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A knowledge based approach for selecting energy-aware and comfort-driven HVAC temperature set points

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ABSTRACT

HVAC systems are responsible for providing acceptable thermal conditions and indoor air quality for building occupants. Increasing thermal comfort and reducing HVAC related energy consumption are often seen as conflicting goals. Few researchers have investigated the feasibility of reducing HVAC related energy consumption by integrating occupants' personalized thermal comfort preferences into the HVAC control logic. In this study, we introduce a knowledge-based approach for improving HVAC system operations through coupling personalized thermal comfort preferences and energy consumption patterns. In our approach, thermal comfort preferences are learned online and then modeled as zone level personalized comfort profiles. Zone temperature set points are then selected through solving an optimization problem for energy, with comfort, indoor air quality, and system performance constraints taken into consideration. In the case that acceptable comfort levels for all occupants of a zone were not achievable, the approach selects set points that minimize the overall thermal discomfort level. Compared to an operational strategy focusing on comfort only, evaluation of our approach, which aims for both maintaining or improving comfort and reducing energy consumption, showed improvements by reducing average daily airflows for about 57.6 m^3/h (12.08%) in three target zones.

1. Introduction

Thermal comfort is one of the most influential factors affecting a building's indoor environmental quality [1]. Parameters influencing thermal comfort can be divided into two categories: environment related parameters (e.g., air temperature, humidity) and occupant related parameters (e.g., clothing level, metabolic rate) [2]. Since occupant related parameters are difficult to be measured frequently and in real-time, building management systems (BMS) are usually operated based on generalized recommendations offered by the standards, such as the ASHRAE Standard 55 (Thermal Environmental Conditions for Human Occupancy) [3] for thermal comfort and ASHRAE Standard 62.1 (Ventilation for Acceptable Indoor Air Quality) for air quality requirements [4]. Thermal comfort standards provide comfort models, which estimate occupants' thermal satisfaction levels based on the environment related and occupant related parameters, measured through controlled experiments. However, lack of information about the actual occupant related parameters often results in conservative HVAC operational settings. Moreover, majority of the HVAC system controllers work with single temperature control loop [5], therefore they cannot comply with the standards' recommendations effectively as these models require sensing several controlling parameters (e.g., humidity, airflow speed, and clothing level). Commercial buildings in the United States consume about 20% of the total energy, 43% of which is consumed by HVAC systems [6]. This significant share demonstrates the importance of investigating efficient HVAC operational strategies that work with existing HVAC systems. It is interesting to note that it had been shown that 7 to 15% of HVAC related energy consumption could be saved by increasing the temperature set point by 1 °C in warm seasons in three large cities (i.e., San Francisco, Phoenix and Miami) in the United States [7].

Several research efforts have tried to address the need for extracting personalized thermal comfort information for individual occupants to enable more efficient HVAC operations [8–13]. These efforts use questionnaires, field surveys, or physiological measurements and they determine individuals' comfort levels, while standards' comfort models do not differentiate between different individuals' needs under similar conditions [14]. Some of the methods used in the above-mentioned efforts could be time consuming, intrusive for occupants, and require installing further controlling

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infrastructure to work with legacy HVAC systems. These efforts aim to provide the most comfortable conditions for the occupants. However, previous research proved that humans experience comfort in a range of environmental conditions [15]. If energy consumption requirements for maintaining personalized and comfortable environmental conditions are understood, HVAC systems could be operated based on not only the personalized comfort information but also based on the energy consequences of different comfort settings.

In our previous studies, we developed a framework that uses a participatory sensing approach for human building interaction for thermal comfort (HBI-TC) [16]. In the HBI-TC framework, occupants' thermal comfort information is learned and modeled as comfort profiles. These profiles present different sensations over a range of room temperatures and are developed using a fuzzy pattern recognition algorithm. The framework interprets occupants' comfort profiles and calculates personalized preferred temperatures (if there is a change in preferences, updates the preferred temperatures over time), and operates the HVAC system using a complementary control algorithm, to minimize the average error between the preferred and actual temperatures in rooms of a zone. This framework was implemented in a test bed and promising results from both comfort and energy perspectives were realized and reported in [17]. However, personalized thermal comfort profiles could also be used to generate a range of environment temperatures where comfort is maintained. Understanding the energy consumption requirements for providing different ranges of indoor temperatures and integrating this information into the HVAC system control loop could potentially be used to select set points, which improve the occupants' overall comfort levels and also increase the energy efficiency of HVAC systems while using existing HVAC controllers in buildings.

In this paper, a knowledge based approach for selecting HVAC set points is introduced by taking into account energy consequences, indoor air quality requirements (i.e., minimum air flow rates and quality driven from ASHRAE Standard 62.1), and occupants' comfort constraints. The approach determines HVAC system set points through solving an optimization problem for HVAC energy usage performance metric (i.e., air flow rates) at the zone level on a daily basis. The structure of the paper is as follows. In Section 2, a review of recent studies that focus on selection of comfort-driven and energy-aware operational strategies is presented. In Section 3, a detailed description of the HBI-TC framework is provided and potential improvement areas are discussed. In Section 4, the methodology for enabling the integration of comfort and energy information is provided. Information about the test bed building and occupants is presented in Section 5. Section 6 presents the validation results and the comfort and energy consequences of the proposed approach. Limitations of the work are presented in Section 7. Finally, conclusions are presented in Section 8.

2. Comfort-driven and energy-aware HVAC operations

There are several research efforts, which aimed to improve HVAC systems' energy efficiency, occupants' thermal comfort, and indoor environmental air quality [18,19]. Thermal comfort driven HVAC operations often use the PMV (predicted mean vote) model [20] as a metric for measuring occupants' thermal comfort. The PMV model is also adopted by several standards such as the ASHRAE 55 [3] and has been extensively used by the industry for determining acceptable thermal conditions in indoor environments [5,21,22]. The PMV model uses a number of environment related parameters (e.g., temperature, humidity) and occupant related parameters (e.g., clothing level) and calculates occupants' average thermal sensations.

Various operational strategies have been used to optimize HVAC energy consumption by utilizing the PMV model for comfort constraints. Some of these operational strategies [23,24], complementary to the existing HVAC control logics, influence the performance of HVAC systems by adjusting set points [25], while other operational strategies intervene existing HVAC control logics. Examples of approaches used in latter category are fuzzy controllers [26], neural network based controllers [27], and genetic algorithm based controllers [28]. Nowak et al. compared few control strategies, such as the dynamic matrix control (DMC) and generalized predictive control (GPC), using a simulation tool for minimizing energy consumption, while maintaining PMV values in an acceptable range (between −0.5 and 0.5 on the PMV index) [29]. Freire et al. [5] proposed two strategies based on the PMV model, one only for comfort and one for both energy and comfort. The latter uses model based predictive control laws for minimizing energy usage, while maintaining acceptable thermal comfort levels. Simulation results from their studies showed that saving energy, while maintaining thermal comfort, is possible. Ferreira et al. [30] proposed a neural network based control strategy and created a simulation model using actual buildings' settings and their results showed that application of their proposed approach could maintain thermal comfort while saving more than 50% of energy consumption. Fong et al. [31] developed a heuristic approach by simulation coupling and proved that their proposed approach could reduce energy consumption by about 7% through adjusting operational settings for the chilled water and supply air temperatures system, while maintaining acceptable thermal comfort levels.

Although researchers have extensively used the PMV model for thermal comfort, the PMV model has a number of downfalls, including its inability to consider behavioral variations and the ability of humans to adapt to thermal environments [32]. Moreover, in order to implement the PMV model, several parameters have to be collected from an environment and from occupants in real time, requiring sensing infrastructure, which could be expensive and complex to be deployed in existing buildings [22]. Recently, to address these challenges, researchers have proposed personalized and real-time comfort sensing approaches, which can potentially be used in existing buildings [8–12,17,33]. These approaches aimed to estimate and model individuals' comfort levels separately in order to enable personalized comfort driven HVAC operations. Erickson and Cerpa [8] used a participatory approach for controlling temperature of rooms and showed all occupants were satisfied while energy consumption was reduced by 10.1% compared to the existing building control system. Murakami et al. [12] proposed an approach, which calculated daily set points through a collective voting by a group of 50 occupants in an open office space and adjusted HVAC set points. The results showed 20% energy savings compared to a constant set point (26 °C). Feldmeier and Paradiso [9] measured various parameters directly on the occupants' bodies to understand occupants' thermal comfort levels. They then used a PI (proportional-integral) controller to adjust HVAC system set points and also adjusted the window locations in their test bed buildings based on personalized comfort preferences, and realized 24% energy savings compared to the standard HVAC control system. These efforts aimed to provide the most comfortable conditions for occupants. However, previous research has shown that humans perceive comfort in a range of environmental conditions [15], similar to the comfort zone in the PMV model (i.e., between −0.5 and 0.5 on the PMV index). If thermally acceptable set points are determined, the selection of set points can be performed based on other criteria, such as system efficiency and different energy consumption objectives.

