Journal of Environmental Management 341 (2023) 117992

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

# Demand response in the workplace: A field experiment[☆]

Daniel Llerena[a], Beatrice Roussillon[a,*], Sabrina Teyssier[a], Adelaïde Fadhuile[a], Penelope Buckley[a], Benoit Delinchant[b], Jérôme Ferrari[b], Tiansi Laranjeira[b], Frédéric Wurtz[b]

[a] Univ. Grenoble Alpes, CNRS, INRAE, Grenoble INP, GAEL, F-38000 Grenoble, France
[b] Univ. Grenoble Alpes, CNRS, Grenoble INP, G2Elab, F-38000 Grenoble, France

ARTICLE INFO

*Keywords:*
Flexibility
Load-shedding signal
Workplace
Living lab

ABSTRACT

To increase the share of intermittent renewable energy in our production mix, occupants of buildings can be called upon to lower, anticipate or postpone their consumption according to the network balance. This article presents a small-scale field experiment aimed at introducing demand response in the workplace. We test the impact of load-shedding signals assorted with incentives on the energy consumption of workers in the tertiary sector. Two incentive schemes are tested, namely, an honorary contest and a monetary tournament. The results show a reduction in workers power demand during the load-shedding periods when the incentives are based on the honorary contest. In contrast, the monetary tournament where workers can win money according to their behavior seems to have no impact. The results also suggest that few workers can be responsible for a large part of energy consumption while the building is partially automatically controlled.

## 1. Introduction

Energy planning programs highlight the importance of diversifying energy mixes, promoting the penetration of renewable energies.[1] The increasing introduction of intermittent energy and the multiplicity and diffuse distribution of these production sites lead to problems related to energy source elasticity at the neighborhood level. Proposing and analyzing a scenario of a 100% renewable mix across France by 2050, the ADEME report suggests that the power demand flexibility of buildings could help to manage the network balance of the peak demand (Artelys et al., 2016). The main flexibility tools of the electrical system used to ensure the balance of supply and demand are related to storage and demand management. Storage capacity seems, however, unlikely to fully compensate for supply volatility (Giulietti et al., 2019). The viability of a future green power market depends critically on a number of innovative ways to increase demand elasticity. Arabzadeh et al. (2020) presented zero-emission scenarios by 2050 for Helsinki city and stressed the role played by cities in the deep decarbonization of energy systems and the need for an efficient demand response program to achieve it. The introduction of automated systems for energy flexibility offers many advantages to meet this challenge. Nevertheless, completely replacing the decisions of the actors is not the solution because satisfying individual objectives remains a real challenge, and their disengagement is a certain cause of failure of the technical solutions implemented (Liang et al., 2018; Liu et al., 2019). Demand response programs that may influence consumers toward more flexibility by willfully agreeing to decrease their energy use in response to demand response programs are seen as central in this context (Palensky and Dietrich, 2011) and present obvious advantages (U.S. Department of Energy, 2006).

Several works have considered energy consumption at home, including Faruqui and Sergici (2010), Ito et al. (2018), Wolak (2011) and Fadhuile et al. (2023), but less attention has been given to the workplace. Efforts to save energy in the workplace are characterized

☆ We gratefully acknowledge support from the Cross Disciplinary Program Eco-SESA funded by the French National Research Agency (ANR) in the framework of the "Investissements d'avenir" program (ANR-15-IDEX-02) and from the Auvergne Rhône-Alpes Region under the "Pack Ambition Recherche 2017 - Expesigno Project" program (17 01110301). We thank Marie Cronfalt for assistance for the conduct of the experiment. We also thank participants of Eco-Sesa seminars for their comments and suggestions.

* Corresponding author.
*E-mail address:* beatrice.roussillon@univ-grenoble-alpes.fr (B. Roussillon).

[1] See for instance the Multiyear Energy Program (namely PPE Program) in France, https://www.ecologique-solidaire.gouv.fr/programmations-pluriannuelles-lenergie-ppe.

[2] An overview of the recent publications is detailed in the Appendix A.

