Social Game for Building Energy Efficiency: Utility Learning, Simulation, Analysis and Incentive Design

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Firstly, I would like to thank my advisor, Professor Spanos Costas for supporting my research, accepting me into his research group and providing me advice and kind encouragement. In addition, I want to thank Professor Shankar Sastry for his help and support. Also, I feel indebted to my collaborators Ming Jin and Lillian Ratliff for their kindly help during my research. Moreover, I am grateful to Kakali Georgia for her valuable support, help and love all these years as well as my family for their love. Finally, the present work was partially financially supported by the "Andreas Mentzelopoulos Scholarships University of Patras".

Social Game for Building Energy Efficiency: Utility Learning, Simulation, Analysis and Incentive Design

by Konstantakopoulos Ioannis

Research Project

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Approval for the Report and Comprehensive Examination:

Committee:

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Date

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Professor S. Shankar Sastry

Date

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Abstract

We describe a social game that we designed for encouraging energy efficient behavior among building occupants with the aim of reducing overall energy consumption in the building. Occupants vote for their desired lighting and HVAC level and win points which are used in a lottery based on how far their vote is from the maximum setting. We assume that the occupants are utility maximizers and that their utility functions capture the trade-off between winning points and their comfort level. We model the occupants as non-cooperative agents in a continuous game and we characterize their play using the Nash equilibrium concept. Using occupant voting data, we parameterize their utility functions and use a convex optimization problem to estimate the parameters. We simulate the game defined by the estimated utility functions and show that the estimated model for occupant behavior is a good predictor of their actual behavior. In addition, we show that due to the social game, there is a significant reduction in energy consumption.

Moreover, we formulate the interaction between the building manager and the occupants as a reversed Stackelberg game in which there are multiple followers that play in a non-cooperative game. The estimated utilities are used for determining the occupant behavior in the non-cooperative game. Due to nonconvexities and complexity of the problem, in particular the size of the joint distribution across the states of the occupants, we solve the resulting the bi- level optimization problem using a particle swarm optimization method. Drawing from the distribution across player states, we compute the Nash equilibrium of the game using the resulting leader choice. We show that the behavior of the agents under the leader choice results in greater utility for the leader.

Chapter 1

Introduction

Energy consumption of buildings, both residential and commercial, accounts for approximately 40% of all energy usage in the U.S. [18]. Lighting is a major consumer of energy in commercial buildings; one-fifth of all energy consumed in buildings is due to lighting [26]. There have been many approaches to improve energy efficiency of buildings through control and automation as well as incentives and pricing. From the meter to the consumer, many control methods, such as model predictive control, have been proposed as a means to improve the efficiency of building operations (see, e.g., [2, 5, 6, 15, 20, 14]). From the meter to the energy utility, many economic solutions have been proposed, such as dynamic pricing and mechanisms including incentives, rebates, and recommendations, to reduce consumption (see, e.g., [16],[24]).

Many of the past approaches to building energy management only focus on heating and cooling of the building [Model Predictive Control]. We are advocating that due to new technological advances in building automation, incentives can be designed around more than just heating, ventilation and air conditioning (HVAC) systems. In particular, our experimental set-up allows us to design incentives based on lighting and individual plug-load in addition to HVAC. In the set-up, the building manager interacts with occupants through a social game. Started from the Spring 2014 an experiment is conducted in the Center for Research in Energy Systems Transformation (CREST) at the University of California, Berkeley.

Actually, the experiment tries to investigate the effects of incentives on the overall energy consumption, as well as patterns of energy usage by occupants of a floor of an office building. The incentives were incorporated into a social game, which rewarded individual users for saving energy. Social games have been used to alleviate congestion in transportation systems [19] as well as in the healthcare domain for understanding the tradeoff between privacy and desire to win by expending calories [4].

It is essential for the building energy management to understand possible patterns of the occupants like their thermal comfort level, their light preferences, their daily schedule to mention but a few. This is an advantage of an application of our social game due to the fact that can derive vital data and occupants' patterns. All these data can be used for an energy efficient automatic control of the office building (lighting and HVAC control).

There are many ways in which a building manager can be motivated to encourage energy efficient behavior. The most obvious is that they pay the bill or, due to some operational excellence measure, are required to maintain an energy efficient building. Beyond these motivations, recently demand response programs are being implemented by utility companies with the goal of correcting for improper load forecasting (see, e.g., [1],[17], [13]). In such a program, consumers enter into a contract with the utility company in which they agree to change their demand in accordance with some agreed upon schedule. In this scenario, the building manager may now be required to keep this schedule.

Our approach to efficient building energy management focuses on office buildings and utilizes new building automation products such as the Lutron lighting system[1]. We design a social game aimed at incentivizing occupants to modify their behavior so that the overall energy consumption in the building is reduced. The social game consists of occupants logging their vote for the lighting setting in the office. They win points based on how energy efficient their vote is compared to other occupants. After each vote is logged, the average of the votes is implemented in the office. The points are used to determine an occupant's likelihood of winning in a lottery.

We designed an online platform so that occupants can log in and vote, view their points, and observe all occupants' consumption patterns and points. This platform also stores all the past data allowing us to use it for estimating occupant behavior and compute online different

[1] `http://www.lutron.com/en-US/Pages/default.aspx`

possible incentives. Moreover, we have recently designed a smartphone app so as the users to view their account's details with a more efficient way as well as to vote for their light and temperature preferences. Our next step is the design of an app for tablets, which will give to the occupants a more convenient way of accessing our platform.

We modeled the occupants as non- cooperative agents who achieve a Nash equilibrium point. Under this assumption, we were able to use necessary and sufficient first and second order conditions [21] to cast the utility estimation problem as a convex optimization problem in the parameters of the occupants' utility functions. We showed that estimating agent utility functions via this method results in a predictive model that out performs several other standard techniques. Furthermore, we showed that based on the estimations of the occupants' utility functions and the past data, we can forecast the building's light / temperature level with small mean square error. For this task, we tried different online techniques so as to use the past data efficiently.

We are able to leverage the fact that we modeled the occupants as utility maximers in a game-theoretic framework in the formulation of the building manager's problem as a reversed Stackelberg game. A major advantage of modeling occupants as utility maximizers competing in a game and using the Nash equilibrium concept is this game theoretic model fits in the Stackelberg framework for incentive design in which the building manager performs an online estimation of occupant's utility function and designs incentives for behavior modification. This, in essence, is a problem of closing- the-loop around the occupants so that the building manager achieves sustained energy savings.

In particular, we formulate the building manager's optimization problem as a bi-level optimization problem in which the inner optimization problem is a non-cooperative game between the occupants and the outer optimization problem is the maximization of the building manager's utility over the total points and default lighting setting.

Given the data from our social game experiment, we estimate the occupants' utility functions. We determine a distribution for each occupant over the set of events, which include the occupant states present and active, present and remaining at the default, and absent. We refer to these as the player states and shorten them to active, default, and absent. Due to the number of events in the joint distribution across possible occupant states, we employ a particle swarm optimization method for solving the building manager's bi- level optimization problem for the total points and default lighting setting. This results in a suboptimal solution; however, we show that the solution leads to an occupant's behavior that results in a larger utility for the building manager as compared to previously implemented schemes.

1.1 Thesis Organization

The rest of this thesis is organized as follows. We begin in Chapter 2 by describing the experimental setup for our social game test-bed. In Chapter 3, we present the game formulation. There are games at two levels; the inner non- cooperative continuous game between the occupants and the outer reversed Stackelberg game between the building manager and the followers. Moreover, we describe the utility estimation and incentive design (solution to the building manager's optimization problem) in Chapter 4. We continue with the results and the discussion at Chapter 5. Finally, in Chapter 6, we offer some concluding remarks and directions for future work.

Chapter 2

Experimental Setup

2.1 Social Game Web portal

The social game for energy savings that we have designed is such that occupants in an office building vote according to their usage preferences of shared resources and are rewarded with points based on how *energy efficient* their strategy is in comparison with the other occupants. Having points increases the likelihood of the occupant winning in a lottery every week. The prizes in the lottery consist of three Amazon gift cards.

As it was mentioned in the introduction, we have installed a Lutron[1] system for the control of the lights and the HVAC system in the office. This system allows us to precisely control the lighting level (the lights are dimmable) of each of the lights in the office as well as to the HVAC temperature set point. We use it to set the default lighting and HVAC level as well as implement the average of the votes each time the occupants change their lighting and/or HVAC preferences. It is vital to mention that the change of the lighting level is instantaneous and for the HVAC there is a delay of 5 up to 10 minutes.

We have divided the office into five lighting zones and each zone has four occupants. Thus, there are 20 occupants who participate in the social game. In addition, we have two heating,

[1] `http://www.lutron.com/en-US/Pages/default.aspx`

ventilating and air conditioning (HVAC) zones and each zone has ten occupants. Figure 2.1 shows how the office is divided in several light / HVAC zones.

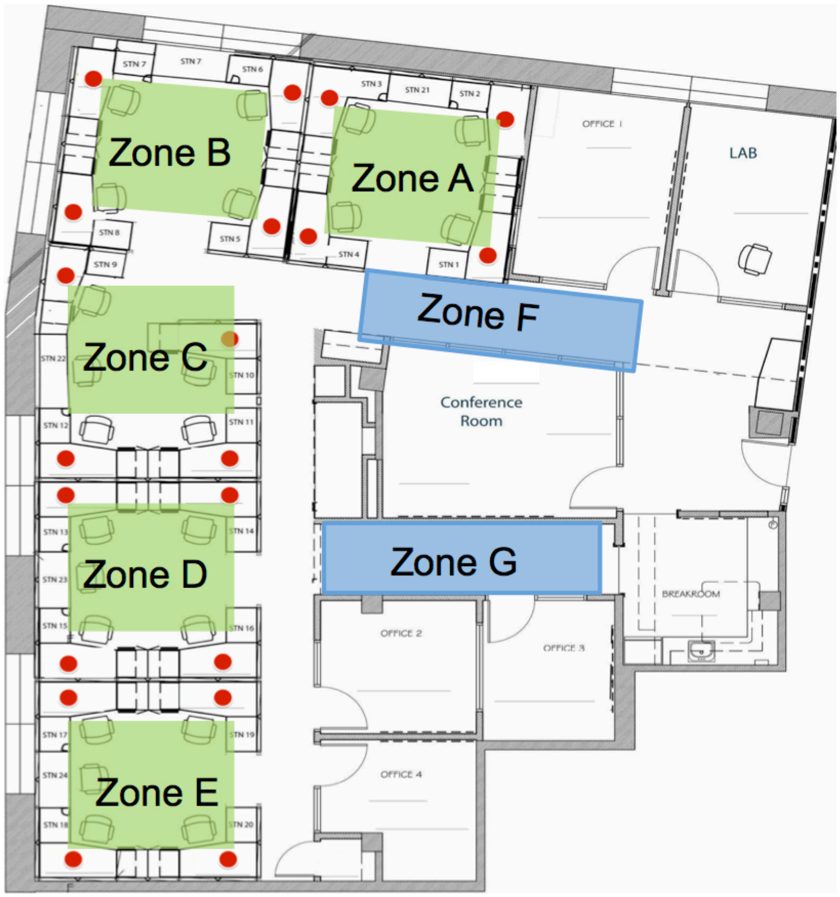


Figure 2.1: Lighting and HVAC zones of the office

Participants of our experiment (20 persons in total) have access to an online social game platform, which is a website that is password protected, and only the research group along with the participants have access to it. Each participant can log-in and participate in the game with his / her personal user name. This website displays the energy usage of all participants' personal cubicle as well as to the shared energy sources (lights and temperature) in 406 Cory Hall. Also, the website gives the ability for the occupants to vote on their lighting and heating, ventilating and air conditioning (HVAC) preferences as well as view all occupant point balances and all occupant consumption patterns including the ability to monitor individual occupant plug-load consumption.

Figure 2.2 shows the power line chart for participant number 17. Each participant can view his / her power line chart in addition to the power line chart of other participants. For example, as we can see from the figure 2.2 participant with id number 17 turn of his / her plug-load at the night before he / she leaves. Therefore, a future part of the social game is to try to motivate the occupants to turn off their plug-load before they leave as well as to understand their working patterns and try to apply an automatic way of controlling the plug-load energy consumption.

Moreover, the participants of the experiment can view lively the conditions on the office. In that way, they are able to vote based on the conditions (shared lights and HVAC level) as well as to their own comfort level. Figure 2.3 shows the page of our web portal that shows lively the level of the shared sources. It is actually a weight between the conditions at the office and their comfort level to the optimal vote so as they to have maximum likelihood of winning the lottery prices. So, they are able to see the light level of the office area as well as above their desk. In addition, they can view the temperature in the office.