In this paper, we use personalized thermal comfort profiles and HVAC energy consumption data for identifying occupants' thermal discomfort levels and energy consequences of different set

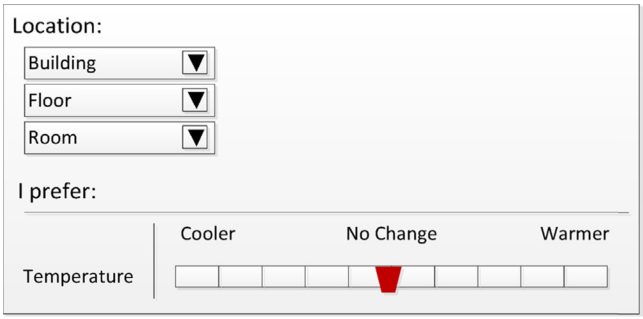


Fig. 1. Components of the proposed user interface and thermal preference scale [16].

points at the zone level through a heuristic system identification approach. We then feed the generated models into an optimization problem for finding zone set points that provide acceptable levels of discomfort for the occupants while minimizing HVAC energy consumption.

3. Framework for thermal comfort driven HVAC operations

The HBI-TC (human building interaction for thermal comfort) framework models occupants' thermal comfort profiles as they interact with the HBI-TC user interface (UI) (Fig. 1), links occupant votes to room temperatures, and uses a complementary control algorithm for provision of preferred indoor thermal conditions. The framework uses a customized participatory sensing interface (i.e., HBI-TC UI) for obtaining occupants' thermal comfort profiles through a novel thermal preference scale, acquiring occupants' votes about the indoor thermal conditions. Occupants move the slider on the HBI-TC UI to express their preferences. The numeric values associated with the slider button's position vary from −5 to 5, which is called thermal perception index (TPI). The TPI values are then collected by the HBI-TC. Details about the design of the UI could be found in [34]. The framework also uses the HBI-TC sensor network (described in Section 5) that provides higher granularity (room level as opposed to the zone level information provided by existing BMS) of indoor environmental thermal conditions. Occupants' thermal votes (TPIs) are then matched with the associated room temperature at the time of voting. Fig. 2 shows a typical data set collected from an occupant. The horizontal axis shows the values of occupants' thermal votes (TPI values, ranging from −5 to 5) and the vertical axis shows the corresponding room temperatures. Since the TPI-temperature data have a fuzzy pattern, the authors adopted a fuzzy pattern recognition approach for learning each occupant's comfort preferences and to model comfort profiles. In this approach, fuzzy sets are assigned to thermal preference votes and a pattern recognition approach [35] is used to determine the temperature ranges associated with the fuzzy sets. Comfort information is collected while occupants are exposed to different thermal conditions during the training period and then updated as occupants keep using the UI. Consequently, occupant related factors like clothing levels and occupant activities, as well as changes in comfort profiles due to seasonal variations (occupants adapt to different outdoor temperatures during different times of the year), are factored in the comfort profiles. Since by using the HBI-TC framework, occupants have control over indoor conditions, they can adapt their clothing levels to their reported preferences or vice versa. A major feature of the HBI-TC framework is online learning, where the profiles are continuously updated over time using occupants' comfort votes, taking into consideration any changes in occupants' preferences. Therefore, an occupants' profile can be interpreted as a snapshot of the occupant's thermal preferences with respect to room temperature. The uncertainties associated with other influential variables (e.g., clothing level, activity level, humidity, etc.) are captured within the fuzzy algorithm for generating the profile. Each new vote updates the profile to account for dynamic needs of occupants. The details of this framework could be found in [16].

In a comfort profile (Fig. 2), we define the acceptable temperatures as the temperatures whose membership degrees to the middle comfort zone (MT—middle temperature) are above 0.5, meaning that the comfort zone (MT) has a higher ownership over the temperature than the other comfort zones (colored in green). Other comfort zones can be interpreted as tiers away from the comfort zone in the middle (MT). LT3, LT2 and LT1 are comfort zones associated with low temperatures and are, respectively, three, two and one tiers away from occupant's comfort zone (MT). HT1, HT2 and HT3 have a similar definition, except they are comfort zones on the warm-hot side of thermal comfort profiles. Thermal comfort level of an occupant for a certain room temperature can be obtained by evaluating the membership degrees of that temperature to the two adjacent fuzzy sets covering it. For example, thermal comfort level of an occupant at temperature T_i in Fig. 2 is expressed as LT2 with a membership degree of M_1 and LT3 with a membership degree of M_2.

The comfort profiles are then used to generate each occupant's preferred room temperatures. The preferred temperature for a specific occupant is the temperature that its membership degree to the middle comfort zone (MT) is 1. A major component of the HBI-TC framework is its control algorithm that uses occupants' comfort profiles to provide and maintain occupants' preferred indoor thermal conditions. The HBI-TC controller is a complementary controller as it does not replace the existing HVAC controller and it is used as a plug-in software agent, which enables dynamic adjustments to the VAV box set points. The HBI-TC controller continuously keeps the average zone temperatures close to the preferred temperatures of the occupants of that zone by determining real-time set points. The HBI-TC controller adjusts the set points in real time to minimize the error:

$$\text{error} = \frac{\sum_{i=1}^{N_o} \boldsymbol{w_i} \left(T_r^i - T_p^i \right)}{N_o} \tag{1}$$

where N_o is number of occupants in a zone, $\boldsymbol{w_i}$ is the weight associated with occupant i comfort superiority, (T_p^i) is preferred temperature of occupant i, and (T_r^i) is room temperature of occupant i.

The implementation of this approach in the test bed building showed considerable comfort improvements (compared to the existing HVAC control strategy). Due to the conservative settings of the existing control strategy (lower set points that what occupants preferred), we also observed considerable energy consumption reduction [17]. However, we argue that an objective function, which couples the zone level occupant thermal comfort levels with the associated energy consequences, could further improve the performance of the controller by selecting a set point (e.g., VAV box temperature set point) with minimum energy use among all possible values for the set point for that zone. In this paper, to understand the thermal comfort-energy consumption trade-off and enable an energy-aware comfort set points selection, we introduce a knowledge based approach with the following objectives: (1) collect occupants' thermal comfort profiles and develop zone level personal thermal discomfort profiles; (2) collect HVAC system data from a BMS database and create zone energy consumption profiles; (3) associate occupants' zone level thermal discomfort profiles with zone energy consumption profiles through fusing environment and BMS related data; and (4) select new set points through solving an optimization problem for zone-level energy

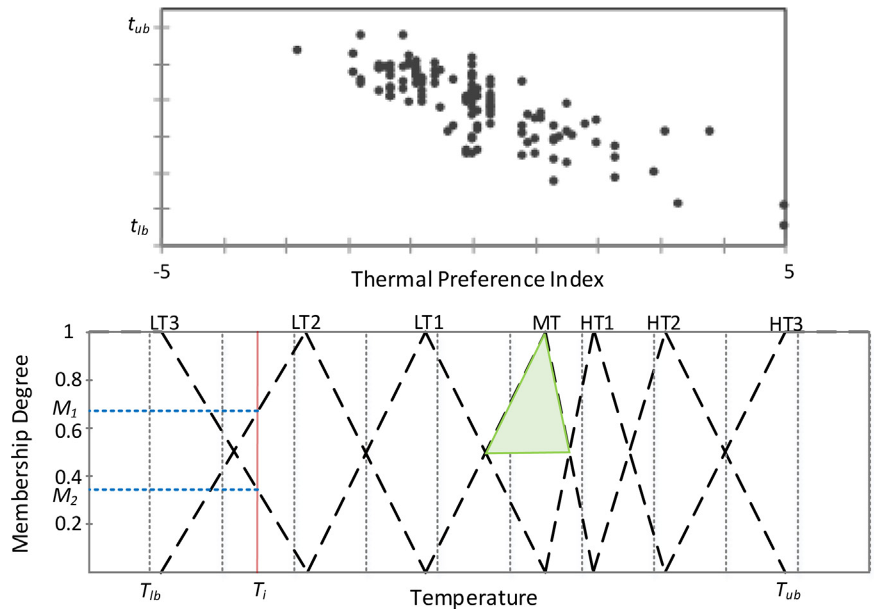


Fig. 2. A thermal comfort profile obtained by using the HBI-TC framework. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

consumption with constraints driven from occupants thermal discomfort profiles. The major contribution of this approach is its ability to learn from occupants' comfort and HVAC system's energy information and integrate them into a scalar optimization problem for selecting HVAC set points with respect to this learned behavior.

4. Methodology

4.1. Zone level personal thermal discomfort profiles

In our approach, occupants' thermal comfort information, expressed as thermal comfort profiles (as shown in Fig. 2), is used. In order to better demonstrate the non-overlapping comfort zones of different occupants, the comfort profiles of the participating occupants are illustrated in Fig. 3 (further information about the participants and test bed can be found in Section 5). As it can be seen in Fig. 3, in this specific case, the comfort range temperatures for six occupants vary from 21.8 °C to 25.4 °C.

