Teaming and Competition for Demand-Side Management in Office Buildings

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***Abstract*—Energy conservation at public/office buildings can be tricky, due to the absence of direct incentives, e.g., regarding the electricity bill, and the potentially higher aversion of employees to comfort loss. Few serious games have been developed for motivating occupants to save energy based on peer pressure and/or prizes. However, the design of these games has mostly been based on a genre-adoption approach, while behavioral traits of employees were either considered on average only (rather than per individual player) or not considered at all. In this paper, we analytically study the design of an effective serious game in a work environment involving team competition and prizes. We introduce an innovative model of the energy-consumption decisions of an employee that includes several factors, namely sensitivity to comfort loss, desire for conformance to the social norm, desire for teaming and appreciation of monetary rewards. We formulate the problem of maximizing the effectiveness of the serious game with respect to the team size and the amount of rewards. Based on numerical evaluation with synthetic and real datasets, we show the significant impact of these game parameters to the effectiveness of the serious game as an incentive mechanism for energy conservation in this context.**

I. Introduction

According to the European Environment Agency (2017), a significant fraction of electricity is consumed by the services sector (29.8%), of which a key part comprises office buildings. Although the energy-consumption reduction in buildings is a complex issue and should also be addressed by means of energy-efficient refurbishing and retrofitting of the buildings, the consumption behavior of the people in these buildings is considered a key factor and it should be properly addressed as well, in order to accomplish energy-consumption reduction and smoothing, because "buildings don't use energy, people do" [1]. Demand-side management (DSM) refers to the adjustment of the demand side of electricity supply, so that it minimizes supply (generation) costs. DSM includes energy efficiency and demand-response (DR) solutions. The latter attempt the modification of electricity demand as a response to some special signals to the customers. While price-based DR programs directly involve economic incentives for user participation through the electricity prices used for charging, most incentive-based DR programs (e.g., Critical Peak Rebate, Direct Load Control) also indirectly involve economic incentives through monetary rewards, discounts or penalties.

Few attempts have been made for DR in office buildings mostly based on automated control of HVAC using sensory data [2], [3]. This is because, more often than not, providing economic incentives for DSM in office buildings may not be practical, while various other behavioral traits of consumers may be equally or more important for their decision-making process than cost-saving [4]. Such behavioral traits for users at a work environment include attitude towards energy conservation, problem awareness, knowledge, habits, desire for conformance to social norms, needs, inclination towards teamwork, mobilization by means of rewards, etc. Serious games and gamification are a means for engaging and motivating people towards specific goals, i.e., learning, training, persuasion, change behavior, etc., as in-game playing strategy. The employment of serious games for DSM is a recent approach followed by few prior works [5]–[7] that statically employed different game genres, e.g., life simulation, sports. In [8], which is co-authored by one of the present authors, the first attempt to mathematically model the problem of optimal design of a serious game for individual players was made. However, to the best of our knowledge, a team-competition setting with team ranking based on aggregate scores has never been analyzed in the past.

In this paper, we investigate the potential effectiveness for energy-consumption reduction of a team-competition game among employees in an office context. We introduce an innovative model for the energy-consumption decisions of an employee, which includes four key behavioral traits of employees, namely their sensitivity to personal-comfort disruption, their desire for conformance to social norms, their desire for teaming and their appreciation of monetary rewards. We mathematically model the user problem regarding her game strategy for energy-consumption reduction. Moreover, we analytically study the problem of the game designer regarding team formation and rewarding scheme, in order to maximize the potential effectiveness of the game. Based on numerical analysis with synthetic and real data from three pilot sites of the EU project ChArGED (http://www.charged-project.eu/), we establish that the team size and the rewarding scheme should be appropriately chosen for different communities of office employees, in order to maximize the net achievable energy savings, i.e., the value of saved energy minus the cost of incentives.

The remainder of this paper is organized as follows: In Section II, we define our game model. In Section III, we define the problem of the individual player of the game for selecting her performance. In Section IV, we define the problem of the game designer for optimally selecting the parameters of the game. In Section V, we numerically evaluate our work for synthetic and real datasets. In Section VI, we review the related work and, finally in Section VII, we present some concluding remarks and directions for future work.