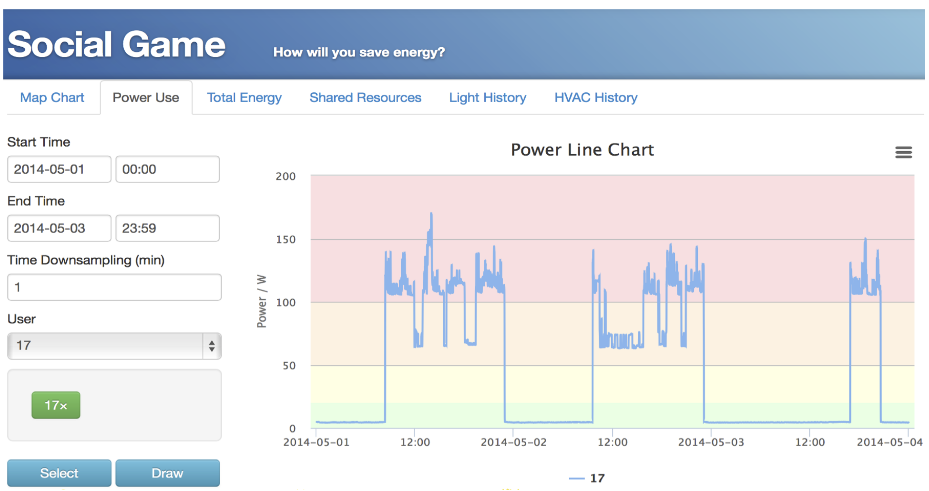


Figure 2.2: Power Line Chart for individual with id number 17

Furthermore, the participants have access in past data through the web site. So, they can view their own votes as well as the light / HVAC conditions of the office for several past dates of their choice. Figure 2.4 shows the light chart of light zones A and B in addition to participant's with id number 2 votes. Also, Figure 2.5 shows HVAC chart of temperature zones A and B in addition to participant's with id number 2 votes.

Figure 2.7 shows the actual page in our web portal at which the occupants can vote for their lighting and heating, ventilating and air conditioning (HVAC) preferences. Also, figure 2.6 shows

Figure 2.3: Live map view of the office for the shared energy sources

a sample of how occupants can see their point balance as well as how their points are in comparison to the other occupant's point balance.

We try to find the optimal way so as to design a game focused on encouraging occupants to select lower lighting settings in exchange for a chance to win in a lottery. An occupant's vote is for the lighting level in their zone as well as for neighboring zones. The lighting setting that is implemented is the average of all the votes.

Each day when an occupant logs into the online platform the first time after they enter the office, they are considered present for the remainder of the day. Upon logging in the web-portal the occupants can log their votes, view their point balance as well as other occupants' points, and view all occupants past consumption patterns. If they actively change their vote from the default to some other value, then we consider them *active*. On the other hand, if they choose not to change their vote from the default setting, then they are considered *default* for the day. If they do not enter the office on a given day, then they are considered *absent*.

There is a default lighting setting. An occupant can leave the lighting setting as the default after logging in or they can change it to some other value in the interval $[0,100]$ ($[70,78]$) for the

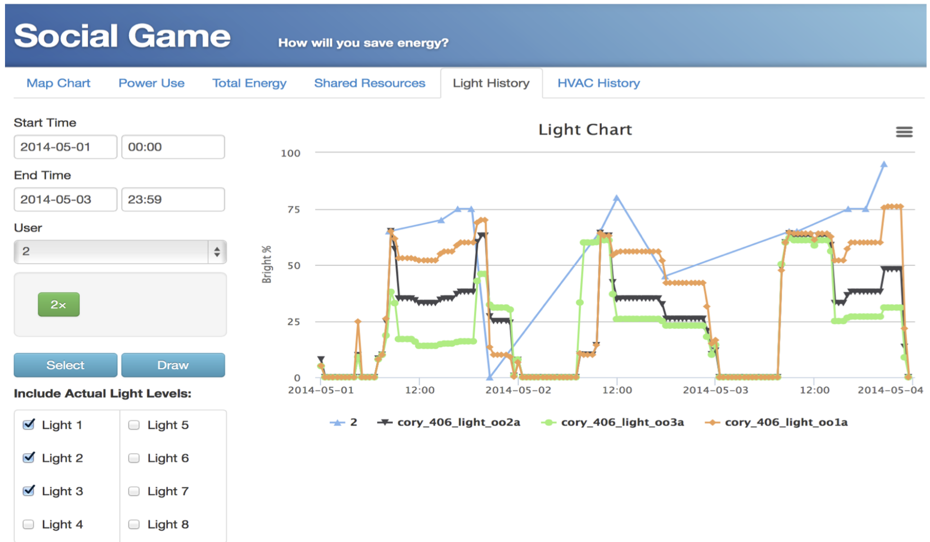


Figure 2.4: Power Line Chart for individual with id number 17

lights (HVAC) respectively depending on their preferences.

Some of the energy savings we achieve is due to the default setting and some due to the social game. It is the building managers duty to ensure that the occupants are satisfied (via appropriate lighting and temperature level) and the building is operating in an energy efficient way. We believe that through optimal design of the incentives, we will be able to achieve greater energy savings than would be possible by only adjusting the default lighting setting and simultaneously give the appropriate incentives.

2.2 App Design

In this section we will present the design of an smart-phone app which is almost ready to be used by the participants. We think that an implementation of an app will make the game easily accessible and will lead to better results. In particular, a lot of the participants of our experiment seemed to need a more efficient way to log-in and vote for their light and HVAC preferences.

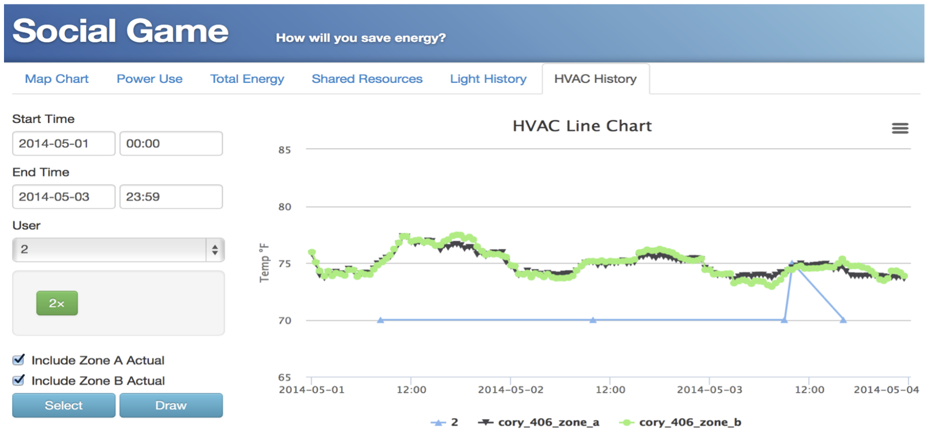


Figure 2.5: Live map view of the office for the shared energy sources

2.2.1 Environment Specifics

The development environment for the project was the following:

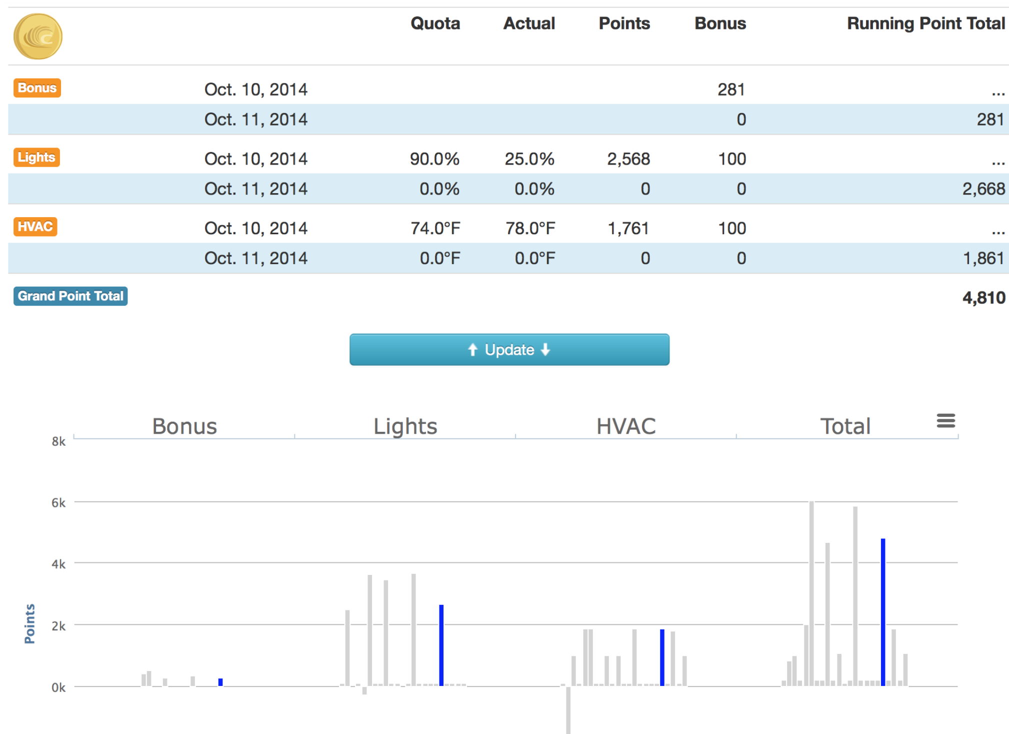
- XCode 5.1.1
- iOS 7 SDK

which were installed and configured in Mac OS X Mavericks 10.8.

Since the application development started only weeks after the announcement and introduction of the new Swift language, using Objective-C was considered a better-documented and more stable approach. In the whole app design, we have implemented the official guidelines and structured our classes diagram so as to implement the Model-View-Controller paradigm (MVC).

2.2.2 Model-View-Controller (MVC)

Model-View-Controller is a software engineering paradigm that was designed in order to correctly implement user interfaces. As one of the most common source of problems in applications is the lack of distinction between the application's logic and the Graphical User Interface,



		Quota	Actual	Points	Bonus	Running Point Total
Bonus	Oct. 10, 2014				281	...
	Oct. 11, 2014				0	281
Lights	Oct. 10, 2014	90.0%	25.0%	2,568	100	...
	Oct. 11, 2014	0.0%	0.0%	0	0	2,668
HVAC	Oct. 10, 2014	74.0°F	78.0°F	1,761	100	...
	Oct. 11, 2014	0.0°F	0.0°F	0	0	1,861
Grand Point Total						4,810

Figure 2.6: Display of an occupant's point balance and a chart of his / her points balance compared with other occupants' point balance

the MVC-pattern introduces three interconnected parts, that clearly define how the application should be structured. That being said, a typical MVC-based application is structured as of below:

- **Model** - the main component of the MVC, as it manages the data and the behavior of the instantiated objects.
- **Views** - the component responsible for the representation of the stored data in a user interface.
- **Controllers** - responsible for sending the requests to the model, according to the user responses.

Thus, in an MVC-based application, the data is stored and managed in the Model component, the user "sees" the data through the available Views and interacts with them through the

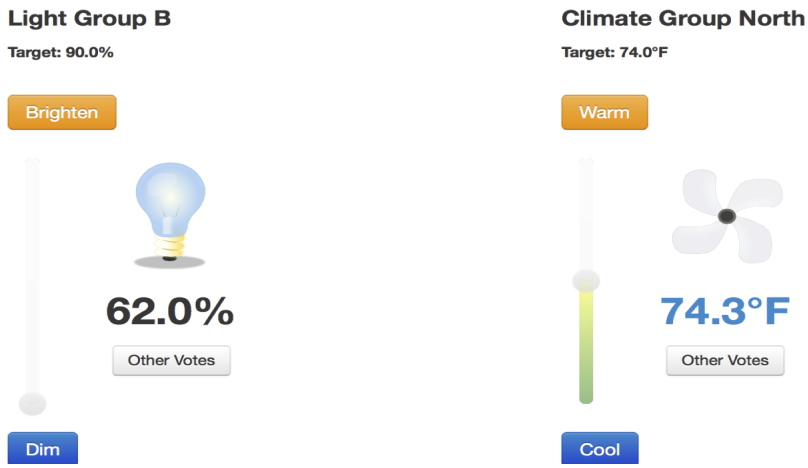


Figure 2.7: Live map view of the office for the shared energy sources

available Controllers. As a result of this distinct and independent role of each component, we can achieve with minimum effort UI or logic changes that do not affect the application on its whole, but only the specific component.

