

# Save Money or Feel Cozy? A Field Experiment Evaluation of a Smart Thermostat that Learns Heating Preferences

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## ABSTRACT

We present the design of a fully autonomous smart thermostat that supports end-users in managing their heating preferences in a real-time pricing regime. The thermostat uses a machine learning algorithm to learn how a user wants to trade off *comfort* versus *cost*. We evaluate the thermostat in a field experiment in the UK involving 30 users over a period of 30 days. We make two main contributions. First, we study whether our smart thermostat enables end-users to handle real-time prices, and in particular, whether machine learning can help them. We find that the users trust the system and that they can successfully express their preferences; overall, the smart thermostat enables the users to manage their heating given real-time prices. Moreover, our machine learning-based thermostats outperform a baseline without machine learning in terms of usability. Second, we present a quantitative analysis of the users' economic behavior, including their reaction to price changes, their price sensitivity, and their comfort-cost trade-offs. We find a wide variety regarding the users' willingness to make trade-offs. But in aggregate, the users' settings enabled a large amount of demand response, reducing the average energy consumption during peak hours by 38%.

## Keywords

Sustainability; home heating; real-time prices; user interfaces; machine learning; field experiment.

## 1. INTRODUCTION

Over the last decade, we have witnessed a steadily increasing effort to realize a paradigm shift in the energy sector. The goal of this shift is to transform energy production from a centralized architecture of power plants that burn the ever dwindling amounts of fossil fuels to a distributed grid of renewable energy sources like wind and solar [30]. This transformation of the electricity grid is motivated by the need to combat the negative economic and sociological effects of climate change as well as by the fact that the production of many conventional oil and gas fields are decreasing.

Implementing such a distributed electricity grid poses a number of challenges due to the current structure of the grid and the volatility in the production of renewable energy. If the share of renewable energy sources keeps growing, maintaining the stability of the grid will become an increasingly challenging problem since the production level of renewables is very hard to control and therefore, matching supply and demand will become much more difficult [11].

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## 1.1 Managing the Demand for Energy

To solve the problem of grid stability, it will be critical to also *manage the demand side* by incentivizing consumers to adapt their consumption levels to the amount of energy available in the grid [20]. One way to encourage consumers to decrease their demand when energy is scarce is via financial incentives [3]. A particular financial mechanism that has been put forward is *real-time pricing*, where the price of electricity varies across the day according to market forces. Real-time pricing has a number of advantages over flat pricing. First, economists argue that real-time pricing improves system reliability and mitigates market power in the long term [6]. Second, it offers consumers the opportunity to save significant amounts of money if they are willing to dynamically adjust their consumption [12]. A number of power companies in the US and Europe have successfully conducted pilot studies, to assess the potential benefits and the feasibility of using real-time pricing for *residential end-users* (see e.g., [13, 14, 15, 29]). Some power companies already offer real-time pricing programs to their end-users.<sup>1</sup>

While energy plays a large role in many domains, residential heating is one of the major drivers of energy consumption, accounting for approximately 45% and 62% of the total household energy consumption in the US and the UK, respectively, which amounts to 10% and 18% of the respective country's total energy consumption [19, 31]. With the goal in mind to move away from fossil fuels, the electrification of heating using heat pumps is seen as a key technology for achieving a society that is more sustainable. Indeed, many low-carbon scenarios assume that in the future, a majority of houses will be heated by heat pumps (see, e.g., [9]). These reasons make home heating a formidable case study to explore the potential for demand-side management with real-time electricity prices.

## 1.2 Home Heating with Smart Thermostats

In this paper, we envision a future electricity grid where a substantial number of private homes are heated by heat pumps and at least some end-users are exposed to real-time prices. Obviously, this poses multiple challenges for the design of a usable heating system.

First, it is not feasible for end-users to constantly monitor the energy price and manually adjust their thermostat whenever prices change. Thus, we need an autonomous agent, which we call the *smart thermostat*, that *automatically* reacts to price changes on the user's behalf. Second, before the smart thermostat can make these decisions autonomously, it needs to know how the user wants to trade off *comfort* (heating to a particular temperature) versus *cost* (for heating to that temperature) at different price levels. Some users might be willing to spend a lot of money to have their home always heated to a comfortable temperature, while others may want

<sup>1</sup>E.g., Commonwealth Edison's "Residential Real-time Pricing Program": <https://rrtp.comed.com/>

to decrease their temperature if energy becomes too expensive. This means that to achieve high *economic efficiency*, it must be possible to personalize the smart thermostat to individual users. However, manually specifying how to trade off comfort and cost at all price levels might lead to high *cognitive costs* on the user’s side.

Obviously, there is a tension between economic efficiency on the one hand high cognitive costs on the other hand. To address this tension, we turn to the *hidden market design* paradigm introduced by Seuken et al. [24], who argued that it is often necessary to *hide* some of the market’s complexity from the end-users. They showed that a hidden market UI can reduce the interaction complexity for the end-users, while still maintaining the loop between the market and the users [25]. In our domain, we instantiate the hidden market design paradigm by designing a smart thermostat that elicits the user’s trade-off between comfort and cost over time while keeping the user’s input at a minimum. To realize this, we build on prior work by Shann and Seuken [26] who proposed a *machine learning algorithm* to solve this exact problem. However, their work was purely theoretical. In particular, they did not design any UIs or a real system. In this research project, we expand on this theoretical work by designing a real-world application of a smart thermostat that supports users in managing their heating preferences in a real-time pricing regime. We deployed this smart thermostat in 30 homes in the UK and ran a 30-day field experiment from February to March 2015 to explore how people interact with such a system.