[3] Jain et al. (2015) also suggested that high rewards that are uncertain are more likely to reduce energy consumption than low certain rewards. In our experiment, one participant receives a higher prize than other participants based on a competitive scheme between the participants. The incentives we use then correspond to highly uncertain rewards.

https://doi.org/10.1016/j.jenvman.2023.117992
Received 29 July 2022; Received in revised form 13 April 2023; Accepted 18 April 2023
Available online 8 May 2023

by the principal–agent problem because the person consuming the energy is not the one who pays for it. As such, it can be difficult to motivate employees to make an energy conservation effort; while the cost of effort (changing behavior by erasing energy use during specific time slots) is immediate, the direct monetary benefits are rarely passed on to employees or are distant (reductions in environmental impact) (Kollock, 1998; Platt, 1973). Some experiments[2] have explored the effect of social and private incentives on overall energy consumption in the workplace. For instance, Handgraaf et al. (2013) showed that social rewards have a greater effect on encouraging energy conservation in the workplace than monetary rewards alone, particularly when feedback is made public rather than private. Other interventions in the workplace have looked at the effect of social comparisons of employees' consumption in relation to colleagues (Murtagh et al., 2013; Ornaghi et al., 2018) and nearby commercial buildings (Charlier et al., 2020) or of changing thermostat defaults on behavior (Brown et al., 2013). Finally, Fanghella et al. (2022) compare the effectiveness of a behavioral intervention with the impact of technological renovation, and find the latter the more efficient. To the best of our knowledge, only one paper has explored energy consumption flexibility or demand response in the workplace, namely, Ida et al. (2019). Focusing on the consumption of desk lamps, the authors compare employee participation and effort in a demand response program implemented over six peak consumption days. They found that while participation in the program is greater if employees are defaulted into the program, greater electricity savings can be achieved using an opt-in performance-based incentive. Finally, it is recommended that demand response signals be coupled with incentives to change behavior (Jain et al., 2015).[3] The honorary contest and the monetary tournament provide such incentives to reduce energy consumption.

Evidence on workers' demand response in the workplace is still very scarce and more difficult to implement. The current study thus proposes a small-scale field experiment aimed at evaluating the potential for flexibility of workers in the tertiary sector through their choice for erasing consumption over time.[4] Our study provides additional and complementary evidence about energy load-shedding in the workplace. Two types of demand management exist, depending on whether it is carried out directly on equipment (direct load control) or by the workers themselves via demand response programs (indirect load control) based on load-shedding signals or advisory services. In this research, we investigate in a building with automatically controlled devices the relative effectiveness of incentive mechanisms on employee responsiveness in terms of energy use to load-shedding signals for erasing the energy consumption of workers in specific time slots of their working day. In particular, this analysis should enable us to assess the capacity for indirect flexibility in a tertiary building. Two types of incentives are investigated to increase effort: an *honorary contest* and a *monetary tournament*; the former calls for self- and social-image motivation (Batson, 1998; Bénabou and Tirole, 2006) – named hereafter *social incentives* – whereas the latter applies the basic principle of economic incentives (Gibbons, 1997; Prendergast, 1999) – named hereafter *private incentives*. This experiment has enabled us to design and validate a technological solution for the deployment of such mechanisms, ranging from occupant interaction systems to automatic data processing. Our study then provides original results regarding the remaining impact of some incentive policy on human behavior and flexibility at work in an automatically controlled environment that is intended to develop.

The experiment took place in a university building, and the participants were either researchers or technical or administrative staff members. The experiment started in October 2018 and lasted for four months, including observation periods without signals or incentives. A system of communicating sensors allowed real-time data collection given 51,660 observations. Two treatment periods were considered, namely, those with load-shedding signals coupled first with the honorary contest and those with the monetary tournament. For either type of incentives, the prize was determined by the sum of the efforts made toward the energy consumption erasing of the participants in the experiment; the lower the energy consumption was in the specified time slots, the higher the prize was. In the honorary contest, the winner, i.e., the participant with the lowest energy consumption during the time slots of load-shedding, chose the NGO to whom the prize would be given, and her name was publicly broadcast on the screens of the building at the end of the experiment. In the monetary tournament, 50% of the prize was given to the winner, and the other 50% went to the other participants. These two types of incentives highlighted contrasting efforts for social reward and efforts for monetary reward.

The current paper is organized as follows. Section 2 presents the field experiment, Section 3 provides the data analysis, and Section 4 concludes the paper.

## 2. Field experiment

The field experiment took place in offices of the tertiary sector where we measured the participants' energy consumption and tested whether load-shedding signals coupled with social or private incentives changed their energy consumption in specific time slots. We first present the working environment and energy consumption, then we detail the experimental design and the incentives, and finally, we describe the experimental procedure.