An operational strategy, which works solely based on minimizing the error from Eq. (1), has a potential drawback of keeping all of the occupants of a zone far from their ideal thermal comfort

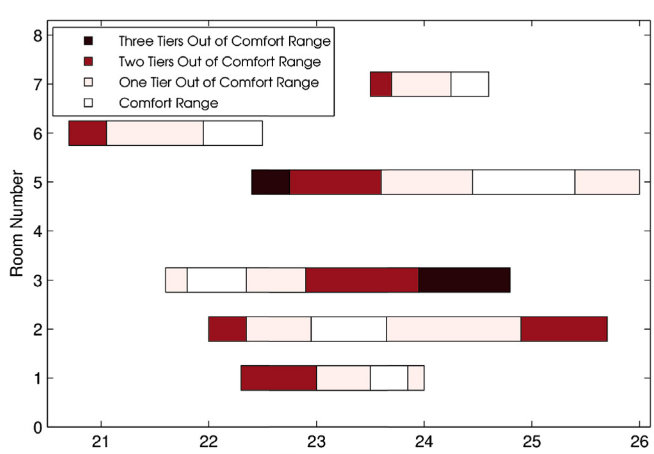


Fig. 3. Thermal comfort profiles of six occupants.

conditions. This issue becomes more important for the zones, where occupants in a zone do not have similar thermal preferences. For example, in a zone with three occupants, where two occupants prefer relatively warm indoor conditions (e.g., 22.5 °C and 22 °C) and one occupant prefers cooler indoor conditions (e.g., 17 °C), the averaging strategy results in a value of 20.5 °C, which is relatively far from all of the occupants' preferred thermal conditions, resulting in three dissatisfied occupants in one zone. In order to improve the operational strategy, we define a function – thermal discomfort value (TD) – that maps all personal discomfort profiles to a profile that represents all of the profiles in a zone. Accordingly in this paper, for calculating the TD values, the summation of absolute numeric values of sensations (TPI) are multiplied by the associated membership degrees for every temperature in a fuzzy comfort profile:

$$\mathrm{TD}(T_i) = \sum_{j=1}^{n} \left(\left| \mathrm{TPI}_j \right| \times \mu_{\mathrm{TPI}_j}(T_i) \right) \tag{2}$$

where TD is thermal discomfort at temperature T_i, TPI_j is thermal preference index associated with fuzzy set j covering the temperature T_i, $\mu_{\mathrm{TPI}_j}(T_i)$ is the membership degree of T_i in the fuzzy set TPI_j, T_i is temperature i, n is the number of fuzzy sets in the occupant's comfort profile. TD values vary between 0 and 5. TD value of 0 corresponds to maximum satisfactory thermal conditions and 5 to maximum dissatisfactory thermal conditions. An individual's thermal discomfort profile is developed through calculating TD_{T_i} for all feasible T_i in the environment. The graphical representation of transforming comfort profiles to discomfort profiles can be found in Fig. 4. For example, TD at T_i is the weighted average of TPI_1 and TPI_2, which are the thermal preferences associated with fuzzy sets covering T_i.

Thermal discomfort profiles express an occupant's thermal dissatisfaction as a function of their room temperatures. However, in a zone with multiple rooms, the rooms' temperatures are not necessarily equal to the zone set point. Room temperatures might hold different values as an HVAC controller tries to keep the thermostat (located usually in one of the rooms) readings and the set point in a close range. Consequently, discomfort profiles cannot solely be used to find an optimal set point for the zone directly, as discomfort

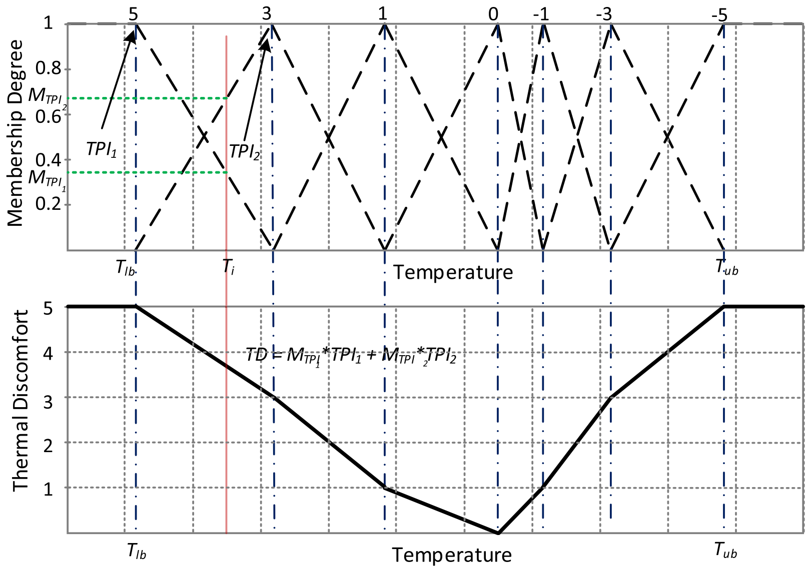


Fig. 4. Transforming personal thermal comfort profiles to personal thermal discomfort profiles.

profiles are functions of different room temperatures. In order to enable a search for optimal set points with respect to comfort at the zone level, we need a model to estimate individual rooms' temperatures as a function of a number of parameters (e.g., zone set point, outside temperature, etc.), measured at the zone level. Therefore, we propose to use a heuristic system identification approach to identify the influential parameters at the zone level and correlate them with room temperatures.

In this approach, we first identify the parameters that are measured at the zone level and affect room temperatures. There are various correlation analysis methods for determining a statistical relationship involving the dependence between room temperatures and other parameters. Spearman's and Kendall's rank correlation coefficient measure is a measure of a correlation even if the relationship is not necessarily linear. We used the Spearman's rank correlation for determining the contributing parameters to room temperature values. This correlation test checks if the relationship between two variables is monotonic. The coefficient is calculated as follows:

$$\rho = \frac{\sum_{n}^{i=1} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{n}^{i=1} (x_i - \bar{x})^2 \sum_{n}^{i=1} (y_i - \bar{y})^2}} \tag{3}$$

where x_i and y_i are converted ranks of corresponding actual X_i and Y_i, $\bar{x}$ and $\bar{y}$ are average of ranks, n is number sample data, and ρ is Spearman's rank correlation coefficient. +1 and −1 values for the correlation coefficient (ρ) show a very strong monotone relationship and as coefficient approaches 0, the monotone correlation shows weaker evidence.

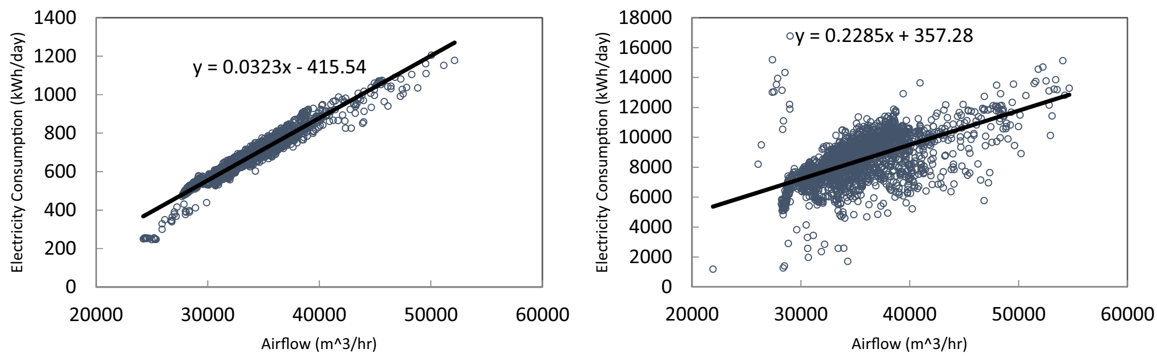
We use regression analysis to determine the model that represents individual room temperatures in terms of effective zone level variables. If a parameter is highly influential on the individual room temperature variation, but it is almost constant (e.g., wall and floor materials), it is considered as constant and is excluded from the model development process in this paper. Another criterion for selecting parameters is the data availability. Parameters that were collected via existing sensing devices in buildings and were monitored in the existing BMS control systems were selected to generate the models. In order to find the influential parameters, we divided them into three categories: (1) parameters related to occupancy, (2) environment related parameters, and (3) HVAC related parameters. The effect of occupancy on HVAC energy consumption could be considered at different levels of details (e.g., knowledge of the presence of at least one occupant in an environment or knowledge of occupant locations and their activity levels [36]). In this study, we took the influence of zone level occupancy into account with a parameter that was set to hold two values: (1) weekdays and (2) weekends. The weekday's value represents the days in which the targeted offices were most likely to be occupied and occupants' activities results in heat generation. The weekend's value represented the days for which the offices were most likely to be unoccupied. Many environmental related parameters might also influence room temperatures such as the outside temperature, humidity, sun radiation, wind level and precipitation. We took outside temperature as the sole variable for representing the influence of environmental parameters, arguing that outside temperature inherently represents the variation of other related parameters (e.g. sunlight, wind level) in the test bed building and is the most feasible parameter to be measured. Since majority of the HVAC system controllers work with single temperature control loop [5], zone temperature set points were selected as the influential parameter on room temperature.

4.2. Zone level energy consumption profiles

The second objective of our proposed approach is to create zone level energy consumption profiles. Since the energy sources (e.g., gas and electricity), used by the HVAC systems, are not usually measured at the zone level, we first need to identify a metric for representing energy use at the zone level. This section details out our methodology for representing zone-level energy consumption.