2.2.3 App design outline

Based on the above, the classes that can be found in the application's project can be categorized into the following categories:

- **Model** The model classes were designed so as to correspond with the already implemented and stored data that were available in the laboratory's servers. For example, the class **Person** is one of the most widely-used and important ones in our project, since it is used to store the users' data: energy consumption, light vote, temperature vote, etc. In general, we have tried to make the application extendable to future game updates.

  For instance, even the user's resources are represented by a class, so that an introduction of another game or voting control can be easily introduced, with the initialization of an object of that class (**Resource**).

  This information is stored in a local SQLite database that is instantiated upon the application's first installation. The database schema is again correspondent to the remote one and to the JSON responses that are available from the server.

The local database is synchronized and updated through asynchronous HTTP requests. It should be noted, that the calls have been properly designed so as to ensure the security of the server, but also possibly provide audit information as to which users use the app more frequently. That being said, each user has a personal authentication token, which is stored in the server. Upon log-in this token is retrieved, and all transaction and communication calls that are made use this token, so as to authenticate with the server. This token is destroyed when the user logs out, so as to prevent unauthorized calls.

- **Views**

  The main user interface is defined in a .storyboard file. Through XCode's development environment, we can easily define the UI elements of each view, and their relationships.

  In our app design, we have used one storyboard file for the iPhone devices and one for the iPad ones.

- **Controllers** Every screen that the user sees is controlled by a View-Controller. In order to write custom logic behind it, we have created for almost all views their respective View-Controller class, which inherit from the **UIViewController** class that the iOS provides.

  Therefore, the behavior of the UI elements that are defined in our views are handled by this category of classes. For exampling, buttons' events (e.g. tap) are handled through these controllers, that in their turn make calls to the SQLite database or HTTP requests that are available through the model's classes.

2.2.4 Use-case scenario

This iOS application was designed in order for the laboratory's users to have better access to the Social Game features. The features include:

- Access to their personal information
- Access to their available resources and vote controls

- Check-in/out mechanism for the game purposes
- Access to their weekly points, as well as statistics about the game previous winners
- A visual representation of the laboratory's users, their votes and energy consumption.

2.2.5 Future improvements

Some of the future improvements and additions are the following:

- Testing and releasing an iPad version of the app
- Introduction of new controls and resources for the users
- An Android version of the app

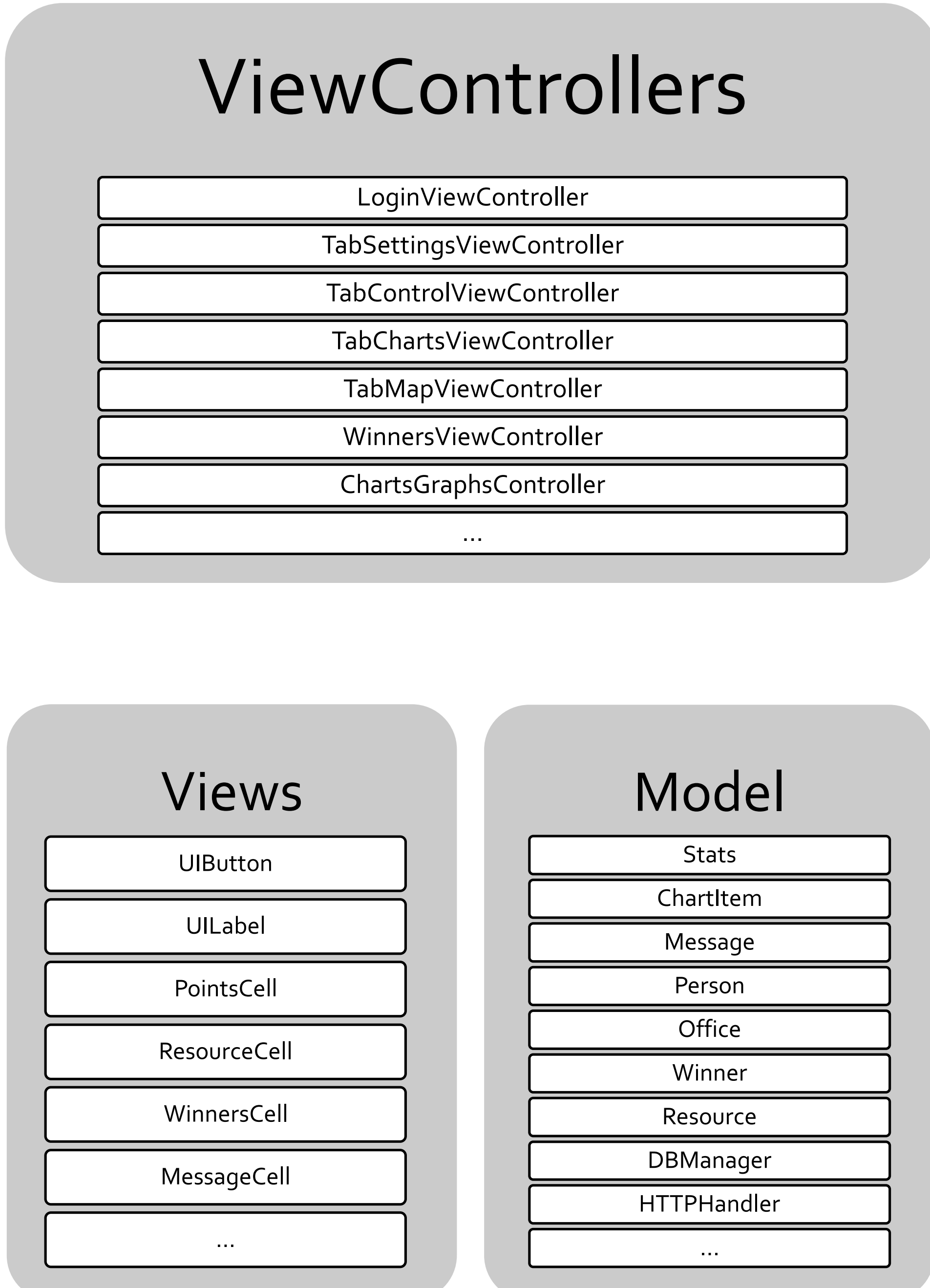


Figure 2.8: The MVC structure of the project's classes

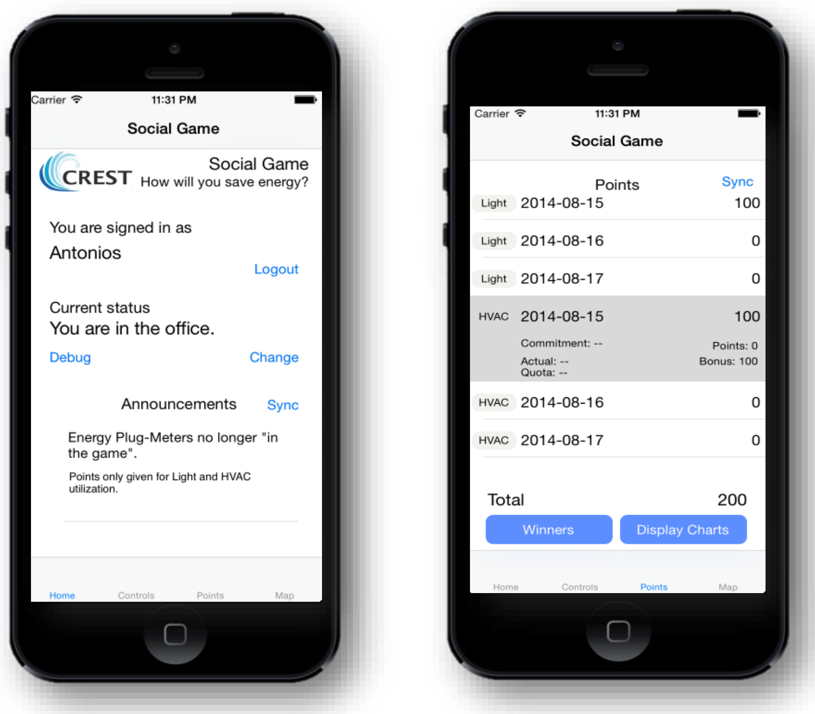


Figure 2.9: Left: The home tab - providing user info and announcements. Right: the user points and statistics

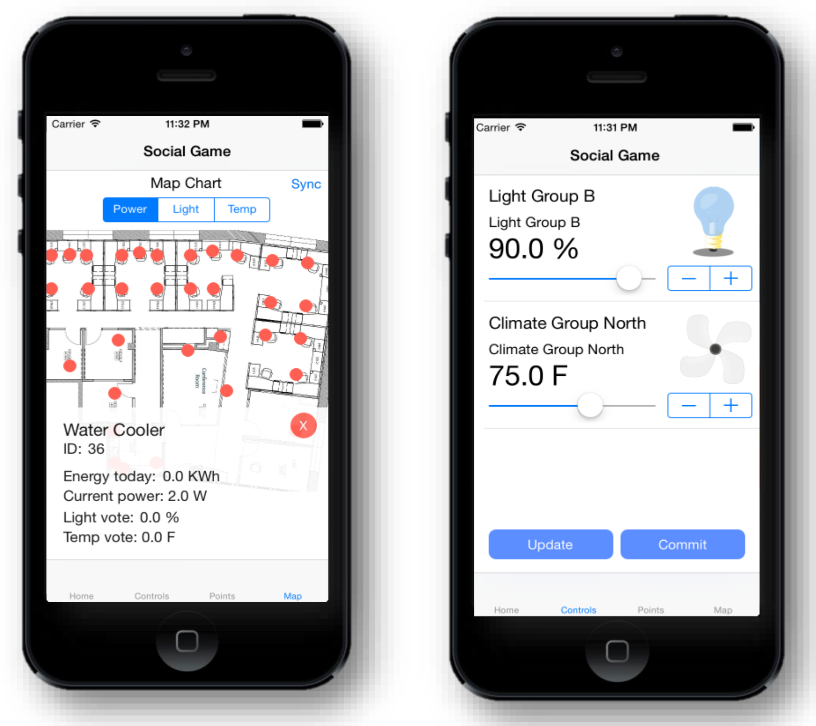


Figure 2.10: Left: The laboratory's map - providing users' votes and energy status Right: the user available resources and controls

Chapter 3

Game Formulation

We model the interaction between the building manager (leader) and the occupants (followers) as a leader-follower type game. We use the terms leader and building manager interchageably and similarly for follower and occupant.

In this model the followers are utility maximizers that play in a non-cooperative game for which we use the Nash equilirbium concept. The leader is also a utility maximizer with a utility that is dependent on the choices of the followers. The leader can influence the equilibrium of the game amongst the followers through the use of incentives and default values of the light as well as to the temperature level, which impact the utility and thereby the decisions of each follower.

The leader desires to reduce the energy consumption in the building as well as formulate a model of how the occupants make decisions about their energy usage. In order to achieve this goal, the leader implements a *social game* in which the followers are pitted against one another. The occupants win points based on their energy consumption choices. These points are then used to determine the individual follower's chance at winning in a lottery. The occupants select the lighting and HVAC setting that they want to be implemented in the office. Actually, based on the votes of the occupants we implement at the office as the lighting and HVAC setting the average of all the occupants' votes.

3.1 Follower Game

We will model the interaction between the occupants and their behavior by the usage of game theory. Game theory for modeling the behavior of the occupants has several advantages. First, it is a natural way to model agents competiting over resources. In our Social Game the resources that the agents compete for them are the Amazon cards or possible other gift cards. Moreover, it can also be leveraged in the design of incentives for behavioral change. It is essential for the building manager to have an accurate model which incorporates the ability to model the occupants as strategic players. In that way, a possible accurate agents' model can capture a possible change in their behavior resulting from a mixture of different incentives (and default values in our game) of the building manager.

Let the number of occupants participating in the game be denoted by n. We model the occupants as utility maximizers having utility functions composed of two terms that capture the trade off between comfort and desire to win. The usage of utility functions with two terms has been done for simplicity in the utility estimation and since we assume that with the choice of these two terms we can capture the trade off between comfort and desire to win. It is upon research the investigation of more accurate class of functions that can be considered as appropriate terms for the agents' utility functions.

