# An Occupant-participatory Approach for Thermal Comfort Enhancement and Energy Conservation in Buildings

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## ABSTRACT

Commercial building is one of the major energy consumers worldwide. Among the building services, Heating, ventilating and air-conditioning (HVAC) system dominates the total energy consumption; hence different approaches have been recently proposed to audit, automate and optimize energy usage. Nevertheless, these schemes seldom touch human thermal comfort. To minimize complaints, the current practice adopted by building operators is to use very conservative temperatures, leading to large energy waste.

In this paper, we take thermal comfort into consideration in an active way. More specifically, we propose a participatory approach where the occupants can provide feedback on their comfort levels. A major challenge for a participatory design is to reduce intrusiveness of the system. To this end, we develop a temperature-comfort correlation model which can build a profile for each occupant; thus the building air-conditioning adjustment decision can be primarily model-driven and only needs minimal inputs from the occupants. Our model also needs certain environmental data that can be easily collected in daily-life using wireless sensing networks. This is in sharp contrast to the models developed in building services engineering, where they pursue model accuracy and require model development in laboratories with special equipment. We admit, however, that we borrow the spirit of model design from building services engineering. We validate our model using field experiments. We develop a setpoint optimization algorithm to handle the thermal comfort requirements of multiple occupants in a room. Our simulation shows that our algorithm can successfully maintain high thermal comfort, while reducing energy consumption for 18%. Finally, we implement a system and conduct field experiments in a University and a commercial office environment. The experiments confirmed the effectiveness of our participatory approach.

## Categories and Subject Descriptors

H.1.2 [**Models and Principles**]: User/Machine Systems

## Keywords

Participatory Thermal Comfort, Energy Conservation, Smart Building

## 1. INTRODUCTION

In recent years, people are paying increasing attentions to energy conservation around the world. The biggest sectors of energy consumption are commercial buildings, residential houses, transportation and manufactory industry. In such regions as Hong Kong, where the industry sectors are small, commercial buildings account for more than 65% of energy consumption of the city [1]. In a typical building, the HVAC (heating, ventilation, and air conditioning) system dominates the energy expenses. For example, it is reported in the Office Segment of Hong Kong 2013, that 53% energy goes to room conditioning [1]. As such, many recent studies propose to conserve energy by more intelligently managing the HVAC systems [2][3].

Energy conservation is on one end of the spectrum. Clearly, we can turn-off all the air-conditioning[1] and we maximize the energy saving. Nevertheless, the HVAC systems are designed to provide a comfort indoor environment for occupants in buildings. As a matter of fact, complaints minimization, rather than energy conservation, is the top priority of buildings and building operators. Therefore, it is important to take human thermal comfort into consideration.

The current practice to support human thermal comfort by building operators is to apply a fixed setpoint temperature. As an example, in Hong Kong, the recommended temperatures for Grade A, Grade B and Grade C buildings are 23.5°C, 24.5° and 25.5° respectively. These temperatures are derived from large scale field surveys or laboratory experiments. Such recommendation provides building operators a benchmark in temperature settings and assists them to stand with complaints. To minimize the number of complaints, these recommended temperatures are usually very conservative (i.e., the setting is on the low temperature side) and uniformly applied to the entire building unless special request is made. All these lead to heavy energy waste.

[1]To ease our presentation, in this paper, we use air-conditioning to represent HVAC systems. In the context of air-conditioning, setting a lower temperature means more energy has to be consumed.

In addition, a low temperature does not necessarily reflect better human thermal comfort and in many high-end buildings with centralized HVAC system, it may not be easy for the occupants to adjust the temperature by themselves. As opposed to such fixed setpoint strategy, there are proposals to dynamically control HVAC systems. One direction is to detect human presence. If a room is not occupied, the air-conditioning of the room will be turned-off. There are a lot of studies with various detection objectives and solutions[4, 5].

In this paper, we explore another direction on dynamic control of the HVAC systems. Rather than passively detecting human presence or comfort levels, we take a participatory approach where occupants can provide inputs. More specifically, human beings can directly provide feedback, e.g., using their smartphones, on whether they are comfort or not. The idea is simple, yet there are several challenges: 1) for a participatory design to succeed, the incentives of occupants are important. The design should be as non-intrusive as possible. Requesting occupants to feedback from their phones every time every room they go will easily discourage people in participation. Privacy concerns are also need to be taken care of whenever necessary; 2) occupants are insensitive to the numerical expression of temperature [6], e.g., one may not be able to differentiate the actual differences between 22.5C and 24.5C. However, engineering systems require numerical values for calculation and comparison. Therefore, it is necessary to have a context-aware translation; 3) there can be multiple occupants in a room; thus an optimized aggregation of different comfort levels is needed; 4) a system needs to be developed with components of data collection, smartphone application, interaction with building controls for air-conditioning adjustment, etc. Many of these challenges are similar to those of typical participatory sensing systems [7, 8], but are specific in the building environment.

To handle these challenges, we first use a comfort index linking human comfort with numerical values. We then develop a temperature-comfort correlation model which can build a profile for each individual occupant. Thus, the air-conditioning adjustment decisions are primarily model-driven and we substantially reduce humans feedback. We borrow the spirit of the thermal comfort model designs from inter-discipline of building services engineering. We made careful simplification, where all data can be easily collected in daily-life. We develop an setpoint optimization algorithm which resolves the comfort requirements from multiple people. We implement a system with smartphone app, a wireless sensing system to collect necessary environmental data and a system that interacts with building controls. We conduct real world experiments to validate of our temperature-comfort correlation model. We use a comprehensive set of simulation to study thermal comfort levels and energy conservation. We conduct real world experiments in our university and a commercial office environment and observe a 18% energy saving. The results confirmed the effectiveness of our participatory approach.

## 2. BACKGROUND AND RELATED WORK

Recently, there are many studies from computer science researchers on buildings. The studies start from energy auditing systems using wireless sensor networks [9][10]. These systems provide fine-grained data on energy usage. There are works on smart wireless systems for better automation and control of building equipment [11]. There are many works on human detection [12][5][13] so that lighting and air-conditioning can be turned-off in a smarter way. There are also studies on more intelligent arrangement of human activities such as meetings and classes with the objective in minimizing energy or electricity bills [14][4].

