hk

Abstract

We study the design of data analytic policies in a campus dormitory where smart meters are installed to gather usage data. Given the availability of such data, we consider policies to give feedback on comparative usage levels on a daily basis, and give price incentives accordingly. This requires us to divide users into groups according to their behaviors, and set prices that are reasonable. Instead of doing grouping and price setting based on intuition and guesses, which may be ineffective and unfair, we propose a data analytic approach. This requires us to start the design with a clear set of principles; based on these, and the collected data, the user grouping and corresponding pricing are automatically determined, satisfying the agreed-to principles. We show how this design approach works in a real setting, with real world usage data. We also discuss the difficulties in introducing such policies as they are more complicated and involve some uncertainties, and a possible solution by using opt-in (or opt-out) at the first introduction of such new policies. We expect the data analytic policy approach and our experience to be applicable and useful in general settings.

Introduction

Energy Conservation is important for relieving the energy-thirst problem of our society. The question is, as we deploy smart meters (sensors) around users and collect more information about user behavior, how can we provide better feedback and incentives to users towards energy (electricity) conservation? This is not a traditional engineering question, as the key component of the system we are working with are humans. Many previous studies have explored the question of how to provide incentives to users to encourage conservation, for example (Chung and Rhee 2014; Marans and Edelstein 2010; Parece et al. 2013) and the studies reviewed in (Abrahamse et al. 2005). For this interdisciplinary question, the approaches studied are usually ad hoc and empirically based. What we explored in this paper is how to systematically apply collected usage data to policy design, including how to provide feedback to users, charge for usage, and give other forms of awards. We refer to this as *Data Analytic Policy Design*, which may be applicable to other scenarios as well.

Our collaborator (LWS College of CUHK) has been pushing for energy conservation and other green goals since it was founded. There are regular activities and competitions to promote energy conservation behaviors among the college students. The college had deployed a smart meter system to measure the electricity usage in all its student rooms. In our previous work, we studied the electricity usage patterns based on the measurement data and the policies introduced to encourage energy conservation among students. The existing policies, like those found in most systems, are based on absolute usage amounts and static rules. For example, users are shown their (absolute) usage amount, and the corresponding charge, based on a progressive rate. The problem is, absolute usage amount provides limited information and it is not clear how to set the progressive rate schedule. Depending on weather and other factors, the reasonable usage amount can be different from day to day, or on a monthly basis. If students are charged on a yearly basis, then there is hardly any feedback.

Our work in this paper, as shown in Figure 1, complements the existing efforts of the college with a feedback platform and new designs of energy policies. We study how to provide a comparative feedback mechanism to users and build a charging scheme on that basis. Users are divided into groups based on their usage levels. It helps reflect users' behavior comparatively and decouple the feedback information from usage dynamics. The question then becomes how to divide users into groups, and how to set chargers based on the grouping. Instead of using static parameters or functions to do the grouping and charging, we take a *data analytic* approach. Following this approach, we establish a set of principles, and compute the grouping and charging based on actual usage data for all users. Our main contribution is to derive these principles for our setting, and then discuss the pros and cons of this approach and its applicability to other policy settings.

The rest of this paper is organized as follows. In Section 2, we first explain the concept of data analytic policy design and take group-based energy policy as an example; this is followed by a detailed introduction for our design of energy polices for LWS college in Section 3, including the group-based comparative feedback and the group-based dynamic pricing. In Section 4, we discuss the policy deployment and challenges. Finally we look at the related work in Section 5

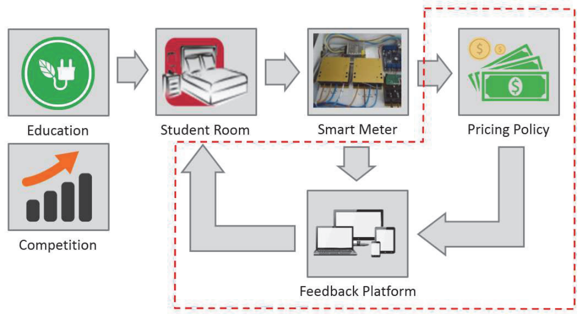


Figure 1: Energy Conservation Framework of LWS College

Pay ($)	First 50	Next 50	Next 50	Next 50+
Unit Price	$0.92	$1.61	$2.07	$2.87

Table 1: The Progressive Rule for Unit Price of Extra Credits in LWS College

and draw our conclusions in Section 6.