We model their comfort level using a Taguchi loss function which is interpreted as modeling occupant dissatisfaction as increasing as variation increases from their desired lighting and HVAC setting. In particular, each occupant has the following Taguchi loss function as one component of their utility function:

$$\psi_i(x_i, x_{-i}) = -(\bar{x} - x_i)^2 \tag{3.1}$$

where $x_i \in R$ is occupant i's lighting vote, $x_{-i} = \{x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n\}$, and

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3.2}$$

is the average of all the occupant votes and is the lighting setting which is implemented. Each occupant's desire to win is modeled using the following function

$$\phi_i(x_i, x_{-i}) = \rho \left(\frac{x_i}{100}\right)^2 \tag{3.3}$$

where ρ is the total number of points distributed by the building manager every day and x_b is the baseline setting for the lights and HVAC. The lighting baseline is considered 90 since the lights were as an average in this setting before the beginning of the experiment. Also, the HVAC baseline setting is 74 (Fahrenheit degrees) which has been selected as an appropriate temperate comfort level. As the agents vote the points are dynamically distributed by the leader using the relationship:

$$\rho \frac{x_b - x_i}{n x_b - \sum_{j=1}^{n} x_j}. \tag{3.4}$$

Thus, a natural way to model occupant's desire to win (function ϕ_i) is by the usage of the natural log function. This can clearly capture the way that the points are distributed to the occupants in our experiment. Furthermore, it has the ability to represent the insensitivity threshold. Figure 3.1 shows the relationship between the utility and the total wealth. It is clear that there is a saturation point in which additional wealth respond to a small range of behavioral change.

We found that the form of ϕ_i as defined in (3.3) provides a better estimation and prediction of the occupant's behavior. It appears that it captures the occupants' perceptions about how the points are distributed and their value more accurately. Also, it seems that the incentives that we currently apply in our experiment aren't so close to the insensitivity threshold and the function that model the desire to win works properly.

Each occupant's utility function is given by:

$$f_i(x_i, x_{-i}) = \psi_i(x_i, x_{-i}) + \theta_i \phi_i(x_i, x_{-i}) \tag{3.5}$$

where θ_i is an unknown parameter.

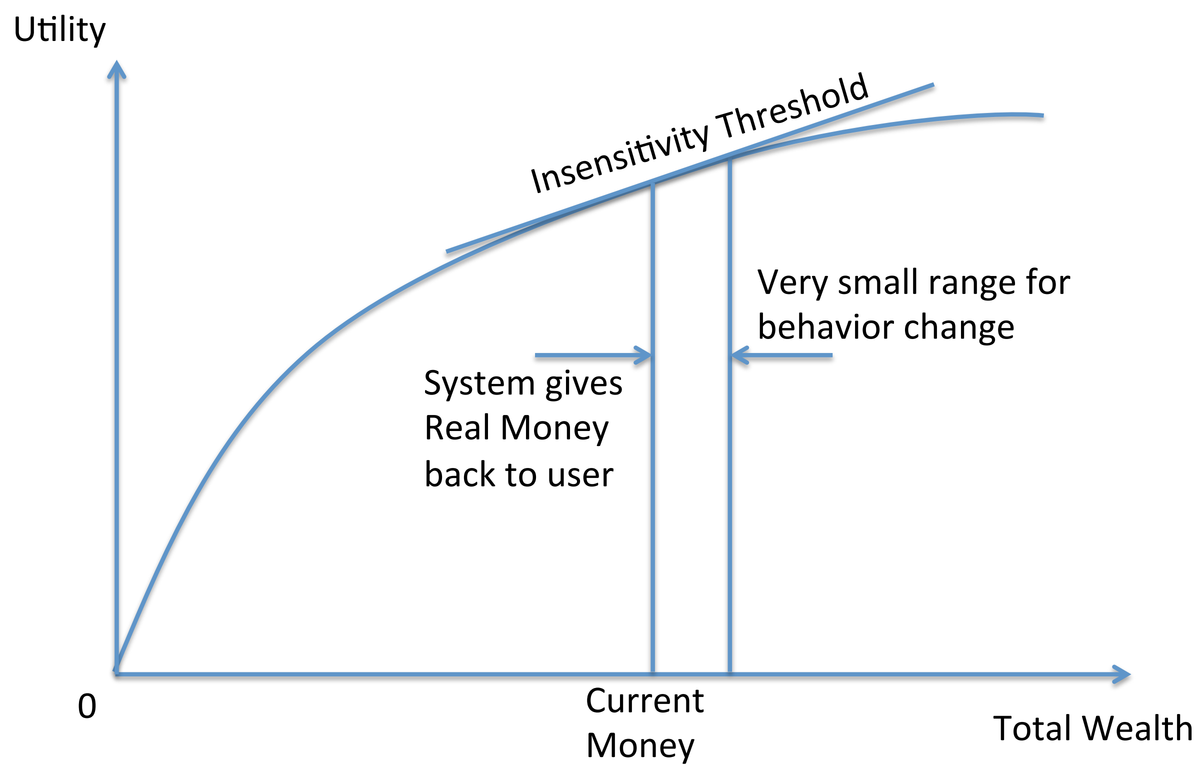


Figure 3.1: Human utility behavior

The occupants face the following optimization problem:

$$\max_{x_i \in S_i} f_i(x_i, x_{-i}) \tag{3.6}$$

where $S_i = [0, 100] \subset R$ is the constraint set for each x_i.

Note that each occupant's optimization problem is dependent on the other occupant's choice variables. We can explicitly write out the constraint set as follows. Let $h_{i,j}(x_i, x_{-i})$ for $j \in \{1,2\}$ denote the constraints on occupant i's optimization problem. In particular, following Rosen [25], for occupant i, the constraints are (for the light setting):

$$h_{i,1}(x_i) = 100 - x_i \tag{3.7}$$

$$h_{i,2}(x_i) = x_i \tag{3.8}$$

Without loss of generality the constraints for HVAC are:

$$\tilde{h}_{i,1}(x_i) = 78 - x_i \tag{3.9}$$

$$\tilde{h}_{i,2}(x_i) = x_i - 70 \tag{3.10}$$

Our analysis will be based on the lighting constraints. However, the results can be generalized for the HVAC too. So, we can define $C_i = \{x_i \in R |\ h_{i,j}(x_i) \geq 0,\ j \in \{1,2\}\}$ and $C = C_1 \times \cdots \times C_n$. Thus, the occupants are non-cooperative agents in a continuous game with convex constraints. We model their interaction using the Nash equilibrium concept.

Definition 1. *A point $x \in C$ is a* **Nash equilibrium** *for the game $(f_1, \ldots, f_n)$ on C if*

$$f_i(x_i, x_{-i}) \geq f_i(x'_i, x_{-i}) \ \ \forall\ x'_i \in C_i \tag{3.11}$$

for each $i \in \{1, \ldots, n\}$.

The definition of Nash equilibrium is a point from which *no player can increase his/her utility by a unilateral change in their strategy.* If the parameters $\theta_i \geq 0$, then the game is a concave n-person game on a convex set.

Theorem 1 (Rosen [25])**.** *A Nash equilibrium exists for every concave n-person game.*

Define the Lagrangian of each player's optimization problem as follows:

$$L_i(x_i, x_{-i}, \mu_i) = f_i(x_i, x_{-i}) + \sum_{j \in A_i(x_i)} \mu_{i,j} h_{i,j}(x_i) \tag{3.12}$$

where $A_i(x_i)$ is the active constraint set at x_i.

We can define

$$\omega(x,\mu) = \begin{pmatrix} D_1 L_1(x,\mu_1) \\ \vdots \\ D_n L_n(x,\mu_n) \end{pmatrix} \tag{3.13}$$

where $D_i L_i$ denoets the derivative of L_i with respect to x_i.

It is the local representation of the differential game form [21] corresponding to the game between the occupants.

Definition 2 (Ratliff, *et al.* [21])**.** *A point $x^* \in C$ is a* **differential Nash equilibrium** *for the game $(f_1,\ldots,f_n)$ on C if $\omega(x^*,\mu^*)=0$, $z^T D_{ii} L_i(x^*,\mu_i^*)z<0$ for all $z\neq 0$ such that $D_i h_{i,j}(x_i^*)^T z = 0$, and $\mu_{i,j}>0$ for $j\in A_i(x_i^*)$.*

Proposition 1. *A differential Nash equilibrium of the n-person concave game $(f_1,\ldots,f_n)$ on C is a Nash equilibrium.*

Proof. The proof is straightforward. Indeed, suppose the assumptions hold. The constraints for each player do not depend on other players' choice variables. We can hold x^*_{-i} fixed and apply Proposition 3.3.2 [3] to the i-th player's optimization problem

$$\max_{x_i\in C_i} f_i(x_i, x^*_{-i}) \tag{3.14}$$

Since each f_i is concave and each C_i is a convex set, x_i^* is a global optimum of the i-th player's optimization problem under the assumptions. Since this is true for each of the $i\in\{1,\ldots,n\}$ players, x^* is a Nash equilibrium.

□

A sufficient condition guaranteeing that a Nash equilibrium x is isolated is that the Jacobian of $\omega(x,\mu)$, denoted $D\omega(x,\mu)$, is invertible [21],[25]. We refer to such points as being *non-degenerate*.

3.2 Leader Optimization Problem – Incentive Design

A reverse Stackelberg game is a hierarchical control problem in which sequential decision making occurs; in particular, there is a leader that announces a mapping of the follower's decision space into the leader's decision space, after which the follower determines his optimal decision [9].

Both the leader and the followers wish to maximize their pay-off determined by the functions $f_L(x, y)$ and $\{f_1(x,\gamma(x)),\ldots, f_n(x,\gamma(x))\}$ respectively where we now consider each of the follower's utility functions to be a function of the incentive mechanism $\gamma : x \mapsto y$ where leader's decision is $y = (d,\rho)$ with d being the default lighting setting and ρ the total number of points. The followers' decisions is denoted by x. The leader's strategy is γ.

The basic approach to solving the reversed Stackelberg game is as follows. Let y and x take values in $Y \subset R^2$ and $C_i \subset R$, respectively and let $f_L, f_i : R^n \times R^2 R$ for each $i \in \{1,\ldots,n\}$. We define the desired choice for the leader as

$$(x^*, y^*) \in \arg\max_{x,y} \{f_L(x, y)|\ y \in Y, x \in C\}. \tag{3.15}$$

Of course, if f_L is concave and $Y \times C$ is convex, then the desired solution is unique. The incentive problem can be stated as follows: Find $\gamma : XY$, $\gamma \in \Gamma$ such that x^* is a differential Nash equilibrium of the follower game $(f_1,\ldots, f_n)$ subject to constraints and $\gamma(x^*) = y^*$ where Γ is the set of admissible incentive mechanisms. By insuring that the desired agent action x^* is a non-degenerate differential Nash equilibrium ensures structural stability of equilibrium helping to make the solution robust to measurement and environmental noise [22]. Further, it insures that it is (locally) isolated — it is globally isolated if the followers' game is concave.

For the lighting social game, the leader's utility function is given as follows:

$$
\begin{aligned}
f_L(x,y) = E\Big[& \underbrace{K - g(y,x)}_{energy} - \underbrace{c_2 p(\rho)}_{effort} \\
& \underbrace{- c_1 \sum_{i=1}^{n} \beta_i f_i(x_i, x_{-i}, y)}_{benevolence} \Big]
\end{aligned}
\tag{3.16}
$$

where K is is the maximum consumption of the Lutron lighting system in kilowatt-hours (kWh), $g(y,x)$ is the is the energy consumption in kWh at a given (y,x), $p(\cdot)$ is a cost-for-effort function on the points ρ and $c_1, c_2 \in R_+$ are scaling factors for the last two terms describing how much utility and total points respectively the leader is willing to exchange for 1 kWh. The last term is the *benevolence* term where the β_i's are the *benevolence factors*. This term captures the fact that the leader to cares about the followers' satisfaction which is related to their productivity level (see [23] for a similar formulation). The expectation is taken with respect to the joint distribution defined by distributions across the player states *absent*, *active*, *default*.

Due to the complexity of computing this expectation, we currently restrict the set of admissible incentive mechanisms to be the constant map $\gamma(x) = (d, \rho)$ for all x so that the leader only selects the constants (d, ρ). This reduces the solution of the reversed Stackelberg game to a bi-level optimization problem. We are exploring more general classes of incentive mechanisms.

Since the prize in the lottery is currently a fixed monetary value delivered to the winner through an Amazon gift card, varying the points does not cost the leader anything explicitly. However, we model the cost of giving points by a function $p(\cdot)$ which captures the fact that after some critical value of ρ the points no longer seem as valuable to the followers, in the sense that it becomes difficult for them to perceive the true value of the points as they affect the follower's chances of winning. It is clear that the occupants follow the log function and the incentives doesn't affect them. It is upon research the effect of different kind of prizes.

The followers' perceive the points that they receive has having some value towards winning the prize. The leader's goal is to choose ρ and d so they induce the followers to play the game and choose the desired lighting setting but not to increase the points beyond a level after which it becomes difficult for the followers to perceive the true value of the points.