These studies are yet to actively take human thermal comfort into the air-conditioning adjustment decision loop. One possible difficulty is that human thermal comfort is not immediately quantitative to computer scientists. A straightforward quantification is difficult, as can be seen from tons of debates on thermal comfort from the inter-discipline of building services engineering. These studies can be summarized into two approaches [15]: heat-balanced approach and adaptive approach. The heat-balanced approach, first studied by Fanger in 1970 [16], observes the linkage between thermal comfort and physiological factors such as skin temperature and sweat rate. It establishes a thermal comfort model with factors such as air temperature, clothing insulation, metabolic rate, etc. To average the comfort of all people, a predicted mean vote (PMV) model is proposed. The heat-balance approach is conducted in laboratory experiments in chambers, where as adaptive approach is based on field studies. The factors considered are adaptations, e.g., behavior adaption, social and cultural background, thermal expectations and psychological adaptations [15] and physical stimuli, such as indoor climate and outdoor temperature [17] .

The objective of these studies is to derive the comfort temperature of an occupant, either from his activity and physiological point of view, or from his behavior, cultural background and surrounding environmental point of view. The more accurate the model is, the better. The state-of-the-art models are thus very complex with many associated parameters. The experiments have heavy reliance on advanced equipment, such as environmental chamber for simulation. These studies have to be conducted in laboratory or field experiments, and is not easy to apply these models in daily life. These studies contribute suggested temperatures for building operators, but are isolated from dynamic room air-conditioning adjustment.

As a result, we see a separation where the advances of smarter and more fine-grained building automation and control seldom take human thermal comfort into consideration, and the study of human thermal comfort modeling development are isolated from room air-conditioning adjustment loop. In this paper, we jointly consider the two. From a high level point of view, the room temperature adjustment takes the feedback of occupants into the decision loop.

A few recent studies have similar ideas, e.g., Thermovote [6] and SPOT+ [18]. There are two common problems. First, these studies usually rely on an existing thermal comfort model from building service engineering (e.g., PMV). As said, some parameters of these models are not easy to obtain in daily life. Therefore, they rely on prior-obtained fixed settings of these parameters, which may lead to errors. Second, these studies usually request a feedback each time each room an occupant goes (when the occupant is not comfort). This may discourage the long term incentives of the participants, as have shown in other participatory sensing systems [19][6]. Of course, these studies have such two problems because their objectives differ from ours. In this paper, we propose a participatory approach that addresses these two problems. We develop a model for human thermal comfort, making the room air-conditioning adjustment primarily model-driven, and thus we can substantially reduce the number of feedback from occupants. We admit that our model also borrows the spirit of building services engineering models, yet with careful simplification. Our model only needs simple parameters where an easily deployable wireless sensing systems can provide. Clearly, our model is not as accurate as building services engineering models. The occupants can feedback, which adjusts the temperature to his comfort level.

## 3. OCCUPANT-PARTICIPATORY THERMAL COMFORT: AN OVERVIEW

From the view of an occupant, we develop a smartphone app so that the occupants can show (or, in other words, vote) their thermal comfort levels when they are not satisfied with the room air-conditioning temperature. The smartphone application can directly communicate with the building management system and the room temperature can be adjusted. The vote will be recorded. Such votes, and other environment data will be used for a thermal comfort model. The temperature adjustment of the room can thus be model-driven most of the time and minimize the intrusiveness to the occupant. In our system, we have a OPTC server to store the data collected from individuals, including his thermal comfort profile. We would like to first clarify the possible privacy concerns. Our system simply requests occupant registration. The registration is standard where he uses an email address to register and he needs to agree a set of rules, e.g., allow us to collect his thermal comfort information. If one does not register, his preference will not be taken into consideration in our air-conditioning adjustment. In our experiment, we find that all people had registered. Our survey after the experiments confirmed that they were not very much concerned that their thermal preference will be recorded; rather, they were more concerned that they would be left out especially when we optimized the setpoint temperature for a room of multiple people who had participated.

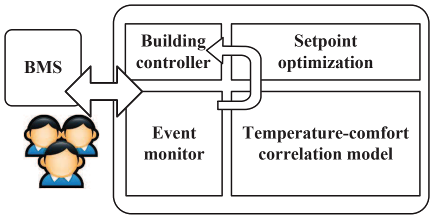


Figure 1: Overview of OPTC

We develop Occupant-Participatory Thermal-Comfort (OPTC) framework (see Fig. 1). We have four main modules: (1) Temperature-comfort correlation (TCC) model: the objective of TCC model is to establish a correlation (or profile) between temperature and comfort for every individual occupant; (2) Setpoint optimization module: based on the TCC model, setpoint optimization calculates the best setpoint temperatures for occupant(s); especially for multiple occupants; (3) Event monitoring module: the event monitoring module collects data from environment (e.g., indoor, outdoor temperature) and occupants for two purposes: to trigger decision making in setpoint optimization; and to gradually train the TCC model; (4) Building control module: After setpoint optimization module makes an adjustment decision, the building controller module communicates with the building management system to change the setpoint of a room. We next discuss each module in more details.

When developing TCC model, we borrow knowledge from building service engineering. However, as explained, the thermal comfort models in building service engineering are complex. The inputs of their models require special equipment and the models have to be validated in field test or laboratory experiments. We only rely on daily collectable data, e.g., indoor, outdoor temperature. The occupants can provide inputs when he is not comfort, which will assist us to adjust. We establish a profile for each occupant, so that the air-conditioning adjustment can be model-driven most of the time. The details are in Section 4.

The setpoint optimization module determines how to adjust room air-conditioning. For example, when abnormal event happens (indoor/outdoor temperature changes, occupants' feeling changes, etc.), the setpoint optimization module is triggered. It translates the input from event monitor module and the TCC model into a decision for air-conditioning temperature adjustement. More importantly, we develop an algorithm to compute the optimized setpoint temperature when there are multiple occupants. The details are in Section 5.