Data Analytic Policy Design

Before our work, the college operated a Progressive Pricing Scheme (PPS) on a monthly basis. At the beginning of each month, some free credits are allocated for each room. The credit balance of rooms are carried forward from month to month and finally refundable at the checkout date. Whenever a room runs out of its credit in the middle of a month, the room lodgers have to buy additional credits and the unit price follows a progressive rule in Table 1. The refundable credit balance and the progressive rule act as the incentives to encourage energy conservation. The progressive rule of PPS is similar to the tier prices of the Tiered Pricing Scheme (TPS), which has been widely adopted for charging electricity usage in many countries and regions. Under TPS, electricity rates rise progressively as usage amount reaches different tiers. In other words, the more energy consumed, the more punitive the scheme is.

Data Analytic Policy

PPS was designed and operated in a conventional manner, that is, parameters of policies (the free credit allocation schedule and the progressive rule of PPS) are figured out empirically or based on historical observations at the design phase. The parameters are usually kept using once determined. This approach of policy design has obvious limitations. On one hand, user behavior and external conditions may change from time to time, which requires frequent reviews and updates of the parameters to guarantee accuracy, fairness, etc. On the other hand, it is difficult to update the parameters, especially for policies involving humans. It has to be clearly explained to users to avoid confusions and complaints. Not to mention the extra efforts for revamping systems to support the updates. The setting and updating of parameters have become a predicament for policy designers.

Actually, such predicament could be avoided if policy parameters are determined at runtime, for example, by adopting data analytic methods and applying them on actual usage data. We refer this kind of policy as *Data Analytic Policy*. For example, in our setting, the feedback information delivered to users and the charge of usage could be figured out based on grouping result by applying grouping (clustering) algorithm on actual usage data of users at runtime.

The data analytic policy requires the designer to establish some principles, which act as the middle layer to translate expected behaviors of the policy into constraints and conditions in executable algorithms. In other words, the policy is defined by the set of principles, rather than by the parameters. Obviously, the data analytic policy design is more flexible to handle the dynamics of user behavior and external conditions.

Group-based Energy Policy

An important application of electricity usage data is generating feedback to users. In previous studies (Abrahamse et al. 2005; Carrico and Riemer 2011; Jain, Chhabra, and Singh 2015; Petersen et al. 2007), comparative feedback has been effective in encouraging energy conservation, especially when users are familiar with each other. This kind of feedback helps evoke the feelings of competition and social pressure among users, thus raise awareness of energy conservation, leading to saving behaviors.

Taking the advantages of comparative feedback and data analytic policy, we proposed group-based energy policies for energy conservation. In our design, users are divided into several groups based on their energy usage data, and the grouping result is then shown to users as feedback. For example, users may belong to group *Energy Saver*, *Moderate User* or *Big Spender* according to their relative usage levels. The grouping results could be used in other policies as well, such as pricing and awards.

Why Group-based? Actually, the most complete comparative feedback is the entire user list ranked by energy consumption. This may be information overloading and has privacy issues. An alternative method is to just provide some statistics instead of the rank list, such as INDEX, MEAN, MAX, MIN, etc. This approach is widely adopted by prior studies. But only statistics may not be sufficiently informative to users. This prompted us to consider group-based feedback.

Comparing to knowing the rank, the assignment of a user to a labeled group (e.g. energy saver, moderate users, or big spender) is expected to give the user a stronger feedback by associating him/her with a type of behavior through appropriate labeling. Of course, the explicit rank information can be regarded as a special form of group-based comparative feedback.

As we explored the design and concrete implementation in our setting, a set of principles were established in terms of the following aspects. We believe that these principles are applicable to more general scenarios.