Currently we do not add individual rationality constraints to the leader's optimization problem which would ensure that the players' utilities are at least as much as what they would get by selecting the default value. The impact being that this constraint would ensure players are active. With respect to economics literature, the default lighting setting compares to the outside option in contract theory. It is interesting that in the current situation the leader has control over the outside option. We leave exploring this for future work.

Due to the complexity of computing the expectation for the joint distribution across player states *absent*, *active*, *default* for $n = 20$ players, we currently restrict the set of admissible incentive mechanisms to be the map $\gamma(x) = (\gamma_d(x), \gamma_\rho(x))$ such that the i-th player's utility is

$$f_i(x, \gamma(x)) = \psi_i(x) - \theta_i \gamma_\rho(x) \left(\frac{x_i}{100}\right)^2 \tag{3.17}$$

where $\gamma(x) \equiv \rho$ for all $i \in \{1, \ldots, n\}$. In addition, the nature of $\gamma_d(x)$ is that it is an option provided to the followers; they must actively vote in order for this value not to be taken as their current vote when they are present in the office. In sense, it is the outside option. Thus, the leader only selects the constants (d, ρ). This reduces the solution of the reversed Stackelberg game to a bi-level optimization problem that we solve with a particle swarm optimization (PSO) technique (see, e.g., [10, 11, 27]).

The particle swarm optimization method is a population based stochastic optimization technique in which the algorithm is initialized with a *population* of random solutions and searches for optima by updating *generations*. The potential solutions are called *particles*. Each particle stores its coordinates in the problems space which are associated with the best solution achieved up to the current time. The best over all particles is also stored and at each iteration the algorithm updates the particles' velocities.

At the inner level of the bi-level optimization problem, we replace the condition that the occupants play a Nash equilibrium with the dynamical system determined by the gradients of each player's utility with respect to their own choice variable, i.e.

$$\dot{x}_i = D_i f_i(x_i, x_{-i}, y), \; x_i \in C_i, \; \forall \; i \in \{1, \ldots, n\}. \tag{3.18}$$

It has been shown that by using a projected gradient descent method for computing stationary points of the dynamical system in (3.18), which is derived from an n-person concave games on convex strategy spaces, converges to Nash equilibria [8]. In our simulations, we add the constraint to the leader's optimization problem that at the stationary points of this dynamical system, i.e. the Nash equilibria, the matrix $-D\omega$ is positive definite thereby ensuring that each of the equilibria are non-degenerate and hence, isolated.

Denote the set of non-degenerate stationary points of the dynamical system $\dot{x}$ as defined in (3.18) as $\text{Stat}(\dot{x})$. The leader then solves the following problem: given the joint distribution across player states *active*, *default*, *absent*, find

$$\begin{aligned} &\max_{y \in Y} f_L(y, x) \\ &\text{s.t. } x \in \text{Stat}(\dot{x}) \end{aligned} \tag{3.19}$$

For each particle in the PSO algorithm, we sample from the distribution across player states and compute Nash equilibrium points for the resulting game via simulation of the dynamical system (3.18). We compute the mean of the votes at the Nash equilibrium to get the lighting setting. We repeat this process and use the mean of the lighting settings over all the simulations to compute the leader's utility for each of the particles. We are currently exploring other techniques for solving bi-level optimization problems in which the degree of complexity of computing leader's utility is very high.

The leader changes ρ to a value that the followers perceive as translating into more value towards winning in the lottery. We remark that the points ρ do not show up in the leader's utility explicitly due to the fact that the prizes in the lottery are currently fixed and the leader can vary the points but it does not actually cost anything to vary these points. The goal in choosing the value of ρ is to see how the players perceive the value of points even though the prize in the lottery is fixed.

Chapter 4

Utility Estimation

We formulate the utility estimation problem as a convex optimization problem by using first-order necessary conditions for Nash equilibria. In particular, the gradient of each occupant's utility function should be identically zero at the observed Nash equilibrium. This is the case since the observed Nash equilibria are all inside the feasible region so that none of the constraints are active, i.e. we do not have to check the derivative of Lagrangian of each occupant's optimization problem.

For each observation $x^{(k)}$, we assume that it corresponds to occupants playing a strategy that is approximately a Nash equilibrium where the superscript notation $(\cdot)^{(k)}$ indicates the k-th observation. Thus, we can consider first-order optimality conditions for each occupants optimization problem and define a residual function capturing the amount of sub-optimality of each occupants choice $x_i^{(k)}$ [12],[23].

Again, since all our observations are on the interior of the constraint set, we consider the residual defined by the stationarity and complementary slackness conditions for each occupant's optimization problem:

$$r_{\mathrm{s},i}^{(k)}(\theta_i,\mu_i) = D_i f_i(x_i^{(k)}, x_{-i}^{(k)}) + \sum_{j=1}^{n} \mu_i^j D_i h_{i,j}(x_i^{(k)}) \tag{4.1}$$

$$r_{\mathrm{c},i}^{j,(k)}(\mu) = \mu_i^j h_{i,j}(x_i^{(k)}) \ \ j \in \{1,2\} \tag{4.2}$$

Define $r_{\mathrm{s}}^{(k)}(\theta) = [r_{\mathrm{s},1}^{(k)}(\theta_1,\mu_1) \ \cdots \ r_{\mathrm{s},n}^{(k)}(\theta_n,\mu_n)]^T$ and $r_{\mathrm{c},i}^{(k)}(\mu_i) = [r_{\mathrm{c},i}^{1,(k)}(\mu_i) \ r_{\mathrm{c},i}^{2,(k)}(\mu_i)]$ so that we can define $r_{\mathrm{c}}^{(k)} = [r_{\mathrm{c},1}^{(k)}(\mu_1) \ \cdots \ r_{\mathrm{c},n}^{(k)}(\mu_n)]^T$ where $\mu_i = (\mu_i^1, \mu_i^2)$.

Given observations $\{x^{(k)}\}_{k=1}^K$ where each $x^{(k)} \in C$, we can solve the following convex optimization problem:

$$\min_{\mu,\theta} \sum_{k=1}^{K} \chi(r_s^{(k)}(\theta,\mu), r_c^{(k)}(\mu)) \tag{4.3}$$

$$\text{s.t. } \ \theta_i \geq 0, \mu_i \geq 0 \ \ \forall \ i \in \{1,\ldots,n\} \tag{4.4}$$

where $\chi : R^n \times R^{2n} R_+$ is a nonnegative, convex penalty function satisfying $\chi(z_1,z_2) = 0$ if and only if $z_1 = 0$ and $z_2 = 0$, i.e. any norm on $R^n \times R^{2n}$, and the inequality $\mu_i \geq 0$ is elementwise.

Note that we constrain the θ_i's to be non-negative. This is to ensure that the estimated utility functions are concave. We add this restriction so that we can employ techniques from simulation of dynamical systems to the computation of the Nash equilibrium in the resulting n-person concave game with convex constraints. In particular, define a gradient-like system using the local representation of the differential game form [21] and using the estimated θ_i's

$$\dot{x}_i = D_i f_i(x_i, x_{-i}; \theta_i) \ \ \forall \ i \in \{1,\ldots,n\}, \tag{4.5}$$

and consider the feasible set defined by the constraints

$$\left. \begin{aligned} h_{i,1}(x_i) &= 100 - x_i \geq 0 \\ h_{i,2}(x_i) &= x_i \geq 0 \end{aligned} \right\} \ \forall \ i \in \{1,\ldots,20\} \tag{4.6}$$

Then, as we mentioned in the previous section, the subgradient projection method applied to the dynamics (4.5) and the constraint set defined by (4.6) is known to converge to the unique Nash equilibrium of the constrained n-person concave game [8].

For the proposed estimation we apply the bootstrapping method to obtain the empirical distribution of θ_i for $i \in \{1,\ldots,20\}$ by randomly sampling a subset from the data [7]. Thus, we have as result different histograms for each user for the estimated parameter θ_i.

We use these histograms as to have more accurate estimations of the unknown parameters θ_i as well as to reduce the residual error. Moreover, we use the histograms and the resulting empirical distributions in order to obtain the mean value of the θ_i parameters. Last but not least, based on the mean values of the θ_i parameters we calculate the resulting Nash equilibrium points and we predict the occupants' next day lighting and HVAC vote.

Chapter 5

Results

In this chapter we report the results on the savings achieved through the game, the utility learning problem as well as simulation of the estimated utilities. Moreover, by the collected data on the energy consumption of the lights for different lighting settings we have created an utility function for the leader so as to solve the incentive design problem. We present by simulations that with an optimal selection of the default values for the lights as well as for the points we can achieve an energy efficient light level.

5.1 Utility estimations - Energy savings

We use the data collected over the period from March 3, 2014 to June 16, 2014 when occupants have regular working schedules in the office. The baseline x_b is 90% for lighting, and 74 Fahrenheit degrees for the HVAC, which was the standard lighting and HVAC level prior to the beginning of the experiment. Throughout this period, we have changed the default lighting level three times (see Table 5.1).

We divide each day into four regions based on the outside lighting in Berkeley during the summer, namely from 7am to 12pm (Morning), 12pm to 5pm (Early afternoon), 5pm to 10pm (Late afternoon), and 10pm to the next day 7am (Night). The data is further processed by taking

Period	Default Level
March 3–April 10	20 %
April 11–May 1	10 %
May 2–May 23	60 %
May 24 – June 16	90 %

Table 5.1: Default levels for four periods during the experiment. By changing the default setting to 90% we isolate the savings due to the social game from those achieved by changing the default setting.

the average of votes in each region of the day for each user.

5.1.1 Savings

Using the mean savings for each of the periods and a rate of \$0.12/kWh we estimate that we saved \$73. In addition, over the period of 101 days that the experiment was conducted the office consumed 2,185 kWh for lighting and we saved approximately 601 kWh. That is a 27.5% reduction in energy. This savings is just due to a change in lighting usage behavior for one small portion of a building.

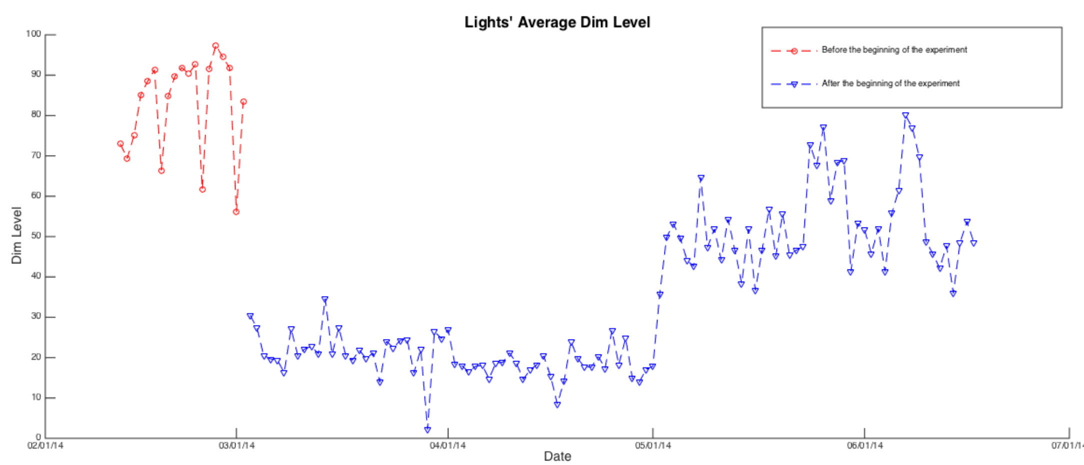


Figure 5.1: Lights' average daily dim level

As we can see in Figure 5.1 we had a significant reduction in the actual lights' power setting through the experiment. Furthermore, in Figure 5.2 we can see a crucial reduction in total daily energy consumption in the office. However, it is upon investigation how much the default level

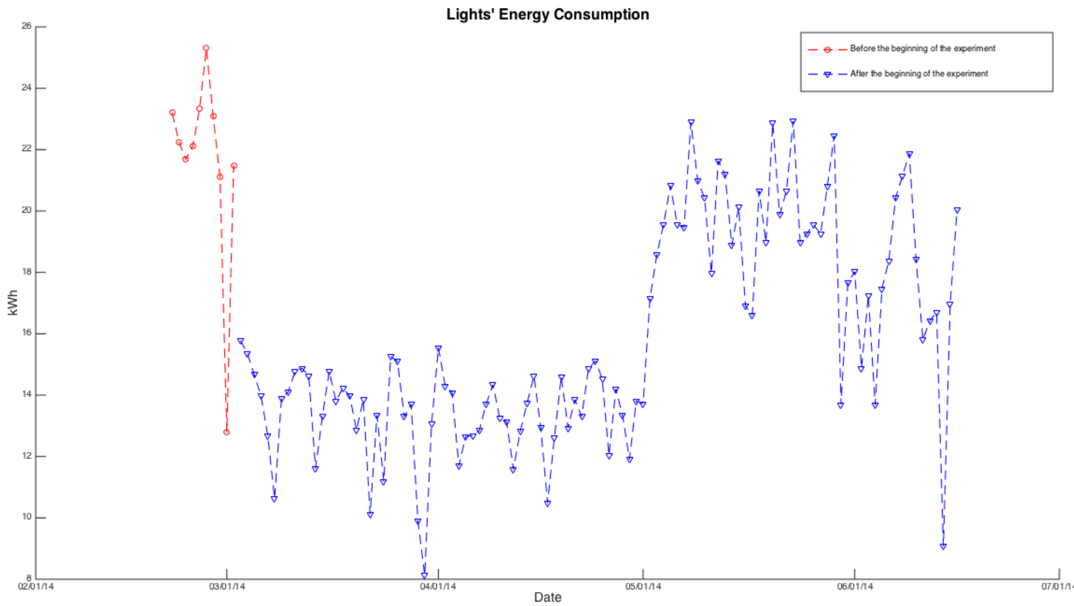


Figure 5.2: Lights' daily total energy consumption

contributes to this reduction in the energy consumption and how the building manager will hold a sufficient light comfort level as well as to maintain an energy efficient light dim level.

