BEES: Real-Time Occupant Feedback and Environmental Learning Framework For Collaborative Thermal Management in Multi-Zone, Multi-Occupant Buildings

Santosh K. Gupta[a,*], Sam Atkinson[b], Ian O'Boyle[b], John Drogo[a], Koushik Kar[a], Sandipan Mishra[c], John T. Wen[a]

[a] *Department of Electrical, Computer, & Systems Engineering*
[b] *Department of Computer Science*
[c] *Department of Mechanical, Aerospace and Nuclear Engineering*
Rensselaer Polytechnic Institute, Troy, NY 12180, USA.

Abstract

In this work we present an end-to-end framework designed for enabling occupant feedback collection and incorporating the feedback data towards energy efficient operation of a building. We have designed a mobile application that occupants can use on their smart phones to provide their thermal preference feedback. When relaying the occupant feedback to the central server the mobile application also uses indoor location techniques to tie the occupant preference to their current thermal zone. Texas Instruments sensortags are used for real time zonal temperature readings. The mobile application relays the occupant preference along with the location to a central server that also hosts our learning algorithm to learn the environment and using occupant feedback calculates the optimal temperature set point. The entire process is triggered upon change of occupancy, environmental conditions, and/or occupant preference. The learning algorithm is scheduled to run at regular intervals to respond dynamically to environmental and occupancy changes. We describe results from experimental studies in two different settings: a single family residential home setting and in a university based laboratory space setting.

Keywords: Collaborative comfort management, Autonomous thermostat control, Multi-zone environment control, Smart HVAC operation, Occupant feedback interface.

1. Introduction

Energy usage in buildings, both residential and commercial, account for one of the major source of energy consumption. Data suggests that nearly 40% of the total energy consumption in US, and 20% of the total energy consumption worldwide, is attributed to the residential and commercial building usage [1]. More than 75% of current electricity consumption is also due to the usage in buildings. Hence, global energy efficiency cannot be obtained without devising ways for energy efficient operation of buildings. Heating, ventilation, and air conditioning (HVAC) system is one of the major energy consumers in buildings. However, even with the existing cost of HVAC systems, the occupant dissatisfaction associated with the prevailing indoor thermal conditions have been highlighted by several studies [2], [3].

Personalized comfort level expectations pose a conflicting situation in multi-occupant spaces such as residential homes, research laboratories, corporate office buildings, student dorms etc., where occupants have their own range of thermal comfort and other environmental settings. This range generally depends on individual occupant body type, external factors such as attire, physical and mental condition, and level of tolerance; and can also vary depending on other environmental factors such as time of the day, lighting conditions etc. [4], [5], [6]. This personalized thermal comfort range can be best captured by individual occupant feedback in real time. Further, in shared multi-occupant spaces personal comfort levels are affected both by the presence of co-occupants and the correlation between temperatures in different zones and rooms occupied [7], [8], [9]. Arriving at temperature set-points to minimize the aggregate discomfort among all occupants of different rooms or zones in a building is an important yet challenging problem. With rising energy cost and emphasis on energy conservation, the total energy cost also needs to be accounted for when trying to determine the optimal temperature set-points in different zones of a building.

Incorporating real-time occupant feedback is key to successful operation of any multi-zone, multi-occupant space that strives to maximize aggregate comfort of all its occupants while limiting the total energy cost. There are multiple aspects to designing an efficient end-to-end system for collection of occupant feedback in real-time and incorporating the same in thermal management of a building. It starts with providing an intuitive and user friendly interface for the mobile occupants to provide their feedback. When collecting the feedback the occupant preference has

*Corresponding Author
Email address: guptas7@rpi.edu (Santosh K. Gupta)

to be tied to a particular zone within the building with reasonable accuracy. A central server that can collate feedback from all the occupants and estimate optimal zonal temperature set points for the entire building would then be needed to complete the loop. It also requires knowledge of the comfort range information (discomfort as a function of the temperature experienced by the occupant, more generally), of all the occupants. In this work we present a framework to achieve this in a multi-zone multi-occupant building, where there is usually significant thermal correlation (energy flows) between different zones, and the exact discomfort functions are held privately by each occupant.

1.1. Literature Review

Numerous design and solution approaches have been proposed for the control and efficiency of HVAC systems. The approaches taken so far can be broadly classified into those focusing on optimal energy usage through variable electricity rates [31], [32], [33], [34], active and passive thermal energy storage [33], [34], and more recently model predictive control (MPC) approach exploiting information through weather forecast [35], [36], [37], [38], [39], [40].

Other set of works have studied advanced HVAC control algorithms with quantification of occupant comfort range. Some prior work [42] have tried to link the cost of building environment control to the occupant efficiency, health and satisfaction. To this effect occupant thermal comfort modeling has been extensively researched and can be summarized into the following three major approaches: (1) the chamber study model, based on mapping thermal comfort from environmental and personal factors to a 7-level comfort value scale, viz. the Predicted Mean Vote - Predicted Percent Dissatisfied (PMV-PPD) [8], [4]; (2) human body physiology based models such as Gagge's core to skin model [24], Stolwijk's comfort model for multi-human segments [25], and Zhang et al.'s sensation on human body segments [26]; and (3) adaptive comfort models developed in field study, viz. Humphreys [27] and [28].

The PMV index has been used as the metric for user comfort integration in multiple studies [10], [11], [12]. Some studies proposed sensor network solutions to increase the accuracy of PMV calculation [13], [14]. Owing to the complexity of sensor network deployment, a number of studies have proposed utilizing occupant feedback for thermal comfort integration into the control logic of building systems. Through custom keyboards in each room, Guillemin and Morel made use of occupant preferences in the form of temperature set points [15]. Murakami et al. used binary preference of warmer and cooler along with a logic to build consensus for controlling the air-conditioning set point [16]. Daum et al. utilized too hot/too cold occupant complaint along with a probabilistic approach for determining user comfort profiles [17]. Thermovote [9] utilized a seven level occupant comfort voting to integrate with the building control logic. Purdon et al. developed a smart phone interface to receive 3-point scale comfort feedback from occupants and determine the direction for temperature drift with a system defined step-size [41]. More recent work having considered thermal complaint behavior using one-class classifier [29], [30] have also been presented. Jazizadeh et al. used a fuzzy predictive model to learn occupant comfort profiles and a complementary control strategy for the HVAC control [19]. Zhao et al. conducted a simulation study tying occupant subjective thermal comfort feedback with MPC control algorithm for the active HVAC system against a baseline rule-based control algorithm [18].

An important aspect of study is evaluating the proposed strategy for improving thermal comfort in buildings. However, many of the proposed solutions require intrusive updates to the building HVAC system making it challenging to be evaluated in real building with occupants. Moreover, majority of the approaches are reactive from the occupant perspective. An occupant is expected to reactively and repetitively provide comfort feedback (in the form of hot/cold in different scales) when he/she is exposed to discomfort. This leads to loss of productivity and inefficiency. In the next section we introduce our framework designed to address the above challenges.