Event monitor module collects necessary data and reacts accordingly. We collect the input of occupant's preference, indoor and outdoor temperatures etc. We develop a smartphone app to collect occupant's preference. We translate the fuzzy preference into computable numerical values. We develop a wireless sensing network to collect building temperatures. The details are in Section 7.

In building controller module, decisions made by setpoint optimization are transferred to the building management system. The details are in Section 7.

The remaining part of the paper is organized as follows. We develop the TCC model in Section 4. We validate our TCC model using field experiments with people. We then present our setpoint optimization algorithm in Section 5. In Section 6, we present a comprehensive set of simulations. We use simulation because we can evaluate a large sets of occupants with different characteristics. We can also evaluate energy saving with various room configurations with different sets of simulated occupants. It is not easy to find large scale of occupants of diverse characteristics for real world experiments. We then present the implementation of an overall system in Section 7. In Section 8, we conduct two sets of experiments, one in a university environment and one in a commercial office environment. These experiments validate our simulation results.

# 4. THE TEMPERATURE-COMFORT CORRELATION (TCC) MODEL

In essence, we need a profile indicating the comfort value of a specified occupant under indoor temperature, outdoor temperature after entering a room at a specified time. One way to develop this model is to follow the studies in [20][21] etc. We can measure metabolism of the occupant and detect his clothes with Microsoft Kinect sensors. Metabolism is a key factor that affects the thermal sensation of a occupant. It is influenced by outdoor temperature, activities, etc. Outdoor temperature also affects other factors such as clothes, i.e., even with a same indoor temperature, occupants have different feelings. This falls into the expertise of building service engineering and medical sciences. Given detailed adaptation information about an occupants and environment information, existing models [22][23][16] can be used to build the TCC model. However, the accuracy of these models heavily rely on real-time measurement of the input information, which is hard to collect without special equipment.

Table 1: 7-point thermal comfort index

| Point | Sensation |
|---|---|
| +3 | Hot |
| +2 | Warm |
| +1 | Slightly Warm |
| 0 | Neutral |
| -1 | Slightly Cool |
| -2 | Cool |
| -3 | Cold |

Our choice is that we build an initial model following the rudimental laws of metabolism. In this model, there are some parameters hard to calculate from theory or hard to collect. These parameters are more or less invariants for a specified occupant. Thus, we collect comfort data from occupants and estimate these parameters.

## 4.1 Thermal Comfort Metric

To quantify thermal comfort, we adopts a seven-point *thermal comfort index* from the American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE). This index scales from $-3$ to 3 and level of comfort ranges from cold to hot correspondingly(see Table 1). A value of 0 indicates that a occupant reaches *thermal neutrality*, meaning heat generation and loss of the occupant is in the state of equilibrium. A negative index means that the occupant loss more heat than his body produces and he feels cool or cold. The smaller the index is, the more uncomfortable the occupant feels. For positive indexes, the larger the index is, the more uncomfortable the occupant is. When the index of an occupant is between -1(Slightly Cool) and 1(Slightly Warm), the occupant is comfort. This index range $(-1, 1)$ is defined as *comfort zone* [24].

## 4.2 Model Development

The objective of our model is to build a correlation between indoor temperature and thermal comfort.

As explained, we will build an initial model where thermal comfort is a function of indoor temperature $T_i$, outdoor temperature $T_o$ and the elapsed time $t$ after occupant enters a room. Its basic format is shown as follows:

$$C(T_i, T_o, t) = G(t) + L(T_i, T_o) \quad (1)$$

Intuitively, thermal sensation is determined by heat generation and loss of human body. We model effect of heat generation in $G(t)$ and model effect of heat loss in $L(T_i, T_o)$.

The amount of heat generated is primarily settled by metabolic rate. It is also affected by the physical activ-

| | Men | Women |
|---|---|---|
| Sedentary | 1.0 | 1.0 |
| Active | 1.25 | 1.27 |

Table 2: Physical activity factor

ity (PA) of people [25], e.g., an occupant has a higher metabolic rate during walking, and lower after staying sedentary. When occupant's PA changes, e.g. sit down after running, metabolic rate adjusts accordingly. Thus, the occupant experiences a change of thermal sensations in same environment. Moreover, the speed of metabolic rate change differs among individuals. In $P(t)$, we consider metabolic rate changes as elapsed time $t$ after occupant enters a room.

The amount of heat lost is determined by indoor temperature and clothes insulation. In operation, information of clothes insulation is difficult to access. However, from results of field studies [26], it is shown the effect of clothes insulation can be reflected by outdoor temperature. Intuitively, when outdoor temperature is higher, occupants wear with less clothes, so they are prone to loss more heat. As a result, they prefer a warmer indoor temperature. In summary, we use indoor temperature and outdoor temperature as determining variables in $L(T_i, T_o)$.

Next, we describe modeling the effect of heat generation and loss in detail.

### 4.2.1 Effect of Heat Generation

We first model from the view of heat generation. According to [27, 28], heat production is proportional to physical activity while metabolic rate adjusts according to physical activity. To estimate metabolic rate of an occupant, we adopt the Estimated Energy Requirement (EER) model [29], which is first proposed by the Institute of Medicine (IOM) that used to estimate a person's daily average of dietary energy intake to maintain his energy balance. It considers the factors of gender, age, height, weight as well as the physical activity of users. It is as follows:

$$EER = k_1 - k_2 \times Age + [PA \times (k_3 \times W + k_4 \times H)] \quad (2)$$

$k_1$ is a constant related to gender and age. $k_2$ is a constant related to age. $k_3$ is a constant weight (W) respectively and $k_4$ is a constant related to height (H). The $PA$ coefficient is related to the physical activity and varies with genders. As we are interested in the change of metabolic rate to a person from outdoor to indoor, hence we consider the coefficients of two physical activities: *active* and *sedentary*. The coefficients of active and sedentary for male and female are shown in Table 2. Details of other coefficients can be found in [29].

Figure 2 demonstrates the EER of a male and a female with different ages, heights and weights, and $t_c$ is the time required by a person to recover from active to sedentary. Beyond $t_c$, EER is assumed to remain as the metabolic rate becomes steady.