In our social game we control HVAC system and very soon we will implement plug-load. However, it is difficult to estimate the energy savings from the HVAC system since the our experiment take place in only one laboratory of Cory Hall in berkeley and so due to lack of appropriate sensors we can't estimate the amount of energy that was saved from HVAC. Figure 5.3 presents the implemented temperature in the office. It is obvious that the implemented temperature is almost always above 72 Fahrenheit degree that was the temperature level before the beginning of the experiment. We have to mention that due to occupants votes we didn't cool the office during the day for almost all the duration of the experiment. Thus, figure 5.3 actually shows in the majority of the days the normal fluctuation of the temperature in the office without any usage of the HVAC system.

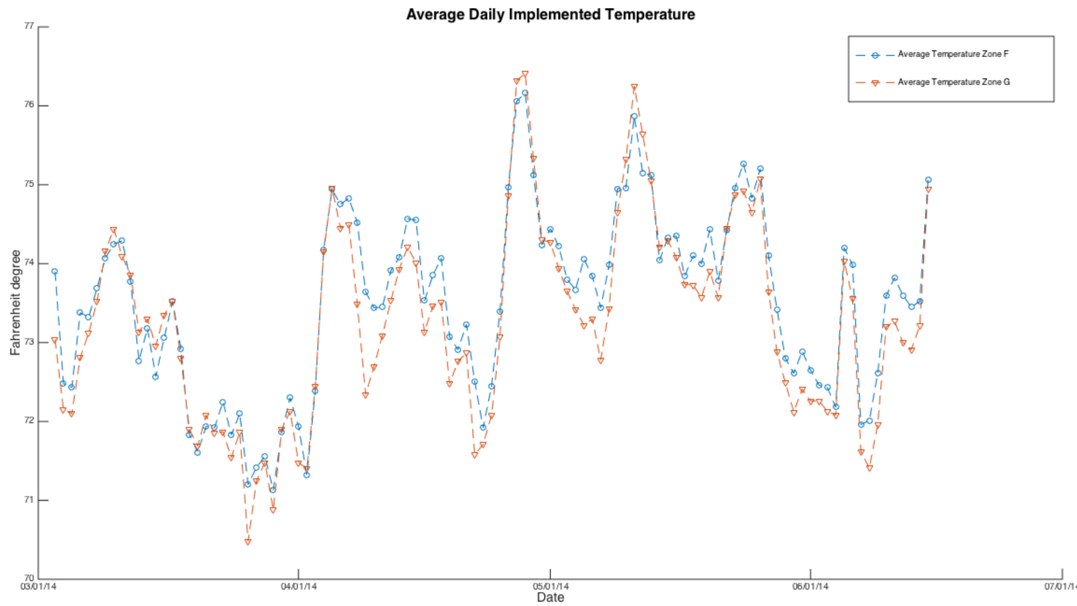


Figure 5.3: Actual implemented temperature levels in the two zones of the office building

5.1.2 Estimation

The estimation proposed is Chapter 4 is performed for each user in each day interval and default lighting and HVAC interval. Only true votes, not the default votes, are considered since we assume that when an occupant doesn't change the default assigned setting he / she doesn't take part in the game with an expected utility function zero. We apply the bootstrapping method to obtain the empirical distribution of θ_i for $i \in \{1, \ldots, 20\}$ by randomly sampling a subset from the data [7]. The mean and standard deviation for the estimations from the average daily votes for the users which are the most active are reported in tables 5.2 and 5.3. In same of these estimations the mean value is less than two times the variance. This happens since the estimations resulting from a distribution that is approximated to a chi-squared distribution since in our optimization problem we don't allow parameter θ_i to take negative values.

Furthermore, we can see that some users at the beginning of the experiment were not so "aggressive" in their votes and that after some weeks they have get used the Social Game. For instance, in table 5.3 users 8 and 20 were not so "aggressive" in their votes at the beginning of the experiment (mean value of their θ_i parameter was almost zero). However, after several weeks they voted with an energy efficient way in order they to gain more points and increase their likelihood of winning the lottery. Furthermore, for the four regions based on the outside lighting in Berkeley during the summer the estimation method is exactly the same and we can derive important information about the light and HVAC level during specific time intervals in a day. Finally, in figure 5.4 and figure 5.5 we can see the histograms of the θ_i of two participants for their average daily votes in the default region 20.

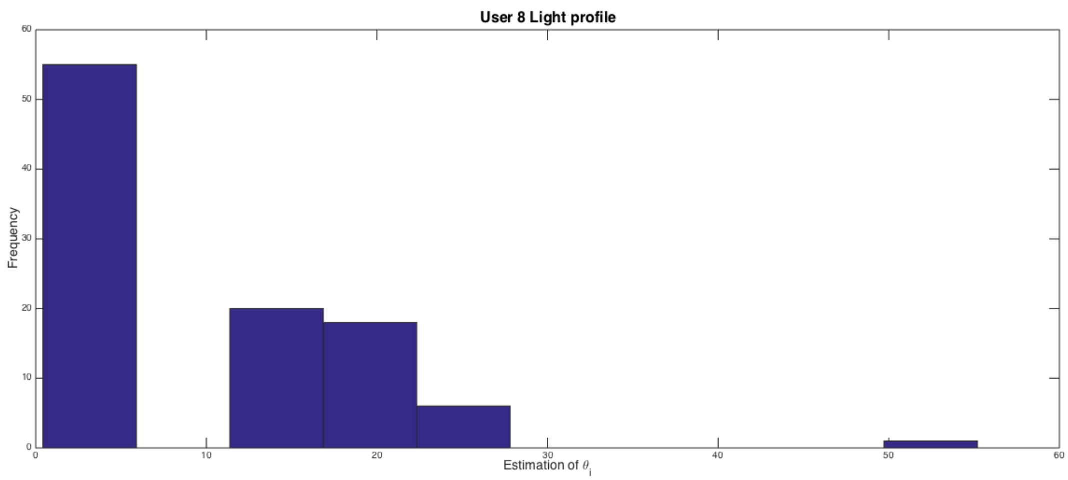


Figure 5.4: User 8 light histogram of estimation of θ_i in the default region 20

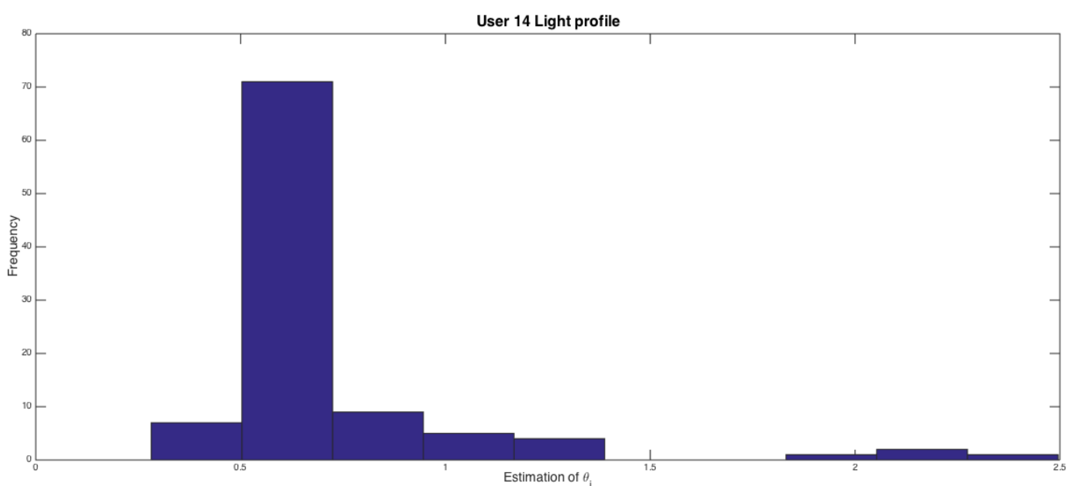


Figure 5.5: User 14 light histogram of estimation of θ_i in the default region 20

Table 5.2: Estimated lighting utility parameter for selected set of active users for the daily average vote. The standard deviation is indicated inside the parentheses and the mean is given outside of the parentheses.

	Users			
Default setting	6#	8#	14#	20#
20%	$4.6 \cdot 10^{-2}$(0.16)	8.8 (10.3)	$6.9 \cdot 10^{-2}$(0.37)	-
10%	$0.8 \cdot 10^{-2}$(0.02)	38.8 (47.6)	0.9 (0.47)	-
60%	1.6 (8.8)	5.3 (22)	279.7 (1653)	203.4 (1411)
90%	174.6 (1280)	163.3 (1238)	136.8 (1135)	117.7 (1054)

Table 5.3: Estimated HVAC utility parameter for selected set of active users for the daily average vote. The standard deviation is indicated inside the parentheses and the mean is given outside of the parentheses.

	Users			
Default setting	6#	8#	14#	20#
20%	$0.3 \cdot 10^{-2}$(0.01)	-	10^{-2}(0.04)	$2 \cdot 10^{-2}$(0.008)
10%	-	27.9 (74.6)	0.8 (1.4)	$8.5 \cdot 10^{-2}$(0.02)
60%	2.2 (9.7)	615 (2964)	1162 (3855)	830 (3299)
90%	808 (3297)	768 (3210)	695 (3009)	598 (2801)

5.1.3 Simulation

To capture the working schedules of each user, we employ a simple probabilistic model which determines the probability of individual user being absent, p_i^{absent}, present and playing default, $p_i^{\text{present, default}}$, and present and actively playing, $p_i^{\text{present, active}}$. By assumption the sample space Ω includes the above three outcomes, and the probability mass functions should sum to unity. This probability is estimated by $p_i^E = \frac{N_{i,E}}{N_i}$, where E is the event of one of the three outcomes, $N_{i,E}$ is the number of event E for user i, and N_i is the number of total events.

For the prediction of the next day lighting and HVAC votes, we randomly sample from this distribution to determine the set of active, default, and absent users, then obtain a local Nash equilibrium for them. Furthermore, we use all the votes that we have available till our prediction of the Nash equilibrium. However, at the first days we don't achieve very accurate predictions as is depicted in figures 5.6 and 5.7. As can be seen from the previously stated figures, the Nash equilibrium captures substantial variations in the data. The Nash equilibrium achieves a prediction that is accurate with a Mean Square Error around 5.3 for the light estimations and

0.8 for the HVAC estimations, which is appropriate for the leader in the Stackelberg game that wants to design optimal incentives to motivate energy saving behaviors. Indeed in the Stackelberg framework, the leader (building manager) assumes that the agents (occupants) are utility maximizers and they achieve Nash equilibria. Hence, we will be able to integrate our estimation algorithm into an online algorithm for designing incentives because with the appropriate incentives the leader can lead the agents in a more energy efficient Nash equilibrium as well as the leader can predict this accurately. With this information the leader can predict the building's energy consumption with some accuracy and can use this valuable information so as to get better cost rates from the energy market companies.