4.2.1. Airflow–energy consumption relationship

Gas and electricity are the major energy sources for HVAC system operations in the United States [6]. They are generally measured at the building level since precise measurement of energy for each zone requires sub-metering of electricity and gas, which is often a difficult task and it is expensive. As an alternative to measuring actual consumptions, we identify a metric that can be measured at the zone level for representing actual energy consumption in HVAC systems. However, HVAC systems have various control and operational settings. Based on the devices and loops,



a) AHU electricity consumption b) AHU chilled-water energy consumption

Fig. 5. Building-level HVAC energy consumption vs. airflow.

they can be divided into 6 categories [37]: (1) HVAC systems with control over outside air quantity; (2) Single zone Air Handling Unit (AHU) HVAC system; (3) Multi-zone AHU HVAC system; (4) Dual-Duct AHU HVAC system; (5) Variable Air Volume (VAV) AHU HVAC system (VAV AHU or VAV systems); (6) HVAC systems with central plant control systems. In this paper, we focus on VAV AHU type of HVAC systems because they have a large share of industry and also the share has been increasing. "VAV systems were developed in response to 1975 energy crisis" [37]. As of 1992, 18.43% of commercial buildings' floor space in the United States was operated with VAV systems [38]. The percentage of floor space operated by VAV systems was increased to 22.92% by 1995 [39]. In 1999, the percentage was increased to 28.79% [40]. As of 2003, 30.25% of commercial buildings' floor space was operated with VAV systems [41]. If the same trend has continued, the percentage will be around 43.5% by 2014.

VAV systems work based on the principle of changing air volume, supplied to each zone, for meeting the load and maintaining a constant static pressure in ductworks [37,42]. They supply air to zones at a constant or almost constant temperature and humidity (different constants for heating and cooling). In VAV systems, fan electricity energy consumption is directly related to airflow rates [37]. The energy required for local heating of air at VAV boxes can be also measured. Required energy is proportional to the airflow rates that enter the thermal zones.

To check the validity of assigning airflow rates as a measure for HVAC energy consumption in our test bed building, we collected HVAC fan and chilled water data in October 2013, for a two-week period with 6 min granularity. The results from the regression analysis for electricity consumption (Fig. 5) show a strong linear dependency for HVAC fans and a relatively strong evidence for chilled water energy consumption.

4.2.2. Zone level energy model identification

An HVAC controller has a significant influence on the system's energy consumption as it sets the operational parameters for HVAC subsystems, such as hot and cold-water valve openings and AHU fan speeds. Controller keeps the environmental parameters, such as room temperature and humidity (output), and the associated set points (performance goals), in a close range. There are also other constraints including the air quality requirements, defined by the standards, such as the ASHRAE Standard 62.1 (Ventilation for Acceptable Indoor Air Quality) [4]. A controller regulates temperature and the discharged air based on the difference between the thermostat readings and set points. Similar to the room temperature model, we implement a heuristic system identification approach for identifying and modeling the influential parameters on the airflow rates. A Spearman's rank correlation and regression analysis were used for identifying the contributing parameters and determining the relationship between airflow rates and the contributing parameters. By obtaining values for the room temperature and zone energy model parameters related to occupancy and environment related parameters using sensing devices installed in the environment, and replacing them in the models, both room temperature and airflow models become the function of a single parameter, which is the zone level control parameter (i.e., zone temperature set point). Consequently, variations in the set point can potentially influence both the occupant thermal comfort and energy consumption. Hence, in this study, set points are used as an intermediary for influencing both the thermal comfort levels and associated energy consumption levels.

4.3. Set point determination

We formulate an optimization problem for determining a fixed daily set point for each zone (objective 4 in Section 3). Our contribution is transforming the traditional multi-objective optimization problem for improving both comfort and energy consumption into a scalar optimization problem (with a single objective function). In order to do so, we transform the comfort objective function to constraints by defining a number of rules. The rules for thermal discomfort define acceptable thermal discomfort conditions for individuals or group of occupants in a thermal zone. As it was mentioned in Section 3, since occupants are likely to perceive comfort when their TDs are below 0.5, we adopted this value for the maximum acceptable personal comfort level. There may exist also some additional constraints and conditions on the selection of set points based on the user or building owner requirements. The scalar optimization problem (no. 1) for each thermal zone is as follows:

$$\begin{aligned}
&\min_{\mathrm{CP}} && \mathrm{AF}(\mathrm{CP}) \\
&\text{Subject to} && \mathrm{TD}_i(\mathrm{CP}) \leq \text{Max Acceptable TD}, \quad i = 1, \ldots, n \\
& && \mathrm{AF}(\mathrm{CP}) \geq \mathrm{AF}_{\mathrm{IAQ}}, \\
& && \mathrm{AF}(\mathrm{CP}) \geq \mathrm{AF}_{\min}, \\
& && \mathrm{AF}(\mathrm{CP}) \leq \mathrm{AF}_{\max},
\end{aligned}$$

where AF is average daily airflow rates, CP is the HVAC control parameter (i.e., zone set point), TD_i is Occupant i thermal discomfort level and varies as a function of CP, n is the number of occupants in a thermal zone, $\mathrm{AF}_{\mathrm{IAQ}}$ is the minimum airflow rates to satisfy indoor air quality requirements driven by the standards [4], and $\mathrm{AF}_{\min}$ and $\mathrm{AF}_{\max}$ are the minimum and maximum airflow rates set on the zone VAV box. It is important to reemphasize that the optimization problem is set in a way that airflow rates do not go below the rates recommended by the standards such as ASHRAE Standard 62.1 [4]. ASHRAE 62.1 specifies outdoor air requirements for specific applications and is based on ventilation rates per person as CFM/person or per area as CFM/SF. Therefore, in HVAC systems that meet the minimum requirements under any load condition, indoor air quality is assumed to be "acceptable" according to the ASHRAE 62.1 [4].

If the above optimization problem has no feasible solution, there is no set point that all occupants in a zone can perceive comfort. This fact can be interpreted as existing differences in occupants' thermal comfort levels or differences in occupants' preferences with respect to designed comfort conditions or inaccurately sized HVAC system components. In this case, we define a variable (maximum allowable discomfort), as the maximum level of discomfort that building stakeholders (e.g., building owners) allow for the occupants in any zone to tolerate and can hold any arbitrary value in [0.5 5]. This variable can be also interpreted as adaptation capabilities for occupants. Based on this definition, this variable can then hold personalized values. In our study, we used the discomfort level of 2 as a constraint for maximum allowable personal discomfort level in the selection of the set points. This value represents a membership degree of 1 to the second tier on the comfort profiles (Section 3). Through defining this variable, we then try to solve the optimization problem no. 1, by relaxing the personal comfort constraints through assigning maximum allowable TD to the maximum acceptable TDs and solving the problem iteratively. Our goal is to find a set point that minimizes the number of occupants, tolerating discomfort in an allowed range in a zone. In cases with similar number of occupants, our goal is to select a set point that minimizes the energy consumption. It is a similar concept to occupants' thermal comfort percentiles (e.g., 90%, 80%, and 70%) in PMV-PPD approach [3]. Standards, such as ASHRAE 55, have procedures and tables for building managers to choose comfort percentiles. The percentiles are then used to for selecting HVAC set points [3]. We start solving the problem by allowing any one occupant to experience discomfort up to maximum allowable and try to find optimal set point using the optimization problem no. 2. If the problem did not have a solution, we allow any group of two occupants to experience discomfort up to the maximum allowable value and we continue by selecting a set of occupants that their thermal discomfort is within comfortable range (U' in optimization problem no. 2), while letting the other occupants in the zone to tolerate a defined level of discomfort (adapt to thermal conditions), until we find a solution. The algorithm is presented in Fig. 6:

```
generator iterativeRelaxing() returns set point
    i ⟵ 1
    U ⟵ [1:n], Occupants' ID
    while i < n do
        rest ⟵ an empty set
        repeat
            V ⟵ create a combination of i from n
            U' ⟵ U & ~V
            (CP, AF) ⟵ solution for optimization problem
                        No.2 for Occupants in U' and V
            add (CP, AF) to rest
        until all combinations of i from n has been tested
        if rest ~empty then
        find (CP, AF) with minimum (AF) in rest
        return (CP)
    i ⟵ i + 1
```

Fig. 6. Iterative relaxing algorithm for finding optimal control parameter.

Optimization problem no. 2:

$$
\begin{aligned}
&\min_{\mathrm{CP}} && \mathrm{AF}(\mathrm{CP})\\
&\text{Subject to} && \mathrm{TD}_i(\mathrm{CP}) \le \text{Max Acceptable TD}, \quad i = 1, \ldots, n' \in U'\\
& && \mathrm{TD}_j(\mathrm{CP}) \le \text{Max Allowable TD}, \quad j = 1, \ldots, m' \in V\\
& && \mathrm{AF}(\mathrm{CP}) \ge \mathrm{AF}_{\mathrm{IAQ}},\\
& && \mathrm{AF}(\mathrm{CP}) \ge \mathrm{AF}_{\min},\\
& && \mathrm{AF}(\mathrm{CP}) \le \mathrm{AF}_{\max},
\end{aligned}
$$

where AF is average daily airflow rates, CP is the HVAC control parameter (i.e., zone set point), TD_i is Occupant i thermal discomfort level and varies as a function of CP, U' is a set of occupants that their thermal discomfort is within comfortable range, V is the complimentary set to U' and is the set of occupants that have to adapt to thermal conditions in a thermal zone, $\mathrm{AF}_{\mathrm{IAQ}}$ is the minimum airflow rates to satisfy indoor air quality requirements driven by the standards [4], and $\mathrm{AF}_{\min}$ and $\mathrm{AF}_{\max}$ are the minimum and maximum airflow rates set on the zone VAV box. If the above iterative relaxing algorithm did not have any solutions, then the set point that provides the minimum discomfort level for all of the occupants in a zone is selected. The formulation of the optimization problem (no. 3) is as follows:

