Carrying My Environment with Me: A Participatory-sensing Approach to Enhance Thermal Comfort

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ABSTRACT

Commercial building is one of the major energy consumers that has drawn worldwide concerns. Heating, ventilating and air-conditioning (HVAC) system constitutes 40% of the total energy consumption in a typical commercial building. While the main objective of HVAC is to provide occupants with a comfort and safe environment, it currently lacks channels to recognize occupants' favourite temperatures as well as reflect their levels of comfort, e.g., too-cold or too-hot. Hence, it is hard to justify the energy consumption without considering end-user needs. Models of thermal comfort and predicted mean vote have been used to estimate such index, however, they are not widely adopted due to their complexity and inaccuracy. In this paper, we design the innovative system CarryEn, which first captures user's favourite temperature non-intrusively from their daily environment. We connect our system with the building management system (BMS), and optimize the setpoint temperature to occupants with our model. When the user moves into other rooms or buildings, his favourite setting will also be carried with him. Based on our experiments, CarryEn is able to achieve an improvement of 28.2% thermal satisfaction from occupants and save 13% of energy consumption.

Categories and Subject Descriptors

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

Keywords

Participatory sensing, BACnet, BMS, PMV

1. INTRODUCTION

Buildings have long been the major energy consumers in different countries and cities. In the U.S., around 46% of the total energy consumption is consumed by commercial buildings [1], of which heating, ventilating and air-conditioning

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(HVAC) constitutes 35%-40% of energy consumption in a typical commercial building.

While there are lots of discussions and measures for energy reduction, the quality of services is always in top priority. Humans spend more than 80% of their daily time in buildings [6], therefore, the condition of indoor environment can affect the health of occupants and their productivity. Smart and intelligent buildings are proposed that aim to reduce building operation and electricity costs, improve indoor air quality and enhance human comforts. Currently, occupant's feedback is discrete from the actual operation of HVAC system, occupants dissatisfaction to the air-conditioning services are common, e.g., too cold or too hot. A fixed setpoint temperature is normally assigned and applied to different zones of buildings with various factors, e.g., the functionalities of zone, occupancy schedule, number of people and building orientation.

In fact, it is challenging to set a fixed temperature that suits everyone's need, since people can hardly have unanimous thermal sensations even though they are under the same environment [7], e.g., a thin person may prefer a higher temperature, whereas a fat person prefers a lower one. Another challenge is that people are insensitive to numerical expression of temperature [8], one may not be able to differentiate the actual differences between 24.5 °C and 23.5 °C, therefore, asking people questions like "What is your favourite temperature?" and set accordingly is not feasible, there are gaps between the system inputs and human sensations that we seek to fill in this paper.

Rather than estimating the occupants comfort based on the traditional predicted mean vote (PMV) model, we address the issue with an innovative approach: we capture the user's favourite temperature setting directly from their daily environment, where sensor data are available and retrievable from BMS. Users can also reflect their perceptions with the use of participatory sensing, thus they can vote in their smartphone anytime they want. Considered the correlation between outdoor temperature and thermal sensation of users, we apply the *adaptive thermal comfort* model in order to provide a better fidelity to our system.

Our contributions in this paper are as follows:

- 1. We showed how to exploit and leverage the data from the sensors in BMS to shape the user's favourite temperature setting.
- 2. We developed an optimized setpoint temperature model that targets to achieve the standard of thermal comfort, which other previous works have not considered.

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- 3. We have implemented our system of CarryEn, which is able to carry user's favourite temperature setting nonintrusively into places he visits, the system is scalable and extendable to other applications.
- 4. We deployed our system in a real environment, the results show that we are able to achieve an improvement to the thermal satisfaction of occupants by 28.2% and save 13% of energy consumption in our experiment.

2. RELATED WORK

There have been vigorous discussions regarding thermal comfort in recent decades. The discussions can be summarized into two approaches [7]: heat-balanced approach and adaptive approach. The heat-balance approach is first proposed by Fanger [16] which uses the physiology of thermoregulation to identify the range of comfort temperature in a building. He later proposed the PMV model, which then incorporated into international standard ISO7730 and industrial standard [4], however, this model has not been widely adopted due to a number of reasons that will be discussed in section 3.1.

