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Hierarchical decision making by leveraging utility theory and game theoretic analysis towards sustainability in building design operation

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In this paper, a hierarchical decision-making model for sustainable building design is presented. In the higher level, the computational framework implements multi-criteria decision making system under uncertainty. Thus, different scenarios are ranked through the Generalized Expected Utility, recently proposed by two of the authors. In this way, the decision support system may provide a tool for optimal integrated design under uncertainty of a smart building during the lifecycle. In this paper, the focus is devoted to the stage of building design operation, with particular reference to the energy efficiency. This is accomplished by applying, in the lower level of the decision-making system, a Monte Carlo Simulation (MCS) to a continuous game between non-cooperative agents. MCS simulates a social game experiment designed to encourage energy efficient behavior amongst smart building occupants. The higher level of the decision-making system ranks the consequences of the incentives in terms of energy consumption. Thus, the building manager can design incentives such that a desired target (e.g. in terms of energy consumption) can be achieved. The proposed framework is also capable of incorporating several shared resources like lighting or HVAC systems and targeting behavioral changes through sociotechnical approaches for more environmental-friendly occupants of green buildings.

Keywords: Game Theory, Information Theory, Machine Learning, Multi-criteria decision making, Smart Building, Uncertainty Quantification, Utility theory, .

1 Introduction

Energy consumption of buildings, both residential and commercial, accounts for approximately 40% of all energy usage in the U.S. Lighting is a major consumer of energy in commercial buildings; one fifth of all energy consumed in buildings is due to lighting. Many approaches have been proposed to improve energy efficiency of buildings through control and automation as well as incentives and pricing. However, most of the past approaches to building energy management mainly focus on heating and cooling of the building. In view of new technological advances in building automation, it is proposed herein to design not only efficient Heating, Ventilation and Air Conditioning (HVAC) systems, but also a *human-*

centric system driven by the behavior and preferences of the occupants. In particular, our experimental set-up designs incentives based on lighting, individual plug-loads and HVAC which interact with the building occupants through a social game.

The aim of the social game is incentivizing occupants to modify their behavior so that the overall energy consumption in the building is reduced. In the framework, the occupants log their vote for the lighting settings in the office and they win points based on how energy efficient their vote is compared to other occupants. The points are used to determine the likelihood of the occupants of winning a prize.

The occupants (or agents) are modeled as utility maximizers who engage in a non-cooperative game playing according to a *Nash equilibrium strategy*. Their preferences are described through utility functions able to model the tradeoff between the desire to win and their own comfort. The parameters of agents' utility functions are estimated through a machine learning methodology proposed in (Konstantakopoulos et al. 2018). The adopted dataset derives from the social game setup that occurred over a period of about three months. The findings of the previous research have shown that: (*i*) the Nash equilibrium is a good predictor of the occupant behavior, and (*ii*) the utility functions of the agents can be modeled through suitable machine learning tools.

A major significance of the game-theoretic framework is its capability to derive insights about the behavior of the occupants, and this can be leveraged in designing mechanisms for incentivizing occupants. This, in essence, is a problem of closing-the-loop so that the building manager achieves sustained energy savings. The task is accomplished in this paper through a hierarchical decision-making system under uncertainty.

Starting from the formulated data-driven utility functions of the occupants, the game theory framework provides the most likely behavior of the occupants when the building manager provides chosen incentives. The problem presents several sources of uncertainty, in particular the probability of any agent of being in the building at a given time of the day, in a given period of the year. To this aim, in the lower level of the decision-making system, through a Monte Carlo Simulation (MCS) we simulate the presence of the occupants. The game-theoretic framework predicts, like a black-box, the reactions of the agents to the incentives, expressed through their votes. This allows, in turn, to determine the probability distribution of annual energy consumption expressed at the community level, represented by the occupants of the building. The probability distributions are determined through the Kernel Density Maximum Entropy Method (KDMEM), which is a machine learning approach based on the Maximum Entropy (Alibrandi and Mosalam 2017). Thus, it is possible to determine the distribution of the consequences of the incentives, whose optimal choice is evaluated through the Generalized Expected Utility (Mosalam et al. 2018), defined to the higher level of the hierarchical decision making.

2 Social Game

In this paper, we focus on encouraging occupants to select lower lighting settings in exchange for a chance to win in a series of lotteries. Occupants' votes are for the lighting settings in their zone as well as for neighboring zones. The game is designed to leverage interactions amongst occupants who win points based on how energy efficient their votes are compared to others. The occupants select their desired lighting settings in the continuous interval $[0,100]$ where each value represents the percentage of the maximum lighting setting possible in the space. The occupants can vote as frequently as they like and the average of all the occupants' current votes sets the implemented lighting setting. One of our control mechanisms is the 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 between 0% and 100% depending on their preferences and environmental factors. Three persistent player behavior profiles have emerged: 1) those who actively participate through voting, 2) those who are present yet keep their vote at the default value, and 3) those who are absent (i.e. do not participate in the game). For the experiment, the baseline lighting setting is taken to be $z_b = 90\%$, which is the value used before the implementation of the social game.