II. The Serious Game Model

We assume K teams of N employees that compete against each other with respect to their respective (relative) aggregate energy consumption reduction in weekly competitions. The respective performance of teams is announced in a leaderboard and each team member receives a reward b_k that varies according to the rank k of its team.

We denote as $\mathcal{G}_j$ the set of employees belonging to team j. Let p_i the power consumption of employee i at a time slot. We define $\Delta p_i = (p_i^0 - p_i)/p_i^0$ to be the normalized energy consumption difference of a player i, where p_i^0 is the nominal energy consumption and p_i is consumption brought about by the game. We refer to Δp_i as the *performance* of each employee i in the game. Similarly, the performance ΔP_j of each team j in the game is given by:

$$\Delta P_j = \frac{\sum_{i \in \mathcal{G}_j} p_i^0 \Delta p_i}{\sum_{i \in \mathcal{G}_j} p_i^0} \tag{1}$$

The game parameters K and $\vec{b} = (b_k)$ are chosen by the game designer and are fixed throughout the game.

III. The Player's Problem

The energy-consumption behavior of an employee is dictated by four components corresponding to four different behavioral traits, namely (i) the inelasticity to any losses in personal comfort, (ii) the desire for conformance to social norms, (iii) the desire for teaming, and (iv) the desire for rewards. Below, we deal separately with each of these components.

A. Discomfort

The energy consumption profile of an employee in an office environment comprises multiple non-shiftable and shiftable devices. A non-shiftable device for a particular employee is one whose power load cannot be reduced or deferred in time in response to a demand-side management (DSM) mechanism, e.g., PC, projector, etc. A shiftable device can be classified as flexible (i.e., power-reducible), such as lighting, HVAC, etc., or deferrable (i.e., time-shiftable), e.g., printing, coffee machine, microwave, etc., in response to DSM. We express the player discontent from an energy-consumption reduction as

$$d_i(\Delta p_i) = a_i(1 - \sqrt{1 - \Delta p_i})\,, \tag{2}$$

where $a_i > 0$ is a factor of *comfort inelasticity* of player i. This function is convex, similarly to the aggregate user dissatisfaction model in [9] for flexible and deferrable loads. To account for the non-shiftable loads, we assume a personalized upper bound $R_i < 1$ in the normalized energy consumption reduction of employee i, i.e., $\Delta p_i < R_i$.

B. Social recognition

During the game the ranking of the K teams is announced in a leaderboard according to their relative performance for energy consumption reduction. We assume that a team member i enjoys some *societal advantage* h_i when her team wins this social competition. Note that h_i expresses a personal behavioral aspect. The performance ΔP_j of team j where employee i belongs to can be written as a function of the performance Δp_i of employee i and the performance of other team members Δp_{-i}, i.e., $\Delta P_j(\Delta p_i, \Delta p_{-i})$, which is given by (1). Overall, the satisfaction of employee i that belongs in team j can be expressed by:

$$s_i(\Delta p_i, \Delta p_{-i}) = h_i \cdot Pr[\Delta P_j(\Delta p_i, \Delta p_{-i}) \geq \Delta P_k, \forall\ k \neq j] \tag{3}$$

Observe that $\Delta P_j(\Delta p_i, \Delta p_{-i})$ increases with Δp_i, which means that higher individual performance increases the probability of her team to win the social competition.

Subsequently, we calculate the probability of team j to be ranked first given the performance of team member i. First, we remind some material from the theory of order statistics [10]. Let $X_1, \ldots, X_{K-1}$ be $K-1$ independent and identically distributed (i.i.d.) random variables. In our case, the random variable X_j denotes the energy consumption reduction of team j. Note that the game designer has to partition users to teams appropriately, i.e, by sampling from the consumer population, so that the i.i.d. assumption applies. However, besides making the analysis more tractable, this will also make the competition among the teams more intense and thus our serious-game more effective.