Adaptive approach focuses on the adaptation of human in terms of behaviour, physiological and psychological adaptation [6][5]. They found that human comforts are affected by the function and nature of buildings. Besides, the outdoor temperature has a correlation with users comfort [6]. Our design considers the advantages from PMV model and the insights from the adaptive thermal comfort model.

In computer science, researchers have recently applied the idea of thermal comfort into application. Participatory sensing is developed as a medium to collect users feedback. Mobile application is used to collect occupants separations regarding the surrounding environment [13][14][8].

The experiments of [14] studied the temperature, lighting and air quality comfort of occupants. The problem of the experiment was the low-incentive of participants. Thermovote [8] designs the mobile application with resemble rationale. The authors try to abstract the parameters of PMV model using the offset value, however, this method is prone-to-error since some of the parameters in PMV model are non-linear. SPOT [13] deploys multiple sensors and tries to obtain all the required parameters of PMV to provide accurate estimation. Though they are able to provide a more reliable parameters to the PMV model, their work can only be used in rooms with a single person. We argue that thermostat will be the best option for users in this case.

In our design, we collect the sensors data directly from BMS. We do not need any extra hardware to be deployed in users workspace. Besides, our system model is built to meet the standard of thermal comfort that others do not, and it is applicable to workspace that occupied by single person or a group of people. More importantly, users are free to move from place to place and their favourite temperature setting will be as if carried to the new location accordingly.

3. OVERVIEW TO THERMAL COMFORT

The American Society of Heating, Refrigerating and Airconditioning Engineers (ASHRAE) has published the standard for thermal comfort, which defines thermal comfort as the condition of mind that expresses satisfaction with the thermal environment [4]. It also specifies the combinations of personal and indoor thermal environmental factors that is acceptable to a majority of the occupants within the space.

Table 1: 7-point thermal sensation scale

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

It has become the rule-of-thumb and international standard ISO7730. As specified, the condition of thermal comfort is said to attain when at least 80% of occupants are satisfied with the thermal environment. Predicted Mean Vote(PMV) model is used to predict such condition based on several personal and environmental factors. We discuss the details of PMV as follows.

3.1 Predicted Mean Vote

To quantify people's thermal sensation, ASHRAE adopts a seven-point thermal sensation scale as shown in table 1. Each of the point (-3 to 3) corresponds to different levels of comfort. PMV is an index used to predict the mean response of a large group of people according to this sensation scale. It considers six factors, including metabolic rate, clothing insulation, air temperature, radiant temperature, air speed and humidity. The first two factors are personal-dependent, whereas the latter four are environmental-dependent. While the PMV index helps quantify the thermal sensation of one, critiques for its impracticality to real-world situation have limited its application and affected the accuracy. For example, metabolic rate and clothing insulation can hardly be obtained without detailed measurements and modeling. Also, the radiant temperature and air speed are normally not sensed by BMS. In actual applications, most of the factors are assumed with constant values, the result is thus inaccurate [8].

We further study the accuracy of the PMV from the dataset obtained from [6]. We retrieved all the field studies data from buildings with HVAC system, it covers more than 20 countries with different climate zones and seasons. We focus on the difference between the PMV values and the Actual Mean Vote (AMV) from more than 10k people. Surprisingly, the result shown in Table 2 indicates that PMV is not able to reflect the actual thermal sensation of the interviewees; there is as large as 2-point difference in the upper 80-percentile. There have been tremendous discussions to the inaccuracy of the PMV model [5][7][6], since this is not the focus of our paper, hence we skip the details here.

3.2 Standard of Thermal Comfort

With the worldwide field studies, ASHRAE provides the guidance and illustrates the comfort zone of humans based on the PMV [4]. It assumes human activity levels with metabolic rates between 1.0 met and 1.3 met and where clothing insulation between 0.5 clo and 1.0 clo. Although the assumption of metabolic rates and clothing insulations have again limited its applications, the concept of comfort zone inspires us to the system design.

For instance, people with totally different preferences to the A/C setting is still possible to find an *optimized temperature* as human beings have a certain levels of thermal

Table 2: Result of RP-884 database

Percentile	PMV - AMV	Diurnal Temperature Range
95	2.7	16.88
90	2.38	14.73
85	2.16	13.5
80	2	12.6
75	1.86	11.8

threshold (i.e., range of comfort zone). There can be tradeoff between the levels of comfort and the number of people, e.g., 10 people with "Slightly Cool" may be more preferred than 5 people with "Warm" and other 5 with "Neutral".

