FORCES: Feedback and control for Occupants to Refine Comfort and Energy Savings

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ABSTRACT

Humans spend 90% of their lives inside buildings, but often the Heating, Ventilation, and Air Conditioning (HVAC) systems of commercial buildings do not properly maintain occupant comfort. Use of feedback through comfort voting applications has been shown to improve the quality of service, but the effects of application feedback and user interface design has not been investigated. In this work, we present several methods of feedback that use data presentation and environmental interaction in comfort voting applications. Through a 40 week user study of 61 University employees across 3 buildings, we show that feedback systems can be used to increase user satisfaction with thermal conditions from 33.9% to 93.3% and reduce energy consumption up to 18.99% compared to a system without voting. In addition, we find that by including a drifting control strategy, we find energy savings up to 37% can be realized without a significant reduction in satisfaction.

ACM Classification Keywords

H.1.2 Information Systems: Human factors.

General Terms

Experimentation; Measurement; Performance.

Author Keywords

HVAC efficiency; thermal comfort.

INTRODUCTION

Although comfortable temperatures in commercial work environments make employees happier and more productive [1, 2], maintaining ideal temperature for occupants is difficult to do correctly. Building managers are responsible for setting temperatures for spaces within buildings,

but the chosen temperature setpoints are general estimates for the building and do not necessarily suit the thermal preferences of the individual occupants. A pre-study survey we conducted, completed by 61 occupants in 3 University buildings, indicated that 96% of those surveyed have had to take individual action to improve their comfort in their work space by using a personal heater or fan, adjusting clothing or using a blanket, adjusting their thermostat (only 18% of those surveyed reported an effective thermostat), relocating, etc. Importantly, 33% of those surveyed indicated that they have had to avoid their work environment due to discomfort, 45% reporting that the thermal conditions of their work environment inhibits their ability to work efficiently.

This occupant discomfort is caused by imperfect temperature setpoint selection. The state-of-the-art method for choosing temperature setpoints is taken from the American Society of Heating, Refrigeration, Air-Conditioning Engineering (ASHRAE) Standard 55 [3], which relies on Predicted Mean Vote (PMV). PMV uses parameters such as temperature and humidity to calculate an expected comfort level for an individual from -3 (“Too Cold”) to 3 (“Too Hot”). A key limitation of using PMV is the difficulty of ascertaining other parameter values, such as clothing level and metabolic rate. Our pre-study survey indicates that occupants prefer temperatures as low as 63°F and as high as 85°F, and so even with perfect PMV factor estimation, variation in occupant temperature preference makes PMV prone to error.

At home, an occupant can adjust a thermostat to suit his or her preference. However, as thermostats often aren’t available to employees in commercial buildings, most who want to modify the temperature in their space must contact the building manager and request an adjustment. According to our pre-study survey, only 13% of participants had contacted the building manager with satisfactory results, and they did so no more than twice a month. As only 34% of those surveyed reported satisfaction with the building HVAC system, this indicates that occupants are deterred by the adjustment process, and would prefer to bear the discomfort rather than repeatedly contact the building manager.

Work done in [4, 5, 6, 7, 8, 9] develop methods of collecting thermal comfort data. [4, 8] continue by using this

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data to manage the thermal characteristics of the space to fit occupant preferences by adaptively conditioning the user's zone. In general, the occupants are found to be significantly more satisfied once given the ability to control building temperatures.

Although these comfort voting applications improve upon standard methods of building interaction, there is still work to be done. A comfort voting application in a commercial building must aim to achieve the primary goals of the building manager, typically either reduction of energy consumption, or maximization of occupant comfort. Our main contributions are the following:

- We develop FORCES, Feedback and control for Occupants to Refine Comfort and Energy Savings, a multi-platform application that a building occupant can use to vote on thermal comfort within a space. The application uses this information to adjust the HVAC system using two different control strategies to improve occupant comfort while trying to minimize energy use.
- We propose 5 application feedback types that use various methods of data presentation and environmental stimuli to promote specific behavior in using FORCES. In a 1-month preliminary study, we analyze how these feedback types affect user behavior for thermal comfort and show that green and physical feedback provide the best energy savings and user comfort satisfaction.
- In a longer 40-week study, these two feedback types coupled with two different control strategies are implemented across 61 participants in 3 different buildings to understand how their use affects HVAC system energy consumption and user satisfaction. We show an increased user satisfaction from 33.9% to 93.3% and a reduced energy consumption by as much as 18.99%. In addition, we find that by including a drifting control strategy, savings up to 37% can be realized without a significant reduction of occupant satisfaction.

To our knowledge, this is the first work that investigates how different feedback mechanisms and control strategies can influence human decisions in a thermal comfort application controlling an HVAC system in production buildings to balance the energy/comfort tradeoff.