### 1.3 Overview of Contributions

We make two main contributions. First, we study whether our smart thermostats can *enable* end-users to successfully handle real-time prices in the home heating domain – in particular, whether using machine learning can *improve the usability* of the thermostat. Our results show that the majority of our users were satisfied with the smart thermostats, and trusted them to automatically adjust the temperature for them. More importantly, the data shows that the machine learning algorithm increased the usability of the system, compared to a baseline implementation that uses no learning.

Second, we present a detailed quantitative analysis of the *economic behavior* of our 30 participants when exposed to real-time pricing. Our results show that the users react to price changes in an economically rational way, and on average, they are willing to decrease their indoor temperature by 3 °C when energy is most expensive. Fortunately, due to the thermal inertia of the homes, the indoor temperature does not decrease by more than 1 °C, even during peak price hours. Still, this price-sensitive behavior leads to a large amount of demand response, reducing the average energy consumption by 38% during peak hours.

## 2. RELATED WORK

**Automated Control in the Smart Grid.** Yang et al. [32] examined the real-world uptake of a smart thermostat with 23 participants. They highlighted how sub-optimal decisions taken by a smart thermostat are likely to cause user frustrations and may lead them to abandon the technology. Bourgeois et al. [8] deployed energy-aware washing machines in 18 households and found that sending suggestions on when to do the laundry via text messages is more effective than other interventions. Costanza et al. [10] conducted a field experiment with 10 participants that used “Agent B,” an agent that helps users book their washing machine given real-time prices. Their results indicate that users are willing to shift their washing in response to real-time prices. Alan et al. [1] tested “Tariff Agent,” an agent that helps users select electricity tariffs on a daily basis, in a field experiment with 10 users. The results show that people are willing to delegate decisions regarding energy consumption to an agent.

Our study differs from the above studies in two key ways. First, our system is *fully autonomous*, i.e., it takes decisions on the users’ behalf instead of just giving advice to the users. Second, the system’s decisions have a direct impact on users’ well-being via the temperature it sets in the respective homes, while previous systems only affected the study participants’ financial rewards.

In our own prior work [2], we already analyzed the exit interviews with the 30 participants of our field experiment from an HCI perspective. Via thematic analysis (qualitative text analysis of the interviews), we studied what kinds of understandings and expectations the participants formed regarding the thermostat. One striking finding was that the participants developed very different mental models regarding how the thermostats were functioning. The present paper is based on the same field experiment; however, we answer different research questions, and we use different data (mostly quantitative data gathered from the users’ interactions with the system).

**Hidden Market Design.** Seuken et al. [24] argued that for many of the new, complex markets that are emerging to be successful (like the smart grid market), it is a necessity to “hide” some of the market’s complexities from the end-users. They proposed the design of a “hidden market user interface (UI)” that makes the interaction with the market more seamless, such that even non-sophisticated users can easily participate in it [25]. To this end, the UI needs to *hide* or reduce some of the interaction complexity for the user. One way to achieve this goal is to design a *learning agent* that operates in the background and mediates between the user and the market. The goal of implementing this agent is to reduce the cognitive costs for the user, while still keeping the important feedback loop between the user and the market that is needed for economic efficiency. In [23], Seuken et al. presented a case study on how to apply hidden market design to the design of a peer-to-peer backup market, demonstrating that it is possible to hide a significant amount of complexity from the end-user, while still keeping the important user–market loop. In [24], Seuken et al. already suggested the smart grid domain as a suitable application area for hidden market design.

**Home Heating.** One approach aimed at energy-efficient heating is to predict future environmental conditions (e.g., weather) to optimize the heating process. The state-of-the-art method used in the control community is *model predictive control* [17, 18]. In contrast, Shann and Seuken [27] used MDPs to compute a sequentially optimal heating policy given uncertainty about future weather conditions and future electricity prices. An orthogonal approach is to develop algorithms that try to sense and predict the occupancy of the house with the goal of reducing the inside temperature when people are not at home. For example, Scott et al. [22] use motion sensing and machine learning to find patterns in user behavior to heat adaptively. A similar approach is taken by Lu et al. [16]. These approaches are all complementary to the approach taken in this paper and could, in principle, also be included in our thermostat.

Occupancy detection has also been applied in commercial thermostats. For example, the Nest thermostat has a motion sensor that detects people’s presence.<sup>2</sup> It learns a heating schedule that conforms to its users’ habits. Recently, Nest has started a voluntary demand response program called “Rush Hour Rewards” that remotely controls the air conditioner during peak hours.<sup>3</sup> However, in contrast to our smart thermostat, the Nest thermostat does not learn an individual user’s trade-off between comfort and cost.

<sup>2</sup><https://nest.com>

<sup>3</sup><https://nest.com/support/article/What-is-Rush-Hour-Rewards>

### The Underlying Machine Learning Algorithm.

We now briefly describe the learning algorithm introduced by Shann and Seuken [26], as this is the algorithm that we implemented in our smart thermostats. The main components are the *user model*, the *update rule* and the *heating rule*.

**User Model.** The user’s heating preferences are modeled with a *utility function* that quantifies a particular user’s trade-off between comfort and cost of heating. Shann and Seuken [26] provide a formula to measure how much utility a user has for a certain indoor temperature at any given price of energy. This utility is composed of a *value* for the indoor temperature minus the *cost* of heating to this temperature. Using this utility function, they derive an individual user’s *optimal indoor temperature* at a given price  $p$ , which is:

$$T^{opt}(p) = T^* - mp, \quad (1)$$

where  $T^*$  is the user’s *most preferred temperature* if energy was for free, and  $m > 0$  is the user’s *sensitivity* to price. Thus, the optimal temperature equation is a weakly decreasing straight line that is defined by the two parameters  $T^*$  and  $m$ , whose values depend on an individual user’s preferences. The linearity of the optimal temperature line follows directly from the assumption of a quadratic loss function regarding the user’s preferences (see [26]). This simplifies the model, but is not essential for the system.