The order statistics $X_{(1)}, X_{(2)}, \ldots, X_{(K-1)}$ are also random variables, defined by sorting the realizations of $X_1, \ldots, X_{K-1}$ in non-decreasing order. Namely, for each realization ω, we arrange the sample values $X_1(\omega), \ldots, X_{K-1}(\omega)$ is non-decreasing order, $X_{(1)}(\omega) \leq X_{(2)}(\omega) \leq \ldots \leq X_{(K-1)}(\omega)$, where $(1), (2), \ldots, (K-1)$ denote that permutation of indices $1, 2, \ldots, K-1$ for which the random variables X are ordered. Thus, we have

$$\begin{aligned} X_{(1)} &= \min\{X_1, \ldots, X_{K-1}\} \\ &\vdots \\ X_{(K-1)} &= \max\{X_1, \ldots, X_{K-1}\}\,. \end{aligned} \tag{4}$$

The PDF of the k-th order statistic, $X_{(k)}$, $k = 1, \ldots, K-1$ is given by

$$f_{X_{(k)}}(x) = \frac{(K-1)!}{(k-1)!(K-1-k)!} F^{k-1}(x)(1-F(x))^{K-1-k} f(x), \tag{5}$$

where $F(\cdot), f(\cdot)$ are the common CDF and PDF respectively of the variables $X_1, \ldots, X_{K-1}$. In our case, in order to derive the probability for a team to be ranked first among K teams, we have to characterize the probability distribution of the (K-1)-th order statistic, $X_{(K-1)}$ of the other K-1 teams; see analysis below. Indeed, notice that in general, the (K-k)-th order statistic denotes the (K-k)-th smallest energy consumption reduction of a team in the rest K-1 teams, or equivalently, the k-th largest team energy-consumption reduction of the rest K-1 teams.

Given the statistical information $f(x), F(x)$, i.e. PDF and CDF respectively, about the ensemble of teams of employees regarding their team performance, a rational software agent residing at the consumer side (e.g., at a properly designed mobile application) calculates the probability that team j of employee i is ranked first, i.e., higher than K-1 others, as a function of Δp_i, as follows:

$$Pr[\Delta P_j(\Delta p_i, \Delta p_{-i}) \geq \Delta P_k,\ \forall\ k \neq j] = Pr[\Delta P_j(\Delta p_i, \Delta p_{-i}) \geq X_{(K-1)}] = \int_0^{\Delta P_j(\Delta p_i, \Delta p_{-i})} f_{X_{(K-1)}}(x)dx\ , \quad (6)$$

where

$$f_{X_{(K-1)}}(x) = \frac{(K-1)!}{(K-2)!} F^{K-2}(x) f(x)\,. \quad (7)$$

However, the manifestation of the performance $\Delta P_j(\Delta p_i, \Delta p_{-i})$ of team j, besides the individual performance Δp_i of employee i, depends on the performance of other members of team j. Given statistical information $g^j_{Y_l}(y), G^j_{Y_l}(y)$ on the individual performance Y^j_l of each member l of team j, one can calculate the expected performance with respect to the vector Δp_{-i} by drawing individual performance values from distribution G^j. Then, equation (6) is rewritten as follows:

$$Pr[\Delta P_j(\Delta p_i, \Delta p_{-i}) \geq X_{(K-1)}] = \int_{Y_1}\int_{Y_2}\cdots\int_{Y_{\frac{N}{K}-1}} g^j_{Y_1,Y_2,\ldots,Y_{\frac{N}{K}-1}}(y_1, y_2, \ldots, y_{\frac{N}{K}-1}) \cdot \int_0^{\Delta P_j(\Delta p_i, y_1, y_2, \ldots, y_{\frac{N}{K}-1})} f_{X_{(K-1)}}(x) dx dy_1 dy_2 \ldots dy_{\frac{N}{K}-1}\ , \quad (8)$$

where $g^j_{Y_1,Y_2,\ldots,Y_{\frac{N}{K}-1}}(\cdot)$ is the joint performance distribution of other members of team j and $\Delta P_j(\Delta p_i, y_1, y_2, \ldots, y_{\frac{N}{K}-1})$ denotes the performance of team j when the individual performance of all other players except i is given, obtained by:

$$\Delta P_j(\Delta p_i, y_1, y_2, \ldots, y_{\frac{N}{K}-1}) = \frac{p^0_i \Delta p_i + \sum_{v=1}^{\frac{K}{N}-1} p^0_v y_v}{p^0_i + \sum_{v=1}^{\frac{K}{N}-1} p^0_v}\,. \quad (9)$$