1.2. BEES Approach

As a solution to the above challenges, we present an integrated framework for real time occupant feedback collection and temperature control in multi-zone multi-occupant buildings and shared spaces.The solution, which we term BEES: *Building Energy Efficiency Solutions*, has the following novel components. 1) It provides an intuitive and user friendly interface (smart-phone application/ website) for occupant feedback collection in real-time. 2) Using a set of distributed sensors and beacons measures zonal temperatures and ties individual occupant feedback to their respective zone of occupancy in real-time. 3) It formulates and solves the collaborative building temperature control problem as a convex optimization question, such that it minimizes the sum of the aggregate occupant discomfort plus total energy cost. 4) It uses a model that captures the thermal correlations (energy flows) between different zones in a building, and ensures that the zonal temperatures are set in a coordinated manner taking such correlations into account. 5) The proposed algorithm is independent of the physical model of the building and of the HVAC system. The necessary parameters for the thermal modeling of the indoor space as required by our algorithm is learned in real-time using input from the sensors, making it a plug-n-play solution that can be retrofitted to existing buildings without any intrusive or expensive updates. The "sufficient parameters" that are needed to implement the algorithm is estimated through standard measurement based learning methods periodically. Figure 1 gives a high level systems representation of the BEES solution.

The acronym BEES is used to emphasize both the *collaboration* (collaboration between occupants, declaring thermal comfort range in self-interest) and *coordination*

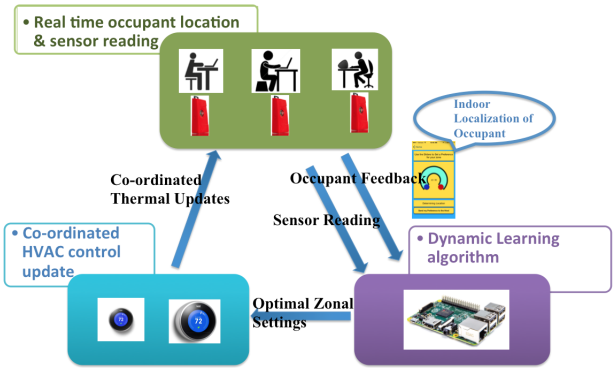

Figure 1: Systems level process flow depiction of the BEES solution.

(the thermostat control is set in a coordinated manner, taking into account the multi-zone thermal correlations). The measurement-based *learning* aspect of BEES[1] must be distinguished from that of the increasingly popular learning thermostats, such as those by Google-Nest [20], Honeywell [21] and GoComfy [22]. Whereas these existing thermostats involve learning of user habits, BEES involves learning of the thermal correlations across zones, towards a coordinated thermostat control solution in a multi-zone environment. Indeed, the BEES learning and control platform is best utilized when overlaid on top of wireless controllable thermostats (such as the Google-Nest or Honeywell thermostat), or a group of such thermostats, deployed in a typical building or shared space environment where multiple zones are almost always strongly thermally correlated. The BEES software helps in integrated control of these thermostats towards creating personalized comfort levels for the occupants, as much as allowed by the inter-zone thermal dynamics, the level of control available, and the user comfort preferences. BEES can be used with a single thermostat as well (typical in residential buildings), but would be more effective with greater number of control points. Taken to another extreme, one can imagine "Total Temperature Control" with one thermostat per user [23], and BEES can be effective in such scenarios in creating a thermal environment that is most comfortable across all users in the shared space. Finally, it is worth noting that we specifically focus only on temperature set-point control problem in multi-zone multi-occupant settings. However, the general framework should also be applicable to collaborative control of other factors that affect human comfort, and possibly involve trade-off between energy cost and comfort levels.

[1]The collaborative and coordinated aspects of BEES, and how it relates to individual learning thermostats, can be succinctly captured as: "A bird builds a nest (alone), BEES build a hive (together)". In this metaphor, an individual 'bee' can symbolize users who are induced to work together for creating an environment that is optimal in a collective sense. Alternatively, it can also symbolize the different elements that coordinate with each other towards the complete solution: the temperature sensors (drone bees), the thermostats (worker bees) and the centralized control server (queen bee).

To make the solution proactive with regard to occupant thermal comfort, rather than reactively seeking occupant discomfort feedback we take into consideration discomfort functions of the occupants individually - modeled as convex quadratic functions of temperature variation. Since the notion of discomfort is very personalized and subjective in nature, it is hard to quantify. We are not aware of any existing work that experimentally evaluates the discomfort function of typical occupants. Therefore our choice of quadratic discomfort function is motivated by the PMV-PPD model [8], [4], which suggests that the number of occupants uncomfortable at a particular temperature varies in a quadratic form with temperature. We adopt occupant discomfort function of the form:

$$D_i(y_j) = \begin{cases} (y_j - y_i^U)^2 & \text{if } y_j > y_i^U, \\ 0 & \text{if } y_i^L \leq y_j \leq y_i^U, \\ (y_j - y_i^L)^2 & \text{if } y_j < y_i^L, \end{cases} \quad (1)$$

where y_i^U and y_i^L are the upper and lower limit temperatures, respectively, of an occupant i located in zone j. Note that with this model the occupants just have to enter their upper y_i^U and lower y_i^L limit temperature values one time. We then pose the effective temperature control of the building formally as an optimization problem that takes into account both the temperature dynamics as a function of the energy input and the thermal discomfort function of the building occupants. We also want to point out that BEES is built upon our previous theoretical research work [43], [44], [45]. However, to contrast it with our recent theoretical work the key differences can be summarized as: (i) the approach in this work in much simpler for the occupants as they just have to share their upper and lower limit temperatures one time without having to worry about pricing or penalty feedback from the building system, (ii) we are presenting a complete systems level solution in this work, (iii) the current work takes an approach that relies on dynamic learning of the thermal environment, and finally (iv) this work incorporates more of experimental study rather than theoretical approach.

The rest of the paper is structured as follows. We present a comprehensive coverage of system features in Section 2, followed by a detailed system anatomy in Section 3. We share the experimental results in Section 4 and finally conclude in Section 5.

2. BEES - System Features

In this section we discuss major features of the BEES solution architecture that sets it apart from the existing solutions on occupant feedback based thermal management systems.

2.1. Occupant Feedback Collection

At the core of our solution is an intuitive and user friendly interface to capture occupant thermal comfort feedback in real-time. Figure 2 denotes the iOS smart phone

application interface that occupants can use to provide their thermal comfort feedback. An occupant i can simply use the central wheel to set their upper and lower limit temperatures (y_i^U and y_i^L from 1). Alternatively, they can use the Hot and Cold buttons to indicate how they are feeling and the comfort range adjusts accordingly. When the Hot or Cold button is used the slider moves accordingly (in steps of $1°F$ if moving towards the external ambient temperature and by $0.5°F$ when moving away from the external ambient temperature) to match the occupant comfort and energy efficiency. We foster energy efficient habit among occupants by using vibrational feedback cue when their thermal comfort choice moves away from the ambient condition (potentially increasing energy cost). The interface also conveys to the occupant their current zone of occupancy.

Using the interface in Figures 3 and 4 occupants can access different settings for the BEES system and also view the historical temperature data of different zones. The occupants with administrator credentials can even set default values for all the zones of their location when no other occupants are around.