### 2.1. Working environment and energy consumption

*Building* The setting for the experiment was a university building showcase for smart energy management, which is part of the Presquîle eco-district in Grenoble (INP, 2018; Delinchant et al., 2016).[5] G2ELab's Predis-MHI platform has been designed and developed since 2008 to monitor energy use in real-life situations (Dang et al., 2013). Since 2016, version 2 of Predis-MHI has been used within the GreEn-ER building and is positioned as a living lab in which it is possible to experiment and innovate in connection with the occupants (Delinchant et al., 2016). This 23,000-$m^2$ building accommodates approximately 2000 people; the majority of the people are students, while some are technical and administrative staff members and researchers. The consumption in 2018 was 120 kWhEP/$m^2$. The share of electricity consumption is preponderant (75%) because only the heating and part of the domestic hot water (kitchen of the university restaurant) are not of electrical origin. Only researchers and technical and administrative staff were eligible to participate in the experiment.

*Energy consumption* Participants worked with standard equipment available in a "typical" office, namely, a computer and its screen, as well as a LED desk lamp. Such a configuration consumes from 20 W to 80 W depending on the computer models and the work done (office automation, numerical simulation, etc.).[6] Our experiment

[4] France was the first European country to allow consumers to make the most of their load-shedding by using a load-shedding operator without having to obtain the prior agreement of their supplier. A payback mechanism is set up from the erasure operator to the supplier in return for energy transfer.

[5] The objective of such eco-districts is to reduce the environmental impact of groups of buildings through the integration of renewable energy sources and the improvement of energy efficiency (Debizet et al., 2016). The latter can be achieved through the optimization of automated responses to inputs such as daylight availability or exterior temperatures, and less emphasis is placed on the role of the individual. In a review of 15 European eco-districts, Menanteau and Blanchard (2014) found that less importance is given to the behavioral dimension to meet energy performance objectives, with only two eco-districts allowing for the use of incentives to encourage behavioral changes.

[6] The load-shedding potential for 200 offices has been evaluated at 8000 W, which remains very low given the scale of the building. Therefore, this study focuses more particularly on the load-shedding methodology than on load-shedding itself.

required the measurement of consumption at the workstation. To do so, it was necessary to deploy a secondary network of sensors which is a system of communicating sensors allowing real-time data collection; see Appendix B for a detailed presentation.[7]

### 2.2 Experimental design

*Sample* Researchers and technical and administrative staff were eligible to participate in the experiment. The number of potential participants was evaluated at 200. The participation rate was 13%, with 26 participants enrolled. Those who responded were administrative staff members (11), technical staff members (4), doctoral students (7) and researchers (4). We observed a low response rate for participating in the experiment. One explanation for this that we can put forward may come from our observation of the energy consumption of employees, which they may have seen as monitoring their productivity. A second explanation may come from the fact that asking employees not to consume energy could have been felt as a hindrance to their productivity. Nevertheless, as we observed the same participants during a long period of time and repeatedly, statistical tools may be used with confidence even given the small number of participants.[8]

*Treatments* We conducted two treatments in a within-subjects design. All participants in the experiment were subject to the two successive treatments. This method allowed us to observe the impact of the two treatments on the whole sample of the participants.[9] In both treatments, the participants received a load-shedding signal coupled with incentives to erase their energy consumption in specific time slots of their working day. Participants were notified with text messages on their phones on the morning of the day of the load-shedding period indicating when they were asked to erase their electricity consumption. During this period of time, participants were instructed to keep their usage (computer, computer screen and an LED desk lamp) to a minimum. The load-shedding periods were either a 45-min period during the lunch break or three 15-min periods spread over the day. Clearing consumption for 45 min during the lunch break allowed us to minimize the disruption to the work of employees while also exploiting a source of flexibility. The other 15-min periods could occur during the day, as their shorter length would have a smaller impact on employee work.

The two treatments differed by the type of incentives that were implemented. First, the participants engaged in an *honorary contest* (Treatment C), they then played a *monetary tournament* (Treatment T). Both incentives were based on competition between employees, where the size of the prize pool depended on the effort of all participants (see Gershkov et al., 2009 for theoretical framework and Bos et al., 2016 for direct application). The prize was proportional to the energy consumption of all participants in the experiment during the load-shedding time periods; i.e., it increased as the energy consumption of the participants decreased toward zero during the load-shedding periods of the work day. Specifically, the prize pool ranged between €0 and €300. It equaled €300 if all participants had an energy consumption equal to zero during the load-shedding periods, i.e., if they all made the maximum possible effort. If their consumption was higher than zero, then the total energy consumption of all participants in all load-shedding periods were compared to a threshold of energy consumption calculated using optimal modeling.[10] In both treatments, the winner was the participant with the lowest energy consumption during the load-shedding periods. The two treatments are as follows:

- **Treatment C**: In the honorary contest, the winner chose an environmental NGO to whom to give the prize pool. She also saw her name publicly broadcast on the screens in the lobby of the building at the end of the experiment. It was indicated that she was the person who made the highest effort to participate in the inclusion of renewable energy.
- **Treatment T**: In the monetary tournament, the winner received %50 of the prize pool, and the other participants shared the other %50, which allowed $\%50/(n-1)$ of the prize pool for each participant (with $n$ being the number of participants).