Note that the exact distribution F of the team performance X can be accurately calculated based on (9). However, the following simplifications are foreseeable: Denote $g(y), G(y)$ the statistical information on the individual performance Y of any employee in the office building. The individual performance of employees are i.i.d. and since teams are formed by random sampling, players within a team are i.i.d. as well. Thus, we can assume that the distribution G^j of the individual performance Y^j of any employee in team j is essentially equal to G, i.e., $Y^j \approx Y,\ j = 1, \ldots, K$. According to (9), team performance is a percentage based on weighted averaging of individual performances, which are also percentages. Hence, the distributions F, G of the random variables X, Y of team and individual performances respectively can be taken to be equal. Based on these assumptions, individual performance variables $Y_1, Y_2, \ldots, Y_{\frac{N}{K}-1}$ can be considered to be i.i.d. with PDF $f(\cdot)$ and CDF $F(\cdot)$. Then, the joint performance distribution of other members of team j can be given by:

$$g^j_{Y_1,Y_2,\ldots,Y_{\frac{N}{K}-1}}(y_1, y_2, \ldots, y_{\frac{N}{K}-1}) = f(y_1) \cdot f(y_2) \cdot \ldots \cdot f(y_{\frac{N}{K}-1}) \quad (10)$$

C. Teaming Advantages

We assume that a member i of a team j enjoys some societal advantage by the fact that it belongs to a team. Such a behavioral trait is prevalent in online-gaming behavior [11] and it is related to locus of control (i.e., personal perception that own actions can have an impact) [4]. It can be expressed as a concave function of the size of team j as follows:

$$t_i(|\mathcal{G}_j|) = \tau_i \min\left\{\sqrt{\frac{|\mathcal{G}_j| - 1}{S_i}}, 1\right\}\ , \quad (11)$$

where S_i is a number of team members that is considered as plentiful for player i and τ_i is a factor expressing the significance that player i assigns to teaming up with other players.

D. Rewards

At the end of each round of the social competition, a prize b_k is given to each member of the team that takes position k in the leaderboard with b_k declining with k. Each player i gets motivated by this reward according to a factor $\theta_i \in [0, 1]$ with $\theta_i = 1$ denoting full economic rationality. The *expected reward* for employee i of team j is given by:

$$r_i(\Delta p_i, \Delta p_{-i}) = \theta_i \Bigg(Pr[\Delta P_j(\Delta p_i, \Delta p_{-i}) \geq X_{(K-1)}] b_1 + \sum_{k=1}^{K-2} Pr[X_{(K-k)} > \Delta P_j(\Delta p_i, \Delta p_{-i}) \geq X_{(K-k-1)}] b_{K-k} + Pr[X_{(1)} > \Delta P_j(\Delta p_i, \Delta p_{-i})] b_K \Bigg) \quad (12)$$

where $X_{(K-k+1)}$ expresses the $(K-k+1)$-th smallest order statistic for the performance of a team, as defined in Section III-B. Alternatively, the reward could be given to a team and split among team members according to their individual performance.

E. Net Benefit

Summing the aforementioned factors, each employee i in team j has a *net benefit* as a function of her performance Δp_i that is given by:

$$u_i(\Delta p_i, \Delta p_{-i}) = \frac{1}{3}\big(s_i(\Delta p_i, \Delta p_{-i}) + t_i(|\mathcal{G}_j|) + r_i(\Delta p_i, \Delta p_{-i})\big) - d_i(\Delta p_i) \quad (13)$$