In the game-theoretic framework, the occupants are defined as *agents*, or *players*. Let p denote the number of agents participating in the game. The agents are modeled as utility maximizers whose utility functions $f_i(z_i, \boldsymbol{z}_{-i})$ are composed of two basis functions that capture the tradeoff between comfort and desire to win as follows,

$$f_i(z_i, \boldsymbol{z}_{-i}) = \psi_i(z_i, \boldsymbol{z}_{-i}) + \vartheta_i \phi_i(z_i, \boldsymbol{z}_{-i}) \tag{1}$$

where $z_i \in [0,100]$ is the vote of the i^{th} agent, $\boldsymbol{z}_{-i} = \{z_1, z_2, \dots, z_{i-1}, z_{i+1}, \dots, z_p\}$ collects the votes of all the agents except i, $\psi_i(z_i, \boldsymbol{z}_{-i})$ and $\phi_i(z_i, \boldsymbol{z}_{-i})$ model the preferences of the agent i with respect to the *comfort* and the *desire to win*, respectively. They are defined as

$$\psi_i(z_i, \boldsymbol{z}_{-i}) = -(\bar{z} - z_i)^2, \quad \phi_i(z_i, \boldsymbol{z}_{-i}) = -\rho \left(\frac{z_i}{100}\right)^2 \tag{2}$$

where $\bar{z} = \frac{1}{p}\sum z_i$ is the average of all the agents' votes and it is the implemented lighting setting. The comfort basis function $\psi_i(z_i, \boldsymbol{z}_{-i})$ measures the discomfort an agent feels given his/her vote z_i and the state of the environment $\bar{z}$. The function $\phi_i(z_i, \boldsymbol{z}_{-i})$, expressing the desire of the agent to win, depends on the total number ρ of points distributed by the building manager. In Eq. (1), ϑ_i is a parameter expressing the degree of importance which the agent attributes to the desire to win. In this paper, it is assumed that ϑ_i are known, and determined through the procedure described in (Konstantakopoulos et al. 2018).

The agents can only log votes in the interval $[0,100]$. Thus, the agent i faces the following constrained optimization problem

$$\begin{cases} \max f_i(z_i, \boldsymbol{z}_{-i}) \\ h_{i,1}(z_i) \geq 0 \\ h_{i,2}(z_i) \geq 0 \end{cases} \tag{4}$$

where $h_{i,1}(z_i) = 100 - z_i$ and $h_{2,i}(z_i) = z_i$. The game $(f_1, f_{2,\dots,} f_p)$ is a continuous game on a convex strategy space, given by $\mathcal{C} = \mathcal{C}_1 \times \mathcal{C}_2 \times \dots \mathcal{C}_p$, with $\mathcal{C}_i = \{z_i \in \mathcal{R} | 0 \leq z_i \leq 100\}$. To model the outcome of the strategic interactions between the agents, we use the *Nash equilibrium point* $\boldsymbol{z}^*$ defined as

$$f_i(z_i^*, \boldsymbol{z}_{-i}^*) \geq f_i(z_i, \boldsymbol{z}_{-i}^*), \ \forall z_i \in [0,100] \tag{5}$$

which consists of strategies that are all best responses to each other. This implies that no player can do better by deviating from a Nash point, assuming that no one else deviates. Additional constraints on the parameters ϑ_i guarantee that the game is concave on a convex set, and that it has unique differential Nash equilibrium point. As a consequence, for chosen incentive ρ

and given number of agents $p' \leq p$ playing the game, the lighting setting of the occupants is uniquely determined by the Nash equilibrium point.

However, the occupancy, including the distribution of people within the building and the variability of this distribution over time, is uncertain. To this aim, a building population model is adopted. The population models describe population patterns varying with time of day (e.g., hours of operation, lunch time fluctuations), day of week (weekdays versus weekends), and month of the year to characterize the effects of holidays. In this way, for any hour of any day of the year, it is possible to estimate the number $p'(t)$ of people present in the office. A Monte Carlo Simulation (MCS) is used to choose which agents are present at time instant t.

Of course, different distributions of occupants will determine different Nash equilibrium points $\boldsymbol{z}^*(t)$. It follows a time-dependent uncertain distribution of the lighting setting, and in turn, of the Energy Consumption $EC(t)$ inside the building. The distribution of any quantity of interest is determined through the recently proposed Kernel Density Maximum Entropy Method (KDMEM). This is a novel machine learning approach based on the Maximum Entropy principle (Alibrandi and Mosalam 2017). It is here adopted because of its capabilities to provide, with reduced computational cost, the *least biased* distribution given the available information.