The two competition incentives were based on two different types of motivation (Bénabou and Tirole, 2006). The honorary contest provided participants with social incentives and appealed to their self- and social-image, as well as their intrinsic motivation, which occurs when individuals are internally motivated to do something because it brings them pleasure, moral satisfaction or otherwise. The monetary tournament offered private incentives to increase participants extrinsic motivation, which occurs when external factors such as the environment, remuneration and working conditions intervene. We supposed that energy consumption would be lower during the load-shedding time periods of the two treatments than in time periods without load-shedding signals or incentives. Our field experiment tested this hypothesis.

*Timing* The experiment consisted of two treatments, with Treatment C occurring first and Treatment T occurring second and lasting from October 2, 2018, to January 25, 2019. Each treatment was composed of three phases: (i) an observation phase where energy consumption was registered for each participant, which ranged from October 2 to 7 in Treatment C and from December 3 to 9 in Treatment T; (ii) the use of load-shedding signals and incentives (honorary contest in Treatment C and monetary tournament in Treatment T), which ranged from October 8 to November 18 in Treatment C and from December 10 to January 10 in Treatment T, with a two-week break with no load-shedding periods occurring after two weeks of incentives due to school holidays; and finally, (iii) a second observation phase, which ranged from November 19 to December 2 in Treatment C and from January 21 to January 25 in Treatment T. Each treatment included one week of observations, two weeks with load-shedding signals and incentives, a two-week break, two weeks with load-shedding signals and incentives, and finally, either one week (Treatment T) or two weeks (Treatment C) of observations. No load-shedding period was planned during holidays.

In total, each treatment consisted of four working days with 45-min load-shedding periods during lunch and six working days with three 15-min erasure periods during the day, with each treatment occurring between 10:00 and 16:15. The working days with load-shedding periods occurred on the same week days and at the same time in both treatments. Table 1 summarizes the dates and times of load-shedding periods participated in by the respondents during Treatments C and T. We indicate the length of the load-shedding period, the day of the week, the beginning of the load-shedding period and the date.

[7] Despite the presence of 1500 sensors in the building, including 300 electrical sensors, individual data per workstation were only available in the Predis-MHI zone and not for the whole building.

[8] See Appendix C for recruitment details.

[9] The within-subjects design is particularly adapted when the size of the sample is limited. We can thus identify overall effects, although this method prevents a proper comparison of the two treatments because they are not implemented in strict similarity of time.

[10] From previous observations, we calculated that the usual consumption during a 7.5 h period would equal a consumption of 365 Wh per worker. Thus, if all the participants in the experiment consumed 365 Wh during the 7.5 h of the load-shedding time, the prize was 0. If the consumption was below this level, then the prize $P$ was awarded proportionally according to $P = \frac{x*300}{365*26}$, with $x$ being the sum of the consumption of all the participants during the load-shedding time.

**Table 1**
Date and hour of load-shedding periods in Treatments C and T.

| | Treatment C Honorary contest | Treatment T Monetary tournament |
|---|---|---|
| *45 min load-shedding period* | | |
| Tuesday - 12:00 | October, 9 | December, 11 |
| Thursday - 13:00 | October, 18 | December, 20 |
| Friday - 12:15 | November, 9 | January, 11 |
| Monday - 13:00 | November, 12 | January, 14 |
| *15 min load-shedding period* | | |
| Thursday - 11:45/14:15/16:00 | October, 11 | December, 13 |
| Friday - 10:15/14:00/15:30 | October, 12 | December, 14 |
| Tuesday - 11:15/14:15/15:30 | October, 16 | December, 18 |
| Tuesday - 10:15/11:15/14:00 | November, 6 | January, 8 |
| Thursday - 10:00/11:00/15:15 | November, 8 | January, 10 |
| Friday - 11:15/14:15/15:30 | November, 16 | January, 18 |