In recent works of thermal comfort, outdoor temperature has been found to play a key role that affects people's thermal sensation. Field studies also show that outdoor temperature is strong correlated with PMV values [6][7]. In our system design, we also incorporate outdoor temperature as a parameter in the optimization model. Our system does not merely correlates the outdoor temperature with user's thermal sensation, we also consider the dynamic change of people's preferences to the temperature. For instance, a person comes back from the outdoor environment with $35^{\circ}C$ is likely to prefer the temperature as low as possible to cool down his body instantly, whereas he may feel cold when he works in front of the computer for several hours afterwards. Hence, our design does not treat each person's preferred temperature as static as PMV does, rather we consider the duration a user stays in a place. Specifically, we use a diminishing weighting factor to consider the effect of outdoor temperature towards the thermal comfort of people. Details of the formulation and design will be discussed in the next section.

4. DESIGN OF CARRYEN

Fig.1 shows the system architecture of our CarryEn design. The core part of the system comprises the following four modules:

- Event Monitoring: handles users connection and monitors the life cycle of each connection. It also maintains the users schedule for future meeting, and fetch instructions to BMS adaptor regularly for setpoint adjustment according to the result from the optimization model.
- Users Profile: handles and keeps users account information, including the historical votes of users, preferred temperature function and meeting schedule. It provides key information to the optimization model.
- Buildings Profile: keeps the connection details of different buildings' BMS. It records the required information from the optimization model, including room temperature reducing rate and location details.
- **Optimization Model**: formulates the user's function of preferable temperature model and calculates the optimized setpoint temperature to a group of people. Details in Sec.4.3.

In the following parts, we first discuss the data acquisition from BMS, followed by our design of mobile application. We will describe the data processing and optimized setpoint temperature model afterwards.

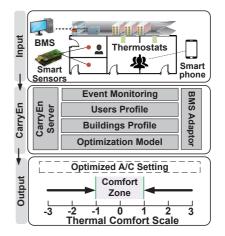


Figure 1: System Architecture of CarryEn

4.1 Data Collection

In a typical HVAC system, there are hundreds to thousands of sensors to monitor the equipment status and condition feedback from the serving areas [10]. We refer the area where a user normally stays in as *base room*, it can be his office or a room that is shared with others.

In this paper, we focus on the temperatures of occupants from their base rooms as these data reflect occupants' actual preferences and shape the occupants' habit regarding the A/C setting. We aim to collect three key information: i) setpoint temperature; ii) room temperature; and iii) occupancy of user.

We define the *setpoint temperature* as the desired room temperature to be attained by the HVAC equipment, whereas *room temperature* refers to the actual temperature that collected from the sensors installed in rooms. In contemporary HVAC design, setpoint temperature can be either set on-site with the use of thermostat or it can be commanded remotely by BMS.

During the construction stage of building, the provision of air-conditioning is basically designed to provide sufficient ventilation and desired cooling for different areas, normally named as *zones*. The area of each zone may not be equal and vary with the functions of building. Thermostat is normally installed in zone basis for people to have direct control upon the zone temperature. Temperature sensor is normally resided in the thermostat to determine if the desired setpoint temperature has been reached.

A network thermostat has the function to feedback such settings to BMS through the direct digital controller (DDC). For places without thermostats, the temperature sensors are

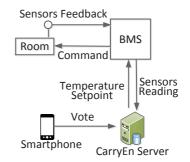


Figure 2: System workflow of CarryEn

installed at ceiling and the zone temperature is set from BMS through network. Ethernet is normally used in this regard due to its common availability.

Our design of CarryEn caters for both types of design, i.e., with or without network thermostats. For occupants with network thermostats and temperature sensors in base room, we can retrieve the setting and data from BMS nonintrusively. For users that do not have temperature sensors in their base rooms, we may deploy smart sensors to collect the temperature data as shown in the input of Fig.1. The methods of collecting temperature data using smart sensors may refer to [12][17][9][13].