Group Names and Intended Representation In coming up with the number of groups and the group names, we need to consider the possible psychological effects on users. On one hand, the group names should convey clearly and explicitly specific behaviors, for feedback purposes. Thus we rule out generic names such as (A, B, C ...) or (1, 2, 3 ...). On the other hand, we want to avoid making the names with too strong labeling effect. For example, we decided to use *big spender* to describe users with top usage levels, instead of *energy waster* or *environment enemy*. In our design, besides *Big Spender*, another three names for describing usage levels are *Energy Saver*, *Moderate User* and *Above Majority*.

Fairness For any grouping technique, the grouping is conducted based on the usage data of users. However, users may not be homogeneous and there are fairness issues if some factors are highly correlated with usage patterns. For example, 2-people-shared rooms and 3-people-shared ones are with quite different usage patterns. It is unfair to conduct the grouping directly on the raw usage data, especially if the grouping result will be further utilized in other policies, such as delivering reward and penalty in pricing policy. A solution for this problem is to pre-process the usage data before grouping, such as normalization. An alternative approach is to split users into subsets by such factors and then conduct grouping for each subset separately, given the user population is large enough.

Exceptional Behavior Apart from the factors mentioned above, there exist some exceptional behaviors of users that will cause fairness issue. For example, in our setting, each day, there are some students absent from their rooms, especially on weekends, public holidays, etc. For such rooms, there is no significant electricity usage and they will be assigned to the group *Energy Saver* for sure. Then the grouping result of other users will be affected. Therefore, the users with exceptional behaviors should be filtered out before grouping, and be handled separately.

Corner Cases As the grouping is conducted at runtime based on actual usage data, some extreme cases could happen. For example, although the desired number of groups is 4, it is possible that all users had exactly the same usage amount in a day, which means they will fall into only one group. Which group (of the 4 predefined groups) will these users belong to. To resolve these corner cases, additional assumptions and constraints need to be established according to our expectation of the grouping result based on large population. For example, a large group is more likely to be moderate users than big spenders.

Energy Policies for LWS College

Group-based Feedback Policy

In our setting, we provide daily grouping results to the college students via the feedback platform we built for the college. The basic operation is as follows: for each day, we filter out the rooms with non-behavior usage as a separate group: *Non-Behavior User*; and then apply the optimal K-Means to split the rest rooms into four groups: *Energy Saver*, *Moderate User*, *Above Majority* and *Big Spender*, based on their usage data. The grouping result is delivered to students together with other information via the feedback platform.

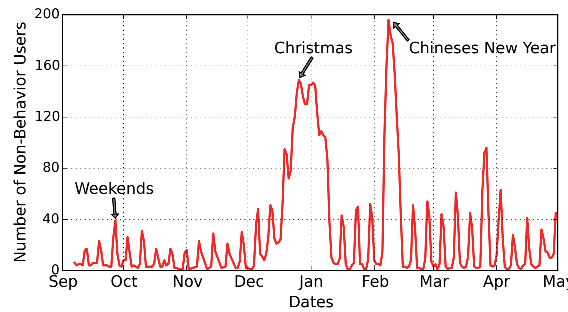


Figure 2: Daily Number of Non-Behavior Users during the Academic Year 2015/09 - 2016/04

Non-behavior Usage As we described in Section 2, there exist some rooms with non-behavior usage, which have to be filtered out as a separate group. The detection of non-behavior usage can be posed as a classification problem based on the energy usage data. We figured out some criteria to identify the non-behavior usage:

1. there must be null usage for on-off appliances, such as A.C and lighting;
2. a tiny amount of usage might be observed from the appliances that have to be kept on, such as refrigerator;
3. the hourly usages of the appliances mentioned in 2 must be with small fluctuation.

Figure 2 depicts the daily number of non-behavior records during an academic year extracted by our detection algorithm. It shows strong weekly pattern with the execution of some special dates and events, such as Christmas and Chinese New Year. It is difficult to evaluate the accuracy of our detection algorithm as we have no ground truth, however, the patterns and events help prove its correctness to some degrees. The accuracy can be higher with higher data capturing frequency. For the scenarios without appliance level usage data, the algorithms of energy disaggregation might help as well.