According to [25][24], metabolic rate changes smoothly after physical activity changes. To obtain the corresponding EER at time $t$, we formulate the EER formula into the following function:

$$EER(t) = \begin{cases} \frac{(EER_s - EER_e)}{t_c}(t_c - t) + EER_e & t < t_c \\ EER_e & t \geq t_c \end{cases} \quad (3)$$

where $EER_s$ and $EER_e$ are EER of a person at active state (i.e., when the person just reaches his base room) and sedentary state respectively.

As described, heat production is proportional to EER, and thus we have the comfort index function from the heat production perspective:

$$G(t) = a_1 \times EER(t) + b_1 \quad (4)$$

where $a_1$ is the activity sensitivity, and $b_1$ is stable comfort preference.

### 4.2.2 Effect of Heat Loss

Next, we model the comfort index from the perspective of heat loss. Recently, there are comprehensive findings from field studies [17][22] showing that there is a noticeable relationship between the outdoor temperature and human's thermal comfort. The correlation is formulated as $T_c(T_o) = a_2 + b_2 \times T_o$, where $T_c$ is the comfort temperature function of outdoor mean temperature, $a_2$ is a constant related to comfort temperature and $b_2$ is the correlation between outdoor temperature change and comfort temperature change. In this paper, we applied the model in [30], where $a_2$ is 17.8 and $b_2$ is 0.31. This model basically tells us that if outdoor temperature increases, occupants prefer higher indoor temperature.

We map the difference between comfort temperature $T_c$ and current indoor temperature $T_i$ into comfort index. Let $k$ be the transform variable that map the temperature difference. Let $R$ be the range of comfort temperature in °C of a person, and thus we have

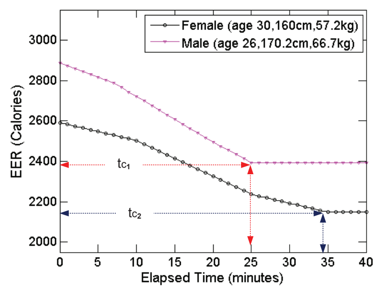



Figure 2: The EER example of two people

Table 3: Category of BMI

| Category | BMI Range |
|---|---|
| Underweight | <18.5 |
| Normal | 18.5-25 |
| Overweight | >25 |

the comfort from the view of heat loss:

$$L(T_i, T_o) = \begin{cases} 3 & T_i - T_c(T_o) \geq R \\ k(T_i - T_c(T_o)) & -R < T_i - T_c(T_o) < R \\ -3 & T_i - T_c(T_o) \leq -R \end{cases} \tag{5}$$

As specified in the standard [24], we use the comfort temperature range $R$ as $7°C$.

## 4.3 Model Validation

We conduct a field experiment to validate our model. The experiment was conducted in a commercial office for 5 consecutive days. 13 occupants were invited to participate in this experiment. Following the conventional approach from World Health Organization (WHO) [31], we classified the occupants according to their body mass index (BMI). BMI is calculated as follows:

$$BMI = \frac{Weight(kg)}{(Height(m))^2)} \tag{6}$$

As WHO specified, there are three categories: underweight(UW), normal(NL) and overweight(OW). Their BMI ranges are shown in Table 3. For 13 occupants in our experiment, there are 3 in UW, 8 in NL and 2 in OW.

In order to develop models for all occupants, we trained our models in iterations. In each iteration, we fixed the indoor temperature. The occupants were required to report their feelings every 5 minutes after they entered the room. Then, we changed the indoor temperature and repeated the process every one hours. The feedback in one iteration is shown in Fig.3a. There are three users displayed: occupant A in OW, occupant B in NL and occupant C in UW. We also calculate EER changes of these occupants (see Fig.3b). Fig.3a and Fig.3b indicate strong correlation between EER changes and feelings of occupants. More specifically, when A, B and C entered the room, A felt warm, B felt slightly warm and C felt comfort because their $EER_s$ are 3100, 2350 and 2100 respectively. Their thermal sensation changes as time goes by. A felt comfort after 30 minutes. B and C felt slightly cool after 40 and 25 minutes. It is worth noticing that the thermal sensations of B and C were closed to each other as the EER of B and C were only slightly difference at the end of the iteration. This result verified the connection between the EER and thermal sensations of people.

We collected occupants' vote and fitted into our temperature comfort correlation model, we then had $a_1$, $b_1$ and $t_c$ for all occupants by using linear regression method. In the next three days, we calculated the preferred setpoint temperatures with our models and adjusted setpoint temperature accordingly. The occupants were asked to report their comfort. We draw real feelings collected from occupants to validate our models in Fig.4. The result shows that there are only small variations between real feeling of occupants and targeted comfort index (0) by our model. Thus we conclude that our model can be used to estimate occupant's feelings.

# 5. SETPOINT OPTIMIZATION ALGORITHM

Armed with the temperature-comfort correlation model, we are prepared to compute the optimal setpoint temperature for occupant(s) in a room. Note that one occupant is subsumed in our multi-occupant case.

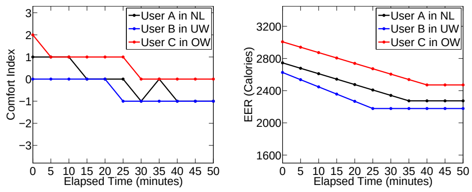
Our objective is to find the optimized setpoint temperature that maximizes thermal comfort of all occupants, given that the required percentage of occupant are staying within the comfort zone. The algorithm is shown in Algorithm 1. There are three input parameters: $\mathbb{O}$, $r$, $T_o$. $\mathbb{O}$ is the set of all occupants in a room. $r$ is the required percentage of people (e.g., 80%) within the comfort zone. For every occupant $j \in \mathbb{O}$, there is a corresponding TCC model $C_j$ and elapsed time $t_j$ after occupant $j$ enters the room.