RELATED WORK

Previous work has used building occupants as participatory sensors [10]. By bringing humans into the loop [4, 5, 6, 7, 8], these systems collect thermal comfort information from building occupants, and then use PMV to determine temperature setpoints to improve comfort. These works conclude that gathering sensation data such as “Feeling Too Hot” improves usability, as users are unable to determine their ideal temperature. All studies resulted in energy savings and improved satisfaction. Besides PMV, a multi-armed bandit framework [11] and an optimization model [12] have been used to find improved temperature setpoints based on voting patterns. Although these systems provide alternative methods to translating human input to HVAC control strategy, they

do not determine how data presentation and environmental feedback can be used to promote certain voting application behavior, which is the focus of our study.

[8] describes operation of a comfort voting application with features similar to our Physical and Drift mechanisms. Although algorithmic details of their control strategies are unavailable, the case study concludes that these features reduce energy consumption by 22.95%. However, due to the age of the building, and the combination of the Physical and Drift mechanisms, it is difficult to distinguish which feature led to energy savings, and how they would generalize to other buildings.

[13] found that a person will act in an altruistic manner if they are shown the consequences of their actions. [14] shows that a 32% energy reduction can be achieved among dormitory residents by presenting energy usage information. However, the participants were incentivized with rewards, and 22% of participants admitted that they would not continue using the strategies after the study. [5] describes the design of a metering system that presents energy consumption data and zone temperature to occupants, and energy traces over a 10 day period show that a 5% energy savings was gained when the users were given control. Providing additional energy-saving tips caused a negligible change in energy consumption. [15] finds that informing people of their energy usage influences their behavior, but not always predictably. Similar results are achieved in residential electricity consumption feedback systems [16, 17]. These studies make it clear that providing this information to participants can cause a change in behavior, but none suggest how this information might be used in an application where the improvement in energy efficiency also presents a trade-off with the voter's satisfaction and comfort. In our work, we wish to determine this relationship, and find how it can be used to create purpose-built applications for either energy efficiency or occupant comfort.

In [18], social norms techniques were used to increase participation in a program at a hotel for towel reuse. They found that telling hotel guests about the percentage of hotel visitors that had also participated in the program led to increased participation. They concluded that reporting building-level participation in the displayed statistic is ideal to draw new users into the study. In [19], it is shown that although people may not believe that the actions of others will motivate them to save energy, the opposite holds true. The behavior of peers was seen to cause a large amount of savings among those users. In our study, we see if this effect holds true in a thermal comfort application when we inform the user about application usage by their peers.

Work done in [20] allows homes to be efficiently heated using occupancy sensing and prediction, replacing user-programmed thermostats. Similarly, the authors of [21] inform the design of future heating and cooling systems by investigating users' experiences with the Nest learning Thermostat, a commercially available smart home

Figure 1: From left to right, iOS, Android, Web version

device. They create a set of design implications for Eco-Interaction, the design of features and human-system interactions with the goal of saving energy.

In [22], a drift control strategy was deployed in the campus housing of 8 University undergraduates for a period of ~ 18 days. The authors learned that some occupants will learn to adopt new thermal regulation strategies (i.e. clothing changes, heating the room in advance) while others will struggle to maintain comfort. Changes in activation of the zones' radiators suggest energy savings up to 42.2%. Despite the similarity in the drift control mechanism, it is difficult to relate the results found in this study to ours, largely due to environmental/study conditions. For instance, the University students' schedules were not known, making it difficult to know what savings were due to the room being empty. In comparison, the participants of our study have very structured hours, and rely on comfort in their space to remain productive. In our work, we wish to determine if this drift strategy can be used in a commercial building to save energy while still maintaining high occupant satisfaction.

Research done in [23] investigates the use of different feedback mechanisms to improve the energy efficiency of an occupant's office space by reminding/enabling the occupant to disable unnecessary equipment (lights, computer, etc.) when the user is not in the office. In our work, we wish to reduce the energy consumption of the HVAC system while it conditions the user's space. For this reason, we must leverage energy savings against occupant comfort. Additional work [24] claims that occupant activity prediction based on real-time plug energy load data can be used to control plug load devices and HVAC system, but no evidence or experimental results are presented to support these claims.

SYSTEM DESIGN OVERVIEW

System Architecture

FORCES is a comfort voting application that allows occupants to vote for their thermal preference. Based on this vote, the room's thermal conditioning is changed to better suit this preference. To facilitate user interaction with FORCES, we developed iOS, Android and Web interfaces as shown in Figure 1. Using strategies

Figure 2: FORCES System Architecture

Name	Value
Air Speed	$0.1m/s$
Mean Radiant Temperature	$25^{\circ}C$
Humidity	30%
Metabolic rate	$70W/m^2$
Clothing Level	$0.5clo$

Table 1: PMV Constants

from [4] we receive votes from users describing how they feel, from Cold (-3) to Hot (3). These values are defined as the Actual Mean Vote (AMV), and are used to find the ideal temperature for the room by setting it equal to Fanger's formulation of PMV [25]. PMV uses parameters such as the clothing coefficient and metabolic rate that are difficult to obtain for each participant, so we use estimated parameter values obtained from [26] that are appropriate for an office worker adjusted by season, as shown in Table 1. A temperature found to be suitable according to ASHRAE Standard 55 [3] is one with a PMV value between 0.5 and -0.5, where the occupant is neither too hot or cold. We can therefore solve for this comfortable temperature and set it for the room.