Note that the user model assumes that a user behaves in an *economically rational* way upon price changes, i.e., when the price increases then the user is assumed to weakly reduce his temperature. Of course, many different models are plausible to capture a user’s trade-off between comfort and cost. For our field experiment, we purposefully chose this relatively simple model, such that the corresponding learning algorithm is robust, and the UI design task (see Section 3.1) was manageable. More sophisticated user models (e.g., [5]) and corresponding learning algorithms could be incorporated into our system, but this is beyond the scope of this paper.

**Update Rule.** Every time the user changes the setpoint on the thermostat, the algorithm updates its knowledge of the user’s preferences. Implicitly, the algorithm assumes that the user solves an optimization problem (how to trade off comfort and cost) when changing the setpoint. To update its knowledge of the user’s optimal temperature line (Equation (1)), the learning algorithm uses *Bayesian inference*. The algorithm starts with some prior and treats every new setpoint as *noisy input*, which it uses to compute the *posterior probability* of the optimal temperature. Every time step, it computes the currently optimal temperature  $\hat{T}_{opt}(p_t)$  using the maximum a posteriori estimates of  $T^*$  and  $m$ . See [26] for details.

**Heating Rule.** The smart thermostat heats the house in the following way. At every time step  $t$ , it sets the setpoint to the estimated optimal temperature for the current price according to the current estimates of the most preferred temperature and the sensitivity:

$$\hat{T}_{opt}(p) = \hat{T}^* - \hat{m}p. \quad (2)$$

## 3. SYSTEM DESIGN

Figure 1 shows a schematic overview of our system. It consists of the following components: a *Horstmann thermostat*, which is a standard programmable thermostat that can be controlled wirelessly via the z-wave radio protocol; a *Raspberry Pi*, which is a pocket-sized computer on which a z-wave software transceiver is installed that enables communication between the Raspberry Pi and the Horstmann thermostat; a *web application*, which the user can use to remote-control the smart thermostat; and a *web server*.

While the Raspberry Pi controls the setpoint of the Horstmann thermostat, it also receives data regarding the current indoor temperature from the Horstmann thermostat. These two components are

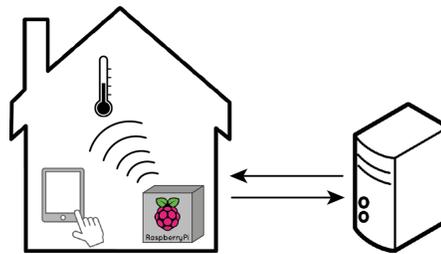


Figure 1: Schematic overview of our smart heating system

installed in a user’s home. The Raspberry Pi periodically connects to the web server to pull the latest schedule on how to heat the house for the next several days (based on a particular user’s settings). With every pull request, it also sends along the current indoor temperature of the house, which is then stored in a database on the web server. As part of the deployment, users are given a tablet running the web application, which they can use to remote-control the smart thermostat (see Figure 2); alternatively, the users can use any other device with a web browser. In either case, the data for the web application is served by the web server, from which the application also receives the current real-time prices every 30 minutes.

### 3.1 Design Challenges

The main challenge in designing the UI of the smart thermostat is the inherent tension between the user input and the machine learning output. The learning algorithm assumes the user input (i.e., the setpoint changes) to be *noisy* data. Thus, when the user changes the temperature, the algorithm will update the parameters of the utility function. However, the *optimal temperature according to the model* might be a different value than what the user just provided.

For example, assume the current price is 20 pence/kWh, and the current optimal setpoint according to the user model is 18.5 °C. Assume the user changes the setpoint to 20 °C, and the learning algorithm does a Bayesian update and concludes that the new optimal temperature (based on all previous inputs) is 19 °C. The design challenge is apparent: if the user sets the setpoint to 20 °C, but the system heats to 19 °C instead, then the user will not be satisfied.

We use two different interaction paradigms to reconcile the user input with the machine learning output. The first paradigm is based on *direct manipulation*, exposing the user more directly to how the algorithm is working. The second paradigm lets the user only *indirectly* interact with the learning algorithm. Based on these two interaction modes we designed two UIs, which we call “*learning direct*” and “*learning indirect*”. In addition to these two learning thermostats, we designed a third UI *without machine learning*. In this UI, the user has to manually configure his optimal temperature line. This UI, which we call “*manual*”, served as the control group.

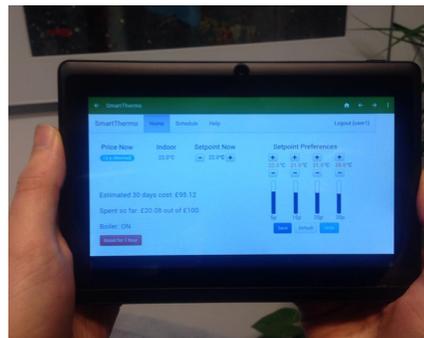


Figure 2: The smart thermostat application running on a tablet

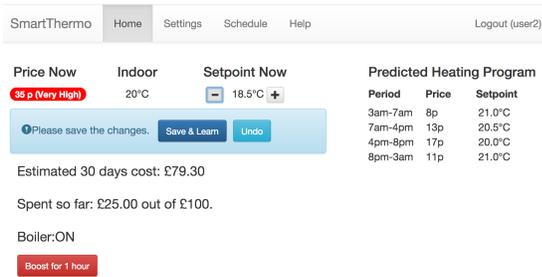


Figure 3: Home page of the “Learning Direct” thermostat

## 3.2 The UIs of the Three Thermostats

We first give an overview of the UI elements that are shared by all three versions. For this, consider Figure 3, which shows the home page of the learning direct UI. The page shows the current indoor temperature as well as the setpoint for the current price. The setpoint can be changed by pressing the  $+/-$  buttons next to it. The price is color coded (with corresponding labels *normal*, *high*, *very high*) to give the user some intuitive feel for the current price level.