Our algorithm first identifies a favorite temperature of every occupant. Then we compute optimized setpoint temperature for all occupant in iterations. In each iteration, we determine a candidate setpoint temperature and check whether this candidate satisfies all occupants. If this candidate fails, we adjust the set of occupants and run another iteration. More specifically, we first calculate a candidate setpoint temperature $T^*$ by minimizing sum of comfort index of all occupants. Then we count the number of occupants who feel comfort, denoted as $N$. If the target requirement (more than $r|\mathbb{O}|$ occupants are satisfied) is met, the optimized setpoint $T^*$ is found. Otherwise, we eliminate an occupant whose favorite temperature is the farthest from the candidate setpoint temperature. This is because we try to satisfy as many occupants as possible while this occupant is the hardest to be satisfied.

# 6. SIMULATION

## 6.1 Simulation Setup

We evaluate our system in two different scales. First, we simulate in one classroom with different profiles of occupants. Second, we adopt academic calendar from The Hong Kong Polytechnic University (denoted PolyU thereafter) to evaluate our system in large scale. We compare our system with fixed setpoint strategy.




(a) Comfort index (b) EER

Figure 3: Modeling period

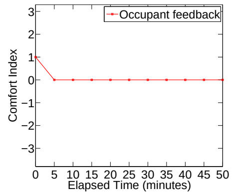



Figure 4: Model validation

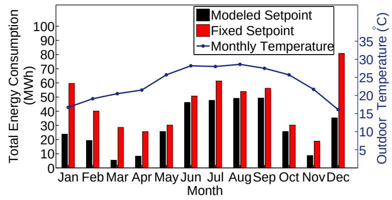



Figure 5: Energy consumption in one year

**Algorithm 1** Optimized Setpoint Temperature

**Input:** $\mathbb{O}$, $r$, $T_o$
**Output:** $T^*$

$T^* \leftarrow \emptyset$;
**for** $\forall j \in \mathbb{O}$ **do**
  $T_j^* = \arg\min_T |C_j(T_o, T, t_j)|$;
**end for**
**while** 1 **do**
  $T^* = \arg\min_T \sum_{j\in\mathbb{O}} |C_j(T_o, T, t_j)|$;
  $N = 0$;
  **for** $\forall j \in \mathbb{O}$ **do**
    **if** $|C_j(T_o, T^*, t_j)| \leq 1$ **then**
      $N = N + 1$;
    **end if**
  **end for**
  **if** $N \geq r|\mathbb{O}|$ **then**
    break;
  **else**
    $\mathbb{O} \leftarrow \mathbb{O} \setminus \{\arg\max_{j\in\mathbb{O}} |T^* - T_j^*|\}$;
  **end if**
**end while**

In our simulation, we generate occupant profiles based on results from our experiment in model validation. We choose one occupants from every BMI category. The profile of an occupant is denoted as $[a_1, b_1, t_c]$. Thus, profiles from occupant in OW category, NL category and UW category are [0.0027, -4.99, 30], [0.0041, -7.08, 40] and [0.002, -2.5325, 25] respectively.

For simulation in one classroom, we generate two group of occupants, named as group A and group B. Every group has 100 occupants. Group A has a ratio of OW:NL:UW as 1:7:2, whereas group B has a ratio of 1:1:3. The outdoor temperature is $30°C$. For each group, they take a class for one hour. The setpoint for fixed setpoint strategy is 22°C.

For PolyU data, there are over 950 classes in every weekday. We evaluate our system in a whole year. In this year, classes repeat every week. We use outdoor temperature data of Hong Kong in 2013 from The Hong Kong Observatory [32] as our system input. From our field measurement, PolyU applies a fixed setpoint temperature as 22°C in summer periods (May to October) and 24°C in winter periods.

To compare the energy consumption, we adopt the energy-temperature correlation model $P = |\frac{\lambda}{M}(T_i - T_o)|$ in [14]. We define $P$ as the energy consumed by HVAC system in every second, $\lambda$ as the conductivity of that particular classroom. Intuitively, the larger the $\lambda$, the less the heat preservation trapped into the room. $M$ is energy transformation ratio of HVAC system, which is used to indicate the energy efficiency to the HVAC system. Again, $T_i$ is the actual room temperature, and $T_o$ is the average outdoor temperature. The model assumes that in a given room, $\frac{\lambda}{M}$ is fixed, and thus more energy is consumed when the room setpoint temperature is far away from the outdoor temperature. The values of $\lambda$ and $M$ for classrooms at PolyU are same to [14], where $M$ is 0.14 for all classrooms. There are 160 classrooms in PolyU main campus, and the details are summarized in Table 4. For simulation in one classroom, we take the parameters of the classroom with a capacity of 100 seats.

Table 4: Classroom at PolyU

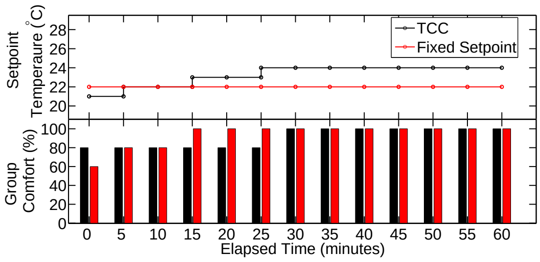
| Cap (Seats) | Num | Size $(L \times W \times H,\ m)$ | $\lambda$ $(J/s \cdot K)$ |
|---|---|---|---|
| 20 | 8 | $4 \times 5 \times 3$ | 70.5 |
| 40 | 42 | $8 \times 5 \times 3$ | 118.5 |
| 60 | 67 | $6 \times 10 \times 3$ | 162 |
| 80 | 10 | $8 \times 10 \times 3$ | 201 |
| 100 | 4 | $10 \times 10 \times 3.3$ | 249 |
| 150 | 17 | $10 \times 15 \times 4$ | 375 |
| 200 | 5 | $15 \times 14 \times 5$ | 533 |
| 300 | 2 | $15 \times 20 \times 6$ | 765 |

## 6.2 Simulation Results

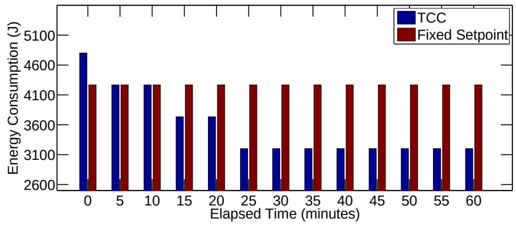
### 6.2.1 *Classroom simulation result*

Figure 6 shows the result of group A. With the starting setpoint calculated by OPTC at 21°C, it progressively increases with time and higher than the fixed setpoint, which is 22 °C after 15 minutes. We can see that OPTC achieves group thermal comfort requirement($\geq$ 80%) all the time, while fixed setpoint fails to meet the requirement in the first few minutes.