2.2. Real-time Indoor Temperature Measurement

An effective thermal management of a multi-zonal space requires real time temperature measurement of all the respective zones. Note that a typical thermostat set-point function is based on the temperature as sensed at the thermostat location. This fails to capture the thermal dynamics and correlation of the entire space, and cannot ensure temperature within acceptable range for each zone. For real time thermal modeling of the space BEES captures temperature of each zone in real time at a frequency of 30 seconds. We use Texas Instrument's sensortag circuit [47], which is based on CC2650 wireless MCU as shown in Figure 5.

The sensortag circuit originally uses CR2032 coin cell batteries. However, we modified it to run on AA batteries for longer battery life and achieve un-interrupted data. Bluetooth Low Energy (BLE) is used as the communication protocol for relaying data from each zone sensortag to the location hub.

2.3. Indoor Localization of Occupants

Most of the existing occupant feedback systems require occupants to select the room/location they are in and then enter their comfort feedback. This is tedious and not occupant friendly, and at the same time may deter the occupants from providing feedback as they move around between different zones and locations throughout the day. BEES does real-time indoor localization of the occupants and automatically applies their comfort preference to their current zone. This is achieved using Gimbal proximity beacon series 10 [48], as shown in Figure 6.

The iBeacon technology [49] is used to communicate with the Gimbal proximity beacon through the BEES smart phone application. Occupants with smart phone or wearables can be localized to a particular zone through the Received Signal Strength Indicator (RSSI) value of signals received from the beacons spread throughout the location in each zone.

2.4. Environment Learning & Optimal Thermal Set-point

Raspberry Pi 2 Model B platform [50], as shown in Figure 7 acts as the location hub for our algorithm. It communicates directly with the sensortags through BLE, using a USB BLE adapter [51].

The real-time temperature readings are stored in a local database. It also pulls the ambient (outside building) temperature readings from Web API in real-time, and the data is used by the learning algorithm hosted on the platform to build the model at regular intervals. It then runs the optimization algorithm to calculate the optimal set-point for the location. Using the Nest API [52], the platform then automatically adjusts the Nest thermostat in the location to set it to the calculated optimal set-point.

3. BEES - System Anatomy

In this section we first provide a high level discussion of the BEES architecture. Then, we go into some in-depth descriptions of different use cases and entity relationship. Finally, we examine the learning model and the optimization algorithm.

3.1. Overall Architecture

The overall systems architecture for the BEES solution is presented in Figure 8. At the core of it is our central server that also hosts the web server for BEES. The server is responsible for authorization and authentication of occupants and stores the mapping of zones and locations. Occupants can also login and manage their BEES system through the website, and can even provide comfort feedback.

At the next level of architectural hierarchy is a BEES location. Each location hosts an individual BEES system running on a Raspberry Pi platform, and is supposed to have a thermostat that can be controlled over wireless (in our experimental study we used a Google-Nest thermostat). Note that in this work we associate each location with a single thermostat that has independent control of its air distribution system. A residential home, for instance, would qualify as a BEES location. Each location is then further granulated into multiple zones. Note that these zones are *soft* zones, in the sense that they are not independently controllable from the central thermostat. These soft zones are virtual zones as determined and created by the BEES system administrator for the location by using the required number of sensortags and Gimbal beacons. Any time an independent thermal control is available for a space it is referred to as a location as per the BEES architecture. However, note that the BEES framework can be

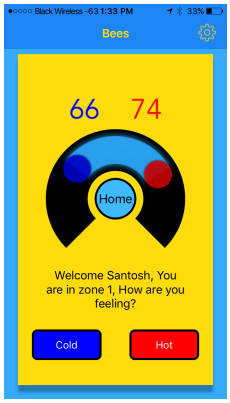

Figure 2: BEES iOS app interface for occupant thermal comfort feedback.

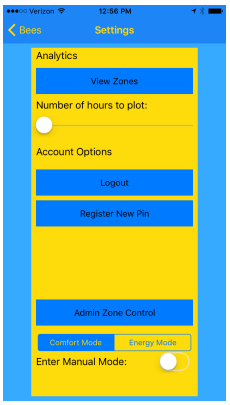

Figure 3: BEES iOS app interface to access and modify settings.

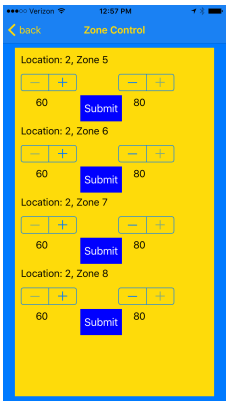

Figure 4: BEES iOS app interface for administrator occupants to set zone defaults.

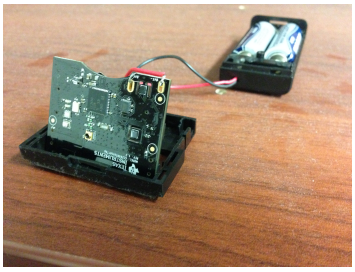

Figure 5: Texas Instrument's sensortag circuit based on CC2650 wireless MCU, used for real time zone temperature measurement.

Figure 6: Gimbal proximity beacon series 10, used for indoor localization of occupants.

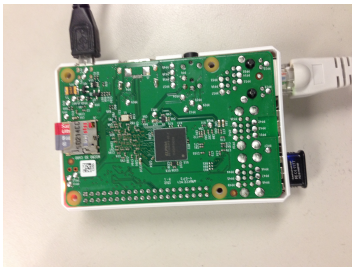

Figure 7: Raspberry Pi board serves as the embedded platform for each BEES location.

extended to include controllable vents, individual AC units or personal heaters that might be available separately in each soft zone. The BEES system administrator could be a home owner in case of a single family residential building, or a building system operator for commercial spaces. A home owner administrator, for instance, can decide to use just two sets of sensors to create two thermal zones (say first and second floor), or can pick a set of sensors for each bedroom creating five thermal zones in a five bedroom home location. Each zone can then accommodate as many occupants as the physical space might permit. Every occupant is actively tracked by BEES system through the smart phone application or wearables. Alternately, the occupants can use the web server to login and provide their information in a reactive manner.

3.2. Occupant Use Cases

In BEES architecture an occupant is classified as a regular occupant or an administrator occupant. Figure 9 shows the use case diagram for the BEES framework.

In the BEES framework, once an occupant logs into the system his/her location is determined. Once the occupant location has been obtained (on location or away from authorized location), the system retrieves the authorization level (regular or administrator) and accordingly available actions are displayed to the occupant. All occupants can provide their comfort feedback and view the thermal history of the location. For on location occupants the feedback is applied to the current zone of occupancy, and in case of remote occupants they have an option of changing their preference for future occupancy or applying it remotely to their last occupied zone. Additionally, as an administrator for a location an occupant can set defaults for all the zones of the location and also switch between different operating modes.

3.3. Network Architecture & Entity Relationships

Network architecture of the BEES system implementation is shown in Figure 10. The central server hosted as a Virtual Private Service (VPS) runs the central database and captures real-time system logs. The entity relationship diagram of the database structure is further represented in Figure 11.