In this paper, we use another promising approach: we collect the temperature data directly from BMS. Building Automation and Control Networks (BACnet) is the most dominant communication protocol in BMS nowadays. In our previous work, we have shown two different methods to communicate with BMS, i.e., using software [18] in application layer or smart sensors [15] in datalink layer. We believe our design of CarryEn that based on BACnet is able to work in most of the buildings today.

In Fig.2, we illustrate the communication of CarryEn with BMS. BACnet has a comprehensive communication suite and BACnet Broadcast Management Device (BBMD) enables the communication across networks and buildings. More details are available in [3].

To acquire the room temperature of occupants, we have to first obtain their locations and map the corresponding sensors from BMS into our CarryEn server. The mapping process requires once for each building, there are several similar works for reference [11][10], which are orthogonal to our approach.

Apart from the setpoint and room temperature, the occupancy of user is also important. Occupancy sensor is one of the possible methods in validating such information, but since it is not commonly installed in most of the rooms, and also bundles of intrinsic problems related to its accuracy made it less useful [8]. More importantly, if the base room is shared by a group of people, it becomes complicated to differentiate the occupancy of each people. To address this problem, we use participatory sensing approach in our design and we discuss it in the next part.

4.2 Mobile Application of CarryEn

Participatory sensing provides gateway for physical systems to acquire and capture ubiquitous data directly from individuals and groups of people through the mobile devices. We design a mobile application, known as *CarryEn App*, which is used to collect user's thermal sensation regarding the surrounding environment. The user interface and operation are simple. Each user has to register using their email address and indicate their base room. An activation email will be sent to verify users' information and a unique ID will also be assigned to them.

User needs to specify his location for each login, and CarryEn App will update the server of user's location. The server will connect with the corresponding BMS where the user located at and communicate with it accordingly. CarryEn App keeps connection with the server by sending packets in 5-minute interval. To prevent users from forgetting to logout the system, CarryEn will automatically logout and alert the user once it detects there is a change of network connection, e.g., different SSID, swap from Wi-Fi to 3G.

There are two main functions of CarryEn App. First,

users can reflect their levels of comfort by "voting" at the screen as shown in Fig.3b. Second, users can create a new schedule by specifying the information of date, time and venue for future meeting. The submission of location, votes and schedule require users to login in advance, so it leaves to users' discretion in providing such information.

4.3 **Optimized Temperature Model**

There are two levels in our model. First, it creates a preferred temperature model for single user. Second, it finds out the optimized setpoint temperature that maximizes the group thermal comforts.

We first discuss the individual preferred temperature model. The model is based on BMS data and votes from users. We collect the vote from users $[t_r, t_o, V]$, where t_r is the room temperature, t_o is the outdoor temperature and V is the actual vote of user.

We first define users voting function $h(t_r)$, i.e., for temperature t_r , what the numerical value of the users "preference" will be. As the thermal sensation of humans is non-linear, we divide the temperature into intervals of λ . Each user's vote (in numerical value) will be mapped into the corresponding interval $(\lambda_{n+1} - \lambda_n)$. $h(t_r)$ is formulated using linear regression of these votes.

We then define $g(t_o)$, the impact of outdoor temperature to individual user voting. $g(t_o)$ is calculated as follows. Note that at each time the user votes, we can have an estimate of the vote $\tilde{V} = h(t_r)$. Clearly, V can be different from \tilde{V} . This difference is affected by outdoor temperature and other side factors. Let the difference between \tilde{V} and V be $\Delta = V - \tilde{V}$. We divide Δ into Δ_1 , the factor of outdoor temperature and Δ_2 , other factors. Hence, $\Delta = \Delta_1 + \Delta_2$. For Δ_2 , we simplify it and use Gaussian normal distribution with $\mu = 0$. As such $\Delta = \Delta_1$. Similar to $h(t_r)$, we calculate $g(t_o)$ using linear regression of the set of Δ .

We investigate the relationship between V and t_r . We assume t_r and Δ_1 are independent, and thus:

$$V = h(t_r) + W_k g(t_o) + \Delta_2 \tag{1}$$

We add the weighting factor W_k to $g(t_o)$ as the impact of outdoor temperature t_o on V diminishes with time and $W_k = 0$ eventually at a threshold k, i.e., the user's thermal sensation is not affected by t_o after a certain period of time k. We develop such model primarily due to its simplicity.