$$
\begin{aligned}
&\min_{\mathrm{CP}} && \sum_{j=1}^{n} \frac{(\mathrm{TD}_i(\mathrm{CP}))}{n}\\
&\text{Subject to} && \mathrm{TD}_i(\mathrm{CP}) \le \text{Max Allowable TD}, \quad i = 1, \ldots, n\\
& && \mathrm{AF}(\mathrm{CP}) \ge \mathrm{AF}_{\mathrm{IAQ}},\\
& && \mathrm{AF}(\mathrm{CP}) \ge \mathrm{AF}_{\min},\\
& && \mathrm{AF}(\mathrm{CP}) \le \mathrm{AF}_{\max},
\end{aligned}
$$

where TD_i is Occupant i thermal discomfort level and varies as a function of CP, n is the number of occupants in a thermal zone, CP is the HVAC control parameter (i.e., zone set point), AF is average daily airflow rates, $\mathrm{AF}_{\mathrm{IAQ}}$ is the minimum airflow rates to satisfy indoor air quality requirements driven by the standards [4], and $\mathrm{AF}_{\min}$ and $\mathrm{AF}_{\max}$ are the minimum and maximum airflow rates set on the zone VAV box. If the above optimization problem also has no feasible solution or the stakeholders do not define any value for maximum allowable discomfort, then we use the HBI-TC control approach (Eq. (1)). The process diagram for this knowledge-based approach is illustrated in Fig. 7. Set point (i.e., zone temperature set point) is the CP in the system identification procedure and the optimization problems. "airflow vs set point" and "room temperature vs set point" represent the zone energy and room temperature profiles, respectively. The bullets at the lower left of the Fig. 7 emphasize on the fact that this process happens for each occupant. Accordingly, a set point is selected and it is transmitted to the BMS controller and the HVAC system operates based on the selected set points for each zone.

5. Test bed description and experimental set up

The test bed building is a three-story building on the University of Southern California campus, located in Los Angeles, California. Based on the Köppen climate classification [43], the climate of the area is defined as a dry-summer subtropical climate (also referred to as the Mediterranean climate). For such climates, the average temperature in the warm months is above 10 °C and in the cold months is between −3 and 18 °C [43]. The building hosts offices,

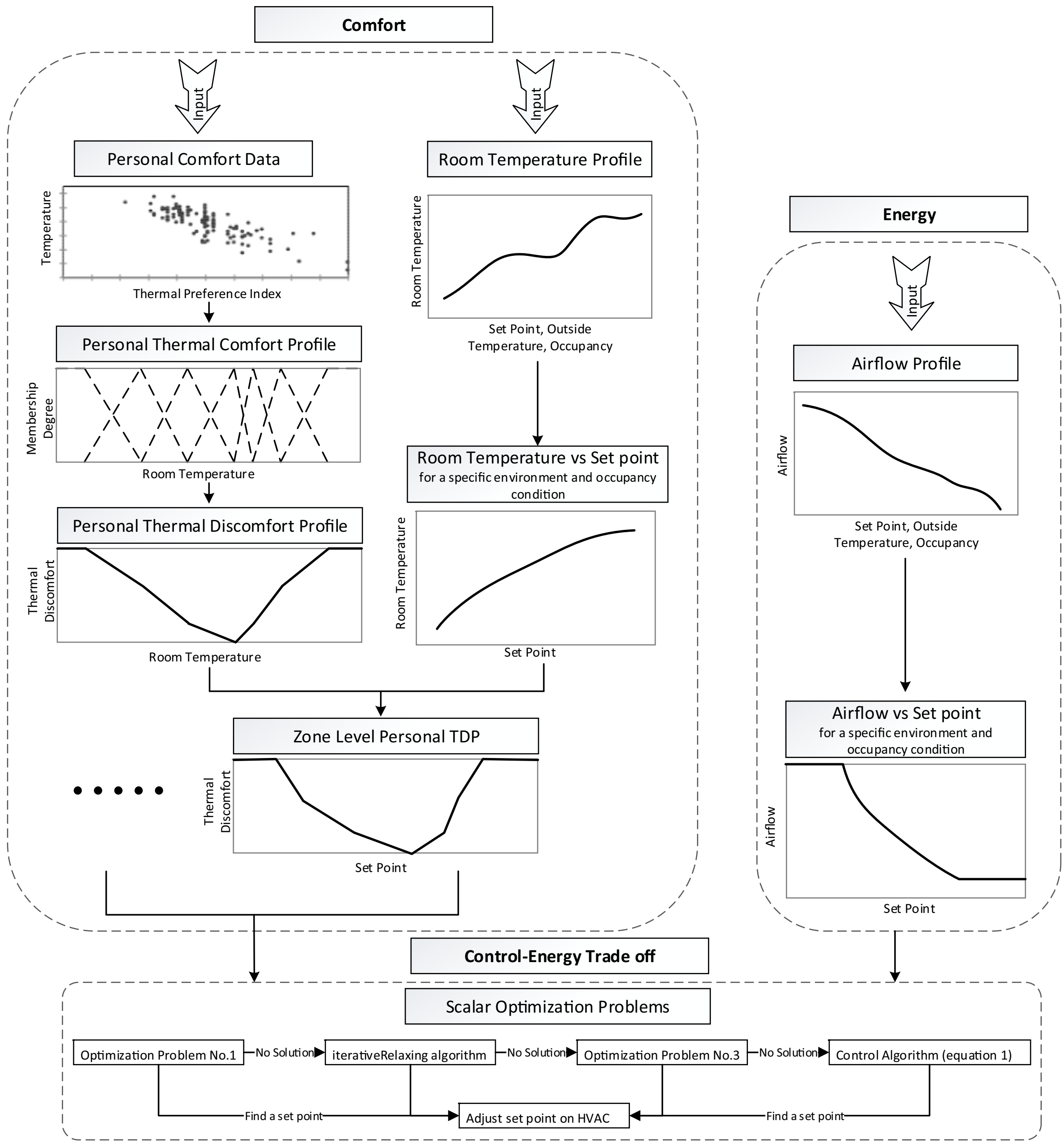


Fig. 7. Process diagram for comfort-driven and energy-aware set point selection.

classrooms, and conference rooms. Zones 1, 2, 3, located in the third floor of the test bed building (Fig. 8), were selected for the validation experiments, with two, one, and three occupants, respectively. Each participating occupant had personal offices. Zone 2 included two rooms and one of the rooms was unoccupied.

The test bed building has a variable air volume (VAV) air handling (AHU) HVAC system [37], a typical HVAC system type used in commercial buildings in the United States, as mentioned earlier. The HVAC system is operated by a centrally controlled system. The HVAC system operates seven days a week from 6:30 to 21:30 with a constant set point, commonly set at 22.8 °C (73 °F). The electricity and chilled water energy usage are monitored at the building level. A schematic representation of the HVAC system components is illustrated in Fig. 9.

Two AHUs circulate the air in the building through the ductworks. Each AHU produces a certain positive pressure for delivering the air to the VAV boxes. An AHU also produces a negative pressure for collecting air from thermal zones. A VAV box is responsible for discharging air into a zone, which may include one or more offices. A VAV box controls the thermal conditions of a zone by adjusting airflow rates. A VAV box also has a minimum airflow rate for maintaining acceptable ventilation for indoor air quality purposes. The airflow rates are monitored and archived by a BMS (Building Management System). The granularity of data is 1 reading for every 6 min for all BMS measurements (e.g. electricity usage, airflow rate, etc.). In order to measure the office temperatures, a temperature sensor was installed in a sensor box and located in the target offices (see Fig. 8). The sensor boxes were installed near the door of each room at a height of 1.2 to 1.5 meters. The temperature sensor used was MaxDetect, RHT03 temperature/humidity, and has a temperature measurement accuracy of ±0.5 °C and the resolution (sensitivity) of 0.1 °C. The sensor boxes utilize an Arduino

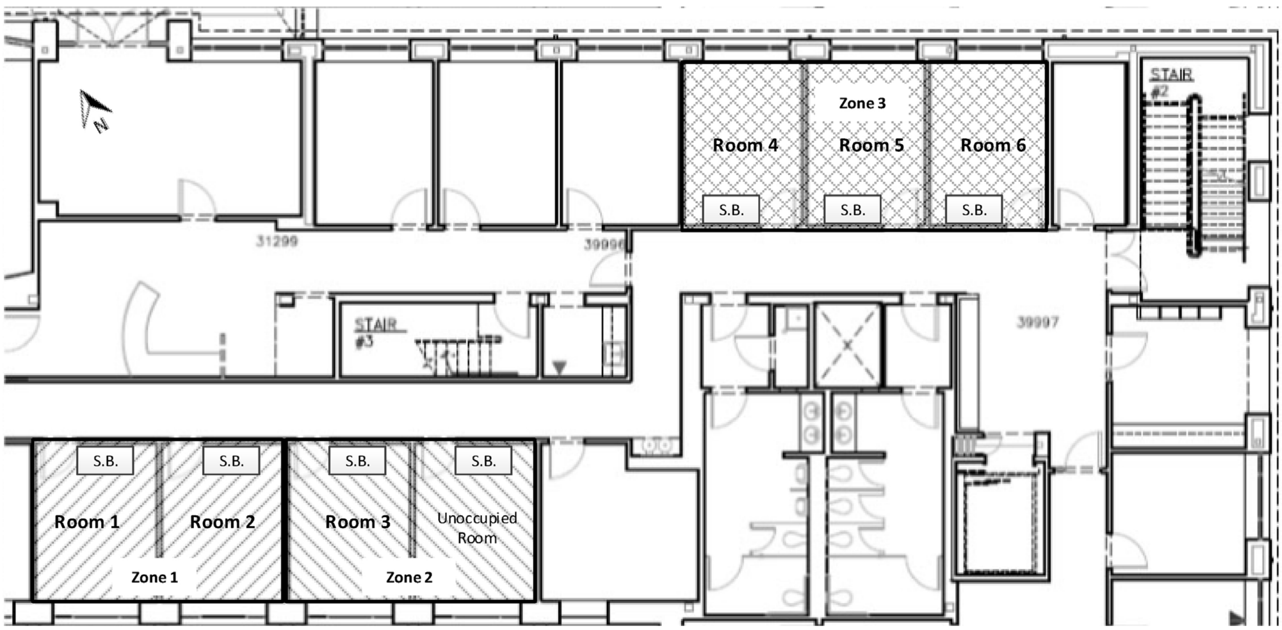


Fig. 8. Room, zone and sensor boxes (SB) locations in the 3rd floor of the test bed building.