Figure 2 shows an overview of the FORCES system. When a user submits a vote for their comfort, it is sent to the FORCES API, and feedback information is sent back to the user. The collected AMVs are tallied every 5 minutes and averaged in zones with multiple users. The AMV is used by the PMV model to determine the next room temperature setpoint, which is given to the Building Management System (BMS) for actuation. The building makes the necessary adjustments to condition the room to the desired temperature. As the thermal conditions are monitored by the user and votes are used to further modify the temperature, FORCES creates a closed loop feedback system with the human as a sensor.

Setpoints are handled by the BMS, which achieves the setpoint. WebCTRL [27] is the BMS system used on our campus. For both sensing and actuation we use sMAP [28], a RESTful API designed to manage building data. By designing an actuation driver that communicates with our building's BMS, we leverage the control systems implemented by designers of the building instead of creating our own local control PID loops. In addition, this also allows facilities crews to have full visibility on any of our changes through the existing BMS.

To monitor the thermal state and ensure correct building operation, we develop a driver that uses the BACnet protocol [29] to communicate with each sensor in a zone. The temperature and air flow rate sensors in each zone are polled at a 2 minute interval, a much finer granularity than the data collected by the BMS.

We want to make FORCES data available to applications on multiple platforms, so we design a RESTful API layer that computes the information displayed in our views. In this layer we can authenticate users, check comfort votes for validity and integrity, and uniformly present data to iOS, Android, and web users.

Application and Feedback Design

Application design affects user interaction in various ways. For instance, improvement of a mobile application's user interface can improve user enjoyment. Additionally, we hypothesize that in control applications like ours where the human is in the loop, feedback provided to the user can also influence their voting patterns. Based on research discussed in *Related Work*, we choose 5 feedback mechanisms for our comfort voting application, described below in detail.

Physical Feedback

By design, the vote collection system architecture defines periods of time for votes to be collected from users before a control decision is made and actuation begins. The period chosen between actuations is typically several minutes, as the amount of time required to condition a room to temperature is large. However, with several minutes between a user casting a vote about thermal comfort and the building's response, a user may become dissatisfied with the quality of the HVAC control.

To minimize this effect, we propose a “physical” feedback that immediately triggers a long burst of air from the HVAC system when a vote is received. This “instant gratification” provides sensory stimulation in the form of sound from the vents and an increase of air movement that assures the user that the system is changing in response to a vote. The additional activation when a vote is received may create wear and tear on the HVAC system; for this reason, we limit the feedback to just one burst per system actuation period. In our experiment, this period was set to 5 minutes. Long-term experiments are required to measure any impact of this feedback on HVAC equipment, so we leave this for future work.

Expected Action Feedback

In commercial buildings, multiple occupants are commonly required to share the same thermal zone and HVAC infrastructure due to system design. To a thermal comfort control application, this causes complications as there is no longer a one-to-one relationship between an occupant and a space. In particular, previous work [4] showed that a shared thermal zone encourages users to exaggerate votes in order to “bias” the system towards their own preferences. One likely cause for this bias is that a user may not know what votes are being cast by other users in the shared space.

Once a user casts a vote, the expected action feedback takes a tally of all votes that have been cast in the last voting period, and then reports back to the user exactly what action the system is expected to take. To a user, this confirms that the system has received the user's vote, and implies what votes are being made by other users in the same space. This feedback can reduce the bias observed in previous works if the system intends to react as the user wants, or could enhance the bias if the system's planned actions conflict with the user's vote.

Social Feedback

By informing a user about their peers' activity, also known as the descriptive norm, it is possible to encourage a particular behavioral pattern. In [18], hotel guests were found to be more willing to participate in an environmental conservation program when told that a large percentage of other hotel guests participated. Similarly, our social feedback notifies a user of the recent voting patterns of their peers, to encourage interaction with FORCES. To calculate peer participation, voting activity is determined across the entire building. The number of active users in the last week is found, and the percentage of those who have voted in the last 24 hours is reported to the user. We calculate activity based only on active users to keep the percentage relatively high even during periods of inactivity.

Leaderboard Feedback

Another feedback type that operates on social stimuli is the leaderboard, a common form of gamification [30]. The leaderboard reports a user's “score”, and shows the user's rank among all users with respect to this score. In our study, vote volume (i.e. total number of votes) was chosen as the score, but other metrics may be used as well. The advantage of the leaderboard is the introduction of competition into the voting platform. Users that are high on the leaderboard will be motivated to continue voting to maintain their high position, and users that are low on the leaderboard can clearly see how they compare to the top leaders. We suspect that leaderboard use helps maintain interest by inspiring competition among voters.