The energy consumption is shown in Fig. 7b. Since fixed setpoint does not changes its setpoint, its energy consumption is steady. For OPTC, when the setpoint is changed, the energy consumption drops dramatically. For the last 40 minutes, OPTC consumes only 35% of the energy of fixed setpoint. As a whole, there is a reduction of 16.5% energy consumption under OPTC.

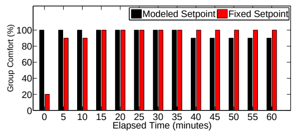



(a) Group comfort

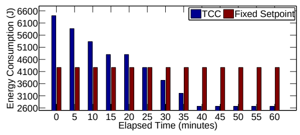



(b) Energy consumption

Figure 6: Group A simulation results




(a) Group comfort




(b) Energy consumption

Figure 7: Group B simulation results

The result of group B is shown in Fig. 7. As compared with group A, the group thermal comfort under fixed setpoint is far from satisfaction when the class begins. Only 20% of the students are within the comfort zone. In contrast, OPTC brings all the students stay within the comfort zone for more than 60% of the time, and it maintains 90% of group comfort for the students in class. From the results, besides the large differences of energy consumption between OPTC and fixed setpoint, we can see that group B saves even more energy. The reason is accounted by the ratio of UW is more than the OW in group B, which the setpoint temperatures from OPTC are generally higher than group A.

### 6.2.2 *Simulation of annual energy consumption*

The results of monthly energy consumption are shown in Fig. 5. The maximum and minimum averaged monthly temperature are between 14°C and 31.1°C respectively. OPTC outperforms the fixed setpoint in 10 months except May and October. During summer period, the difference between OPTC and fixed setpoint are approximately 5%. However, such differences enlarged rapidly when the outdoor temperature drops, especially at it-

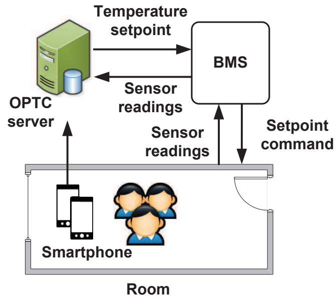



Figure 8: System workflow of OPTC

s bottom in January and December, the fixed setpoint consumes more than twice of the energy than OPTC. When compared with the fixed setpoint, OPTC saves 23.1% annual energy consumption.

## 7. IMPLEMENTATION DETAILS

To validate our idea, we implement a prototype of OPTC in buildings. The system workflow is shown in Fig. 8. The system is deployed in an OPTC server. Event monitor module in OPTC server collects data from environment and occupants. After optimal setpoint temperature is calculated, building control module request BMS to adjust indoor temperature in a room. To collect data from occupants, we develop a mobile application. Then occupants report their feelings and base rooms to OPTC server through this mobile application. Beside collecting data from occupants, OPTC server communicates with BMS for two objectives: 1) to collect indoor temperature and outdoor temperature; 2) to control indoor temperature of a room. We next discuss each part in more details.

### 7.1 Mobile Application for Occupants

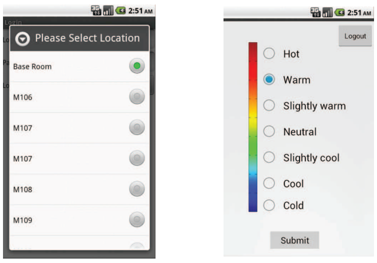
The mobile app collects the following information:

1) Occupant identity information; As explain, our system simply requests occupant registration. This registration is one-off and also collects such data as weight, age, gender, etc of the occupants. Recall from Section 4 that these information are needed for our TCC model.

2) The occupant are requested to register their base rooms, see Fig.9a; This registration is also one-off. If the occupant only has one base room, all the computation and adjustment will be based in this room. Note that in this situation, the air-conditioning still needs to be adjusted from time to time, and primarily non-intrusively. If this room hosts multiple occupants, the setpoint optimization algorithm needs to be applied. If an occupant has multiple base rooms, we need to obtain his location. To minimize the input from the occupant, the location can be obtained either from his meeting schedule, or a location detection algorithm can be applied. In a commercial office environment, an occupant usually has very small number of base rooms. This

makes the challenge for the location detection algorithm reasonable. The detailed location detection algorithm is out of the scope of our paper. In Section 8, our experiment is confined to the single room case.

3) Thermal comfort index when our model-driven adjustment does not satisfy the occupant thermal comfort. We collect their thermal sensation (see Fig.9b). The options are designed according to 7-point thermal comfort index. Then choices results can be transformed to thermal comfort index directly as explained in Section 4.3.




(a) Location selection (b) Voting screen

Figure 9: Mobile app for occupants.

## 7.2 Data Collection and Temperature Control in Building

In a typical HVAC system, there are thousands of sensors to monitor the equipment status and condition feedback from the serving areas [11]. The temperature sensors are normally mounted on wall or at the ceiling of room. There are also sensors installed outside the buildings to collect outdoor sensors data. Both of these data are sent to BMS through network. As the indoor and outdoor temperature are required by our OPTC, which are available in existing BMS, we hence retrieve such data directly from the BMS [33].

Apart from the data collection at BMS, we also require to control the setpoint temperature of rooms. This function can be realized through the Building Automation and Control Networks (BACnet) protocol in our OPTC framework. As BACnet is the most dominant communication protocol in BMS nowadays, we believe our system can be widely adopted into different buildings today.

# 8. EXPERIMENT

## 8.1 Experiment Setup

We use two performance metrics: 1) the improvement of thermal comfort of occupants, i.e., the change of comfort index; and 2) the missing rate in satisfying group thermal comforts. We adopt a threshold of 80% following the ASHRAE standard.