All utility terms are normalized by the price of an energy unit, which is considered to be fixed. Note that since we have three positive utility components, namely satisfaction from compliance to social norms, satisfaction from teaming, satisfaction from rewards, whose relative significance for employee i is expressed by the factors h_i, τ_i, θ_i respectively, we should take their average to express the user satisfaction. This is required for the overall user satisfaction to be comparable with the overall user dissatisfaction due to comfort losses. The employee i selects her performance Δp_i, so as to maximize her net benefit, i.e., she solves the following maximization problem:

$$\max_{\Delta p_i} u_i(\Delta p_i, \Delta p_{-i}) \quad (14)$$

IV. THE GAME DESIGNER'S PROBLEM

If every player plays according to (14), so as to maximize her individual net benefit, then, given a number of teams K and a rewards vector $\vec{b}$, all players compete against each other through their teams for prizes and societal advantages. According to the first fundamental theorem of welfare economics, any competitive equilibrium to this game leads to a *Pareto efficient allocation* of these resources (i.e., prizes and societal advantages).

The game designer can influence the Pareto-efficient allocation point by adequately selecting $\vec{b} = (b_k)$ and K, so as to maximize the total energy-consumption savings minus the total budget B for consumer rewards, henceforth referred to as *net energy savings*. More formally, the game designer solves the following problem:

$$\max_{\vec{b},K} \sum_{i \in N} p_i^0 \Delta p_i(\vec{b}, K) - B \tag{15}$$

Note that this problem is *feasible* when there exist $\vec{b}, K$, such that the net energy savings are positive. Moreover, note that $B = \sum_{k=1}^{K} b_k$ is normalized by the price of an energy unit.

Two cases may arise for the solution of this problem:

(a) *Full information*: We assume that all parameters regarding the user utility model are known to the designer. For each pair of $(\vec{b}, K)$ a Pareto efficient allocation point can be found by the game designer as a solution to the following problem:

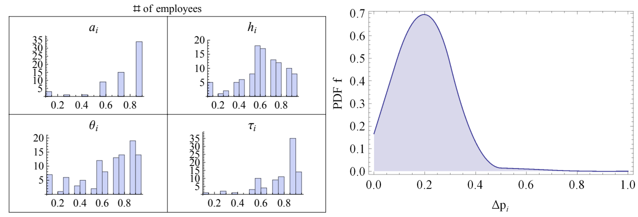
$$\max_{\vec{\Delta p}} \sum_{i \in \mathcal{N}} u_i(\Delta p_i, \Delta p_{-i}) \tag{16}$$

where $\vec{\Delta p} = (\Delta p_i),\ \forall\ i \in \mathcal{N}$, i.e., an individual performance is found for each employee i. The game designer iterates among different choices of $\vec{b}$ and K, so that the net energy-consumption savings are maximized. Note that the problem could also be algebraically solved for an invertible prior distribution of performance.

(b) *Hidden information*: No information is known regarding the user utility function to the game designer. In this case, the game designer sets the game parameters $(\vec{b}, K)$ and observes distributed game equilibrium. Then, again iteratively, the game parameters are changed, so as to improve net energy-consumption savings.