Green Feedback

The primary objective of a building's HVAC system is to make occupants comfortable, so a user of an app like FORCES may vote with no thought to system energy efficiency. However, if a control change will significantly improve the building's efficiency but minimally affect occupant comfort, the occupant may be willing to make the more sustainable vote. Green feedback informs users of the environmental implications of their voting pattern to encourage votes that are more energy-aware.

By comparing a zone's default temperature setpoints to those used by FORCES and considering the outside temperature, we can determine how much more or less energy will be consumed by responding to a vote. This difference is reported back to the user in terms of energy saved or wasted. To make the feedback easier to understand, the energy saved/wasted is converted into metrics

Figure 3: Drift strategy set-points to save energy

of energy that most people will understand, such as numbers of hours a microwave could be powered or miles an electric car could travel using the saved or wasted energy.

$$\Delta T = |T_d - T_o| - |T_n - T_o| \quad (1)$$

$$E = \Delta T \Delta t (VR)$$

The energy savings/waste calculation is calculated as shown in Equation 1. We find the absolute differences between the default temperature set by campus policy T_d and the outside temperature T_o , and then between new temperature setpoint T_n and T_o . Subtracting these two values will give us how much more cooling or heating is required for that room. The energy is then calculated as the product of ΔT , the volume of the room V , the efficiency of cooling the room R , and time Δt . Before reporting to the user, we convert the energy savings/waste into more intuitive units by multiplying it by appropriate conversion factors. Examples of units presented to the users are: “You have saved/wasted enough energy to cook g_p pizzas”, “drive an electric car g_c miles”, etc.

Drift Control

Previous work in building control strategies [31, 32] dictates that it is difficult to maintain user interest in a comfort voting application once thermal comfort is achieved. Similarly to [22], we introduce a control strategy that allows heating/cooling setpoints of a room to drift apart. This allows temperature to “float” within these expanding bounds, allowing energy savings. Example use of such a drift strategy can be seen in Figure 3.

In normal usage, heating/cooling setpoints are chosen based on occupant voting patterns. However, if these bounds are held unnecessarily tightly, extra energy will be consumed. We imagine drift providing the most benefit in two situations. The first is when outside temperature is comfortable, so minimal ventilation will be sufficient to maintain thermal comfort. The second is when occupants only need temporary conditioning, for example while they are cooling off from walking inside on a hot day, or if they come in and out of the office and don’t need their room conditioned the whole time.

In our experiments, we allow the bounds to start drifting apart 30 minutes after the occupants’ last vote, and the drift moves each bound apart by $1/2$ °F every 30 minutes. In practice, the bounds are reset to ± 1 °F from the last

	Male		Female		Declined
Gender	30.5%		66.1%		3.4%
	18-29	30-39	40-49	50+	Declined
Age	33.9%	22.0%	28.8%	13.6%	1.7%

Table 2: Demographics of Study Population

voted temperature each morning, and unless votes occur will be allowed to float to the farthest possible bounds of 66°F and 76°F, as chosen by the building managers.

EXPERIMENTAL SETUP

In this section we explain the participant recruitment process, the demographics of the recruited participants, the buildings used in the study, and their installed HVAC systems. Our preliminary study examines the effect of the 5 proposed feedback systems on participant satisfaction and energy consumption across a 4-week period. The results are then used to narrow down on the two most promising feedbacks for a long-term study. In total, our studies include 61 participants over a span of 40 weeks, with more than 1300 comfort votes collected.

Population Description

To discern differences in voting patterns due to feedback modification, FORCES was deployed across a diverse population. The majority of the FORCES participants are full-time employees in administrative offices or research labs, with 76% working 30+ hours/week. 71% of those included in the study share their work space with one or more people. Interestingly, our study is predominantly female, aligned with the current population that occupies the building. Additional population demographics can be found in Table 2.

Recruitment Process

The study begins for each participant upon completion of a skill session with one of the project’s researchers. The skill session allows us to complete four objectives:

- 1) The participant reviews and signs the Institutional Review Board (IRB) consent form.
- 2) The participant completes a pre-study survey, providing demographics, workspace information, and initial comfort in the space. The participant will complete a post-study survey later for comparison.
- 3) The researcher helps install the application on iOS, android, or bookmark the web-voting page based on the participant’s preference. Application use is explained to the participant, describing feedback in a neutral way.
- 4) The participant was provided login credentials as well as contact information for the researchers, in case an issue was encountered.

The FORCES system operates autonomously, with manual intervention required only if a fault in the HVAC system were to occur. Building managers love the FORCES system as it reduces the need for frequent requests for temperature adjustment, reducing their workload and keeping building users more satisfied.

Feedback Assignment

In the preliminary study, we sequentially assigned feedback types as we recruited participants with the exception of physical feedback. As the physical feedback of one user's vote would alter the thermal sensation of another, we chose to specifically assign physical feedback only to participants that had their own thermal zones. As the remaining feedback methods were assigned semi-randomly, participants that shared a thermal zone often received different feedback types. In this manner, we get a nearly-equal number of participants in each feedback type, and a fairly random spatial distribution.