Optimal K-Means We planned to apply a typical data analytic method K-Means to conduct grouping based on usage data of users. K-Means minimizes *the within-cluster sum of squares* by following iterative relocation procedures. It ensures that a record will be assigned to the group, whose centroid is closest to the record. However, commonly used program to derive K-Means does not guarantee the global optimum, but outputs a local optimum. The grouping result of K-Means is affected by the selection of initial group centroids. Therefore, K-Means does not match our setting. Fortunately, for the one-dimensional version of the problem, as in our case, there is a fast algorithm to arrive at the optimal solution (Wang and Song 2011), which we use.

Besides, we add some additional constraints to address extreme corner cases of grouping. Basically, we assume that Energy Saver and Moderate User together take the majority of users, otherwise, we align the grouping results to form only one Moderate User group. For the cases that the number

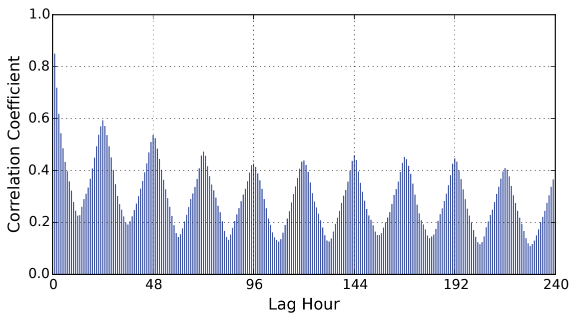


Figure 3: Auto Correlation of Hourly Consumption of a Room

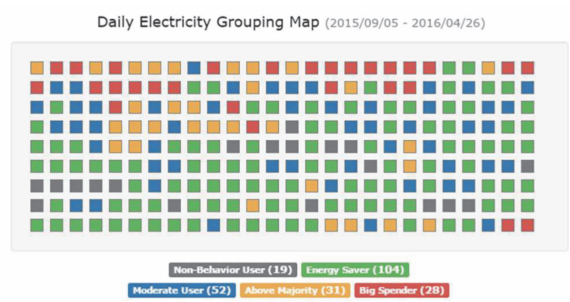


Figure 4: Daily Grouping Map of a Room during the Academic Year 2015/09 - 2016/04

of unique usage amount is less than 4, i.e. there exists empty group, we also override the results as one group. Other alternative approaches are possible to handle these cases as long as the design principles are implemented and guaranteed.

Daily-based Operation In our setting, grouping is conducted everyday, so as to provide quick opportunities for users to review and respond. On one hand, we observed strong daily and weekly patterns of electricity usage by the students. Figure 3 illustrates the Auto-Correlation of the hourly electricity usage amount of a room. The figure shows daily and weekly patterns clearly, therefore, the daily operation of grouping matches the usage pattern of users.

On the other hand, as the feedback is delivered mainly via the web-based feedback platform, it requires negligible operational cost even the grouping is performed daily-based. For other candidate feedback techniques with higher operational cost, such as email and SMS, the feedback could be delivered less frequently by summarizing the daily grouping results during the delivery period. Figure 4 shows the daily grouping result map we provide to students on our feedback platform. It can clearly reflect how the student performed in previous days.

Group-based Pricing Policy

The group-based comparative feedback aims to help users better understand their behaviors and raise their awareness of energy conservation. Its effectiveness could be amplified with some incentive designs. For example, the grouping result could be applied to determine reward and penalty in pricing policy of electricity usage as financial incentives.

Dynamic Pricing Actually, in some prior studies of energy conservation in households, incentives via pricing scheme showed limited effectiveness. The primary problem is the inattention or imperfect information, which is classified to be information or market failure by economists (Asensio and Delmas 2015). In our setting, the feedback platform and the group-based comparative feedback we designed can help solve the problem by providing users more frequent and informative feedback. We proposed the Group-based Dynamic Pricing (GDP) scheme, which determines reward and penalty as financial incentives based on the grouping result from the group-based comparative feedback.