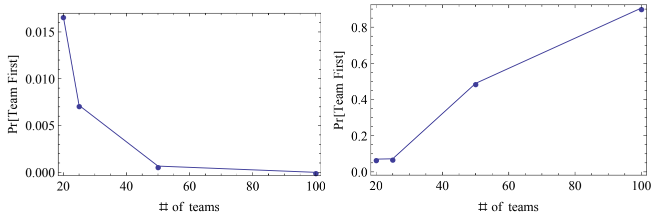
V. NUMERICAL EVALUATION

In this section, we numerically evaluate our model for finding the optimal team-game parameters for synthetic and real datasets. In all synthetic datasets for employee i, the sensitivity a_i to any decrease in personal comfort is Uniform in [0.2, 0.8], the social sensitivity h_i is Uniform in [0, 1], the desire for teaming τ_i is Uniform in [0, 1] and the mobilization θ_i by means of rewards is Uniform in [0.4, 1]. In the real dataset, the parameters a_i, h_i, θ_i, τ_i are derived based on the responses of 115 employees to an online survey in the 3 pilot sites of the ChArGED project, specifically two office buildings in Greece and Spain, and one museum in Luxembourg. The histograms for the parameters a_i, h_i, θ_i, τ_i are depicted in Fig. 1a. We assume that the PDF $f(\cdot)$ of the distribution F of the discretized individual performance of employees resembles Normal and it is depicted in Fig. 1b. In all experiments, we assume that an individual reward b is given only to each member of the first team, while all other players get nothing, i.e. $\vec{b} = \{b, 0, \ldots, 0\}$. For clarity of results, we assume that the baseline energy consumption of each employee i is p_i^0=1 KWh in all cases, while the upper bound for Δp_i for each employee i is set to R_i=1 and teaming value is maximized for S_i=5.



(a) (b)

Fig. 1. (a) The histograms of the behavioral factors $a_i, h_i, \theta_i, \tau_i$ of employees in the real dataset. (b) The prior distribution of individual performance of employees with μ=0.197 and σ=0.117.



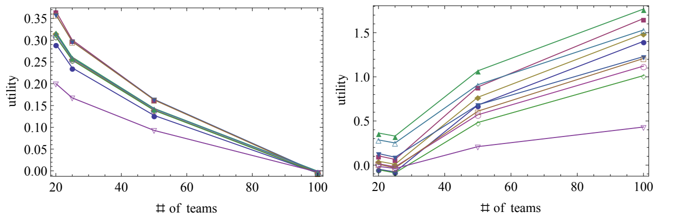
(a) (b)

Fig. 2. The probability of her team to be first for (a) a low-performing employee and (b) a high-performing employee, as compared to others.

A. Teaming Effects

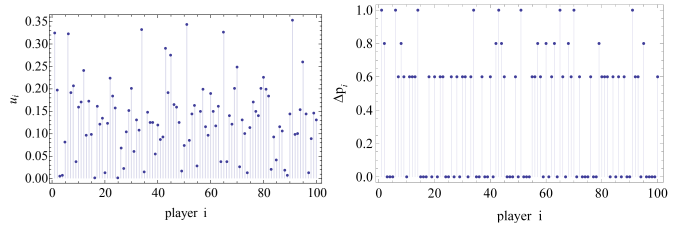
We consider a random set of N=100 employees from the real dataset and examine the effect of teaming. We assume two performance types of employees, a low-performance one with Δp_1=0.01 and a high-performance one with Δp_2=0.7, as compared to the others based on the performance distribution F. Then, as depicted in Fig. 2a, the probability of the team of the low-performing employee to be first deteriorates with the number of teams, while the opposite stands true for the high-performing employee (see Fig. 2b). This was expected, as the more the team members, the better the low-performing employee is able to hide her low-performance among them. On the contrary, the high-performing employee is better-off alone and her probability to be first in the competition is maximized for 100 teams, i.e., when she plays alone. Therefore, the number of teams is a sensitive parameter of the game and affects players differently depending on their own performance.

We also examine the effect of the team size on the utility function of employees. The individual reward is set to b=6 regardless of the team size. We consider two cases for employees: one where all perform low with Δp_1=0.01 and one where all perform high with Δp_2=0.7. The user utilities of 10 (random) real employees with respect to the team size for these two cases are depicted in Fig. 3. As shown in Fig. 3, the utility functions of employees of low and high performances follow their respective trends of the probability of their team to be first.



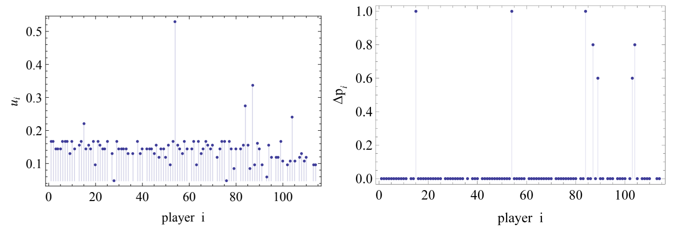
(a) (b)

Fig. 3. (a) The utility functions of 10 random real employees that perform *low* with the number of teams. (b) The utility functions of 10 random real employees that perform *high* with the number of teams.