At the end of the preliminary study, we found that having different feedback methods within a single HVAC zone makes energy analysis of the feedback types difficult. In the primary study, we corrected this by assigning feedback randomly across the HVAC zones, but assigning all users within a zone to the same feedback condition.

Building Description

FORCES was activated across three buildings, covering a total of 2 open receptionist areas, 33 offices, 8 research labs, and 14 cubicles. Most of the offices house one or two participants, while the cubicle areas and research labs can hold as many as 6 and 10, respectively. In BLD2, a terminal reheat system is present with thermafusers, allowing zones with a shared variable air volume (VAV) box to receive individual control (excluding cubicle areas, which must share control). In BLD1 and BLD3, thermafusers are not available, so in some cases individual control is not possible, even in offices.

Energy Calculation

Our campus has a central cooling/heating plant which stores chilled/heated water that is distributed to our buildings, which use single duct terminal reheat HVAC systems. We use a model of energy usage from [33], which calculates energy usage based on air temperature differentials through the cooling/heating coils and the fan electricity used to move the air. Here we describe how we follow [33] for use in our buildings.

The outside and circulated inside air are mixed in the economizer to T_m , the "mixed air temperature". The Air Handler Unit (AHU) cooling coil then cools T_m to the supplied temperature T_s , to be pushed to each room for conditioning. The cost of cooling for a particular zone is computed as the mass flow of air to the zone $\dot{m}_z$ (A fraction of the total $\dot{m}_z$ from the AHU) multiplied by the change of temperature. A massive fan in the AHU provides air for the a group of zones. A cooling coefficient, η_c , is applied to the result as shown in Equation 2

$$P_c = \eta_c(T_m - T_s)\dot{m}_z \quad (2)$$

Once past the cooling coil, the temperature is increased by the zone's heating coil from T_s to the discharge temperature, T_d . The power for heating is therefore the increase in temperature times the mass flow for the zone

Figure 4: PMV vote distribution for each feedback type and a heating coefficient, η_h as shown in Equation 3.

$$P_h = \eta_h(T_s - T_d)\dot{m}_z \quad (3)$$

The final addition to total power use is that of the air supply fan. The power is the square of the total mass flow, m_t , multiplied by fan efficiency coefficient κ .

$$\Delta P_f = \kappa \dot{m}_t^2 \quad (4)$$

The AHU supplies air to multiple VAVs and thermafusers, so to separate energy cost per zone we calculate the fraction of total air used for each zone. The cooling, heating, and fan power is used to find the total power to condition the zone, P_z as follows:

$$P_z = P_h + (P_f + P_c)m_z/m_t \quad (5)$$

To determine FORCES's effect on energy use, we compare each room's energy use during the study with the *same* room's energy use before the study, for each individual day. To minimize error due to weather variation, the pre-study day used for comparison is chosen such that its weather profile is as similar as possible to the study day. This is done by minimizing the root mean squared error between hourly outside-air temperature data trends of the study and pre-study day. As the buildings used in our experiments have never been repurposed and the employees that occupy the spaces are stable, we expect behavioral variations to be negligible in this comparison. Furthermore we only analyze weekdays, as HVAC is turned off during the weekends.

As each participant is separated into different feedback types in the preliminary study, it is difficult to map a feedback to a room's energy usage. We select rooms where more than 80% of votes have come from a single feedback group. In addition, we only look into zones within the same building, BLD2, to prevent bias due to differences between VAV systems. In the primary study, this is not necessary, as all participants in a shared zone are assigned the same feedback type, as discussed.

RESULTS

Preliminary Study

The preliminary study deployed all 5 feedback types to narrow down the ones that showed the most promise

Feedback Type	Baseline Energy (KWH/day)	Feedback Energy (KWH/day)	Percentage Incr.	Projected Cost Incr. (USD)
Social	83.38	89.23	7.01 %	\$17,584.74
Green	28.93	30.06	3.90 %	\$9,782.48
Physical	13.36	14.26	6.76 %	\$16,973.22
Expected	81.03	87.29	7.73 %	\$19,393.60
Leaderboard	19.05	20.98	10.12 %	\$25,389.26

Table 3: Energy Cost per Feedback - Preliminary

with respect to energy efficiency and user satisfaction. As this experiment was to compare feedback types only, the drift control strategy is not evaluated here.

In Figure 4 we see the distribution of votes along the PMV scale for each feedback tested in our preliminary study. On the x axis, the PMV range is shown from “Too Cold” (-3) to “Too Hot” (3). On the y axis, the fraction of votes with that value is shown, such that the sum of a feedback type across all comfort levels is equal to 1. The distribution of votes gives intuition into the goal of the users. For instance, leaderboard and physical have the majority of votes on the right of the scale, indicating a preference for cooler temperatures. Due to the hot weather during the study, providing cooler temperatures will result in increased energy usage. However, the vote distribution of users with the green feedback is greater on the lower end of the scale, with 47.41% of participants voting below neutral, 35.56% above neutral, and 17.04% voting for neutral comfort. As each vote below neutral is a request for warmer air, it shows that users were willing to increase the temperature, decreasing energy usage.