Importantly, we also show the user his *Estimated 30 days cost*, i.e., an estimate how high his heating bill will be, given his current settings. By exploring the financial consequences of different settings, the user can decide how to trade off *comfort* (a warm house) versus *cost* (the monthly heating bill). To compute an estimate of the 30-day costs, we use a simple thermal model of the user’s home (see Section 4.1), as well as predictions of the energy prices and the outdoor temperature for the next 30 days. Finally, we also show the user how much of his heating budget he has already spent.

### 3.2.1 Learning Direct UI

The distinctive feature of the learning direct UI is the fact that *the setpoint that is displayed is always the learned setpoint by the thermostat*. Thus, the semantics of the  $+/-$  buttons changes over time. Assume that the current setpoint is 18.5 °C. If the user now presses the warmer button once, the algorithm will take 19 °C as input and do a Bayesian update, resulting in a learned optimal setpoint of 18.7 °C, which is then rounded to 18.5 °C (the granularity is in steps of 0.5 °C). Thus, the user does not see any change in the setpoint. However, if he presses a second time, the algorithm will take 19.5 °C as input and the learned optimal setpoint increases to 18.9 °C, which will then result in a setpoint change to 19 °C. Thus, in this hypothetical example, the user had to press the  $+$  button twice to increase the setpoint from 18.5 to 19 °C.

### 3.2.2 Learning Indirect UI

Figure 5 shows the home page of the learning indirect UI. In this UI, the user is less directly exposed to the machine learning algorithm. The interaction mode for changing the setpoint is as follows. The temperature the user inputs *temporarily overrides* the



Figure 4: Home page of the “Manual” thermostat

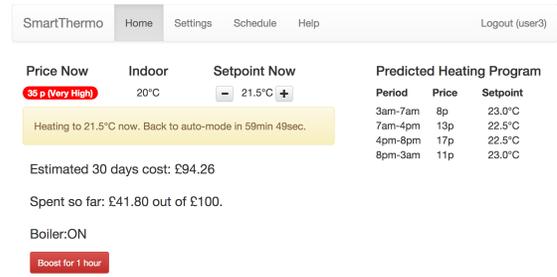


Figure 5: Home page of the “Learning Indirect” thermostat

optimal temperature the algorithm would set. For example, when the user sets the temperature to 20 °C, the thermostat will heat to this exact temperature *for one hour*. In the background, it takes the 20 °C as a new learning input and performs a Bayesian update. After one hour, the thermostat switches to the temperature that will be optimal (according to its new user model) at the then current price.

### 3.2.3 Manual UI

Figure 4 shows the home page of the manual thermostat. In contrast to the two learning UIs, here the user has to manually specify how the temperature should be set at different prices. He can do this using the *four sliders* on the right side of the UI. The sliders represent the temperature setpoints at 5, 15, 25, and 35 pence/kWh (which covers the whole price range). To maximize the comparability of the manual thermostat with the two learning thermostats, the sliders were constrained to always form a *straight line*, to adhere to the user model underlying the learning algorithm. Thus, if the user changes the setpoint at any slider, the other sliders change their values as well to conform to the linear model.

### 3.2.4 Settings Page

The settings page (not shown) is an additional screen that is only provided to users of the two learning thermostats. Here, they can review and manage their learned setpoint preferences. The motivation for this screen is to provide an additional level of control for users who are either not satisfied with the price–temperature mapping the thermostat has learned, or who prefer not to interact with the machine learning algorithm. The settings are displayed in the form of four sliders in the same way as on the home page of the manual UI (showing the price–temperature mapping). The user can manually change the temperature on each of the four sliders, and the slider functionality is the same as for the manual UI.

### 3.2.5 Schedule Page

Our smart thermostat also offers a *schedule page* (see Figure 6) that allows the user to program the heating times of the boiler based on hourly time slots. Here, the user also sees how choosing a particular schedule impacts his estimated 30-days heating cost.

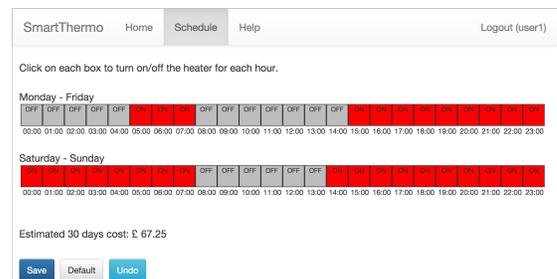


Figure 6: The schedule page

## 4. EVALUATION

To evaluate our thermostats, we conducted a *field experiment*. We recruited 30 participants living in England who used the system in their homes for 30 days from February to March 2015. The participants came from diverse backgrounds, had an average age of 50, and had no prior experience with smart thermostats (see [2] for detailed demographics). We randomly assigned the participants to two *treatment groups* and one *control group*, each with 10 participants. The treatment groups used the learning direct and the learning indirect UI, respectively; the control group used the manual UI.

### 4.1 Deployment & Incentives

The whole field experiment was divided into a 7-day *data collection phase* and a 30-day *experimental phase*. In a first step, an experimenter went to the users' homes and installed the Horstmann thermostat and the Raspberry Pi. This was followed by the 7-day data collection phase in which we let the users heat their homes normally and recorded their indoor temperature as collected by the Horstmann thermostat. This phase was necessary to personalize the software to each user. In particular, the temperature recordings allowed us to fit the parameter values of the thermal model to each individual home. This served two purposes: first, it created more realism in the study as the predicted heating costs would more closely match the actual costs. Second, it allowed us to create financial incentives tailored to each user (which we will describe shortly).