3 Generalized Expected Utility (GEU)

In the theory of decision under risk, the main focus of the decision maker is the choice of the optimal solution with respect to a chosen performance G (e.g. the annual Energy Consumption in the building) given a set of m alternatives $G^{(i)} = G\left[\boldsymbol{x}^{(i)}, \boldsymbol{v}\left(\boldsymbol{x}^{(i)}\right)\right], i = 1,2, \dots, m$. The vector $\boldsymbol{x}^{(i)} = \left\{x_1^{(i)} \quad x_2^{(i)} \quad \cdots \quad x_n^{(i)}\right\}$ collects all the *design variables* containing the control variable values representing the set of preselected alternatives. The vector $\boldsymbol{v}(\boldsymbol{x}) = \{\boldsymbol{v_B} \quad \boldsymbol{v_D}(\boldsymbol{x})\}$ collects all the uncertain parameters appearing in the decision-making problem where $\boldsymbol{v_B}$ collects the *basic random variables*, which are the parameters that cannot be controlled by the decision-maker, e.g. environmental conditions or population distribution, while $\boldsymbol{v_D}(\boldsymbol{x})$ collects the *derived parameters* that are affected by the design variables, e.g. responses of the occupants to the incentives or the environmental conditions.

The optimal choice is determined through the definition of a functional $\mathcal{V}(\cdot)$ applied to the performance G, such that if $\mathcal{V}\left(G^{(1)}\right) \geq \mathcal{V}\left(G^{(2)}\right)$, then the alternative $G^{(1)}$ is preferred over the alternative $G^{(2)}$. The Generalized Expected Utility (GEU) (Mosalam et al. 2018) is adopted and expressed as follows,

$$GEU^{(i)} = \int u^{(i)}\, d\left[h\left(F_U^{(i)}\right)\right] \tag{6}$$

where $u^{(i)}$ is the utility of the i^{th} alternative, $F_U^{(i)}$ is its Cumulative Distribution Function (CDF), while $h(\cdot)$ is a suitable function describing the risk perception of the decision maker, here represented by the decision maker. The utility $u^{(i)}$ is defined through the *utility function* $u(g)$ which is a function converting the values g of the performance G into the degree of preference of the decision maker. The GEU embodies a distinction between the attitudes to the outcomes, measured by $u(g)$, and attitudes to the probabilities, distorted through $h(F_U)$. The optimal decision maximizes the GEU.

If the probabilities are not distorted by the risk perception of the decision maker, i.e. $h(F_U) \equiv F_U$, then the GEU coincides with the largely adopted Expected Utility EU (Von Neumann and Morgenstern, 1944)

$$GEU^{(i)} \equiv E\left[U^{(i)}\right] = \int u^{(i)}\, dF_U^{(i)}(u) = \int u(g)\, dF_G^{(i)}(g) \equiv EU^{(i)} \tag{7}$$

where $F_G^{(i)}$ is the CDF of the performance G. In the literature, some researchers state that a rational decision maker should be risk-neutral by considering complete consequence models. Under this further assumption, then $u(g) = g$ and

$$GEU^{(i)} \equiv E\left[U^{(i)}\right] = \int g\, dF_G^{(i)}(g) = \int g f_G^{(i)}(g)\, dg \equiv E\left[G^{(i)}\right] \tag{8}$$

where $f_G^{(i)}(g)$ is the Probability Density Function (PDF) of $G^{(i)}$. The optimal alternative provides the maximum GEU, i.e.

$$\max_{G^{(i)}} GEU \equiv \max_{G^{(i)}} EU \equiv \max_{G^{(i)}} E[G] \tag{9}$$

Thus, a rational building manager will pursue the maximum expected performance. In this paper, the considered performance is represented by the annual Energy Consumption of the building (EC), i.e. $G \equiv EC$ and thus the maximum benefit is coinciding with the minimum expected EC. In the considered case, $G \equiv EC[\boldsymbol{x}, \boldsymbol{v}(\boldsymbol{x})]$ where the control variables are the distributed points and the baseline lighting setting, i.e. $\boldsymbol{x} = \{\rho \quad z_b\}$, while $\boldsymbol{v}(\boldsymbol{x})$ collects the uncertain parameters. The basic random variables are the random population $\boldsymbol{p}(t) = \{p_1(t), p_2(t), \dots, p_p(t)\}$, representing a multivariate stochastic process, where the process $p_j(t)$ describes the probability of occupancy of the agent j at time t. The derived variables are the votes $\boldsymbol{z}(t; \boldsymbol{x}) = \boldsymbol{z}[\boldsymbol{p}(t); \boldsymbol{x}]$, which in turn affect the lighting setting $\bar{z}(t; \boldsymbol{x})$ which in turn affects the considered performance $G(\boldsymbol{x}) \equiv EC(\boldsymbol{x}) = f[\bar{z}(t; \boldsymbol{x})]$.