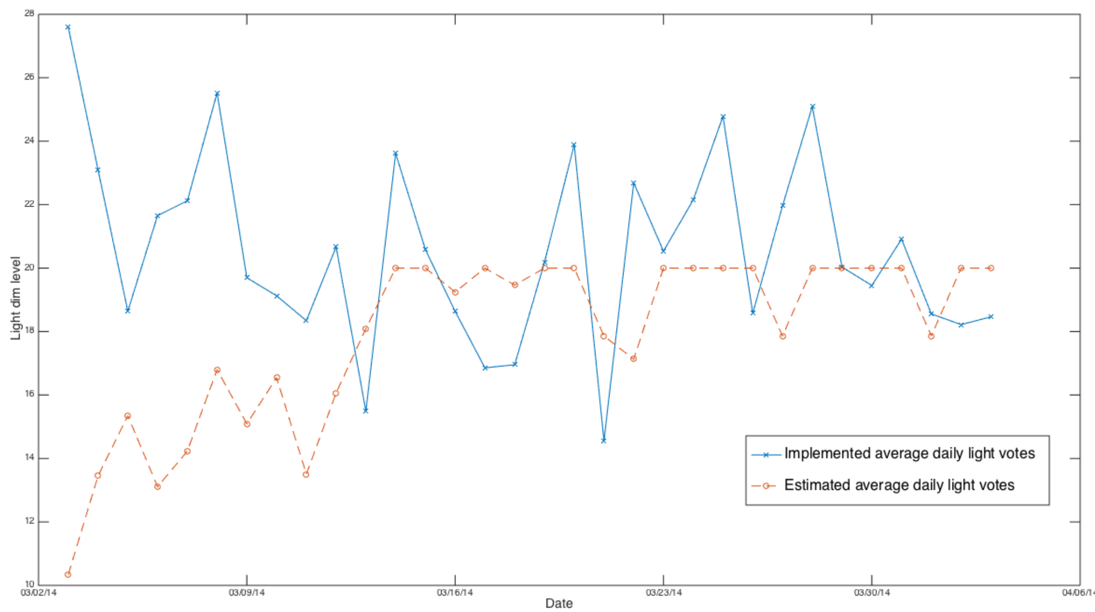


Figure 5.6: Estimation of average daily light votes

5.2 Incentive Design

We collected data on the energy consumption of the lights for different lighting settings (see Figure 5.8) and created a piece-wise affine map from the lighting dim level to energy consumption in kilowatt–hours (kWh). Using this map, we formulate a utility for the leader which takes the average lighting votes as the input and returns the difference between the maximum consump-

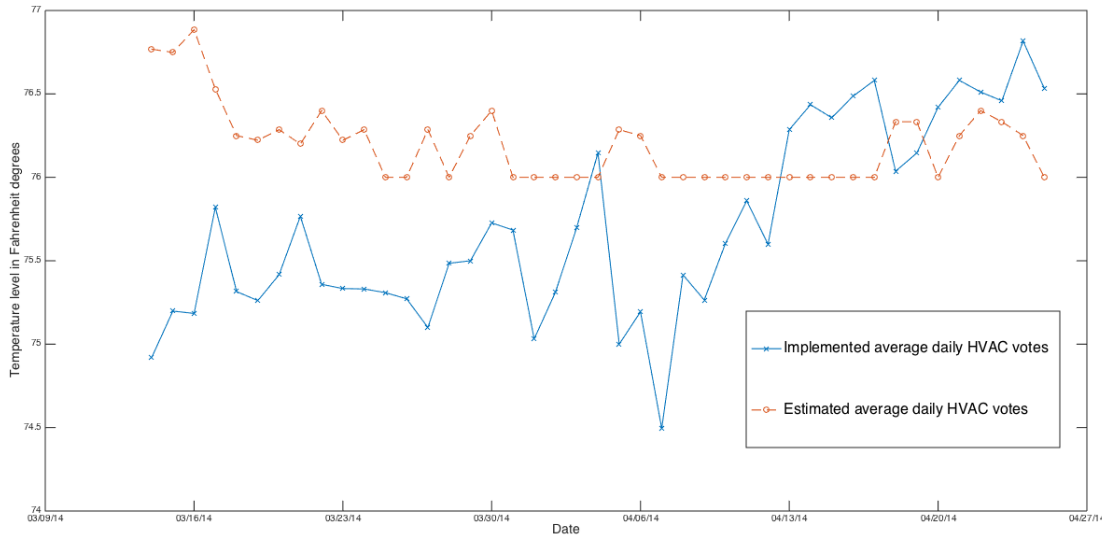


Figure 5.7: Estimation of average daily HVAC votes

tion in kWh, i.e. 25 kWh, and the piece-wise affine map for energy consumption of the lights.

Using the past data, i.e. data collected for default settings $\{10, 20, 60, 90\}$, and θ_i estimates for each occupant, we create a piece-wise affine map for interpolating the parameters of the occupants utility functions for different default settings. Similarly, we interpolated the joint distribution across player states (*absent*, *active*, *default*) as a function of the default setting. This allows use to optimize the leaders utility function, given in (3.16), over both the total points ρ and the default setting d. Due to the complexity of the expectation and the nature of the bi-level optimization problem, we solve the leader's problem by employing a particle swarm optimization method.

We will develop an example of a sample solution to the leader's optimization problem under some selection of the parameters c_1, c_2 and the benevolence factor $\beta = (\beta_1, \ldots, \beta_n)$.

In the implementation of the leader's optimization problem in this example we make the following choices for the parameters and scaling of the leader's utility function. For each particle in the PSO algorithm, we map each follower's true utility f_i to an interpolated utility $\hat{f}_i$ taking a value in the range $[0, 100]$ by finding the global maximum and minimum of their utility under

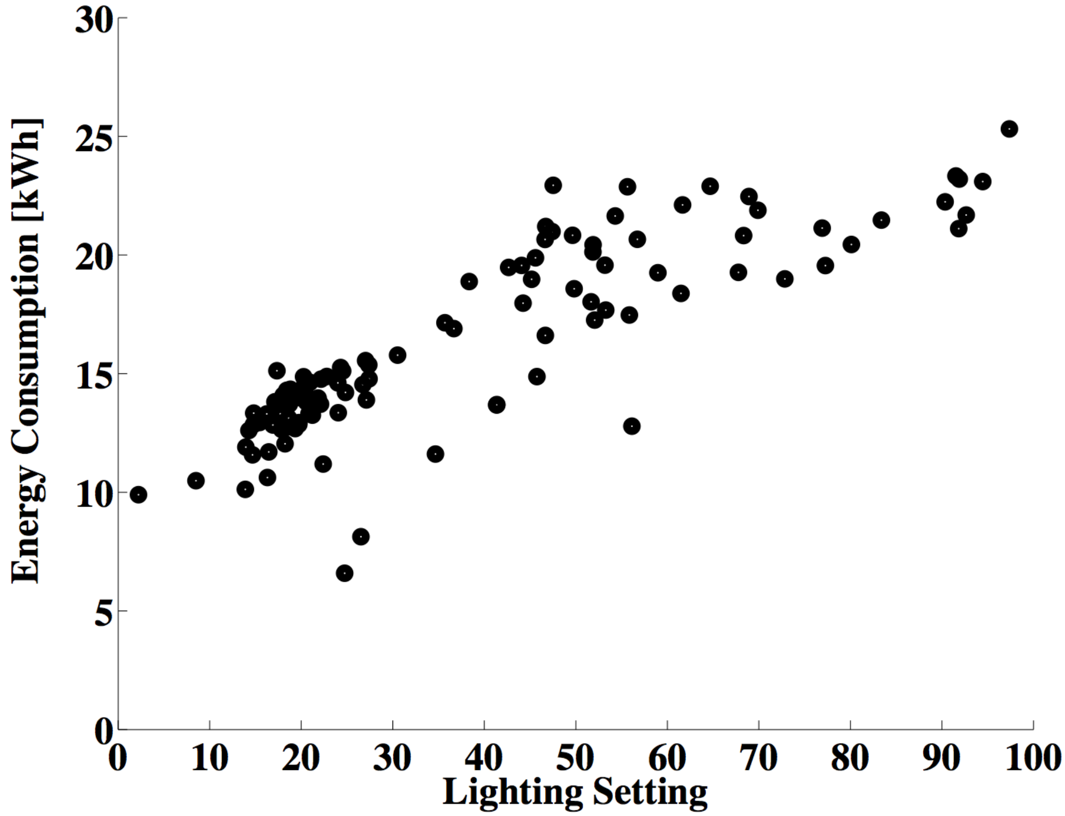


Figure 5.8: Energy consumption data for the Lutron lighting system in kWh as a function of the lighting setting.

the current particle to determine an appropriate affine scaling of their original utility. We use $\hat{f}_i$ in place of f_i in the leader's utilty.

We use $c_1 = 1/2$ which represents the fact that the leader is willing to exchange 1 kWh savings for a utility value of 2 in the total sum of the followers' utilities $\sum_i \beta_i \hat{f}_i$ under the current particle value for $y = (d, \rho)$. Similarly, we use $c_2 = 1/500$ which represents the fact that the leader is willing to exchange 500 points in return for 1 kWh of savings.

At present the choice of these parameters is just for the purpose of creating an example with interesting behavior and we leave full exploration of these parameters to future work in which we implement various solutions in practice and obtain feedback from the occupants' via survey about their satisfaction.

Examining each of the occupant's estimated utility functions has given us a sense of which

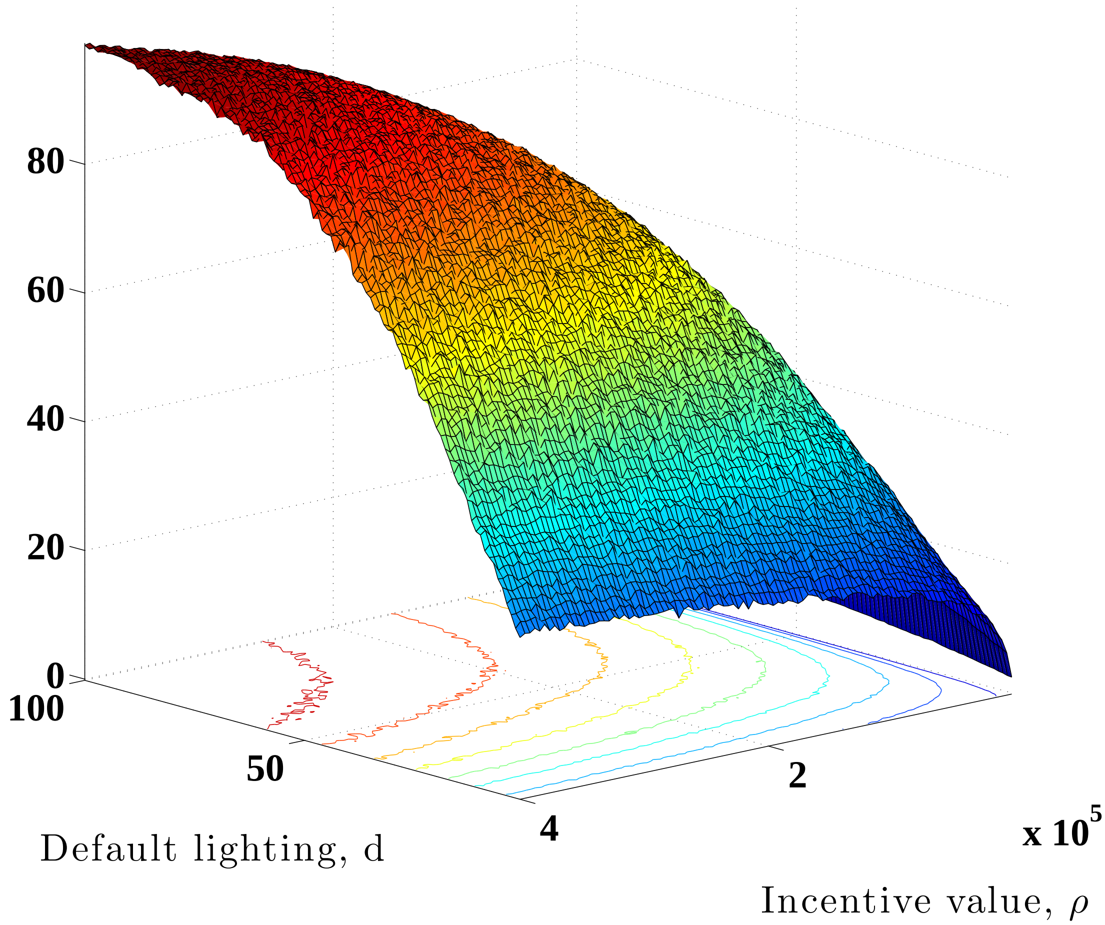


Figure 5.9: Utility of occupant 2 as a function of (d,ρ) at the mean Nash equilibrium after running 1000 simulations. Notice that for fixed values of d the utility value is near constant in ρ. Also, occupant 2 has very large utility when the default setting is around 70.

occupants are the most sensitive to changes in ρ and d. Occupant 2 is quite inflexible to changes in the points ρ and appears to care less about winning and more about his comfort level (see Figure 5.9). This fact is also reflected in the very low parameter estimate for θ_2. It is also the case that occupant 2's behavior is largely affected by others' votes.