After the data collection phase, an experimenter visited the users' homes a second time. He instructed the users on how to use the web application using the tablet that was provided (or with any other device running a web browser). Then the actual study with a length of 30 days started. Going forward, every evening, the users were sent a text message to remind them of their current heating budget, their current setpoint, and the current energy price.

**Incentives.** To create realistic financial incentives, we endowed every participant with a heating budget of £100.<sup>4</sup> We explained to them that they would take part in a *virtual market* for heating in which energy prices change every 30 minutes. We explained that, every day, the heating costs in the virtual market would be subtracted from their virtual heating budget, and at the end of the study, they could keep whatever budget they had left as an experimental reward. Note that it was necessary to simulate the heating costs in a virtual market since nowadays, end-users in the UK do not yet face dynamically changing electricity prices.

**Calculating Heating Costs.** The calculation of the estimated heating costs was personalized for every user as follows. After the data collection phase, we computed a best fit of the parameters for the thermal model (i.e., leakage rate  $\lambda$  and heater output  $r_h$ ; see [21]) to the data collected for every user. Furthermore, based on the recorded heating data, we estimated their preferred temperature  $T_{prior}^*$ . Finally, we took into account the predictions of the energy prices and the outdoor temperature for the remaining days of the experiment. Given all of this, we then calibrated the heating costs such that heating constantly to  $(T_{prior}^* + 1)^\circ C$  for the whole month would cost the user £80. Thus, even if the user increased his average setpoint by  $1^\circ C$  during the experimental phase (and otherwise heated as before), he could still get a £20 reward. Of course, if the user changed his settings, his estimated heating costs changed accordingly. To ultimately calculate the *true* heating costs, we used the same formula, and simply assumed that the heater was on at time  $t$  if the recorded temperature was below the current setpoint, and off

<sup>4</sup>This corresponds approximately to the amount of money an average UK households spends on *total energy* per month: [https://www.gov.uk/government/uploads/system/uploads/attachment\\_data/file/487650/table\\_262.xls](https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/487650/table_262.xls)

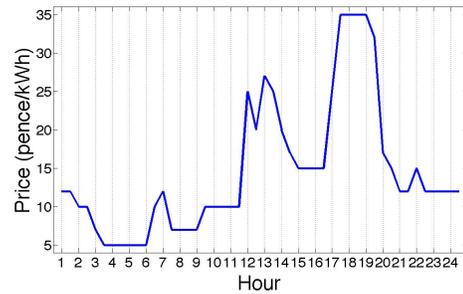


Figure 7: Prices on a sample day

when the recorded temperature was above the current setpoint. Note that we employed this indirect way to determine when the boiler was on because our system did not have direct access to the boiler.

### 4.2 Prices

To add realism, the prices the users encountered during the study were taken from the UK electricity spot market, dating from January 1 to January 30, 2014.<sup>5</sup> We normalized the prices to range from 5 pence to 35 pence (removing extreme outliers), which resulted in an average price of 12 pence/kWh. The price points are half hourly so that also in the study, prices changed every 30 minutes.<sup>6</sup> While the calculation of the heating cost was personalized to every user, the prices were the same for all users. A *sample* price profile is shown in Figure 7. The prices are low during the night and increase to about the average price level between 8 am and 4 pm. A roughly two-hour long price peak is found between 4 pm and 8 pm, where the price increases around three times compared to the base price. Overall, the price data shows enough variation (intra-day, intra-week, as well as between weekdays and weekends) that we expected the users to face challenging decisions regarding their heating during the study.

### 4.3 Data Collection

During the study, we gathered both quantitative and qualitative data. We recorded the actual indoor temperature as well as the setpoints every five minutes. In addition to that, we logged all of the users' interactions with the web UI. After the study, we conducted semi-structured interviews with the users. Furthermore, the users filled out a questionnaire with six Likert-scale questions that asked the users to indicate their agreement with a selection of statements on a scale from 1 ("Strongly disagree") to 7 ("Strongly agree").

We analyzed the data in two ways. First, we considered all 30 users. Second, we excluded all users that had fewer than 5 setpoint changes on the home page, leaving us with 21 users (6 in the indirect group, 7 in the direct group, and 8 in the manual group). We call the remaining 21 users the "*active*" users. Whenever it makes sense, we report the results for all users as well as the active users.

## 5. RESULTS

We now discuss our findings based on the quantitative and qualitative data we collected during the experiment.

### 5.1 User Experience Analysis

In this section, we first study the user experience of our participants. We ask the following three questions: (1) Did the smart thermostat enable the end-users to handle real-time prices? (2) Did the machine learning algorithm improve the usability of the system? (3) Which of the two learning-based user interfaces worked better?

<sup>5</sup><https://www.bmreports.com/>

<sup>6</sup>We initialized the study in such a way that the day of the week the prices were taken from corresponded to the day of the week during the study. For example, January 1, 2014 was a Monday; thus, the users saw the prices from this day on a Monday as well.

**Overall Satisfaction.** Analyzing the interaction logs revealed that all but 3 users interacted with the system at least up to the last week of the study, demonstrating a good level of engagement. The majority of the users seemed relatively happy to delegate control over their heating system to an autonomous system. This is reflected by the average agreement of 5.2 with the sentence: “I trust the thermostat to set the right temperature for me.” Users felt in control of their heating and were confident that the system worked correctly. Furthermore, most users seemed satisfied regarding how well they could communicate their heating preferences to the smart thermostat, given the average agreement of 5.4 with the statement “The smart thermostat enables me to express my preferences regarding how to trade off comfort and cost.” Overall, the data supports our finding that the smart thermostat achieved its primary goal – to enable users to successfully handle real-time prices. Note that for five out of the six Likert-scale questions, we did not find a statistically significant difference between the three user groups. The only statistically significant result we found was regarding the usability of the system, as we will discuss in the next paragraph.