Our algorithm to compute the best setpoint temperature for a group of people is based on this model where the preferred temperature function for each individual be

$$\tilde{f}(t_r, t_o) = h(t_r) + W_k g(t_o) \tag{2}$$

Our objective is to find the optimized setpoint temperature that maximizes the group thermal comfort, given that the required percentage of people are staying within the comfort zone. The algorithm is shown in Algorithm 1. There are four input parameters, which are $f_i(...)$, N, r and T_c . $f_i(...)$ refers to function of individual preferred temperature, i.e., $f(t_r) = \tilde{f}(t_r, \tilde{t}_o)$, N is the total number of people, r is the required percentage of people (e.g., 80%) within the comfort zone and T_c defines the boundary of comfort zone in absolute value (e.g., 1). Note that the \tilde{t}_o of $f(t_r)$ can be assigned with actual t_o or a fixed temperature.

The model first identifies the optimized temperature of each user with the best vote (i.e., 0), followed by the whole group of people and computes the optimized setpoint tem-

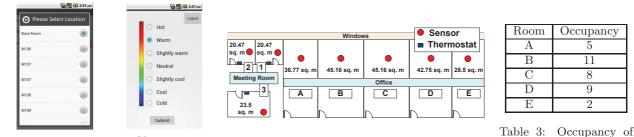


Figure 4: Floorplan to office

(a) Location selection (b) Voting screen

Figure 3: The CarryEn mobile App

Algorithm 1 Optimized setpoint temperature		
Input: $f_i(), N, r, T_c$		
Output: T^*		
1: $T^* \leftarrow \emptyset$, S = {1, 2,, N};		
2: for $\forall i \in S$ do		
3: $T_i^* \leftarrow \arg\min_T f_i(T);$		
4: end for		
5: while $ S > rN$ do		
6: $T^* \leftarrow \arg\min_T \sum f_i(T);$		
$i \in S$		
7: $N_1 = 0;$		
8: for $\forall i \in S$ do		
9: $ f_i(T^*) \le T_c;$		
10: $N_1 \leftarrow N_1 + 1;$		
11: end for		
12: if $N_1 \ge rN$ then		
13: break;		
14: else		
15: $J = \arg \max_{i \in S} T^* - T_i^* ;$		
16: $S \leftarrow S \setminus \{J\};$		
17: end if		
18: end while		

perature. The setpoint temperature is then used to determine the number of people N_1 who is able to stay within the comfort zone. After the first round of calculation, it compares N_1 with the required number of people rN. If it is able to meet the target requirement $(N_1 \ge rN)$, the optimized setpoint T^* is then found. Otherwise, the model keeps running and using the *best effort* by locating the extreme user who stays farthest away from the group optimized setpoint, and removes him from the user's group S. It then calculates again for the group optimized temperature and perform the condition checking again. Note that it is possible for the model fails to find the optimized setpoint temperature that meets the requirement, especially when the users' optimized temperature are unevenly distributed or the r value is harsh to be achieved.

5. EXPERIMENT

In this section, we first describe the experiment setup, followed by the two experiments conducted in a commercial building and our university.

5.1 Experiment Setup

To evaluate the system performance, we define the performance metrics of the system as i) the improvement of thermal comfort to occupants; and ii) the *missing* rate in meeting group thermal comforts.

We conducted the experiment in an office and on our campus. Fig.4 shows the floorplan and size of the office. There

are 5 individual rooms (room A to E) and 3 meeting rooms (room 1 to 3). The occupancy is summarized in Table 3.

offices

In our university, we chose 20 classrooms with different capacities, ranging from 40 to 80 people. All rooms are equipped with thermostats and connected to the campus BMS. During the study period, these classrooms were unoccupied and hence the measured data was free from human factors. Fig.8 shows one of the classrooms in our study, which the thermostats are installed at the entrance.

We setup our CarryEn server on campus and connect it to both the BMSes of campus and office. As the BMS of office is located at the campus Intranet, we thus set up a virtual private network (VPN) to access it.