## 3 Results

### 3.1 Sample and observations

In total, 26 employees registered to participate in our experiment. Due to unexpected movement, we dropped six employees from our database, as their energy consumption remained very low at any period of time, meaning that their offices were not occupied.[11] This led us to have 20 participants in Treatment C. Six participants decided to stop the experiment after Treatment C, and two participants moved for professional reasons and did not participate in Treatment T.[12] We thus observed 12 participants in Treatment T. The prize pool was approximately €150 in Treatment C, which was calculated from a consumption of 4747.6 Wh, and was given to an environmental NGO. Considering the absence of prizes, no winner was announced in Treatment T because the overall consumption greatly exceeded the 365.0 W per hour per participant calculated for the load-shedding time.[13]

For data analysis, we considered as observations only days where the worker was at her office; we drop data for working days that have a consumption below 80 W, which corresponds to the minimum possible consumption for three hours a day. We also did not analyze either data from school holidays, because an important number of employees were also on holiday on such days, or data from the weekends, as these periods were not representative of standard week days.[14] To ease the reader's understanding, we present energy consumption as workers' power demand in watts.

### 3.2 Individual data investigation

Fig. 1 presents the consumption of all the workers during the whole period of the experiment. Every bar represents a working day, and every color represents a participant's power demand during this day. The two large blanks (end of October and end of December-beginning of January) correspond to the weeks of school holidays. Weekends are also indicated with blanks. We observe higher power demand in December and January than in October and November, and this difference seems mainly driven by the behavior of a few participants.

A further investigation of the data provided the information found in Table 2 that presents, for each treatment, differentiating load-shedding from no load-shedding periods and each participant's average power demand for 15-min intervals, as well as standard deviations and number of observations. The table emphasizes important heterogeneity in energy consumption behaviors. More specifically, it shows that three participants, namely, X10, X22, X24 (in dark blue, light pink and orange, respectively, in Fig. 1), exhibited the highest average power demand and were responsible for 56.6% of the consumption during Treatment T.[15] The most extreme energy consumption path is observed for Participant X24, who had an average power demand of 287.8 W in Treatment C and 283.8 W in Treatment T, which was approximately 9 times the "usual" average of other participants in treatment T (i.e., excluding participants identified as X22 and X10 in Treatment T). Participant X22 also presented extreme behavior, with an average power demand of 91.1 W in Treatment C and 93.9 W in Treatment T. Participant X10 exhibited extreme consumption in Treatment T with a power demand of 128.8 W but not in Treatment C, where her power demand was 22.3 W. For further analyses, we thus excluded Participants X24 and X22 for both treatments and Participant X10 for Treatment T.

### 3.3 Treatment effects

In addition to the heterogeneity of energy consumption behaviors, Table 2 also shows that several participants had a lower power demand during load-shedding periods than during no load-shedding periods in Treatment C. In Treatment T, among the participants registered in this treatment, some also had a lower energy consumption during load-shedding periods, but this number was lower than that in Treatment C (7 participants in Treatment C versus 2 participants in Treatment T). Thus, incentives for load-shedding periods given through either the honorary contest (Treatment C) or the monetary tournament (Treatment T) changed participants behaviors. We now investigate the aggregate effect of each type of incentives on the power demand of the participants.

Fig. 2a. and b. present the average power demand depending on whether load-shedding periods occurred during lunch time or during working time, respectively. In these figures, we separate not only load-shedding from no load-shedding periods but also treatments. Every color represents the power demand of a participant. We can observe a decrease in power demand during the load-shedding periods for both lunch time and working time in Treatment C but only during lunch time in Treatment T.

To deepen our analysis, we conducted a linear regression to explain individual power demand for each 15-min time interval depending on whether it was a load-shedding period and controlling for the month, the day of the week, the hour of the day and individual characteristics using a dummy for each participant.[16] Table 3 presents the results of the OLS estimations.

The regressions confirm that the incentives based on the honorary contest (Treatment C) decreased power demand during load-shedding periods. We found a significant decrease in power demand of approximately 3.2 W during the load-shedding periods in Treatment C. However, incentives based on the monetary tournament (Treatment T) were not found to significantly affect behavior. Hence, in Treatment C, the power demand decreased by 8.5% compared to the 38.5 W average power demand.

[11] The six employees identified as X14, X16, X17, X21, X23, and X26 had a total power demand below 1008 W during the whole experiment, meaning that they were almost never present.

[12] The employees identified as X1, X2, X6, X14, X15, and X25 wanted to stop after Treatment C, and the employees identified as X7 and X19 left their office.

[13] The consumption of one participant during 7.5 h was estimated to be 365.0 Wh. The total consumption in Treatment T was 7960.7 Wh, representing an average consumption of 442.3 Wh.

[14] The daily consumption was indeed, for most cases, below our threshold of 80 W during school holidays.