**Usability.** We now analyze whether using a machine learning algorithm had a positive effect on usability. Towards this end, we compare the two learning UIs with the manual UI (the control group) regarding the users’ average agreement with the statement “The smart thermostat was easy to use.” For all 30 users, the averages are 4.9 for learning direct, 5.7 for learning indirect, and 4.0 for manual. A one-way ANOVA finds no significant differences between the three groups ( $p = 0.14$ ). However, for the restricted set of active users, the values are 5.5 for direct, 6.2 for indirect, and 3.3 for manual, and here an ANOVA finds a significant difference between the three groups ( $p = 0.01$ ). Post-hoc comparisons using the Tukey test show that *both learning UIs were rated significantly easier to use than the manual UI*. This supports our original idea of using hidden market design, and in particular to use machine learning, to simplify the interaction with the thermostat.

**Comparison of the two Learning UIs.** After having seen that the learning feature had a positive effect on the usability, we now compare the two learning UIs and discuss which learning UI was more successful at mediating between the user and the machine learning algorithm (there was no statistically significant difference regarding the users’ usability rating of the two UIs). It is important to understand that the two UIs use very different interaction paradigms. Recall that the indirect learning UI temporarily overrides the machine learning output with the user’s current setpoint input. This way, the user can easily set the setpoint to any desired temperature - however, after one hour, the setpoint will go back to the learned temperature. In contrast, the direct learning UI always uses and displays the learned setpoint. At the beginning, this may lead to a more “immediate” interaction between the user and the thermostat, because there are not two different temperatures, like with the indirect learning UI. However, after many setpoint inputs have been collected, the learning algorithm starts to converge to a particular setpoint - a natural consequence of the Bayesian updating algorithm. At that time, the  $+/-$  buttons on the home page become less reactive. Eventually, if a user provides many inputs (e.g., more than 10), he might need to press the  $+/-$  buttons many times until the setpoint changes by 0.5 °C. This might be a source of user frustration. Given this, our hypothesis is that the learning indirect UI was more successful at mediating between the user and the learning algorithm than the learning direct UI. In the following, we present two findings that support this hypothesis.

The first piece of evidence concerns the use of the learning feature. Recall that users of the two learning UIs had two options to change their setpoint preferences: either change the setpoint on the

home page, which triggers a Bayesian update, or manually manipulate the sliders on the settings page. Our intention was that people would mostly use the home page to change the setpoint, and only users not satisfied with the learned settings would go to the settings page. To analyze the relative frequency of each setpoint change method, for each user, we measure the ratio  $N_{home}/N_{settings}$ , where  $N_{home}$  is the total number of setpoint changes on the home page, and  $N_{settings}$  is the total number of setpoint changes on the settings page. We remove those users that had zero interactions on the settings page because it would result in a division by zero (two users in each group). Then, the average ratio is 2.6 for learning direct, and 12.9 for learning indirect. A two-sided t-test shows that this difference is statistically significant ( $p = 0.02$ ). Thus, the users of the indirect group used the learning feature much more than the preference changes on the settings page, compared to the users of the direct group.

The second piece of evidence comes from the user interviews. There are at least two users in the direct learning group who complained about the thermostat not changing the setpoint when pressing the  $+/-$  buttons:

P3: “[...] trying to turn the temperature down. Sometimes you’d go down, down, down, down, down, and it doesn’t register. And you’re going, I pressed down. I pressed down. [...] Wow it needs four presses per half degree or something. [...] So, that was a little bit frustrating [...]”

P10: “It [the thermostat] was more... temperamental. You know you press it sometimes it didn’t work”

Summarizing, we state the three main findings of this section. First, users were happy to delegate control over their heating to an autonomous system, which enabled them to successfully handle real-time prices. Second, the learning UIs were rated significantly easier to use than the manual UI, which confirms our hypothesis that hidden market design principles are a valuable tool to design smart grid applications. Third, we presented some evidence that the learning indirect UI was the more successful of the two learning UIs, since it was used as intended and led to a smoother user experience. However, regarding the third point: more research is needed to investigate the optimal design of user interfaces that can effectively mediate between end-users and machine learning algorithms.

## 5.2 Economic Behavior Analysis

In this section, we discuss our results related to the question how real-time pricing affected the users’ economic decision making. In particular, we answer four questions: (1) How did users react to prices changes? (2) Were they willing to reduce their comfort to save money? (3) How much money could they save, and what is the impact of their settings on their comfort? (4) Can we induce a significant amount of demand response during peak hours?

### 5.2.1 How Do Users React to Price Changes?

Recall that the user model underlying the learning algorithm assumes that people will react to price changes in an “economically rational” way, i.e., when the price increases they will weakly decrease (but not increase) their temperature. Using the real behavior observed in our study, we wanted to verify whether this assumption was ever violated – essentially a sanity check on the model underlying the learning algorithm.