The server provides HTTPS APIs for different components of the system (smart phone application, website, thermostat, location hub) to update and retrieve data values as needed.

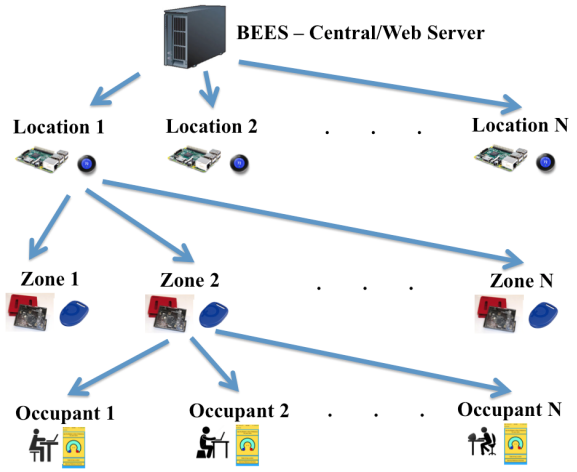

Figure 8: Central Architecture for the BEES system.

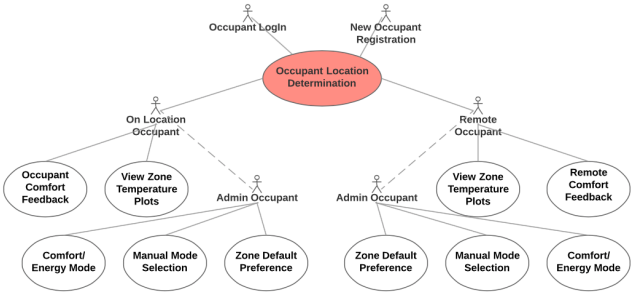

Figure 9: Occupant use case diagram depicting different use cases from the user perspective.

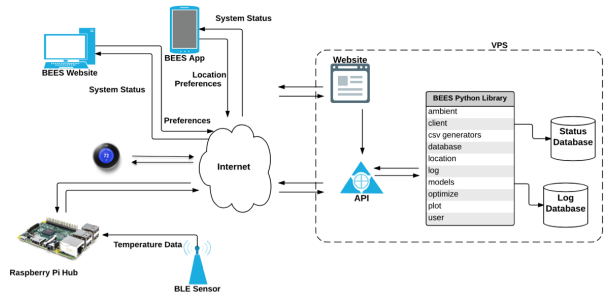

Figure 10: BEES network architecture depicting information exchange among different components of the system.

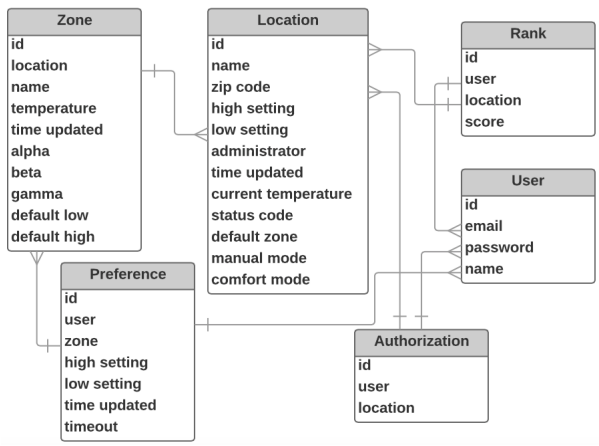

Figure 11: Entity Relationship Diagram (ERD) for the BEES system representing the relationship among different entity in the database.

3.4. Dynamic Learning Algorithm

Complete model independence in the form of plug-n-play solution is achieved by BEES framework through its dynamic environmental learning algorithm. Consider a BEES location with m zones. Let vector $\mathbf{y}$ denote the temperature vector of the location, where y_j represents the temperature of zone j within the location. The thermal state of the location can be represented as a function of its dependents:

$$\mathbf{y} = f(\Theta, T_\infty, \Gamma), \tag{2}$$

where Θ is the state of thermostat in the location, which in turn determines the external heating/cooling input. T_∞ is the outdoor ambient temperature and Γ represents all the other heat sources or sinks associated with the location. The function $f(.)$ is highly non-linear in general and would change with changes in environmental conditions, such as opening and closing of doors and windows, making it very challenging to estimate in real-time. However, for simplicity we model temperature of each zone as a linear function of the form:

$$y_j = \alpha_j \Theta + \beta_j T_\infty + \gamma_j. \tag{3}$$

Due to the thermal inertia of the building, the dependency of the current zonal temperature (y_j) on the external ambient (T_∞) and thermostatic temperature setting (Θ) is in general non-linear. However, in "steady-state" (i.e., when the transients have died down and the zonal temperatures have settled down to their equilibrium values), this dependency can be modeled as a linear relationship. This is true for the building thermal model used in our prior work [43], [44], [45], which are derived from the popular electrical analogy for modeling of a building with 3R2C model approach for the walls and rooms [46]. Note that in practice, there will also be non-stationary (time-varying) factors that will influence this dependency. Since we estimate the parameters α_j, β_j and γ_j is a time-dependent manner, we expect that these parameters will capture the effect of such non-stationary factors as well. In particular, the BEES system adapts the linear model in (3) for each zone of a location at every 10 minute intervals utilizing the real-time data values of y_j, Θ, and T_∞ captured in the past 60 minute duration. Note that this regular refreshing of data helps in incorporating possible environmental changes in the location. The coefficients α_j, β_j, and γ_j can further act as indicators of abnormal behavior in a particular zone over time with regard to very high correlation

with the ambient conditions or negligible effect of changes in thermostat setting. Further, note that the coefficient γ_j incorporates external heat source/sink such as equipment, personal heaters/coolers, etc. This model is next utilized in the optimization algorithm for calculating the optimal thermostat setting Θ for each location.

3.5. Optimization Algorithm

The optimization objective for a given BEES location with m zones can be represented as:

$$J = \min_{\Theta} \sum_{j=1}^{m} \sum_{i \in S_j} D_i(y_j) + \eta |\Theta - T_\infty|^2, \tag{4}$$

where $D_i(y_j)$ represents the discomfort function of occupant i in zone j given by (1), and S_j denotes the set of occupants in zone j. Note, that the value of η depends upon the choice of Comfort Mode ($\eta = 0$) v/s Energy Mode ($\eta > 0$) made by the location administrator occupant. In case of energy mode selection the user would be further asked to enter a positive value of eta. For the purpose of this study we implemented a default value of $\eta = 1$ for energy mode, but in the future version of the application the user would be asked to enter a value in an intuitive and user friendly manner. Using 3, the objective can be further written as:

$$J = \min_{\Theta} \sum_{j=1}^{m} \sum_{i \in S_j} D_i(\alpha_j \Theta + \beta_j T_\infty + \gamma_j) + \eta |\Theta - T_\infty|^2, \tag{5}$$

where the coefficients $\alpha_j, \beta_j, \gamma_j$ are estimated in real-time using the learning algorithm.