[15] Such a high power demand by these participants may be due to the use of an individual electrical heater. Indeed, during the experiment, we were informed that it was very cold in the building during winter months in some offices; thus, some workers brought individual electrical heaters to warm their offices.

[16] We pooled all the observations instead of conducting a panel analysis because this approach allowed us to consider only days where the worker was present. For robustness checks, we also conducted estimations with a classic panel analysis that led to similar qualitative results.

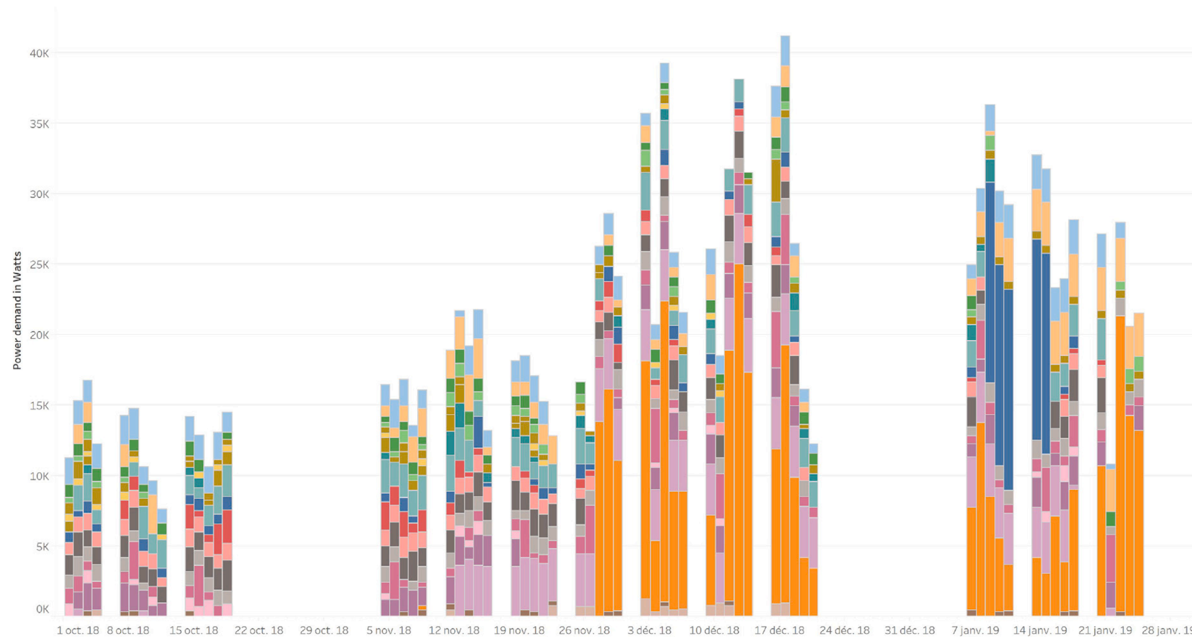
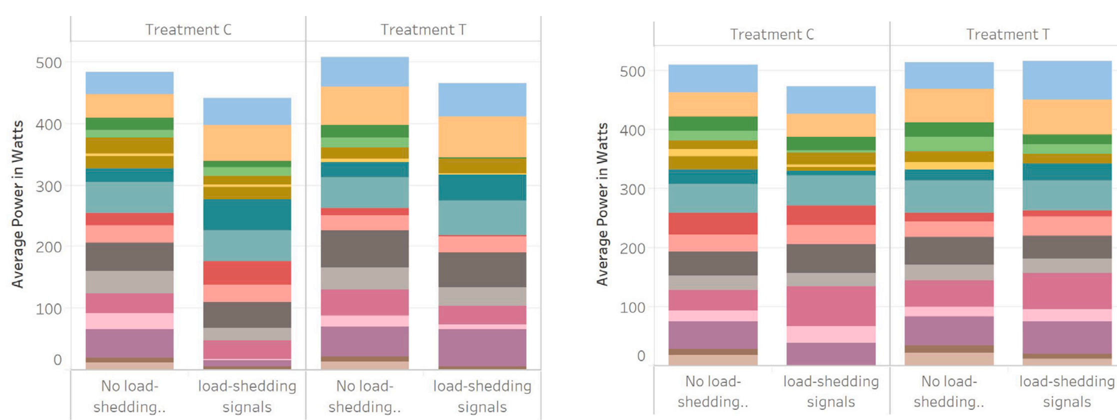



**Fig. 1.** Total power demand per day in watts. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)




a. During lunch time

b. During working time

**Fig. 2.** Average power demand by treatment for each 15-min interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

As previously mentioned, these results hide a wide range of behaviors regarding participants reactions to load-shedding signals. We can observe that no subject was able to successfully react to all load-shedding signals (see Figures D.1 and D.2 in the Appendix D that present, for both Treatments C and T, each participant's power demand for every load-shedding signal relative to their average power demand when there was no load-shedding signal).