To this end, we analyzed all of the users’ setpoint inputs they provided to the system during the study. Each of these data points is a pair  $(p, T^{set})$ , where  $p$  is the price at which the setpoint  $T^{set}$  was saved. We performed the following analysis: given all inputs of

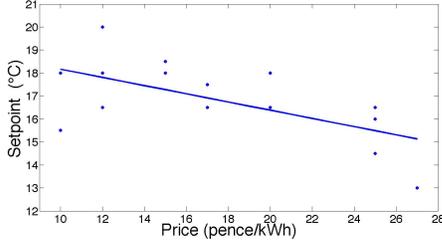


Figure 8: Example setpoint inputs from one particular user, together with best linear fit from linear regression

a user, we ran a linear regression to check for a linear trend in the temperature adjustments. Figure 8 shows an example setpoint cloud from a rational user (each point is a setpoint provided by the user), together with the fitted regression line.

Table 1 summarizes the results of this regression analysis. For 6 out of all 30 users, we find a statistically significant negative slope ( $p < 0.05$ ), which means that their inputs confirm our assumption that people will reduce the temperature if the price increases. For the remaining 24 users, we find slopes that are not statistically significantly different from 0, and thus these users neither confirm nor violate the assumptions of the model (note that the relatively large number of statistically insignificant slopes is largely due to the fact that most users did not provide enough setpoint inputs for the regression to generate statistically significant results). Summarizing, there was no user that violated the rationality assumption of our model, whereas 6 users adjusted the setpoints in a way as predicted by the model. Of course, this does not show that all users acted fully rationally. But it provides us with a certain level of confidence that, at least on average, the basic assumption underlying our model (i.e., that users make trade-offs between comfort and costs) seems reasonable and that our experiment design thus makes sense.

Slope	Direct	Indirect	Manual	Total
Negative ( $p < 0.05$ )	0	3	3	6
Flat	10	7	7	24
Positive ( $p < 0.05$ )	0	0	0	0
Total	10	10	10	30

Table 1: “Rationality” Analysis

### 5.2.2 User Preferences

In the previous section, we have analyzed the *stream* of individual setpoint inputs at different prices and at different points in time. In contrast, we now look at the resulting *slope* of the users’ optimal temperature lines (whether learned or set manually) at the end of the 30 days, since this slope indicates by how much the users were willing to reduce their temperature when prices were high.

Table 2 shows the users’ average slopes; once for all users, and once for all active users, separated by the three groups. None of the differences between the averages are statistically significant. However, the variance of the slopes between the users is noteworthy, varying between -0.31 and 0, which demonstrates the large heterogeneity in the users’ preferences.

Slope of $T^{opt}$	Direct	Indirect	Manual	min/avg/max
All users	-0.11	-0.09	-0.1	-0.31 / -0.1 / 0
Active users	-0.06	-0.11	-0.09	-0.23 / -0.09 / 0

Table 2: The slopes of the optimal temperature lines

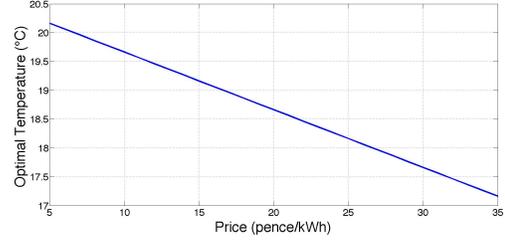


Figure 9: Average optimal temperature line

To visualize what these slopes mean, Figure 9 shows the optimal temperature line for an *average user* with slope  $m = -0.1$ . The x-axis denotes the price, while the y-axis denotes the optimal temperature. On average, the users’ optimal setpoint at 5 pence/kWh was 20.1 °C, and (on average) they were willing to reduce their setpoint to 17.1 °C at 35 pence/kWh, which is a reduction of 3 °C during the price peak. Compare this to the most price-sensitive user, who had a slope of  $m = -0.31$ . Thus, he was willing to reduce his temperature by 9.3 °C during the price peak. Note, however, that this particular user had a very high “most preferred temperature” of  $T^* = 26.5$  °C. Thus, when prices were low, he was heating to a very high setpoint, but when prices were high, then this user was willing to radically reduce his temperature – in theory to 17.2 °C.

However, as we will discuss in the next section, even though some users had a very large *willingness* to reduce their temperature when prices were high, the actual temperature drop during price peaks was much smaller, due to the thermal inertia of most homes.

### 5.2.3 Comfort-Cost Trade-off

We have seen that, on average, the users’ thermostat settings suggest that they were willing to sacrifice some of their thermal comfort to save some money. The questions that follow from this observation are: how much money did they actually save, and how did their settings actually influence the temperature in their homes?

**Cost Analysis.** Table 3 summarizes the total cost data. On average, the users’ heating costs (over 30 days) were £47. Thus, at the end of the study, they had an average of £53 left from the £100 heating budget. While the learning indirect group had lower costs than the other two groups, this difference is not statistically significant ( $p = 0.06$ ). The most likely explanation for this difference is a difference in the heating schedules. The learning indirect users heated least (6.4 hours per day on average, weighted over work days and weekends), while the learning direct and the manual users heated more (9.3 and 9.2 hours per day, respectively). Note, however, that this difference is also not statistically significant ( $p = 0.17$ ), but still big enough to have an observable impact on the costs.

Total cost	Direct	Indirect	Manual	min / avg / max
All users	£55	£32	£55	£14 / £47 / £100

Table 3: Participants’ total heating cost over 30 days

**Comfort Analysis.** Note that, even though the users *allowed* the smart thermostat to decrease the setpoint by 3 °C on average during price peaks, the *actual* temperature drop was much smaller due to the thermal inertia of a home and the limited duration of the peak. In the context of our study, we define a peak to be an event during which the price stays above twice the average price of 12 pence/kWh for at least 2 hours. A duration of 2 hours is interesting because only if the peak is long enough, then the users are expected to experience the impact of the temperature settings on their comfort. Using this definition, we identify four price peaks in our study.