Black Widow stand-alone single-board microcontroller with integrated support for 802.11 WiFi communications. The granularity of the data was 1 reading for every 5 min and the data was stored in a database. The data collection was completed in two periods, from April 1, 2013 to June 20, 2013 and from October 1, 2013 to October 25, 2013. The periods belonged to warm and cool seasons for including various environmental conditions. Throughout these periods, different set points were set for the VAV boxes. The data for room temperature, set point, airflow, outside temperature, air temperature at different locations in the HVAC system were monitored and collected during these periods and daily average values of the data were used to generate the models. Following the methodology described in Section 3, occupants' votes at different room temperatures were communicated to the framework via the UI to generate their comfort profiles. We collected the personal thermal comfort votes and indoor environment temperatures in a 6 week period in the test bed building. We then developed the personalized thermal comfort profiles by applying the fuzzy pattern recognition approach. The detailed procedure of data collection, and modeling for 6 occupants' thermal comfort profiles are reported in [17].

6. Validation results

6.1. Thermal discomfort profiles

Few of the comfort ranges for some of the occupants were not available as these occupants might not have experienced indoor thermal conditions that result in a complete comfort profile. Since the goal of the study is to evaluate different comfort levels and their respected energy consumption, the missing comfort zones

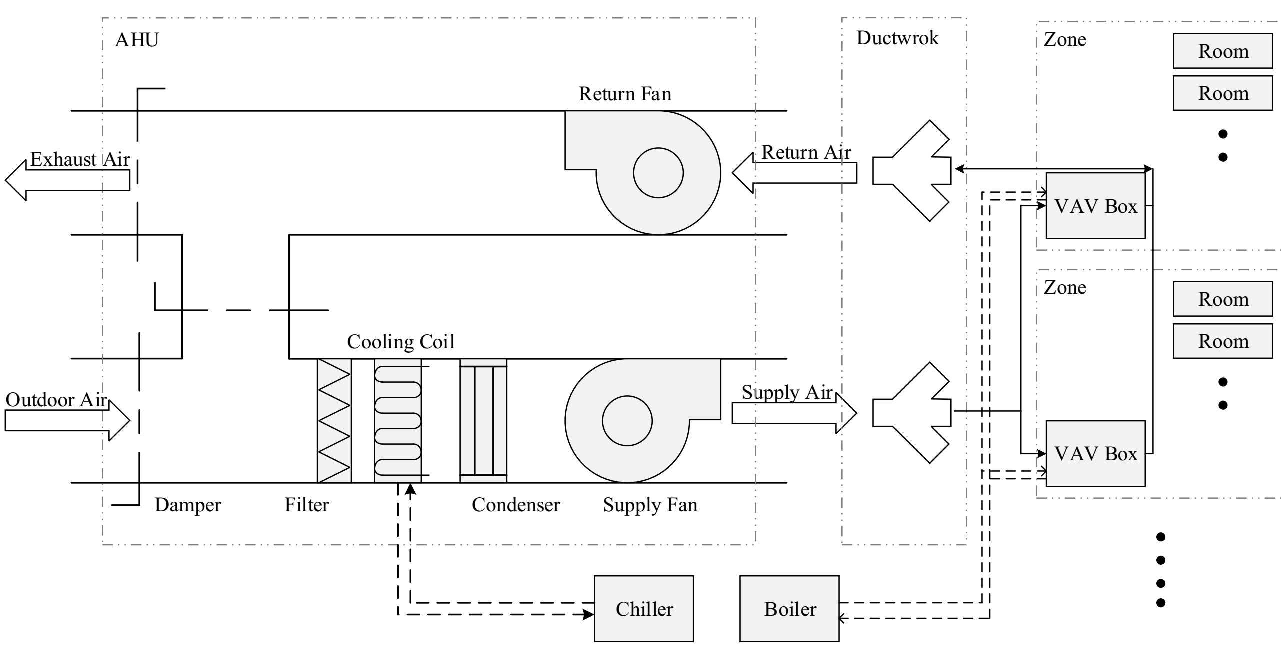


Fig. 9. Test bed building HVAC system components.

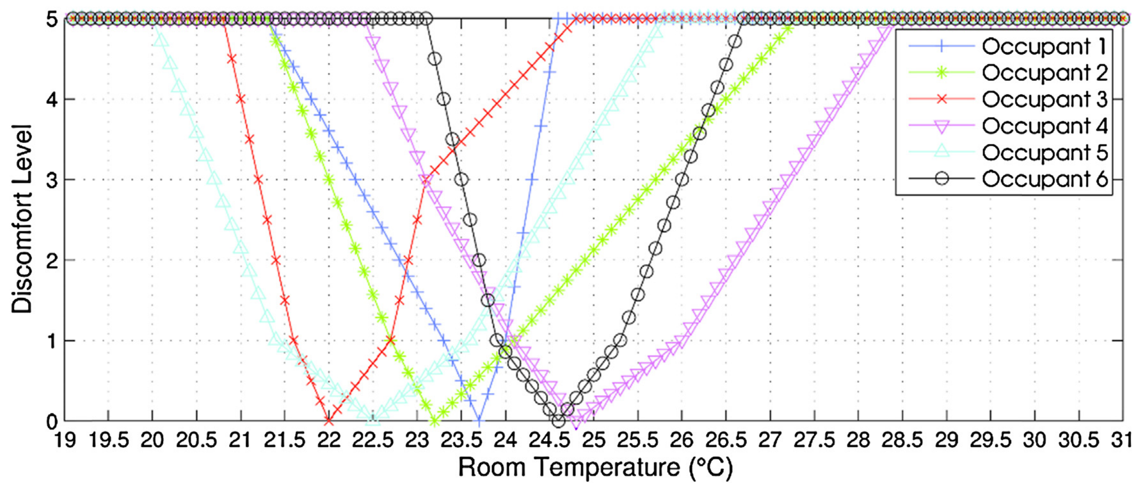


Fig. 10. Thermal discomfort profiles of six occupants.

were extrapolated using the temperature width of adjacent zones. The thermal comfort profiles for all six occupants were extrapolated and transformed to thermal discomfort profiles based on the approach explained in the methodology (Section 4.1). The thermal discomfort profiles are illustrated in Fig. 10.

As it can be seen in Fig. 10, the comfort zones for occupant 4 and 6 have relatively higher room temperatures, and it is in agreement with previous site measurements that they prefer warmer conditions. In contrary, occupants 3 and 5 prefer relatively lower room temperatures than other occupants.

6.1.1. *Room temperature model results*

Following the methodology outlined in Section 4.1, Spearman's rank correlation coefficients for different parameters were calculated to find the contributing parameters. Table 1 summarizes the correlation results. In all cases, the temperature set points had strong correlations with the room temperatures, while outside temperatures were found to have small correlations with room temperatures. Since occupancy mode was adopted to have value of 1 during weekdays and 0 during weekends, a regression analysis was used to test if occupancy mode is a contributing parameter to airflow rates. In regression analysis, *P*-values for all of the rooms except room 3 are below 0.05, implying that occupancy mode is significantly (with 95% confidence level) correlated with the room temperature. One reasonable explanation for the lack of correlation could be the vacancy of the adjacent room in zone 2.

Spearman's (SP) and regression (Reg) correlation coefficients for room temperatures The collected data for the weekend days in room 5 was not enough to generate a statistical model. After determining the contributing parameters, a linear regression analysis was carried out for all rooms' temperatures and the contributing parameters. As it can be seen in Table 1, large *R*-squared values show that using linear regression for describing the relationship between parameters in the model was reasonable.

6.1.2. *Zone energy model results*

Similar to the room temperature model process, the Spearman's rank correlation analysis was utilized to determine the contributing parameters in three zones. Table 2 presents the coefficients from the correlation analysis. As it can be seen in Table 2, airflow rates and temperature set points are highly correlated. However, outside temperature was found to have almost no correlation with airflow rates. Regression analysis was used to test if occupancy mode is a contributing parameter. All *P*-values are below 0.05, therefore occupancy mode significantly influences the average daily airflows for all of the zones. Large *R*-squared values calculated from the linear regression analysis show strong linearity between airflow rates and set points (Table 2). A representation of the profiles generated from the regression analysis for all of the zones is illustrated in Fig. 11.