## 4 Conclusion and policy implications

In this article, we have shown the scientific interest in studying flexibility by integrating users in the control loop. Indirect control by occupants is an important issue in diffuse flexibility when it is deployed on a large scale. On the one hand, the costs of equipment, installation and maintenance are considerably reduced compared to those of an automatic control system, and the potential for flexibility is extended to noncontrollable equipment. On the other hand, it is important to understand the incentive mechanisms that maximize the effectiveness of flexibility.

We have studied the effectiveness of two types of incentives, namely, an honorary contest and a monetary tournament, among a population of workers in the GreEn-Er tertiary building. Real-time monitoring was implemented with the centralized and redundant reporting of anonymous data. These data were processed and then automatically analyzed to produce indicators that defined the winners of the two treatments and indicators that allowed us to analyze efficiency in terms of the energy consumption of the proposed mechanisms. The results show that workers were able to react to load-shedding signals by lowering their power demand when honorary contest incentives were set up. Therefore, incentives lead to the flexibility of workers, provided that they respond to incentives. Indeed, the monetary tournament was found to not lead to a change in behaviors during the load-shedding periods.

Our study has some limitations. We first note that the external validity of the experiment is weak due to the limited number of

**Table 2**
Individual power demand for load-shedding and no load-shedding periods, by treatment.

| | No load-shedding Period | | | Load-shedding Period | | |
|---|---|---|---|---|---|---|
| | Mean | Sd | Obs. (/1230) | Mean | Sd | Obs. (/30) |
| *Treatment C* | | | | | | |
| X1 | 44.35 | 24.40 | 1052 | 45.65 | 23.57 | 27 |
| X2 | 41.41 | 28.39 | 738 | 46.26 | 28.00 | 18 |
| X3 | 22.14 | 13.32 | 911 | 17.69 | 14.12 | 24 |
| X4 | 16.21 | 14.71 | 707 | 9.59 | 12.98 | 12 |
| X5 | 17.10 | 19.62 | 953 | 15.35 | 11.97 | 18 |
| X6 | 11.48 | 8.61 | 524 | 4.51 | 7.09 | 15 |
| X7 | 20.98 | 18.21 | 563 | 16.98 | 15.00 | 12 |
| X8 | 22.05 | 24.33 | 459 | 22.06 | 24.54 | 9 |
| X9 | 50.18 | 33.96 | 1017 | 50.59 | 33.54 | 27 |
| X10 | 22.28 | 35.11 | 845 | 7.95 | 12.26 | 18 |
| X11 | 30.29 | 30.02 | 807 | 35.71 | 25.07 | 21 |
| X12 | 29.58 | 11.29 | 1157 | 30.22 | 9.91 | 30 |
| X13 | 42.02 | 26.57 | 1157 | 46.44 | 22.72 | 30 |
| X15 | 27.93 | 25.70 | 1055 | 21.54 | 15.32 | 24 |
| X18 | 31.03 | 26.38 | 986 | 43.96 | 31.95 | 21 |
| X19 | 20.39 | 19.69 | 458 | 15.81 | 22.75 | 9 |
| X20 | 43.91 | 27.13 | 696 | 27.64 | 26.34 | 24 |
| X22 | 91.08 | 34.62 | 573 | 102.40 | 0.00 | 3 |
| X24 | 287.75 | 484.66 | 141 | 34.93 | 3.40 | 3 |
| X25 | 10.44 | 6.41 | 459 | 5.80 | 7.80 | 9 |
| X26 | 16.74 | 17.85 | 177 | 0.60 | 0.00 | 3 |
| *Treatment T* | | | | | | |
| **X1** | 45.46 | 25.10 | 876 | 58.94 | 17.18 | 24 |
| **X2** | 57.04 | 32.50 | 843 | 63.28 | 25.36 | 21 |
| X3 | 22.54 | 14.29 | 456 | 8.59 | 13.07 | 12 |
| X4 | 20.69 | 14.39 | 393 | 14.80 | 0.00 | 3 |
| X5 | 18.18 | 34.36 | 873 | 20.48 | 24.40 | 27 |
| **X6** | 10.74 | 8.66 | 177 | 0.60 | 0.00 | 3 |
| X8 | 24.71 | 23.17 | 282 | 36.61 | 17.47 | 6 |
| X9 | 53.95 | 32.99 | 735 | 53.45 | 27.26 | 21 |
| X10 | 128.77 | 174.21 | 594 | 214.18 | 198.95 | 18 |
| X11 | 14.61 | 15.61 | 351 | 7.88 | 14.50 | 9 |
| X12 | 26.89 | 10.88 | 627 | 29.90 | 8.78 | 21 |
| X13 | 48.91 | 30.70 | 630 | 43.93 | 31.93 | 18 |
| **X15** | 29.83 | 26.10 | 1014 | 27.21 | 24.71 | 30 |
| X18 | 39.93 | 37.35 | 1014 | 46.38 | 42.90 | 30 |
| X20 | 48.74 | 23.98 | 771 | 56.85 | 18.89 | 21 |
| X22 | 93.94 | 29.40 | 942 | 93.53 | 31.51 | 30 |
| X24 | 283.76 | 472.78 | 981 | 707.84 | 616.47 | 27 |
| **X25** | 9.79 | 5.94 | 279 | 7.24 | 6.49 | 9 |
| X26 | 20.71 | 17.89 | 354 | 6.14 | 13.58 | 6 |