(a) (b)

Fig. 4. (a) The maximum user utility values of the employees of (a) the synthetic dataset for K=50 and b=1. (b) The utility-maximizing individual performance for each employee in the synthetic dataset when K=50 and b=1.

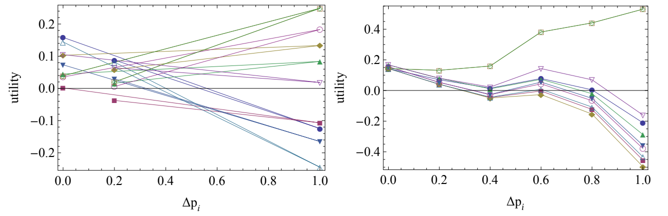


(a) (b)

Fig. 5. a) The maximum user utility values of the employees of (a) the real dataset for K=50 and b=1. (b) The utility-maximizing individual performance for each employee in the real dataset when K=50 and b=1.

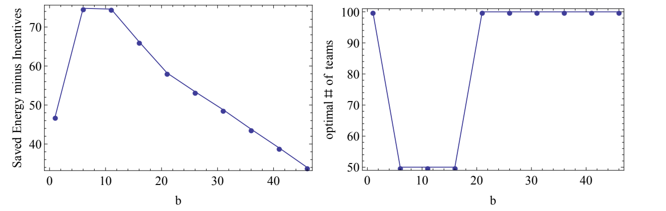
B. User Utility Maximization

We consider a synthetic dataset of N=100 employees and a number of teams K=50. We set the individual reward b=1. The employees choose the optimal energy-consumption reduction fraction Δp_i from the set $\{0, 0.2, 0.4, 0.6, 0.8, 1\}$. The maximum utility of each employee i with respect to her performance Δp_i is depicted in Fig. 4a and her corresponding utility-maximizing performance in Fig. 4b. As evident therein, different employees maximize their utilities at different energy-consumption performance points for a specific team size. The overall energy-consumption reduction that is achieved by this game setting at the social-welfare maximizing point is 38KWh out of the baseline 100KWh for all employees in total. Similarly, for the same number of teams (K=50) and for N=100 real employees -randomly selected-, the maximum utility of each employee and her utility-maximizing performance are depicted in Fig. 5. The overall energy-consumption reduction that is achieved in this case by the game at the social-welfare maximizing point is 5.6KWh out of the baseline 100KWh for all employees in total. Observe in Figs. 4a and 5a that the utility for some employees is positive, while for others it is close to 0, meaning that this game setting overall is beneficial for some and non-beneficial for others depending on their own utility-function parameters. The utility functions for 10 random employees from the synthetic and the real datasets with respect to their performance for teams of 2 employees are depicted in Fig. 6a and Fig. 6b respectively.



(a) (b)

Fig. 6. The utility functions of 10 employees from (a) the synthetic dataset (left) and (b) the real dataset (right) with respect to their performance for K=50 and b=1.



(a) (b)

Fig. 7. (a) Net energy savings with respect to individual reward b for optimal number of teams K. (b) Optimal number of teams K for different individual rewards b.

C. Game Optimization

We now optimize the parameters of the game, namely the team size and the amount of reward for the first team, in order to maximize the achievable energy savings by the game. We randomly select N=100 employees from the real dataset. We iterate for $b = \{1, 6, 11, \ldots, 46\}$ and $K = 20, 25, 50, 100$. For each value of b, the optimal team size N/K is selected, i.e., the one that maximizes the total energy savings of players. At each game setting, each employee selects her game performance, so as to maximize her individual utility. The game performance of employees for a specific (b, K) pair are used by the game designer to calculate the net achievable energy savings by this game setting. Fig. 7a shows the net energy-savings for the different values of individual reward b for the members of the first team and Fig. 7b the optimal number of teams for each value of b. Observe that the highest net savings are achieved for b=11 and K=50, i.e., for teams of 2 players. Also, notice that when individual rewards are high, it is optimal in terms of achievable energy savings that players play the game individually. However, the net energy savings drop with the amount of individual rewards.