Given that the occupant discomfort functions are non-smooth and optimizing (5) through the use of standard convex optimization solvers can be inefficient, we provide an efficient algorithm to find the optimal. Define Δ_{ij}^L as:

$$y_i^L = \alpha_j \Delta_{ij}^L + \beta_j T_\infty + \gamma_j, \tag{6}$$

using $y_j = y_i^L$ and $\Theta = \Delta_{ij}^L$ in (3). Similarly define Δ_{ij}^U as:,

$$y_i^U = \alpha_j \Delta_{ij}^U + \beta_j T_\infty + \gamma_j. \tag{7}$$

Hence, we obtain:

$$\Delta_{ij}^L = \frac{y_i^L - \beta_j T_\infty - \gamma_j}{\alpha_j}, \tag{8}$$

and

$$\Delta_{ij}^U = \frac{y_i^U - \beta_j T_\infty - \gamma_j}{\alpha_j}. \tag{9}$$

For a location with m zones and n occupants in each zone, we obtain a total of $2mn$ values of Δ_{ij}^L, and Δ_{ij}^U. Note that $\Delta_{ij}^L \leq \Delta_{ij}^U$, given $y_i^L \leq y_i^U$. Next, we sort the list of $2mn$ values and let the sorted values be denoted as $\delta_1, \delta_2, ..., \delta_k, ..., \delta_{2mn}$. Using $\Theta_L = \delta_0$ and $\Theta_U = \delta_{2mn+1}$ values as the location thermostat limit values we obtain $2mn + 1$ intervals $I_1, I_2, ..., I_k, ..., I_{2mn+1}$, where I_k is the interval between values δ_{k-1} and δ_k. Now, in each interval I the derivative of objective function J from (5) is of the same form, but the values differ across different intervals. Let's compute the derivative of J over an arbitrary interval $I_k = [\delta_{k-1}, \delta_k]$. Let

$$d_{ij}(\Theta) = D_i(\alpha_j \Theta + \beta_j T_\infty + \gamma_j), \tag{10}$$

then the objective in interval k can be re-written as:

$$J_k = \sum_i \sum_j d_{ij}(\Theta) + \eta |\Theta - T_\infty|^2. \tag{11}$$

Derivative of $d_{ij}(\Theta)$ over interval I_k:

$$d_{ij}^{'}(\Theta) = \begin{cases} 2\alpha_j(y_j - y_i^U) & \text{if } \delta_{k-1} \geq y_i^U, \\ 2\alpha_j(y_j - y_i^L) & \text{if } \delta_k \leq y_i^L, \\ 0 & \text{otherwise.} \end{cases} \tag{12}$$

Or using indicator function,

$$\frac{d_{ij}^{'}(\Theta)}{2\alpha_j} = \mathbb{1}_{(\delta_{k-1} \geq y_i^U)}(y_j - y_i^U) + \mathbb{1}_{(\delta_k \leq y_i^L)}(y_j - y_i^L). \tag{13}$$

Hence, derivative of J_k in interval I_k:

$$\sum_i \sum_j 2\alpha_j [\mathbb{1}_{(\delta_{k-1} \geq y_i^U)}(y_j - y_i^U) + \mathbb{1}_{(\delta_k \leq y_i^L)}(y_j - y_i^L)] + 2\eta(\Theta - T_\infty). \tag{14}$$

For optimum Θ, this derivative in the interval I_k should be zero. Let this optimum if one exists be denoted by Θ^*. Then,

$$\begin{aligned} \Theta_k^* &= \frac{A + B + 2\eta T_\infty}{C + 2\eta}, \text{ where} \\ A &= \sum_i \sum_j \mathbb{1}_{(\delta_{k-1} \geq y_i^U)} 2\alpha_j (y_i^U - \gamma_j - \beta_j T_\infty) \\ B &= \sum_i \sum_j \mathbb{1}_{(\delta_k \leq y_i^L)} 2\alpha_j (y_i^L - \gamma_j - \beta_j T_\infty) \\ C &= \sum_i \sum_j \mathbb{1}_{(\delta_{k-1} \geq y_i^U)} (2\alpha_j^2) + \mathbb{1}_{(\delta_k \leq y_i^L)} (2\alpha_j^2). \end{aligned} \tag{15}$$

If this $\Theta_k^* \in I_k = [\delta_{k-1}, \delta_k]$, then it is a true optimum. We need to calculate the optimal value in (15) over all the intervals I_k to find the global optimum value. Since there are $2mn + 1$ such intervals, the optimum calculation requires up to $2mn + 1$ evaluations of (15). Then based on the administrator occupant preference of energy optimization or comfort optimization the algorithm can make a pick of the corresponding interval for the location. Note that this optimization algorithm is triggered by the BEES framework every 10 minutes after the model is learned. Any occupant movement (change of zone or location) or change of occupant preference further triggers the optimization algorithm instantly.

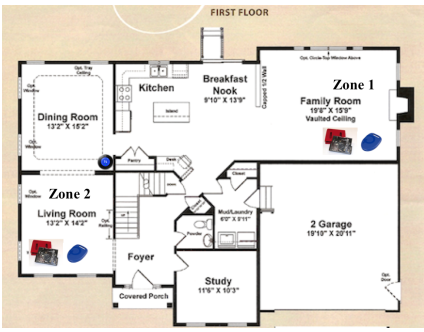

Figure 12: Private residence (first floor) layout (Waterford, NY) with sensors and thermostat location.

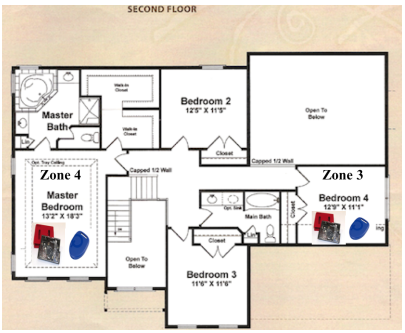

Figure 13: Private residence (second floor) layout (Waterford, NY).

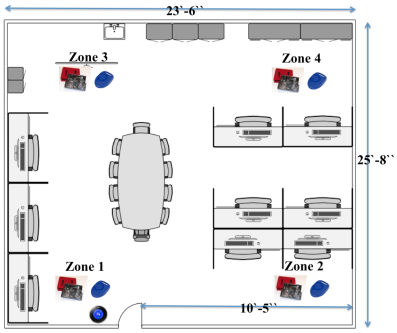

Figure 14: Laboratory space layout (6th floor - RPI JEC building) with sensors and thermostat location.

4. Experimental Study

In this section we present results pertaining to experimental study carried out in two different settings: Residential setting and Laboratory setting. These represent two independent locations as per BEES architecture in Figure 8. We also present some statistical analysis of the overall experimental data from occupant perspective.

4.1. Residential Setting

Experimental study in residential setting was conducted by installing the BEES system in one of the faculty member's home located in the city of Waterford, NY. There is a single thermostat that controls central air based HVAC system for the entire residence. Figures 12 and 13 represent the first and second floor layout of the home with the corresponding soft zones.