We conducted experiments in our university and a A-class commercial office. In our university, the air-conditioning of lecture theatres were controlled by the BMS, and the lecture theatre in our experiment had a capacity of 130 people at the building of Y-core.

For the experiment in the commercial office, the provision of air-conditioning was 24/7 and the floorplan and size of each room in office are shown in Fig.14. There were 5 individual rooms (room A to E) and 3 meeting rooms (room 1 to 3).

We setup our OPTC server on campus and connect both the BMSes of campus and office using virtual private network (VPN) as the network on campus is located at Intranet. To collect the votes of students, we designed the mobile app as discussed in Sec. 7.1.

## 8.2 Experiment results in our university

We conducted our experiment during a 3-hour lecture in our university. There was 87 students on the day of experiment, and the outdoor temperature was 31.4 °C. From our pre-measurement, the university has a fixed setpoint temperature of 21.5 °C.

Before the class, students were guided to install with our smartphone app. They were instructed to feedback their thermal sensations (as shown in Table 1) at an interval of 10 minutes. To develop the TCC model of each student, we also collected student's age, height and weight respectively.

In Fig. 10, we show the results of different group comfort under the fixed setpoint and our TCC modeled setpoint. The x-axis is the elapsed time from students to arrive the lecture theatre. The y-axis of the upper part of the figure is the corresponding setpoint given by fixed and TCC, and the y-axis of the lower part of the figure is the overall feedback of students. We compare the two setpoint approaches. For example, when the elapsed time is between 0 and 10 minutes, we see that the TCC setpoint (22 °) is slightly higher than the fixed setpoint, and the difference enlarged at between the 10 and 30 minutes. At the time of 40 minutes, fixed setpoint has achived its highest group comfort, which is only about 40% of the students. In summary, the result shows that more than 85% of the students were not at a comfort condition when they were just arrived the lecture theatre, i.e., the comfort index was outside the comfort zone. 25 students even voted 3, and only 5 students with thermal neutrality. On the contrary, our TCC setpoint is able to achieve required group comfort

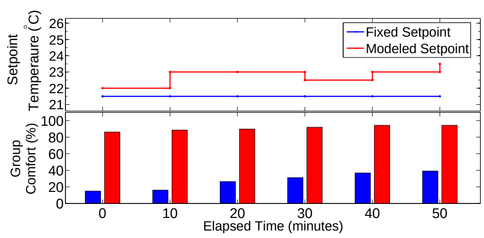
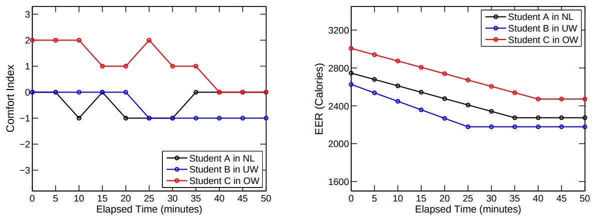



Figure 10: Setpoint temperature with comfort index




(a) Comfort index (b) EER

Figure 11: Students from different BMI groups

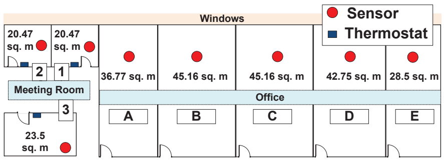



Figure 14: Floorplan of office

(i.e., *geq* 80%) for the whole period of time.

We then applied our model by first developing their TCC with the given data. For better elaboration, we categorized the students into three groups according to their BMIs as discussed in Section 4.3. We select one student from each group and show their comfort indices and $EER$ in Fig. 11a and 11b respectively.

It was not surprised that students in OW group had a higher $EER_s$, followed by the student in NL group, who had a relatively mild change of $EER$ with time. The student in the UW group had both the highest and least $EER_s$ and $EER_e$ respectively among the other groups.

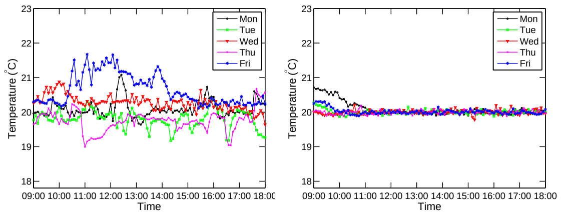
To compare the improvement brought by our TCC model, we started to adjust the setpoint temperature of the lecture theatre via our OPTC server after the 10-minute break at the second hour of the lecture. Students were again told to vote at every 10 minutes.

We demonstrate the setpoint adjustment from our TCC model in align with the feedback from students in Fig. 10. The result showed that there was a great improvement to their conditions of thermal comfort as compared with the default fixed setpoint at 21.5 °C. Only 9 students (10.3%) were not at the comfort zone in the first 20 minutes, and later reduced to 5 students (5.7%) after 30 minutes.

As compared with the group comfort before the TCC model was applied, there was an average of 63% thermal comfort improvement to the students in our experiment.

### 8.3 Experiment results in a commercial office

In this part, we discuss the experiment conducted in the commercial office. To study the existing indoor temperature and occupants comfort, we initially deployed three temperature sensors at different rooms for three weeks, and aimed to study the trend of temperature change under different outdoor temperatures.




(a) Room B (b) Room E

Figure 15: Temperature of two rooms

There were several interesting findings here. First, the results indicated that for rooms with more people (e.g., room B with 13 people), they have experienced a more significant change of temperature than rooms with less people (e.g., room E with 2 people). Fig.15a and 15b illustrate this phenomenon in room B and E respectively from one sample day during working hours.

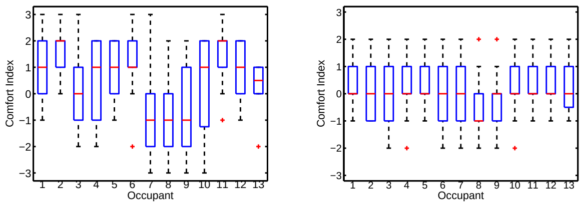
Second, we observed that there were temperature differences as wide as 2.5 °C at different zones in same room, and such differences were considerable that constitute to the discomfort of occupants. We traced the reasons and found that areas with printer and computers were the main culprits for a warmer temperature; and during the noon period, the areas near windows were affected by the sunlight and thus created a small warm zone.