Interesting artifacts can be found in other feedback vote distributions, as well. Leaderboard users, for instance, generate 1.61x more neutral votes than the feedback with the second highest neutral votes (green). This indicates a strategy for users to inflate their rank on the leaderboard using votes that don’t greatly affect the temperature. As the Leaderboard’s “gamified” interface encourages its users to provide more votes (even neutral ones), the FORCES system will have explicit affirmation that the user is comfortable (neutral), helping FORCES to establish and maintain comfortable temperatures. In contrast, with other feedback methods, FORCES must make an implicit assumption that the user is comfortable based on the absence of votes. Physical feedback is designed to provide an immediate impression to the user that the HVAC system is working. However, the application provides no incentives to reduce energy consumption. This is shown in the figure, as 61.97% of the votes submitted by users with physical feedback are above neutral, requesting cooler air at the cost of more energy. Both social and expected feedback can be seen to have a higher concentration of votes on the extremes and a reduction near neutral. This is expected, as somebody in a comfortable zone feels less need to vote.

Using the procedure discussed in *Calculating Energy*, we analyzed the energy efficiency of the 5 deployed feedback types over the one-month study. Table 3 reports the energy usage, as well as the projected cost if FORCES

Feedback	Useful	Neutral	Not Useful
Green	33.33	33.33	33.33
Social	60.00	20.00	20.00
Leaderboard	50.00	50.00	0.00
Physical	100.00	0.00	0.00
Expected	100.00	0.00	0.00

Table 4: Survey: Did the user find the app useful?

were installed on an entire building. As shown, the energy consumption of all feedback types increased over the baseline comparison point. The variations in baseline energy shown in Table 3 are caused by the differences in square footage of the spaces, number of occupants, thermal load, solar gain, and other factors. Although many of these variations are unavoidable, we don’t compare these rooms to each other, but to themselves with and without the FORCES system. In this way, we can use the feedbacks’ relative performance to choose the ones that performed most efficiently. In particular, these results show that Green feedback led to the least energy usage by a fair margin, with Physical and Social as runners-up.

In addition to the energy analysis performed on the 5 feedback types, we also investigate what the building occupants thought of the app’s usefulness by having them complete a survey at the end of the study. As shown in Table 4, both Physical and Expected feedback methods were found to be useful by unanimous vote. Due to the relatively low energy usage of Green and Physical feedbacks and the usefulness of Physical feedback, we think these two are best suited for the long-term study.

Primary Study

In the preliminary study, Green and Physical feedbacks consumed the least energy. In addition, Physical feedback received a 100% usefulness vote on our post-study survey, so these two feedbacks were chosen for the Primary Study. Although “Expected Action” was a close third, we chose to limit those tested to maintain a high number of participants in each group. In addition to these two feedback types, we also chose to explore the Drift control strategy, introduced in *Application and Feedback Design*, which would be coupled with the Green feedback on the user applications. These feedback conditions are then assigned to our Primary Study population as described in *Feedback Assignment*.

If occupants have perfect knowledge of their ideal temperature, a standard thermostat would help users to maintain comfort. However, as an occupant’s ideal temperature changes with unpredictable factors such as metabolic rate, clothing type, air speed, etc., this is not the case in general. In our pre-study survey, we ask

Figure 5: User temperature preference as indicated by Survey (left) and Voting patterns (right)

Figure 6: Vote volume for each day of study

participants for their perceived ideal temperature. As participants vote for their comfort across the study, the building learns their thermal preference. As comfort levels are shown in Table 5 to be significantly improved at the end of the study, we determine the users' ideal temperature by examining their average room temperature across the last week of the study. The perceived ideal temperatures and the actual ideal temperatures are shown in Figure 5. As shown, survey results suggest that occupants prefer temperatures in the range of 61 – 85°F, with a mean preference at 74°F. However, their voting patterns show that the participants' preferred temperatures fall on the range of 64 – 76°F, with a mean preference at 73°F. The second standard deviations are calculated to be 65°F and 83°F across the survey responses and 67°F and 78°F across the study results. 20% of surveyed users think their ideal temperature is outside of two standard deviations of the actual preferred temperature. If they were in charge of the building, these participants would set the setpoints to an uncomfortable temperature for themselves and others. It is clear from the distributions that users believe they are more comfortable in temperatures further from the mean than they are in practice. Additionally, users believe they would be more comfortable in higher temperatures than their voting patterns indicate (during the summer when outside temperature is higher). This can have an impact on energy consumption, as it is more costly to cool hot outside air to a lower temperature set point.