Design Goals As we explored the design of GDP, we setup some goals to avoid the problems of PPS and to implement the principles regarding fairness, flexibility, etc.

Basically, the incentive for users should be consistent and continuous along with time and external conditions, which is the primary challenge for PPS. This is achieved by design for GDP as the grouping result is decoupled from usage dynamics but depends on user behavior comparatively. Secondly, reward and penalty should be determined reasonably and fairly. For example, higher reward is for users that conserve more, and so is the penalty for heavy users. It is an extra feedback for users as well. What is more, it should be a principle and promise to users that their financial benefits are guaranteed both individually and as a whole, so as to dispel concerns or pressure of users regarding the pricing scheme.

Implementation of GDP Under GDP, we set the unit price of electricity usage for each room according to its group assignment from the group-based comparative feedback. Discount or surcharge are delivered to certain groups as reward and penalty respectively. The concrete implementation of the price setting is as follows.

Each day, all rooms are assigned into groups (Non-Behavior User, Energy Saver, Moderate User, Above Majority and Big Spender) by their electricity usage data during that day. Let the average usage amount of each group be U_{NBU}, U_{ES}, U_{MU}, U_{AM} and U_{BS}; and the group size of each group be S_{NBU}, S_{ES}, S_{MU}, S_{AM} and S_{BS} accordingly. The unit prices of each group, P_{NBU}, P_{ES}, P_{MU}, P_{AM} and P_{BS}, are determined following several principles:

1. **Normal Price for Normal Behavior (and No Behavior)** Unit prices of Moderate User P_{MU} and Non-Behavior User P_{NBU} are set to be the cost price P_{market} that the college pays to power supplier, i.e.
$$P_{MU} = P_{market},\ P_{NBU} = P_{market}$$
2. **Proportional Penalty** Surcharges are delivered to Above Majority and Big Spender with $P_{AM} > P_{market}$ and $P_{BS} > P_{market}$; the price gaps ($P_{AM} - P_{market}$ and $P_{BS} - P_{market}$) are proportional to the average usage amount gaps ($U_{AM} - U_{MU}$ and $U_{BS} - U_{MU}$), i.e.
$$\frac{P_{AM} - P_{market}}{U_{AM} - U_{MU}} = \frac{P_{BS} - P_{market}}{U_{BS} - U_{MU}}$$

3. **Budget-Balance**
Discount is delivered to group Energy Saver with $P_{ES} < P_{market}$; the reward amount for Energy Saver is equal to the overall amount of penalties for Above Majority and Big Spender, i.e.

$$\sum_{k \in \{AM, BS\}} (P_k - P_{market}) U_k S_k = (P_{market} - P_{ES}) U_{ES} S_{ES}$$

4. **Bound Dynamic Pricing**
The unit prices of all groups are expected to be within the range $[P_L, P_U]$, whereas $P_L < P_{market} < P_U$. The price setting follows an adaptive procedure:
a) letting P_U be the price of Big Spender;
b) figure out prices for the rest groups;
c) if the price of Energy Saver is lower than P_L, we reset the price of Energy Saver as P_L and figure out prices for the other groups.

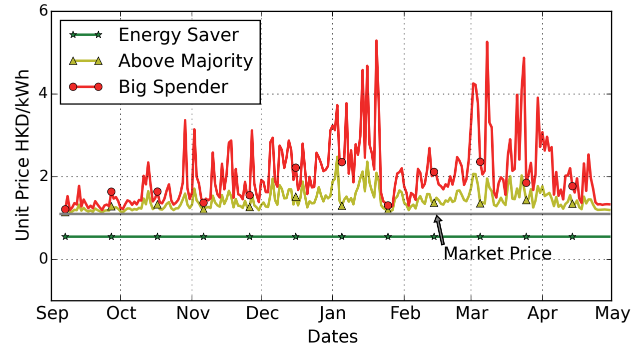
Formula #1 implements the principle that no reward or penalty will be delivered to Non-Behavior User and Moderate User. Formula #2 is derived from the fairness principle that the penalty levels must match their performances comparing to normal behavior regarding energy usage. Formula #3 indicates that the college is financially neutral by constraining equivalent overall amounts of reward and penalty for students.