To collect users' vote, we designed the Android mobile application $CarryEn \ App$ as discussed in Sec. 4.2. We also provide an alternative for voting on web-based platform to cater for those using other operation systems (e.g., iOS) or without a smartphone. Users are reminded to activate their wireless communications such as Wi-Fi and 3G/4G to keep connecting with the CarryEn server.

Several key information is required for daily operations: i) Users location (default as their *base room*) ii) Schedule (time and venue) iii) Thermal sensation (as shown in Table 1). To maintain the consistency of our experiments, we take $\tau = 10$ and W = 0.2, i.e., the setpoint adjustment is carried out in an interval of 10-minute, and the weighting factor of the effect brought by outdoor temperature diminishes at the rate of 0.2 for each interval.

Besides the BMS, we use data loggers to verify the data accuracy of BMS in our experiments. The data logger is Hobo U12-012 as shown in Fig.7a, with handheld-sized and is able to measure temperature, relative humidity and light intensity. The sensors are calibrated and with a resolution of 0.03° C. We set the data logging interval in 1-minute throughout the experiments, and the datasets are retrievable using the software provided by the manufacturer. Besides, we use 6 smart sensors TelosB as shown in Fig.7b with resolution of 0.01° C to establish the buildings and users' profile as well. The sink of the sensors node is connected to our notebook and sent to the CarryEn server on campus.

5.2 Experiment results in a commercial office

The experiment conducted in the commercial office is discussed in this part. All of the occupants were invited to participate in this experiment. We first established the building profiles with three weeks data, including the change of temperature and time required to reach desired temperature of each room. Results show that the temperature change is more significant in rooms with more people (e.g., room B and

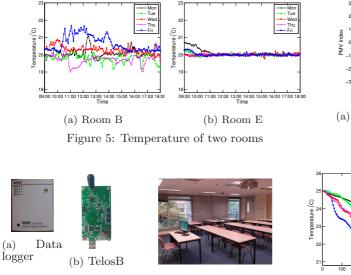
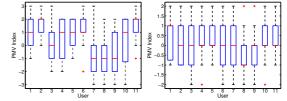


Figure 7: Experiment Figure 8: Classroom on campus



(a) Before using CarryEn (b) After using CarryEn

Figure 6: Votes collected

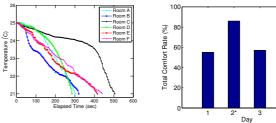
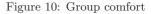


Figure 9: Temperature Reducing Rate



D) than rooms with less people (e.g., room A and E). Fig.5a and 5b demonstrate the daily temperature differences in one sample week. The result justifies the usefulness of participatory sensing as it can help differentiate users' perception from a group of people sharing the room. The diverging perceptions of users are modeled into their individual user profile.

After the building profile was established, we carried out a 5-day (Mon to Fri) measurement to collect users' thermal sensation without implementing our system as control dataset. We chose room B in this experiment as it has the highest occupancy and the attendance was steady during the period of experiment. We deployed two smart sensors of TelosB (Fig.7b) and evenly placed these in the room. Occupants were told to *vote* in the CarryEn App to reflect their thermal sensations anytime when they feel an obvious change of sensation during the working hours (9:00a.m.-6:00p.m.). Note that the room setpoint temperature was fixed at 22° C (summer period) by default of the building.

We finally collected 361 votes, which were fairly distributed from 11 occupants. The result is shown in Fig. 6a using variability chart. The central red line represents 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", where the outlier data is indicated using the "plus" sign.

The result indicates that there is a significant dissatisfaction from the occupants to the room temperature setting. In details, around 46.2% of the votes were lying outside the comfort zone (1 to -1), and 8% of the votes were even in extreme points (-3 or 3), which were voted by 6 people. Obviously, it is not an ideal practice to occupants comforts by assigning a fixed setpoint temperature which is commonly found in most of the buildings today.

We deployed our CarryEn for comparison. With the users' previous votes, we continually collect new feedback (votes) in the following week with several setpoint temperatures, ranging from 21-25 °C with an interval of 0.5° C in each adjustment. The purpose is to widen the temperature varieties to the optimization model. We also concurrently capture other room characteristics required by the model, e.g., the temperature decreasing rate and room temperature.

To provide a better elaboration, we demonstrate one of the experiment days in timeline format, and display the information of setpoint temperature, group thermal comfort percentage calculated from the optimization model in Fig. 11. Note that the average outdoor temperature of the day is 31.34° C, with diurnal temperature range of 5.23° C.