The experimental results are shown in Figures 15 and 16 corresponding to a 24 hour period from 11-22-2015 11am to 11-23-2015 11am. Figure 15 shows the temperature variation of the four zones, along with the occupancy pattern of the occupant on the right y-axis. The occupancy zone of -1 indicates the absence of the occupant from the residence. The occupant had his preference limits set at $y^L = 68°F$ and $y^U = 80°F$. Figure 16 shows the corresponding thermostat set points as calculated by the BEES algorithm. The HVAC state shown in the right y-axis corresponds to the heating (1) versus idle (0) state of the HVAC system. Note how the thermostat set points follow the movement of the occupant and attempts to maintain the thermal condition of the currently occupied zone within the occupant's preference limits. Initially the occupant's zone (zone 4) is within the preference limits. Shortly after, when the optimization algorithm is triggered (every 10 minutes), the set points change towards being energy optimal. Later when the occupant moves to zone 2 the set points are changed to ensure occupant comfort. During absence of occupant from the residence (between 2pm to 4:25pm) the set point moves to the default values of $60°F$ and $80°F$ representing energy conservation state. On return of occupant the set points change and also heating is engaged to achieve occupant comfort. During the night time the occupancy is pretty unchanged (zone 4), and the thermostat set points adapt to the falling ambient temperature to maintain occupant comfort and save energy. Around 7am when the occupancy zone changes the set points once again change and heating is engaged to maintain the currently occupied zone (zone 1 and later zone2) at the occupant specified temperature.

For comparison purpose we also present the temperature dynamics of the residential space for another 24 hours period (11-21-2015 11am to 11-22-2015 11am) using a static set point method. The thermostat set points remain fixed at the lower and upper limits of $68°F$ and $80°F$ respectively, irrespective of the occupant's current zone and even presence or absence of the occupant within the residence. Note that the two days being consecutive the ambient conditions are fairly similar, and the zone occupancy pattern is also comparable. The HVAC system engagement for heating is at 14.1% when BEES system is employed versus 18.47% when the residence was set at static set points. This represents a relative energy saving of 23.6% with the BEES system. Moreover, with multiple residents the system can be used to actively track zone occupancy and cater to that particular zone. Overall, this 24 hour period experimental data suggests that the BEES system can achieve both energy conservation and increased occupancy comfort using active indoor localization.

4.2. Laboratory Setting

For the purpose of experimental study in a laboratory setting, we installed the BEES system in the Networking Lab space located in the 6th floor of JEC building in RPI campus. The layout of the lab space with the soft zones are as shown in Figure 14. The lab space is a typical representation of cubicle farm structure in large corporate buildings. There is a central thermostat that controls an independent VAV system dedicated for this space. A total of nine research associates occupying the lab space where registered in the BEES system and authorized for the location.

Figure 18 represents the results for a 12 hour experimental run in the laboratory setting on 11-19-2015 from

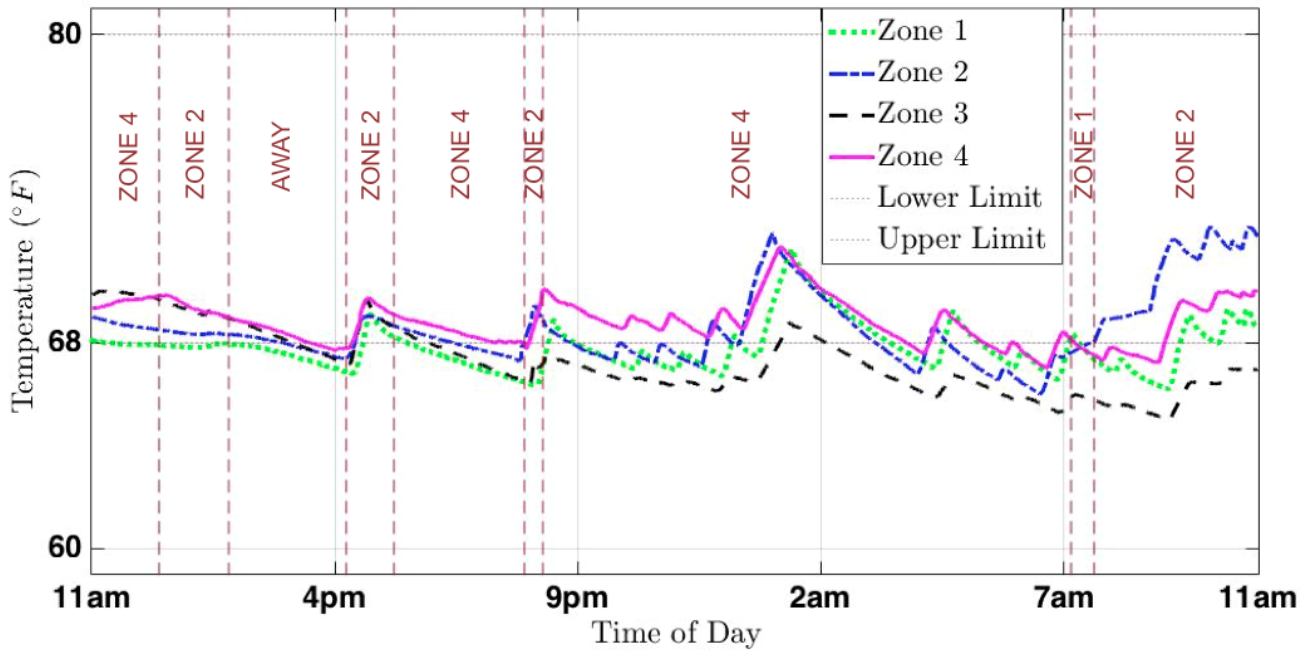

Figure 15: Zonal temperature dynamics for the 24 hour experimental study in residential setting. Change of occupancy zone is indicated by dotted vertical lines and the occupied zone is indicated within each block.

9am to 9pm. Each of the subplots in the figure shows the temperature dynamics for the zones with the corresponding occupant's upper and lower temperature preference with the markers. The location of the markers also indicate the initial arrival and final departure time of each occupant into their zone of primary occupancy. The fifth subplot shows the upper and lower set point temperature for the thermostat as calculated by the BEES system. Somewhere around 12.30 pm for few minutes all the occupants are out of the laboratory, which makes the system go to the default (energy saving) set point of $60°F$ and $80°F$. By 4.30 pm all the occupants have left the laboratory space and the system once again goes to the energy saving default set points. Throughout the duration of occupancy the system tries to adjust the set points to minimize discomfort of the occupants based on the thermal dynamics of the zone occupied. The summary of the experimental data is captured in Table 1. Occupant 6 lower limit and occupant 4 upper limit ends up serving as limits for the system. They face few minutes of discomfort (although not extreme variation from their preference), mainly due to set point adjustments and momentary overshoots. Note that the location of the laboratory is such that it has minimal ambient effect (thick walls with no windows). Further due to machining laboratory on the upper floor it gets a lot of external heat input. Owing to this even during winter months the temperature of the laboratory space remains pretty high with no HVAC heating input of its own. That explains the steady rise in zonal temperatures once the occupants have left the space.