As it can be seen in Fig. 11, when the temperature set point is 18 °C, the average daily airflows are around 1080 and 960 and 1320 m^3/h for zones 1, 2 and 3 during weekdays. Zone 3 has slightly more average airflow due to the fact that this zone has 3 rooms while other zones only have 2 rooms. In all of the zones, airflows have greater values during weekdays compared to weekends for all set points, implying that occupancy increases the airflow and thus energy consumption. At higher temperature set points, the average airflows approach a minimum value and remain constant since a minimum ventilation rate is set on the VAV boxes.

6.2. *Selection of temperature set points*

In order to evaluate our approach, we calculated temperature set points by solving the optimization problems described in Section

Table 1
Spearman's (SP) and regression (Reg) correlation coefficients for room temperatures.

	Occupancy mode (regression)	Outside temperature (Spearman)	Set point (Spearman)	*R*-squared	
				W/D	W/E
Room 1	0.046	−0.3561	0.9160	0.9406	0.9041
Room 2	0.010	−0.1650	0.6591	0.741	0.888
Room 3	0.684	−0.5531	0.9423	0.745	0.745
Room 4	0.011	−0.3299	0.7143	0.793	0.725
Room 5	N/A	−0.2442	0.8103	0.8017	N/A
Room 6	0.020	−0.0775	0.7665	0.859	0.922

W/D: Weekdays, W/E: weekends, N/A: not enough data to generate the model.

Table 2
Spearman's (SP) and regression (Reg) correlation coefficients for airflow rates.

	Occupancy mode (regression)	Outside temperature (Spearman)	Set point (Spearman)	R-squared	
				W/D	W/E
Zone 1	0.00016	0.0105	−0.8578	0.8379	0.8881
Zone 2	0.032	0.1821	−0.8588	0.8010	0.8176
Zone 3	0.000014	−0.1200	−0.9139	0.9245	0.8034

W/D: weekdays, W/E: weekends.

Table 3
Average daily airflow (m^3/h) in targeted zones for different operating strategies.

Strategy	Zone 1	Zone 2	Zone 3	Overall
HBI-TC	332.4	555.6	542.4	477
KB-HBI-TC	225	451.2	582	419.4

4.3 and compared them with the results driven from the previous HBI-TC operational strategy, where comfort profiles of occupants in a zone were averaged [17] as opposed to the knowledge based approach presented in this paper (KB-HBI-TC). Fig. 12 presents the thermal comfort results for the two operational strategies for weekdays (HBI-TC and KB-HBI-TC) in the three target zones.

Table 3 summarizes the regression average daily airflow results for different strategies (during weekdays) for three zones. In the case of single occupancy (zone 2—Fig. 12b), the advantage of the KB-HBI-TC strategy over the HBI-TC is to select set points that require less energy, as the HBI-TC already provides a temperature in the comfort range (Fig. 12a). Compared to the HBI-TC, choosing a daily set point in the comfort range with the minimum associated airflow results in about 18.8% (107.4 m^3/h) average daily airflow reduction, compared to the HBI-TC strategy (staying within the range of standard's airflow requirements).

In the case of zone 1 (Fig. 12a), occupants 1 and 2 have relatively similar comfort profiles. There is a range of temperature set points, where both occupants experience comfort (TDs below 0.5 (21–21.5 °C)). Similar to the case of single occupancy in zone 2, the major advantage of using the KB-HBI-TC strategy over the HBI-TC strategy is for improving energy efficiency as the HBI-TC strategy can already provide comfortable conditions (Table 3). In zone 1, using the optimization strategy results in 32.3% (104.4 m^3/h) average daily airflow reduction, compared to the HBI-TC strategy.

In the case of zone 3 (Fig. 12c), one of the occupants experiences thermal comfort in temperature set points, which do not overlap with the other occupants (TDs below 0.5). Therefore, the KB-HBI-TC strategy calculates a set point (23.30 °C), which results in the TDs below 0.5 for occupant 5 and occupant 6 while keeping TD for occupant 4 below 2, and minimizes airflow rates. Using this strategy

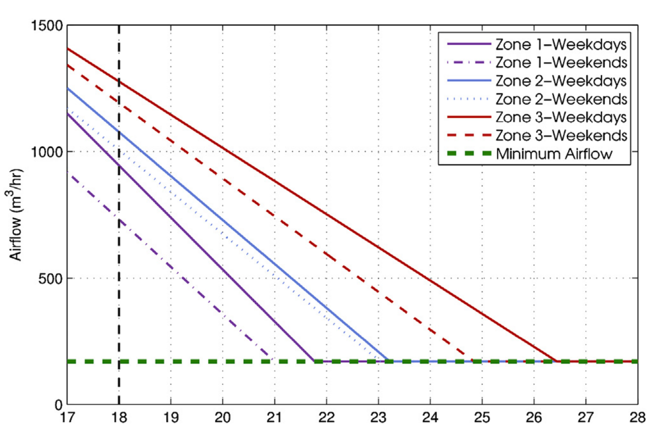


Fig. 11. Airflow-set point relations driven from the linear regression analysis.

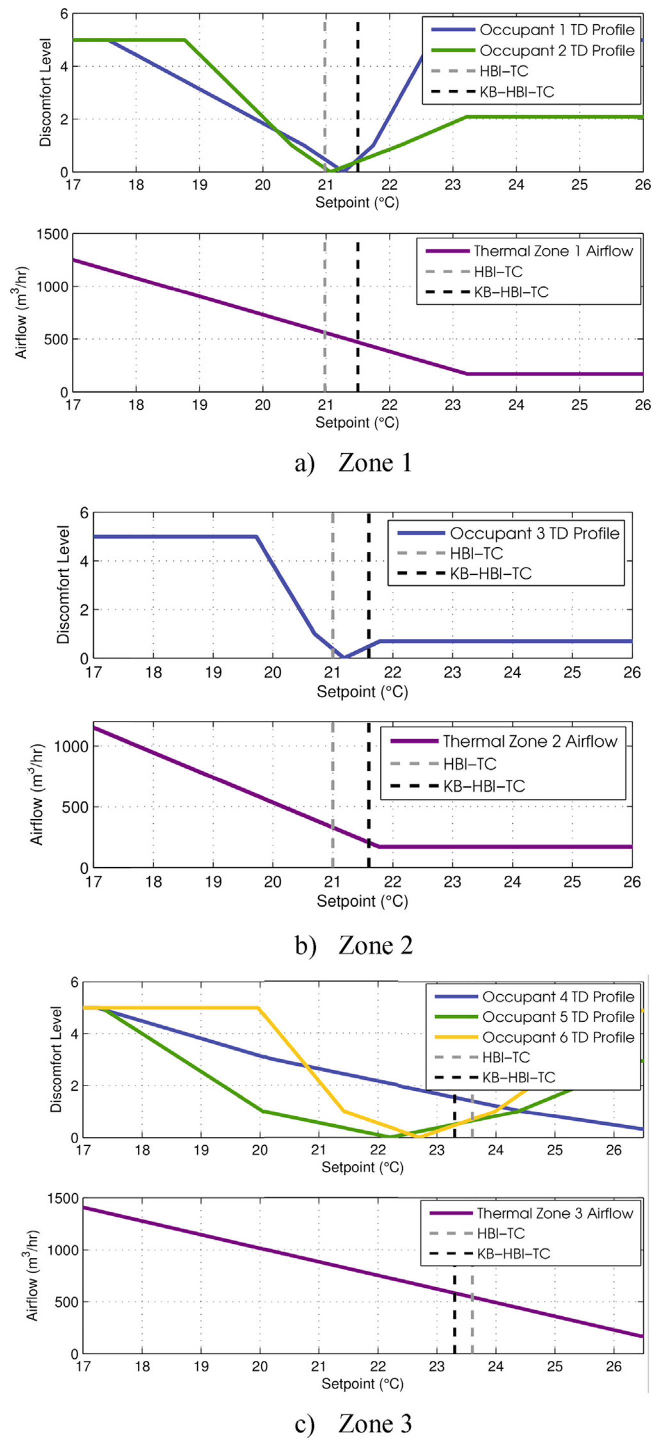


Fig. 12. Thermal discomfort (TD) and energy consequences consequences of different operational strategies for three zones.

increases the average daily airflow rates by 7.3% (39.6 m^3/h), compared to the HBI-TC strategy.

7. Discussion

The accuracy of the room temperature model directly influences the zone level thermal discomfort profiles and therefore, the optimization problems' results. More complex approaches can be used in the heuristic approach for understanding the relationship between room temperatures, set points, and airflow rates, as they are the core variables in solving the optimization problem. In addition, in climate zone such as continental and polar [43], the heating at the zone level (VAV box) could grow to significant amounts. Therefore, the energy consumption measure in the objective functions of the optimization problems should also include zone level heating as explained in Section 4.2. In order to integrate the two terms (i.e., airflow and heating) in the objective function, a utility function that maps them to a scalar function can be defined. Variables influencing the utility function may include resource availability and expenditures and owner preferences. Applying the methodology introduced in this paper can achieve energy-aware and comfort-driven operations in office buildings, however large-scale experiments could be needed for further validation of the approach. Currently, the authors are in the process of collecting personalized thermal comfort data from several occupants. As part of our future work, we plan to use the personalized comfort data to study how we can identify the thresholds for comfort and discomfort, using probabilistic machine learning techniques. The approach presented in this paper is for daily set points and does not take into account fluctuations in daily preferences. However, if there is a change in occupants' preferences in long term, the approach updates occupants' preferences online. We assume HVAC system responds to the changes in set points however, in some cases, this may not be the case due to aging or incorrect operational configurations. Another assumption is for a specific set point, and room temperatures do not have high fluctuations that result in comfort violations during the daily operations of a building. This assumption has to be methodically studied in future studies. We adapted a maximum allowable discomfort value for iterative relaxing algorithm in our test bed, however personal thermal adaptation is an important factor that can help selecting the maximum allowable discomfort value and can be the subject of another study. Finally, the mathematical models and selected parameters that were used to generate the models could also be tested in other climatic zones and HVAC types.