Figure 6 shows how FORCES vote volume changes as the study progresses. As not all participants could be recruited on the same day, we have shifted the vote timeline so that the day of the study session aligns with “Day 0” in the figure. This also means that votes on the final

Figure 7: Example fault detection usage

Satisfaction Level	Pre-Survey	Post-Survey
Satisfied	11.9%	66.67%
Somewhat Satisfied	22.0%	26.67%
Neutral	18.6%	6.67%
Somewhat Dissatisfied	28.8%	0.0%
Dissatisfied	18.6%	0.0%

Thermal Comfort	First Vote	Post-Survey
Cold	22.0%	0.0%
Cool	6.0%	0.0%
Slightly Cool	20.0%	12.0%
Neutral	8.0%	60.0%
Slightly Warm	18.0%	12.0%
Warm	6.0%	8.0%
Hot	20.0%	8.0%

Table 5: Satisfaction and comfort

days represent *only* votes from users that started using the system the earliest. We can see that application usage during the first month is relatively high. As the novelty period wears off and the buildings learn the occupants' preference, the amount the users vote tends to diminish. Despite the novelty wearing off, we see that FORCES application usage continues into the long-term as users periodically provide corrections to the temperature of their zone. In addition, as usage settles into a background voting pattern, spikes in occupant voting patterns often signify faults in the HVAC system, and can be easily used for fault detection and diagnostics (FDD). One example is shown in Figure 7, where spikes in voting patterns for users 44 and 49, who work in separate cubicles in the same office, are correctly time-aligned. Inspecting the data, we found that these peaks correspond to BLD2 HVAC maintenance, where the system was being intermittently disabled.

In previous data, we often see patterns where users vote for their comfort, wait a short period of time, and then cast the same vote again. We refer to these duplicate

Figure 8: Reiterated votes

votes as “reiterated votes”, an indication that the user is not yet able to feel the effects of the requested conditioning, and is submitting additional votes to reiterate their request. Three examples of reiterated votes in voting patterns of users with various feedback types can be seen in Figure 8. The amount of time required for a room to be conditioned to temperature following a vote depends on the size of the room, amount of ventilation, and other factors. Vote reiteration occurs because it can often take on the order of 15 minutes for an office to reach a desired temperature setpoint, even to perform only a few degrees of temperature change.

The benefit of physical feedback is the immediate HVAC action in the voter’s space. Although physical feedback does not necessarily help the room reach its desired setpoint significantly faster, the actuation will make clear to the voter that the vote has been received, and the space is being conditioned. If this feedback makes clear to voters that the room is quickly responding to a vote, our data should show fewer reiterated votes from users with physical feedback than with any of the non-physical feedbacks. To determine this, we separate the voting patterns of each individual voter, and find all occurrences of two votes being submitted within some Δt of each other. This Δt is chosen to be twice the system actuation period, or 10 minutes in our experiments. This is because in the worst case, the user votes at the very beginning of a voting period, waits 5 minutes for the vote tally and beginning of the next actuation period, and then waits another entire system actuation period for the room to change to the user’s liking. If a user feels the need to re-vote within this period, we consider it a reiterated vote, caused by the slow response of the system. The results of this analysis can be seen in Table 6, where our 23 users with physical feedback are shown to reiterate their votes in 80 clusters, and the remaining 38 users with non-physical feedback cast 377 reiterated votes. Across the 40-week study, users with non-physical feedback cast, on average, $2.9\times$ more reiterated votes than users with physical feedback, supporting the hypothesis that the effects of physical feedback provide immediate feedback that help to quickly satisfy the occupants.

The pre-study survey allowed us to see the initial conditions of the users and their space. At the conclusion

	Total	Avg/User
Physical	80	3.48
Non-Physical	377	9.92

Table 6: Reiterated votes for (Non-)Physical feedbacks

Satisfaction Level	Green	Physical	Green+Drift
Satisfied	66.67	75.00	62.50
Somewhat Satisfied	0.00	25.00	37.50
Neutral	33.33	0.00	0.00
Somewhat Dissatisfied	0.00	0.00	0.00
Dissatisfied	0.00	0.00	0.00

Table 7: Satisfaction of Primary Study Feedbacks

of the study, we note what changes the application has made with the comfort and satisfaction of the users.

The thermal comfort at the beginning of the study as shown in Table 5 was distributed; 48% of participants were cold to some degree, 44% were hot to some degree, and only the remaining 8% were neutral. As the study progressed and the thermal state changed, the number of neutral (comfortable) participants increased to 60%. Interestingly, no participants reported feeling cold or cool at the end of the study, and the number of those feeling hot dropped from 20% to 8%. The reduction in the extremes, cold, cool, and hot, shows that the thermal status of the room had made a large shift towards an equilibrium around the users’ comforts. Additionally, this reduction in extreme votes shows a strong reduction in the amount of over-conditioning occurring in the building, undoubtedly making a strong impact on the energy profile of the building.