In our design, GDP is operated on daily basis. The coherent operation of the comparative feedback and GDP can motivate users to conserve energy with awareness more effectively. The daily operation of GDP requires daily review of group prices, i.e. Dynamic Pricing. The main challenge of dynamic pricing locates at the acceptability of users. The group prices are determined post-consumption for each day. The uncertainty of charging will discomfort users and thus lead to complaints. The adaptive procedures in formula #4 are for addressing this challenge by controlling the uncertainty with bounded prices.

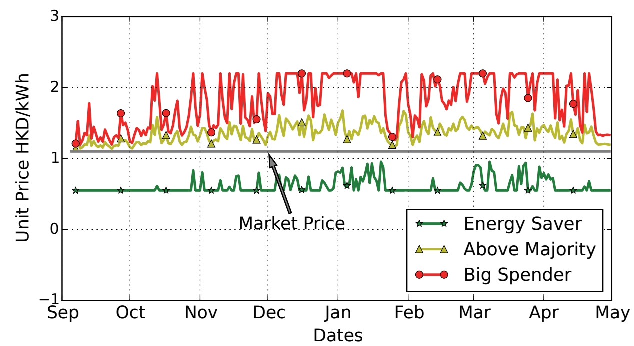
Actually, we have other options to operate GDP different from formula #4. Figure 5a depicts the daily group prices by fixing the price for Energy Saver ($0.5 * P_{market}$). The unit price of Big Spender extends to an unreasonably high level during some periods. Similar result is observed regarding the unit price of Energy Saver for the case of fixing the price for Big Spender. Figure 5b plots the daily group prices by applying our adaptive approach ($[0.5 * P_{market},\ 2 * P_{market}]$) for the price setting of GDP. Obviously, the adaptive approach helps control the uncertain feeling of users by promising bounded reward and penalty.

Other Group-based Policies

Apart from the group-based comparative feedback and pricing policy, there are many other possible designs of group-based policy for energy conservation. One type of design is to combine grouping with existing interventions or policies. For example, a) the grouping result could be used to determine awards in competitions; b) the college might invite the students that are frequently grouped as *Energy Saver* to share their experiences of energy saving; c) tailored information has proven to be an effective way to educate users



(a) Fix Price for Energy Saver



(b) Adaptive Approach with Bounds

Figure 5: Daily Group Prices of GDP under Different Approaches

to conserve energy, which could be drawn from the daily grouping map of users, etc. Besides, the grouping result could help extract behavior patterns and detect anomalies from different perspectives. We believe that the introduction of grouping benefits the energy conservation framework and the applicable contexts are not limited to campus dormitories.

Deployment and Challenges

There are some challenges faced by the data analytic policy design (so it is with our group-based policies). The most notable one is the uncertainty it creates for users, such as the possible uncontrolled levels of discount or surcharge created by pricing algorithms. The uncertainty might lead to complaints and even rejections from users regarding the policy. To address this challenge, principles to control the uncertainty must be considered and implemented. Meanwhile, the policy design should be explained to users clearly with patience to ease its deployment. An effective approach to smooth the policy deployment is to conduct some trials before users can accept it, or use opt-in (or opt-out) at the first introduction of such new policies.

Our work of designing the energy policies for the college experienced several stages. On one hand, we collected feedback from different parties and refined the policy design in different stages. On the other hand, we noticed that the success of a policy not only depends on the policy design itself, but also relies on the deployment process of the policy.