4 Numerical Application

The procedure is applied to a hypothetical office building located in Berkeley, California. The office area is $A = 300\ m^2$, with a peak population of $p = 12$ people. The population model proposed by FEMA is adopted. A time window of an average year is chosen, with an interval time $\Delta t = 1\ hour$, so that $365 \times 24 = 8{,}760$ time slots per year are considered. The processes $p_j(t)$ describing the occupancy of the agents are discretized through a vector of random variables, i.e. $\boldsymbol{p}_j = \{p_{j1}, p_{j2}, \dots, p_{jk}\}$ where $p_{jk} = p_j(t = t_k)$, $j = 1,2,\dots,12$ and $k = 1,2,\dots,8760$. Monte Carlo Simulation (MCS) is applied to simulate the probability of occupancy of the 12 occupants along the average year. Five different years are simulated.

In (Konstatakopoulos et al., 2018), values of the parameters ϑ_i are determined through a machine learning procedure. The adopted dataset derives from the social game setup, developed in a collaboratory space within a building on the UC Berkeley campus, occurred over the period of about three months. Starting from these findings, some representative values of ϑ_j, $j = 1,2,\dots,12$ are chosen in this numerical application. Thus, for each time slot, the votes $z_j(t)$ are determined as Nash equilibrium points. It follows the lighting setting $\bar{z}(t)$ and the energy consumption of the building $EC(t)$. The daily value of EC is determined, giving rise to vectors of size 365×5, where five is the number of simulated years. The distributions of the uncertain parameters are determined through the Kernel Density Maximum Entropy Method (Alibrandi and Mosalam 2017). In the analysis, it has been assumed a baseline lighting setting $z_b = 90\%$, while different values of the distributed points are considered, ranging from $\rho = 0$ to $\rho = 10{,}000$ with steps $\Delta\rho = 1{,}000$. The results are shown in Figure 1.

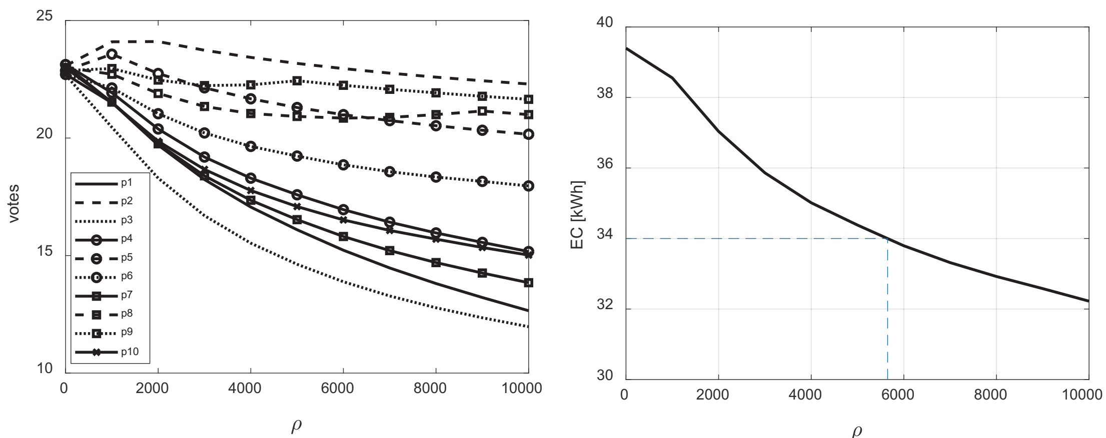

Figure 1. (left) daily average votes of the active agents, (right) energy consumption

On the left part of Figure 1, we show how the daily average votes of the active agents vary with the incentives, which shows the different behavior of the occupants to the incentives. On the right part of Figure 1, the corresponding reduction of energy consumption of the building is presented. It is seen that if the building manager desires to achieve an average energy lighting consumption of $34\,kWh$ (i.e. energy saving of about 14% compared to the consumption without incentives, i.e. $39.5\ kWh$), he/she needs to distribute 5,650 point.

5 Concluding Remarks

A hierarchical decision-making system under uncertainty for sustainable building design is presented. It is based on a human-centric design driven by the behavior and preferences of the occupants, described through a continuous game between non-cooperative agents. The lower level of the decision making applies a Monte Carlo Simulation to the social game, while the higher level ranks the consequences of the incentives. A simple numerical example shows the capabilities of the presented system in designing incentives for more environmental-friendly occupants.

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