These findings provide the insights that the placement of temperature sensors have a direct effect to the control accuracy of BMS and thus the room temperature. The number of sensors and location should be carefully considered; otherwise, occupants will be modeled with bias from other external factors.

Surprisingly, we also observed that it took approximately 4.5 minutes in average for a room to reach the setpoint. From our discussion with building services engineers, the adjustment of setpoint takes time for the chilled water and air flow from the air-conditioning terminal units (e.g., fan coil unit and variable air volume box) to work together so as to attain the desired setpoint. The time-lag varies with building designs and air-conditioning systems, hence in the latter stage of our experiment, the setpoint temperature is determined by the TCC model at every 5-minute.

We then carried out a 5 days (Monday to Friday) measurement before adopting our OPTC and collect occupants' feedback upon the thermal condition as control dataset. Room B was chosen in this experiment as it has the highest and steady occupancy. Two smart sensors TelosB were additionally deployed in room to provide a finer measurement.

Occupants were invited to provide feedback using our smartphone application anytime when they felt there was an obvious change to the thermal sensation. Noted that the default setpoint temperature was fixed at




(a) Before using OPTC (b) After using OPTC

Figure 12: Feedback from office experiment

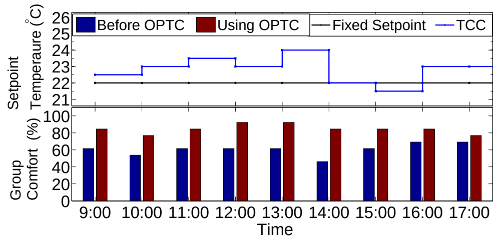



Figure 13: Setpoint and occupants comfort in office

22°C (summer period) by the facility management of the building.

We totally collected 403 votes, which were fairly from the 13 occupants. The result is shown in Fig. 12a using the variability chart. The central red line is the median, the height of the box is the inter-quartile range of the votes, where the top and bottom of the box are the 75$^{th}$ and 25$^{th}$ percentile of the votes. Extreme data that are not considered outliers is shown using the "whiskers", and the outlier data is indicated with a "plus" sign.

The result indicates that there was a significant dissatisfaction from the occupants to their existing fixed setpoint temperature. In details, there were around 45% of the votes were outside the comfort zone, where 7.4% of them were even in extreme comfort index (-3 or 3) that were voted by 7 people.

We then deployed our OPTC for comparison. With the previous feedback and information of occupants (i.e., age, weight and height), we develop the TCC model for each occupant. We kept collecting occupants' vote for another 5 days, and finally collected 334 votes.

For better elaboration, we demonstrate one of the experiment days in timeline format as shown in Fig. 13. There are two parts for the figure. The upper part shows the setpoint adjustment under fixed setpoint and our TCC model. The lower part displays the group thermal comfort from the votes of occupants. Noted that the average outdoor temperature of the day is 30.52°C, with a diurnal temperature of 3.17°C.

We also use variability chart to show the overal result in Fig.12b. The chart reflects a major improvement to occupants. 89% of the votes were within the comfort zone and none of the votes were from the extreme comfort index (-3 or 3). There were 115 votes with thermal neutrality that fairly collected from the 13 occupants. 12 of the occupants had a median of comfort neutrality, compared with 1 only in the first week experiment. There was an overall improvement of 33.8%.

Intrinsically, fixed setpoint strategy fails to bring occupants with a comfort condition as it does not consider the actual sensation of occupants. Unfortunately, it has become the common practice in most of the buildings today due to costs and management concerns.

Beside the improvement of thermal comfort, our OPTC also proposes energy conservation. With the baseline of setpoint temperature at 22°C, there was an average of 1.75°C setpoint increment during the experiment period. Studies indicate that one-degree setpoint difference yields around 10% difference to energy use [34].

Considered the energy input for the air-conditioning terminal units (kWh),

$$\sum_{i=1}^{n}\left\{\left(\frac{\dot{m}_i c \Delta T_i}{\eta_i \cdot COP} + P_{f_i}\right) hr_i\right\}, \tag{7}$$

where $\dot{m}$ is the air mass flow rate (kg/s), c is the specific heat capacity of air (kJ/kgK), ΔT is the difference between supply and return air temperature (K), $\eta$ is the heat transfer efficiency of the air-conditioning unit using chilled water, $P_f$ is the operating fan motor power, COP is the coefficient of performance of the central chiller plant and $hr$ is the cooling duration (hours).

In addition, the energy input was calculated by using the operating logs of BMS in 5-minute interval (i.e., $hr = 1/12$). Assuming the operating conditions were the same during the experiment, the result shows that our OPTC was able to save 18% of energy consumption of the air-conditioning terminal units.

## 9. CONCLUSION AND FUTURE WORK

In this paper, we present a occupant participatory thermal comfort framework. This framework incorporates occupants feedback into the loop of air-conditioning adjustment decisions. In the core of this framework, we develop a temperature-comfort correlation model that captures users favorite temperatures non-intrusively from their daily environment. Our model adopts the spirits of traditional PMV index and the adaptive approach developed from building services engineering. Nevertheless, to make sure that the model can fit in daily usage, we make certain modifications where we select the model input data so that they can be easily collected and the occupant has incentives to participate. To the best of our knowledge, we are the first to truly modify a building service human comfort model from a computer science point of view. We develop an algorithm which resolves thermal comfort for multiple people. We have a full set of field validations, comprehensive simulations and real world experiments. We show that we can maintain thermal comfort while substantially reducing energy consumption for 18%.

Our work has limitations. Among the many things that can be improved, we see it is necessary to develop a benchmark for such dynamic control and dynamic thermal comfort, so that building operators can adopt facing complaints. It is also possible to substantially refine our design with humans feedback in the control loop using adaptive control theory. We admit that our experiments are limited with both the number of participants and the duration. We plan to conduct a larger scale of validation, so that we can better quantify the number of feedback we can reduce and how this quantitatively affects user's incentives.

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