4.3. Occupant Data Analytics

In this section we present some statistical analysis of the experimental data obtained so far. A total of 3612 occupant preference data points has been collected so far, with 3281 preference input obtained in laboratory setting and the rest 331 in residential setting. Figure 19 represents the box plot for all 3612 data points for all the ten users registered. The occupant ID 55 corresponds to the input in the residential setting. Although we don't have a large data set yet, but it demonstrates that the occupant preferences do vary even under similar occupancy setting, and can further vary over time for the same user. This variation in thermal preferences among occupants and even for the same occupant over time emphasizes the usefulness of a thermal comfort system based on occupants behavior, such as the proposed BEES framework. We also calculated the median of all occupant preference data, giving us values of $66°F$ and $74°F$ for the lower and upper limit respectively. These values can be used as default values when the system is first launched, or as the default settings for the zones on behalf of administrator (the administrator can later modify them as desired).

5. Concluding Remarks

In this work we have presented the design and architecture of an end-to-end framework for enabling occupant feedback collection and incorporating the data towards energy efficient operation of a multi-zone, multi-occupant

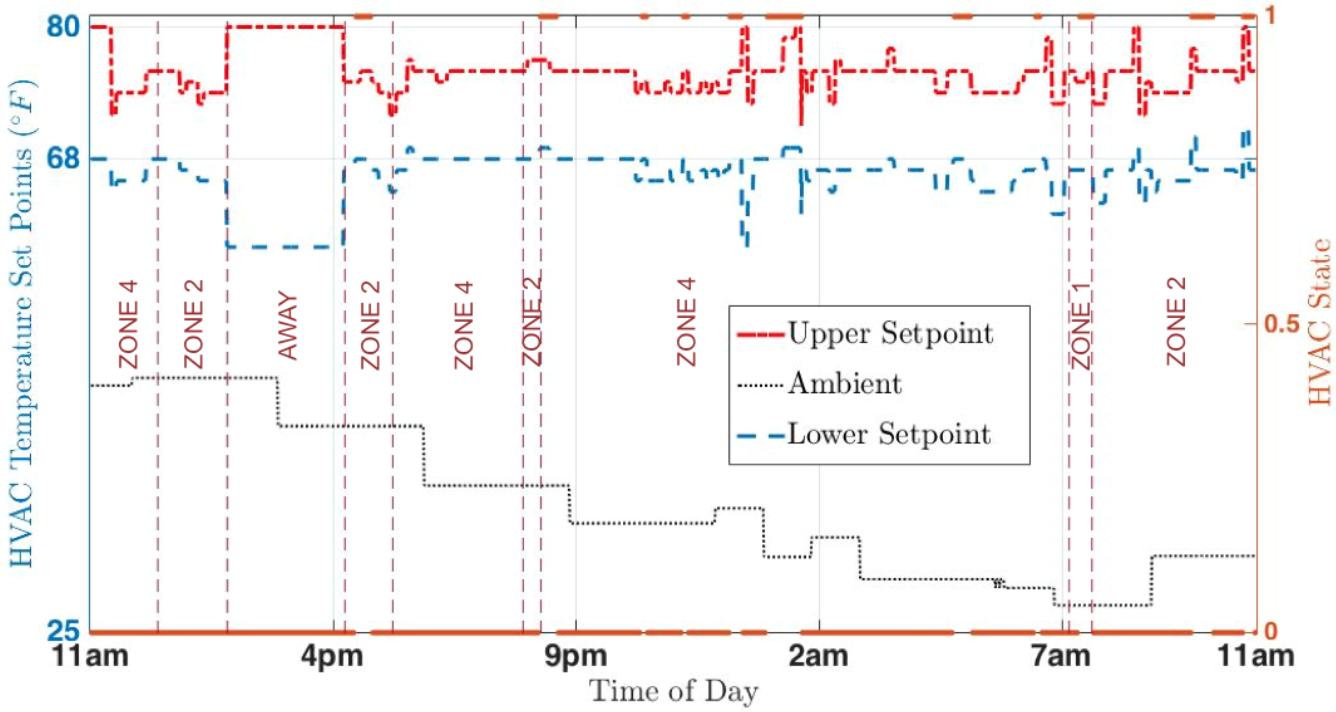

Figure 16: Thermostat set points as calculated by the BEES algorithm for the residential experimental study, along with the ambient variation, occupancy zone and HVAC state. HVAC state on right y-axis represents heating (1) v/s idle (0) mode. The set points adapt to occupant movement and ambient conditions, saving energy during non-occupancy.

Table 1: Occupant comfort metrics in the laboratory space over the 12 hour experimental period, along with occupancy pattern. We just present the initial arrival and final departure time with the zone of primary occupancy. Note that the system however captures every movement of the occupants and adjusts accordingly.

Occupant	**Preference**		**Final Time**		**Primary Zone**	**Total Discomfort Caused**	
	y_i^L	y_i^U	Arrival	Departure		% Time	Max Deviation ($^\circ F$)
1	65	76	9am	4:10pm	Zone 1	0	0
2	66	74	10:19am	4:35pm	Zone 1	0	0
3	67	74	9:54am	3:30pm	Zone 2	4.5	0.78
4	65	71	9:10am	1:57pm	Zone 2	17.2	0.98
5	66	75	9:51am	3:56pm	Zone 2	0	0
6	70	76	10:20am	3:01pm	Zone 2	19.1	1.17
7	65	77	9:45am	4:10pm	Zone 3	0	0
8	65	74	9:37am	4:35pm	Zone 4	0	0
9	67	73	9:42am	2:40pm	Zone 4	0.6	0.11

space based on indoor localization and real-time occupancy. First prototype of the system has been implemented using a combination of off-the-shelf sensors and wireless capable thermostat. Using this prototype we conducted experimental study in residential and laboratory space setting to establish effectiveness of the proposed framework.

This study - and our approach in general - suffers from a few limitations that will be addressed in future work. Firstly, note that our experiments have been conducted in a central air based HVAC system setting. Our overall framework however does not make this assumption, and can also be extended to a scenario where continuous control of the airflow (not just the thermostat temperature) is available. Efficacy of our solution in a water/steam based HVAC or electric heating systems need to be evaluated through further investigation. Moreover, for homes that are equipped with multiple AC units (possibly one per room), the AC units must be operated in a coordinated manner for maximum comfort and energy efficiency. The