Although the target for CarryEn is to maintain at least 80% of people staying within the comfort zone (-1 to 1), it does not imply that it is always achievable all the time. Specifically, CarryEn makes its *best effort* in maximizing the number of people staying comfortably with the optimized setpoint temperature. We can see that there are also times that it *misses* the comfort requirement, e.g., 10:00a.m. and 2:00p.m. as shown in Fig.11.

With the occupancy information in Table 3, we can account for the miss. As users came back in office at different period of time, our system does not re-calculate and adjust to the optimized setpoint instantly. Rather, it has to wait until the next adjustment interval, which is controlled by τ . There are several reasons we strictly keep the adjustment with interval. First, if the setpoint is adjusted instantly with

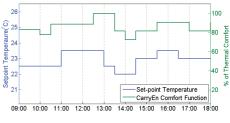


Figure 11: Setpoint v.s. group comfort

users' vote, the room temperature will swing back and forth when the mobility of users are frequent and their thermal preferences are highly diverging. Besides, the frequent adjustment is not a desired phenomenon that will shorten the lifespan of A/C equipment and create complexity in mapping users vote to the corresponding setpoint temperature of our model.

We observe that there was a 1°C increase at 11:00a.m. and later decreased substantially with 1.5° C around 13:00. The previous increase was due to the diminishing factor Wfades out (i.e., W = 0) from the three people who came back around 10:00a.m. and the latter decrease was due to 7 people left for lunch, and 2 people who stayed in the room had a relatively low-temperature preference. Finally, the system received 4 people voted for "Slightly Cool" between 14:00 and 14:20, resulting in the change of temperature to 23° C.

We keep collecting users' vote and concurrently training users preferred temperature model during the experiment. We show the variability of votes collected from the users during the week in Fig.6b, the notations are same as fig. 6a. The result shows that there is a major improvement. We received totally 287 votes that fairly distributed from the 11 occupants. Around 17.8% of the votes were outside the comfort zone (-1 to 1) while the medians of the 11 people were lying within the comfort zone.

In this experiment, the result shows an improvement to the occupants thermal comfort by 28.2% after adopting our CarryEn system. It is remarkable that none of the occupants have experienced extreme discomforts (3 or -3) during our second experiment. In contrast, 6 out of 11 people have had such extreme experiences before implementing CarryEn.

5.3 Experiment results in our university

Our experiment details conducted on campus are as follows. 12 users came from different base rooms of the office were arranged to hold their four consecutive weekly meetings on campus. They were came from room A (3 people), B (5 people) and D (4 people) respectively. To better evaluate the system performance with fairness and credibility, they were not told of the days our system was operated.

Prior to the experiment, we created the building profile in CarryEn and study the temperature reducing rate. We used two Hobo data loggers and evenly placed in each room. We averaged the two temperature dataset afterwards. We typically chose 6 classrooms with the same size and each room capacity was 40 people. In Fig.9, we show the temperature reducing rate decreased from 25 to 21 °C. Note that room C and E have non-openable windows, whereas other rooms do not have windows at all. Interestingly, none of them had the same reducing rate, e.g., room E takes 2 minutes longer than room D to reach the desired temperature. It implies that for rooms in same size, the temperature change rate does not necessary the same. Time difference implies important considerations to our design: we can make better decision such as when to turn on the A/C when meeting details (e.g., people and venue) are known in advance.

The 4 consecutive weekly meetings were held in Room E between 13:00 to 17:00 on Monday in June. Also, the 12 users have preset the date of meeting and venue into the CarryEn App with our assistance. We chose the *second* and *fourth* meeting to implement CarryEn in adjusting the room temperature.

The meeting began at 13:00, users were asked to vote af-

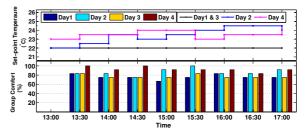


Figure 12: Comfortability and setpoint temperature

ter staying in the room for each half-hour. Each vote should reflect the overall perception in response to the previous 30 minutes. With reference to their base office, we used the set-point temperature of 22° C for the *first* and *third* meetings.