Clearly, the greatest impact on users’ comfort happens during these four price peaks. However, when we analyze the temperature data (focusing on the *active users*), we see that even during these peak events, the comfort loss was within acceptable bounds. Only in 2 (10%) of the homes the temperature fell by 1 °C during the peaks, while in 13 homes (62%), the temperature did not change. The temperature in the remaining 6 homes (28%) increased by 1 °C during the peaks.<sup>7</sup> This indicates that most users did not suffer from big temperature drops even during price peaks.<sup>8</sup>

### 5.2.4 Demand Response Analysis

When designing a smart thermostat to enable demand-side management, it is important to note that the overall goal of demand-side management is to reduce the demand during *peak hours*, i.e., during price peaks that last a significant amount of time [3]. This can be looked at from two perspectives: the *users’ perspective* and the *network operator’s perspective*. We have already covered the user’s perspective in the previous sections, i.e., how much they are willing to decrease the setpoint during price peaks, and, importantly, how much actual comfort loss they will suffer for doing so.

For the network operators, the goal is to reduce the demand for energy during peak hours. A common metric used for evaluating demand response programs is the normalized actual *demand reduction* which measures the percentage reduction in energy consumption during price peaks [3], and is defined as

$$DR = \frac{C_{\text{offpeak}} - C_{\text{peak}}}{C_{\text{offpeak}}},$$

where  $C_{\text{peak}}$  is the consumption that was actually measured during the peak, and  $C_{\text{offpeak}}$  is the hypothetical (baseline) consumption *that would have been measured* had there been off-peak prices instead.<sup>9</sup> We use the same definition of peak as in the previous section. As the baseline (i.e.,  $C_{\text{offpeak}}$ ), we take the consumption that would have occurred if the price had stayed at 12 pence/kWh instead. Since only  $C_{\text{peak}}$  is observed,  $C_{\text{offpeak}}$  must be estimated. However, due to the relatively short duration of the study and the high variation in each user’s settings and occupancy patterns, it was not possible to reliably estimate the counterfactual “off-peak demand” from the experimental data. For this reason, we used our simulation model for this estimation. To this end, for every user, we use the thermal model of the user’s house, the user’s setpoint preferences and his schedule at the time of the peak, to estimate what this user’s consumption would have been at the same time when the price peak occurred, but assuming a constant price of 12 pence/kWh instead.

Using this approach, we estimate the average demand reduction to be DR = 38% (Table 4 provides additional results). Interestingly, when considering the set of active users, we obtain 50% of demand response via the indirect UI, and this is almost twice as large as the demand response achieved by the direct UI (27%). However, this difference is not statistically significant (p=0.097).

**Comparison to other Trials.** Compared to other demand response trials from the literature, the amount of demand response we found (DR=38%) is relatively large. A meta-study by Stromback et al. [28] found that, using automation technology, an average

<sup>7</sup>The temperature can increase during a price peak for multiple reasons. For example, for users with zero slope, prices have no effect. But even for price-sensitive users, their heating may coincidentally be scheduled such that it happens to start heating in the middle of a price peak, and then the boiler may be on despite high prices.

<sup>8</sup>Note that the precision of the thermostat is 1 °C and therefore, we cannot present more exact data.

<sup>9</sup>An alternative measure that is used in the context of real-time pricing is the *price-elasticity of demand* [29]. We do not use it because we are interested in the actual reduction during price peaks.

Demand response	Direct	Indirect	Manual	min / avg / max
All users	34%	47%	36%	0% / 38% / 100%
Active users	27%	50%	35%	0% / 36% / 100%

Table 4: Demand response analysis

reduction of 21% can be achieved. The study evaluated 85 field pilots conducted in the US, Canada, Europe, and Japan. Apart from real-time pricing, these pilots also tested times-of-use tariffs and critical peak pricing. The study found that critical peak pricing generally leads to the highest amount of demand response (31% on average). A notable example is Gulf Power’s residential service variable pricing pilot in Florida [7]. Their customers could program their thermostats to automatically react to the current electricity price, similarly to our smart thermostat. The average demand response during critical price periods (where the price was approximately 5 times the average price) was estimated to be 41%. This matches our finding that high amounts of demand response can indeed be achieved in the residential sector with automation technology.

## 6. LIMITATIONS

Our work has a number of limitations. First, we use the indoor temperature as a proxy for a user’s comfort, although thermal comfort is a complex phenomenon that depends on many variables [4]. We decided to use the indoor temperature as a proxy for comfort because it is a very important factor influencing comfort and because it is simple and robust to measure. A second limitation concerns the thermal heating model that we employed. While this model has been validated by prior research [21], it is a relatively simple model, and there do exist more complex models, capturing the thermal properties of buildings and the physical process of heating more accurately. However, the purpose of using a thermal model in our study was not to provide the most accurate 30-day cost prediction possible, but to create enough realism such that the users could immerse themselves into the scenario of heating with real-time prices.

## 7. CONCLUSION

The goal of this research project was to design a smart thermostat that enables users to handle home heating in a real-time pricing regime. We followed the hidden market UI design approach and built an autonomous heating system that automates the heating by responding to price signals on a user’s behalf and learns a user’s comfort-cost trade-off over time. We tested two designs of the learning thermostat against a non-learning, manual, baseline in a field experiment in the UK with 30 users over a period of 30 days.

Our results show that the smart thermostat enabled users to deal with real-time prices, leading to a large amount of demand response while keeping users’ comfort within acceptable bounds even during price peaks. Furthermore, the learning UIs were rated significantly easier to use than the manual one, which confirms the value of hiding some of the interaction complexity from the user.

Overall, we conclude that it is possible to induce a large amount of demand response even with a small amount of interaction. This suggests that smart (learning) thermostats could provide a viable alternative for users that prefer less complex user interactions.

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