In addition, occupants in the set $C = \{2,6,8,14,20\}$ are the most active players in a probabilistic sense. As a result, in this example we give non-zero benevolence terms to players in this set. We refer to this set as the leader's *care-set*. For all $i \in \{1,\dots,20\}\backslash C$, we set $\beta_i = 0$. Further, we force $\sum_{j\in C}\beta_j = 1$. Since occupant 2 has particularly interesting behavior, we vary β_2, and let $\beta_j = (1-\beta_2)\frac{1}{|C|}$ for all $j \in C$ and where $|C|$ is the cardinality of C. 0.2cm

$(d,\rho,\beta_2,\sum_{j\in A}\beta_j)$	utility
$(63, 200\times 10^3, 0.9, 0.1)$	\$4.56
$(56, 169.6\times 10^3, 0.75, 0.25)$	\$4.73
$(55.5, 175.2\times 10^3, 0.6, 0.4)$	\$4.67
$(48, 142.2\times 10^3, 0.45, 0.55)$	\$4.69
$(10.47, 173\times 10^3, 0.3, 0.7)$	\$5.07
$(7.23, 194.6\times 10^3, 0.2, 0.8)$	\$5.43

Table 5.4: Leader's utility in dollars for the values $(d^*,\rho^*,\beta_2,\sum_{j\in A}\beta_j)$ where β_2 is the benevolence factor for user 2 and $1-\beta_2=\sum_{j\in A}\beta_j$ is the sum of the benevolence factors for the occupants $A=\{6,8,14,20\}$. The utility value is determined by solving the leader's optimization problem using the PSO method and simulating the occupant game via the dynamical system given in (22). The value of the utility is interpreted as the energy saved in dollars by the leader plus the utility as measured in dollars. We use a rate of \$0.12 per kWh.

		β					
		0.9,0.1	0.75,0.25	0.6,0.4	0.45,0.55	0.3,0.7	0.2,0.8
d,ρ	$(10, 7000)$	\$2.01	\$2.10	\$2.19	\$2.28	\$2.37	\$2.42
d,ρ	$(20, 7000)$	\$1.98	\$2.01	\$2.06	\$2.08	\$2.10	\$2.13
d,ρ	$(60, 7000)$	\$1.70	\$1.67	\$1.66	\$1.65	\$1.65	\$1.64
d,ρ	$(90, 7000)$	\$1.35	\$1.33	\$1.32	\$1.31	\$1.31	\$1.30

Table 5.5: Leader's utility in dollars for the previously implemented (d,ρ) for various benevolence factors $\beta=(\beta_2,\sum_{j\in A}\beta_j)$ where $A=\{6,8,14,20\}$. The value is interpreted as the energy saved in dollars by the leader plus the utility as measured in dollars. We use a rate of \$0.12 per kWh as this is the approximate rate charged by the buildings on the UC Berkeley campus.

Tables 5.5 and 5.4 contain the energy savings in dollars per day for the leader given the energy cost of the lights and how much of the occupants' utility and the total points distributed per day that the leader is willing to exchange for 1 kWh in dollars using a cost per kWh of \$0.12. The values were computed by solving the leader's optimization problem via the PSO method where we simulate the game of the occupants via the dynamics system in (22). Table 5.5 has the leader's utility in dollars for previous values of (d,ρ) after the start of the social game. In Table 5.4 we report the values after optimizing over (d,ρ) for some given benevolence factor $\beta = (\beta_1,\ldots,\beta_n)$. We can see that computing even the suboptimal (d,ρ) by solving the leader's bi-level optimization problem via PSO, the leader has a much higher utility.

We have not yet factored in the cost of the prize in the lottery. Currently it is at a value of \$100 per week. The values we report in Tables 5.5 and 5.4 are per day savings on weekdays. Hence, with a prize cost of \$20 per day for our particular experimental set-up the leader does not save. Using this case-study as proof-of-concept, we are in the process of implementing a social game in an entire building in Singapore with more than $1,000$ occupants. This social game will include options for the consumer to choose lighting setting, HVAC and personal cubicle plug-load consumption. In addition, we plan to implement a social game of this nature in Sutarja Dai Hall on the UC Berkeley campus. At this scale, with a week-day lottery cost of \$100 the building manager stands to save a considerable amount.

In Figure 5.10, we show the results of simulating the game under the (d,ρ)'s that we found for various benevolence factors. We show the mean of the lighting votes averaged over 1000 simulations. It is interesting to see that the average Nash equilibrium under the various default settings is actually less than the default setting itself except in the case when the default setting is below a threshold below which occupants actually log votes above the default setting. For example, with a default setting of 10.74, the mean of the Nash equilibria is ~ 15. The case when the default setting is above this threshold of basic operation, the most aggressive players' desire to win pushes the Nash equilibrium below the default. On the other hand, when the default is below this threshold, all the players' comfort comes into play and shifts the Nash equilibrium above the default setting. This is likely due to the desire to win by the most aggressive players.

By examining user 2's utility as a function of (d,ρ), we determined that this occupant is the most dissatisfied when the default lighting setting is below a setting of 70. Hence, we simulated is the occupant who is the most dissatisfied We select the following benevolence vector: $\beta_2 = 0.9$

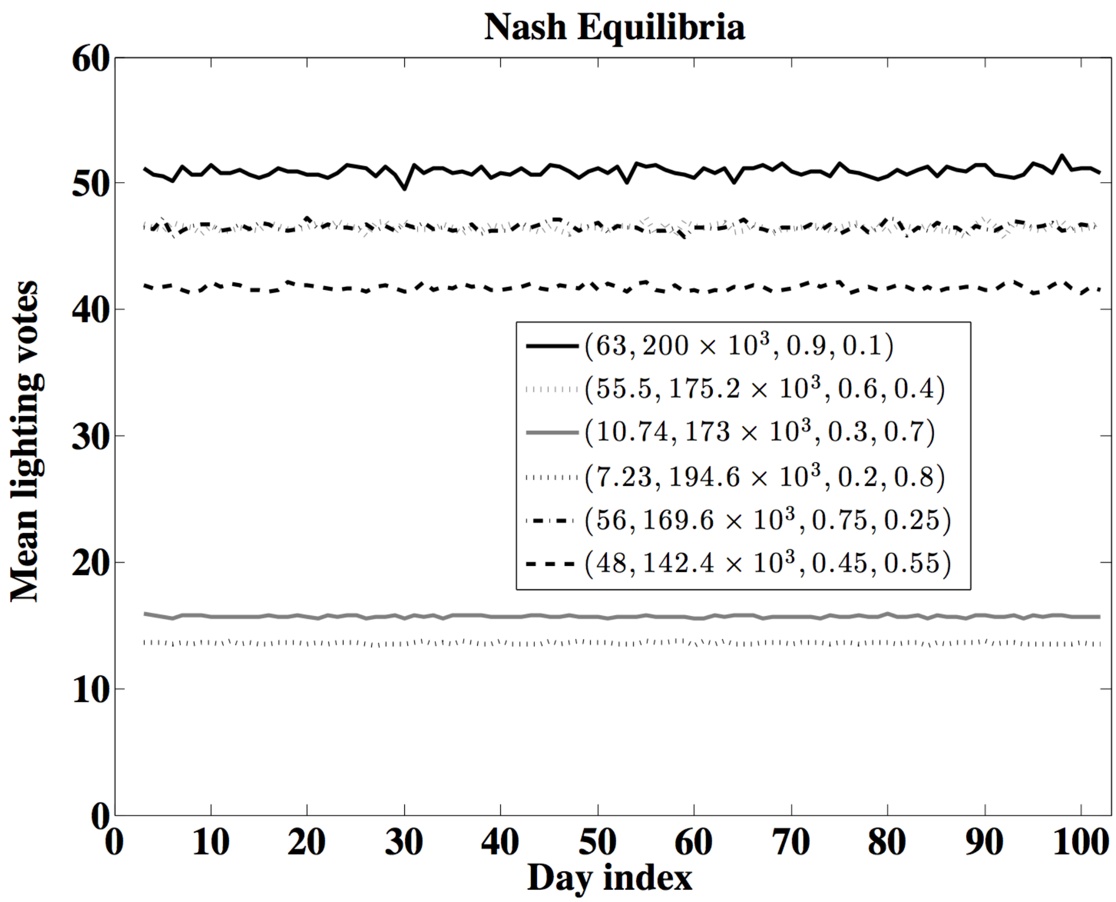


Figure 5.10: Mean of the Nash equilibria of the simulated games over 103 days under estimated occupant utilities with leader incentives found via PSO and parameters given by $(d, \rho, \beta_2, \sum_{j\in A}\beta_j)$ where $A = \{6, 8, 14, 20\}$. Note that the mean Nash equilibrium in each case is slightly below the default setting.

Chapter 6

Conclusions

6.1 Summary

We have designed and implemented a social game for inducing building occupants to behave in an energy efficient manner. We presented data and results pertaining to the game in which occupants select their lighting preferences and win points depending on how far their vote is from the baseline lighting setting and proportional to other occupants' votes distances from the baseline. As a result, the occupants are interacting in a competitive environment which we model as a non-cooperative game. We show that we get significant savings as compared to usage prior to the implementation of the social game. This savings is due to both a change in the default setting as well as due to the incentives offered in the social game.

We described the experimental set-up which includes an online platform for the implementation of the social game as well as the use of a Lutron lighting system for precise control of the lighting and HVAC setting. We have formulated the problem of estimating the occupant utility functions as a convex optimization problem and estimated occupant utilities in a 20 player social game. We simulated the game using the estimated utility functions and showed that our model is a good predictor for occupant behavior.

By using the estimated utilities, we formulated and solved the building manager's bi-level optimization problem for the total points and default setting. Due to the large number of events underlying the joint distribution across player states and non-convexities, we utilized a particle swarm optimization method. We are exploring more efficient methods for solving for the optimal points and default setting as well as implementing the current (d, ρ) that we found through PSO in our test bed.

The leader's utility function contains a number of parameters such as c_1, c_2 and the benevolence factor which represent how much utility or *happiness* the leader is willing to exchange for savings. We are in the process of examining the impact of these factors on the leader savings as well as the occupant satisfaction in practice. We are implementing surveys to collect additional data about the occupants' satisfaction which we plan to incorporate into our solution.

In addition, we did not include individual rationality constraints in the leader's optimization problem. It would be interesting to explore incorporating such a constraint in the optimization problem where we consider the outside good to be the default setting. This problem is slightly different than what is seen in the economics literature because the leader here has control over the default setting, and thus, the outside good.

6.2 Future Work

Our platform also includes the ability to implement a social game for occupant plug-load consumption. We are on the bring of a social game which will try to incentivize occupants to reduce their plug-load consumption. Another interesting direction for future research that we are exploring is understanding the type (parameter) space of the occupants and how the Nash equilibria of the follower game depend on these parameters. Specificically it is interesting to take a dynamical systems perspective and study parameter configurations leading to the desired Nash equilibrium being structurally stable.

Furthermore, there are several ways in which we believe we can improve our estimate of the utility functions of the occupants. We did not consider the environmental noise such as variations in natural light. We instead used a heuristic to capture this variation by breaking the day into intervals in which the natural light entering the office is most consistent. In addition, we did not consider any information on the occupants' schedules or location in the office with respect to windows. We could incorporate these aspects into our estimation as priors on the parameters of the occupants utility function or as a noise process in the estimated behavior model.

Moreover, as to achieve better predictions we currently explore non linear regression models for the occupants. We try to find appropriate Kernel functions as to improve our understanding of human's behavior model reacting to the Social Game and boost our daily predictions for the office's average implemented light and HVAC condition.

In addition, we want to improve our estimation techniques of the utility function parameters in the case of a large scale implementation of the Social Game in whole building(s). In this case we don't want to optimize over a sampling subset of the data since the computational effort would be increased as the Social Game will have a great many occupants. Our goal is to build an optimization problem for the moment function of the distribution of the occupants parameter θ_i.

List of symbols

Symbol	Unit	Meaning
β_i	-	benevolence factor
c_1	-	scaling factor
c_2	-	scaling factor
d	%	default light setting
θ_i	-	utility's function parameter
K	kWh	maximum consumption of the Lutron lighting system
ρ	-	points distributed by the building manager each day
$\bar{x}$	%	implemented lighting setting
x_b	%	baseline setting for lights
x_i	%	occupant's light vote

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