The setpoint temperature and users vote in half-hour interval are shown in Fig.12. With the building profile that built in previous stage, CarryEn started to command the BMS to turn on the A/C before the start of the second and fourth meeting, at which were 12:58 and 12:57 respectively. The initial setpoint temperature at 13:00 from CarryEn was not the same due to the differences of outdoor temperature of the day (29.2°C and 32.1°C respectively), the result calculated from the optimization model were thus different. The setpoint temperature increased slightly due to the diminishing factor W, i.e., people are less affected by the outdoor temperature after half an hour staying in the room. The setpoint temperature were adjusted mildly throughout the two meetings using CarryEn, one of the factors is that the room temperature to the users do not incur extreme cases, i.e., -3 or 3. Note that the setpoint adjustment is limited with the maximum adjustment of max_{adj} , which was 5°C during our experiments. However, none of the setpoint adjustment (increase or decrease) in our experiment were needed to be adjusted that exceed this.

In short, the range of setpoint differences for the second and fourth meetings were 2.5° C and 1° C respectively. Note that we do not mean the range of setpoint is able to indicate the goodness of fit to our optimization model, as there are many other factors affecting such index, e.g., diurnal temperature range (DTR), elasticity to users' thermal threshold; however, this can be an useful index to infer the energy saved.

Fig.12 shows the votes collected from the 12 users for each half-hour interval. During the second and fourth meeting, CarryEn is able to achieve as high as 87% and 100% of time that meeting the required standard. On the contrary, the result of the first and third meeting that without using CarryEn can both only meet 25% of time meeting the requirement. The total comfort rate which includes all other votes from the users during the four meetings are also shown in Fig.10. We can see that the first and third meeting can only maintain users comfort for 55% and 57% of time, whereas the second and fourth meeting are able to achieve 86% and 91% respectively.

Apart from the improvement of thermal comfort, CarryEn also proposes energy-saving. With the baseline of setpoint temperature at 22°C, there was an average of 1.5° C setpoint increment during the second and fourth meetings. Studies indicate that one-degree setpoint difference yields around 10% difference to energy use [2].

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

$$\sum_{i=1}^{n} \left\{ \left(\frac{\dot{m}_i c \Delta T_i}{\eta_i \cdot COP} + P_{f_i} \right) hr_i \right\},\tag{3}$$

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), η 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 (hr = 1/12). Assuming the operating conditions were the same, the result shows that CarryEn was able to save 13% of energy consumption of the air-conditioning units.

5.4 Lessons Learnt

Our experiments provide us with some general experiences: 1) before the experiment, we were worried about the incentives of user participation. We were delighted that we finally collected sustainable votes during the experiments. From our discussion with participants, we learnt that the incentives of users are affected by the usefulness and easiness of the application. Usefulness refers to the actual benefits of users after their contribution, and easiness is concerned with the design and complexity of using the application, 2) users are sensitive for the time it takes to experience the expected change. Therefore, the setting of temperature adjustment interval τ is an important factor in our system and it should be carefully determined, 3) BMS is separated from public network due to security concern, considerable communications with parties like facility managers and IT department are necessary. This can be time-consuming. If more public platform, e.g., Internet-of-Things can be realized, this process may be automated, 4) since we need to modify the setpoint temperature of BMS, we need to know the name of the BMS points in advance. However, there is currently a lack of a standard way in points naming. Often, the names of the points can hardly be understood without the assistance of BMS vendors. A unified naming can significantly improve the scalability.

6. CONCLUSION AND FUTURE WORK

In this paper, we present the design of CarryEn, which is able to capture users favorite temperatures non-intrusively from their daily environment via the BMS, and operate without using extra hardware. Our optimization model adopts the traditional PMV index with the adaptive model, and the mobile application is designed to collect users' votes from time to time in accordance with their changes in temperature preference. Also, our system is able to maximize the comfort to people with pre-defined schedule according to the standard. From our experiment, we achieve an improvement of 28.2% thermal satisfaction from occupants and save 13% of energy consumption.

In our work, we assumed the temperature sensed from BMS is equal to the temperature at the occupant's location. The distance between the two in practice, may affect the accuracy of our model. We plan to develop correlation models to offset such differences. There are always security problems for wireless connections, and this does make buildings hesitate for adoption. Dedicated studies are thus needed.

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