Users were asked before and after the study about their overall satisfaction as shown in Table 5. Of the 47.4% that claimed to be dissatisfied to some extent at the beginning of the study, none remained dissatisfied at the end. Only 33.9% of their participants considered themselves at least “Somewhat Satisfied” at the beginning, increasing to a much-improved 93.3% by the end. In the pre-study, 33% of participants reported actively avoiding their office due to uncomfortable temperatures, and 96% reported taking individual action to improve their comfort before FORCES. At the end of the FORCES study, none of the participants reported actively avoiding their office, and a reduced 63.3% took individual action to improve their thermal comfort.

In addition to general satisfaction with FORCES, we wish to know how the various feedback types affect user satisfaction. Table 7 shows the reported satisfaction after the primary study was complete. Physical feedback resulted in the highest user satisfaction, likely caused by the instant thermal gratification experienced by the user. The Green+Drift feedback resulted in the lowest satisfaction, but all users were still at least “Somewhat Satisfied”, much improved from the pre-study conditions.

As explained in *Feedback Assignment*, each participant in a zone shared the same feedback type for our primary study. Following the procedure described in *Calculating*

Feedback Type	Baseline Energy (KWH/day)	Feedback Energy (KWH/day)	Percentage Decr.	Projected Cost Decr. (USD)
Green+Drift	95.83	60.27	37.11%	\$93,113.80
Green	54.70	52.31	4.38%	\$10,984.34
Physical	88.65	71.81	18.99%	\$47,663.29

Table 8: Energy Cost per Feedback - Primary Study

Energy, the change in energy consumption is computed for each zone, which is then averaged for each feedback type. As shown in Table 8, FORCES operation caused a decrease in energy usage for all feedback types, with Green feedback using the most energy at just a 4.4% reduction, and Green+Drift strategy obtaining a 37.1% decrease in energy usage. Although Physical feedback was found to consume more energy than Green feedback in the short-term preliminary study, analysis of the long-term study data found Physical to result in significant energy savings over Green feedback alone.

To show how the energy savings found in the Primary study would affect a building's energy bill, we project the energy reduction computed for each feedback types onto an example building on our campus, Building 0 (BLD0). BLD0 used 1,091,429 ton-hr for cooling and 124,860.76 therms for heating in 2014. As our campus pays \$0.175(USD)/ ton-hr for cooling and \$0.14(USD)/ therm for heating, \$250,933.24 was spent to condition BLD0 for 1 year. The projected change in cost is reported in the last column of Table 8.

DISCUSSION

The energy model used for energy analysis does not take into consideration the additional wear on the machinery that *may* occur in the system, potentially increasing overall capital costs. Changes in the fan speed and damper position occur over large periods of time and causing a burst of air to be provided to a room may cause a reduction in the life of the system. This additional cost may be considered negligible but further research should be done to confirm this assertion.

In the baseline energy consumption used for comparison, we did *not* include the energy used by occupants using their own personal electrical resistive heaters or fans to improve their personal comfort (a significant number of users based on our pre-study survey data), so the energy savings results reported are conservative.

In our preliminary study, all feedback types showed an increase in energy consumption with respect to the baseline. We believe this was an artifact of the very few zones that could be analyzed due to the random feedback assignments strategy used in the preliminary study, as it was explained in *Energy Calculation*. Furthermore, the results shown in Fig. 4 using all user data would indicate that at least Green feedback should have produced a decrease in energy consumption from baseline. Nevertheless, the results allow us to establish a *relative* comparison among the different feedback types. In the primary study, *every* zone was used in the energy calculation, since each zone was assigned just *one* feedback

type. We believe the feedback assignment in the primary study combined with the longer experimental time allowed us to get more meaningful results.

In the primary study, all feedback types decreased energy consumption while improving user satisfaction. Physical feedback saved more energy than Green, but less than Green+Drift. We hypothesize that this may be the result of the human perception of control, as psychological studies have also shown that direct control can lead to greater satisfaction [34]. Users may be willing to vote and/or allow the system to drift to a slight discomfort area, but still be satisfied with the system since they are in control. Although Green+Drift led to significant energy savings, satisfaction was only slightly lower than that of Green and Physical, and higher than baseline.

We believe the results in this work open new potentially exciting interdisciplinary research avenues. By including the human-in-the-loop, we need to further investigate the intersection of human incentives structures (behavioral economists and cognitive scientists) together with control of large cyberphysical systems (engineers) to further understand the inter-relationships between human behavior and system control.

CONCLUSION

Comfort voting applications are becoming more prevalent, but work has not been done to examine how application feedback can affect HVAC energy consumption and occupant satisfaction. In this work, we developed a multi-platform comfort voting application with 5 different methods of feedback. Through a 1-month preliminary study, we investigate how these feedback types affect the satisfaction of the users and the energy consumption of the building. We then use the results to narrow down on the two most promising feedbacks, for evaluation for a long-term study. Across a 40-week study covering 3 buildings and 61 participants, we find that using feedback systems can improve satisfaction from 33.9% to 93.3%, and reduce energy consumption by 18.99%. Furthermore, with the inclusion of a drifting control strategy, a 37% energy reduction can be realized without significantly reducing occupant comfort.

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