Note: Participants' numbers in bold are workers who participated in Treatment C but stopped afterwards and thus did not participate in Treatment T.

participants. Second, the results reflect workers' behaviors in a specific context in a specific place. Conclusions must thus be taken with caution. They call for further research on this topic as well both at a larger scale to improve the external validity of the results and in different places in various regions of the world with different cultures to provide more general results. The literature is very scarce at the moment, certainly due to the difficulty to organize such field experiments with individual monitoring of behaviors over time among a large number of workers. The results of our study showing that flexibility is possible among workers in the tertiary sector when incentives are correctly chosen, even given the limited control of workers regarding devices, encourage such efforts. Further experiments on this topic would allow to characterize the drivers and barriers to reducing workers' energy use at specific times of their workday in the tertiary sector such as testing various incentive schemes, either monetary or non-monetary based on moral or social motivations, controlling for the workers' preferences and their heterogeneity or varying the scope of the automated systems. Our experiment also provides a methodological framework and a first case study to guide future experiments at a larger scale. Finally, in our study, we faced the inherent difficulty of satisfying the heterogeneity of preferences with automated systems in new buildings such as the GreEn-ER building. The differences in energy consumption among the workers were immensely large, which illustrates the need to account for differences in human preferences in the design of automated systems.

**Table 3**
OLS regression of the power demand in watts for each 15-min interval.

| | *Dependent variable: Power demand in W* | |
|---|---|---|
| | Treatment C | Treatment T |
| Load-shedding Period | −3.214** | −1.337 |
| | (1.299) | (2.164) |
| Monday | 0.647 | 7.483*** |
| | (0.617) | (1.047) |
| Tuesday | 1.801*** | 11.335*** |
| | (0.615) | (1.126) |
| Wednesday | −1.600*** | 0.965 |
| | (0.612) | (1.130) |
| Friday | −2.167*** | 2.281** |
| | (0.630) | (1.149) |
| November | −0.034 | |
| | (0.405) | |
| December | | 0.992 |
| | | (0.725) |
| Constant | 38.576*** | 2.661 |
| | (1.002) | (1.907) |
| Observations | 14,892 | 6300 |
| $R^2$ | 0.211 | 0.237 |
| Adjusted $R^2$ | 0.209 | 0.234 |
| Residual Std. Error | 23.647 (df = 14,860) | 27.219 (df = 6276) |
| F Statistic | 127.815*** (df = 31; 14,860) | 84.603*** (df = 23; 6276) |

*Note:* *p < 0.1; **p < 0.05; ***p < 0.01.
Control for each participant and each hour of the day.

## CRediT authorship contribution statement

**Daniel Llerena:** Conceptualization, Methodology, Validation, Investigation, Supervision, Project administration, Funding acquisition. **Beatrice Roussillon:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Sabrina Teyssier:** Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing. **Adelaïde Fadhuile:** Formal analysis, Writing – review & editing, Visualization. **Penelope Buckley:** Resources. **Benoit Delinchant:** Conceptualization, Software, Resources, Data curation, Supervision. **Jérôme Ferrari:** Software, Investigation, Resources, Data curation, Writing – original draft. **Tiansi Laranjeira:** Software, Formal analysis, Resources, Data curation. **Frédéric Wurtz:** Project administration, Funding acquisition.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The authors do not have permission to share data.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.117992.

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