8. Conclusions

In this study, a knowledge-based approach, which couples occupants' personalized thermal comfort and zone level energy consumption, and selects comfort-driven and energy-aware temperature set points, is introduced. The proposed approach uses occupants' personal thermal comfort information, which is presented as fuzzy sets over a range of room temperatures to generate personal discomfort profiles. Personal discomfort profiles were transformed into zone level discomfort profiles, which express personal discomfort level as a function of zone temperature set points, using the room temperature profiles. Zone level energy consumption profiles, similar to the room temperature profiles, were constructed through measuring environmental, occupant and HVAC system related parameters and correlating them with airflow rates. Zone level personal discomfort and energy consumption models are then fed into an optimization problem for finding optimal set points. By specifying two rules (i.e., 0.5 for assuring comfort and 2 for maximum allowable discomfort) for individuals' discomfort values, a set point was selected. Considering a HVAC operation strategy that also considers occupancy information, this set point can be assigned as the set point for occupied periods. This set point minimized the energy consumption and maintained the required comfort level, while ensuring minimum airflow requirements are met. The results showed 12.08% (57.6 m^3/h). It is important to note that this saving was realized in addition to 39% savings of HBI-TC compared to the legacy BMS operations [17]. Reducing the airflow rates at the zone level improves the HVAC efficiency, as there is a direct relationship between airflow rates and building chilled water and electricity consumption. Defining different maximum allowable discomfort values and calculating the associated temperature set points and energy requirements integrated with real time occupancy information might help building managers to compare the consequences of different operational strategies and select thermal comfort-driven and energy-aware temperature set points.

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References

[1] M. Frontczak, P. Wargocki, Literature survey on how different factors influence human comfort in indoor environments, Building and Environment 46 (2011) 922–937.
[2] B.W. Olesen, International standards for the indoor environment, Indoor Air 14 (2004) 18–26.
[3] A. Standard, Thermal environmental conditions for human occupancy, in: Standard 55-2004, 2004.
[4] A. Standard, Ventilation for acceptable indoor air quality, in: Standard 62.1-2010, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., Atlanta, GA, 2010.
[5] R.Z. Freire, G.H. Oliveira, N. Mendes, Predictive controllers for thermal comfort optimization and energy savings, Energy and Buildings 40 (2008) 1353–1365.
[6] US Department of Energy, B.E.D. Book, 2011, US Department of Energy, 2010.
[7] T. Hoyt, K.H. Lee, H. Zhang, E. Arens, T. Webster, Energy Savings from Extended Air Temperature Setpoints and Reductions in Room Air Mixing, 2009.
[8] V.L. Erickson, A.E. Cerpa, Thermovote: Participatory Sensing for Efficient Building HVAC Conditioning, 2012, pp. 9–16.
[9] M. Feldmeier, J.A. Paradiso, Personalized HVAC Control System, 2010, pp. 1–8.
[10] D. Daum, F. Haldi, N. Morel, A personalized measure of thermal comfort for building controls, Building and Environment 46 (2011) 3–11.
[11] J.D. Hewlett, M. Manic, C.G. Rieger, WESBES. A Wireless Embedded Sensor for Improving Human Comfort Metrics Using Temporospatially Correlated Data, 2012, pp. 31–36.
[12] Y. Murakami, M. Terano, K. Mizutani, M. Harada, S. Kuno, Field experiments on energy consumption and thermal comfort in the office environment controlled by occupants' requirements from PC terminal, Building and Environment 42 (2007) 4022–4027.
[13] P. Bermejo, L. Redondo, D.L. Ossa, D. Rodriguez, J. Flores, C. Urea, J.A. Gamez, J.M. Puerta, Design and simulation of a thermal comfort adaptive system based on fuzzy logic and on-line learning, Energy and Buildings 49 (2012) 367–379.
[14] A. Auliciems, S.V. Szokolay, Thermal Comfort, 1997.
[15] J.F. Nicol, M.A. Humphreys, Adaptive thermal comfort and sustainable thermal standards for buildings, Energy and Buildings 34 (2002) 563–572.
[16] F. Jazizadeh, A. Ghahramani, B. Becerik-Gerber, T. Kichkaylo, M. Orosz, Human–building interaction framework for personalized thermal comfort-driven systems in office buildings, Journal of Computing in Civil Engineering 28.1 (2013) 2–16.
[17] F. Jazizadeh, A. Ghahramani, B. Becerik-Gerber, T. Kichkaylo, M. Orosz, User-led decentralized thermal comfort driven HVAC operations for improved efficiency in office buildings, Energy and Buildings 70 (2014) 398–410.
[18] S. Wang, Z. Ma, Supervisory and optimal control of building HVAC systems: a review, HVAC&R Research 14 (2008) 3–32.
[19] A. Costa, M. Keane, P. Raftery, J. O'Donnell, Key Factors—Methodology for Enhancement and Support of Building Energy Performance, 2009.
[20] P.O. Fanger, Thermal Comfort. Analysis and Applications in Environmental Engineering, 1970.
[21] A.I. Dounis, C. Caraiscos, Advanced control systems engineering for energy and comfort management in a building environment—a review, Renewable and Sustainable Energy Reviews 13 (2009) 1246–1261.

[22] W. Guo, M. Zhou, Technologies Toward Thermal Comfort-based and Energy-efficient HVAC Systems: A Review, 2009, pp. 3883–3888.
[23] N. Nassif, S. Kajl, R. Sabourin, Optimization of HVAC control system strategy using two-objective genetic algorithm, HVAC&R Research 11 (2005) 459–486.
[24] G. Zheng, M. Zaheer-Uddin, Optimization of thermal processes in a variable air volume HVAC system, Energy 21 (1996) 407–420.
[25] N. Nassif, S. Moujaes, A cost-effective operating strategy to reduce energy consumption in a HVAC system, International Journal of Energy Research 32 (2008) 543–558.
[26] M. Gouda, S. Danaher, C. Underwood, Thermal comfort based fuzzy logic controller, Building Services Engineering Research and Technology 22 (2001) 237–253.
[27] J. Liang, R. Du, Thermal Comfort Control Based on Neural Network for HVAC Application, 2005, pp. 819–824.
[28] N. Nassif, S. Kajl, R. Sabourin, Two-objective on-line optimization of supervisory control strategy, Building Services Engineering Research and Technology 25 (2004) 241–251.
[29] M. Nowak, A. Urbaniak, Utilization of Intelligent Control Algorithms for Thermal Comfort Optimization and Energy Saving, 2011, pp. 270–274.
[30] P.M. Ferreira, A. Ruano, S. Silva, E. Conceição, Neural networks based predictive control for thermal comfort and energy savings in public buildings, Energy and Buildings 55 (2012) 238–251.
[31] K.F. Fong, V.I. Hanby, T. Chow, HVAC system optimization for energy management by evolutionary programming, Energy and Buildings 38 (2006) 220–231.
[32] G.S. Brager, R.J. de Dear, Thermal adaptation in the built environment: a literature review, Energy and Buildings 27 (1998) 83–96.
[33] F. Jazizadeh, B. Becerik-Gerber, Toward Adaptive Comfort Management in Office Buildings Using Participatory Sensing for End User Driven Control, 2012, pp. 1–8.
[34] F. Jazizadeh, F.M. Marin, B. Becerik-Gerber, A thermal preference scale for personalized comfort profile identification via participatory sensing, Building and Environment 68 (2013) 140–149.
[35] L. Wang, The WM method completed: a flexible fuzzy system approach to data mining, IEEE Transactions on Fuzzy Systems 11 (2003) 768–782.
[36] T. Teixeira, G. Dublon, A. Savvides, A survey of human-sensing: methods for detecting presence, count, location, track, and identity, ACM Computing Surveys 5 (2010).
[37] R.W. Haines, M. Myers, HVAC Systems Design Handbook, fifth ed., McGraw-Hill, New York, NY, 2009.
[38] Energy Information Administration, 1992 Commercial Buildings Energy Consumption Survey (CBECS), End-Use Equipment Tables, Tables A44 and A45, 1992.
[39] Energy Information Administration, 1995 Commercial Buildings Energy Consumption Survey (CBECS), End-Use Equipment Tables, Tables 29 and 30, 1995.
[40] Energy Information Administration, 1999 Commercial Buildings Energy Consumption Survey (CBECS), End-Use Equipment Tables, Tables B33 and B35, 1999.
[41] Energy Information Administration, 2003 Commercial Buildings Energy Consumption Survey (CBECS), End-Use Equipment Tables, Tables B39 and B41, 2006.
[42] R.W. Haines, D.C. Hittle, Control Systems for Heating, Ventilating, and Air Conditioning, Springer, New York, NY, 2006.
[43] M.C. Peel, B.L. Finlayson, T.A. McMahon, Updated world map of the Köppen–Geiger climate classification, Hydrology and Earth System Sciences Discussions 4 (2007) 439–473.