VI. Related Work

There have been some prior efforts to employ serious games for demand side management [5]–[7] in public/office buildings. Competition as a means of incentive has been effective in incentivizing individuals to reduce energy consumption. A serious-game point-competition for energy conservation and participation in training activities among dormitory residents in a Hawaiian university was introduced in [6] with no monetary rewards. They found that energy feedback systems should be actionable (i.e., propose certain actions to achieve the game objectives), include training and be sticky (i.e., time-persistent), in order to have any long-term effect into energy consumption behaviour. Similarly, Johnson *et al.* [7] reviewed multiple energy competitions among university students and identified several pitfalls in their design. Specifically, the use of absolute or relative energy-consumption reduction for winner determination was deemed as not adequate when static baseline calculation methods are employed and may be unfair for already green consumers. Anticipating these in our approach, dynamic baseline calculation will be employed along the game and p_i^0 can be considered to represent not the total nominal energy consumption of employee i, but her nominal consumption due to misbehavior. Overall, none of these competition game-settings were analytically studied in terms of effectiveness, as opposed to our work. Also, a virtual pet game for energy use reduction in a commercial office setting was introduced in [5]; device-specific energy consumption was reflected in the fitness of virtual pets.

Multiple serious games were also proposed for energy conservation in residential settings [8], [12]–[14]. Geelen *et al.* [12] performed a pilot study on motivating occupants of student-households to save energy by means of team competition with a prize, similarly to our game setting. They found that this game setting achieved 24% savings on average, however, not long-lasting ones. A serious game for sharing a Medium/Low Voltage transformer among prosumers was organized as a virtual world with many user roles and actions in [13], albeit without exploiting any means of social pressure. Another game, called Power House, for improving residential energy behaviour was proposed in [14]. Incentive mechanisms included score boards with links to real-world social networks and virtual currency awards. The first approach to mathematically model and optimally choose the design parameters of a serious game was made by Papaioannou *et al.* [8]. Only social pressure was considered there as a means of incentive in a simple game, where consumers were competing to each other for their relative energy-consumption reduction at a peak-time slot, and then top-K and bottom-M consumers were announced as winners and losers respectively.

There are also a number of studies on gamification in general [15], which verify that specific serious-game design elements, such as leaderboards, points and levels, positively influence user participation, engagement and behavioural change without compromising the users intrinsic motivation. Also, Wang et al. studied efficient team creation for team competition games in [11] to maximize game enjoyment. They aimed to create teams of comparative strength, as we also do in our approach based on sampling. However, in [11], they also consider playing style of players apart from their individual performance for team formation. They found that enjoyment is positively correlated to the team presence of players with global-liberal playing style, i.e., those that assist others. We leave the consideration of this aspect for team formation as a future work. Moreover, team competition was game-theoretically studied in [16], however, in a very different setting than ours: winner determination was based on a one-to-one matchmaking among ordered team players according to their reported strength.

VII. Conclusion

In this paper, we analytically studied the potential effectiveness of a serious game involving team competition and prizes for energy conservation in public/office buildings. We considered four behavioral traits that guide the energy-consumption behavior of employees in our analysis: (i) sensitivity to personal discomfort, (ii) desire for compliance to the social norm, (iii) enjoyment from teaming, and (iv) desire for prizes. We analytically modeled the problem of the player for choosing her in-game performance, so as to maximize her net benefit and the problem of the game designer for optimally selecting the number of teams and the amount of rewards, so as to maximize the achievable *net energy savings* of the game. Based on numerical evaluation with synthetic and real data, we proved that the number of teams and the amount of rewards play significant role on the effectiveness of this game setting for energy conservation and they should be carefully chosen based on our optimization approach. However, the level of the validity of our model remains to be assessed by running our serious game in the pilot sites of ChArGED. As a future work, we will perform a sensitivity analysis on the impact of the various behavioral aspects on the model. Also, we intend to investigate appropriate team formation, apart from team size, optimal reward allocation and a more detailed user-utility model at the device level.

Acknowledgement

This work has been supported by the activities of H2020 EU project ChArGED (Grant Agreement No 696170).

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