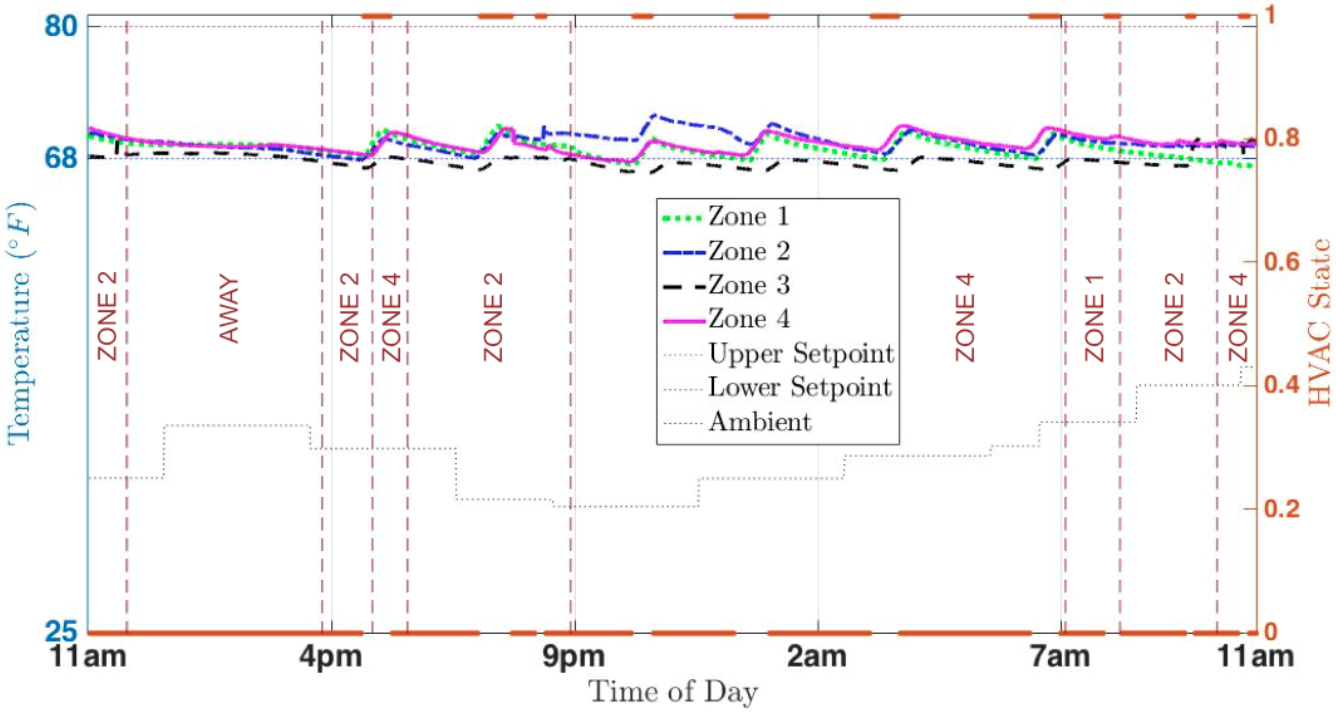

Figure 17: Zonal temperature variation for the residential space with fixed thermal set points at $68°F$ and $80°F$. Compared to the BEES system it engages HVAC heating more (BEES system has relative energy saving of 23.6%), and the occupant comfort doesn't necessarily adjust as per the zone occupancy. The HVAC engagement is independent of the zone occupancy and the presence of occupant in the residence.

BEES framework remains to be extended and evaluated for this scenario. Secondly, while our steady-state based linear learning model works well in the experiments conducted so far, it is possible that a more complex non-linear learning model (that takes into account transient effects in the thermal model) may perform better. Further, although our dynamically learned model parameters can adaptively capture environmental changes, the robustness of the solution to major changes in the zonal thermal environment (such as opening/closing of windows, turning on/off fans or personal heaters) needs to be evaluated further. In particular, future investigation is needed to understand how quickly our solution can adapt to such environmental changes. Thirdly, in this study we have considered one temperature sensor per zone, and each occupant is localized to only one sensor. In smart buildings of the future, one can imagine a denser deployment of sensors where an occupant can be surrounded with many such sensors, which may allow tracking of the thermal differences within the same zone. The question of how this multiplicity of thermal data can be effectively processed (through scalable data analytic techniques) and utilized towards providing better comfort to the occupants, remains open for future investigation. Finally, on the practical side, we plan to expand the system to cover smart wearables so that we can track and localize occupants moving around without their smart phones at all times. Further note that as we run more experiments and collect substantial occupant data, analytics would be used to understand potential sources for differences in thermal comfort choices made by the occupants.

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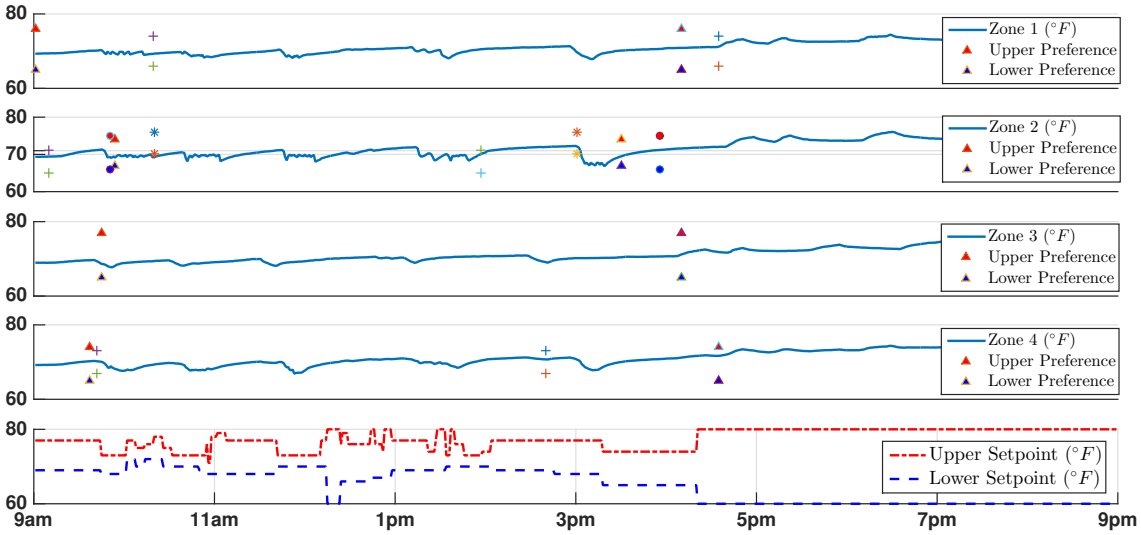

Figure 18: First four subplots represent the temperature dynamics with occupant thermal preference for each zone corresponding to 12 hour experimental study in the laboratory space within RPI building. The markers in each subplot represent the occupant preference limits along with their initial arrival and final departure times. The last subplot shows the thermal set points adjusting as per occupancy, and default energy saving values in absence of any occupants.

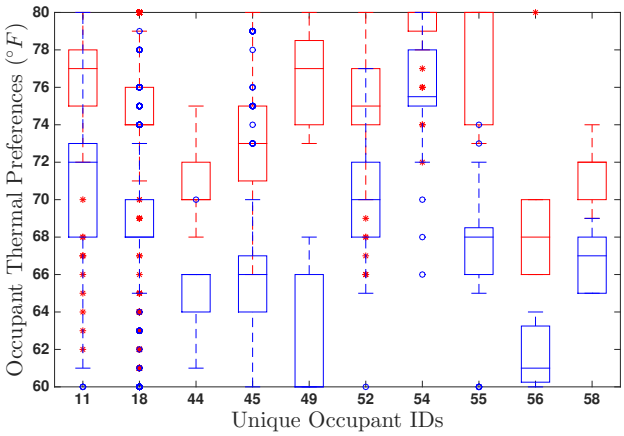

Figure 19: Statistical box plot representation of the occupant thermal preference data from experimental study (blue represents the lower preference(y_i^L) and red the upper preference(y_i^U).

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