We are now planning to deploy the group-based polices in LWS college to validate its feasibility and effects on encouraging energy conservation. Starting from mid-Sept of 2016, the college students can check their electricity usages, grouping results, and the charging details for their usages in real-time on the feedback platform. To encourage their participations and make the polices more transparent, they are allowed to view the charging details of both PPS and GDP. Based on their own observations and comparisons, they might determine to switch to GDP from the default PPS within a period (two weeks). With enough participants for the new policies, we could analyze the policy performance and we would like to share the experiment results then.

Related Work

Most of the early studies on energy conservation are for residential households. In (Abrahamse et al. 2005), the authors have reviewed 38 studies that applied interventions to encourage energy conservation for households. In recent years, more attentions are paid to buildings, including commercial ones and those on campus (Chung and Rhee 2014; Emeakaroha, Ang, and Yan 2012; Jain, Chhabra, and Singh 2015; Marans and Edelstein 2010; Parece et al. 2013; Petersen et al. 2007). Our work is also motivated by a desire to use monitoring, feedback and charging policies for encouraging energy conservation in campus dormitory (Zhan and Chiu 2015).

The authors of (Abrahamse et al. 2005) have grouped all interventions for energy conservation in households into two categories: Antecedent (i.e. commitment, goal settings, information, modeling) and Consequence (i.e. feedback, rewards). They concluded that the interventions show varying degree of success on encouraging energy conservation, among which feedback and rewards are proven to be effective. In the context of campus dormitory, feedback also shows its effectiveness (Jain, Chhabra, and Singh 2015; Petersen et al. 2007; Parece et al. 2013). The authors of (Jain, Chhabra, and Singh 2015) have compared different feedback techniques for dormitory students and concluded that daily individual paper feedback encourages more conservation. In (Petersen et al. 2007), different resolutions are applied to provide feedback of resource consumption for dormitory students. The authors concluded that tailored feedback with high resolution is more effective. In our work, we also make use of feedback and focus on the comparative feedback. Our infrastructure also allows individual-level feedback of electricity usage, instead of floor-level or even building-level feedback in (Jain, Chhabra, and Singh 2015; Petersen et al. 2007). We believe that the individual-level feedback is more personal and insightful for users. Both (Petersen et al. 2007) and our work implement real-time web-based platform for providing feedback.

Some prior studies and programs (Abrahamse et al. 2005; Petersen et al. 2007; PALMER 2004; University of Illinois) explored design of financial incentives to encourage energy conservation. The studied incentives were either awards delivered via competitions and activities, or discount and surcharge implemented in the pricing scheme for charging energy usage. Actually, in most of campus dormitories, students do not need to pay the utility bills and financial incentives are rarely implemented via pricing scheme. In our prior work, we reported the progressive pricing scheme adopted by the college, and in this work, we summarized several principles for the financial incentive design and explained the group-based pricing scheme in our setting.

Conclusion

In this paper, we introduced the group-based comparative feedback and the corresponding pricing policy to the energy conservation in college dormitories. The group-based policies rely on relative behaviors, instead of absolute usage amount, to provide feedback and deliver incentives. The relative comparison helps draw users' attention to social norm and evoke the feelings of competition and social pressure. Thus it motivates users to review and change their behaviors towards energy conservation.

More importantly, we described the concept of data analytic policy design. In our setting, we firstly established a set of principles for the policies, and then applied data analytic approach following the principles to do grouping and calculate charging dynamically. The approach adjusts policy parameters at runtime based on actual usage data, rather than using static parameters, which are usually estimated empirically or from historical observations. The data analytic approach helps improve the robustness of policy design and implement the principles to guarantee fairness, accuracy, etc.

The concept of *data analytic policy design* should have broader applicability. In fact, it is not hard to identify scenarios where this approach is practiced in an ad hoc and manual fashion. For example, a funding agency receives N applications, and wish to sort the applications into three groups: *fully funded*, *partially funded* and *not funded*, based on reviewers' scores. In the end, exactly how applications get sorted into these three piles may follow a procedure similar to our data analytic policy, though it is usually done manually, by a committee, since sometimes the reviewer scores may not all be trustworthy. The contribution of our work is to formalize the concept so that it can be systematically applied to more situations, and make the process more transparent.

Acknowledgments

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